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TITLE

Deep Learning and parallelization of Meta-heuristic Methods for IoT Cloud

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Presented by **Khelili Mohamed Akram**

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Abstract

Healthcare 4.0 is one of the Fourth Industrial Revolution's outcomes that make a big revolution in the medical field. Healthcare 4.0 came with more facilities advantages that improved the average life expectancy and reduced population mortality. This paradigm depends on intelligent medical devices (wearable devices, sensors), which are supposed to generate a massive amount of data that need to be analyzed and treated with appropriate data-driven algorithms powered by Artificial Intelligence such as machine learning and deep learning (DL). However, one of the most significant limits of DL techniques is the long time required for the training process. Meanwhile, the real-time application of DL techniques, especially in sensitive domains such as healthcare, is still an open question that needs to be treated. On the other hand, meta-heuristic achieved good results in optimizing machine learning models. The Internet of Things (IoT) integrates billions of smart devices that can communicate with one another with minimal human intervention. IoT technologies are crucial in enhancing several real-life smart applications that can improve life quality. Cloud Computing has emerged as a key enabler for IoT applications because it provides scalable and on-demand, anytime, anywhere access to the computing resources.

In this thesis, we are interested in improving the efficacity and performance of Computer-aided diagnosis systems in the medical field by decreasing the complexity of the model and increasing the quality of data. To accomplish this, three contributions have been proposed. First, we proposed a computer aid diagnosis system for neonatal seizures detection using metaheuristics and convolutional neural network (CNN) model to enhance the system's performance by optimizing the CNN model. Secondly, we focused our interest on the covid-19 pandemic and proposed a computer-aided diagnosis system for its detection. In this contribution, we investigate Marine Predator Algorithm to optimize the configuration of the CNN model that will improve the system's performance. In the third contribution, we aimed to improve the performance of the computer aid diagnosis system for covid-19. This contribution aims to discover the power of optimizing the data using different AI methods such as Principal Component Analysis (PCA), Discrete wavelet transform (DWT), and Teager Kaiser Energy Operator (TKEO). The proposed methods and the obtained results were validated with comparative studies using benchmark and public medical data.

Keywords: *healthcare 4.0*,*Neonatal seizures*, *Covid-19*, *Artificial Intelligence*, *Deep Learning*, *Marine Predator Algorithm*, *Principal Component Analysis*, *Discrete Wavelet Transform*, *Teager Kaiser Energy Operator*,*Cloud computing*, *IoT*.

Résumé

Healthcare 4.0 est l'un des résultats de la quatrième révolution industrielle qui fait une grande révolution dans le domaine médical. Le Healthcare 4.0 est venu avec plus d'avantages d'installations qui ont amélioré l'espérance de vie moyenne et réduit la mortalité de la population. Ce paradigme dépend des dispositifs médicaux intelligents (dispositifs portables, capteurs) qui sont censés générer une quantité massive de données qui doivent être analysées et traitées avec des algorithmes appropriés basés sur les données et alimentés par l'intelligence artificielle (IA), tels que l'apprentissage automatique et l'apprentissage en profondeur (AP). Cependant, l'une des limites les plus importantes des techniques AP est le long temps requis pour le processus de formation. Pendant ce temps, l'application en temps réel des techniques AP, en particulier dans des domaines sensibles tels que le domaine de la santé, reste une question ouverte qui doit être traitée. D'autre part, la méta-heuristique a obtenu de bons résultats dans l'optimisation des modèles d'apprentissage automatique. L'Internet des objets (IoT) intègre des milliards d'appareils intelligents qui peuvent communiquer entre eux avec une intervention humaine minimale. Les technologies IoT jouent un rôle crucial dans l'amélioration de plusieurs applications intelligentes réelles qui peuvent améliorer la qualité de vie. Le Cloud Computing est devenu un catalyseur clé pour l'application IoT en raison de sa capacité à fournir un accès évolutif et à la demande, à tout moment et en tout lieu aux ressources informatiques.

Dans cette thèse, nous nous intéressons à l'amélioration de l'efficacité et des performances des systèmes d'aide au diagnostic par ordinateur dans le domaine médical en diminuant la complexité du modèle et en augmentant la qualité des données. Pour ce faire, trois contributions ont été proposées. Premièrement, nous avons proposé un système d'aide au diagnostic informatique pour la détection des crises néonatales à l'aide de métaheuristiques et du modèle réseau de neurones convolutifs (RNC) afin d'améliorer les performances du système en optimisant le modèle RNC. Dans un second temps, nous avons focalisé notre intérêt sur la pandémie de covid-19 et proposé un système de diagnostic informatique pour sa détection. Dans cette contribution, nous étudions l'algorithme Marine Predator pour optimiser la configuration du modèle RNC qui améliorera les performances du système. Dans la troisième contribution, nous avons cherché à améliorer les performances du système d'aide au diagnostic informatique pour le covid-19. L'idée de cette contribution est de découvrir la puissance de l'optimisation des données en utilisant différents types de méthodes d'IA telles que Analyse des Composants Principales (ACP), Transformation en Ondelettes Discrètes (TOD), Operateur d'Energie Teager Kaiser (OETK). Les méthodes proposées et les résultats obtenus validés par des études comparatives utilisant des données médicales de référence et publiques.

Mots clés: *soins de santé 4.0*,*crises néonatales*, *Covid-19*, *intelligence artificielle*, *Aapprentissage en profondeur*, *algorithme des prédateurs marins*, *analyse des composants principales*, *transformation en ondelettes discrètes*, *Operateur d'Energie Teager Kaiser*, *Cloud computing* , *IoT*.

الملخص

الرعاية الصحية ٤.٠ هي إحدى نتائج الثورة الصناعية الرابعة التي أحدثت ثورة كبيرة في المجال الطبي. جاءت الرعاية الصحية ٤.٠ مع المزيد من مزايا المرافق التي حسنت متوسط العمر المتوقع وخفضت وفيات السكان. يعتمد هذا النموذج على الأجهزة الطبية الذكية (الأجهزة القابلة للارتداء، وأجهزة الاستشعار) التي من المفترض أن تولد كمية هائلة من البيانات التي تحتاج إلى تحليل ومعالجة باستخدام خوارزميات مناسبة تعتمد على البيانات مدعومة بالذكاء الاصطناعي مثل التعلم الآلي والتعلم العميق. ومع ذلك، فإن أحد أكثر حدود تقنيات التعلم العميق هو الوقت الطويل اللازم لعملية التدريب. في حين التطبيق الآني لتقنية التعلم العميق، خاصة في المجالات الحساسة مثل مجال الرعاية الصحية يبقى سؤالًا مفتوحًا يحتاج إلى معالجة. من ناحية أخرى، حققت الأدلة العليا نتائج جيدة في تحسين نماذج التعلم الآلي. تدمج إنترنت الأشياء مليارات الأجهزة الذكية التي يمكنها التواصل مع بعضها البعض بأقل تدخل بشري. تلعب تقنيات إنترنت الأشياء دورًا مهمًا في تعزيز العديد من التطبيقات الذكية الواقعية التي يمكنها تحسين جودة الحياة. برزت الحوسبة السحابية لتكون عاملاً تمكيني رئيسيًا لتطبيق إنترنت الأشياء نظرًا لقدرتها على توفير خدمات الوصول إلى موارد الحوسبة بطرق قابلة للتطوير وعند الطلب في أي وقت وفي أي مكان. في هذه الرسالة، نهتم بتحسين كفاءة وأداء أنظمة التشخيص بمساعدة الكمبيوتر في المجال الطبي من خلال تقليل تعقيد النموذج وزيادة جودة البيانات. ولتحقيق ذلك، تم اقتراح ثلاث مساهمات. أولاً، اقترحنا نظام تشخيص المساعدة الحاسوبية لإكتشاف نوبات حديثي الولادة باستخدام الشبكة العصبية التلافيفية والأدلة العليا من أجل تحسين أداء النظام من خلال تحسين النموذج. ثانيًا، ركزنا اهتمامنا على جائحة كوفيد ١٩ واقترحنا نظام التشخيص الحاسوبي لاكتشافه. في هذه المساهمة، قمنا بدراسة خوارزمية المفترس البحري لتحسين تكوين نموذج الشبكة العصبية التلافيفية الذي من شأنه تحسين أداء النظام. في المساهمة الثالثة، هدفنا إلى تحسين أداء نظام تشخيص المساعدة الحاسوبية لفيروس كوفيد ١٩. تتمثل فكرة هذه المساهمة في اكتشاف قوة تحسين البيانات باستخدام أنواع مختلفة من أساليب الذكاء الاصطناعي مثل: تحليل المكونات الأساسية، تحويل الموجات المنفصلة ومشغل الطاقة تيقر كيسر. تم التحقق من صحة الطرق المقترحة والنتائج التي تم الحصول عليها من خلال الدراسات المقارنة باستخدام البيانات الطبية المعيارية والعامة.

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LIST OF PUBLICATIONS

Journal Papers

1. Khelili Mohamed Akram, Slatnia Sihem, Kazar Okba, and Harous Saad. "IoMT-fog-cloud based architecture for Covid-19 detection". Biomedical Signal Processing and Control. 2022, vol: 76, 103715.
   Doi: https://doi.org/10.1016/j.bspc.2022.103715.

2. Khelili Mohamed Akram, Slatnia Sihem, Kazar Okba, Mirjalili Seyedali, Bourekkache Samir, Ortiz Guadalupe and Jiang Yizhang. "New bio-inspired approach for deep learning techniques applied to neonatal seizures". International Journal of Medical Engineering and Informatics. 2022.
   Doi: 10.1504/IJMEI.2022.10046880. (In Press).

3. Khelili Mohamed Akram, Slatnia Sihem, Kazar Okba, merizig Abdelhak, and Mirjalili Seyedali. "Deep Learning and Metaheuristics application in Internet of Things: A literature review". Microprocessors and Microsystems. 2022.(In Press).

Conference Papers

1. Khelili Mohamed Akram, Slatnia Sihem, and Kazar Okba. "Convolution Neural network based Marine Predator Algorithm for COVID-19 detection". 2021 International Conference on Information Systems and Advanced Technologies (ICISAT). IEEE, Doi: 2021.10.1109/ICISAT54145.2021.9678468.

2. Khelili Mohamed Akram, Slatnia Sihem, and Kazar Okba. "Deep Learning Technique for Covid-19 Detection". The Eurasia Proceedings of Health, Environment and Life Sciences 1 (2021): 15-19, Doi: https://doi.org/10.55549/ephels.3.

Chapter book

1. Khelili Mohamed Akram, Slatnia Sihem, and Kazar Okba (2021). "Covid-19 variants and vaccines: An overview". In M. Ozaslan Y. Junejo (Eds.), Current Studies in Basic Sciences, Engineering and Technology 2021(pp.276-288). ISRES Publishing.

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In the first, dedicate my dissertation work to **my Mother: Safia, Father: Abd ElAziz, Grandfather: Said, and Grandmother: Naziha.**

I dedicate this work to my:
Brothers: Samer, Iheb, Mondher, Mohamed, Anas, Amir, Ishak, and Adam.
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I dedicate this work to **my Lovely** friends **Amira Benterki, Ali Benammar, Nardjes Sehaibi, Imene Latreche, and Imad Tibermacine.**

Contents

List of Figures

List of Tables

List of abbreviations

NS	Neonatal Seizures
Covid-19	coronavirus disease 2019
AI	Artificial Intelligence
AUC	Area Under Curve
CAD	Computer-Aided Diagnosis
CNN	Convolutional neural networks
CT	Computed Tomography
RNN	Recurrent Neural Network
DL	Deep Learning
LSTM	Long Short-Term Memory
GAN	Generative Adversarial Networks
RBM	Restricted Boltzmann Machines
DBN	Deep Belief Network
DBM	Deep Boltzmann Machines
AE	Autoencoder
DAE	Denoising Autoencoder
SDAE	Stacked (Denoising)Autoencoders
QoS	Quality of Service
EAs	Evolutionary Algorithms
GA	Genetic algorithm
SI	Swarm intelligence
PSO	Particle Swarm Optimization
ACO	Ant Colony Optimization
AIS	Artificial Immune Systems

NSA	Negative Selection Algorithms
CLONALG	Clonal Selection Algorithm
opt-AINET	optimization version of Artificial Immune Network
CRO	Chemical Reaction Optimization
GBMO	Gases Brownian Motion Optimization
HS	Harmony Search
MMC	Method of Musical Composition
BOA	Base Optimization Algorithm
SCA	Sine Cosine Algorithm
SA	Simulated Annealing
GSA	Gravitational Search Algorithm
TLBO	Teaching Learning-Based Optimization
LCA	League Championship Algorithm
TS	TABU SEARCH
VNS	Variable Neighborhood Search
POPMUSIC	Partial Optimization Metaheuristic Under Special Intensification Conditions
IoT	Internet of Things
ECG	ElectroCardioGraphy
RFID	Radio-Frequency Identification
EPC	Electronic Product Code
NFC	Near Field Communication
LR-WPAN	Low-Rate Wireless Personal Area Network
FFD	Full-Function Devices
RFD	Reduced Function Devices

PAN	Personal Area Network
WLAN	Wireless Local Area Network
WiMAX	Worldwide interoperability for Microwave Access
Wi-Fi	Wireless Fidelity
WSN	Wireless sensor networks
DNA	Deoxyribonucleic Acid
CoAP	Constrained Application Protocol
HTTP	Hypertext Transfer Protocol
IETF	Internet Engineer Task Force
MQTT	Message Queue Telemetry Transport
XMPP	Extensible Messaging and Presence Protocol
TCP/IP	Transmission Control Protocol/Internet Protocol
LoWPAN	Low-power Wireless Personal Area Networks
SaaS	Software as a Service
PaaS	Platform as a Service
IaaS	Infrastructure as a Service
CaaS	Container as a Service
GPUs	Graphics Processing Units
SLAs	Service Level Agreements
CNS	Central Nervous System
WHO	World Health Organization
IoMT	Internet of Medical Things
AF	Atrial Fibrillation
BSN	Body Sensor Network

DNN	Deep Neural Network
DCNN	Deep Convolution Neural Network
MLP	Multi Layer Perceptron
BCI	Brain Computer Interface
EMR	Electronic Medical Record
EMG	ElectroMyoGram
AED	AntiepilEptic Drugs
ICT	Information and Communications Technology
ITS	Intelligent Transport Systems
EEG	ElectroEncephaloGram
aEEG	amplitude-integrated EEG
ICA	Independent Component Analysis
K-ICA	Kurtosis-ICA
SOBI	Second-Order Blind Identification
CHB-MIT	Children's Hospital Boston and the Massachusetts Institute of Technology
MRI	Magnetic Resonance Imaging
MEG	Magnetoencephalography
FPR	False Prediction Rates
SWT	Stationary Wavelet Transform
cEEG	continuous conventional ElectroEncephalography
ANSeR	Algorithm for Neonatal Seizure Recognition
SVM	Support Vector Machine
PET	Positron Emission Tomography

NICUs	Neonatal Intensive Care Units
MPA	Marine Predator Algorithm
GWO	Grey wolf optimizer
WHO	Whale Optimization Algorithm
ABC	Artificial Bee Colony
FADS	Fish Aggregating Devices
NLP	Natural Language Processing
PFD	Petrosian Fractal Dimension
IQR	InterQuartile Range
BW	Birth Wight
HIE	hypoxic-Ischemic Encephalopathy
GA	Gestational Age
PMA	Post-Menstrual Age
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
CM	Confusion Matrix
IFC-Covid	IoMT–fog–cloud-based Covid-19
PC	Personal Computers
AKA	Authenticated Key Agreement
CRL	Certificate Revocation List
OCSP	Online Certificate Status Protocol
ECC	Elliptic-Curve Cryptography

PFHD	Privacy-Preserving Fog-Assisted Information Sharing Scheme
MECC	Modified Elliptic Curve Cryptography
FHE	Fully Homomorphic Encryption Scheme
EVS	Enhanced Value Substitution
PCA	Principal Component Analysis
DWT	Discrete Wavelet Transform
SWEE	Shannon Wavelet Entropy Energy
LEE	Log Energy Entropy
TPR	True Positive Rate
FPR	False Positive Rate
SNR	Signal-to-Noise Ratio
PSNR	Peak Signal-to-Noise Ratio
ROC	Receiver Operating Characteristic Curve
EWT	Empirical Wavelet Transform
GPU	Graphics Processing Unit
RAM	Random Access Memory

Chapter I

General introduction

1 Context

Healthcare 4.0 paradigm emerged as the new innovation of the conventional healthcare sector, which used to be more flexible, data-driven, and patient-centric healthcare [11]. This new paradigm provides intelligent medical devices (wearable devices, sensors) which supposed to generate a massive amount of data that need to be analyzed and treated with appropriate technologies such as machine learning and deep learning [12].

This modern healthcare system largely relies on cross-organizational services that encourage customization and personalized healthcare help and support through the use of big data analytics [13]. In the context of healthcare systems, enabling technologies such as data analytics and recommender systems offer enormous research potential. As a result of this transition, individualized suggestions may be delivered to patients suffering from various ailments through supporting technology [14].

The healthcare industry might be further divided into physical healthcare such as Covid-19 and mental healthcare such as Seizures [15]. The healthcare 4.0 community used to reduce population mortality and improve average life span. Generally, this healthcare system is built on two pillars: Physical components (patient) and virtual components (cloud computing, fog computing, and other self-contained systems) [16]. For this context, several devices need to be connected, and a huge amount of data will be generated. One of the most challenging tasks is how this data could be analyzed? And how much time this analysis takes?

Meanwhile, real-time analysis of this data might be highly beneficial in illness detection, online monitoring of patients' symptoms by doctors, and computer-aided diagnosis advantages that improve the healthcare industry in many ways. Because of advanced technologies such as machine learning and deep learning, for diagnosis analysis on the first side and metaheuristic, and other optimization techniques such as Entropy variants, Principal Component Analytics, Wavelet transform, and so on, artificial intelligence is critical to all of this development and achievement.

Depending on the desired problem, diagnostic analysis techniques are used for various purposes such as classification, prediction, grouping, and regression. The most common criticisms for selecting the most appropriate technology are: for the first stage, the problem itself (its objectives and consequences), and for the second step, the data, which includes the nature of the data and how it is kept or stored.

2 Problem statements

In this thesis we tackle, in the first, the problem of developing an accurate system to assist the neurologist in recognizing seizures in newborn infants. Seizure is one of the prevalent diseases related to the mental healthcare which is a synchronized electrical discharge (depolarization) of a group of neurons in the central nervous system that is aberrant [17]. However, children are the most impacted by seizures, particularly during the newborn period. Moreover, this neurological event might be caused by several conditions [18] [19], which make serious risks on the newborn's mental health and might lead to the infant's death. Many states of the art are done in the field of neonatal seizure detection; however, this subject does not achieve remarkable outcomes because of the nature of this illness and the lack of sufficient data. For these reasons, neonatal seizure detection is still an open, challenging task that needs an accurate and efficient treatment.

The auto-detection of the presence of seizures in newborn infants is one of the most challenging tasks due to the difficulties in detecting the abnormalities in the EEG signal of infant, the absence of additional clinical data from neurologists, the various types of neonatal seizures which result variety of features that need to be considered, lack of datasets. On the other hand, choosing an appropriate DL model with accurate parameters is still one of the big problems in the optimization tasks because it relies on the complexity of the system and the time required for the training process. Therefore, several questions could be posed in this context related to: The impact of data quality on the performance of neonatal seizure computer-aided diagnosis, the lack of neonatal seizures data, the way of detecting the abnormal phases in the signal records, the choice of channels that have to be focused on in the feature extraction phase of the seizures, the advantages of combining between the EEG records of patients and their clinical data, and the impact of optimizing the model on the performance of neonatal seizures detection.

In the second part of this thesis, we focused our interest on the newest worldwide pandemic, Covid-19, that threatens the health of humanity. With the mutation of the virus over time and the absence of an accurate drug, precautions and early detection are still the best ways to limit the spread of this virus. Therefore, various techniques were used by the community of researchers for their detection, such as X-ray images and CT-scan images. However, the first limitation in their work is the similarity of features of covid-19 images and the other lung diseases such as Pneumonia. Also, the use of small datasets is still an open question. Moreover, using pre-trained models in the medical field will give good results and sometimes wrong ones, especially in terms of specification. For instance, using a pre-trained model on numbers for detecting the Covid-19 from an image did not yield good results. Furthermore, optimizing the whole system still challenged tasks that need improvement. To overcome these limitations, several tasks need to be treated, such as the lack of Covid-19 data, the similarity between the Covid-19 and Pneumonia disease, the impact of the quality of data in improving the performance of the system, the best way to reduce the complexity of the whole system depends on optimizing the model or the data, and the possibility to improve the quality of service of this system and make them friendly user.

3 Contributions

To overcome the aforementioned problems, we proposed three contributions:

New bio-inspired approach for deep learning techniques applied to neonatal

seizures: The first contribution proposed in this thesis is applying a deep learning model for neonatal seizure detection. Public neonatal seizures dataset from NICU [20] were used to accomplish this contribution. The proposed system consists of:

- Data segmentation to fragment the newborn's complete signal into windows with the same number of channels but with a tiny number of samples (using Petrosian Fractal Dimension PFD).
- Preprocessing step to filter and analyze the band-pass of the windows generated from the previous step (using band-pass filtering, Z-Scores normalization, and Independent Component Analysis ICA).
- Augmented features to combine the features extracted from the previous step and combine it with the clinic data approved by the neurologists.
- In the Preparation of the model, we automatically select the accurate hyperparameters of the model using the new bio-inspired metaheuristic (Marine Predator Algorithm).
- The next step will be the Train of the model on the prepared dataset to obtain a trained model that will be used next.
- The last step in this contribution depends on identifying the presence or the absence of seizures in the newborn using the trained model.

Convolution Neural network based Marine Predator Algorithm for COVID-19 detection: The second contribution consists of classifying the worldwide pandemic, Covid-19 disease. To accomplish this work, we use public datasets containing multiple classes such as Pneumonia, Covid-19, and normal cases [21]. The main purpose of this contribution is:

- To improve the precision in detecting the covid-19 cases and differentiate it from the other similar diseases such as Pneumonia.
- To solve the problem of the imbalanced data used.
- To prove the impact of using different metaheuristics for auto-selection of the model's hyperparameters.
- To ensure the outperformance of our proposed MPA in optimizing the model,

which is, to the best of our knowledge, the first application for the Covid-19 detection.

The steps of achieving this contribution could be summarized as follow: in the first step, we preprocess our dataset by resizing images and transferring them to the grey scale. Also, we augmented our dataset by zooming and rotating the images. After pre-processing our dataset, we pass to the phase of preparing our CNN model by choosing the appropriate hyperparameters using the MPA. Then, we train this model on the prepared dataset.

IoMT-fog-cloud based architecture for Covid-19 detection: In the third contribution of our thesis, we focus on providing an IFC-Covid system that will be a real-time and effective application for covid-19 detection, which is user-friendly and cost less. In this contribution, we are interested in:

- Evaluating the impact of optimizing data in the full complexity of the system. To the best of our knowledge, this is the first use of hybrid methods for feature extractions such as PCA, TKEO, and Discrete Wavelet Transform, in the covid-19 detection.
- Proposing a system that provides an online service for classifying the covid-19 and pneumonia diseases.
- Solving the latency and computational cost of cloud computing and improving the QoS by introducing the fog as an intermediary layer.
- The use of Fog computing ensures the privacy and security of the patients' data.

To accomplish this contribution, we followed some steps, such as the Discrete Wavelet Transform (Biorthogonal 1.3) for decomposing the image into segments. Next, we apply the PCA module to extract the image's principle and most essential features, reducing the model's complexity. Then, we introduce the TKEO technique to track the energy in the image, which contains valuable data. Finally, in the following step, propose full Fog-Cloud computing architecture to fill the latency problem gap and improve the full system's QoS.

4 Thesis Structure

The rest of this thesis is organised as follows:

Chapter II introduces the basic concepts related to this thesis: Machine Learning, Metaheuristic, Big Data, Internet of Things, Cloud Computing, Healthcare, Neonatal Seizures, and Covid-19.

Chapter III presents the state-of-the-art works that done for healthcare 4.0 in general and in neonatal seizures and in Covid-19 specifically.

Chapter IV shows the first contribution of applying deep learning techniques for neonatal seizures to diagnose the presence of seizures. We begin our chapter by giving an overview of neonatal seizures; then, we provide details about the architecture of the used CNN, the MPA technique used in the auto-selection of the hyperparameters, data description, data preprocessing, and classification. Next, experimental results to demonstrate the effectiveness and performance of the system are provided. Finally, a conclusion and future work are presented.

Chapter V presents the second contribution, which focuses on applying a new metaheuristic technique with a deep learning technique to classify Covid-19 and Pneumonia diseases. First, we start our chapter with an overview of the covid-19, then we give details about the used dataset, CNN model, and the implementation of the MPA on the model. Next, we show the experimental analysis of the proposed system and conclude our chapter with a conclusion and future work.

Chapter VI introduces the third contribution of our thesis aims to test various AI methods on computer aid diagnosis systems for detecting the presence of covid-19 and pneumonia disease. To accomplish this work, we investigate different king of techniques such as DWT, PCA, and TKEO. First, we start our chapter with an overview of CAD systems used for covid-19 detection. Then, we show our proposed system with details of the components of each layer. Next, we present the deep learning model that we used in the system. After that, we give details about the different AI methods used for data preprocessing, such as DWT, PCA, and TKEO. At the end of the data preprocessing step, we pass this prepared dataset to our model and start the training phase. Also, we highlight our proposed system's experimental results, which reflect our system's performance. Finally, we conclude our chapter with a conclusion and future work.

ChapterVII Conclude the whole thesis by giving an overview of the problems treated and the suggested solutions. Also, we discuss the achieved results and then, we finalize with prescriptive and future work.

Chapter II

Preliminaries and Basic Concepts

1 Introduction

This chapter presents the main concepts related to our thesis and gives an overview of the domains we will use. Section 2 presents machine learning and its different categories. Section 3 gives an overview of deep learning and its different models. However, metaheuristic and their related concepts are introduced in section 4. Also, big data, IoT, and cloud computing are presented in sections 5,6, and 7. At the end of this chapter, we give an overview of neonatal seizures and covid-19 in sections 8 and 9.

2 Machine learning

Machine learning is a branch of Artificial Intelligence (AI) that emerged from pattern recognition to examine the data model and integrate it into patterns that people could understand and use [22]. A machine learning algorithm is a computing process that utilizes input data to accomplish a goal without being explicitly written to achieve that goal [23]. In literature, Tom Mitchell defined ML as “A computer program is said to learn from experience (E) with respect to some class of tasks (T) and performance measure (P), if its performance at tasks in T, as measured by P, improves with experience E” [24]. Also, Ethem Alpaydin presented it as the field of “Programming computers to optimize a performance criterion using example data or past experience" [25]. According to these definitions of ML, the main role of ML is to make the computer learn from various instances of the surrounding environment to accomplish specific tasks [23].

Nowadays, machine learning is integrated in the majority of technologies such as: facial recognition technology for tagging people in social media, recommendation engines for suggesting movies and other TV shows to the user, converting text images into editable types using Optical Character Recognition (OCR), Self-driving cars. As a result, machine learning is a constantly expanding and developing discipline in which some recognized and new issues must be addressed.

Machine learning is broadly classified as supervised, unsupervised, semi-supervised, reinforcement learning, and transfer learning. A supervised learning model has two major tasks: classification and regression. Classification is about predicting a nominal class label, whereas regression is about predicting the numeric value for the class label. [22].

According to the nature of training data, we can classify machine learning as follows (Figure II.1).

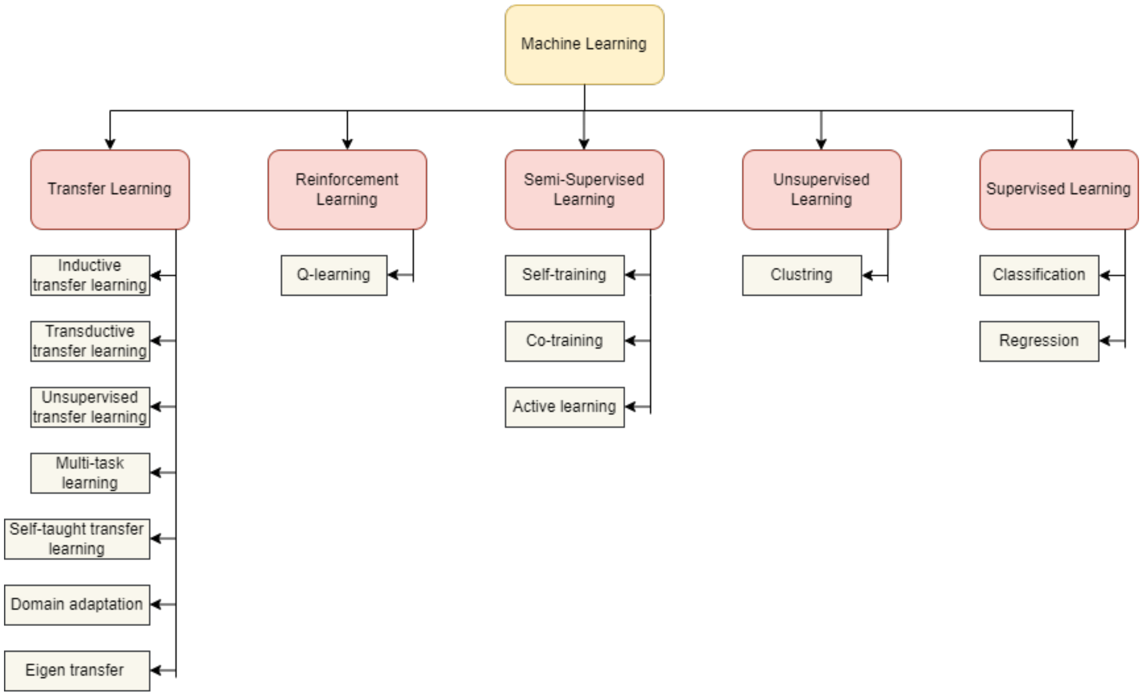

Figure II.1: Machine learning Classification

2.1 Supervised Learning

In the presence of an unexpected input instance, a supervised learning model is meant to provide predictions. The model in supervised learning employs a specified set of input datasets and their known responses to the data $(X_{train}, Y_{train}) = (x_1, y_1), ..., (x_l, y_l)$.The model is then trained using a learning algorithm to provide a forecast for the reaction to fresh data or the test dataset. For instance, supervised learning is like teaching a child how to read words. In the first step, you have to make them learn letters and then how to spell them. After that, you have to read words for them and make them repeat them to make them understand how to collect the letters and spell the full word. In this way, the child will be able to read by himself.
The majority of algorithms used for supervised learning used various algorithms such as linear regression, logistic regression, neural networks, decision tree, SVM, random forest, naive bayes, and k-nearest neighbor [26].

2.2 Unsupervised Learning

Unlike supervised learning, the unsupervised learning does not know previously what the output will be, and depend on the input that has not been tagged $X_{train} = X_u = x_1, ..., x_u$. The machine learner's primary duty is to find solutions on its own. This is analogous to assigning a group of patterns to a student and asking them to identify the underlying themes that formed the patterns. This means that the machine learns on its own and does not need the supervision [26].

2.3 Semi-supervised Learning

When a limited quantity of labeled data is discovered for a specific application, this learning approach mixes supervised and unsupervised learning. It produces a function mapping from labeled and unlabeled data inputs. Using the labeled information set, semi-supervised learning attempts to categorize some of the unlabeled data. The unlabeled dataset should be significantly bigger than the labeled data in a semi-supervised learning situation. Otherwise, supervised methods might be used to solve the problem. Real-world examples include protein sequence classification, online content categorization, and voice analysis, where categorizing audio recordings is a laborious operation that necessitates extensive human interaction. [22].

Semi-supervised learning may be classified into the following categories [26]:

- **Self-training** is semi-supervised learning that teaches itself based on its predictions.
- **Co-training** is weakly semi-supervised learning for multi-view data utilizing the co-training setup and teaching themselves using their predictions.
- **Active learning** is semi-supervised learning in which the student has an active or participatory involvement in deciding which data points to ask an expert or instructor to label.

2.4 Reinforcement learning

Interaction with the environment is required for reinforcement learning. Reinforcement learning considers how an autonomous agent that detects and acts in its environment may learn to select optimum behaviors to achieve its goals. The activities that an agent does in the environment are used to reward its behavior. It examines the repercussions of its activities and takes the best next measures. Examples of reinforcement learning include a computer playing chess with a person, learning to identify spoken phrases, and learning to categorize new astronomical formations [22].

2.5 Transfer learning

In many real-world applications, data distribution shifts or data becomes obsolete. As a result, transfer learning must be used to address knowledge transfer from the source domain to the target domain. Inductive transfer learning, transductive transfer learning, unsupervised transfer learning, multitask learning, self-taught transfer learning, domain adaptation, and EigenTransfer are examples of transfer learning [26].

3 Deep Learning

Deep Learning (DL) is an artificial intelligence discipline and a new branch of Machine Learning incepted by Hinton [27]. DL is based on building huge neural network models that can make correct data-driven judgments. It is a new branch of Machine Learning which involves a series of interconnected multiple processing layers. It is best used when the data is complicated, and there are vast datasets to work with. Nowadays, deep learning is used by the majority of internet businesses and high-end consumer devices. For instance, Facebook utilizes deep learning to examine the content in online interactions, among other things. Also, Deep learning is used by Google, Baidu, and Microsoft for image search and machine translation. Moreover, Deep learning algorithms run on all current smartphones; for example, deep learning is now the industry standard for digital camera speech recognition and facial identification. Furthermore, Deep learning is used in the healthcare industry to interpret medical pictures (X-rays, CT scans, and MRI scans) to diagnose health issues. Deep learning is also at the heart of self-driving cars, where it's utilized for things like localization and mapping, motion planning and steering, and perception of the surroundings, as well as tracking driver status [28].

Deep learning is one of the most successful innovations that bring revolution to the world in various domains. AlphaGo is a computer program that could play the Go game, developed by DeepMind technologies [29].

The first idea of deep learning refers to Hinton et al. in 2006 [27], when they created a Deep Neural Network (DNN). DL gained its interest from researchers when they applied it in different fields such as: natural language processing [30], image retrieval [31], Image recognition [32], search engines and information retrieval [33][34], etc. And it achieves excellent results in terms of performance [35]. The purpose of creating DL methods is to exceed the limitations of the traditional techniques, Artificial Neural Networks (ANNs) [36] and Multilayer Perceptrons (MLPs) [37] which are: First, the difficulty of training the modal with a large number of layers. Also, the overfitted models because of the small size of training data. Furthermore, the limitation in the computational capabilities of the hardware at that time [38]. However, DL methods, with their deep architecture and supervised or unsupervised learning techniques, gain a lot of advantages [39]. They use efficient techniques such as: Rectified Linear Units (ReLUs) [40] as activation function, dropout methods [41], flatten methods [42], optimizers [43], backpropagation and auto-updating the weights of the neurons, etc. [44].

One of the most potent characteristics of DL methods is the ability to extract hiding features from the input data. Another advantage of DL is the interconnectivity between the current layer and the previous layer, which makes the model combine the features of all layers. This combination makes the model learns complex features; for example: when the input is a cat picture, some filters are applied to this image. The first hidden layer extracts the features concerned with the shape of the cat, and the second one extracts the features of the color of the cat, etc. The last layer collects these features together to produce the cat image [45]. In general, a deep model is a model that uses two or more hidden layers with advanced methods.

According to [46], the general architecture of a deep neural network presented as follow:

- **Input layer** in this layer, several neurons are reserved to represent data in vectors, generate vectors of weights, and pass it as an output to the following layer.
- **Hidden layers** these layers also include neurons; they consider the previous layer's output as input and apply several processes to it, such as filtering, applying feature map, etc. Then, pass the resulting data to the final layer.
- **Output layer** receives the output of the last hidden layer and then collects them together to get the final result such as: classification, prediction, and loss function, obtained from the correct prediction and the wrong one, using optimization algorithms. After that, the training cycle will be repeated to adjust the weights until the error rate gets down and achieve a suitable threshold.

3.1 Convolutional Neural Network (CNN)

A convolutional neural network (CNN) used in various domains such as recognition, classification, detection, prediction, etc. The biggest advantage of convolutional neural networks that came with is the ability to automatically learn a broad and an abstract number of features in parallel training of the dataset under the constraints of a specific predictive modeling problem [47]. Due to the carefully designed architecture of CNN, especially the use of filters, convolutional layers, pooling layers, dense layer, etc. figure II.2, CNN achieved great success, making it applicable in several research areas. The first input layer of the CNN is specified to receive different dimensions of data such as 1D, 2D, and 3D, the most used is 2D inputs (i.e., images and audio signal) [47]. The hidden layers consist of kernels that can extract abstract features by applying some functions like the production, sum, etc., on vectors of weights that create the feature map and pass it to the dense layer. Also, poling layers are one of the hidden layers' components that reduce the input's dimensions. This sub-sampling or down-sampling of the input provides simultaneous loss of information that reduces the computational overhead of the next layers.

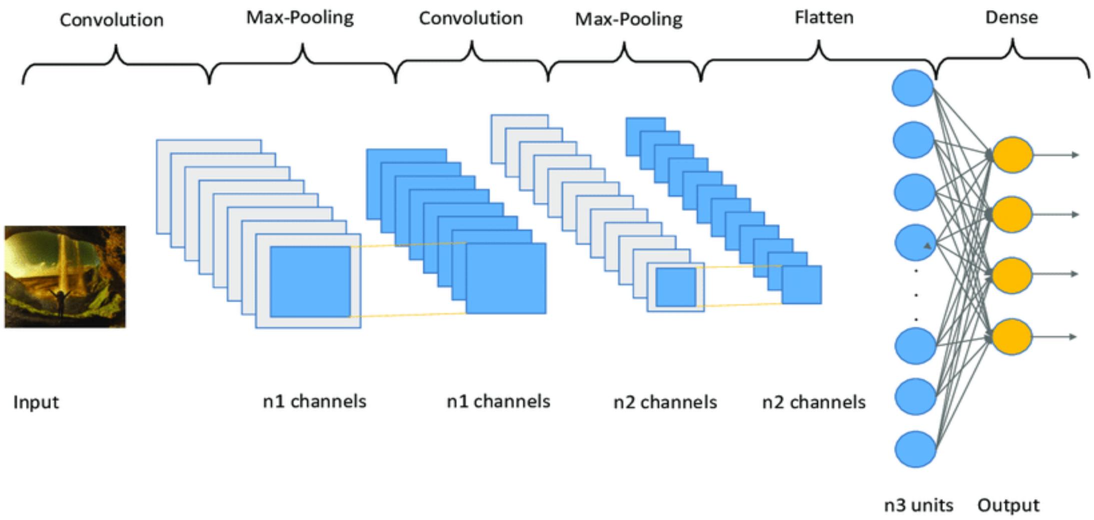

Figure II.2: Convolution Neural Network [1]

3.2 Recurrent Neural Network

A recurrent neural network (RNN) is a deep learning algorithm specialized in sequential or time-series data. Due to this specification, RNN is used for real-time issues, such as natural language processing (NLP), speech recognition, and image captioning [48]. One of the common problems of traditional deep neural networks is the independence of the input layer from the output layer, e.g., in the case of prediction the next word of a sentence, it is axiomatic that the previous words are required. Hence, there is a need to remember the last words. However, RNN came to solve this problem by adding new properties to the neural network model: the feed-forward and Backpropagation Through Time (BPTT). These properties create the dependency between the input and the output layers, which means that the output of the final layer (output layer) depends on the output of the first layer (input layer). Due to the internal memory in each neuron in the model, all the information and calculations of the current layer are saved and prepared to be delivered to the next layer Figure II.3. As a result, there is a reliance between the input and the output [49].

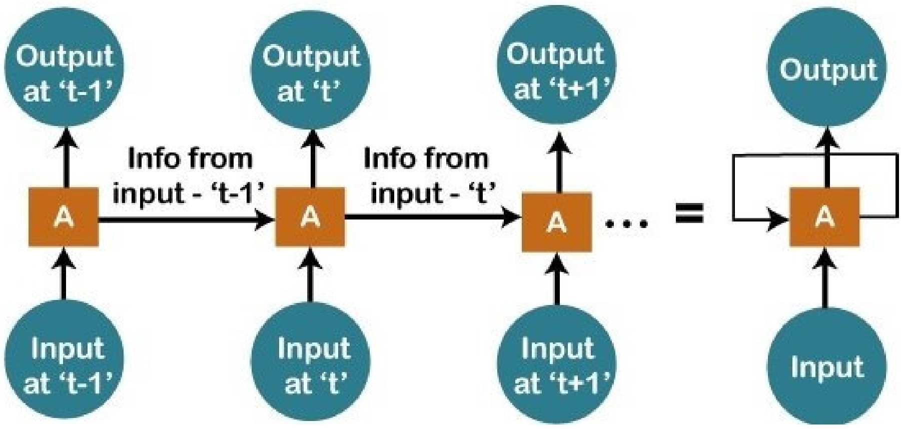

Figure II.3: Recurrent Neural Network [2]

3.3 Long short-term memory

Long short-term memory (LSTM) is a kind of recurrent neural network (RNN). The idea that LSTM came with is the possibility of connecting to previous neurons that allow feedback and store data by using a memory cell in each neuron. Unlike standard RNN, LSTM uses an input gate, an output gate, and a forget gate to manage memory cells' access Figure II.4. Forget gate has the most critical role in LSTM by applying some processes such as reading from the memory cells, writing in the memory cells, and deleting the content of the memory cells [50]. LSTM can be applied in several tasks such as unsegmented, connected handwriting recognition, speech recognition, and anomaly detection in network traffic. Moreover, Backpropagation Through Time (BPTT) decreases the error rate of LSTM, which gives it popularity to be used for different objectives like classification, prediction, and recognition [51].

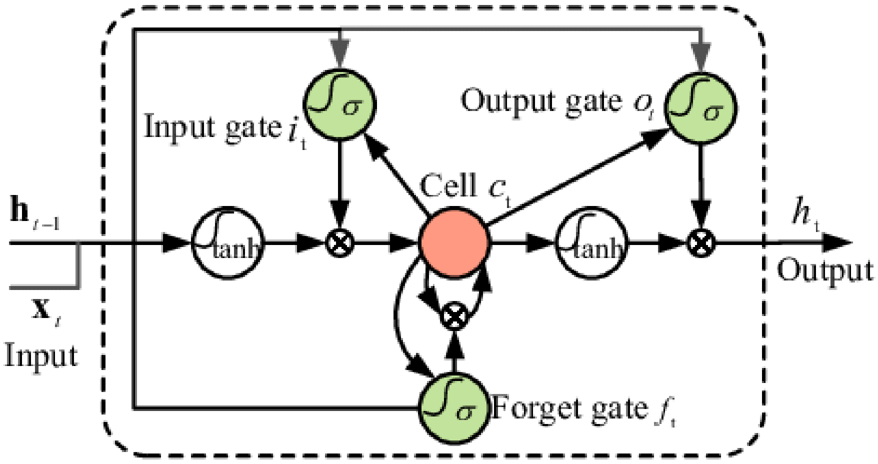

Figure II.4: Long short-term memory [3]

3.4 Generative adversarial network

A generative adversarial network (GAN) is a deep learning model introduced by Goodfellow et al. [52]. GANs are based on the minimax games' theory in generating new images using generative and discriminative networks(see Figure II.5). The main function of discriminative networks is to differentiate between input data and generative networks' data [53]. Due to this power of generation, GANs realized good results in several applications like image processing, natural language processing tasks, etc. [54].

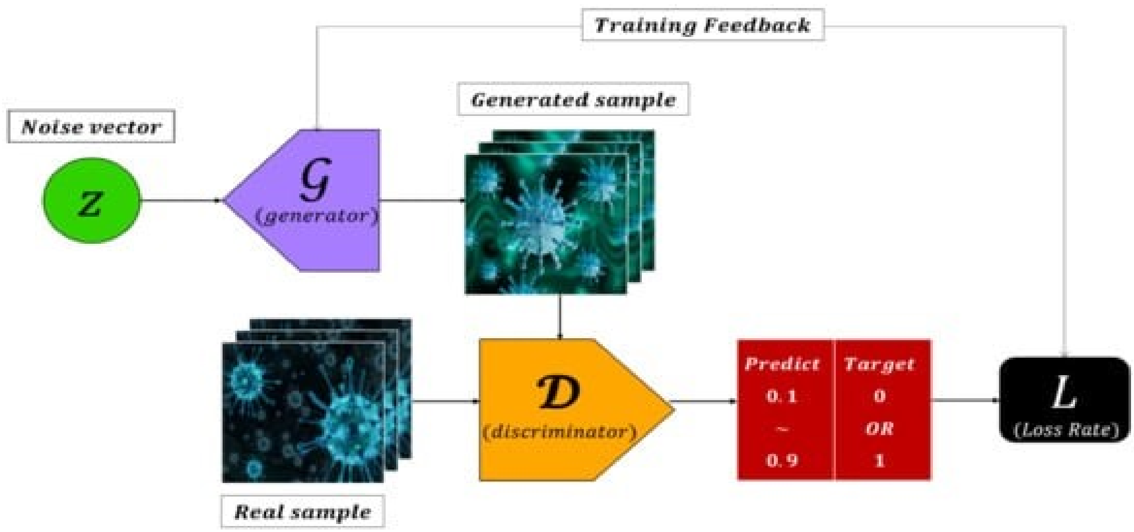

Figure II.5: Generative adversarial network [4]

3.5 Restricted Boltzmann Machines

Restricted Boltzmann Machines, one of the Boltzmann Machine's variants, is a generative stochastic neural network that forms a bipartite graphical model. The RBM model allows the connection between the visible variables and the hidden variables, which provides more efficient training algorithms [55] [56] as it is showed in the Figure II.6.

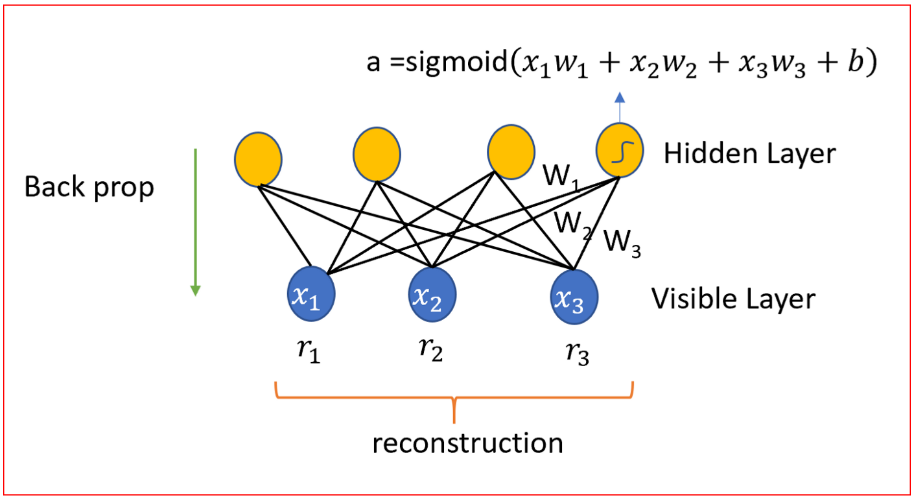

Figure II.6: Restricted Boltzmann Machine [5]

3.6 Deep Belief Network

Deep Belief Network, one of the Boltzmann Machine's variants, is a generative probabilistic model based on the RBM. The DBN is a graphical model that uses unsupervised greedy learning to learn and extract a deep hierarchical representation of the training data. [57]. The DBN's overall design is shown in Figure II.7, with the top two layers forming an undirected graphical model and the bottom levels forming a directed generative model. The main advantages of DBN architecture are ignoring the labeling phase of the data and ensuring the right initialization of the model's parameters.

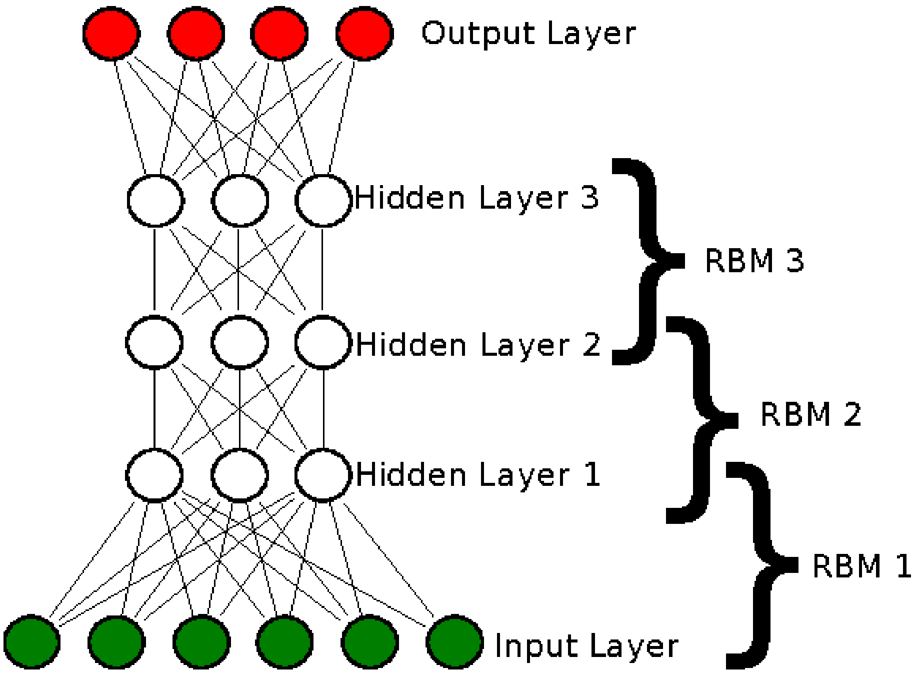

Figure II.7: Deep Belief Network [6]

3.7 Deep Boltzmann Machines

Deep Boltzmann Machines is an RBM-based model that uses a unidirectional connection between visible and hidden units. The DBM also used a greedy layer-wise training strategy [58] to train each layer separately from the other layers. Like DBN, the RBM uses stochastic maximum likelihood (SML) [59] as an optimizing technic to avoid the local minima. Figure II.8 represents the general architecture of DBM.

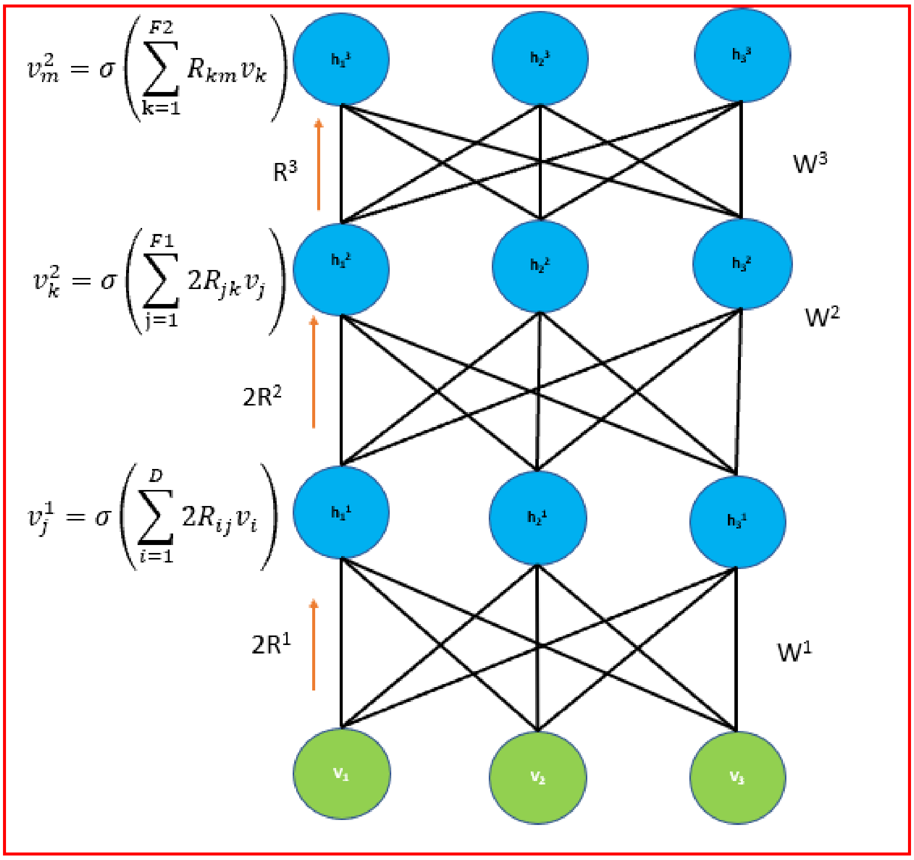

Figure II.8: Deep Boltzmann Machine [7]

3.8 Autoencoder

An autoencoder neural network is a symmetrical neural network that uses back-propagation to learn unsupervised features, with the goal value equal to the inputs. AEs have the same number of input and output units [60]. Similar to the premise of Principal Components Analysis, AEs employed encoding and decoding operations to build a representation from the inputs, often for dimensionality reduction, by training the network to disregard signal "noise". The basic goal of AEs is to develop a reconstructing side from a reduced encoding of a representation that is as near to its original input as feasible Figure II.9. There are several types of AEs, including denoising autoencoders, counteractive autoencoders, stacked autoencoders, sparse autoencoders, and variational autoencoders, each of which has demonstrated performance in a certain area, such as detection, recognition, and classification [53].

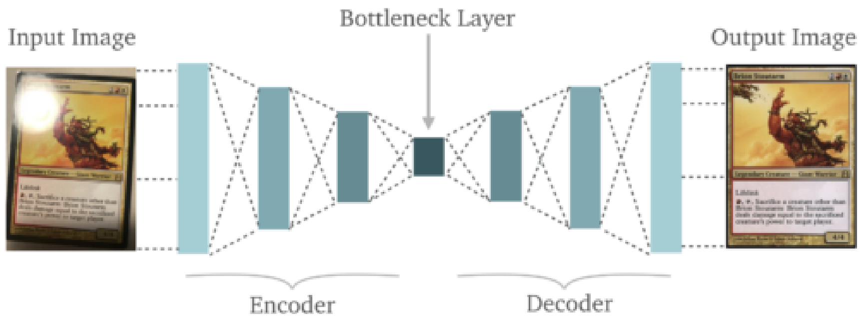

Figure II.9: Autoencoder [8]

3.9 Denoising Autoencoder

The denoising autoencoder [61] is a variation of the autoencoder that accepts both corrupted and uncorrupted input. In general, the denoising autoencoder encodes the input in the first stage before canceling the impact of the random corruption process applied to the autoencoder's input, where the stochastic corruption process sets a number of inputs to zero. Then, for randomly selected subsets of missing patterns, the denoising autoencoder attempts to predict the corrupted values from the uncorrupted ones, Figure II.10.

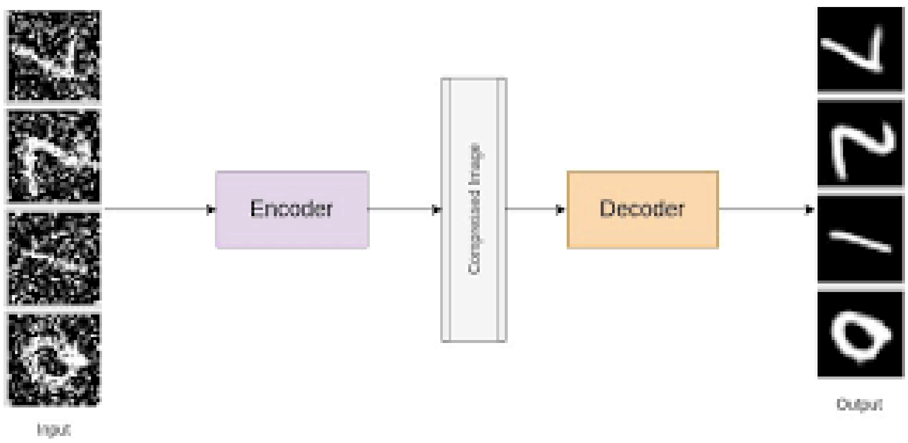

Figure II.10: Denoising Autoencoder [9]

3.10 Stacked (Denoising)Autoencoders

The primary purpose of stacking the denoising autoencoder is to create a deep network by feeding the denoising autoencoder's output layer to the next layer. Because its input is the preceding layer's output, each model layer is trained as a denoising autoencoder by reducing the error in reconstructing its input. After all layers have been pre-trained, the network moves on to the second step of training, known as fine-tuning. When the aim is to optimize prediction error on a supervised task, supervised fine-tuning is addressed. To that goal, a logistic regression layer is added to the network's output code of the output layer, Figure II.11. The resulting network is subsequently trained as a multilayer perceptron, with just the encoding components of each autoencoder considered at this stage. This level is monitored since the goal class is considered during the training [62].

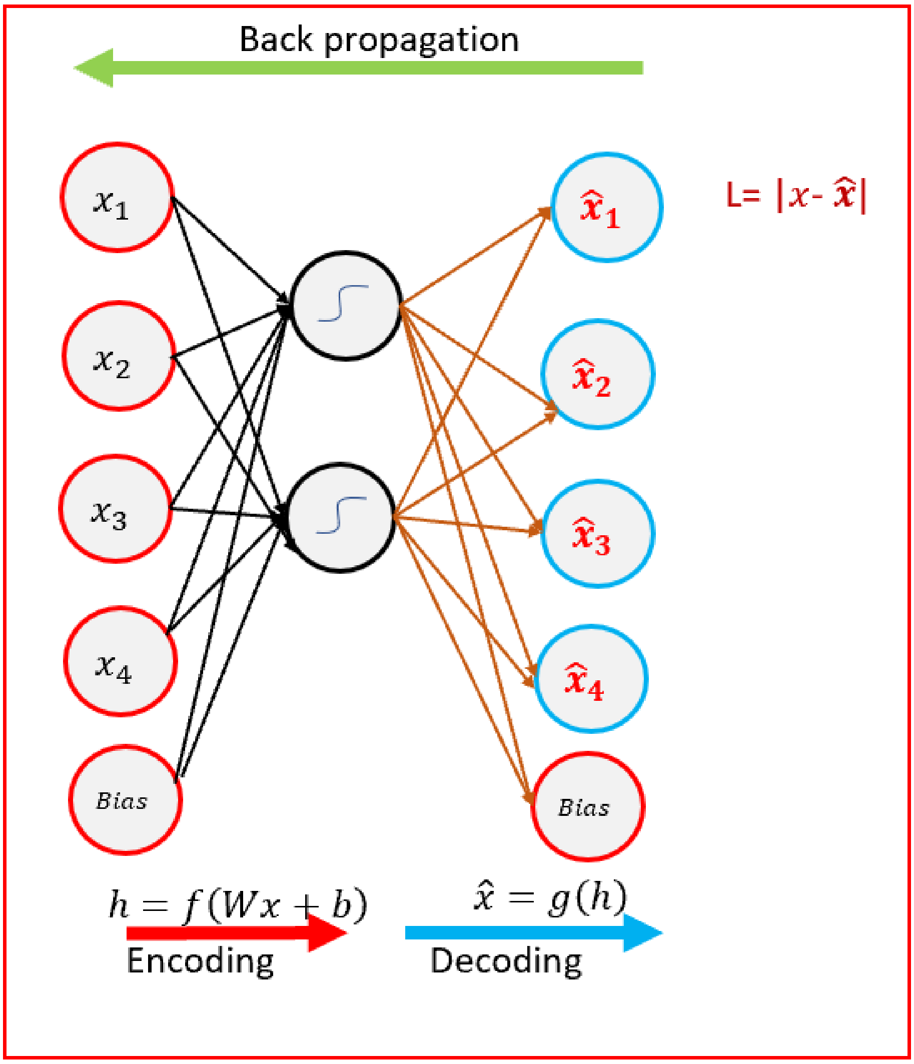

Figure II.11: Stacked (Denoising)Autoencoder [10]

4 Metaheuristic

Every day, engineers and decision-makers face more complicated difficulties in a variety of technological fields, such as operations research, mechanical system design, image processing, and, in particular, electronics. The situation at hand is frequently represented as an optimization problem [63]. The phrase optimization has numerous meanings, including lowering time, cost, and hazards; it might also be used to optimize profit, quality, and system efficiency. Because many real-life problems cannot be solved precisely in a short period of time, such as in science, healthcare, economics, industry, agriculture, education, and so on, approximate algorithms are the main alternative to solve these types of problems, such as scheduling production for time optimization, producing specific networks for optimizing cost and QoS, predicting abnormalities in patients' bodies, and so on. Approximate algorithms are divided into two types: specific heuristics used for a specific problem and metaheuristics used to address a variety of optimization problems [64].

A metaheuristic is a heuristic strategy for discovering approximate or near-optimal solutions to various problems, particularly when there is incomplete or defective information or limited computer capability [65]. Metaheuristics investigate the often-extensive solution search space of issues that are assumed to be tough. This is accomplished by reducing the effective size of the place and successfully exploring it. Metaheuristics are useful for three things: solving problems faster, handling large issues, and obtaining robust algorithms. They are very simple to design and deploy, as well as highly versatile [64].

The name "heuristic" comes from the Greek word "heuriskein," which means "the art of devising new strategies (rules) for problem solving." The suffix "meta" in Greek means "higher-level approach." F. Glover created the term "metaheuristic"[66]. Metaheuristic search strategies are higher-level general processes (templates) that may be used to guide the development of underlying heuristics to solve specific optimization problems [64].

There are two types of optimization issues: "discrete" problems and problems with continuous variables. To be more explicit, consider the following two examples. The well-known traveling salesman issue, which requires reducing the path of a "traveling salesman" who must visit a specified number of sites before returning to his starting point, is one of the discrete tasks. The search for the values to give to the parameters of a numerical model of a process so that the model faithfully reproduces the observed real behavior is a common continuous challenge. In actuality, "mixed issues" with discrete and continuous variables may develop. This distinction is required to define the domain of hard optimization [63].

Specific discrete optimization problems for which no reliable polynomial approach (i.e., one with proportionate computation time) is known to N^n, where N is the number of unknown issue parameters, where n is an integer constant). This is especially true for "NP-hard" problems, where it has been proposed that there is no constant n for which a polynomial of degree limits the solution time.

For a long time, many attempts have been made to address these two types of problems. As a result, in the subject of continuous optimization, there is a significant arsenal of traditional methods for global optimization [67]. However, if the goal function lacks a certain structural property, such as convexity, these strategies are typically ineffective. Many heuristics that yield near-optimal solutions have been discovered in the field of discrete optimization; nevertheless, the majority of them were built specifically for a specific situation.
Metaheuristics provide a synthesis of the two domains that may be used to all forms of discrete problems as well as continuous ones. These approaches also share the following characteristics [63] :

- They are, to some extent, stochastic: using this strategy, we may avoid the combinatorial proliferation of options.
- They are characteristic of discrete origin and have the advantage, critical in the continuous case, of being direct.
- Analogies in physics, biology , and ethology drive them.
- They also have the same drawbacks: difficulties in modifying the method's parameters and a lengthy calculation time.

These techniques are not mutually exclusive; with present knowledge, it is often impossible to forecast the effectiveness of a certain approach when applied to a given scenario with certainty. Furthermore, the advent of hybrid approaches, which aim to capitalize on the different traits of many methodologies by combining them, is a contemporary trend. Finally, one of the many advantages of metaheuristics is that they lend themselves to diverse extensions. We can provide a particular quote:

- multi-objective optimization [68], which involves optimizing several contradictory objectives at the same time;
- multimodal optimization, which involves attempting to locate a whole set of global or local optima;
- dynamic optimization, which deals with temporal variations of the objective function; and the use of parallel implementations.

4.1 Complexity Theory

The complexity of definable issues is our focus in this section. Even with infinite time and space resources, no algorithm could ever tackle intractable problems [69].

4.1.1 Complexity of Algorithms

To solve a problem, an algorithm requires two critical resources: time and space. As a result, an algorithm's temporal complexity is defined as the number of steps required to solve a problem of size n. The worst-case scenario analysis is frequently used to define complexity. The goal of calculating the computational complexity of an algorithm is to obtain an asymptotic bound on the step count rather than an actual step count. Asymptotic analysis is used in the Big$-O$ notation. It is one of the most often used notations in algorithm analysis.

4.1.2 Big$-O$ notation

If there are positive constants n_0 and c such that $\forall n > n_0, f(n) \leq c.g(n)$, an algorithm has a complexity $f(n) = O(g(n))$. The function $g(n)$ upper bounds the function $f(n)$ in this example. The Big$-O$ notation can be used to compute an algorithm's time or space complexity.

4.1.3 Polynomial-time algorithm

A polynomial-time algorithm has a complexity of $O(p(n))$, where $p(n)$ is a polynomial function of n. A degree k polynomial function is defined as follows: $p(n) = a_k.n^{k+\cdots+a_j.n^j+\cdots+a_1.n+n_0}$ where $a_k > 0$ and $a_j \geq 0, \forall 1 \leq j \leq k-1$. The polynomial complexity of the corresponding algorithm is $O(n^k)$.

4.1.4 Complexity of shortest path algorithms

Given a linked graph, $G = (V, E)$, where V represents the nodes and E represents the edges. Let $D = (d_{ij})$ be a distance matrix with d_{ij} representing the distance between nodes i and j (we assume $d_{ij} = d_{ji} > 0$). The shortest path issue entails determining the shortest path from a source node i to a destination node j. A path $\pi(i, j)$ from i to j can be defined as a sequence $(i, i_1, i_2, \ldots, i_k, j)$, such that $(i, i_1) \in E, (i_k, j) \in E, (i_l, i_{l+1}) \in E, \forall 1 \leq l \leq k-1$. The length of a path $\pi(i, j)$ equals the total of its edge weights:
$length(\pi(i, j)) = d_{ii1} + d_{(i_{kj})} + \Sigma_{l=1}^{k-1} d_{i_l i_l+1}$

4.1.5 Exponential-time algorithm

The complexity of an exponential-time algorithm is $O(c^n)$, where c is a real number strictly higher than 1. When compared to polynomial complexity, the table clearly shows the combinatorial growth of exponential problems where an increase follows the increase in size in the search time. In practice, millennia cannot be used to resolve a problem. The difficulty given in the table's last line needs the age of the cosmos to be exactly determined by an extensive search. The Big$-\Omega$ and Big$-\Theta$ notations are also used to examine algorithms.

4.1.6 Big$-\Omega$ notation

If there are positive constants n_0 and c such that $\forall n > n_0, f(n) \geq c.g(n)$, an algorithm has a complexity $f(n) = \Omega(g(n))$. The function $g(n)$ limits the complexity of the algorithm $f(n)$.

4.1.7 Big$-\Theta$ notation

The complexity of an algorithm is $f(n) = \Theta(g(n))$ if there are positive constants $n_0, c_1, and c_2$ such that $\forall n > n_0, c_1.g(n) \leq f(n) \leq c_2.g(n)$. The function $g(n)$ limits

Complexity	Size = 10	Size = 20	Size = 30	Size = 40	Size = 50
$O(n)$	0.00001 s	0.00002 s	0.00003	0.00004 s	0.00005 s
$O(n^2)$	0.0001 s	0.0004 s	0.0009 s	0.0016 s	0.0025 s
$O(n^5)$	0.1 s	0.32 s	24.3 s	1.7 mn	5.2 mn
$O(2^x)$	0.001 s	1.0 s	17.9 mn	12.7 days	35.7 years
$O(3^x)$	0.059 s	58.0 mn	6.5 years	3855 centuries	$2 * 10^8$ centuries

Table II.1: Complexity examples

the complexity of the algorithm $f(n)$. It is simpler to discover an algorithm's Big$-O$ complexity first, then the Big$-\Omega$ and Big$-\Theta$ complexities later. The Big$-\Theta$ notation specifies the exact bound (lower and upper) on an algorithm's time complexity.
The asymptotic analysis of algorithms describes the rate at which their time complexity increases as the size of the task increases (scalability issues). It allows for the theoretical comparison of several algorithms in terms of worst-case complexity. It does not offer the real run time of the algorithm for a single issue case. Instead, the execution time of an algorithm is determined by the input data. Average-case complexities, a more difficult procedure, can be estimated for a more full evaluation.

4.2 Complexity of Problems

A task's difficulty equals the complexity of the best algorithm for solving that problem. A problem is tractable if it can be solved in polynomial time (or easy). If there is no polynomial-time algorithm to solve a problem, it is intractable (or hard). The theory of problem complexity is concerned with choice issues. A yes or no response is always provided for a choice problem [64].
Answering the question "Is a given number B a prime number?" is a common choice dilemma. It will return yes if the number B is a prime number; else, it will return no. An optimization issue may always be transformed from a choice problem. The classification of problems into complexity classes is an important aspect of computational theory. A complexity class is a grouping of all issues that can be solved with a specific set of computer resources. There are two major types of problems: NP and P (Figure II.12) [64].

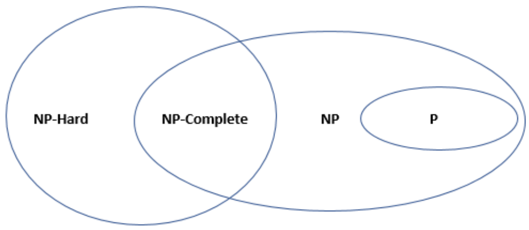

Figure II.12: Complexity Classes Of problems

4.2.1 problems of class P

P denotes the collection of all decision problems that a deterministic computer can solve in polynomial time. A (deterministic) technique is polynomial for decision problem A if its worst complexity is limited by a polynomial function p(n), where n is the size of the input instance I. As a result, the class P defines the family of problems for which there is a known polynomial-time algorithm. As a result, class P issues are relatively "easy" to solve [64]. Classical problems in class P include the minimal spanning tree, shortest path problems, maximum flow network, maximum bipartite matching, and linear programming continuous models [70].

4.2.2 problems of class NP

The complexity class NP encompasses any decision problems that can be solved in polynomial time using a nondeterministic technique. A nondeterministic algorithm has one or more decision points where several possible continuations are possible but no indication of which one will be picked. It makes use of the following primitives: choice, which provides a solution (oracle); check, which checks if a solution proposal (certificate) delivers a positive or negative response in polynomial time; success when the algorithm replies "yes" after the check application, and failure when the algorithm does not respond "yes." If the choice primitive gives a solution that produces a "yes" answer and the oracle is capable of doing so, the computing complexity is polynomial [64]. Because of the extensive implications for computational complexity theory, one of the most important unanswered concerns is whether $P = NP$. We have a nondeterministic method for each problem in P. After that, $P \subseteq NP$ (Figure II.12). However, the following supposition $P \subset NP$ remains unanswered. A choice problem A is polynomially reduced to a decision issue B if, for all input instances IA for A, a

polynomial-time function to the size L(IA) can always construct an input instance IB for B, such that IA is a positive instance of A if and only if IB is a positive instance of B.
Optimization problems with NP-complete decision problems are known as NP-hard problems. The majority of real-world optimization problems are NP-hard, and there are no provably efficient approaches. They are best solved in exponential time (unless $P = NP$). Metaheuristics are an important option for dealing with this sort of problem [64]. Cook in [71] was the first to show that the satisfiability issue is NP-complete (SAT). The remaining NP-complete problems are as least as challenging as the SAT problem. Furthermore, several popular academic problems are NP-hard, including:

- Sequencing and scheduling issues like flow-shop scheduling, job-shop scheduling, or open-shop scheduling.
- Assignment and location difficulties, such as the quadratic assignment problem (QAP), the generalized assignment problem (GAP), the location facility, and the p-median problem.
- Data clustering, graph partitioning, and graph coloring are grouping issues.
- Routing and covering issues, including vehicle routing problems (VRP), set covering problems (SCP), the Steiner tree problem, and the covering tour problem (CTP).

Some issues have yet to be proven NP-hard. The graph isomorphism problem, which determines if two graphs are isomorphic, is a prominent example. It is unclear if the issue is P or NP-complete [70].

4.3 Categories of Metaheuristics

Metaheuristic methods could be divided into two main categories:

4.3.1 Single-Solution Based Metaheuristics

S-metaheuristics (single-solution-based metaheuristics) improve a single solution for solving optimization challenges. They might be seen as "walks" across neighborhoods or search paths inside the problem's search area [72]. The walks are performed by iterative algorithms that move from one solution to another in the search space (or trajectories). S-metaheuristics have been shown to be successful in tackling a wide range of optimization problems in a variety of domains. S-metaheuristics regularly use generation and replacement procedures from an existing single solution. During the generation phase, a collection of potential solutions is produced from the existing solutions. Local solution transformations are typically employed to generate this set C(s). During the replacement phase, a candidate solution set C(s) is selected to replace the current solution; that is, solution s C(s) is selected as the new solution.

This technique is repeated until a certain stopping condition is fulfilled. Memory-free creation and replacement stages are thus conceivable. In this case, the two processes are purely reliant on the current solution. Alternatively, some search history preserved in memory can be used to construct the candidate list of solutions and select the new answer. Popular S-metaheuristics include local search, simulated annealing, and tabu search. The common search principles for all S-metaheuristics are specifying the neighborhood structure and identifying the initial solution. The most often used algorithms in this class are: Tabu Search [73] and Simulated Annealing [74].

4.3.2 Population-based Metaheuristics

Population-based metaheuristics share many ideas (P-metaheuristics). They might be viewed as gradual enhancements to a population of solutions. The population is initially created. After that, a new population of solutions is produced. Finally, numerous selection techniques are employed in order to integrate this new population into the old one. When a given condition is satisfied, the search procedure is terminated (stopping criterion). Techniques in this class of metaheuristics include Genetic Algorithm [75], Particle Swarm Optimization [76], Grey wolf Optimizer [77], Artificial Bee Colony [78], and Whale Optimization Algorithm [79].

Population-based metaheuristics start with a set of solutions. Then they apply the production of a new population and the replacement of the current population repeatedly. During the generation phase, a new population of solutions is produced. During the replacement phase, a selection from both the current and new populations is made. This technique is repeated until a certain stopping condition is fulfilled. It is feasible to generate and change stages without using any memory. In this case, the two processes are entirely reliant on the current population.

Otherwise, some search history stored in memory can be used to create new populations and replace current ones. The vast majority of P-metaheuristics are algorithms inspired by nature. P metaheuristics can be found in evolutionary algorithms, ant colony optimization, scatter search, particle swarm optimization, bee colonies, and artificial immune systems, to name a few. P-metaheuristics differ in how they carry out generation and selection operations, as well as the search memory they use.

4.4 Types of Metaheuristics

According to [80] metaheuristics algorithms can be divided into Metaphor based metaheuristics and Non-Metaphor based metaheuristics.

1. Metaphor based metaheuristics which can be classified into:
    - Biology-based metaheuristics: Genetic algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Negative Selection Algorithms, Clonal Selection algorithms (CLONALG), optimization version of Artificial Immune Network (opt-AINET), B-Cell Algorithm.
    - Chemistry-based metaheuristics such as Chemical Reaction Optimization (CRO), Gases Brownian Motion Optimization (GBMO).
    - Music-based metaheuristics such as Harmony Search (HS), Method of Musical Composition (MMC).
    - Math-based metaheuristics such as Base Optimization Algorithm (BOA), Sine Cosine Algorithm (SCA).
    - Physics-based metaheuristics such as Simulated Annealing (SA), Gravitational Search Algorithm (GSA).
    - Social and sport-based metaheuristics such as Teaching Learning-Based Optimization (TLBO), League Championship Algorithm (LCA).
2. Non-Metaphor-based metaheuristics such as TABU SEARCH (TS), Variable Neighborhood Search (VNS), and Partial Optimization Metaheuristic Under Special Intensification Conditions (POPMUSIC).

5 Big Data

In the late 1990s, Michael Cox and David Ellsworth [81] saw visualization as a Big Data challenge and coined the term "Big Data". The first description of Big Data [82] is "explosion in quantity (and sometimes, quality) of available and potentially relevant data" from 2000. Volume, velocity, and variety (the 3Vs), the key dimensions of Big Data, were later extracted from Doug Laney's 2001 research [83]. Other factors were addressed in big data because they were important, such as "value" [84] and "truth" in the healthcare application [85]. Furthermore, big data came with the ability to gather values throughout time, resulting in a multi-dimensional dataset that could be utilized and reused [86].

5.1 Big Data applications

Here are some examples of Big Data applications [87]:

5.1.1 Smart Grid

Controlling national electronic power consumption in real-time for monitoring the smart grid based on the connectivity of multiple infrastructures such as smart meters, sensors, control centers, and so on is one of the most difficult challenges of big data. Big Data analytics is utilized to identify at-risk transformers and detect anomalous activity in associated devices, allowing the grid to choose the best treatment or reaction. Real-time analysis of generated Big Data is critical for building effective preventative initiatives and decreasing remedial expenses. In the case of energy, it also manages the power demand load, plans resources, and so maximizes profitability [88].

5.1.2 E-health

Nowadays, technological advancements in the health sector enable the connection of health equipment and platforms, giving rise to a new concept known as "E-health". The E-health domain, like the other domains, is made up of many linked devices and platforms, which create a vast quantity of data. However, the analysis of this generated big data came with a lot of benefits, such as the possibility of the doctor monitoring the patients' symptoms online, adjusting the public health plan based on the analyzed data, controlling the spread of diseases, and it could be one of the key processes that help in optimizing hospital operations and lowering the patient's medical costs [89].

5.1.3 Internet of Things (IoT)

Because of its dynamic nature, the Internet of Things has become a part of our daily lives in transportation, education, agriculture, sports, and energy, among other areas. Because the Internet of Things allows for the connection of a wide range of devices, which generates different types of data for a specific purpose. The generated data have to be analyzed. The outcome of this analysis could be extremely beneficial, such as in the case of tracking the positions of cars using GPS and wireless sensors. The application's output facilitates the racking process while optimizing delivery routes [90].

5.1.4 Political services and government monitoring

Data analysis is crucial in key fields such as political services and government surveillance. For example, the government extracted several hidden issues in society using data from social network communication, personal interviews, and other media sources. Another application of big data may be the optimization of important resources, such as the management of water leaks [87].

5.1.5 Big Data in healthcare

Diagnostics, treatment, and prevention of illnesses and other human body concerns are all possible using big data in healthcare. To organize and extract suitable characteristics from unstructured healthcare data and internal and external sources, such as clinical annotation, medical pictures, environmental data, health economics, and so on, big data relies on numerous analytic methodologies. [91]. Generally, healthcare data could be:

- Physiological data encompasses behavioral, molecular, clinical, environmental exposure, medical imaging, illness treatment history, pharmaceutical prescription history, food, and exercise characteristics [92].

- Databases for administrative purposes Administrative databases (insurance claims and prescriptions), clinical databases, electronic health record data [93], and laboratory information system data are some of the most prominent sources of Big

Data in healthcare.

- Biometric data (wearable or sensor-generated), patient-reported data (standardized health surveys), data from social media [94], medical imaging data, and biomarker data round up the whole range of 'omics' data. (This information contains genomic, proteomic, and metabolomic data).

- Genomic data powered by genomics Healthcare data resources include Big Data such as genotyping, gene expression, and sequencing data [95]. Furthermore, electronic health records, insurance information, pharmacy prescriptions, and patient comments and reactions are critical components of healthcare big data [96].

5.2 Big data analytical techniques and technologies in healthcare

Researchers face a significant challenge in combining and analyzing this unstructured amount of data due to the variety of healthcare data, such as medical images (X-ray, MRI images), biomedical signals (EEG, ECG, EMG, etc.), audio transcripts, handwritten prescriptions, and structured data from EMRs [97].

There are few analytical methodologies capable of dealing with such varied data and facilitating decision-making. Nevertheless, some analytical methodologies that may be used in healthcare and medicine are mentioned in the literature. Healthcare organizations have improved their quality of care by combining descriptive and comparative analytics, as detailed by [98] and [99]. However, they claim that predictive analytics can result in long-term tangible advantages. Predictive analytics, according to the research, may be used to anticipate high-cost patients, readmissions, triage, decompensation (when a patient's health deteriorates), adverse events, and therapy optimization for diseases involving multiple organ systems [100] [101].

Furthermore, Mohammed et al. [102] emphasized a number of applications of Big Data Technologies like MapReduce and Hadoop for healthcare analytics, which were supported by other studies:

- MapReduce can improve the performance of standard pharmacovigilance signal identification approaches at about linear speeds.

- Algorithms based on the Hadoop distributed platform can enhance protein structure alignments more precisely than earlier approaches.
- Methods based on MapReduce can improve the performance of neural signal processing.
- Image reconstruction techniques aid in the rebuilding process. In [103], the author used the MapReduce architecture to establish acceptable parameters for lung texture classification and to accelerate medical image processing.

5.3 Challenges in big data analytics in healthcare

The healthcare industry continues to confront hurdles in evaluating the created big data, creating significant challenges for academics to overcome these concerns, which might be summarized as follows:

- With so much data available, there is confusion regarding which data to use and for what purpose [104].
- The lack of appropriate IT infrastructure [101].
- Healthcare is still a long way from realizing the promise of Big Data analytics due to a lack of knowledge on the appropriate algorithm and tool for analysis [105], as well as a shortage of skilled clinical scientists and Big Data managers to analyze Big Data results [106].
- The absence of human supervision in healthcare data analytics reduces the efficacity of the system and causes a fault in the processing [107].
- The combination of various kinds of data such as structured, semi-structured, and unstructured data from a variety of resources [92].
- The security of the big data in the healthcare [94].
- Patient privacy and confidentiality[108].

6 Internet of Things

The Internet of Things (IoT) has given the internet a new edge, from computers networked by the internet to anything that can receive or transfer digital data that is interconnected. As a result, IoT might become a large source of data [109]. IoT is defined as "things with identities and virtual personalities operating in smart spaces using intelligent interfaces to connect and communicate within social, environmental, and user contexts" or "interconnected objects playing an active role in what could be called the Future Internet" by the European Commission Information Society [110]. The 'things' in IoT can range from a smartwatch to a cruise control system outfitted with sensors (e.g., location, switch on/off other devices (TV), and so on).

[111] Augmented intelligence may significantly improve the decision-making abilities of IoT customers. Because of the broad deployment of IoT technology, enterprises may now improve work processes and increase productivity by collecting and reporting environmental data. Prior research indicates that IoT will be the next significant destination for investment by a range of enterprises. [112] [110].
As a result of IoT opportunities, the healthcare environment will soon be revolutionized. This method will be useful in hospital telemonitoring and, more crucially, at home [113]. Remote patient monitoring offers huge promise for not only increasing healthcare quality but also cutting healthcare costs by recognizing and preventing diseases and potentially harmful situations.
Our healthcare services are now more expensive than ever, and the majority of patients are required to stay in the hospital for the course of their treatment. These issues can be overcome by utilizing technology that allow for remote monitoring of patients. By collecting and transmitting real-time health data from patients to caregivers, IoT technology will not only reduce the cost of healthcare services but will also allow for the treatment of health problems before they become critical [114].

6.1 IoT technologies

Because of the low cost, compact size, and low energy consumption of IoT devices, it has attained state of the art in numerous sectors, including healthcare, which will witness a drastic transformation and widespread adoption of the IoT [115]. However, the Internet of Things is dependent on a number of technologies, including :

6.1.1 Radio-Frequency Identification (RFID)

Radio-Frequency Identification (RFID) is a short-range communication technique. RFID consists of a tag and a reader that communicate to receive and transmit signals. The majority of the data in RFID tags used in IoT applications is electronic product codes (EPC). The Electronic Product Code (EPC) is a means of individually identifying products. We may use these tags to verify that each device in the IoT ecosystem has a unique identity by [116]. RFID technology, with distinguishing features such as low-cost, dependable tags and tracking capabilities, is now a viable option for IoT [117].

6.1.2 Near Field Communication (NFC)

NFC technology is a short-range communication system that allows for simple and secure authentication between multiple objects. Devices can use this technology in three modes: reader or writer, peer-to-peer, and card emulation. The system acts as a contactless reader or writer in reader and writer mode to collect information or trigger an action. In peer-to-peer mode, the system operates as a two-way communication channel. Finally, in card emulation mode, NFC enables devices to operate in a manner similar to smart cards [118].

6.1.3 Low-Rate Wireless personal area network (LR-WPAN)

Low-Rate Wireless Personal Area Network (LR-WPAN) is a kind of WPAN that provides low-cost communication networks, consumes less power, and employs a reliable data transfer protocol [119] [120]. In general, full-function (FFD) and reduced-function (RFD) devices can be used in an LR-WPAN network (RFD). The FFD type may function in three modes: PAN coordinator, coordinator, or device. Furthermore, RFD may be used in applications that do not require large amounts of data to be sent [121].

6.1.4 Bluetooth

Bluetooth is a short-distance wireless communication network. This technology connects two or more devices and includes authentication and encryption-based security features. The 2.4 GHz band uses 79 radio frequency channels with 1 MHz bandwidth. This technology, according to the Bluetooth device class, can enable communication up to 100 m at a speed of up to 3 Mbps. Because of IoT applications are typically used in telemonitoring nowadays, all devices in this situation rely on low-power techniques like Bluetooth [122] [123].

6.1.5 ZigBee

Zigbee is a wireless technology that was developed to provide a foundation for IoT by allowing objects to interact with one another. The architecture of this protocol comprises of end-nodes, routers, a coordinator, and a processing center. The processing center is in charge of data collection and analysis [124]. ZigBee is commonly suggested in IoT implementation because to its major benefits such as security and network resilience, interoperability, and low power consumption. This technology is based on a mesh network, which allows the system to continue running even if one of the things fails, while the other objects continue to communicate with one another without interruption [125].

6.1.6 Wireless Fidelity (Wi-Fi)

The Internet of Things is built on wireless technology. Wi-Fi is utilized in a variety of applications, including home automation, wearable sensor devices, mobile devices, and smart grids, to name a few. Based on Wi-Fi, a Wireless Local Area Network (WLAN) device is deemed to be in the Wi-Fi category if it fulfills IEEE 802.11 specifications [126].

6.1.7 Worldwide interoperability for Microwave Access (WiMAX)

Worldwide interoperability for microwave access [127] is one of the 802.16 series standards for wireless metropolitan area networks (WMAN). The capacity to operate in both licensed and unlicensed frequency bands, with a frequency band spectrum extending from 2 to 11 GHz, was one of the major attributes of the first WiMAX standard IEEE 802.16a. IEEE 802.16a does not require a direct line of sight between the source and destination transceiver antennas since the devices operate in low-frequency bands [128]. The IEEE 802.16b standard was developed by the WiMAX forum to offer clients with high-quality real-time voice and data services. It works in the frequency range of 5–6 GHz. Furthermore, WiMAX IEEE 802.16c has an operating frequency band range of 10–66 GHz and facilitates interoperability across diverse vendor devices and gadgets [129].

6.1.8 Mobile communications

Significant progress has been made in mobile communication networks. The initial version used analog technology to transmit real-time voice across a network. Text messaging is possible on second-generation (2G) networks due to their digital design. Furthermore, the requirement for online information exchange highlighted the importance of creating third-generation (3G) technologies [130]. 3G technology has the ability to create a worldwide infrastructure capable of supporting a variety of services. However, this infrastructure needs to be improved in order to accommodate future technological revolutions. This need may be satisfied if data access equipment, transportation infrastructure, and user applications were kept separate [131]. The fourth-generation (4G) idea has been proposed to solve some of the constraints of 3G while also improving service quality and bandwidth and lowering resource costs. This mobile wireless network offers the same level of service as fixed internet. Furthermore, 5th generation (5G) internet networks may offer optimal wireless connectivity with no constraints. 5G networks outperform 4G networks in terms of system capacity and energy efficiency. Furthermore, the sixth generation (6G) network was intended to integrate satellites in order to give higher coverage across a bigger area [127].

6.1.9 Wireless sensor networks (WSN)

Wireless sensor networks are made up of several sensors that are used to monitor the conditions of the physical environment. To acquire information from the environment, this design includes three key components (nodes, routers, and a gateway). WSN systems are either wearable or implanted. These sensors are commonly used in healthcare to monitor patient conditions in-home healthcare and home automation, to name a few applications [132]. Furthermore, because of benefits like as vast coverage, low installation costs, and real-time data collecting, WSNs have been employed in a variety of sectors, including disaster management, military operations, tracking the movement of animals, and healthcare monitoring systems.

Human physiological data monitoring, medicine and device monitoring in hospitals, and emergency scenario management are all examples of WSN capabilities for healthcare monitoring [133]. Sensing technology are essential for extracting physiological parameters from patients [134]. In healthcare facilities, sensors are typically used to assess point-of-care parameters such as medical screening and diagnostic applications. Biomedical signal collection enables novel sensors with wireless connectivity, opening up new paths for continuous patient condition monitoring. Sensors that detect food allergies, monitor pregnancy, and monitor cholesterol levels, as well as Deoxyribonucleic Acid (DNA)-based electrochemical analysis, are gaining popularity. Furthermore, the outputs of such sensors may be used to make suitable judgments about the circumstances of patients [134]. In healthcare monitoring, inertial sensors (such as accelerometers, gyroscopes, and pressure sensors), biosensors (such as electrocardiography (ECG) monitoring, temperature, and heart rate sensors), and wearable sensors (such as fitness bands and mobile phones) are often used.

6.2 IoT protocols

Various protocols are used for IoT such as:

6.2.1 Constrained application protocol (CoAP)

Sensor networks are significant in IoT design since they connect to the web or the cloud [135]. Due to its complexity, the Hypertext Transfer Protocol (HTTP) cannot be used in IoT since most IoT devices have limited storage and computing capability. The Internet Engineer Task Force (IETF) proposed the COAP standard, which contains numerous notable features that may change HTTP attributes to meet IoT requirements. The key features of this protocol include group communication, resource observation, direct interaction with HTTP, and security requirement evaluation [136] [137].

6.2.2 Message queue telemetry transport (MQTT)

The message queue Telemetry transport is a message transport protocol whose primary goal is to collect and transmit sensed data from the environment to servers [138]. MQTT supports unstable networks with limited capacity and may instantly connect "things" to the internet. This protocol is compatible and may be used to connect many platforms to the internet. Because of its minimal overhead and power consumption, MQTT is an attractive alternative for IoT implementation [139].

6.2.3 Extensible messaging and presence protocol (XMPP)

Extensible messaging and presence protocol is based on XML protocols; this protocol is well-known for important features such as open-source and public security procedures, as well as being completely free. Furthermore, this communications protocol allows users to connect regardless of the operating system. The client, server, and gateway are the three essential components of XMPP. The client establishes a connection with the server using the transmission control protocol/internet protocol (TCP/IP) protocol and sends context via the XML protocol. The server is in charge of message routing. The gateway is in charge of ensuring that connections between various systems remain reliable. XMPP may be used effectively in IoT architecture by allowing devices to interact with one another [140].

6.2.4 Low-power wireless personal area networks (LoWPAN)

When compared to other protocols, LoWPAN provides benefits such as lower packet sizes, low power consumption, and bandwidth, making it one of the best options for IoT applications. In addition, the 6LoWPAN protocol was developed by combining the latest version of the internet protocol (IPv6) with LoWPAN. This protocol is well-organized in order to compress IPv6 network headers into IEEE802.15.4 small packets in order to reduce error rates and facilitate data transport. 6LoWPAN is well-suited for IoT implementation because to major benefits such as cheap cost and power consumption [141].

6.2.5 Z-Wave

Z-Wave is a technology that utilizes the least amount of power to communicate in a wireless network and has been widely utilized in remote monitoring in a variety of industries. Z-wave technology is largely utilized for short-range wireless communication and reliable data transmission. It is recommended for low-bandwidth networks [141]. Furthermore, in IoT healthcare applications such as wearable device monitoring, this technology has the potential to change machine-to-machine communication [139].

7 Cloud Computing

Cloud computing's most prominent traits include rapid elasticity, measured service, on-demand self-service, and ubiquitous networks access and resource sharing [142].

7.1 Types of Cloud computing

Cloud computing is classified into several categories, including public cloud, private cloud, hybrid cloud, and community cloud [142][143].

- **Public cloud** is a public infrastructure offered by an organization to provide public resources and business that the public user will use for specific activities.
- **Private cloud** supply private infrastructure offered by an organization generally used for critical and sensitive data such as medical data and other internal business of an organization. It provides security, flexibility, and service quality to the user.
- **Hybrid cloud** in the hybrid cloud, a combination between private cloud and public cloud is used to manage both private personal data and normal data.
- **Community cloud** cooperates with various organizations to create a common service such as security or other shared services.

7.2 Services of Cloud computing

There are already four major service models that have aided in cloud adoption [144]:

- **Software as a Service (SaaS)** The cloud provides several programs and APIs to be used via the internet without the need to install them on his local device. This service solves the problem of storage and devices' capacity to run such programs. Generally, the user has to pay to use these services.
- **Platform as a Service (Paas)** the cloud supplies the full staff and requirement for the programmers and developers to produce and generate software and programs which ensure the control of his Information Technology (IT) resources. The PaaS guarantee the confidentiality and security of the information for the user.

- **Infrastructure as a Service (IaaS)** It offers a range of resources, including an unlimited storage capacity, network, and computing to run arbitrary applications and operating systems. Also, it guarantees the data's security and reliability, making it essential for the PaaS and SaaS use.
- **Container as a Service (Caas)** the container is new emergent of cloud services that aims to fill the gaps between the development of the programs and the Platform as A Service issue by making it independent of it.

7.3 Cloud computing challenges

According to [142] various tasks in cloud networking were introduced:

7.3.1 Scalable Storage

The ideal cloud resource is one with no running costs, infinite on-demand capacity, and processing powers. In this situation, researchers may create a storage infrastructure to meet these demands while also including the cloud benefits of dynamically scaling up and down as needed.

7.3.2 Load Balancing

A cloud computing platform must constantly control server demand to prevent hotspots and improve resource efficiency. The issue for academics is thus how to manage money effectively and consistently to meet the demands of subscribers. Virtualization technology provides an efficient way to manage complicated cloud-based services. The virtual machines acknowledge all requests, and the cloudlet scheduler is assigned to the relevant physical servers. VMs must be migrated to provide proper load handling and resource utilization.

7.3.3 Security

One of the major issues is that, despite its benefits, customers are sometimes unwilling to invest in the cloud. They cannot safeguard customer information against unwanted access since it is held outside the facilities and its origin is unknown. The cloud provider is responsible for ensuring record preservation and security. This necessitates the deployment of advanced computer management security methods as well as strictly controlled user access permission.

7.3.4 Scalability and Elasticity

The cloud computing paradigm makes a range of computational resources available to the user on demand. Meanwhile, the user must only pay for the resources consumed. One of the most significant advantages of cloud computing is the ability to add more computational resources and services, which has a direct impact on the QoS of the uploaded program. This method, however, requires cloud scalability, which is one of the cloud computing difficulties. Scalability in the cloud may include hardware, middleware, and application layers. Numerous hardware requirements must be satisfied for IaaS, including a powerful CPU, GPUs, and the use of non-traditional architectures [145]. Furthermore, the heterogeneous between these components must be guaranteed via VMs and containers to maintain system isolation and performance. However, in the middleware, the most concerning form are PaaS, which focuses on functional concerns. Meanwhile, the scalability constraints of sequential deterministic algorithms must be addressed at the application level through the use of diverse metaheuristic algorithms.

Also, when it comes to manipulating computational resources across clouds or between clouds and IoT sensors, the flexibility of services is a challenging problem in cloud computing [146] and many applications of VMs and containers [147].

7.3.5 Resource Management and Scheduling

One of the most important responsibilities in cloud computing is resource management and scheduling, which has an influence on their varied services (IaaS, PaaS, SaaS). Furthermore, it manages the resources of several distributed applications, such as virtual machines, containers, web services, and microservices. Traditional management approaches, on the other hand, continue to suffer from inaccurate resource estimation. Furthermore, it is unclear if implementing Artificial Intelligence (AI) technologies on workload prediction approaches and demand projections will address these issues. Furthermore, resource management strategies for optimizing specific metrics and resources usually lack a systematic approach to coexisting various control loops in the same environment, guaranteeing equitable resource access among users, and optimizing holistically across layers of the Cloud stack [148].

7.3.6 Reliability

Given the distributed nature of cloud computing, several systems are interconnected and interdependent, which consist of special care for their scale and complexity. However, several problems might occur in cloud computing, such as hardware failures, missing resources, network problems, latency, and software failure. These kinds of failures threaten the reliability of the system [149].

7.3.7 Sustainability

Because of its massive power consumption, sustainability is one of the most difficulties linked to information computer technology. Meanwhile, networks and the cloud might save energy in a variety of ways, such as in smart cities, or it could be used to combine renewable and non-renewable energy. However, energy consumption is often tied to QoS offered, which implies that lowering energy consumption has a direct impact on the QoS required. In important cases, such as healthcare applications, a decrease in QoS endangers the patient's life [150].

7.3.8 Heterogeneity

Due to the increased demand for cloud computing, the service providers increased their hosting of the services to meet the client's needs while conserving the performance and the efficiency. For this reason, a new challenge is created: heterogeneity at different levels of the cloud, such as VMs, Vendors, and hardware architecture [150]. The heterogeneity in the cloud could be embodied in managing resources and workload in heterogeneous environments. Also, it can be related to developing an application that uses specific programming, which is different from the one used for hardware accelerators [151].

7.3.9 Interconnected Clouds

Since cloud computing is adopted in various domains, the interoperation of cloud types and other systems is a challenging topic. Where the interoperation aims to allow the exchange of data without any problem concerned with authentication and authorization [152].

7.3.10 Security and Privacy

In general, Security and privacy of data are the most challenging topics in ICT systems, and the cloud computing is one of these technologies; it has to provide the aspect of Security and privacy in managing the user's data and in their provided services such as confidentiality, integrity, and availability. Several issues must be addressed to ensure secrecy, including the encryption used to encrypt the data. However, it limits the provider's support for query evaluation. Furthermore, the usage of secrecy in crucial domains such as healthcare, fraud traffic, and national security, which have access to several resources with cross-domain information, makes the work difficult.

Moreover, the integrity of data and the authority of the user are still outstanding concerns in cloud computing. Furthermore, one of the cloud providers' jobs that must be addressed is the provision of the security services that the customer need in order to preserve his privacy [153].

7.3.11 Economics of Cloud Computing

As one of the IT systems, cloud computing includes an economic side that is connected to how the price of the cloud service offered to the customer is created, and which aspect is dependent on it. Also, it might be related to the search for the required service with specific financial criteria that often depend on the broker strategies. Moreover, service level agreements (SLAs) have to be considered to check user's satisfaction with their delivered services and manage the payment process between the cloud provider and the user [154].

7.3.12 Application Development and Delivery

Another challenge in cloud computing consists of controlling the infrastructure resources provided by SaaS, which are programmable. Also, the delivery of the modification applied on the supported platform has its impact on the complexity, optimization, and parallelization of the full service provided[155].

7.3.13 Data Management

Since cloud computing is based on the distribution aspect, which allows the data exchange from various devices, this propriety makes the cloud challenging to guarantee a lot of services such as the availability of affordable, reliable, and elastic storage. As a consequence, a new challenge has been created, which is how to manage all this big data [156].

7.3.14 Networking

The fundamental feature of cloud computing is networking, which connects cloud services and user requests. To ensure this link, several layers of communication need be carried out within and between data centers. However, network performance criteria such as latency and bandwidth guarantee continue to limit this relationship and create open, challenging tasks that need to be solved [157]. Also, the reduction of energy consumption of the networking staff in the data center is still an open task that needs to be treated.

7.3.15 Usability

The Cloud's usability is critical to lowering the costs of adopting Cloud services and infrastructure. Furthermore, cloud usability seeks to please the user by providing the essential cloud service, providing the user with easy and pleasant service functioning, and ensuring the privacy and security of the services' user [158]. These properties are considered challenging tasks of cloud computing that need to be solved.

8 Neonatal seizure

Seizure is one of the prevalent diseases related to mental healthcare, which is a synchronized electrical discharge (depolarization) of a group of neurons in the central nervous system that is aberrant. When sodium ions enter neuronal cells, they depolarize, whereas potassium ions escape the cell, resulting in the typical negative electrical potential across the cell membrane. A sodium-potassium pump powered by adenosine triphosphate (ATP) maintains this electrical potential (see Figure II.13). Excessive depolarization is often regarded as the ultimate common process via which seizures occur [159]. However, children are the most impacted by seizures, particularly during the newborn period. Neonatal seizures or neonatal convulsions are one of the most frequent neurological events in newborns. This neurological event occurs in up to 1.4%

of term infants and 20% of premature infants caused by postnatal disorders of the Central Nervous System (CNS), lack of myelination and incomplete formation of dendrites and synapses in the brain, meningitis, ischemic stroke, encephalitis, intracranial hemorrhage, and tumor [160][161]. The neonatal seizures take 10 seconds to 1–2 minutes, with a median of 8 minutes in between each seizure. Their recognition is necessary because they affect 1 to 3 in 1000 infants in their lifetime with several consequences such as death, neurological impairment, developmental delay, post-neonatal epilepsy, and other neuromorbidity [161][162].

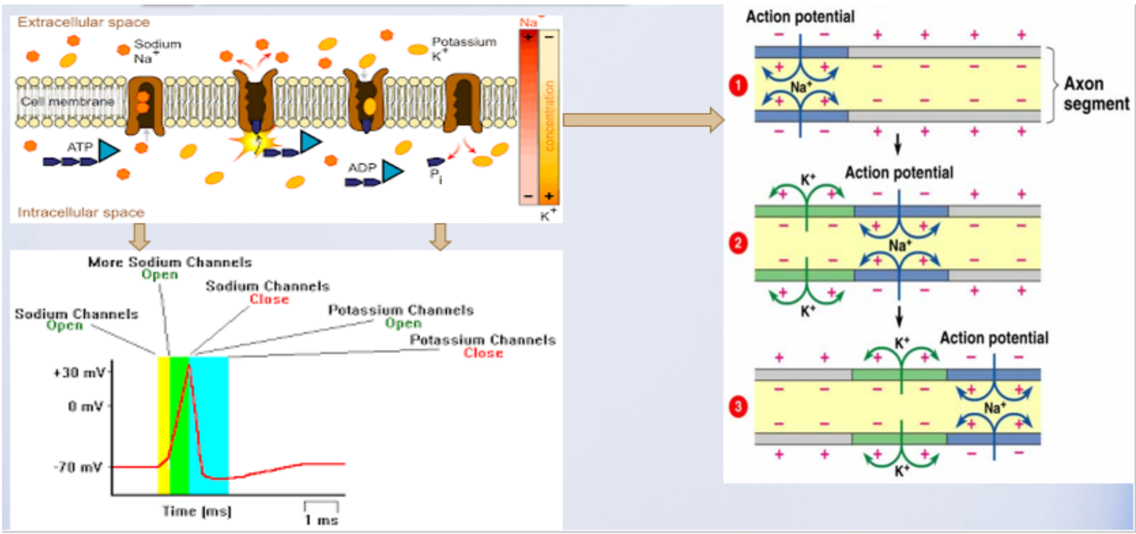

Figure II.13: Depolarization process

8.1 Seizure semiology by lobe

Close examination of a seizure's semiology can be immensely helpful in locating the ictal genesis to a hemisphere or a brain area. Seizures have a wide range of semiology because the outward indications of a seizure vary depending on the cortical region affected. We can connect clinical characteristics with epileptic discharges on the EEG using video EEG recording. Because EEG only detects aberrant activity on the cortical surface, surface EEG can only provide limited localization. Imaging tools including ictal single-photon emission computed tomography (SPECT) scans and MEG (magnetoencephalogram) can help with seizure onset assessment, but reliable localization is still hindered by poor access to deeper tissues. [163].

- **Frontal** a substantial motor component is commonly present in focal seizures that begin in the frontal lobe. Frontal seizures have an unusual appearance and might be mostly or entirely nocturnal. They are sometimes confused with parasomnias. Frontal seizures, unlike parasomnias, typically occur throughout the night rather than during specific periods of the sleep cycle. They are usually short (2 minutes), stereotyped, and occur in groups.

- **Temporal** auras and/or automatisms are commonly linked with temporal lobe seizures, which are generally accompanied by diminished consciousness. An aura, a subjectively sensed sensory or mental experience caused by ictal activity, precedes certain seizures. When an aura occurs in isolation, it is classified as a focused sensory seizure. Most auras are temporal lobe-specific, however they are not always lateralizing. Auras can be sensory or experiential in nature. Sensory auras can include any of the five officially recognized senses, as well as less traditional ones like an abdominal/epigastric or cephalic aura. Auras of experience are sometimes known as psychic auras. They entail the encounter with complicated sentiments such as terror, "seen before", "never seen", out of body sensations, or a religious mood.
- **Parietal** seizures in the parietal lobe are uncommon, although they frequently include a significant sensory component due to ictal start in the main sensory cortex. Focal paresthesias (usually numbness or tingling) of one body area point to the contralateral primary sensory cortex as the source of the seizure.
- **Occipital** Occipital seizures are distinguished by simple visual hallucinations. Simple visual auras, such as geometric forms (especially spheres), lights, or loss of vision, are restricted to the primary visual cortex.
- **Insula** the insula is a fold of cortex that lies under the central sulcus and separates the temporal, frontal, and parietal lobes. Due to fast transmission to frontal or temporal areas, insular semiology has historically been difficult to distinguish from other lobes. Insular seizures follow a predictable pattern, beginning with an unpleasant laryngeal or pharyngeal aura, generally tightness or dyspnea. They subsequently progress to paresthesia, which is frequently described as a periorally or widespread electrical feeling or warmth. The majority of these seizures are accompanied with typical focal motor semiology.

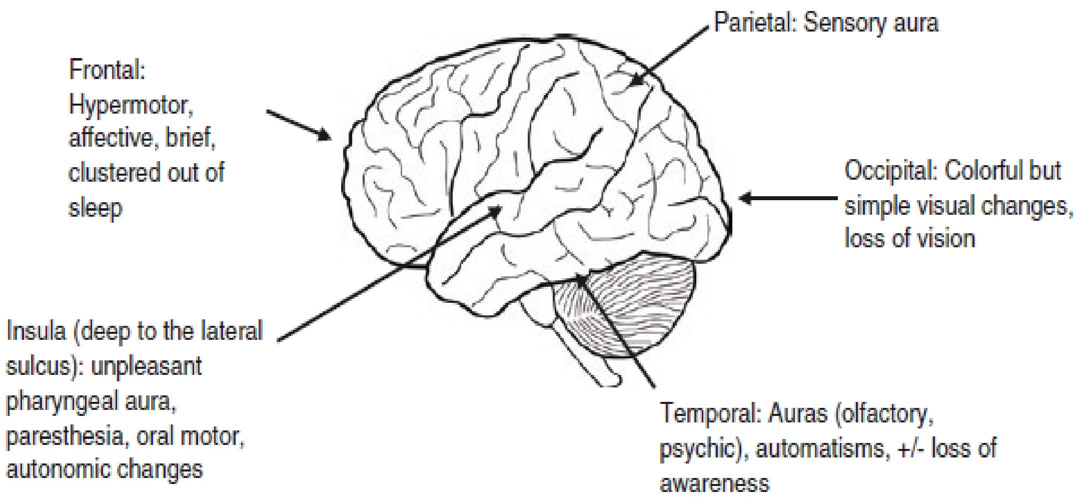

Figure II.14: Seizure semiology by lobe

8.2 Newborn treatment

According to the WHO, investigations into the cause of seizures in neonates should begin as soon as possible. They discovered no randomized controlled trials or well-conducted observational studies that compared the effects of AED medication (phenobarbital and phenytoin) with no therapy in neonates with NS. Though no significant therapeutic advantage has been demonstrated, the potential benefit of AED treatment outweighs the possible risk, with no evidence of clinically significant side effects of adequate and short-term AED dosing. However, the WHO advised the use of AED in the following situations:

- If the seizures present clinically in the newborn and last more than 3 minutes or are brief serial seizures.
- Even in the absence of clinically evident seizures, all electrical seizures should be treated in specialized care facilities where electroencephalography is available [161].

8.3 The clinical efficacy of the treatment in the newborn

The prevalence of hypoglycemia in newborns with seizures is between 3 and 7.5 percent. Hypoglycemia can be harmful and is linked to complications such as epilepsy. There is no risk/benefit analysis of empirical hypoglycemic therapy available. The potential side effect of therapy is increasing hypoglycemia in certain infants with HIE. Because blood glucose levels may be quickly checked and at a reasonable cost, this should be done before therapy [161]. The frequency of hypocalcemia in newborns with seizures ranges from 2.3 to 9%. Blood calcium measurement is achievable in hospital settings without time delay. However, it is less readily available than blood sugar measurement. Calcium may cause considerable damage when administered intravenously, such as asystole or skin necrosis [161].

The oral treatment of neonate sepsis or pyogenic meningitis was not considered standard therapy in the clinical research of Bacterial infection in newborns with convulsions. The empirical treatment, on the other hand, would involve intravenous therapy [161].

The clinical investigation of Congenital herpes simplex virus infection, an uncommon cause of NS, did not include oral medication as routine therapy. The empirical treatment, on the other hand, would involve intravenous therapy [161]. Pyridoxine-dependent epilepsy is a rare condition that can be diagnosed clinically by a good response to pyridoxine therapy. Meanwhile, failing to diagnose this illness may have negative consequences for afflicted neonates, but failure to diagnose other underlying causes may also cause harm [161].

8.4 WHO recommendation for newborn treatment

The WHO considered some recommendation for the treatment of the newborn based on the cause of neonatal seizures [161].

- Before considering AED treatment in all newborns with seizures, hypoglycemia should be screened out and addressed if present.
- If glucose measurement facilities are not accessible, consider using glucose as empirical therapy.
- If there are clinical symptoms of concomitant sepsis or meningitis, a lumbar puncture should be performed to rule out central nervous system infection, which should be treated with appropriate antibiotics if present.
- If lumbar puncture facilities are unavailable, consider empirical antibiotic therapy

for neonates with clinical indications of sepsis or meningitis.

- Serum calcium should be tested in all infants with seizures and treated if hypocalcemia is detected.
- In the absence of hypoglycemia, meningitis, hypocalcemia, or another clear underlying cause, such as hypoxic-ischaemic encephalopathy, cerebral hemorrhage, or infraction, pyridoxine medication may be investigated before AED treatment in a specialist center where this treatment is accessible.

9 Covid-19

Covid-19 is a Coronaviridae family illness caused by severe acute respiratory syndrome (SARS-CoV-2). The illness first appeared in China in December 2019 (Wuhan). Because of its rapid growth, it has become a major public health issue throughout the world [164]. Covid-19 is a respiratory illness that can be deadly in elderly or chronically ill people. It spreads by intimate contact with sick individuals. Asymptomatic patients may potentially spread the illness, but scientific evidence to establish this is inadequate [165]. Meanwhile, the most prevalent COVID-19 symptoms are fever, dry cough, and fatigue. Other less frequent symptoms that some people may have include: loss of taste or smell, nasal congestion, conjunctivitis (also known as red eyes), Throat ache, Headache, Muscle or joint discomfort, Skin rash of various sorts, Nausea or vomiting, Diarrhea, Dizziness or chills [166].

9.1 Covid-19 Variants

Due to the lack of a viral vaccination against COVID-19, the virus has evolved and shown new versions divided into [167] :

- **Variants of Concern (VOCs)** such as Alpha (B.1.1.7 lineage), Gamma (P.1 lineage), Delta (B.1.617.2), Beta (B.1.351).
- **Variants of Interest (VOIs)** such as Epsilon (B.1.427 and B.1.429), Zeta (P.2), Eta (B.1.525), Theta (P.3), Iota (B.1.526), Kappa (B.1.617.1) and Lambda (C.37).

9.2 Types of Covid-19 Vaccine

According to WHO, four main types of vaccines are approved [167]:

- **Whole Virus** whole virus vaccines use a weakened (attenuated) or inactivated form of the pathogen to establish protective immunity against it. There are two types of whole viral vaccines. In live attenuated vaccines, a weakened version of the virus is utilized, which can still grow and reproduce but does not cause illness. Viruses with inactivated vaccines have had their genetic code destroyed by heat, chemicals, or radiation, preventing them from infecting and multiplying cells but still evoking an immune response.

- **Protein Subunit** acellular or subunit vaccinations are isolated pieces of a bacterial pathogen that activate immune cells. In general, these specialized pieces, known as protein, induce a potent and efficient immune response, lowering the possibility of side effects. Subunit vaccines, on the other hand, may decrease immune responses because the antigens used to produce an immune response may lack pathogen-linked molecular patterns shared by a class of diseases. These structures can be read by immune cells and recognized as danger signals.

- **Nucleic Acid** by using genetic material (DNA or RNA) from the virus or bacterium, nucleic acid vaccines stimulate an immune response against a disease-causing virus or bacteria. This genetic material is made up of specific nucleotides linked together in a long chain that is injected into host cells to make antigens (protein) using protein-making machinery and provoke an immune response.

- **Viral Vector** in contrast to other types of immunizations In viral vector-based vaccines, the spike proteins on the virus's surface are employed as genetic instructions to make antigens by transferring these genetic codes into the cell. Once the cells have received these instructions, they will use the body's cellular machinery to produce large amounts of antigens, resulting in an immunological response.

According to the World Health Organization, the pandemic threatens human life, with 511,965,711 confirmed cases and 6,240,619 fatalities. Despite the vaccinations developed by scientists [167], the virus is still capable of mutating and producing new forms, further complicating the problem [168].

10 Conclusion

This chapter introduced the main concepts used in this thesis, such as Machine Learning, Deep Learning, Metaheuristic, IoT, Big Data, and Cloud Computing. Also, we gave an overview of medical domains that we will within our thesis, such as neonatal seizures and covid-19.

Healthcare 4.0 is a vast domain combining medicine and cutting-edge technologies. The AI and its different technics must power this combination. For this reason, in the following chapter, we aim to give an overview of the state of the art works that combine AI and healthcare in general and for neonatal seizures and covid-19 especially.

Chapter III

AI in Healthcare: State of the art

1 Introduction

Deep learning has achieved considerable success in various ICT-enabled sectors over the last few decades, including industry, healthcare, agriculture, smart city, energy, IoT infrastructure, smart home, education, sport, ITS, government, and retail Figure III.1. Deep learning is commonly used to treat massive data supplied by IoT devices. In particular, the healthcare industry has substantially boosted its use of IA techniques like IoT, DL, Cloud computing, Fog computing, etc. The notion of connecting physical items to the internet and sharing data amongst different devices in the healthcare domain gave birth to a new concept known as the Medical Internet of Things (MIoT). From the patient to the doctor, the MIoT delivers excellent services to medical personnel [168].

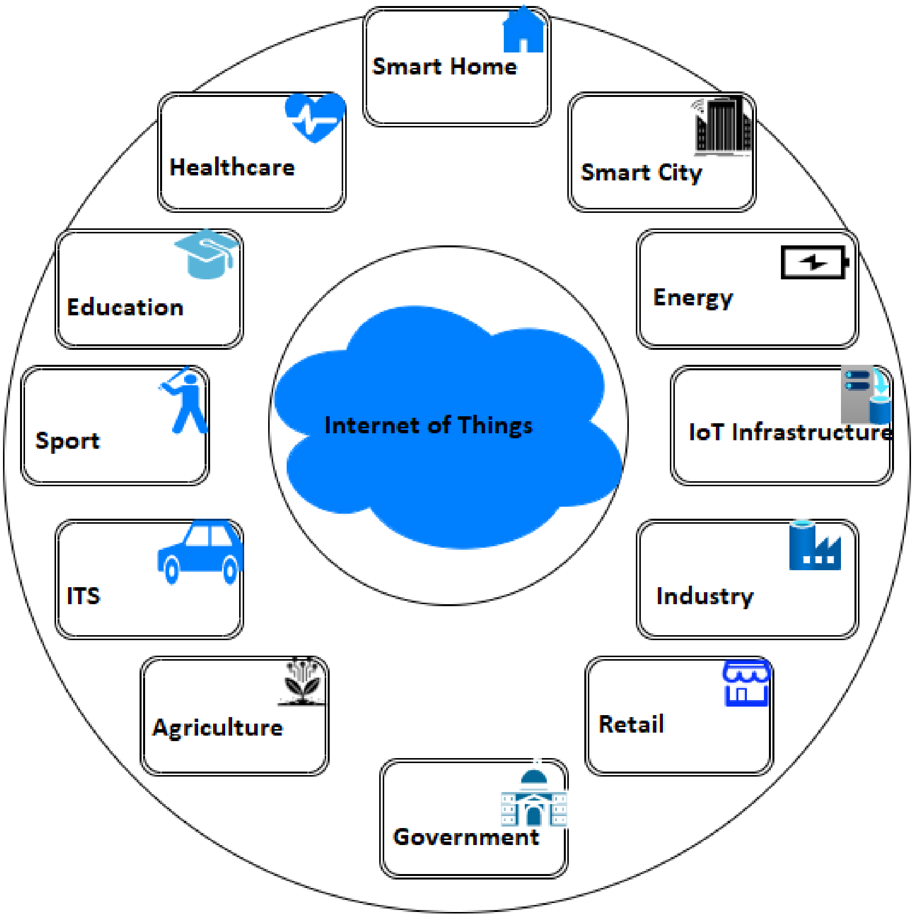

Figure III.1: IoT Application

As IoT devices spread, a massive quantity of data is created that must be cleaned and analyzed. The DL will be an accurate instrument for this work, and it will be able to use this vast data in prediction, diagnosis, clinical decision-making, and so on [169] (See Tables III.1 and III.2).

2 Medical diagnosis and differentiate applications

In the literature, IoT technology invades the medical field and achieves state of the art. For example, Tuli et al. [170] applied deep learning and IoT to diagnose heart disease patients. In addition, the authors included fog computing, named HealthFog, in their system to collect data from different IoT devices and manage it, saving energy and reducing latency issues. Filho et al. [171] developed an IoT and CNN system using the CT images of the brain to classify the brain state healthy or stroke (ischemic or bleeding). Another work done by 179 based on LSTM and heart rate signals for Atrial

Fibrillation (AF) episodes detection. Moreover, deep reinforcement learning models are combined with the IoT, such as in [172]. The authors investigated reinforcement learning for diagnosing lung cancer and classifying it as benign or malignant. Zhen et al.[173] proposed a Skin cancer detection system based on CNN and IoT. The authors applied CNN on ImageNet to identify common nevi, atypical nevi, and melanomas. Also, Convent with IoT framework used to decode EEG datasets and extract meaningful information such as in [174].

2.1 Home-based and personal healthcare applications

The application of deep learning and IoT in the medical area does not limit to medical diagnosis only; it also could touch the living of the patient by providing intelligent spaces in the home for chronic patients, such as in the work of Fonseca et al. [175]. Moreover, an IoT system with the help of deep learning could be used for teeth disorders detection and classification, such as in [176]. Furthermore, Sagar et al. [177] used Body Sensor Network (BSN) to develop a physiological monitoring system. The authors aimed to predict and diagnose the state of the body using physiological signals and a Deep Neural Network (DNN). This framework could be used for chronic fever, heart attacks, and care for the elderly. Also, Jeyaraj et al. [178] proposed a monitoring signal system to detect the abnormality of the patients' psychology. The authors used ECG, EEG, temperature, and pulse rate as input metrics for DCNN. The work aims is to predict the psychological signal of the patient.
Also, Kinnison et al. [179] investigate the use of IoT and DL in detecting the muscle injury of a sports player. IoT-based cloud systems are investigated in the work of Azimi et al. [180] using CNN and MLP techniques to perform real-time heart-related disease detection using ECG signals.

2.2 Disease prediction applications

Epileptic seizures have been investigated in the work of [181] [182] using Brain-Computer Interface (BCI). The authors used electronic devices to extract the EEG signal and then apply it to the processing modules and machine learning technics to predict the brain state. ST-Med-Box is a smart device for recognizing medication based on deep learning technologies that may help patients with chronic conditions take mul-

tiple medications accurately and ensure they take the prescription [183].
Deep learning and IoT techniques were proposed in the work of [11] smart Alzheimer assistance system. The authors used a recurrent neural network for Alzheimer's prediction and a convolutional neural network for tracking the abnormalities in the patient's emotions.

2.3 Related work for Neonatal seizures detection

In the literature, there is a big body of work for neonatal seizures detection using EEG records and deep learning methods such as EEG and amplitude-integrated EEG (aEEG) because of their importance in diagnosing and monitoring neonatal epilepsies. For instance, Yang et al. [185] proposed ocular artifacts removal in an EEG system based on deep learning. The authors used deep learning in the offline and online steps for better training. The results of their study indicated the performance of their method compared to independent component analysis (ICA), kurtosis-ICA (K-ICA), and Second-order blind identification (SOBI). However, the small size of the dataset still limits their work.
Tsiouris et al. [186] proposed a deep learning system based on EEG signals to predict epileptic seizures. The proposed system combined CNN and LSTM to train the data collected from CHB-MIT Scalp EEG database. The evaluation of the system showed good results in predicting epileptic seizures with low False Prediction Rates (FPR). Even so, using a small dataset is still the most limitation of the system. Tjepkema-Cloostermans et al. [187] proposed focal epileptiform discharges in scalp EEG recordings detection system. The system used deep learning models such as CNN and LSTM with variant dimensions (1D, 2D). The obtained results indicate that 2D CNNs and 2D CNN-LSTMs perform better than the other models in terms of sensitivity and specificity.
Ansari et al. [188] proposed hybridized CNNs and random forests to detect Neonatal Seizures. The authors aimed to use the heuristic method to optimize feature selection from EEG records. The evaluation of the system showed the proposed model's performance in terms of a false alarm rate of 0.9 per hour and time-consuming. However, they used a small dataset and did not compare their results with other works.
Frassineti et al. [189] Proposed system for detecting neonatal seizures based on deep

	System	Advantages	Limits
[170]	A lightweight fog service and effective management of data to diagnose heart diseases automatically. Optimization of QoS parameters in real-time fog environments.	Low latency. Energy-efficient solutions to process data.	Latency and QoS optimization problem.
[177]	A DNN proposed to find qualities of the signal in the sensor array to understand the body conditions of the patients.	High accuracy. Low cost.	Require a large amount of data.
[184]	LSTM based DL system.	Less limited as against machine learning approaches. Information elicited from a small training dataset may be generalized to a bigger dataset.	No test.
[172]	Deep reinforcement learning models for computer-assisted diagnosis and cure of lung cancer.	The problem of localizing cancer in the lungs shall be solved.	Q-value shall be updated.
[173]	A system based on IoT technology is used to classify skin lesions.	Accessible usage in different regions. Easy to handle manner.	Requires a good connection.
[174]	Methods of visualizing the learned features were presented. Represents the process of ConvNets for decoding data related to tasks.	ConvNets suit end-to-end learning. Their scalability for huge datasets is satisfactory.	They may show false predictions. Need a huge body of data for training purposes.

Table III.1: Related work of DL with Cloud and IoT in the healthcare (1)

	System	Advantages	Limits
[175]	Make smart living conditions for home-based healthcare in the multimorbidity of chronic patients.	A new wave of caregiving amenities Controlling costs	No statistics to prove the effectiveness
[177]	A DNN proposed to find qualities of the signal in the sensor array to understand the body conditions of the patients.	High accuracy. Low cost.	Require a large amount of data.
[179]	Using IoT in the area of sports injuries.	Working better in packet loss rate and accuracy.	The small size of the system experiment feedback population.
[181]	Seizure prediction BCI.	The Learning possibility through huge data which is not supervised. Productive method for real-time patient-based seizure prediction and localization system.	Trap at local minima. Lower performance. High computational time.
[183]	A smart system to recognize medication based on deep learning methods (ST-Med-Box).	Perfect recording. High-precision Recognition. Simple operation.	The recognition accuracy should be improved.
[11]	Smart Alzheimer assistance system.	Detecting tracking and predicting Alzheimer's patients. Support the assistance to the Alzheimer's patients.	The accuracy of the system needs to be improved

Table III.2: Related work of DL with Cloud and IoT in the healthcare (2) learning and Stationary Wavelet Transform (SWT). The authors used two deep learning models, CNN and FCN, on the EEG records collected from Helsinki University Hospital. The evaluation of the system showed 81% of AUC, 77% of GDR, and 1.6 of FD per hour.

Pavel et al. [190] present an automatic Algorithm for Neonatal Seizure Recognition (ANSeR). The authors' used a dataset of 13827 h of continuous conventional electroencephalography (cEEG) extracted from the Neonatal Intensive Care Unit (NICU). The evaluation of their experience indicated remarkable results in terms of seizure recognition.

O'Shea et al. [191] developed a system based on a full convolution network to detect a neonatal seizure. The authors used a dataset of 834h of cEEG recording to test their model and compared it with a Support Vector Machine (SVM). The obtained results showed good performance of the proposed model in terms of AUC (98.5%). Nevertheless, they just compare their model with SVM, a machine learning method. Also, they depend only on AUC metrics as classification metrics.

In general, most of the limitations of the presented works were the use of small and different datasets; besides, some of them are public, and the others are private. Also, they depend only on a few classification metrics, and each uses specific metrics, making it difficult to compare with their works. Furthermore, they depend on the manual organization of their models, which means that they use the manual selection of the model's parameters, which causes time consumption and over-fitting or under-fitting of the model in case of non-homogeneity of the parameter's selection. Also, the manual selection of the model's parameters increases the complexity of the model.

2.4 Related work for Covid-19 detection

Researchers utilized CNN for Covid-19 identification due to the tremendous success of CNN as a deep learning approach in image processing such as classification, prediction, and other metrics in other domains. Many studies have been conducted in Covid-19 identification employing chest X-ray datasets of normal and Covid-19 patients with various CNN implementations, such as [192]. The authors presented the ResNet-101 convolutional neural network architecture for predicting COVID-19 using a dataset of 1547 X-ray images for training. Their proposed model has an accuracy

of 71.9 percent. In addition, [193] provided a comparative evaluation of the ResNeXt, Inception V3, and Xception models for classifying COVID-19 infected individuals. As a dataset for Chest X-ray pictures, they used the Kaggle repository. The results reveal that the Xception model outperforms other utilized models like ResNeXt and Inception V3, with an accuracy of 97.97 percent.
The work of [194] Used a combination of three public datasets (1102 chest X-ray images in total) as the main data source for the conventional transfer learning method and a pre-trained deep learning model and traditional machine learning classification to identify COVID-19 in chest X-rays. The approach's experimental analysis yields 96.75 percent accuracy. Furthermore, CNN models using capsules were presented by [195]. They intended to optimize the model by employing a small number of trainable parameters. Their study's findings show an accuracy of 95.7 percent. Other works are presented in Table III.3.

3 Conclusion

As a conclusion to this chapter, we ensure that the application of AI and Deep Learning touches the majority of domains and has become an elementary component of the development. Unlike other domains, healthcare has wide adoption of the new technologies powered by AI, Cloud computing, and IoT. However, combining these technologies for specific tasks, such as healthcare, is a big challenge that needs to be well studied and hard working. The application of deep learning in healthcare is believed to be a good technic for extracting insights from big medical data and aids in diagnosing various diseases. Meanwhile, the healthcare sector is very sensitive and requires an accurate and real-time tool because the patients' life is on edge. Also, the application of IoT technologies in the healthcare sector is a great upcoming for improving the quality of human life because it saves lives, provides big services for humanity, and ameliorates their healthcare. Whereas, The IoT systems in the healthcare sector require critical conditions such as the real-time response, the security of the patients' data, the availability, and other properties. Moreover, the use of IoT technology is conducted with cloud computing because of its ability to provide scalable and on-demand services and resources anywhere, anytime. However, the application of cloud computing is a challenging task requiring many points that need to be treated, such as security and

Ref	Method	Dataset	Evaluation Metrics	Research challenges
[194]	VGG16, InceptionV3, ResNet50, Xception, DenseNet121, Decision Tree, Random Forest, AdaBoost, Bagging, SVM.	Dataset of X-ray images and CT scan images provided by Dr. Joseph Cohen from the GitHub repository + COVID-19 Chest X-ray Dataset Initiative + Chest X-ray image dataset provided by Kaggle.	Accuracy, Sensitivity, Specificity, F1-Score, AUC.	Depend only on the classification of Covid-19 and normal X-ray images.
[196]	PA , ARIMA, and LSTM + VGG16	Chest X-ray images of COVID-19 obtained from the Kaggle database.	Precision, Recall, and F-measure, Accuracy, RMSE.	Depend only on the classification of Covid-19 and normal X-ray images.
[197]	ResNet101 and ResNet-50	X-ray images of the chest from Cohen and Kaggle repositories.	Precision, Recall, Accuracy.	The limited number of COVID-19 images.
[198]	ResNet-101	ChestX-ray14 dataset extracted from National Institutes of Health Clinical Center, USA +Covid-19 X-ray images from University of Montreal.	Sensitivity, Specificity, Accuracy and AUC.	Lack of images used in the testing phase.
[199]	Inception V3, Xception, and ResNeXt.	Chest x-ray scans Kaggle repository.	Accuracy. Precision, Recall, F1-Score.	Small dataset.
[200]	VGG16	Public Dataset of X-ray images from healthy, pneumonia, and covid-19 patients.	AUC, Accuracy.	Small dataset.

Table III.3: State-of-art-work that used ML and DL for Covid-19 (1)

Ref	Method	Dataset	Evaluation Metrics	Research challenges
[201]	ResNet, VGG, Inception and Efficient Net.	Publicly available COVID-19 chest X-ray image repository and Pneumonia.	Accuracy	Small number of images in validation.
[202]	SVM	A total of 1100 chest X-ray images selected from three different open sources: the GitHub repository shared by Joseph Cohen, Kaggle, Bachir, and Mooney.	Sensitivity, Specificity, AUC, PPV, NPV, and Accuracy.	Lack of COVID-19 X-ray images.
[203]	CCSHNet	Chest CT (CCT) images from local hospitals.	Micro-averaged F1 score, Sensitivity, Precision.	Small dataset.
[204]	FGCNet	Chest CT images.	Fowlkes–Mallows index, Matthews correlation coefficient, F1, Sensitivity, Specificity, Precision, and Accuracy.	Lack of clinical testing.
[205]	COVID-Net-CT and ResNet-v2	COVIDx CT-2A and COVIDx CT-2B datasets.	Sensitivity, Specificity, PPV, NPV, and Accuracy.	Small dataset.

Table III.4: State-of-art-work that used ML and DL for Covid-19 (2) privacy of the data, scalability of the system, the data heterogeneity and management, response time, availability, and other challenging tasks.

From these points, we have to define our problematic, which is how we can overpass the limit of the long time required for training the deep learning models, especially in such critical domains. Also, the application of IoT and cloud computing technologies in the critical sectors should provide real-time responses to what needs to improve the QoS of the system. Moreover, combining such big terms as deep learning, IoT, big data, and cloud computing is a really big challenge.

Chapter IV

New bio-inspired approach for deep learning techniques applied to neonatal seizures

1 Introduction

Detecting neonatal seizures and their classification is one of the biggest challenges neurologists face, especially when relying on clinical observation [206]). Meanwhile, various screening techniques and brain signals have been developed to diagnose epileptic seizures [207], including Magnetic Resonance Imaging (MRI) [208], Electroencephalogram (EEG) [209], Magnetoencephalography (MEG) [210] and Positron Emission Tomography (PET) [211]. In fact, with the increased use of EEG in the field of neuroscience and their effective representation of the human's physiological and pathological states, especially in the Neonatal Intensive Care Units (NICUs), it is considered a pattern for the diagnosis of neonatal epileptic seizures [212][213]. EEG was one of the essential components of the brain-computer interface (BCI) that was used to integrate researchers from neuroscience, physiology, psychology, engineering, computer science, rehabilitation, and other technical and healthcare disciplines. Moreover, EEG is an accurate and widely-used technique because it reflects the state of the brain, easy to access, low cost, and has a high temporal resolution [214][215].

In practice, the interpretation of the EEG requires neurologists' experience and time which creates big problems for the global neonatal health and the necessity of the intervention of the World Health Organization (WHO). On the other hand, integrating Artificial Intelligence (AI) in medical domains achieved good results in various tasks. One of the powerful AI tools is deep learning, which has been widely used in analyzing, classifying, detecting, and recognizing data. The field of medicine has received a lot of attention in deep learning investigation, especially for neurology science that uses EEG signals to discover the physiology and pathology of the human states and detect the abnormality events such as seizures, Alzheimer's disease, and tumors, etc. The application of deep learning approaches for EEG tasks achieves good results, according to Craik et al. [216] and Gao et al. [212]. Therefore, even though deep learning approaches have been recently used for detecting seizures in newborn infants with remarkable outcomes and benefits, their time-consuming nature and the complexity of the model still hinder its use. Also, most of the works done in literature use small datasets and depend on various measures to calculate the performance of their system. Getting the appropriate and accurate structure of the model is one of the biggest challenges scientists face when using deep learning models because of the particular features and needs of each application. This can be facilitated using metaheuristics such as Marine Predator Algorithm [217], Grey wolf optimizer (GWO) [218], whale optimization algorithm (WHO) [219], Particle Swarm Optimization [220], Artificial Bee Colony [221], Tabu Search [222] and Simulated Annealing [223].
Metaheuristic algorithms can be good enough to fill the gaps mentioned above by optimizing the features extracted by the model, optimizing the model by selecting the appropriate parameters, reducing the complexity of the model, etc.

Therefore, this chapter aims to present a neonatal seizures detection system using deep learning and the power of parallel metaheuristic optimization for auto-selecting the hyperparameters to optimize our model. We also provide various classification metrics and measures to evaluate and prove the performance of our proposed model.

2 Materials And Methods

In this section, we present the different methods used for our experiment.

2.1 Convolutional Neural Network

CNN's are one of computer vision's most widely used and successful deep learning models. The power of CNN lies in the automatic extraction of features and the hierarchical structure, which allows the model to obtain good results in various applications such as pictures, signals, NLP, and so on [223]. CNN is made up of convolutional layers (Conv), nonlinear layers, pooling layers, and dense layers. Each layer includes its specifiers, input types, and unique functions that create an output for the next tier (Figure IV.1).

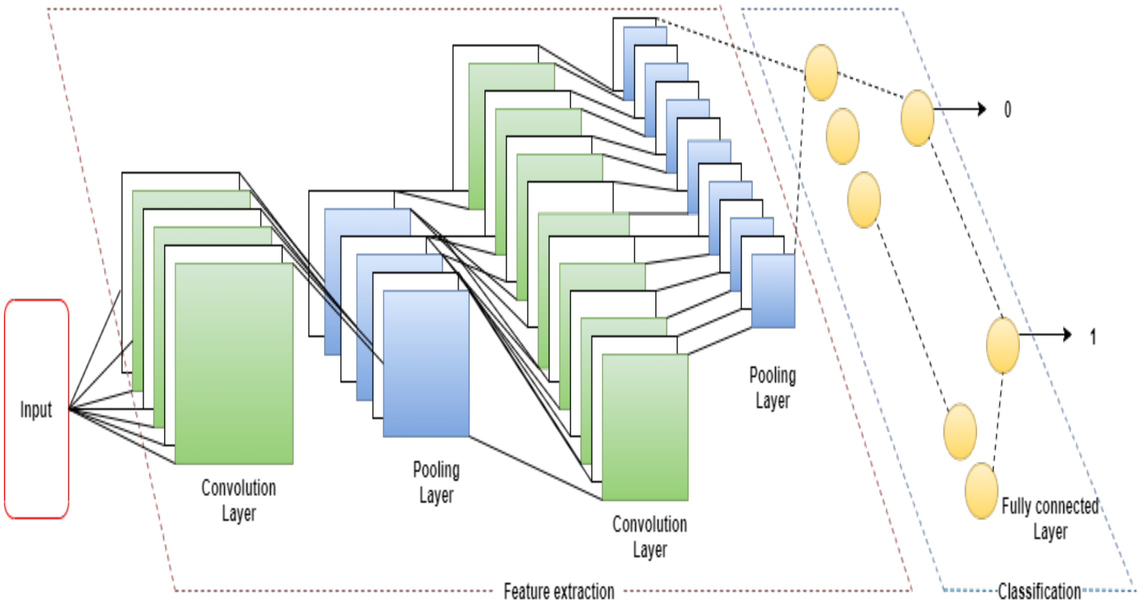

Figure IV.1: General architecture of the Convolution Neural Network

Regardless of the demand for AI capability to solve medical problems, deep learning may be useful for aiding diagnosis in time series. CNN has significantly influenced the medical field, where it is used for classification, prediction, and other purposes. CNN may be utilized for EEG analysis with either 1D or 2D architecture [207].

2.2 Marine Predators Algorithm

The Marine Predators Algorithm is a metaheuristic population-based approach inspired by predator-prey foraging strategies in marine habitats. The algorithm is designed to optimize the predator's foraging trajectory by utilizing three tactics based on the mobility and concentration of the prey. For example, predators utilize the Brownian approach for unit velocity ratios but the Lévy technique for low-velocity ratios. In high-velocity ratios, predators remain motionless [217]. Furthermore, Yousri et al. [224], Zhong et al. [225], Abdel-Basset et al. [226], Yousri et al. [227], and Yang et al. [228] demonstrated excellent outcomes using the MPA.

2.2.1 Brownian equation

Brownian motion is a stochastic method based on probability function, where μ represents the mean distribution ($\mu = 0$) and σ^2 is the variance ($\sigma^2 = 1$). The governing Probably Density Function (PDF) at point x for this motion is as follow (Eq IV.1 and Eq IV.2) [229]:

$$B(x; \mu, \sigma) = \frac{1}{\sqrt{(2\pi\sigma^2)}} exp^{(-\frac{(x-\mu)^2}{(2\sigma^2)})} \tag{IV.1}$$

After the simplification of the equation:

$$B(x; \mu, \sigma) = \frac{1}{\sqrt{2\pi}} exp^{(-\frac{x^2}{2})} \tag{IV.2}$$

2.2.2 Lévy equation

Lévy is a type of random walk which the step sizes are determined from a probability function defined by Lévy distribution [230][231]:

$$L(x; \mu, \sigma) = \frac{1}{\pi} \int_0^{\pi} exp^{(-\gamma q^{\alpha})} \cos(qx) dq \tag{IV.3}$$

$$L(x; \mu, \sigma) \approx \frac{\gamma \Gamma(1+\alpha) \sin(\frac{\pi\alpha}{2})}{\pi x^{(1+\alpha)}}, x \to \infty \tag{IV.4}$$

Where $1 \geq \alpha \leq 2$, γ selects the scale unit and $\Gamma(1+\alpha) = \alpha!$.

2.2.3 MPA structure

While the predators are looking for prey, the victims must likewise look for nourishment. As a result, two matrices must be defined: the first, Elite, which represents the fittest predator, and the second, *Indv*, which reflects the location of the prey depending on the Elite. They can be expressed mathematically as:

$$Indv = \begin{bmatrix} Indv_1 1 & \dots & Indv_1 m \\ \vdots & \ddots & \vdots \\ Indv_n 1 & \dots & Indv_n m \end{bmatrix} \tag{IV.5}$$

$$Elite = \begin{bmatrix} Indv_1 1^1 & \dots & Indv_1 m^1 \\ \vdots & \ddots & \vdots \\ Indv_n 1^1 & \dots & Indv_n m^1 \end{bmatrix} \tag{IV.6}$$

Step 1: The Initialization of the algorithm is done in a uniform random way to create the first population based on fitness to get the best predator using Eq (IV.7).

$$Indv_{ik} = LB_k + rand(UB_k - LB_k); i = 1, 2, \dots, n; k = 1, 2, \dots, m \tag{IV.7}$$

Where LB_k and UB_k are the lower and upper boundaries for the i^{th} variable with k dimension and *rand* is the uniform random number between 0 and 1 [217].

Step 2: After acquiring the best predator in terms of fitness, their movement is determined by the velocity ratio and the speed of the prey. When the predator moves slowly compared to the prey, the greatest technique for better foraging is staying still, and the predator must establish its position. This strategy occurs in the first 1/3 of the population, and it aims to explore the area [217].

$$M_i = R_B \otimes (Elite_i - R_B \otimes Indv_i), i = 1, 2, \dots, n \tag{IV.8}$$

$$Indv_i = Indv_i + P.R \otimes M_i \tag{IV.9}$$

Step 3: On the contrary, the prey is slower than the predator, indicating a lower velocity ratio. In that circumstance, the predator must use Lévy mobility to better utilize the region and encounter the maximum quantity of prey. This is more common in the bottom third of the population. [217].

$$M_i = R_L \otimes (R_L \otimes Elite_i - Indv_i), i = 1, 2, \ldots, n \tag{IV.10}$$

$$Indv_i = Elite_i + P.CF \otimes M_i \tag{IV.11}$$

$$CF = (1 - \frac{t}{t_m ax})^{(2\frac{t}{t_m ax})} \tag{IV.12}$$

Step 4: When the predator and prey have the same speed and velocity (Unit velocity), the predator's correct reaction is to take Brownian movements, while the prey follows the Lévy movement. Predators improve their chances of optimal hunting by travelling in this manner owing to the ability of this strategy to assure both exploitation and exploration mechanisms by employing half of the population for exploitation and the other half for exploration [217].

$$M_i = R_L \otimes (Elite_i - R_L \otimes Indv_i), i = 1, 2, \ldots, \frac{n}{2} \tag{IV.13}$$

$$Indv_i = Indv_i + P.R \otimes M_i \tag{IV.14}$$

Where R_L is random vector of the Lévy movement and the simulation of Lévy movement of the prey defined by the multiplication of R_L and Indv for the half of population (Eq IV.13 and Eq IV.14). R_B is random vector of the Brownian movement and the multiplication of R_B and Elite simulates the Brownian movement of the predator in the second half of population (Eq IV.15 and Eq IV.16).

$$M_i = R_B \otimes (R_B \otimes Elite_i - M_i), i = 1, 2, \ldots, \frac{n}{2} \tag{IV.15}$$

$$Indv_i = Elite_i + P.CF \otimes M_i \tag{IV.16}$$

$$CF = (1 - \frac{t}{t_max})^{(2\frac{t}{t_max})} \tag{IV.17}$$

Where CF is a coefficient that controls the step size of predator, t is the actual iteration, and t_max is the maximum iteration.

2.2.4 Eddy formation and Fish Aggregating Device' effect

According to the following equations, the impacts of Fish Aggregating Devices (FADs) and Eddy formation are among the environmental challenges that most affect the marine ecosystem and compel predator and prey to adjust their behavior in order to avoid falling into the local optimum:

$$Indv_i = Indv_i + CF[Indv_min + R \otimes (Indv_{max} - Indv_{min})] \otimes U, r_0 \leq FADs \tag{IV.18}$$

$$Indv_i = Indv_i + [FADs(1 - r_0) + r_0](Indv_{r_1} - Indv_{r_2}), r_0 > FADs \tag{IV.19}$$

Where $FADs = 0.2$, U is binary vector composed from 0 and 1 and it depends on the random values $r_0 \in [0, 1]$. r_1 and r_2 refers to the preys list.

2.2.5 Marine memory

Predators may recall locations where they found the best foraging. The memory displays this quality in the MPA by comparing the real fitness of the solution to the past ones and changing the order of the solution if necessary.

2.3 DATA Preprocessing

In this step, we prepare our dataset, which contains patient EEG signals, using certain preprocessing methods to denoise the signals and extract the necessary characteristics. (see Figure IV.2).

Algorithm 1 Marine Predator Pseudo Algorithm

n: number of population, t_{max} :number of iteration.
Initialize population using **Eq (IV.7)**.
$t = 0$
$i = 1$
while $i \neq n$ *and* $t \neq t_{max}$ **do**
    Calculate the fitness.
    Assign the Elite Eq (IV.6).
    if $t < t_{max}/3$ **then**
        Update the population's positions based on Eq (IV.8) and Eq (IV.9).
    if $t_{max}/3 < t < 2 * t_{max}/3$ **then**
        while $i < n/2$ **do**
            Update the prey based on Eq (IV.13) and Eq (IV.14).
            $i++$
        while $i > n/2$ *and* $i < n$ **do**
            Update the prey based on Eq (IV.15) and Eq (IV.16).
            $i++$
    if $t > 2 * t_{max}/3$ **then**
        Update the population's positions using Eq (IV.10) and Eq (IV.11).
        Memorize the modified position of the Elite.
    Accomplish the memory saving.
    Update the actual predator using FADs based on Eq (IV.18) and Eq (IV.19).
    $t = t + 1$

- Data Segmentation: Using Petrosian Fractal Dimension, we fragment the patient's complete signal into windows, each with the same number of channels but a tiny number of samples (PFD).
- Preprocessing: We filter the band-pass of these windows after decomposing the signal into windows, normalize them using Z-Scores normalization, then analyze them using Independent Component Analysis (ICA).
- Augmented Features: In this stage, we extract the features of each window and concatenate them with clinical data from the patient, then save the resulting data in a CSV file to be used in the training process.

Algorithm 2 Data Preparation Pseudo Algorithm

Step 1:
Load EEG signals ().
Step 2:
Signal decomposition ().
Petrosian Fractal Dimension ().
Step 3:
Band-pass filtering ().
Z-Scores normalization ().
Independent Component Analysis ().
Step 4:
Features extraction ().
Load clinical data ().
Concatenate features and clinical data in CSV file ().

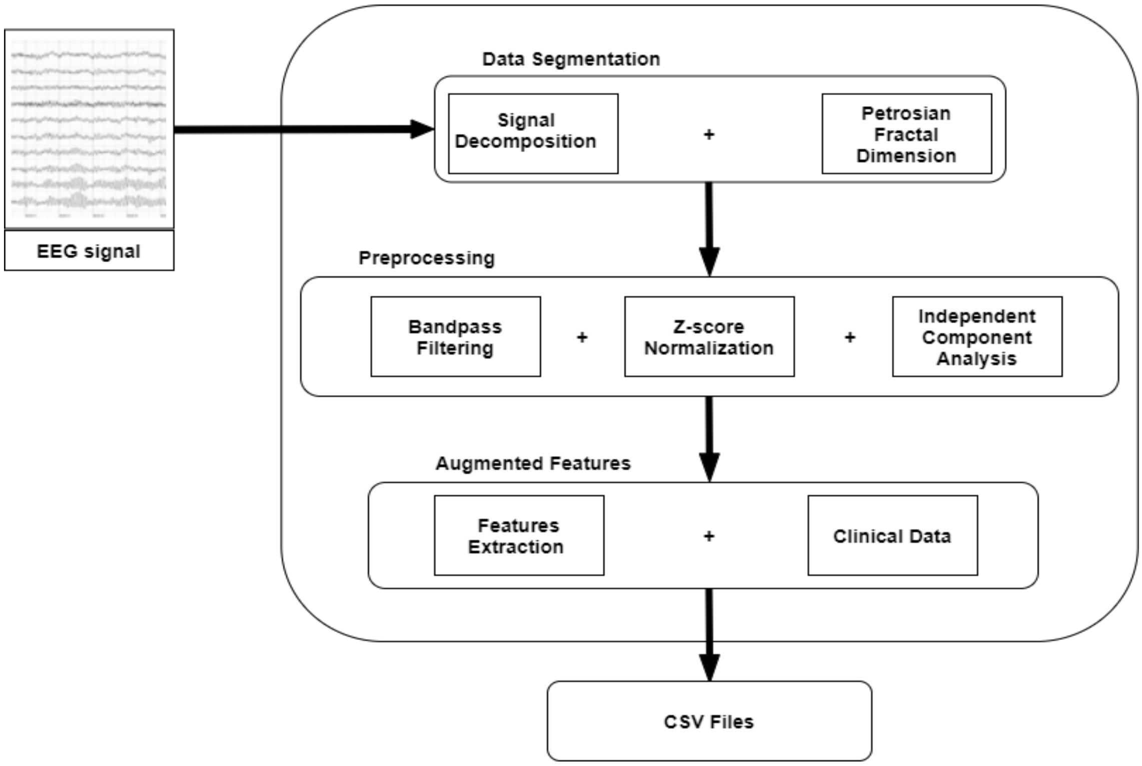

Figure IV.2: Dataset preparation

2.4 Proposed Model MPA-CNN

We suggest using an MPA-CNN to detect epileptic episodes automatically. As previously stated, the key benefit of the proposed technique is the use of MPA for auto-selecting the model's hyperparameters to improve the CNN. In other words, the primary goal of using MPA is to optimize the entire model by picking precise hyperparameters that speed up the learning process and improve the classification task. To optimize the performance of our model, we begin with a preprocessing phase that prepares the general structure of the CNN based on the MPA's specified hyperparameters. After these hyperparameters, we can create our CNN model and begin training on our dataset. We utilize 75 percent of our dataset for training and 25 percent for validation. The model's fitness created by the selected hyperparameters from the MPA is next evaluated using accuracy metrics to test the homogeneity of the selected hyperparameters (Figure IV.3 and Figure IV.4).

Furthermore, to validate the power and performance of our model (Figure IV.5), we compare it to GA-CNN (Figure IV.6), CNN without metaheuristic (Figure IV.7), and

CNN with just fully connected layers (Figure IV.8). The goal of utilizing models with metaheuristic techniques with models without metaheuristic methods is to evaluate the performance of models that used human hyperparameter selection to models that utilized auto-selection of hyperparameters.

Algorithm 3 Pseudo code of the proposed algorithm

```
Initialize the hyperparameters of the model.
Construct the model.
Train the model.
Calculate the fitness.
t = 0
while t < t_max do
    if fitness = 0.99 then
        Save the position of the solution and exit.
    if fitness < 0.80 then
        Apply Brownian movement Eq (IV.15) and Eq (IV.16).
    if 0.99 > fitness ≤ 0.80 then
        Apply Levy movement using Eq (IV.10) and Eq (IV.11).
    Calculate the fitness.
    Accomplish the memory saving.
    Apply FADs effects for the updating using Eq (IV.18) and Eq (IV.19).
```

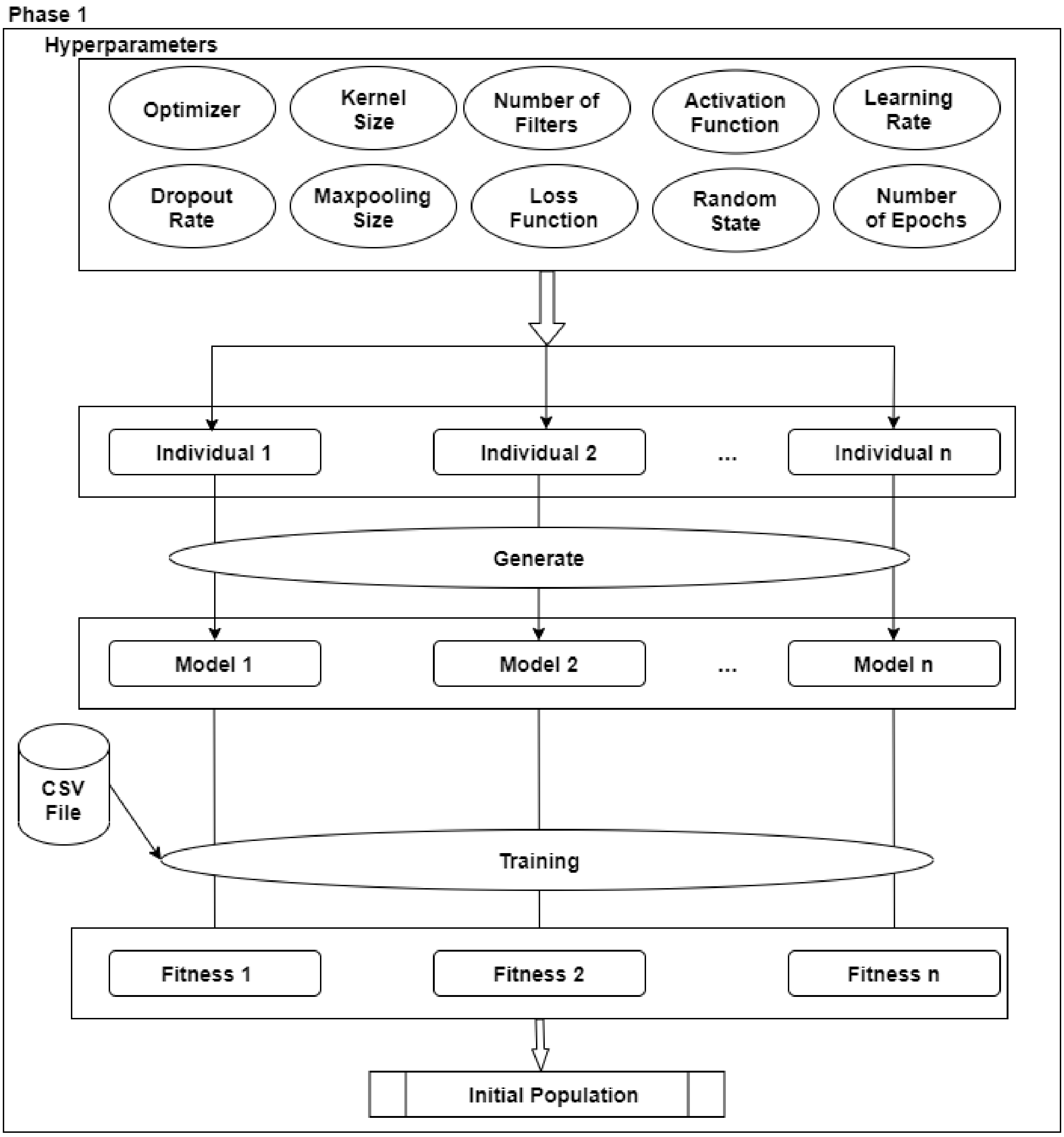

Figure IV.3: The generation of the initial population

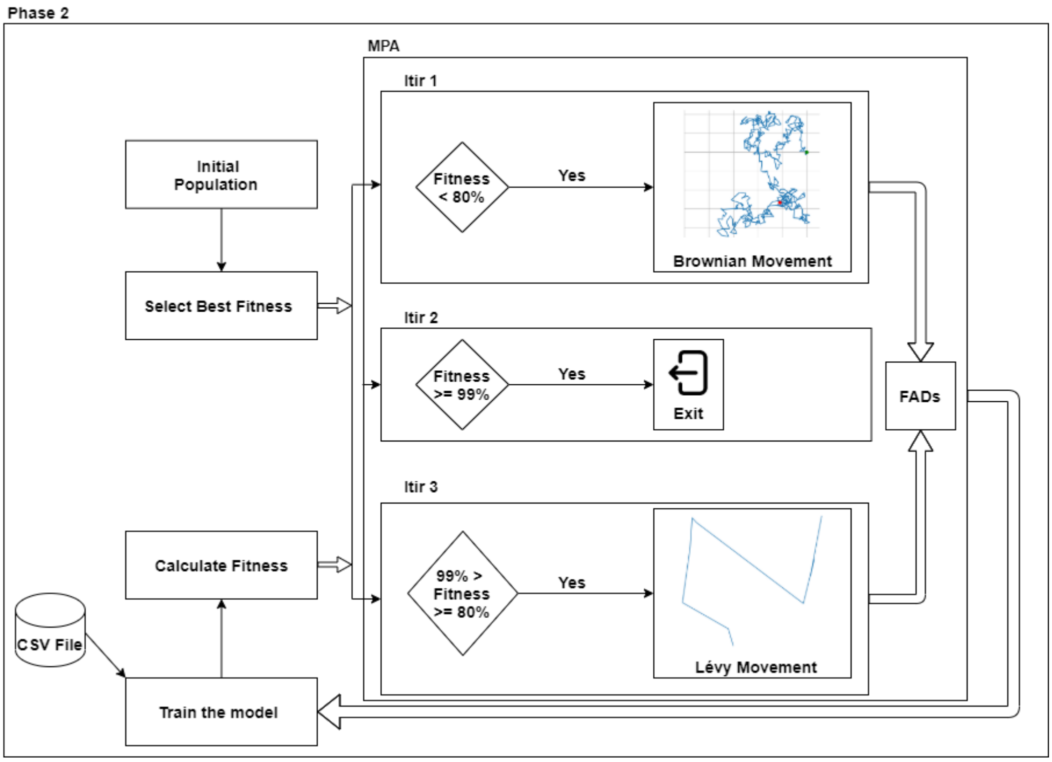

Figure IV.4: The detailed architecture of the proposed model

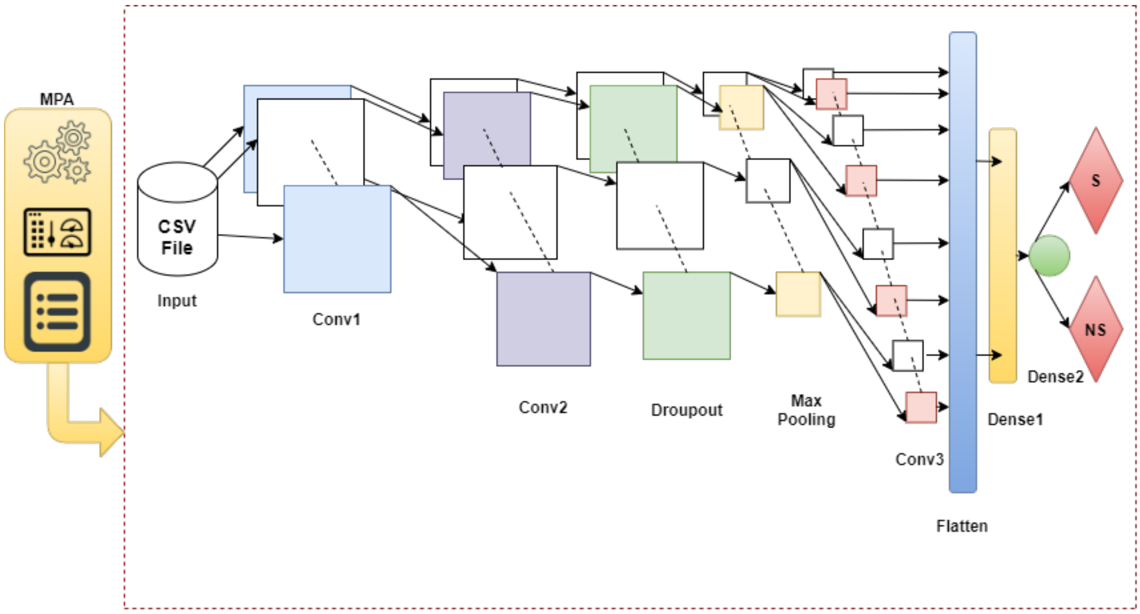

Figure IV.5: The architecture of MPA-CNN

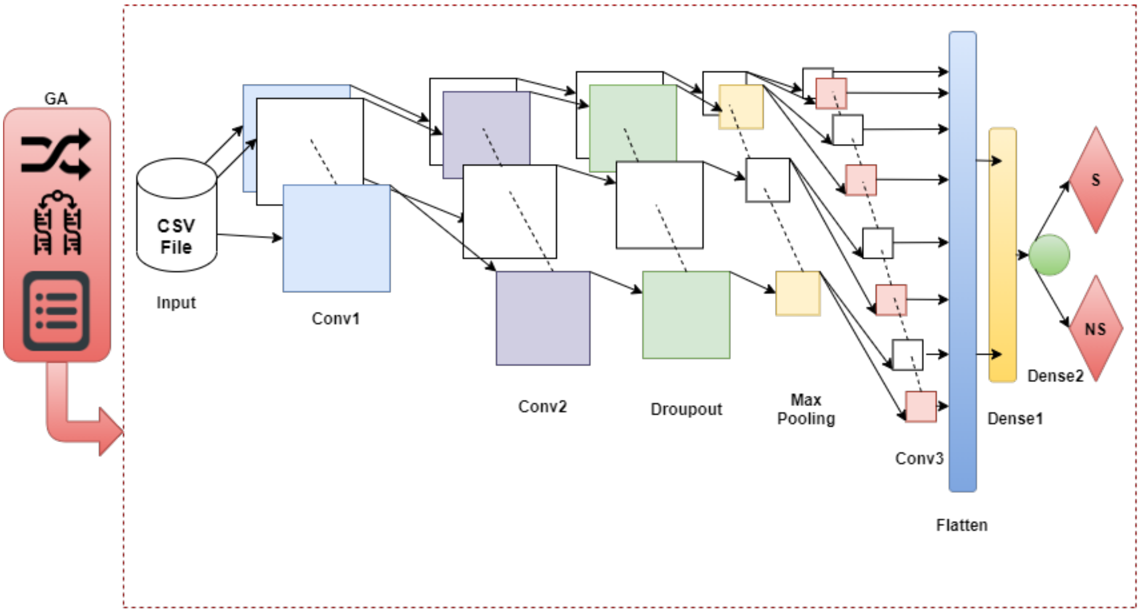

Figure IV.6: The architecture of GA-CNN

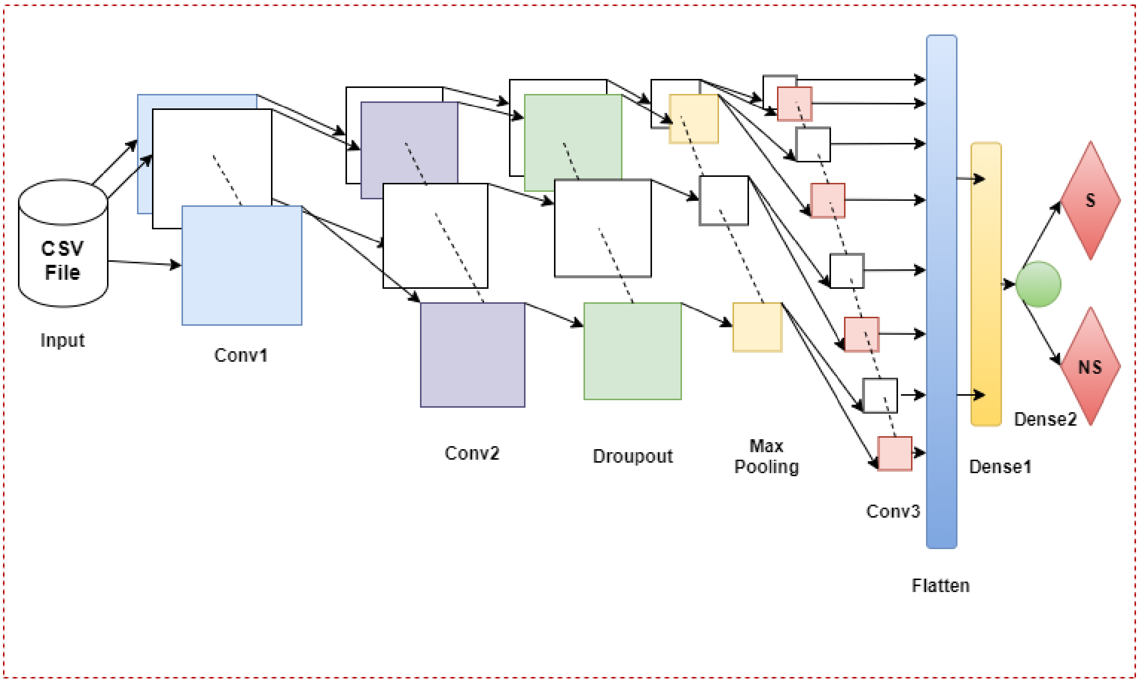

Figure IV.7: The architecture of Simple-CNN

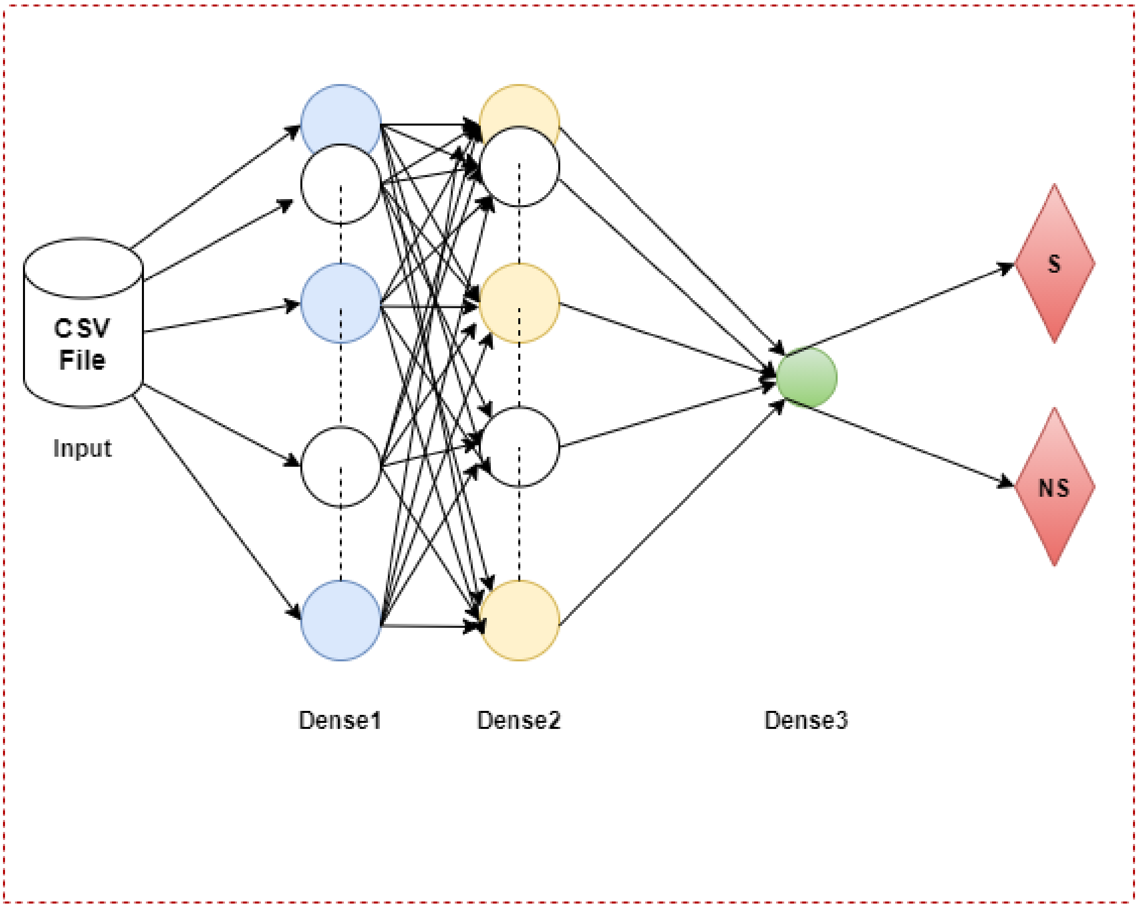

Figure IV.8: The architecture of CNN with fully connected layers

3 Results and Discussion

The algorithms were trained and tested using EEG recordings from 79 newborns. These recordings came from the NICU at Helsinki University Hospital. The EEG data were obtained using a NicOne EEG amplifier (256 Hz sampling frequency; Natus, USA) and EEG caps (sintered Ag/AgCl electrodes; Waveguard, ANT-Neuro, Germany) with 19 electrodes positioned according to the worldwide 10–20 standard, including a recording reference at the midline (Figure IV.9 and IV.10). The babies utilized in the subjects were 32-45 weeks gestational age, with a median recording time of 74 minutes (IQR: 64 to 96 minutes) [20].

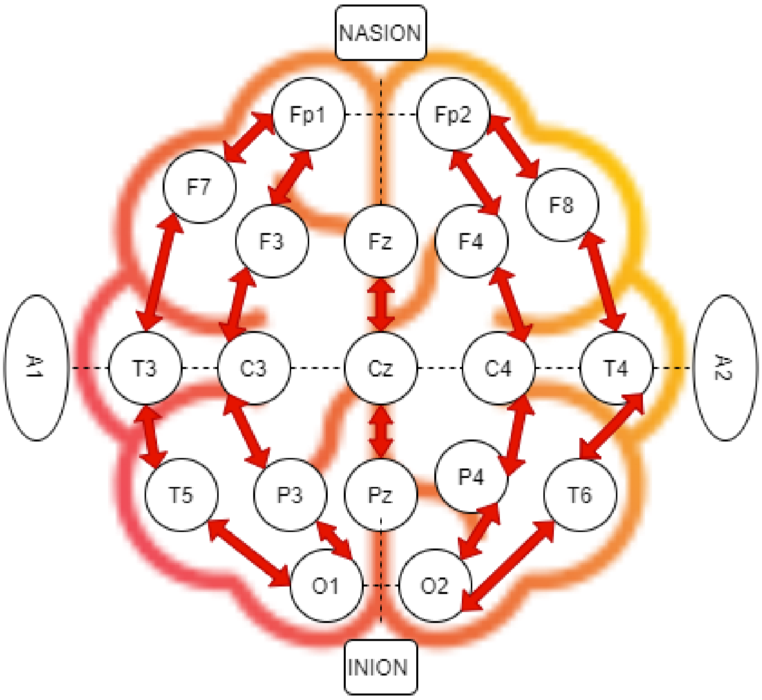

Figure IV.9: The position of the electrodes used for recording the EEG signals

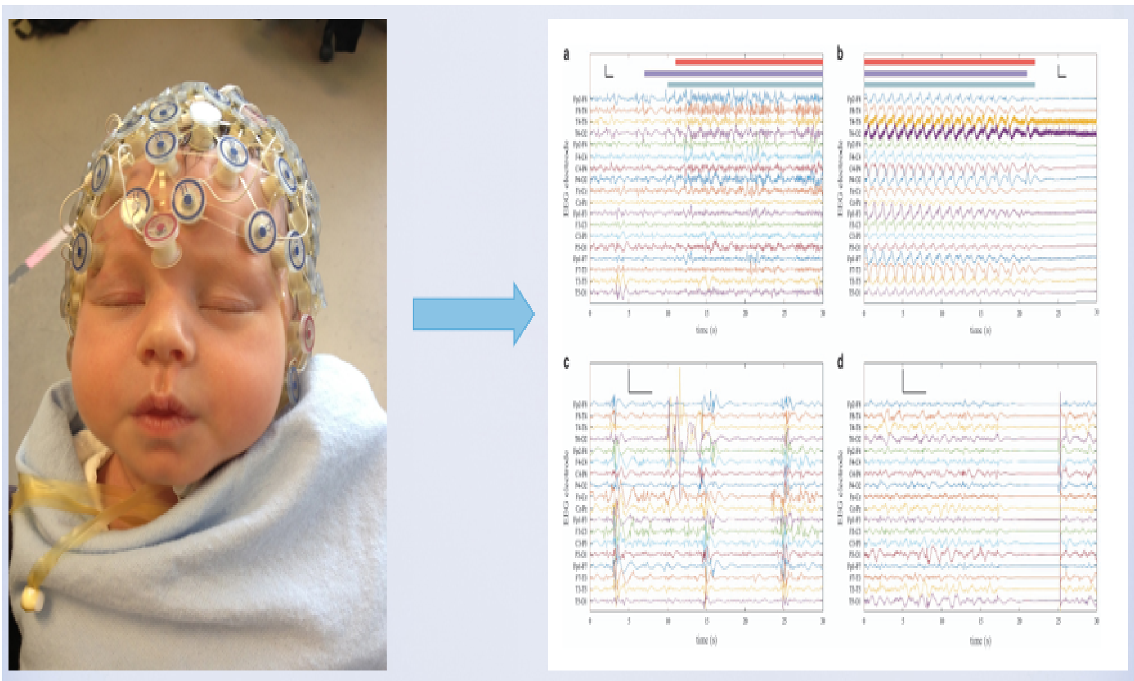

Figure IV.10: EEG records of newborns

Gender	Seizures	No-Seizures
Male	26	16
Female	29	6
N/A	2	0
Total Number	57	22

Table IV.1: The number and gender of patients in the dataset

The availability of clinical annotation from three specialists is one of the most significant benefits of using this dataset. These experts agree on the annotation of 460 seizures and affirm the existence of seizures in 57 infants. (Table III.3 and Table IV.1) [230].

In this chapter, we optimized the model's hyperparameters using MPA, a new metaheuristic optimizer. The goal of adopting a metaheuristic optimizer for CNN is to minimize training time while improving model performance. Furthermore, metaheuristics are commonly employed to optimize deep learning models. In our experiment, we first build a random population, each person being a vector of hyperparameters. In our experiment, the following hyperparameters were used: optimizer, learning rate, activation function, dropout rate, max-pooling size, kernel size, loss Function, number of filters, number of epochs, and random state.

We calculate the fitness of each individual in the population after producing the initial population by developing models based on the individuals recovered. As a fitness function, we assess the model's accuracy. Then we select the appropriate person to forward it to the MPA. The initial stage in MPA is to compare the fitness of the selected individual with 1. We chose 0.99 or 1 as the stop condition because we have a binary classification, which implies the outcome will be between [0 - 1]. The Brownian approach for values 0.8 is used in the second stage to boost the power of exploration in the Brownian manner of movement and attain the global optimum.

However, because of the short searching interval, we employ the Lévy flight principle in the third step to assure the exploitation process. This means that obtaining the local optimum is adequate in this situation. In addition, we employed FADs to update the individual's location and then preserve it in memory. Finally, the results are sent back into the training process to evaluate the new solution and determine its fitness.

ID	1	...	4	...	70	...
EEG File	eeg1	...	eeg4	...	eeg70	...
Gender	f	...	m	...	m	...
BW(g)	less than 2500g	...	3000 to 3500g	...	greater than 4000g	...
GA(weeks)	37 to 38	...	39 to 40	...	40 to 41	...
EEG to PMA (weeks)	37 to 38	...	39 to 40	...	40 to 41	...
Diagnosis	mild/moderate asphyxia	...	mild/moderate asphyxia	...	asphyxia	...
Neuroimaging findings	widespread ischemic changes	...	bilateral watershed area infarction	...	MRI normal	...
PMA of imaging(days)	0 to 4	...	4 to 7	...	0 to 4	...
Number of viewers annotating seizures	3	...	3	...	0	...
Primary localization	both hemispheres; alternating	...	right centro-parietal	...	/	...

Table IV.2: Clinical annotation of the dataset from three experts

If the chosen solution meets the requirements, it is saved as the best solution, and the chosen combination of hyperparameters determines its position. The complete design of our suggested system is shown in Figure. II.4.

We used the NICU dataset from Helsinki University Hospital and classification measures to evaluate the proposed model's performance. In addition, we employed CNN-based GA (Figure IV.6) to compare and enhance the efficiency of the CNN-based MPA (Figure IV.5) as a hybrid model with a metaheuristic approach. Furthermore, to demonstrate the performance of the proposed model, we compare it to basic CNN with three Conv1D layers, one dropout, one maxpooling1D, and two dense layers (see Figure IV.7), and CNN with three dense layers (see Figure IV.8). The implementations are carried out using Python 3.6, Keras 2.2.4, and Tensorflow 1.12, all of which are installed on Windows 10 Pro (64 bit) and run on a CPU Intel Core i3 380M @ 2.53GHz with RAM of 4GB [232].

Table IV.2, Table IV.3, Table IV.4 and Table IV.5 Present the description of the used models, including their number of layers, shapes, parameters, activation functions, loss function, and optimizer. As we see in these tables, a variety of hyperparameters leads to various results.

3.1 Classification Performance Evaluation

To evaluate the performance of the classification of our proposed method, we determine True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). These measures used to calculate Recall, Precision, Specificity, Sensitivity, F1-score, and Accuracy are considered classification indicators.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{IV.20}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{IV.21}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{IV.22}$$

Layer	Shape	Parameters	Activation function	Optimizer	Loss
Dense	(1,128)	1664	/		
Dense	(1,128)	16512	Relu		
Dense	(1)	129	Sigmoid		
				Adam	
					Binary crossentropy
Total Parameters		18305			

Table IV.3: Description of Dense-CNN parameters

Layer	Shape	Parameters	Activation function	Optimizer	Loss
Conv1D	(10,32)	128	Tanh		
Conv1D	(8,64)	6208	Tanh		
Dropout	(0.5)	0			
MaxPooling1D	(4,64)	0		Adam	
Conv1D	(2,128)	24704	Softsign		Binary crossentropy
Flatten	(256)	0			
Dense	(100)	25700	Relu		
Dense	(1)	101	Softplus		
				Adam	
					Mean Squared Error
Total Parameters		56841			

Table IV.4: Description of Simple-CNN parameters

Layer	Shape	Parameters	Activation function	Optimizer	Loss
Conv1D	(10,32)	128	Tanh		
Conv1D	(8,16)	1552	Tanh		
Dropout	(0.5)	0			
MaxPooling1D	(4,16)	0			
Conv1D	(2,16)	784	Relu		
Flatten	(32)	0			
Dense	(100)	3300	Softsign		
Dense	(1)	101	Softplus		
				Adagrad	
					Mean Squared Error
Total Parameters		5865			

Table IV.5: Description of GA-CNN parameters

Layer	Shape	Parameters	Activation function	Optimizer	Loss
Conv1D	(10,16)	64	Softsign		
Conv1D	(8,32)	1568	Tanh		
Dropout	(0.5)	0			
MaxPooling1D	(4,32)	0			
Conv1D	(2,64)	6208	Softmax		
Flatten	(128)	0			
Dense	(100)	12900	Softsign		
Dense	(1)	101	Softplus		
				Adagrad	
					Mean Squared Error
Total Parameters		20841			

Table IV.6: Description of MPA-CNN parameters

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{IV.23}$$

$$\text{Accuracy} = \frac{TP + TN}{TN + TP + FP + FN} \tag{IV.24}$$

$$\text{F1-measure} = 2\frac{\text{Precision} * Sensitivity}{\text{Precision} + Sensitivity} \tag{IV.25}$$

Table IV.6 Displays the classification metrics (precision, recall, F1-score, accuracy, and loss) achieved for the various models utilized. Table IV.4 demonstrates the large difference in precision, F1-score, accuracy, and loss amongst the models. The suggested MPA-CNN performed best with 1 in precision, recall, F1-score, and accuracy, followed by GA-CNN with 0.90 in precision, 1 in the recall, 0.95 in F1-score, and 0.95 in accuracy. Furthermore, Dense CNN achieves exceptional accuracy of 0.95. However, of the models tested, the Simple CNN had the poorest results. Furthermore, the suggested model achieved the lowest loss of 0.028, followed by GA-CNN [232].

	Precision	Recall	F1-score	Accuracy	Loss
MPA-CNN	1	1	1	1	0.028
GA-CNN	0.90	1	0.95	0.95	0.087
Simple CNN	0.66	1	0.75	0.85	2.39
Dense	1	0.89	0.94	0.95	0.11

Table IV.7: Classification results of the used models

Figure IV.11 depicts the training accuracy of the various models utilized over the same number of epochs (50). This graph shows that the convergence speed of MPA-CNN and Dense CNN is faster than that of other models. Dense CNN's accuracy evolution is better than that of numerous other peer models, but when compared to MPA-CNN, MPA-CNN performs much better.

Figure IV.11: Training accuracy of the models

Figure IV.12 depicts the training loss curves of the models utilized over the same number of epochs. For example, the MPA-CNN and GA-CNN curves are similar in the first 20 epochs; however, beyond those epochs, the MPA-CNN curve converges better than the other models with a low loss rate. Meanwhile, the basic CNN continues to achieve the poorest convergence.

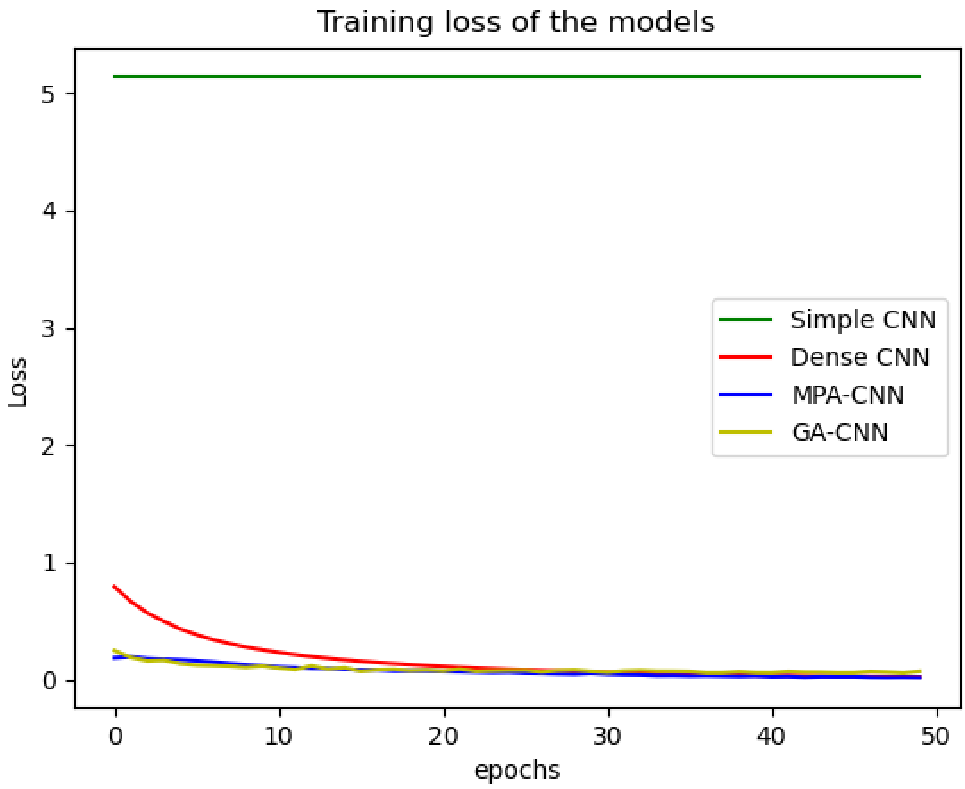

Figure IV.12: Training loss of the models

Regarding training time, the suggested model, MPA-CNN, is faster than existing models that employ metaheuristic techniques, such as GA-CNN. Table IV.5 also shows the sensitivity and specificity of the models utilized. As demonstrated in Table IV.7, MPA-CNN may achieve sensitivity and specificity of 1 in 0.30 minutes. GA-CNN, on the other hand, can achieve 1 for sensitivity and 0.90 for specificity in 1.27 minutes. Dense CNN, on the other hand, outperforms basic CNN with astounding results [232].

	Time/min	Sensitivity	Specificity
MPA-CNN	0.30	1	1
GA-CNN	1.27	1	0.90
Simple CNN	0.17	0.67	0.88
Dense	0.17	0.88	1

Table IV.8: Time required and the achieved sensitivity and specificity of the different models

In addition, to better understand the findings, we illustrate the different metrics employed, such as accuracy, recall, F1-score, specificity, and sensitivity, in Figures

IV.13, IV.14, IV.15, IV.16, and IV.17. As shown in the figures, MPA-CNN outperforms the other models in the majority of parameters, including accuracy, recall, F1-score, specificity, and sensitivity [232].

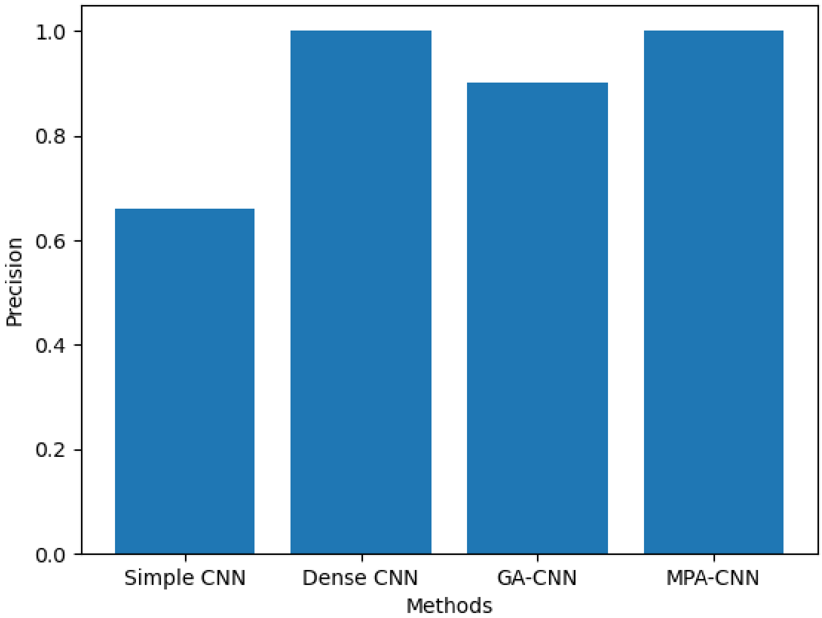

Figure IV.13: The precision of the models

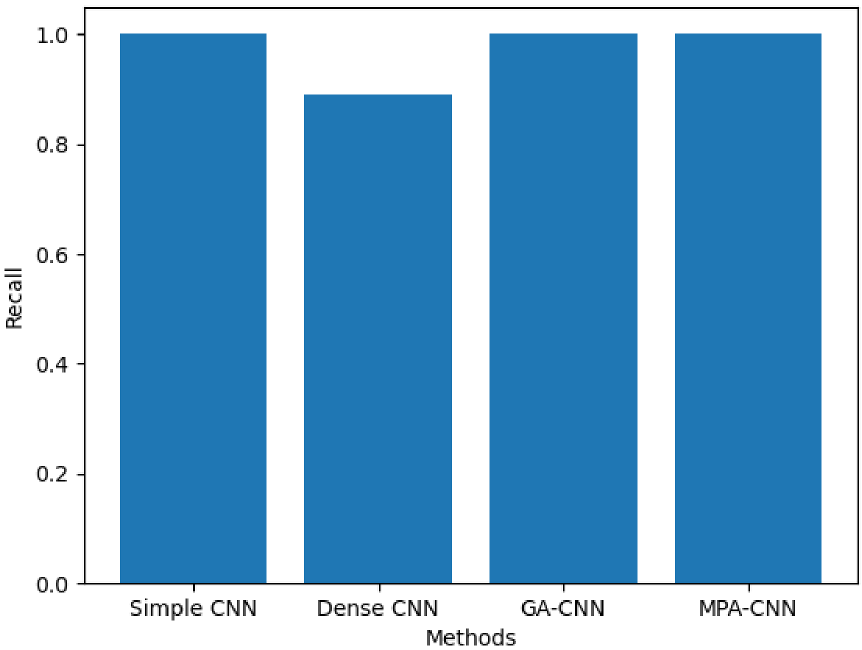

Figure IV.14: The recall of the models

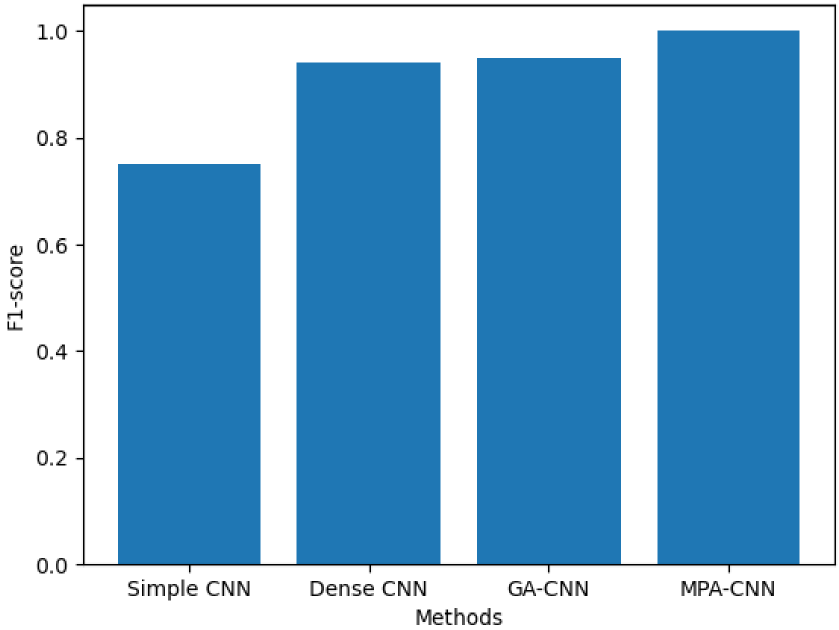

Figure IV.15: The F1-score of the models

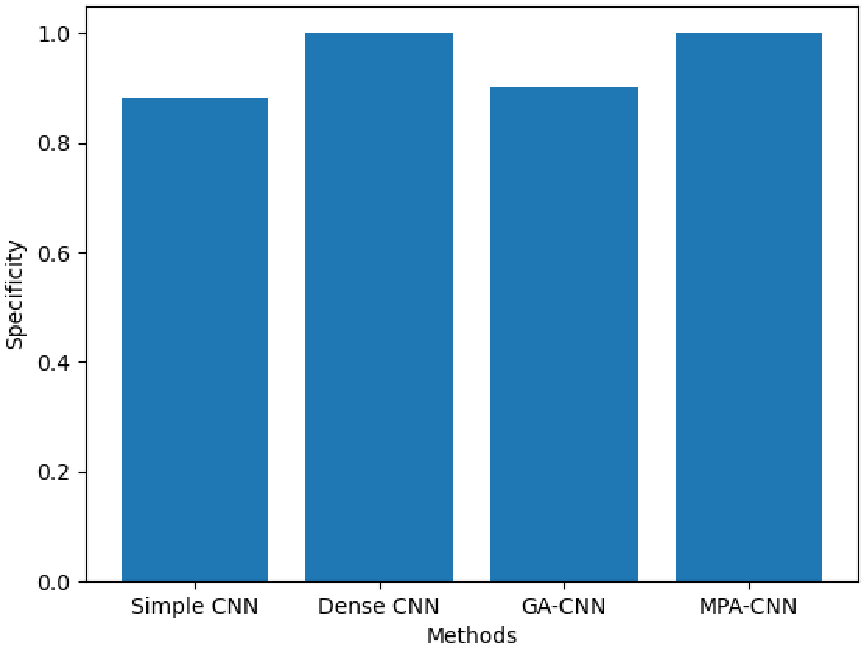

Figure IV.16: The specificity of the models

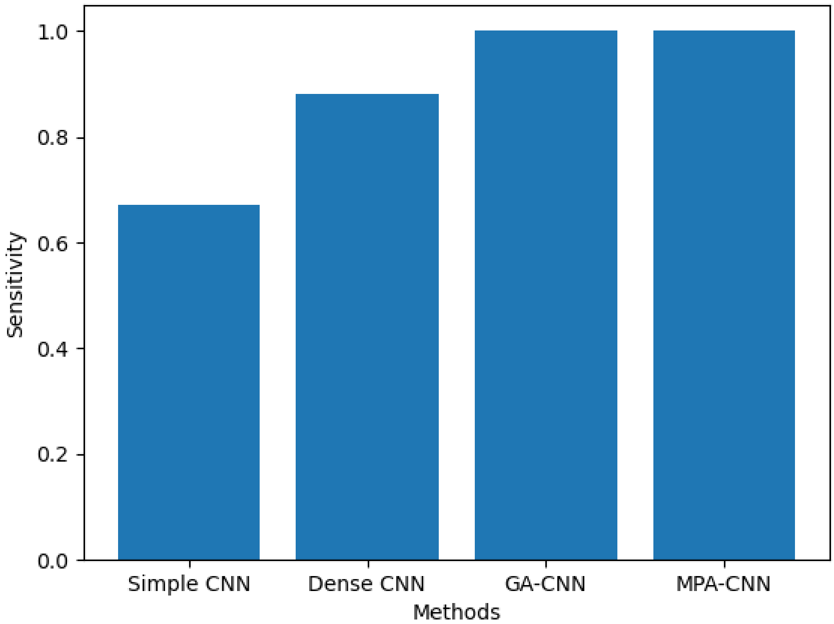

Figure IV.17: The sensitivity of the models

Figures IV.13, IV.14, IV.15, IV.16, IV.17, and Tables IV.6 and IV.7 show that the proposed model MPA-CNN outperforms GA-CNN with 1 accuracy and 1 precision, 1 recall, 1 F1-score, and 0.028 loss. Furthermore, Dense CNN achieves exceptional results such as accuracy (0.95) and precision (1). However, basic CNN performs worse than the current models, with an accuracy of 0.85 and a loss of 2.39 [232].

3.2 Area Under Curve

To improve the suggested model's classification performance, we incorporated a false positive rate of zero and a true positive rate of one, reflecting the ideal point known as the Area Under Curve (AUC). Employing AUC aims to maximize true positives while decreasing false positives. The AUC values of each model are shown in Table IV.6, with MPA-CNN outperforming the others with 1 AUC, GA-CNN with 0.95, and Dense CNN with 0.94. Simple CNN, on the other hand, has the lowest AUC value. Figure IV.18 depicts the AUC of the various models utilized [232].

Model	AUC
MPA-CNN	1
GA-CNN	0.95
Simple CNN	0.77
Dense	0.94

Table IV.9: AUC of the different models

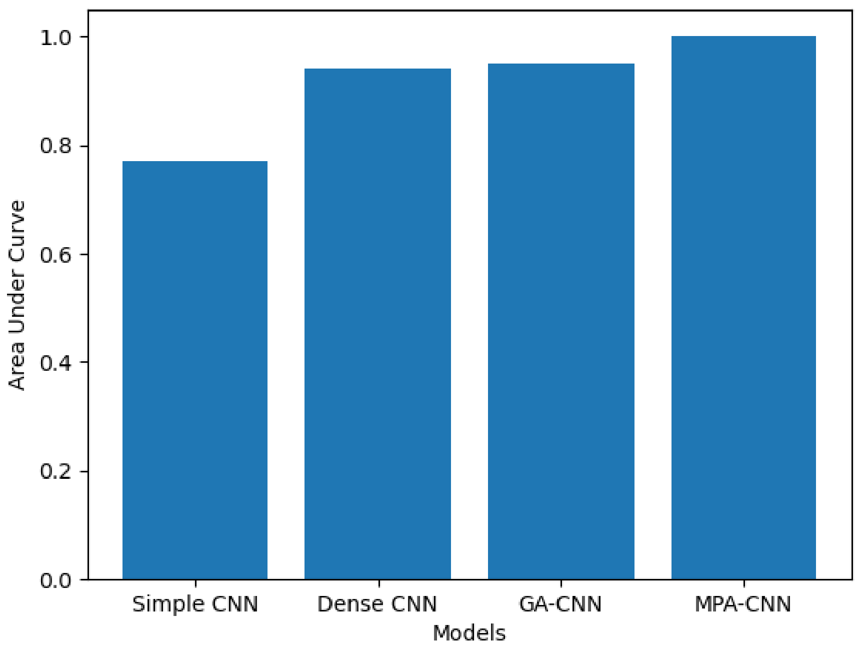

Figure IV.18: The AUC of the models

3.3 Confusion Matrix

The confusion matrix is one of the most often used metrics for evaluating classification performance using predicted and actual or real labels. It is used to assess the model's capacity to handle ambiguous labels. Figures IV.19, IV.20, IV.21, and IV.22 depict the confusion matrix (CM) of the various techniques utilized, where CM [0,0] is the TP value and CM [0,1] is the FN value, CM [1,0] is the FP value, and CM [1,1] is the TN value. As seen in Figure IV.6, GA-CNN correctly predicts all true classes but incorrectly predicts one false class as true. Dense CNN also forecasts one true class as a fake class. MPA-CNN, on the other hand, accurately predicts both the true and false classes (Figure IV.21). In the final classification, the Simple CNN performs poorly in the prediction process for both the true and false classes [232].

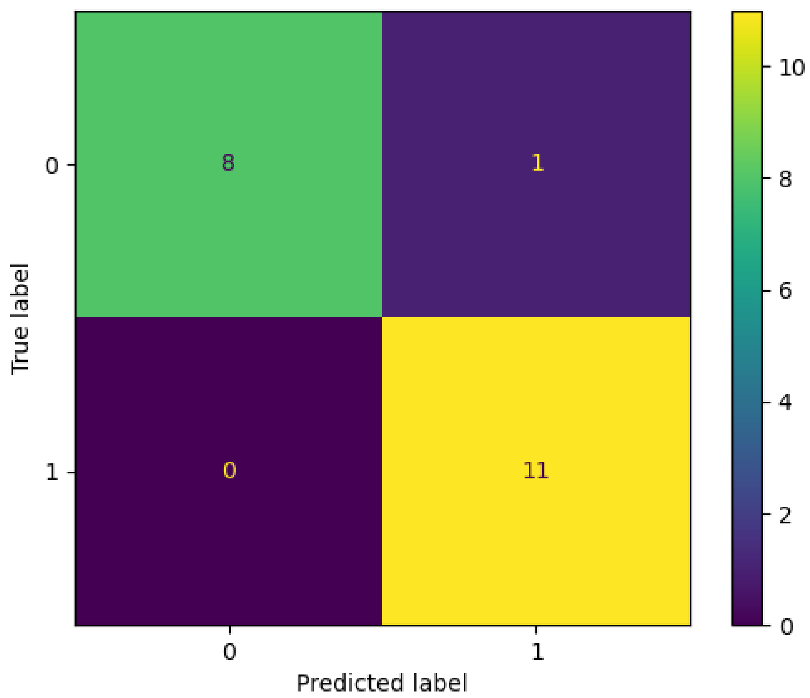

Figure IV.19: Confusion Matrix of Dense-CNN

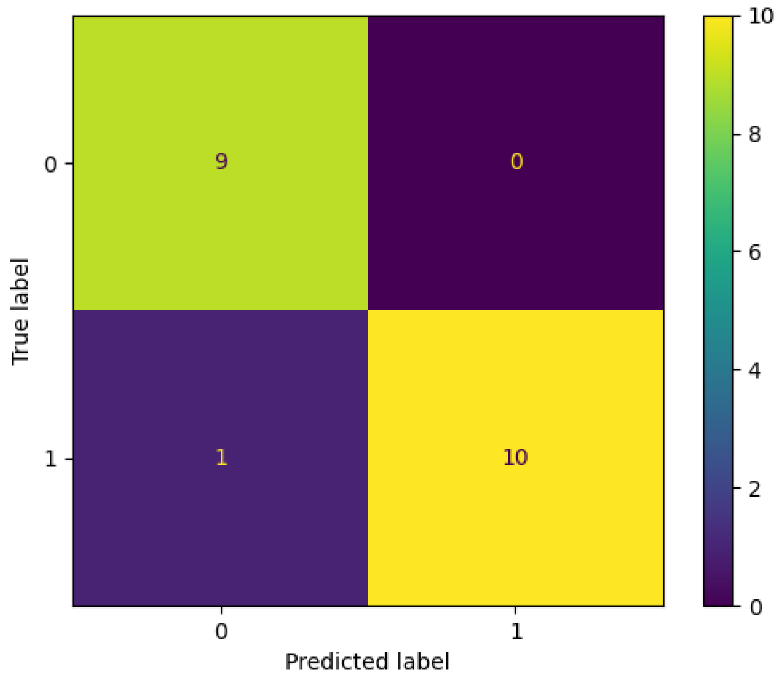

Figure IV.20: Confusion Matrix of GA-CNN

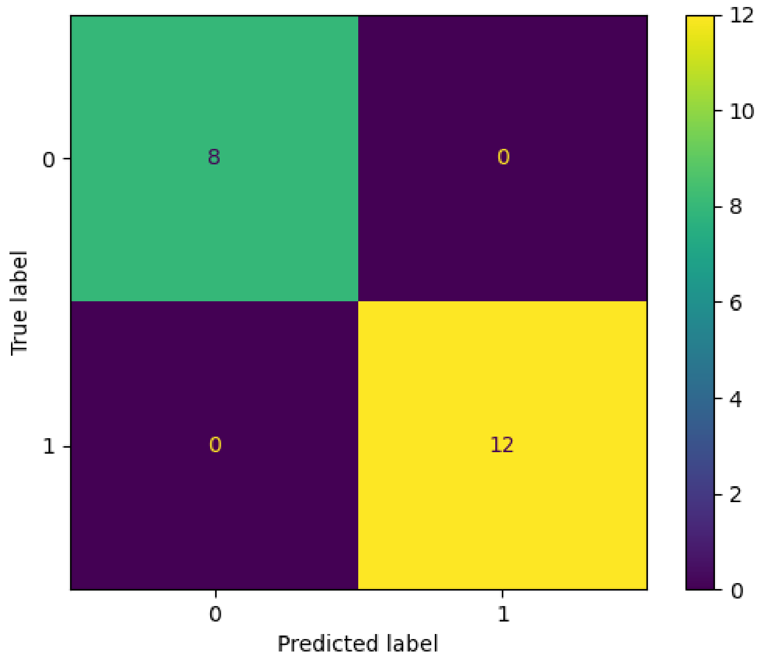

Figure IV.21: Confusion Matrix of MPA-CNN

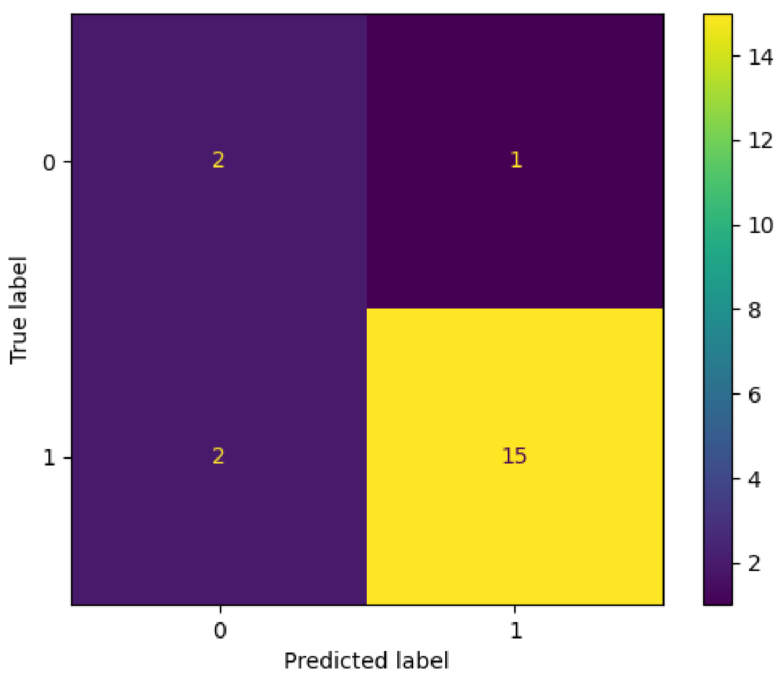

Figure IV.22: Confusion Matrix of Simple-CNN

3.4 The complexity of the proposed model

Obtaining suitable hyperparameters is one of the most difficult challenges. It is categorized as an NP-hard task due to the exhaustive size of the search space, implying that the algorithm's complexity will be exponential $O(n^p)$. Nevertheless, due to its search tactics, MPA can lower the complexity of our model by activating the exploitation and exploration processes. The power of MPA reduces the model's complexity and makes it linear O(n) [232].

The given findings in Figures: Figure IV.19, Figure IV.20, Figure IV.21, Figure IV.22, Figure IV.18, Figure IV.1325, Figure IV.14, Figure IV.15, Figure IV.16, and Figure IV.17 demonstrate the suggested model's good performance in most of the metrics evaluated. The suggested strategy is found to be extremely competitive, and it even outperforms unlabeled or missing data. Based on the results and the considerable difference between the other models utilized, the suggested one may be called a real-time model [232]. Also, the proposed system outperforms the state of the art work such as the ones mentioned in Table IV.10.
The key to the suggested model's outcomes is the auto-selection of hyperparameters utilizing one of the most recent metaheuristics that may enable exploration and exploitation in a unique method that guarantees full exploitation of the region. As a result, the resulting hyperparameters might be more precise due to their homogeneity, reflecting the model's good performance. Furthermore, the GA-employed model gets good results due to the power of mutation and cross-over for determining the hyperparameters. However, the two other models did not produce satisfactory results due to the manual selection of hyperparameters, which takes time and increases the model's complexity [232].

4 Conclusion

To address the issues of accuracy, loss rate, precision, recall, f1-score, specificity, and computational time, our suggested approach employs a CNN model based on the MPA (MPA-CNN). The MPA was utilized in this study to improve the model by picking precise hyperparameters that increase the model's performance while minimizing its complexity. We used a dataset of 79 neonate signals to analyze and test the

Ref	Dataset	Model	AUC	ACC	Sensitivity	Specificity	F1-score
[189]	EEG	CNN + FCNN + SWT	81%	82%	63%	83%	48
[190]	13827 h of cEEG	ANSeR	/	73%	81.3%	84·4%	/
[191]	834h of cEEG 79	CNN	98.5%	/	/	/	/
[188]	EEG of 48 neonates	CNNs + RF	/	77%	/	/	/
Our proposed system	EEG of 79 neonates	MPA + CNN	100%	100%	100%	100%	100%

Table IV.10: Comparative study of the system proposed model to compare it to three existing models: GA-CNN, Dense CNN, and basic CNN. This suggested system performs better than existing systems in terms of accuracy, precision, recall, specificity, and error rate. However, one of the proposed methodologies' disadvantages is the dataset's limited size.

We intend to examine the suggested model in the context of cloud tasks to provide answers to the existing challenges in future work. In addition, we intend to develop and compare various models based on WHO guidelines. In addition, we want to provide a novel approach for automatic model creation comprised of hyperparameters and model structure.

Chapter V

Convolution Neural network based Marine Predator Algorithm for COVID-19 detection

1 Introduction

Covid-19 is a Coronaviridae family illness caused by severe acute respiratory syndrome (SARS-CoV-2). The illness first appeared in China (Wuhan) in December 2019. WHO has certified the reverse transcription-polymerase chain reaction (RT-PCR) method as the standard diagnostic technique for identifying the virus [194]. RT-PCR assays use fluorescence to assess ribonucleic (RNA) and deoxyribonucleic acids (DNA) in nasal secretions. Recent research has identified radiological imaging, such as X-ray and CT-scan, as a significant screening tool for COVID-19 diagnosis.

The experimental tests using X-ray imaging confirmed the feasibility of identifying COVID-19 in its early lung phases. Furthermore, X-ray imaging is a real-time procedure, and their equipment is inexpensive and simple to use. The presence of medical specialists and the time necessary to evaluate X-ray pictures are now the major challenges, creating an urgent need for a computer-aided diagnosis system to help radiologists interpret images faster and more accurately. Meanwhile, modern Artificial Intelligence approaches such as Deep Learning, which has demonstrated promising outcomes in the medical arena, may be ideal for similar difficulties. [233].

The reported research relies solely on tiny datasets containing x-ray pictures of normal and covid-19 patients. Meanwhile, certain illnesses, such as Pneumonia, have X-ray pictures strikingly similar to Covid-19, causing confusion in the model and preventing appropriate categorization. When a patient has Pneumonia and submits his X-ray picture to a model that has only been trained on normal and Covid-19 X-ray images, the model will identify it as Covid-19, which is incorrect. On the other hand, the use of Artificial Intelligence (AI) techniques such as deep learning (DL) substantially impacts the resolution of many medical issues, notably in photo identification anomalies, yielding good outcomes. Many articles on Covid-19 detection have been published, including [192], [193], [194], and [195]. However, most of these studies focused primarily on the detection of Covid-19 and gave little consideration to the complexities of the model used.

Throughout this research, we provide a novel metaheuristic strategy for optimizing our model to handle the problem of extracting features from X-ray pictures to enhance the performance of the model, which will be trained on three different examples of X-ray images: Covid-19, normal, and Pneumonia illness.

2 Materials and methods

In our experiment, we used a large public dataset of 6432 X-ray pictures retrieved from the Kaggle repository [21]. The dataset is separated into two folders for training (5144 X-ray pictures) and testing (1288 X-ray images), each of which has three subfolders entitled Covid-19, Normal, and Pneumonia. We use several pre-processing methods after extracting the dataset, such as scaling the photographs and producing fresh images for data augmentation (Figure V.2). Finally, before passing the dataset to the model, we must use the Marine Predator Algorithm (MPA) to optimize the model's hyperparameters.

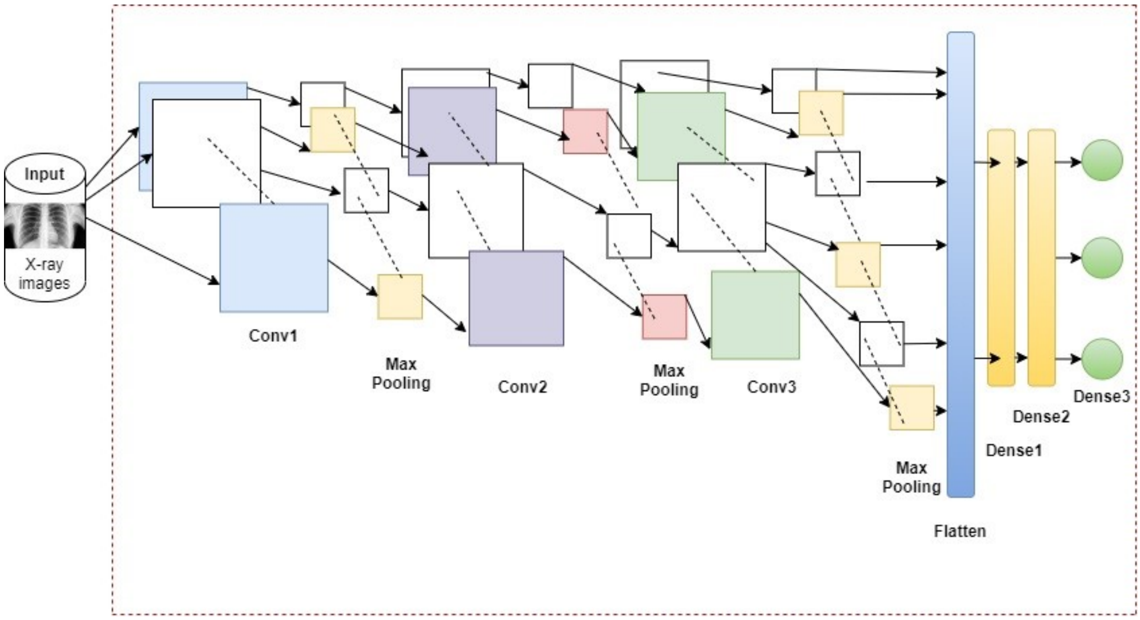

Figure V.1: The architecture of the CNN model

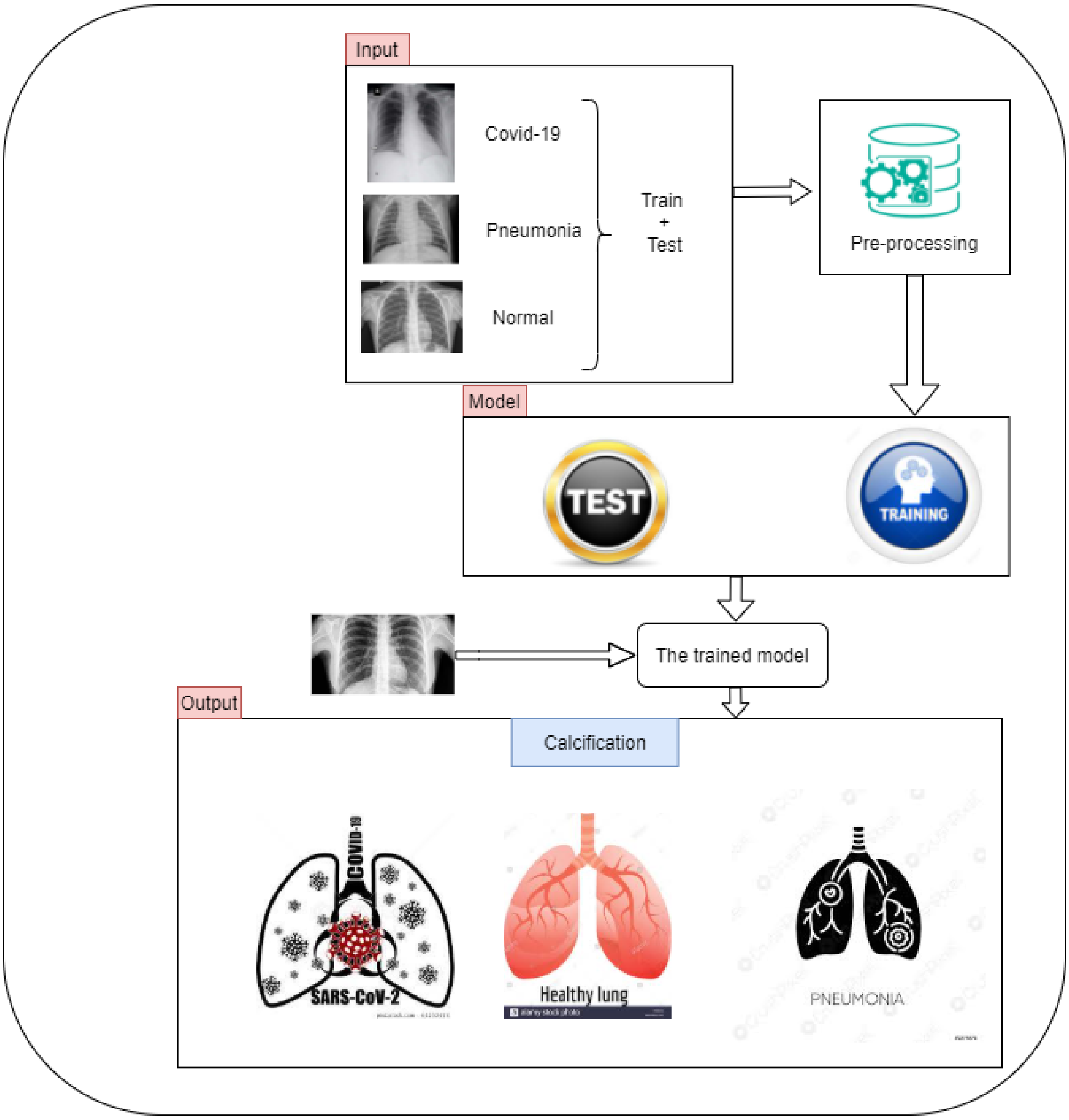

Figure V.2: General architecture of the model

2.1 Marine predator algorithm

MPA is a metaheuristic approach introduced by Faramarzi et al. [217], which employed both Lévy and Brownian movement to assure exploitation and exploration in the search region (Figure V.3).

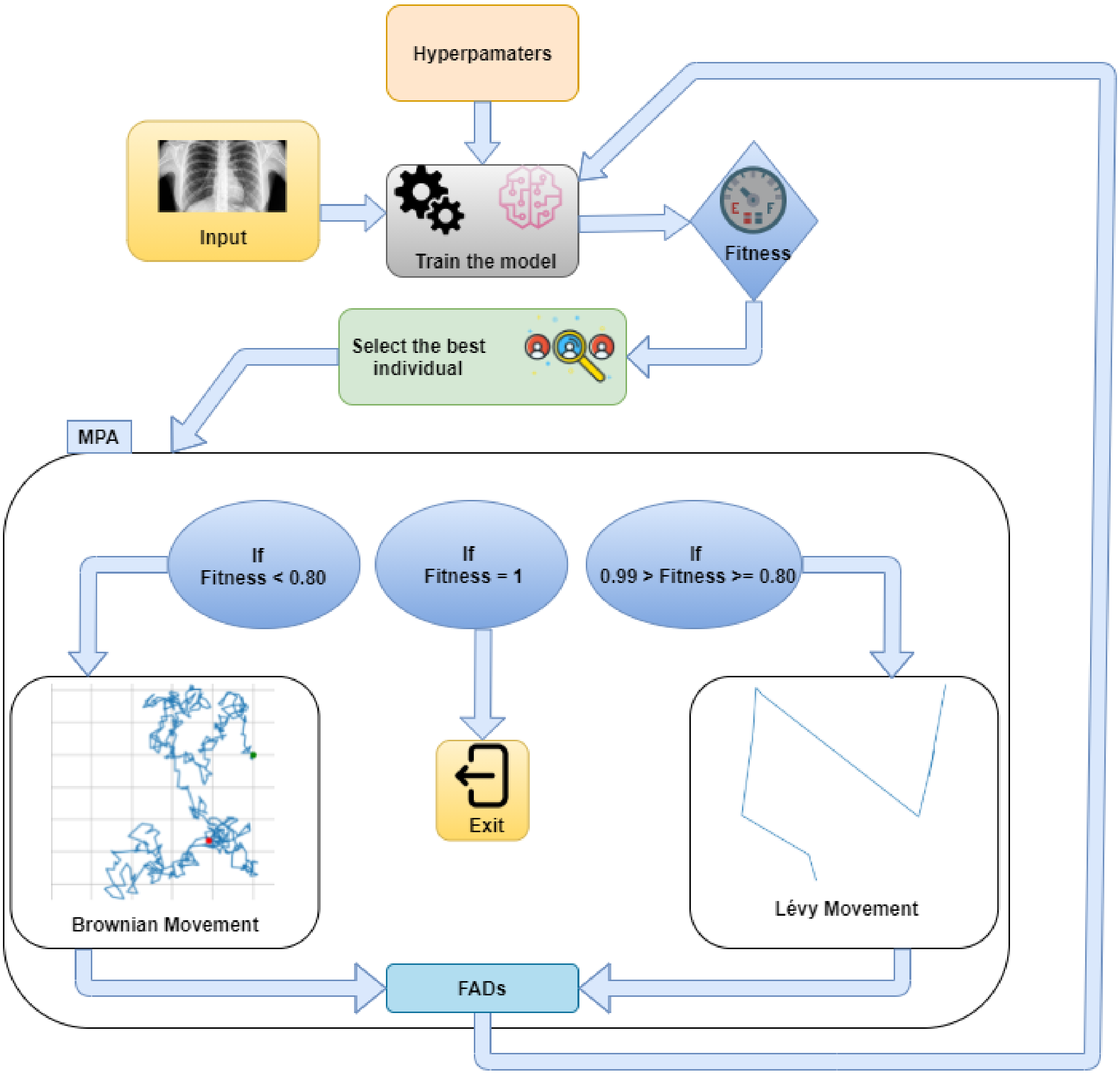

Figure V.3: Marine Predator Algorithm

2.1.1 Lévy movement

Lévy movement is probability function defined as:

$$L(x;\mu,\sigma) = \frac{1}{\pi}\int_0^{\pi} exp^{(-\gamma q^{\alpha})}\cos{(qx)}dq \tag{V.1}$$

$$L(x;\mu,\sigma) \approx \frac{\gamma\Gamma(1+\alpha)\sin{(\frac{\pi\alpha}{2})}}{\pi x^{(1+\alpha)}}, x \to \infty \tag{V.2}$$

Where $1 \geq \alpha \leq 2$, γ selects the scale unit and $\Gamma(1+\alpha) = \alpha!$. Brownian movement

Brownian movement is probability function defined as:

$$B(x;\mu,\sigma) = \frac{1}{\sqrt{(2\pi\sigma^2)}} exp^{(-\frac{(x-\mu)^2}{(2\sigma^2)})} \tag{V.3}$$

After the simplification of the equation:

$$B(x;\mu,\sigma) = \frac{1}{\sqrt{2\pi}} exp^{(-\frac{x^2}{2})} \tag{V.4}$$

Where μ represents the mean distribution ($\mu = 0$) and σ^2 is the variance ($\sigma^2 = 1$).

As we see in (Figure V.2), we used the model's accuracy as a fitness metric for the evaluation process. In low-velocity, where the fitness is between (0.80 and 0.99), we used the Lévy movement, and for high-velocity, where the fitness is less than (0.80), we used the Brownian movement. Also, we used Fish Aggregating Devices (FADs) to update an individual's position, then save it in the memory. [233].

3 Results and Discussion

We utilized Python with our solution's Keras and Tensorflow libraries, which provide the most important tools for deep learning implementation. These libraries are constructed on top of the PyCharm environment. Lenovo PC with Windows 10 Pro 64-bit, Intel Core i7, 3.60GHz CPU, 16 GB RAM, Intel HD Graphics 4600 GPU, and 1 TB hard disk. Our model gets such results as 93 percent accuracy, 95 percent precision, 97 percent recall, and 95 percent F1 score. We can also examine how our system performs during the training phase using accuracy and loss data. The graph shows that increasing the green curve improves the high accuracy. In the meantime, the loss function is lowered until it reaches low levels (Figure V.4) [233]. Moreover, we compare it with the state of the art works (see Table V.1)

Ref	Dataset	Model	ACC	Sensitivity	Specificity	F1-score	**Precision**
[192]	1547 X-ray images (Covid-19 + Normal)	ResNet-101	71.9 %	77.3%,	71.8%	/	/
[193]	6432 x-ray images (Covid-19 + Pneumonia + Normal)	Xception	97.97 %	/	/	/	/
[194]	1102 X-ray images (Covid-19 + Normal)	Transfer learning	96.75 %	94.16%	99.17%	96.38%	/
[195]	1668 X-ray images (Covid-19+ Normal+ Bacterial)	CNN + Capsules	95.7%	90%	95.8%	/	/
[196]	1000 X-ray images (Covid-19 + Normal)	PA , ARIMA, LSTM + VGG16	88.43%	/	/	95%	/
[200]	792 X-ray images (Covid-19 + Normal)	VGG16	86%	86%	93%	86%	86%
MPA-CNN	**6432 X-ray images (Covid-19 + Pneumonia + Normal)**	**MPA + CNN**	93%	95%	95%	97%	95%

Table V.1: Comparative study of the proposed system

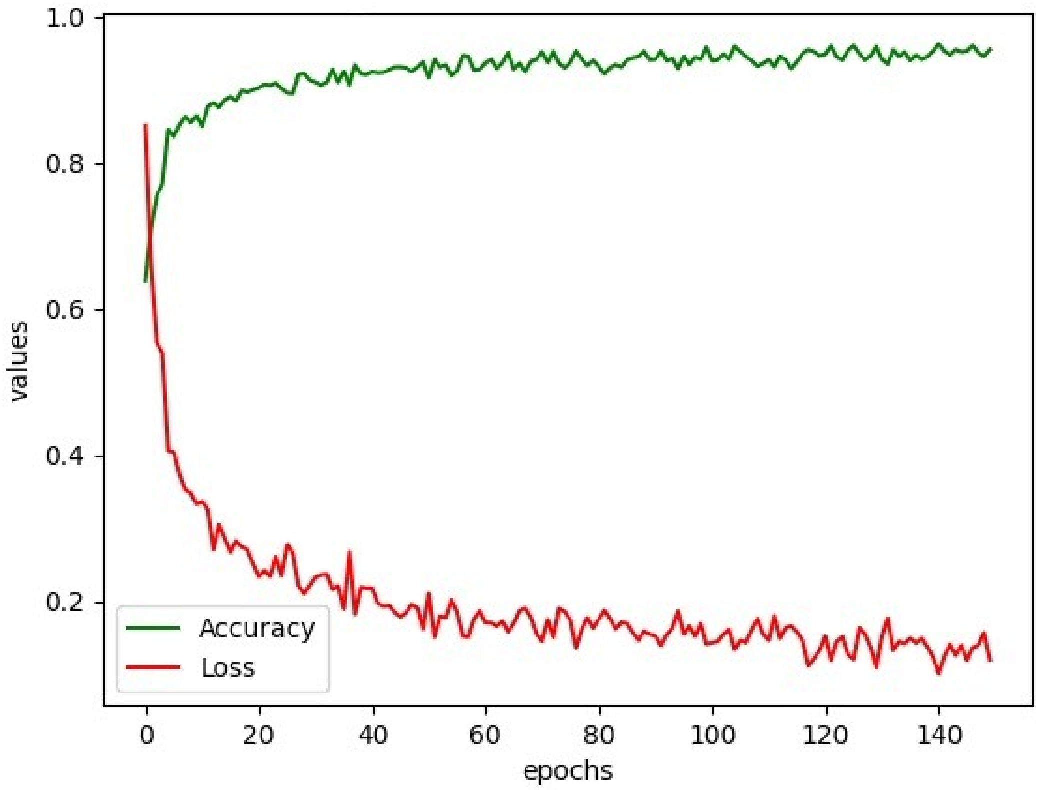

Figure V.4: The accuracy and loss of the model

4 Conclusion

With more confirmed instances of the virus throughout the world and new varieties of this pandemic in the lack of an appropriate vaccine, physical separation, mask usage, and hand washing remain the most often utilized precautions to limit the spread of this epidemic. In this chapter, we developed a CNN-based MPA approach for detecting Covid-19. We effectively classified Normal, Covid-19, and Pneumonia illnesses, which are the most comparable in terms of X-ray pictures but quite different in terms of medical therapy. The findings of our experiment show that the system performs well, with 93% accuracy in the classification metrics, 95% precision, and 97 % and 95% confirmation of the classification metrics in the recall and F1-score, respectively.

However, using a similar dataset across investigations to perform fair comparisons and enhance the quality of results remains a limitation of this effort. In the future, we want to employ additional related illness datasets, such as Tuberculosis and other chest disorders, to improve the precision of the X-ray picture diagnosis.

Chapter VI

IoMT-fog-cloud based architecture for Covid-19 detection

1 Introduction

Because of its mutation over time, coronavirus disease 2019 (COVID-19) is now a worldwide epidemic. Several pieces of research have been done for covid-19 identification using various strategies; however, tiny datasets and the absence of validation testing continue to restrict their work. Furthermore, they rely solely on enhancing the accuracy and precision of the model while ignoring their complexity, which is one of the essential prerequisites in healthcare application. Furthermore, most cloud-based healthcare apps employ a centralized transmission method of varied and huge amounts of information, making the privacy and security of sensitive patient data vulnerable to hackers. Furthermore, the previous cloud architecture has several flaws, such as latency and persistent low performance.

On the other hand, advances in healthcare technology give significant benefits in terms of bettering and protecting people's lives worldwide. Furthermore, contemporary communication technology has enabled remote access to medical treatments. Real-time monitoring and automated prediction and detection technologies aim to save lives while reducing medical expenditures. Combining cloud technology with the Internet of

Things (IoT) or the Internet of Medical Things (IoMT), for example, enables real-time detection and diagnosis of a disease, resulting in early intervention that saves lives and decreases healthcare costs [234][235].

Cloud computing is a prominent computing paradigm in the field of information technology [236]. The role of cloud computing is to fulfill users' demands for computer resources at any time and from any location, [237]. Cloud deployments can generally be Private Cloud, Public Cloud, Community Cloud, or Hybrid Cloud [238]. The Cloud offers three services: Software as a Service (SaaS), which distributes software to customers; platform as a Service (PaaS), which allows for the development of software and applications; and Infrastructure as a Service (IaaS), which allows for storage, processing processes, and network usage [236].

Fog Computing is an intermediary layer between IoT devices and the cloud that tries to improve the Cloud's Quality of Service (QoS) by offering many scattered nodes. Fog nodes are used to decrease traffic and latency difficulties and energy usage between users and the cloud. They also offer computation and storage capability, as well as secure communication between IoT devices and the cloud [239].

1.1 Cloud Computing in healthcare application

Cloud computing for medical purposes is built on a mobile device, cloud servers, and a network that allows for real-time access to resources at any time and from any location [240]. However, this classic cloud design had several flaws, such as the time necessary for emergency circumstances. Another shortcoming is the increasing quantity of power consumption and the expense of data transfer to the cloud. Furthermore, the problem of latency and persistent low performance are limitations of the typical cloud structure. Furthermore, the high expense of the transportable environment is required for the patient's medical situation. [241].

1.2 Fog Computing in healthcare application

Fog computing is a dispersed cloud computing framework that tries to move data processing closer to the network edge, providing more suitable solutions for overcoming cloud computing restrictions [240]. For starters, it lowers the cost of memory utilization, processing, and sensor power consumption. In addition, fog computing provides reduced latency by expanding the number of fog nodes or employing different edge mining techniques to minimize data transmission time. Furthermore, the edge computing applications contain a high level of security and authentication to guarantee that patient information is kept private [241]. In addition, rather than employing detecting sensors or GPS location systems, edge apps employ unique localization algorithms that identify the patient's position more precisely and efficiently. The shared structure of edge computing, encryption methods and categorization methodologies for healthcare applications, edge mining, and effective resource management lower energy usage. Easy-to-use healthcare applications should be able to deliver various services to patients without requiring technical skills or medical experience [241].

The fundamental goal of our contribution is to slow the development of this pandemic by detecting sick persons early and taking appropriate action as soon as feasible. Medical therapies are more successful when administered after the infection is diagnosed. We used sophisticated technologies in the healthcare field, such as IoMT, Cloud computing, and Fog computing, to develop such a system. The combination of such components yields a real-time and secure system that is simple for any user [241].

2 Proposed Approach

Detecting Covid-19 early and adopting the required precautions might help slow this pandemic's development. As a result, developing solutions that use the capabilities of artificial intelligence, such as deep learning, the benefits of IoMT, fog computing, and cloud computing, might be a highly promising strategy [241].

2.1 Deep Learning Approach

Real-time system implementation remains one of the most difficult tasks for developers. On the other hand, the pressing problem worldwide is to discover a means to identify covid-19 quickly and efficiently. These are the primary motivations for introducing an IoMT-based fog cloud for Covid-19 detection.

Our proposed IoMT–fog–cloud-based Covid-19 detection technology (IFC-Covid) has three layers: a user layer, a fog layer, and a cloud layer. The overall design of our suggested model is depicted in Figure VI.1. A cloud and fog-based system generally

Work	Application	IoT	Fog	Cloud	DL
[242]	An automatic COVID-19 detection system	Yes	No	Yes	ResNet50
[243]	Corona virus detection	Yes	Yes	Yes	SVM, DNN, K-NN, LSTM, Naïve Bayes, One Rule, NN, Decision Table
[244]	COVID-19 risky behavior monitoring system	Yes	No	Yes	CNN
[245]	Prototypes of autism and COVID-19 monitoring systems	Yes	Yes	Yes	N/A
[246]	Predict the potential threat of COVID-19	No	No	Yes	ML
Our approach (IFC-Covid)	COVID-19 and Pneumonia detection	Yes	Yes	Yes	CNN

Table VI.1: Comparative analysis with state-of-art-work that used cloud computing and DL for Covid-19 necessitate IoT devices, sensors, user devices, and other nodes that provide cloud and fog services. Various communication technologies, including Bluetooth, IEEE 802.15.4, 3G, 4G, 5G, and IEEE 802.11, are also required [241].

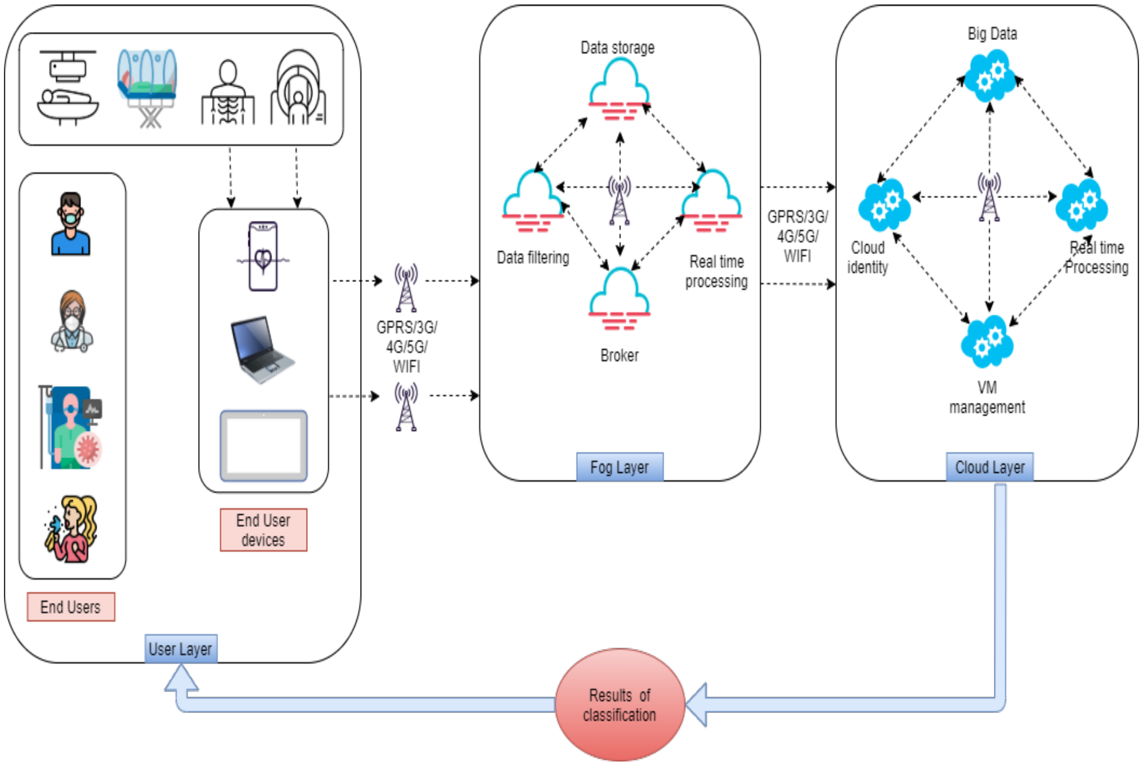

Figure VI.1: The proposed IoMT based Fog-Cloud architecture for Covid-19

- **User Layer** As IoT devices, several versions of mobile or portable radiography are employed in this tier. These gadgets are custom-made to meet the demands of critical care units and emergency departments. They are ideally maneuverable in any healthcare setting because of their strength and dependability, as well as their levels of safety and comfort. Furthermore, they enable the capture of high-quality photos even under adverse situations [241].

- **End-user device** The user can use various devices, including cellphones, personal computers (PC), and tablets. These devices accept data from IoT devices and transmit it to the fog layer. They also display the findings and notifications acquired from the fog or cloud for end-users. Making sure that users' devices are visible is a key aspect of developing a useful medical system [241].

- **End-User** End-users in such medical applications often include doctors, patients, nurses, and/or other users associated with the patient. The end-duty user is to submit patient's data to the fog (in our case, X-ray images). He/she receives the findings of the data analytics that were supplied as input after several processing stages in the fog and cloud [241].

- **Fog Layer** The key to incorporating a fog computing layer into a cloud-based architecture is to bridge the cloud layer gap and provide real-time data processing and categorization. Furthermore, it assures numerous properties such as patient data privacy and security. Furthermore, additional preprocessing procedures are performed in the fog layer to aid and expedite the cloud layer's analysis and classification process, reducing latency and ensuring service quality [241].
- **Cloud Layer** The key to adding a fog computing layer into a cloud-based architecture is to bridge the gap between the cloud layers and offer real-time data processing and classification. Furthermore, it ensures a variety of qualities, including patient data privacy and security. Furthermore, extra preprocessing operations are carried out in the fog layer to enhance and accelerate the cloud layer's analysis and classification process, hence lowering latency and assuring service quality [241].

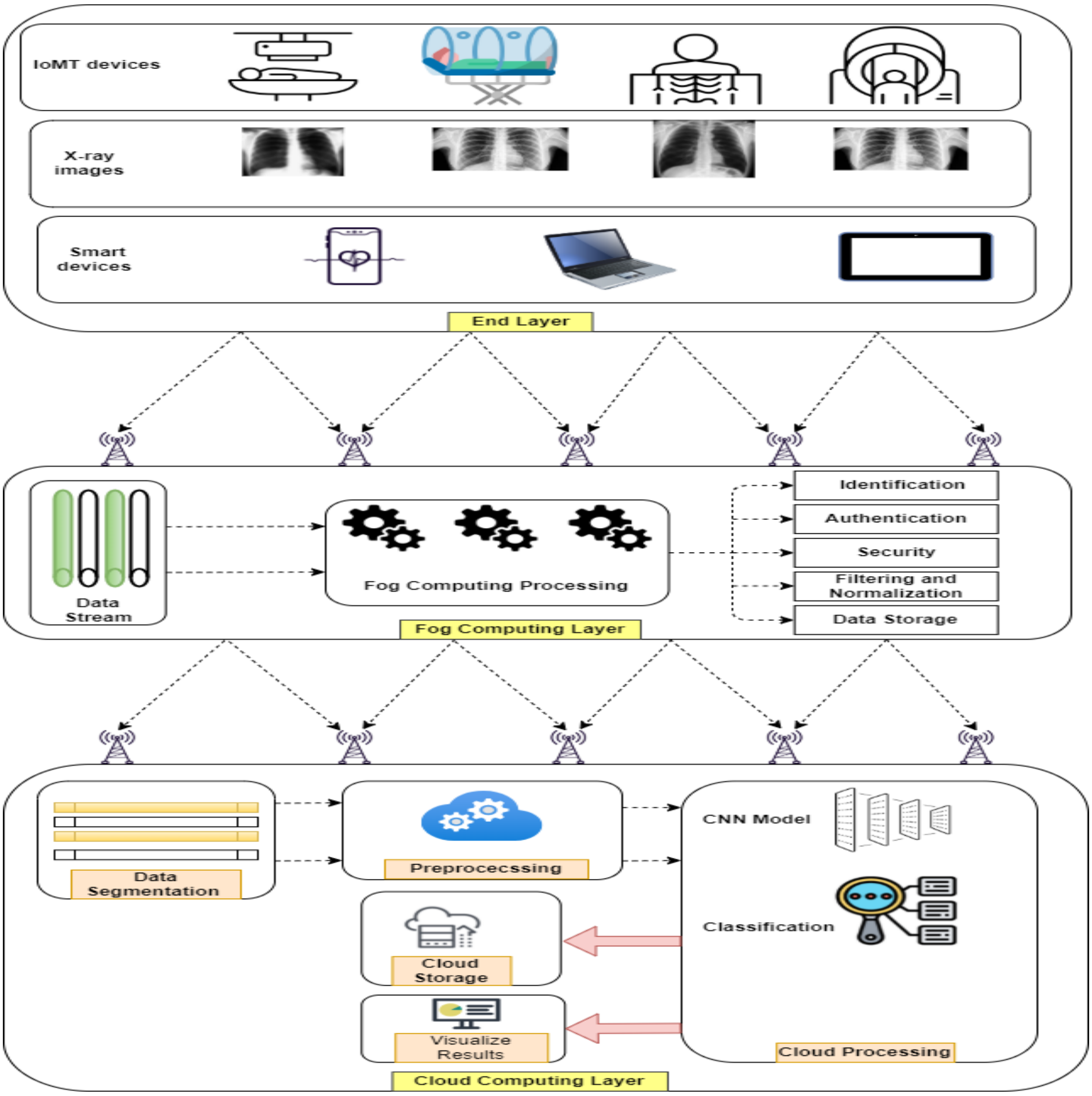

Figure VI.2: The Composition of each layer of the IoMT based Fog-Cloud system for Covid-19

2.2 Detailed Architecture

In this section, we discuss our system's design and demonstrate how each layer's components interact securely (Figure VI.2). We begin with a description of the system architecture, followed by a discussion of the security technique used to protect patient data privacy at various processing stages. Following that, we demonstrate how we train our CNN model on the passed dataset. Finally, because Pneumonia X-ray and Covid-19 X-ray are so similar, we train our algorithm to distinguish between the two for better classification results [241].

2.2.1 End layer

This layer of the Fog-Cloud-Covid19 system is made up of radiological equipment and smart gadgets. The radiological gadgets may capture the patient's x-ray picture. These radiological gadgets have sensors that let them interact with other devices through Bluetooth, WiFi, 3G, 4G, and 5G. The doctor sends the x-ray pictures to smart devices such as phones, tablets, or laptop computers after recording them. The patient or doctor who receives the x-ray picture on his or her smart device must then communicate it, along with other personal data, to the fog layer. The key advantage of adopting an intermediate layer such as the fog layer is that it saves time and money while improving the quality of service provided by our system [241].

2.2.2 Fog layer

Because of the centralized transmission process of varied and huge quantities of information, the privacy and security of the patient's personal data can be readily compromised in most healthcare apps that employ cloud computing. We implemented a fog layer in our system to protect data privacy and security by utilizing numerous services such as [241]:

- **Identification** The fog layer's initial operation is identifying the person submitting the data or allowing new users to create profiles.
- **Authentication** At this point, the fog service must validate the user's identity using authentication protocols such as Authenticated Key Agreement (AKA), Certificate Revocation List (CRL), and an Online Certificate Status Protocol (OCSP).
- **Security** To encrypt user data and maintain its security, fog computing provides an encryption service. Elliptic-Curve Cryptography (ECC), Privacy-Preserving Fog-Assisted Information Sharing Scheme (PFHD), Bilinear Pairing IBE, Modified Elliptic Curve Cryptography (MECC), Fully Homomorphic Encryption Scheme (FHE), and Enhanced Value Substitution (EVS) are some of the encryption techniques used in the literature.
- **Filtering and normalization** After obtaining user data, preparatory activities such as filtering and normalizing the data are conducted to prepare it for process-

ing in the cloud layer. The goal of this stage is to reduce the cloud's processing steps, hence reducing computing time.

- **Data storage** Part of the user data must be kept in the fog layer following preparation processes for security and authentication procedures to facilitate the access and lockout process, ensure data validity, and minimize the access control delivery cost.

2.2.3 Cloud layer

The cloud layer is the primary layer, which comprises of data analysis and processing processes, followed by data storage in the cloud and visualization of the generated data [241].

- **Preprocessing** This stage requires some processing after receiving data segmentation from the fog layer, such as normalization and preparing the data to be given to the processing step.

- **Cloud Processing** Several activities must be completed at the processing layer, such as preparing the Convolution Neural Network model to be trained on a dataset that comprises three types of samples: Covid-19 instances, Pneumonia cases, and Normal cases.

- **CNN Model** Over the last several decades, the medical research community has created several healthcare systems that allow doctors to express their choice in the case of their patients. Furthermore, due to human nature and the risk of making mistakes in diagnosing instances unrelated to doctors' level of expertise, but rather to how they deal with patient problems and other factors. However, the revolution of Artificial Intelligence (AI) in many sectors aids in the semi-automated or automatic response of several issues. For example, deep learning (DL) is an AI technology for detecting and predicting problems. Like the other domains, the healthcare domain deployed several DL applications that produced excellent outcomes in many medical instances because of their capacity to learn from context by employing supervised learning, semi-supervised learning, and unsupervised learning. CNN is a deep learning technique specializing in picture identification, image classification, image prediction, identifying abnormalities in signal recordings, and so on. The auto extraction of features from photos and CNN's deep analytics are the primary reasons we chose to employ CNN for the training process in our system. Several researchers have utilized CNN to identify covid-19.

Because of its efficacy in image processing, we adopted a CNN model with convolution and pooling layers in our system. Furthermore, we rely on deep neurons with tiny kernel windows to improve feature learning and reduce model complexity. The Covid-19 and pneumonia detection systems employ x-ray images to build a deep model that takes the most information from the image. Our model has six convolution layers and three coupled layers (Table VI.2). After creating the features map, it must be delivered to the flattened layer to be prepared for the entire connected layers. The last fully connected layer is dedicated to the categorization findings.

	Layer	Feature Map	Size	Kernel Size	Stride	Activation
Input	Image	1	400×400×3	-	-	-
1	Convolution 2D	32	400×400×3	2×2	2×2	Tanh
	Max Pooling 2D	32	200×200×32	2×2	2×2	
3	Convolution 2D	32	100×100×32	2×2	2×2	Tanh
	Max Pooling 2D	32	50×50×32	2×2	2×2	
5	Convolution 2D	64	25×25×64	2×2	2×2	Softsign
	Max Pooling 2D		13×13×64	2×2	2×2	
	Flatten	2304	-	-	-	-
8	FC	132	304260	-	-	Relu
9	FC	60	7980	-	-	Relu
Output	FC	3	183	-	-	Softmax

Table VI.2: Summary of CNN model

- **Dataset** In our experiments, we used a free huge dataset of 6432 X-ray pictures from the Kaggle repository [21]. The dataset is separated into two folders: training (5144 X-ray images) and test (1288 X-ray pictures). Each of these folders has three sub-folders: Covid-19, Normal, and Pneumonia (Figure VI.3). Following dataset extraction, we employ certain pre-processing algorithms before creating additional photos for data augmentation.

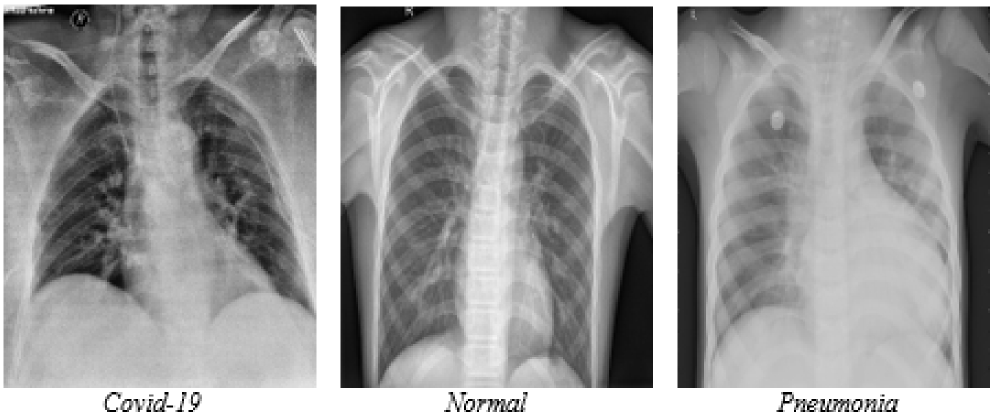

Figure VI.3: Dataset samples

- **Dataset preprocessing** Medical Picture processing is a vital stage in the medical sector that tries to visualize the anomalies and particular concerns inside the image. Image segmentation is a medical picture processing procedure that divides the original image into areas based on image attributes such as brightness and grey level.

  The wavelet transform is a valuable technique utilized for various medical difficulties such as signal decomposition and image decomposition [241]. In our situation, we employ Discrete wavelet transform (DWT) with Biorthogonal 1.3 for segmentation to remove extraneous data and improve analysis effort (Figure VI.4).

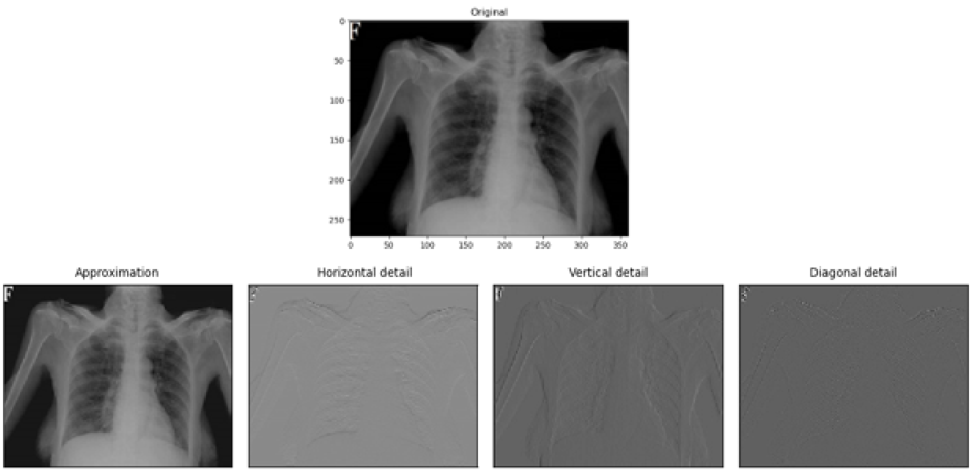

Figure VI.4: The application of DWT on image with bior 1.3

Furthermore, the combination of wavelet transformations and reduction approaches such as Principal Component Analysis accomplished state of the art in picking the ideal features, lowering complexity, and improving neural network accuracy [241]. Principal Component Analysis (PCA) is a linear algebra approach used to extract features and reduce dimensionality. The goal of PCA is to minimize the number of features while retaining the majority of the original ones to reduce the model's complexity. The primary phases of the PCA are to standardize the dataset into d dimensions, create the covariance matrix, compute the eigenvectors and eigenvalues, choose the k eigenvalues, and finally generate the new k-dimensional features of the original dataset [241]. In our example, we employed PCA with only 80 of the principal components, as described below:

1. Splitting the picture into three channels (Red, Green, and Blue).
2. Using PCA on each channel.
3. Using the inverse transform on the converted array.
4. Reversing the process to recreate the original image using only 80 of the primary components.

Figure VI.5 depicts the final image after varying the PCA settings.

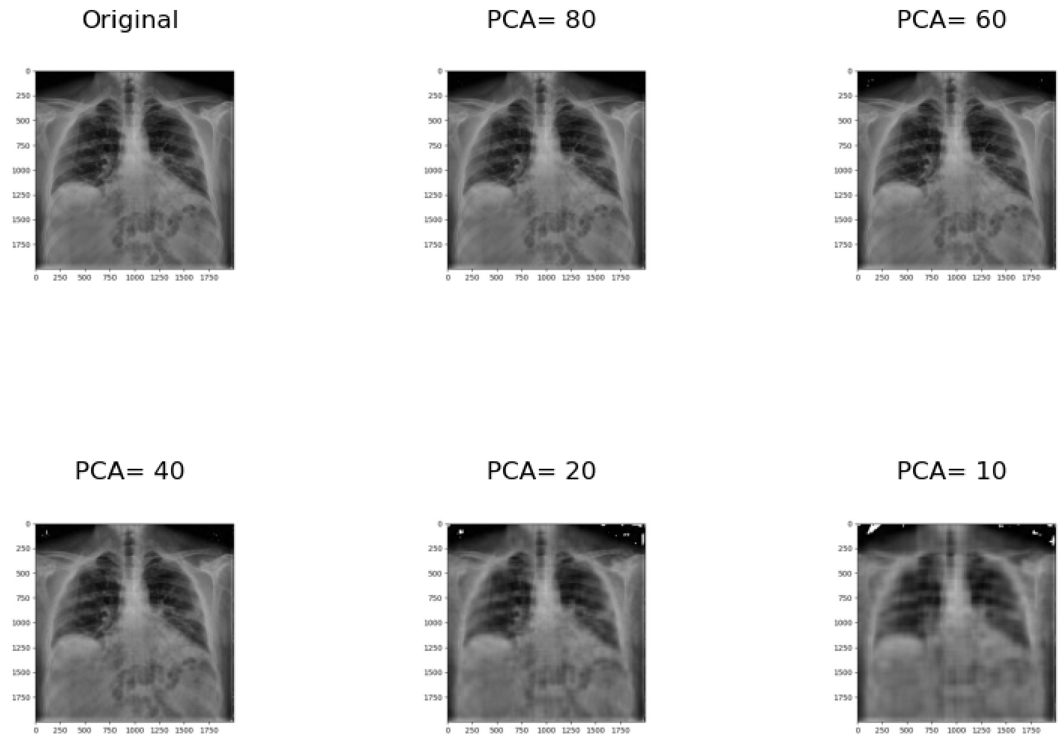

Figure VI.5: The application of PCA with different values

Following the application of DWT to the pictures, we calculated the entropy for each coefficient to extract the optimum features using several entropy's methods such as Teager Kaiser Energy Operator, Log Energy Entropy, and Shannon wavelet entropy energy.

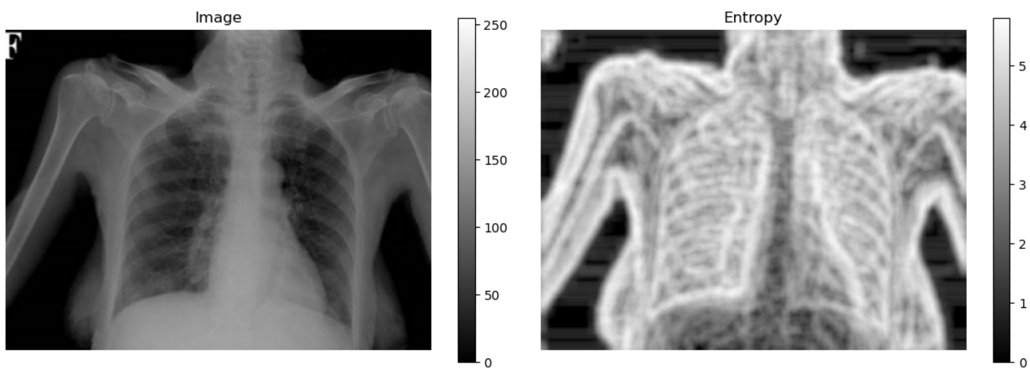

Figure VI.6: The application of entropy on the image

Teager Kaiser Energy Operator (TKEO) is a non-linear energy tracking operator for signal and image processing. The TKEO analyzes data using Amplitude

Modulated-Frequency Modulated (AM-FM). TKEO represented by the equation (VI.1).

$$\phi_2[I(x,y)] = ||\nabla I(x,y)||^2 - I(x,y).\nabla^2[I(x,y)] \tag{VI.1}$$

$$\nabla(I(x,y)) = (\frac{(\partial I(x,y))}{\partial x}, \frac{\partial I(x,y)}{\partial y}) \tag{VI.2}$$

$$I(x,y) = \Sigma_{k=1}^{K} a_k(x,y) \cos\left(\xi_k(x,y)\right) \tag{VI.3}$$

Where $a_k(x,y)$ represents the amplitude modulating of the image contrast in the k narrow-band component and $\nabla\xi_k(x,y)$ represents frequency modulation of image structure properties in the instantaneous phase component $\xi_k(x,y)$.
Shannon Wavelet Entropy Energy (SWEE) is a mix of wavelet, Shannon entropy, and energy. This combination is utilized for efficient analysis that extracts optimal features based on time-frequency. For example, the equation might represent the Shannon wavelet entropy energy (VI.4):

$$\eta(d) = \frac{E(d)}{Shannon_{Entropy}(d)} \tag{VI.4}$$

$$E(d) = \Sigma_{k=1}^{c} |M_k(d)|^2 \tag{VI.5}$$

Where E is energy of data (d) in each wavelet coefficient (c)

$$Shannon_{Entropy}(d) = -\Sigma_{k=1}^{c} P_k log P_k \tag{VI.6}$$

Where P_k is the energy probability of each wavelet coefficient and $\Sigma_{k=1}^{c} P_k = 1$.

$$P_k = \frac{|M_k(d)|^2}{E(d)} \tag{VI.7}$$

Log Energy Entropy (LEE) is an energy-based feature extraction approach that is comparable to Shannon entropy. Its primary use is to compute the uncertainty of characteristics in data using an equation (IV.5).

$$LogEnergy_{Entropy}(d) = \Sigma_{k=1}^{c} log(P_k^2) \tag{VI.8}$$

Where P_k is the energy probability of each wavelet coefficient and $\Sigma_{k=1}^{c} P_k = 1$

- **Classification** Another important stage in medical image processing that is employed in Computer-Aided Diagnosis (CAD). The received pictures are given to the CNN model to be categorized during the classification phase. The class of each image is the result of this step. We have three groups in our case: Covid-19, Normal, and Pneumonia (Figures VI.3, VI.4, VI.5). For the evaluation of our model, we employed the following classification metrics: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) (FN). Recall, True Positive Rate (TPR), False Positive Rate (FPR), Precision, Specificity, Sensitivity, F1-score, and Accuracy, are calculated using these measurements.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{VI.9}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{VI.10}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{VI.11}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{VI.12}$$

$$\text{Accuracy} = \frac{TP + TN}{TN + TP + FP + FN} \tag{VI.13}$$

$$\text{F1-measure} = 2\frac{\text{Precision} * Sensitivity}{\text{Precision} + Sensitivity} \tag{VI.14}$$

- **Cloud Storage** The cloud layer has a large storage capacity and saves the huge data received from the fog layer, creating the user profile and storing the outcomes of the categorized data.

- **Visualize results** This phase concentrated in showing analytical dashboards and categorization findings.

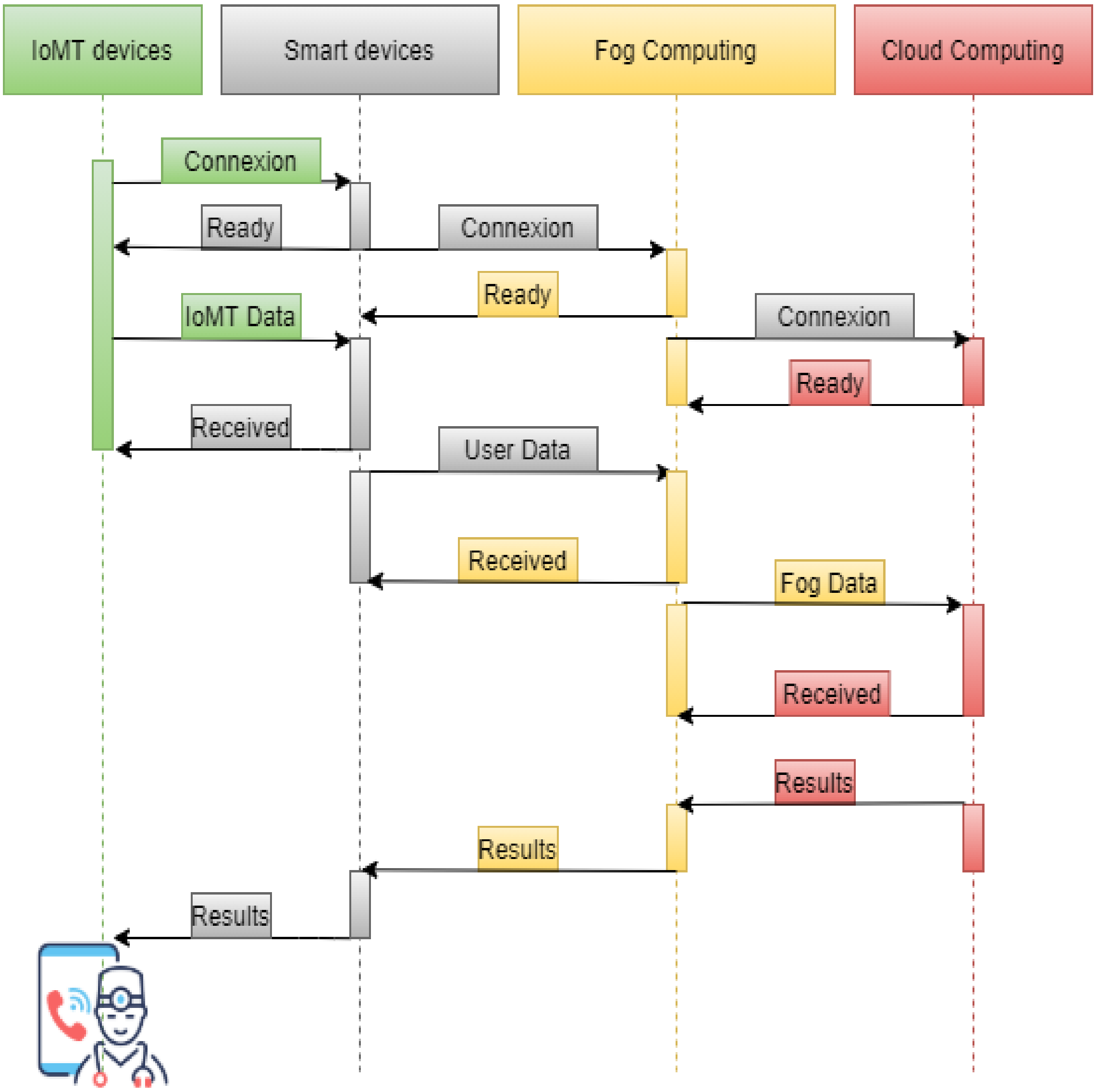

Figure VI.7: Scenario of the proposed system

3 Results And Discussion

We employed Python with the Keras and Tensorflow libraries, which provide the necessary tools for deep learning implementation, in our solution. The PyCharm environment is used to build these libraries. Lenovo PC with Windows 10 Pro 64-bit, Intel Core i7 3.60GHz CPU, 16 GB RAM, Intel HD Graphics 4600 GPU, and 1TB storage. In terms of classification measures, our model delivers efficient results: 97 percent accuracy, 100 percent precision, 97 percent recall, and 99 percent F1-score. Table VI.3 summarizes the model's categorization findings [241].

	Precision	Recall	F1- Score	Accuracy
Covid-19	100%	97%	99%	97%
Normal	94%	90%	92%	97%
Pneumonia	96%	98%	97%	97%

Table VI.3: Classification results

The use of DWT-PCA as a preprocessing step on the dataset significantly improves the model and lowers its complexity by reducing the trainable parameters. According to Table VI.4, 28.24 percent of parameters are lowered to reduce training time and the overall complexity of the model. In addition, we calculate the signal-to-noise ratio (SNR) of the original picture and the preprocessed image Table VI.5. Furthermore, we employed a peak signal-to-noise ratio (PSNR) to examine the influence of the preprocessing step on the original dataset by comparing an original image to its preprocessed counterpart. The PSNR value of 3.14 dB indicates that the maximum permissible power and the corrupting noise power have no influence on the resultant picture and that the usage of DWT-PCA in the preprocessing stage is successful.

	Trainable parameters
Original dataset	658119
Pre-processed dataset	472263

Table VI.4: The number of trainable parameters of the original dataset and the pre-processed dataset

	SNR (dB)	PSNR (dB)
Original image	1.48	3.14
Pre-processed image	1.47	

Table VI.5: The SNR and PSNR values of the original image and the preprocessed image

On the other hand, we start the identification process by calculating the pixel energy of the picture using several approaches such as TKEO, SHEE, and LEE.

	TKEO (bits/pixel)	SHEE (bits/pixel)	LEE (bits/pixel)
Image	3.26	6.75	4.68

Table VI.6: The result of application TKEO, SWEE and LEE on the image

Table VI.6 shows that TKEO has the lowest energy with just 3.26 bits/pixel, which increases its effectiveness in monitoring the energy of non-linear features. The application of TKEO in such essential situations as x-ray pictures significantly influenced the accurate identification of the x-ray images and wished to increase the system's performance in distinguishing between covid-19, normal, and pneumonia cases. We can also assess how our system performed throughout the training phase by comparing accuracy and loss metrics in the original and preprocessed datasets. However, training with a preprocessed dataset that contains just 71.76 percent of the original trainable parameters produced superior results in terms of accuracy and loss, with the growing green curve improving high accuracy. In the meantime, the loss function is lowered until it reaches low levels (see Figure VI.8)[241].

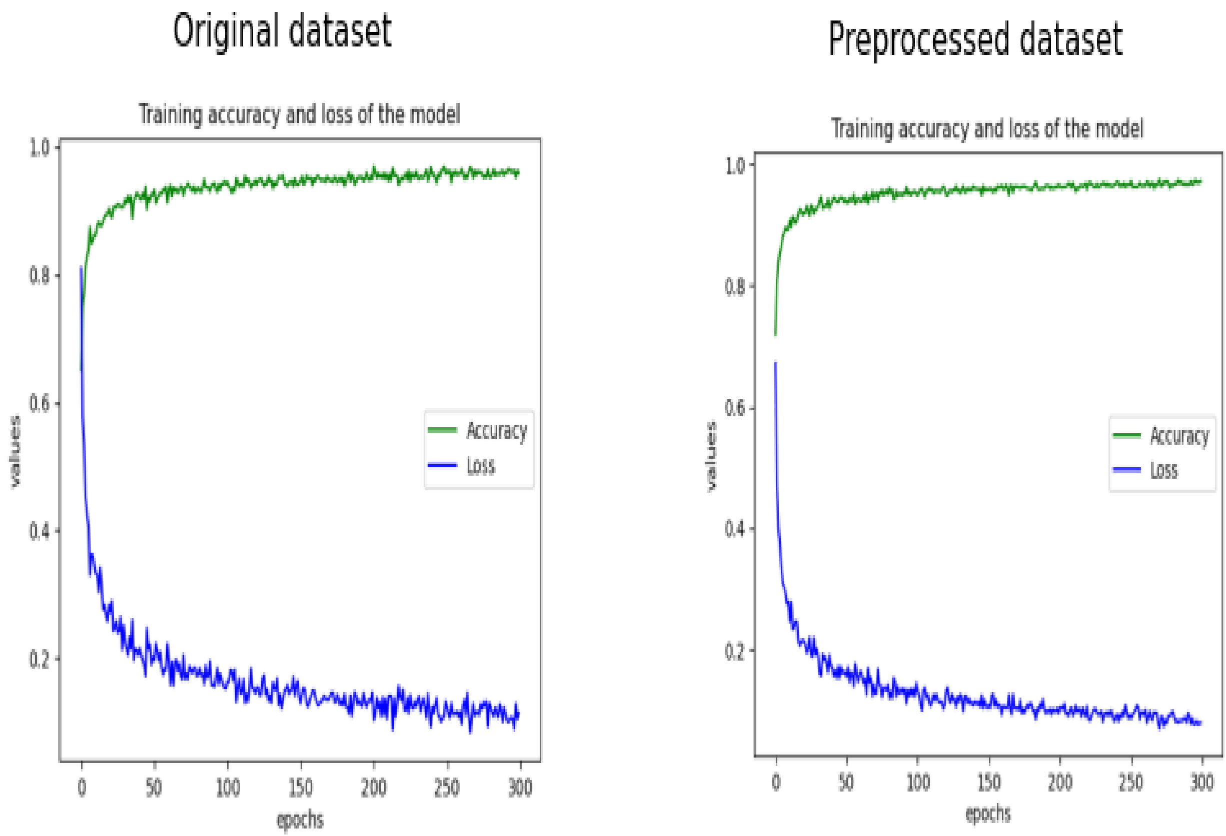

Figure VI.8: The training accuracy and loss of the CNN model on the original dataset and preprocessed dataset

3.1 Confusion Matrix

A confusion matrix is a machine learning parameter used to assess the system's efficacy and performance. It is typically used for binary or multi-class classification problems. The confusion matrix's primary use is to assist in understanding how the classification model becomes confused while generating predictions. This allows you to observe how many errors were made and what type of errors were committed, with the rows of the matrix reflecting real class occurrences and the columns representing instances of the predicted category. In other words, it maintains track of the right and incorrect predictions made by each class.
To assure the system's performance, we compute True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). These measures are used to show the outcomes of each class's prediction. Figure VI.9 shows that the model accurately

predicted virtually all of the covid-19 samples used for the validation dataset, except one sample, which was predicted as a normal case, and five samples as pneumonia. Furthermore, the algorithm properly predicted normal samples while missing a few (1 as covid-19 and 18 as pneumonia). Furthermore, the algorithm properly predicts 98 percent of pneumonia samples. (Figure VI.10).

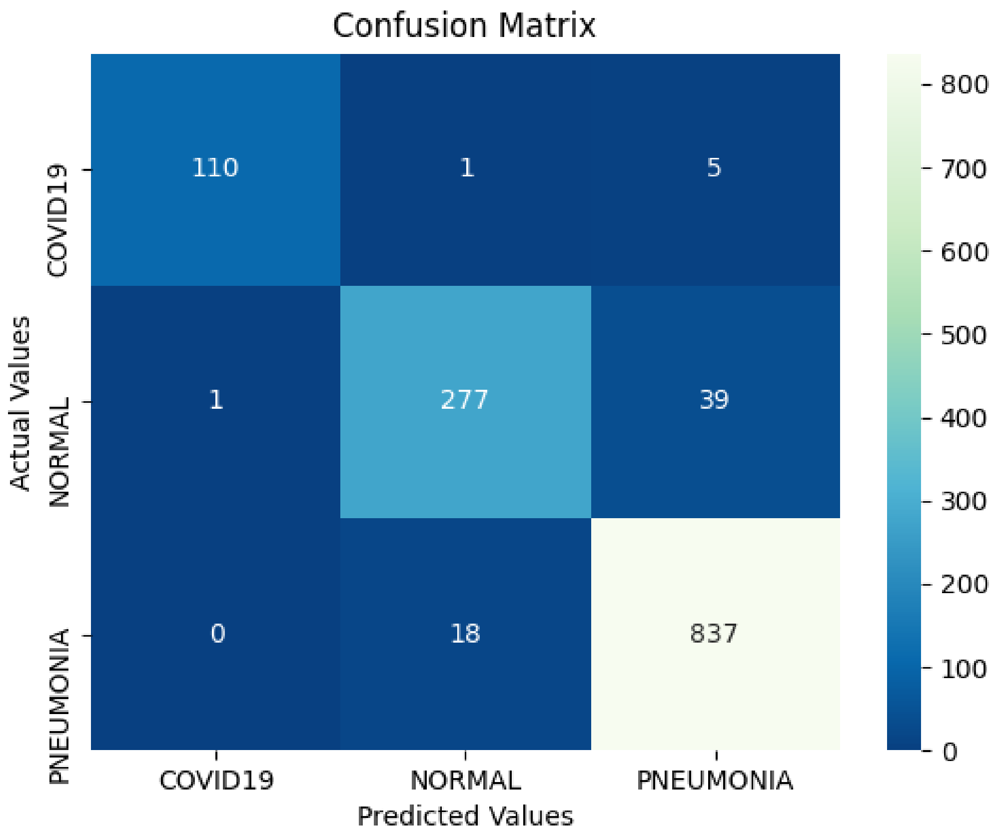

Figure VI.9: Confusion matrix of the predicted classes

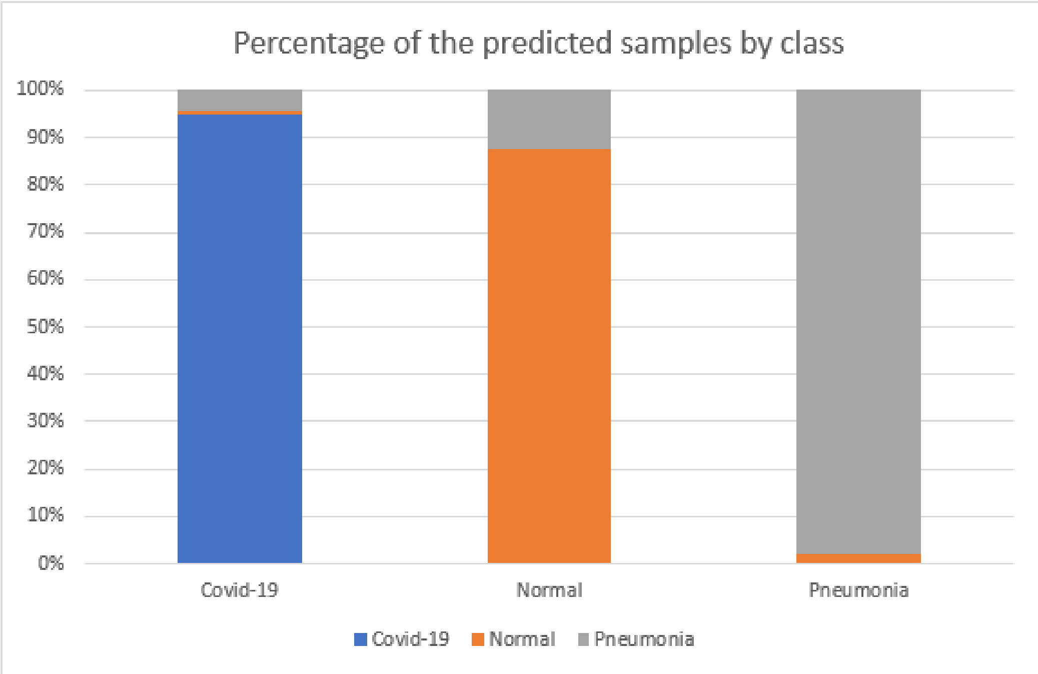

Figure VI.10: The percentage of predicted samples by classes

3.2 Area Under the ROC Curve

The Receiver Operating Characteristic Curve (ROC curve), which examines a classifier's ability to discriminate between classes, is described by the Area Under Curve (AUC). Meanwhile, the ROC curve is a graph that displays the True Positive Rate (TPR) and False Positive Rate (FPR) of a classification model overall categorization levels (FPR) [241].

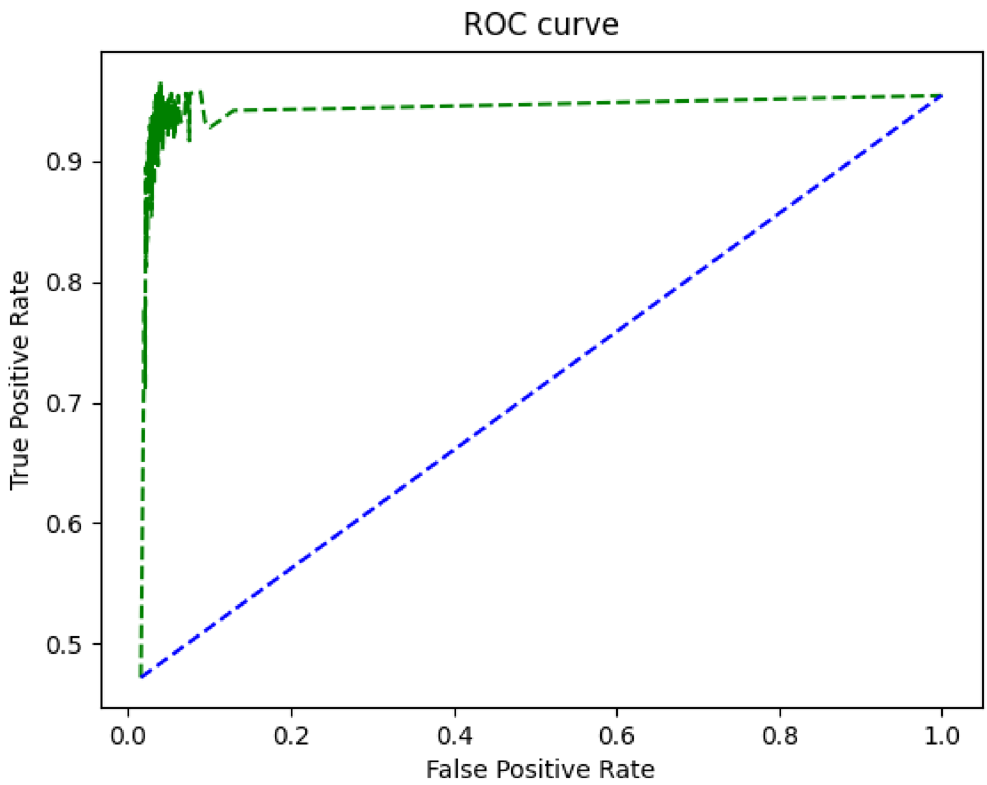

Figure VI.11: The ROC curve of the model

The ROC curve of our model is displayed to validate its classification performance. As seen in Figure VI.11, the large gap between the green and blue lines determines the model's AUC, which reaches 0.98. The optimal diagnostic test for the classes was 1. Furthermore, reaching AUC = 0.98 reflects the model's accuracy in predicting classes, assuring outperformance, and the model's capability to categorize classes.

4 Conclusion

Covid-19 is a severe issue that must be addressed because it influences numerous fields, including industry, education, economics, etc. Because there is no efficient treatment for this pandemic, the only way to deal with it is to minimize its spread by precautionary measures and early identification of affected persons. With the artificial intelligence revolution and its influence on multiple domains, the healthcare industry, like other domains, embraced AI methodologies, resulting in significant medical advancements such as the Internet of medical things (IoMT). The IoMT has been discovered to treat a wide range of medical concerns that require immediate attention. We propose an IoMT-fog-cloud-based architecture for covid-19 identification in this study. Furthermore, this chapter tries to slow the development of the pandemic by detecting affected persons early. Another goal of this suggested technology is to make it easier to identify covid-19 anywhere, at any time, and with anybody by making it simple to use and user pleasant. In addition, we prioritize cloud Quality of Service (QoS) by providing an intermediary layer between the user and the cloud to decrease latency and provide real-time response. Furthermore, the privacy and security of the patient's data were important goals of our research.

We employed a combination of Discrete Wavelet Transform and Principal Component Analysis (DWT-PCA) to extract the ideal features and lower the dimension for improved classification and identification outcomes. In addition, we applied several types of energy tracking in the pictures to improve identification in the x-ray images. Our suggested filtering strategy reduces model complexity by decreasing trainable parameters and saving time. The classification assessment of our CNN model revealed an efficient performance that can categorize the covid-19, pneumonia, and normal cases with 97 percent accuracy and a precision rate of 100 percent. Based on the experimental results, our suggested approach might assist in identifying covid-19.

We want to employ the ElectroCardioGraph (ECG) for covid-19 identification in the future since late covid-19 variations influence the cardiovascular system. Furthermore, CT and X-ray pictures might not be a good source for identifying these novel variations. In addition, we intend to examine Empirical Wavelet Transform (EWT) and PCA for data filtering. Finally, this future effort will be a cloud-based program that hospitals and society may utilize.

Chapter VII

General conclusion

This chapter summarizes the contributions of this thesis and presents the results achieved. Also, a discussion of the limitations of the realized contributions and prescriptive and research directions for future work will be presented.

1 Summary

This thesis combined Big Data, Cloud Computing, IoT, and Artificial Intelligence in the medical field. The research conducted in this thesis consists of developing computer aid diagnosis to assist the doctor in diagnosing patients in general and precisely in Covid-19 and Neonatal seizures. The challenges addressed in this thesis resulted in three major contributions that address the questions raised in the introduction. These contributions are summarized below:

- An accurate computer aid diagnosis system for neonatal seizures detection is proposed. This system is based on a new bio-inspired method called Marine Predator Algorithm, for hyperparameters selection of the model. The system's main purpose is to improve the system's performance in detecting the abnormalities in the EEG records by combining features extracted from EEG records and the additional clinical data posted by neurologists. The proposed system clarifies the improvement of using metaheuristic techniques in selecting the hyperparameters and tests the effectiveness of the proposed Marine Predator Algorithm technic compared with the Genetic Algorithm. This advanced work could be considered a good step in mental disease detection, especially neonatal seizures detection. The proposed system achieved greater classification results by optimizing the CNN model, improving the quality of data, and combining two kinds of data, which improved the system's performance and precision and reduced the training time. The MPA-CNN for neonatal seizures can be used as a medical decision support system for neurologists to make an accurate classification with lower cost, time, and effort.

- In the second contribution, the Covid-19 pandemic was addressed using deep learning technique and Marine Predator Algorithm. The developed system tests the MPA's effectiveness on other kinds of data, such as X-ray images. Several preprocessing steps were used for the dataset to eliminate the problem of imbalanced data, such as resizing the images, re-scaling, and rotating. The main addition of this contribution is:

  a) improving the system's precision in classifying covid-19 cases and the other lung diseases such as Pneumonia; b) reducing the complexity of the system by reducing the training time using the MPA in the auto-selection of the hyperparameters, which gives us the best configuration of the model. The experimental results indicate the system's performance in classifying the covid-19 and pneumonia disease in the various classification metrics such as F1-score, Accuracy, Sensitivity, Specificity, and Precision.

- For the third contribution, we tried to change the idea of optimizing the CNN model, and we focused only on optimizing the data. A new computer aid diagnosis system was proposed for better classification of covid-19, and pneumonia disease was. In this contribution, we used the same dataset that used the second contribution to compare the impact of optimizing the model and the impact of optimizing the data. We start our contribution with the application of Discrete Wavelet Transfer for decomposing the dataset's images into segments. Then, we apply the PCA module to extract the principle and the most important features of the image, reducing the model's complexity next. Next, we introduce the TKEO technique to track the energy in the image, which reflects the position of the valuable information in the image. The combination of these technics gives us the best results for classifying covid-19 and Pneumonia in reduced time. The experimental results of this contribution and the previous one indicate the efficacity and the outperformance of optimizing data instead of the model. At the end of this contribution, the IoMT-cloud architecture for the system aims to reduce the latency and improve the system's quality of service by introducing fog as an intermediary layer. The proposed system is supposed to be the real application of the model and computer aid diagnosis for the radiologists, cost-less, and user-friendly.

2 Prescriptive

Numerous enhancements to the contributions done in this thesis might be made, as well as research topics that deserve additional consideration in the future. Some of them are listed below:

- The first limitation in the CAD systems in general is the data, which controls and directs us in the research. Soon, a) for neonatal seizures: we aim to study the impact of other kinds of features such as the baby's cry sound during the phase of seizures, ECG records during the seizures, and discover whether there is a correlation between the heart and nervous system or not. Also, we intend to study the impact and the possibility of causing the brain tumor in the baby in the future. Moreover, we aim to study the medical history of the family and conclude whether this disease could be genetically passed or not; b) for covid-19, we aim to improve the precision of our system by using an extended dataset that contains the majority of lung diseases. Also, we look for testing our model on CT-scan images of the covid-19 and compare the results with our obtained results from X-ray images.
- The real application of the proposed systems is our main goal. To realize that, collaboration with neurologists and radiologists is needed to better understand the pathology and the needs of doctors. According to this collaboration, several facilities will be made, such as the development of visualization applications for the doctors and CAD systems that specialize in Neonatal seizures detection and covid-19 detection. Furthermore, we could extend our systems with the help of

these specialists to make them able to predict the covid-19 and neonatal seizures based on the doctors' expertise.

- The success achieved by our CNN model in different kinds of data and diseases motivates us to investigate them on other diseases such as heart diseases.
- The healthcare is our area of interest, and we are motivated to do our best to develop CAD that facilitates the daily life of the patient and the doctor. From this point, we will concentrate our focus on the healthcare of our country Algeria. To accomplish that, we need to collaborate with Algeria medical staff from public hospitals, private hospitals, and clinics to exchange the information and make conventions that come back with benefits for the patients in the first place.

Bibliography

[1] García-Ordás, María Teresa, and al. Detecting respiratory pathologies using convolutional neural networks and variational autoencoders for unbalancing data. *Sensors*, 20(4):1214, 2020.

[2] Recurrent neural networks. *Java T point*, Accessed: 20/05/2022, https://www.javatpoint.com/keras-recurrent-neural-networks.

[3] Zhang, Pengfei, and al. View adaptive recurrent neural networks for high performance human action recognition from skeleton data. *Proceedings of the IEEE international conference on computer vision*, 2017.

[4] S.W Park, J.S Ko, J.H Huh, and J.C Kim. Review on generative adversarial networks: Focusing on computer vision and its applications. *Electronics*, 10:1216, 2021.

[5] Renu Khandelwal. Deep learning — restricted boltzmann machine. *Data Driven Investor*, 2018, https://medium.datadriveninvestor.com/deep-learning-restricted-boltzmann-machine-b76241af7a92?gi=4c0b0819389b.

[6] Philippe Hamel and Douglas Eck. Learning features from music audio with deep belief networks. In *ISMIR*, 2010.

[7] Renu Khandelwal. Deep learning — deep boltzmann machine (dbm). *Data Driven Investor*, 2018, https://medium.datadriveninvestor.com/deep-learning-deep-boltzmann-machine-dbm-e3253bb95d0f.

[8] Sayantini. Autoencoders tutorial : A beginner's guide to autoencoders. *Edureka*, 2020, https://www.edureka.co/blog/autoencoders-tutorial/.

[9] Denoising autoencoders. Accessed 20/10/2021, https://miro.medium.com/max/724/1*qKiQ1noZdw8k05-YRIl6hw.jpeg.

[10] Renu Khandelwal. Deep learning — different types of autoencoders. *Data Driven Investor*, 2018, https://medium.datadriveninvestor.com/deep-learning-different-types-of-autoencoders-41d4fa5f7570.

[11] Sharma Sumit, Dudeja Rajan Kumar, Aujla Gagangeet Singh, Bali Rasmeet Singh, and Kumar Neeraj. Detras: deep learning-based healthcare framework for iot-based assistance of alzheimer patients. *Neural Computing and Applications*, 2020, Doi: https://doi.org/10.1007/s00521-020-05327-2.

[12] Kaur K Garg S Kumar N Ranjan R Aujla GS, Chaudhary R. Safe: Sdn-assisted framework for edge-cloud interplay in secure healthcare ecosystem. *IEEE Trans Ind Inform*, 15(1):469–480, 2018.

[13] GS Aujla, A Jindal, R Chaudhary, N Kumar, S Vashist, N Sharma, and MS Obaidat. Dlrs: deep learning-based recommender system for smart healthcare ecosystem. pages 1–6, 2019, Doi: 10.1109/ICC.2019.8761416.

[14] R Chaudhary, A Jindal, GS Aujla, N Kumar, AK Das, and N Saxena. Lscsh: lattice-based secure cryptosystem for smart healthcare in smart cities environment. *IEEE Commun Mag*, 56(4):24—-32, 2018.

[15] C Hollis, R Morriss, J Martin, S Amani, R Cotton, M Denis, and S Lewis. Technological innovations in mental healthcare: harnessing the digital revolution. *Br J Psychiatry*, 206(4):263–265, 2015.

[16] D Sharma, G Aujla, Singh, and R Bajaj. Evolution from ancient medication to human-centered healthcare 4.0: a review on health care recommender systems. *Int J Commun Syst*, page e4058, 2019.

[17] MD Mary L.and Zupanc. Neonatal seizures. *Pediatr Clinics North America*, 51(4):961—- 978, 2004, Doi: 10.1016/j.pcl.2004.03.002.

[18] Rosa De giorgio. *Guidelines on neonatal World Health Organization*. Springer, 2011, https://apps.who.int/iris/handle/10665/77756, 2011.

[19] Victorio and M. Cristina. Neonatal seizure disorders. 2021, Accessed: 22/06/2021, https://www.msdmanuals.com/professional/pediatrics/neurologic-disorders-in-children/neonatal-seizure-disorders.

[20] N.J.Stevenson, K.Tapani, L.Lauronen, and S.Vanhatalo. A dataset of neonatal eeg recordings with seizure annotations. *Scientific data*, 6(1):1–8, 2019, Doi: https://doi.org/10.1038/sdata.2019.39.

[21] P Patel. Chest x-ray (covid-19 pneumonia). *Kaggle*, 2021, Accesed 23/04/2021, https://www.kaggle.com/prashant268/chest-xray-covid19-pneumonia.

[22] Gangadhar Shobha and Shanta Rangaswamy. Machine learning. *Handbook of Statistics*, 38:197–228, 2018, Doi: https://doi.org/10.1016/bs.host.2018.07.004.

[23] I El Naqa and M.J. Murphy. What is machine learning? *Machine Learning in Radiation Oncology*, pages 3–11, 2015, Doi: https://doi.org/10.1007/978-3-319-18305-3_1.

[24] Mitchell TM. *Machine learning.* McGraw-Hill, 1997.

[25] E Alpaydin. *Introduction to machine learning. 3rd ed.* MA: The MIT Press, 2014.

[26] X.D Zhang. Machine learning. *In: A Matrix Algebra Approach to Artificial Intelligence*, 2020, Doi: https://doi.org/10.1007/978-981-15-2770-8_6.

[27] Osindero; W. Teh Y. E, Hinton G.; S. A fast learning algorithm for deep belief nets. *Neural computation*, 18(7):1527–1554, 2006, Doi: https://doi.org/10.1162/neco.2006.18.7.1527.

[28] De John D Kelleher. *Deep Learning.* The MIT press essential knowledge series, 2019.

[29] Pumperla Max and Ferguson Kevin. *Deep Learning and the Game of Go*, volume 231. Manning Publications Company, 2019m https://www.manning.com/books/deep-learning-and-the-game-of-gotoc.

[30] D. W Otter, J. R Medina, and J. K. Kalita. A survey of the usages of deep learning for natural language processing. *IEEE Transactions on Neural Networks and Learning Systems*, 2020.

[31] R. R Saritha, V Paul, and P. G Kumar. Content based image retrieval using deep learning process. *Cluster Computing*, 22(2):4187–4200, 2019.

[32] M Pak and S Kim. A review of deep learning in image recognition. *In 2017 4th international conference on computer applications and information processing technology (CAIPT)*, pages 1–3, 2017.

[33] M Gupta, N Kumar, B. K Singh, and N Gupta. Nsga-iii- based deep-learning model

for biomedical search engines. *Mathematical Problems in Engineering*, 2021.

[34] H Li and Z Lu. Deep learning for information retrieval. *In Proceedings of the 39th International ACM SIGIR conference on Research and Development in Information Retrieval*, pages 1203–1206, 2016.

[35] J Schmidhuber. Deep learning in neural networks: An overview. *Neural networks*, 61:85–117, 2015, https://doi.org/10.1016/j.neunet.2014.09.003.

[36] B Yegnanarayana. Artificial neural networks. *PHI Learning Pvt*, 2009.

[37] H Ramchoun, M. A. J Idrissi, Y Ghanou, and M. Ettaouil. Multilayer perceptron: Architecture optimization and training. *IJIMAI*, 4(1):26–30, 2016.

[38] Glorot X, Bordes A, and Bengio Y. Deep sparse rectifier neural networks. *In Proceedings of the fourteenth international conference on artificial intelligence and statistics*, pages 315–323, 2011.

[39] Srivastava E, Hinton G.and N, Krizhevsky A, Sutskever I, and Salakhutdinov R. R. Improving neural networks by preventing co-adaptation of feature detectors. *arXiv preprint arXiv:1207.0580*, 2012.

[40] A. F Agarap. Deep learning using rectified linear units (relu). *arXiv preprint arXiv:1803.08375*, 2018.

[41] J. L. Ba. Adaptive dropout for training deep neural networks. *University of Toronto (Canada)*, 2014.

[42] J Jin, A Dundar, and E Culurciello. Flattened convolutional neural networks for feedforward acceleration. *arXiv preprint arXiv:1412.5474*, 2014.

[43] E Okewu, P Adewole, and O Sennaike. Experimental comparison of stochastic optimizers in deep learning. *In International Conference on Computational Science and Its Applications*, pages 704–715, 2019.

[44] D; Tweed D. B; Akerman C.J Lillicrap, T. P; Cownden. Random synaptic feedback weights support error backpropagation for deep learning. *Nature communications*, 7(1):1–10, 2016.

[45] L Deng. A tutorial survey of architectures, algorithms, and applications for deep learning. *APSIPA Transactions on Signal and Information Processing*, 3, 2014, Doi: https://doi.org/10.1017/atsip.2013.9.

[46] L Bottou. Large-scale machine learning with stochastic gradient descent. *In Proceedings of COMPSTAT'2010. Physica-Verlag HD*, pages 177–186, 2010, Doi: https://doi.org/10.1007/978-3- 7908-2604-$3_1$6.

[47] Mohammadi M, Al-Fuqaha A, Sorour S, and Guizani M. Deep learning for iot big data and streaming analytics: A survey. *IEEE Communications Surveys Tutorials*, 20(4):2923–2960, 2018.

[48] Pascanu R, Gulcehre C, Cho K, and Bengio Y. How to construct deep recurrent neural networks. *arXiv preprint arXiv:1312.6026*, 2013.

[49] Chung J, Gulcehre C, Cho K, and Bengio Y. Empirical evaluation of gated recurrent neural networks on sequence modeling. *arXiv preprint arXiv:1412.3555*, 2014.

[50] Mikolov T, Joulin A, Chopra S, Mathieu M, and Ranzato M A. Learning longer memory in recurrent neural networks. *arXiv preprint arXiv:1412.7753*, 2014.

[51] P Baldi. Autoencoders, unsupervised learning, and deep architectures. *In Proceedings of ICML workshop on unsupervised and transfer learning. JMLR Workshop and Conference Proceedings*, pages 37–49, 2012.

[52] Dai B, Fidler S, Urtasun R, and Lin D. Towards diverse and natural image descrip-

tions via a conditional gan. *In Proceedings of the IEEE International Conference on Computer Vision*, pages 2970–2979, 2017.
[53] Mohammadi M, Al-Fuqaha A, Sorour S, and Guizani M. Deep learning for iot big data and streaming analytics: A survey. *IEEE Communications Surveys Tutorials*, 20(4):2923–2960, 2018.
[54] Bengio Y. Learning deep architectures for ai. 2(1):1—-127, 2009.
[55] G. Hinton. A practical guide to training restricted boltzmann machines. *Momentum*, 926(9), 2010.
[56] K Cho, T Raiko, and A Ilin. Enhanced gradient for training restricted boltzmann machines. *Neural Computation*, 25(3):805—-831, 2013.
[57] G. E Hinton and R. R Salakhutdinov. Reducing the dimensionality of data with neural networks. *American Association for the Advancement of Science: Science*, 313(5786):504—-507, 2006.
[58] R Salakhutdinov and H Larochelle. Efficient learning of deep boltzmann machines. *in Proceedings of the AISTATS*, 2010.
[59] L Younes. On the convergence of markovian stochastic algorithms with rapidly decreasing ergodicity rates. *Stochastics and Stochastics Reports*, 65(3-4):177—-228, 1999.
[60] C Doersch. Tutorial on variational autoencoders. *arXiv preprint arXiv:1606.05908*, 2016.
[61] P Vincent, H Larochelle, Y Bengio, and P.-A Manzagol. Extracting and composing robust features with denoising autoencoders. *In Proceedings of the Twenty-fifth International Conference on Machine Learning (ICML'08)*, page 1096–*1103, 2008.
[62] Athanasios Voulodimos, Nikolaos Doulamis, Anastasios Doulamis, and Eftychios Protopapadakis. Deep learning for computer vision: A brief review. *Computational Intelligence and Neuroscience*, page 13, 2018, Doi: https://doi.org/10.1155/2018/7068349.
[63] Patrick Siarry. Metaheuristics. *Springer International Publishing Switzerland*, 2016.
[64] Talbi El-Ghazali. *Metaheuristics From Design To Implementation*, 2009.
[65] Glover F. Future paths for integer programming and links to artificial intelligence. *Computers operations research*, 13(5):533–549, 1986, Doi: https://doi.org/10.1016/0305-0548(86)90048-1.
[66] F Glover. Future paths for integer programming and links to artificial intelligence. *Computers and Operation Research*, 13(5):533—-549, 1986.
[67] S Al-Sharhan and M Omran. A parameter-free barebones particle swarm algorithm for unsupervised pattern classification. *International Journal of Hybrid Intelligent Systems*, 9:135—-143, 2012.
[68] P.J Blackwell, T.M; Bentley. Dynamic search with charged swarms. *In: Genetic and Evolutionary Computation Conference. Morgan Kaufmann, San Francisco*, pages 19—-26, 2002.
[69] T Sudkamp. Languages and machines: An introduction to the theory of computer science. *Addison-Wesley*, 2005.
[70] M. Johnson and Garey D. Computers and intractability: A guide to the theory onnp-completeness. 1979.
[71] S. A Cook. The complexity of theorem-proving procedures. *In Proceedings of the third annual ACM symposium on Theory of computing*, pages 151–158, 1971.
[72] T. G Toulouse and M Crainic. Parallel strategies for metaheuristics. *In F.W. Glover and G. A. Kochenberger, editors, Handbook of Metaheuristics*, pages 475—-513, 2003.

[73] F Glover and M Laguna. Tabu search. *In Handbook of combinatorial optimization*, pages 2093–2229, 1998.

[74] S Kirkpatrick, C. D Gelatt, and M. P Vecchi. Optimization by simulated annealing. *Science*, 220(4598):671–680, 1983 Doi: 10.1126/science.220.4598.671.

[75] Holland J. H. Genetic algorithms. *Scientific american*, 127(1):66–73, 1992, www.jstor.org/stable/24939139.

[76] J Kennedy and R Eberhart. Particle swarm optimization. *In Proceedings of ICNN'95-international conference on neural networks*, 4:1942–1948, 1955, Doi: 10.1109/ICNN.1995.488968.

[77] Mirjalili S, Mirjalili S. M, and Lewis A. Grey wolf optimizer. *Advances in engineering software*, 69:46–61, 2014, Doi: https://doi.org/10.1016/j.advengsoft.2013.12.007.

[78] D Karaboga and B Basturk. On the performance of artificial bee colony (abc) algorithm. *Applied soft computing*, 8(1):687–697, 2008, Doi: https://doi.org/10.1016/j.asoc.2007.05.007.

[79] Mirjalili S and Lewis A. The whale optimization algorithm. *Advances in engineering software*, 95:51–67, 2016, Doi: https://doi.org/10.1016/j.advengsoft.2016.01.008.

[80] Mohamed Abdel-Basset, Laila Abdel-Fatah, and Arun Kumar Sangaiah. Metaheuristic algorithms: A comprehensive review. *Computational Intelligence for Multimedia Big Data on the Cloud with Engineering Applications*, pages 185–231, 2018.

[81] D. Cox, M.; Ellsworth. Application-controlled demand paging for out-of-core visualization. *Proceedings of the 8th Conference on Visualization '97*, 97:235—-244, 1997, Doi: http://dx.doi.org/10.1109/VISUAL.1997.663888.

[82] F.X Diebold. Big data dynamic factor models for macroeconomic measuring and forecasting, adv. *Econ. Econom. Eighth World Congr. Econom. Soc*, pages 115–122, 2003.

[83] D. Laney. Meta delta, appl. *Deliv. Strateg*, 949(4), 2001, Doi: http://dx.doi.org/10.1016/j.infsof.2008.09.005.

[84] J Manyika, M Chui, B Brown, and al. Big data:the next frontier for innovation competition, and productivity. *McKinsey Global Institute*, 2018.

[85] B Feldman, E.M Martin, and T. Skotnes. Big data in healthcare–hype and hope. *Dr. Bonnie 360 degree, Bus. Dev. Digit. Heal*, page 122–125, 2013, Doi: http://www.riss.kr/link?id=A99883549.

[86] Mehtaa Nishita and Panditb Anil. Concurrence of big data analytics and healthcare: A systematic review. *International Journal of Medical Informatics*, 114:57–65, 2018.

[87] Ahmed Oussous, Fatima-Zahra Benjelloun, Ayoub Ait Lahcen, and Samir Belfkih. Big data technologies: A survey. *Journal of King Saud University - Computer and Information*, 2017, Doi: http://dx.doi.org/10.1016/j.jksuci.2017.06.001.

[88] C. L Stimmel. Big data analytics strategies for the smart grid. 2014.

[89] R Nambiar, R Bhardwaj, A Sethi, and R Vargheese. A look at challenges and opportunities of big data analytics in healthcare. *In Big Data, 2013 IEEE International Conference on*, pages 17–22, 2013.

[90] V Rajaraman. Big data analytics. *Resonance*, 21:695—716, 2016.

[91] I.D Dinov. Volume and value of big healthcare data. *Journal of Medical Statistics and Informatics*, 4, 2016, Doi: http://dx.doi.org/10.7243/2053-7662-4-3.

[92] C Auffray, R Balling, I Barroso, L Bencze, M Benson, and al. Making sense of big data in health research: towards an eu action plan. *Genome Med*, 8(71), 2016, Doi: http://dx.doi.org/10.1186/s13073-016-0323-y.

[93] J.S Rumsfeld, K.E Joynt, and T.M Maddox. Big data analytics to improve cardiovascular care: promise and challenges. *Nature Reviews Cardiology*, 13:350—-359, 2016, Doi: http://dx.doi.org/10.1038/nrcardio.2016.42.

[94] C Weng and M.G Kahn. Clinical research informatics for big data and precision medicine. *Yearbook of Medical Informatics*, pages 211—-218, 2016, Doi: http://dx.doi.org/10.15265/IY-2016-019.

[95] K Miller. Big data analytics in biomedical research. *Biomed. Comput. Rev*, pages 15—-21, 2012.

[96] M Swan. The quantified self: fundamental disruption in big data science and biological discovery. *Big Data*, 1, 2013.

[97] D.V Dimitrov. Medical internet of things and big data in healthcare. *Healthcare Inf Res*, 22:156—-163, 2016,Doi: http://dx.doi.org/10.4258/hir.2016.22.3.156.

[98] A Asante-Korang and J.P Jacobs. Big data and paediatric cardiovascular disease in the era of transparency in healthcare. *Cardiology in the Young*, 26:1597—-1602, 2016, Doi: http://dx.doi.org/10.1017/S1047951116001736.

[99] S Groves, Basel Van Kayyali, David Knott, and P Kuiken. The big data revolution in healthcare: Accelerating value and innovation. 2013.

[100] D.W Bates, S Saria, L Ohno-Machado, A Shah, and G Escobar. Big data in health care: using analytics to identify and manage high-risk and high-cost patients. *Health Aff*, 33:1123—-1131, 2014,Doi: http://dx.doi.org/10.1377/hlthaff.2014.0041.

[101] Y Wang, L.A Kung, and T.A Byrd. Big data analytics: understanding its capabilities and potential benefits for healthcare organizations. *Technol. Forecast. Soc. Change*, 2015, Doi: http://dx.doi.org/10.1016/j.techfore.2015.12.019.

[102] E.A Mohammed, B.H Far, and C Naugler. Applications of the mapreduce programming framework to clinical big data analysis: current landscape and future trends. *BioData Min*, 7(22), 2014, Doi: http://dx.doi.org/10.1186/1756-0381-7-22.

[103] D. Markonis, R. Schaer, I. Eggel, H. Muller, and A Depeursinge. Using mapreduce for large-scale medical image analysis. *2012 IEEE Second Int. Conf. Healthcare Informatics. Imaging Syst. Biol*, 1, 2012, Doi: http://dx.doi.org/10.1109/HISB.2012.8.

[104] N. Szlezák, M. Evers, Wang, and L Pérez. The role of big data and advanced analytics in drug discovery, development, and commercialization. *Clin. Pharmacol. Ther*, 95:492—-495, 2014,Doi: http://dx.doi.org/10.1038/clpt.2014.29.

[105] A.T. Maia, S.J. Sammut, A. Jacinta-Fernandes, and S.-F Chin. Big data in cancer genomics. *Curr. Opin. Syst. Biol*, 4:78—-84, 2017, Doi: http://dx.doi.org/10.1016/j.coisb.2017.07.007.

[106] S Fodeh and Q Zeng. Mining big data in biomedicine and health care. *J. Biomed. Inf*, 63:400—403, 2016, Doi: http://dx.doi.org/10.1016/j.jbi.2016.09.014.

[107] G Asokan and V Asokan. Leveraging big data to enhance the effectiveness of one health in an era of health informatics. *J. Epidemiol. Global Health*, 5:311—-314, 2015.

[108] J. Wu, H. Li, S. Cheng, and Z Lin. The promising future of healthcare services: when big data analytics meets wearable technology. *Inf. Manag*, 53:1020—-1033, 2016,Doi: http://dx.doi.org/10.1016/j.im.2016.07.003.

[109] Yamine Bouzembrak, Marcel Klüche, Anand Gavai, and Hans J.P Marvin. Internet of things in food safety: Literature review and a bibliometric analysis. *Trends in Food Science Technology*, 2019, Doi: https://doi.org/10.1016/j.tifs.2019.11.002.

[110] M Zarei, A Mohammadian, and R Ghasemi. Internet of things in industries: a survey

for sustainable development. *Int. J. Innov. Sustain. Dev*, 10(4):419—-442, 2016.

[111] Lee K Lee, I. The internet of things (iot): applications investments, and challenges for enterprises. *Bus. Horiz*, 58(4):431—-440, 2015.

[112] D Bremner. Analysing the iot ecosystem: The barriers to commercial traction. *The Barriers to Commercial Traction*, 2016, http://eprin ts.gla.ac.uk/11731 3/.

[113] A.J Jara, M.A Zamora-Izquierdo, and A.F Skarmeta. Interconnection framework for mhealth and remote monitoring based on the internet of things. *IEEE J. Sel. Areas Commun*, 31(9):47—-65, 2013.

[114] Hossein Ahmadi, Goli Arji, Leila Shahmoradi, Reza Safdari, Mehrbakhsh Nilashi, and Mojtaba Alizadeh. The application of internet of things in healthcare: a systematic literature review and classification. *Universal Access in the Information Society*, 19:837—-869, 2018, https://doi.org/10.1007/s10209-018-0618-4.

[115] F Mattern and C Floerkemeier. From the internet of computers to the internet of things. *From active data management to event-based systems and more*, pages 242–259, 2010.

[116] Agarwal A. Da Xu L Whitmore, A. The internet of things a survey of topics and trends. *Inf. Syst. Front*, 17(2):261—274, 2015.

[117] M Buettner, B Greenstein, A Sample, J.R Smith, and D Wetherall. Revisiting smart dust with rfid sensor networks. *In: Proceedings of the 7th ACM workshop on hot topics in networks(HotNets-VII)*, 2008.

[118] E Welbourne, L Battle, G Cole, K Gould, K Rector, S Raymer, and al. Building the internet of things using rfid:the rfid ecosystem experience. *IEEE Internet Comput*, 13(3):48—-55, 2009.

[119] K Pothuganti and A Chitneni. A comparative study of wireless protocols: Bluetooth, uwb, zigbee, and wi-fi. *Elect. Eng*, 4(6):655—-662, 2014.

[120] Wang N. German R. Dressler F Chen, F. Performance evaluation of ieee 802.15. 4 lr-wpan for industrial applications. *In: Wireless on demand network systems and services. WONS 2008 fifth annual conference*, 2008.

[121] I Howitt and J.A Gutierrez. Ieee 802.15. 4 low rate wireless personal area network coexistence issues. *In: Wireless communications and networking, WCNC 2003 IEEE*, 2003.

[122] R.A Ramlee, M.H Leong, R.S.A Sarban Singh, M.M Ismail, M.A Othman, H.A Sulaiman, and al. Bluetooth remote home automation system using android application. *Int. J. Adv. Technol Innov. Res*, 7(10):1815—-1818, 2013.

[123] M Gentili, R Sannino, and M. Bluevoice Petracca. Voice communications over bluetooth low energy in the internet of things scenario. *Comput. Commun*, 89:51—-59, 2016.

[124] Leu J.-S. Li K.-H. Wu J.-L.C Lin, M.-S. Zigbee-based internet of things in 3d terrains. *Comput. Electr. Eng*, 39(6):1667—-1683, 2013.

[125] E.D.N Ndih and S Cherkaoui. On enhancing technology coexistence in the iot era: Zigbee and 802.11 case. *IEEE Access*, 4:1835—-1844, 2016.

[126] V.C Gungor, D Sahin, T Kocak, S Ergut, C Buccella, C Cecati, and al. Smart grid technologies: Communication technologies and standards. *IEEE Trans. Ind. Inform*, 7(4):529—-539, 2011.

[127] P.P Parikh, M.G Kanabar, and T.S Sidhu. Opportunities and challenges of wireless communication technologies for smart grid applications. *In: Power and Energy Society*

General Meeting 2010 IEEE, 2010.

[128] C.H Yeh, C.W Chow, Y.L Liu, S.K Wen, S.Y Chen, C.R Sheu, and al. Theory and technology for standard wimax over fiber in high speed train systems. *J. Lightwave Technol*, 18(16):2327—-2336, 2010.

[129] H Dua. Wi-max technology for broadband wireless communication. *Boca Raton*, pages 50—-101, 2008.

[130] G.R Gonzalez, M.M Organero, and C.D Kloos. Early infrastructure of an internet of things in spaces for learning. *In: Advanced learning technologies, 2008 ICALT'08 eighth IEEE international conference*, 2008.

[131] S.Y Hui and K.H Yeung. Challenges in the migration to 4g mobile systems. *IEEE Commun. Mag*, 41(12):54—-59, 2003.

[132] A Darwish and A.E Hassanien. Wearable and implantable wireless sensor network solutions for healthcare monitoring. *Sensors*, 11(6):5561—-5595, 2011.

[133] P.S Pandian, K.P Safeer, P Gupta, D.T.I Shakunthala, B Sundersheshu, and V.C Padaki. Wireless sensor network for wearable physiological monitoring. *JNW*, 3(5):21–29, 2008.

[134] G Ciuti, L Ricotti, A Menciassi, and P Dario. Mems sensor technologies for human centred applications in healthcare, physical activities, safety and environmental sensing: a review on research activities in italy. *Sensors*, 15(3):6441—-6468, 2015.

[135] D.G Korzun, I Nikolaevskiy, and A Gurtov. Service intelligence support for medical sensor networks in personalized mobile health systems. *In: Conference on smart spaces*, 2015.

[136] C Hennebert and J Dos Santos. Security protocols and privacy issues into 6lowpan stack: a synthesis. *IEEE Internet Things J*, 1(5):384—-398, 2014.

[137] B.S Babu, K Srikanth, T Ramanjaneyulu, and I.L Narayana. Iot for healthcare. *Int. J. Sci. Res*, 5(2), 2016.

[138] B.S Babu, T Ramanjaneyulu, I.L Narayana, K Srikanth, and D.H Sindhu. Smart vehicle management through iot. *Int. J. Emerg. Trends Technol. Comput. Sci. (IJETTCS)*, 5(3):26–31, 2016.

[139] T Salman and R Jain. Networking protocols and standards for internet of things. *Internet Things Data Anal. Handb*, pages 215—-238, 2015.

[140] A Rizzardi, S Sicari, D Miorandi, and A Coen-Porisini. Aups: an open source authenticated publish/subscribe system for the internet of things. *Inf. Syst*, 62:29—-41, 2016.

[141] J Lin, W Yu, N Zhang, X Yang, H Zhang, and W Zhao. A survey on internet of things: architecture, enabling technologies,security and privacy, and applications. *IEEE Internet Things J*, 4(5):1125—-1142, 2017.

[142] Singh Jaswinder and Dhiman Gaurav. A survey on cloud computing approaches. *Materials Today: Proceedings*, 2021.

[143] Ullah Arif, Nawi Nazri, Mohd, and Khan Mubashir, Hayat. Bat algorithm used for load balancing purpose in cloud computing: an overview. *Int. J. High Performance Computing and Networking*, 16(1), 2020.

[144] Alouffi Bader, Hasnain Muhammad, Alharbi Abdullah, and Alosaimi Wael. A systematic literature review on cloud computing security: Threats and mitigation strategies. *IEEE Access*, 9:57792–57807, 2021, Doi: 10.1109/ACCESS.2021.3073203.

[145] Dhiman Gaurav and Kumar Vijay. Emperor penguin optimizer: A bio-inspired algo-

rithm for engineering problems. *Knowledge-Based Systems*, 159:20—-50, 2018.

[146] P Singh, K Rabadiya, and G Dhiman. A four-way decision making system for the indian summer monsoon rainfall. *Modern Physics Letters B*, 32(25), 2018.

[147] G Kumar and V Dhiman. Astrophysics inspired multi-objective approach for automatic clustering and feature selection in real-life environment. *Modern Physics Letters B*, 32(31), 2018.

[148] P Singh, G Dhiman, and A Kaur. A quantum approach for time series data based on graph and schrödinger equations methods. *Modern Physics Letters*, 33(35), 2018.

[149] S. Gunawi Haryadi, Do Thanh, M. Hellerstein Joseph, Stoica Ion, Borthakur Dhruba, and Robbins Jesse. Failure as a service (faas): A cloud service for large-scale, online failure drills. *Technical Report UCB/EECS-2011-87. University of California, Berkeley*, 2011.

[150] Junaid Shuja, Raja Wasim Ahmad, Abdullah Gani, Abdelmuttlib Ibrahim Abdalla Ahmed, Aisha Siddiqa, Kashif Nisar, Samee U Khan, , and Albert Y Zomaya. Greening emerging it technologies: Techniques and practices. *J. Internet Serv. Appl*, 8(1):9, 2017.

[151] Christoforos Kachris, Dimitrios Soudris, Georgi Gaydadjiev, Huy-Nam Nguyen, Dimitrios S Nikolopoulos, Angelos Bilas, Neil Morgan, Christos Strydis, and al. The vineyard approach: Versatile, integrated, accelerator-based, heterogeneous data centres. *In Proceedings of the International Symposium on Applied Reconfigurable Computing*, pages 3–13, 2016.

[152] Sotomayor Borja, S. Montero Rubén, M. Llorente Ignacio, and Foster Ian. Virtual infrastructure management in private and hybrid clouds. *IEEE Internet Comput*, 13(5), 2009.

[153] Amir Vahid Dastjerdi and Rajkumar Buyya. Compatibility-aware cloud service composition under fuzzy preferences of users. *IEEE Trans. Cloud Comput*, 2(1):1–13, 2014.

[154] Alain Andrieux, Karl Czajkowski, Asit Dan, Kate Keahey, Heiko Ludwig, Toshiyuki Nakata, Jim Pruyne, John Rofrano, Steve Tuecke, and Ming Xu. Web services agreement specification (ws-agreement). *In Open Grid Forum*, 128(216), 2007.

[155] Rajkumar Buyya and al. A manifesto for future generation cloud computing: Research directions for the next decade. *ACM computing surveys (CSUR)*, 51(5):1–38, 2018.

[156] Kumar Kiran, Reddy Muniswamy, and Margo Seltzer. Provenance as first class cloud data. *ACM SIGOPS Operat Syst. Rev*, 43(4):11—-16, 2010.

[157] Nadjaran Toosi Adel, N. Calheiros Rodrigo, and Buyya Rajkumar. Interconnected cloud computing environments: Challenges, taxonomy, and survey. *ACM Comput. Surv*, 47(1):7, 2014.

[158] Brian Stanton, Mary Theofanos, and Karuna P Joshi. Framework for cloud usability. *In Proceedings of the International Conference on Human Aspects of Information Security, Privacy, and Trust. Springer*, pages 664–671, 2015.

[159] Mary L. and MD Zupanc. Neonatal seizures. *Pediatr Clinics North America*, 51:961—-978, 2004,Doi: 10.1016/j.pcl.2004.03.002.

[160] World Health Organization. Guidelines on neonatal world health organization. *Villaggio Cristo Redentore Srl*, 2011, https://apps.who.int/iris/handle/10665/77756, 2011.

[161] M. Cristina Victorio. Neonatal seizure disorders. Accessed on 13/09/2020, https://www.msdmanuals.com/professional/pediatrics/neurologic-disorders-in-children/neonatal-seizure-disorders.

[162] D Samanta. Recent advances in the diagnosis and treatment of neonatal seizures.

Neuropediatrics, 2020, Doi: 10.1055/s-0040-1721702.
[163] David C. Dredge. Handbook of pediatric epilepsy. page 256, 2020,Doi: https://doi.org/10.1007/978-3-319-08290-5.
[164] J. Kern. Futura sciences. *Futura santé*, Accessed on 06/02/2021, https://www.futura-sciences.com/sante/definitions/coronavirus-covid-19-18585/.
[165] WHO. Who coronavirus (covid-19) dashboard. Accessed on 10/06/2021, https://covid19.who.int/.
[166] World Health Organization. Covid-19. Accessed on 02/01/2021, https://www.who.int/fr.
[167] Mohamed Akram Khelili, Sihem Slatnia, and Okba Kazar. Covid-19 variants and vaccines: An overview. *The Eurasia Proceedings of Health, Environment and Life Sciences (EPHELS)*, 1:15–19, 2021.
[168] Hamidreza Bolhasani, Maryam Mohseni, and Amir Masoud Rahmani. Deep learning applications for iot in health care: A systematic review. *Informatics in Medicine Unlocked*, 23:100550, 2021.
[169] Esteva Andre and al. A guide to deep learning in healthcare. *Nat Med*, 25:24—-9, 2019.
[170] Tuli and al. Healthfog: an ensemble deep learning based smart healthcare system for automatic diagnosis of heart diseases in integrated iot and fog computing environments. *Future Generat Comput Syst*, 104:187—-200, 2020.
[171] Filho PPR, Sarmento RM, Holanda GB, and de Alencar Lima D. New approach to detect and classify stroke in skull ct images via analysis of brain tissue densities. *Comput Methods Progr Biomed*, 148:27—-43, 2017.
[172] F Bray and al. Global cancer statistics 2018: Globocan estimates of incidence and mortality worldwide for 36 cancers in 185 countries. *CA A Cancer J Clin*, 68(6):394—-424, 2018.
[173] Zhen Ma and João Manuel RS Tavares. A novel approach to segment skin lesions in dermo scopic images based on a deformable model. *IEEE Journal of Biomedical and Health Informatics*, 20(2):615—-23, 2016.
[174] Schirrmeister and al. Deep learning with convolutional neural networks for eeg decoding and visualization. *Hum Brain Mapp*, 38(11):5391—-420, 2017.
[175] Fonseca and al. Deep learning and iot to assist multimorbidity home based healthcare. *J Health Med Inf*, 8(3):1—-4, 2017.
[176] Liu and al. A smart dental health-iot platform based on intelligent hardware, deep learning and mobile terminal. *IEEE Journal of Biomedical and Health Informatics*, 14(8), 2015.
[177] S Sagar, C Keke, and S Amit. Toward practical privacy preserving analytics for iot and cloud-based healthcare systems. *IEEE Internet Computing Jan*, 22(2):42—-51, 2018.
[178] Pandia Rajan Jeyaraj and Edward Rajan Samuel Nadar. Smart-monitor: Patient monitoring system for iot-based healthcare system using deep learning. *IETE Journal of research*, 2019.
[179] Kinnison T and May SA. Evidence-based healthcare: the importance of effective interprofessional working for high quality veterinary services, a uk example. *Veterinary Evidence*, 1(4), 2016.
[180] Iman Azimi, Janne Takalo-Mattila, Arman Anzanpour, Amir M Rahmani, Juha-Pekka Soininen, and Pasi Liljeberg. Empowering healthcare iot systems with hierarchical

edge-based deep learning. *2018 IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies(CHASE)*, pages 63–68, 2018,Doi: https://doi.org/10.1145/3278576.3278597.

[181] He W, Zhao Y, Tang H, Sun C, and Fu W. A wireless bci and bmi system for wearable robots. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 46(7):936—-46, 2016.

[182] V Gandhi, G Prasad, D Coyle, L Behera, and TM McGinnity. Eegbased mobile robot control through an adaptive brain–robot interface. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 44(9):1278—-85, 2014.

[183] Chang and al. A deep learning-based intelligent medicine recognition system for chronic patients. *IEEE Access*, 7:44441–58, 2019.

[184] O Faust and al. Automated detection of atrial fibrillation using long short-term memory network with rr interval signals. *Comput Biol Med*, 102(3):27—-35, 2018.

[185] B Yang, K Duan, C Fan, C Hu, and J Wang. Automatic ocular artifacts removal in eeg using deep learning. *Biomedical Signal Processing and Control*, 43:148–158, 2018, Doi:https://doi.org/10.1016/j.bspc.2018.02.021.

[186] K.M Tsiouris, V. C Pezoulas, M. Zervakis, S Konitsiotis, D.D Koutsouris, and D.I Fotiadis. A long short-term memory deep learning network for the prediction of epileptic seizures using eeg signals. *Computers in biology and medicine*, 99:24–37, 2018.

[187] M.C Tjepkema-Cloostermans, R. C de Carvalho, and M.J Putten, van. Deep learning for detection of focal epileptiform discharges from scalp eeg recordings. *Clinical neurophysiology*, 129(10):2191–2196, 2018, Doi: https://doi.org/10.1016/j.clinph.2018.06.024.

[188] A.H Ansari, P.J Cherian, A Caicedo, G Naulaers, M.De Vos, and S.Van Huffel. Neonatal seizure detection using deep convolutional neural networks. *International journal of neural systems*, 29(4):1850011, 2019.

[189] L Frassineti, D Ermini, R.Fabbri, and C Manfredi. Neonatal seizures detection using stationary wavelet transform and deep neural networks: Preliminary results. *IEEE 20th Mediterranean Electrotechnical Conference (MELECON), Palermo, Italy*, pages 344–349, 2020,Doi: 10.1109/MELECON48756.2020.9140713.

[190] A.M. Pavel, J.M. Rennie, L.S. de Vries, M. Blennow, A. Foran, D.K. Shah, G.B. Boylan, and al. A machine-learning algorithm for neonatal seizure recognition: a multicentre, randomised, controlled trial. *The Lancet Child Adolescent Health*, 4(10):740–749, 2020,Doi: https://doi.org/10.1016/S2352-4642(20)30239-X.

[191] A O'Shea, G Lightbody, G Boylan, and A Temko. Neonatal seizure detection from raw multi-channel eeg using a fully convolutional architecture. *Neural Networks*, 123:12–25, 2020,Doi: https://doi.org/10.1016/j.neunet.2019.11.023.

[192] M. Z. Che Azemin, R. Hassan, M. I. Mohd Tamrin, M. A, and Md Ali. Covid-19 deep learning prediction model using covid-19 deep learning prediction model using publicly available radiologist-adjudicated chest x-ray images as training data: preliminary findings. *International Journal of Biomedical Imaging*, 2020.

[193] R. Jain, M. Gupta, S. Taneja, D. J, and Hemanth. Deep learning based detection and analysis of covid-19 on chest x-ray images. *Applied Intelligence*, 51(3):1690–1700, 2021.

[194] D Wang, J Mo, G Zhou, L Xu, and Y Liu. An efficient mixture of deep and machine learning models for covid-19 diagnosis in chest x-ray images. *PloS one*, 15(11), 2020,Doi: https://doi.org/10.1371/journal.pone.0242535.

[195] P. H Afshar. Covid-caps: A capsule network-based framework for identification of covid-19 cases from x-ray images. *Pattern Recognition Letters*, 138:638–643, 2020,Doi: https://doi.org/10.1016/j.patrec.2020.09.010.

[196] Moutaz Alazab and al. Covid-19 prediction and detection using deep learning. *International Journal of Computer Information Systems and Industrial Management Applications*, 12:168–181, 2020, http://www.softcomputing.net/ijcisim$_1$*.pdf*.

[197] G Jain, D Mittal, D Thakur, and K Mittal, M. A deep learning approach to detect covid-19 coronavirus with x-ray images. *Biocybernetics and biomedical engineering*, 4(40):1391–1405, 2020,Doi: https://doi.org/10.1016/j.bbe.2020.08.008.

[198] Z Che Azemin, M, R Hassan, I Mohd Tamrin, M, and A Md Ali, M. Covid-19 deep learning prediction model using publicly available radiologist-adjudicated chest x-ray images as training data: preliminary findings. *International Journal of Biomedical Imaging*, 2020,Doi: https://doi.org/10.1155/2020/8828855.

[199] R Jain, M Gupta, S Taneja, and J Hemanth, D. Deep learning based detection and analysis of covid-19 on chest x-ray images. *Applied Intelligence*, 51(3), 2021,Doi: https://doi.org/10.1007/s10489-020-01902-1.

[200] J Civit-Masot, F Luna-Perejón, M Domínguez Morales, and A Civit. Deep learning system for covid-19 diagnosis aid using x-ray pulmonary images. *Applied Sciences*, 10(13):4640, 2020,Doi: https://doi.org/10.3390/app10134640.

[201] S Dey, G. C Bacellar, M. B Chandrappa, and R Kulkarni. Covid-19 chest x-ray image classification using deep learning. *medRxiv*, 2021,Doi: https://doi.org/10.1101/2021.07.15.21260605.

[202] Y Erdaw and E Tachbele. Machine learning model applied on chest x-ray images enables automatic detection of covid-19 cases with high accuracy. *International Journal of General Medicine*, 14:4923–4931, 2021,Doi: https://doi.org/10.2147/IJGM.S325609.

[203] Shui-Hua Wang, Deepak Ranjan Nayak, David S.Guttery, Xin Zhang, and Yu-Dong Zhang. Covid-19 classification by ccshnet with deep fusion using transfer learning and discriminant correlation analysis. *Information Fusion*, 68:131–148, 2021,Doi: doi:10.1016/j.inffus.2020.11.005.

[204] Shui-Hua Wang, Vishnu Varthanan Govindaraj, Juan Manuel G´orriz, Xin Zhang, and Yu-Dong Zhang. Covid-19 classification by fgcnet with deep feature fusion from graph convolutional network and convolutional neural network. *Information Fusion*, 67:208–229, 2021.

[205] W Zhao, W Jiang, and X Qiu. Deep learning for covid-19 detection based on ct images. *Scientific Reports*, 11(1):1–12, 2021,Doi: https://doi.org/10.1038/s41598-021-93832-2.

[206] G.Ramantani. Neonatal epilepsy and underlying aetiology: to what extent do seizures and eeg abnormalities influence outcome? *Epileptic disorders*, 15(4):365–375, 2013,Doi: https://doi.org/10.1684/epd.2013.0619.

[207] A.Shoeibi, N.Ghassemi, M.Khodatars, M.Jafari, S.Hussain, R.Alizadehsani, U.R.Acharya, and al. Epileptic seizure detection using deep learning techniques: A review. *arXiv preprint arXiv:2007.01276*, 2020.

[208] S Kulaseharan, A Aminpour, M Ebrahimi, and E Widjaja. Identifying lesions in paediatric epilepsy using morphometric and textural analysis of magnetic resonance images. *NeuroImage: Clinical*, 21:101663, 2019,Doi: https://doi.org/10.1016/j.nicl.2019.

[209] G. Zazzaro, S. Cuomo, A. Martone, R. V. Montaquila, G. Toraldo, and L Pavone. Eeg signal analysis for epileptic seizures detection by applying data mining techniques.

Internet of Things, page 100048, 2019,Doi: https://doi.org/10.1016/j.iot.2019.03.002.

[210] N van Klink, A Mooij, G Huiskamp, C Ferrier, K Braun, A Hillebrand, and M Zijlmans. Simultaneous meg and eeg to detect ripples in people with focal epilepsy. *Clinical Neurophysiology*, 130(7):1175–1183, 2019,Doi: https://doi.org/10.1016/j.clinph.

[211] N Chatziioannou and S Pianou. Imaging with pet/ct in patients with epilepsy. *Epilepsy Surgery and Intrinsic Brain Tumor Surgery*, pages 45–50, 2019,Doi: https://doi.org/10.1007/978-3-319-95918-4_4.

[212] Z. Gao, W. Dang, X. Wang, X. Hong, L. Hou, K. Ma, and M Perc. Complex networks and deep learning for eeg signal analysis. *Cognitive Neurodynamics*, pages 1–20, 2020,Doi: https://doi.org/10.1007/s11571-020-09626-1.

[213] L Frassineti, D Ermini, R Fabbri, and C Manfredi. Neonatal seizures detection using stationary wavelet transform and deep neural networks: Preliminary results. *IEEE 20th Mediterranean Electrotechnical Conference (MELECON), Palermo, Italy*, pages 344–349, 2020,Doi: 10.1109/MELECON48756.2020.9140713.

[214] D.Y. Isaev, D. Tchapyjnikov, C.M. Cotten, N. Tanaka, D.and Martinez, M. Bertran, and al. Attention-based network for weak labels in neonatal seizure detection. *Proceedings of machine learning research*, 479:126, 2020.

[215] E. Pavlidis and F Pisani. The role of electroencephalogram in neonatal seizure detection. *Expert review of Neurotherapeutics*, 18(2):95–100, 2018,Doi: 10.1080/14737175.2018.1413352.

[216] A. Craik, Y. He, and J. L Contreras-Vidal. Deep learning for electroencephalogram (eeg) classification tasks: a review. *Journal of neural engineering*, 16(3):031001, 2019,Doi: https://doi.org/10.1088/1741-2552/ab0ab5.

[217] A. Faramarzi, M. Heidarinejad, S. Mirjalili, and A. H Gandomi. Marine predators algorithm: A nature-inspired metaheuristic. *Expert Systems with Applications*, 152:113377, 2020.

[218] S. Mirjalili, S. M. Mirjalili, and A Lewis. Grey wolf optimizer. *Advances in engineering software*, 69:46–61, 2014,Doi: https://doi.org/10.1016/j.advengsoft.2013.12.007.

[219] A. Lewis and S Mirjalili. The whale optimization algorithm. *Advances in engineering software*, 95:51–67, 2016,Doi: https://doi.org/10.1016/j.advengsoft.2016.01.008.

[220] R. Eberhart and J Kennedy. Particle swarm optimization. *Proceedings of ICNN'95-international conference on neural networks*, 4, 1995,Doi: 10.1109/ICNN.1995.488968.

[221] D. Karaboga and B Basturk. On the performance of artificial bee colony (abc) algorithm. *Applied soft computing*, 8(1):687–697, 2008,Doi: https://doi.org/10.1016/j.asoc.2007.05.007.

[222] F. Glover and M Laguna. Tabu search. *In Handbook of combinatorial optimization*, pages 2093–2229, 1998,Doi: https://doi.org/10.1007/978-1-4613-0303-9 33.

[223] S Kirkpatrick, C. D Gelatt, and M. P Vecchi. Optimization by simulated annealing. *Science*, 220(4598):671–680, 1983,Doi: 10.1126/science.220.4598.671.

[224] D. Yousri, H.M. Hasanien, and A Fathy. Parameters identification of solid oxide fuel cell for static and dynamic simulation using comprehensive learning dynamic multi-swarm marine predators algorithm. *Energy Conversion and Management*, 228:113692, 2021,Doi: https://doi.org/10.1016/j.enconman.2020.113692.

[225] K. Zhong, Q. Luo, Y. Zhou, and M Jiang. Tlmpa: Teaching-learning-based marine predators algorithm. *AIMS Mathematics*, 6(2):1395–1442, 2021,Doi: 10.3934/math.2021087.

[226] M. Abdel-Basset, R. Mohamed, R.K. Chakrabortty, M. Ryan, and S Mirjalili. New binary marine predators optimization algorithms for 0–1 knapsack problems. *Computers Industrial Engineering*, page 106949, 2020.

[227] D. Yousri, T.S. Babu, E. Beshr, M. B. Eteiba, and D Allam. A robust strategy based on marine predators algorithm for large scale photovoltaic array reconfiguration to mitigate the partial shading effect on the performance of pv system. *IEEE Access*, 8:112407–112426, 2020.

[228] W. Yang, K. Xia, T. Li, M. Xie, and F Song. A multi-strategy marine predator algorithm and its application in joint regularization semi-supervised elm. *Mathematics*, 9(3):291, 2021,Doi: https://doi.org/10.3390/math9030291.

[229] A Einstein. Investigations on the theory of the brownian movement. *Courier Corporation*, 1956.

[230] N.E. Humphries, N. Queiroz, J. R. Dyer, N. G. Pade, K. Musyl, K. M. Schaefer, and al. Environmental context explains lévy and brownian movement patterns of marine predators. *Nature*, pages 1066–1069, 2010,Doi: 10.1038/nature09116.

[231] R.N Mantegna. Fast, accurate algorithm for numerical simulation of levy stable stochastic processes. *Physical Review E*, 9(5):4677, 1994,Doi: 10.1103/ PhysRevE.49.4677.

[232] Mohamed Akram Khelili, Sihem Slatnia, Okba Kazar, Seyedali Mirjalili, Samir Bourekkache, Guadalupe Ortiz, and Yizhang Jiang. New bio-inspired approach for deep learning techniques applied to neonatal seizures. *International Journal of Medical Engineering and Informatics*, 2022,Doi: 10.1504/IJMEI.2022.10046880.

[233] Mohamed Akram Khelili, Sihem Slatnia, and Okba Kazar. Convolution neural network based marine predator algorithm for covid-19 detection. *International Conference on Information Systems and Advanced Technologies (ICISAT)*, pages 1–4, 2021,Doi: 10.1109/ICISAT54145.2021.9678468.

[234] A Alabdulatif, I Khalil, A. R. M Forkan, and M Atiquzzaman. Real-time secure health surveillance for smarter health communities. *IEEE Communications Magazine*, 1(57):122–129, 2019,Doi: 10.1109/MCOM.2017.1700547.

[235] Hafizah Mohd Aman Azana, Haslina Hassan Wan, Sameen Shilan, Senan Attarbashi Zainab, Alizadeh Mojtaba, and Abdul Latiff Liza. Iomt amid covid-19 pandemic: Application, architecture, technology, and security. *Journal of Network and Computer Applications.*, 174:102886, 2020,Doi: https://doi.org/10.1016/j.jnca.2020.102886.

[236] Tanweer Alam. Cloud computing and its role in the information technology. *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, 1:108–115, 2021.

[237] M Hussain, M, M S Beg, M, and S Alam, M. Fog computing for big data analytics in iot aided smart grid networks. *Wireless Pers Commun*, 114:3395—-3418, 2020,Doi: https://doi.org/10.1007/s11277-020-07538-1.

[238] Suyel Namasudra. Data access control in the cloud computing environment for bioinformatics. *International Journal of Applied Research in Bioinformatics (IJARB)*, 11(1):40–50, 2021,Doi: 10.4018/IJARB.2021010105.

[239] Esmat Fathel Samann, Fady, Zeebaree Subhi, RM, and Askar. Shavan. Iot provisioning qos based on cloud and fog computing. *Journal of Applied Science and Technology Trends*, 2(1):29–40, 2021,https://jastt.org/index.php/jasttpath/article/download/90/25.

[240] M Hartmann, S Hashmi, U, and A Imran. Edge computing in smart health care systems: Review, challenges, and research directions. *Transactions on Emerging Telecom-*

munications Technologies, 25, 2019,Doi: https://doi.org/10.1002/ett.3710.

[241] M.A Khelili, S Slatnia, O Kazar, and S Harous. Iomt-fog-cloud based architecture for covid-19 detection. *Biomedical Signal Processing and Control*, 76:103715, 2022,Doi: https://doi.org/10.1016/j.bspc.2022.103715.

[242] N Nasser, Q Emad-ul Haq, M Imran, and al. A smart healthcare framework for detection and monitoring of covid-19 using iot and cloud computing. *Neural Computing and Applications*, pages 1–15, 2021,https://doi.org/10.1007/s00521-021-06396-7.

[243] Abdullah Aljumah. Assessment of machine learning techniques in iot-based architecture for the monitoring and prediction of covid-19. *Electronics*, 10(15):1834, 2021,Doi: https://doi.org/10.3390/electronics10151834.

[244] Liang, HL Steve, and al. An interoperable architecture for the internet of covid-19 things (ioct) using open geospatial standards—case study: Workplace reopening. *Sensors*, 21(1):50, 2021,Doi: https://doi.org/10.3390/s21010050.

[245] Ameni Kallel, Rekik Molka, and Khemakhem Mahdi. Iot-fog-cloud based architecture for smart systems: Prototypes of autism and covid-19 monitoring systems. *Software: Practice and Experience*, 51(1):91–116, 2021,Doi: https://doi.org/10.1002/spe.2924.

[246] Tuli Shreshth, Tuli Shikhar, Tuli Rakesh, and Singh Gill Sukhpal. Predicting the growth and trend of covid-19 pandemic using machine learning and cloud computing. *Internet of Things*, 11:100222, 2020,Doi: https://doi.org/10.1016/j.iot.2020.100222.