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Master's Degree

Specialty: Artificial Intelligence (AI)

AI-Powered Platform For E-Health and Paludism Diagnosis Using Deep Learning

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Abstract

In recent years, digitization has transformed medical practices globally, yet Algeria still faces significant healthcare challenges, including unequal access to specialized services, a shortage of medical professionals, and the compounded effects of an aging population and complex diseases. This thesis tackles two crucial challenges in this context by building a personalized AI-powered healthcare platform along with an effective diagnostic tool for Paludism. The proposed e-health platform aims to overcome existing barriers by providing a dedicated space for doctors and researchers. This platform features secure storage and access to a rich repository of healthcare-related academic papers, datasets, and models realized initially at Laboratoire de l'INFormatique Intelligente (LINFI) laboratory and eventually at other laboratories. Additionally, the current work introduces a robust Convolutional Neural Network (CNN) model designed for the precise classification of malaria-infected red blood cells. By employing various loss functions, several efficient techniques, and a hybrid dataset composed of images from a public dataset and images collected from seven cities in Algeria, with the assistance of paramedical specialists. Experimental results demonstrate the effectiveness of our approach. The custom CNN model achieved an accuracy of 99% with binary cross-entropy loss, and thus outperforming other tested models. The findings of this research promise substantial improvements in healthcare resource management and Paludism detection, ultimately contributing to better healthcare outcomes in Algeria and beyond.

Keywords: *Digitization, E-Health, Artificial Intelligence, Machine Learning, Deep Learning, Paludism.*

Résumé

Ces dernières années, la numérisation a transformé les pratiques médicales à l'échelle mondiale, mais l'Algérie reste confrontée à d'importants défis en matière de santé, notamment un accès inégal aux services spécialisés, une pénurie de professionnels de la santé, ainsi que les effets cumulés du vieillissement de la population et de maladies complexes. Cette thèse aborde deux défis cruciaux dans ce contexte en développant une plateforme de soins de santé personnalisée alimentée par l'intelligence artificielle, accompagnée d'un outil de diagnostic efficace pour le paludisme. La plateforme e-santé proposée vise à surmonter les obstacles existants en offrant un espace dédié aux médecins et aux chercheurs, avec un stockage sécurisé et un accès à un riche répertoire de documents académiques, de jeux de données et de modèles liés à la santé, réalisés initialement au laboratoire LINFI et ultérieurement dans d'autres laboratoires. De plus, ce travail introduit un modèle robuste de Réseau de Neurones Convolutifs (CNN) conçu pour la classification précise des globules rouges infectés par le paludisme. En utilisant diverses fonctions de perte, plusieurs techniques efficaces et un jeu de données hybride composé d'images provenant d'un ensemble de données public et d'images collectées dans sept villes en Algérie, avec l'aide de spécialistes paramédicaux. Les résultats expérimentaux démontrent l'efficacité de notre approche. Le modèle CNN personnalisé a atteint une précision de 99 % avec une perte d'entropie croisée, surpassant ainsi les autres modèles testés. Les résultats de cette recherche promettent des améliorations substantielles dans la gestion des ressources de santé et la détection du paludisme, contribuant finalement à de meilleurs résultats de santé en Algérie et au-delà.

Mots clés : *Digitalisation, e-santé, Intelligence Artificielle, Apprentissage automatique, Apprentissage Profond, Paludisme.*

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Fadia Baissi

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General Introduction

Medical Background

In recent years, digitization has revolutionized numerous domains, and healthcare is no exception. This digital transformation is reshaping how medical services are delivered and accessed globally. The COVID-19 pandemic has highlighted the urgent need for accessible healthcare solutions, bringing to the forefront the importance of digital health technologies. These advancements have enabled remote consultations, telemedicine, and the use of artificial intelligence in diagnostics, significantly improving healthcare delivery. Additionally, the integration of big data and machine learning into healthcare systems has enhanced disease prediction, patient management, and treatment outcomes. However, these technological advancements have not been evenly distributed, leading to significant disparities in healthcare access, especially in developing countries like Algeria.

Context and Problems

Despite the global progress in healthcare digitization, Algeria's healthcare system faces significant challenges. These include an uneven distribution of resources, particularly in underserved areas, which leads to limited access to specialized care. This issue is compounded by a shortage of medical professionals and inadequate infrastructure, making it difficult to manage and treat diseases that require advanced medical examinations. This disparity creates significant obstacles for patients in remote areas who need specialized care available only in major institutions. Moreover, a recent study found that nearly two-thirds of Internet users (64.9%) rely on the Internet as a primary resource for health information, highlighting the growing reliance on digital platforms [46]. These issues underscore the critical need for innovative digital solutions to bridge the gap in healthcare delivery. By leveraging the power of digitization, we can ensure that all populations benefit from advancements in medical technology and data science, ultimately leading to a more robust and accessible healthcare system in Algeria, Africa, and worldwide.

Related Works

Artificial Intelligence (AI) is driving a major revolution in healthcare, and this transformation has been underway for several decades. Several platforms have been proposed to support diagnosis. One of the pioneering platforms in this field, developed in the 1970s was MYCIN, which demonstrated the potential of AI to provide decision support in medical contexts, laying the groundwork for future developments [69]. Today, there are millions of AI-powered E-Health platforms, which can be broadly classified into two major categories: general use and specialized use.

General-use platforms, such as Enlitic [51] for Managing medical imaging data, Merative [47] for clinical decision support and healthcare analytics, Regard [33] for Automating clinical tasks, Google Vertex AI [8] for information retrieval, Care.ai [38] for AI-assisted virtual care, and Kaggle, which is commonly used to collect datasets, models, and research on many topics.

On the other hand, specialized platforms focus on specific medical needs, such as Freenome [65] for early cancer detection, Iterative Health [34] for detection of gastrointestinal (GI) diseases, and VirtuSense [66] for predictive fall prevention.

Additionally, Several studies have deeply explored the application of AI in healthcare to address similar challenges. For instance, Esraa Hassan et al [24] proposed a deep learning model for malaria detection using VGG19, achieving significant accuracy by leveraging transfer learning and fine-tuning techniques. Another notable work by Sarkar et al [55] introduced a shallow CNN architecture for malaria diagnosis using thin blood smear images, which matched the classification accuracy of more complex models like VGG-16 and ResNet-50 while reducing computational time. These studies underscore the potential of AI in enhancing diagnostic accuracy and efficiency in resource-constrained settings.

However, none of these platforms or studies offer the specialized and shared gateway tailored to healthcare actors and researchers that our platform aims to provide. Our platform not only aims to support the testing of new models but also to facilitate the sharing and collaboration on various healthcare projects. Additionally, our project focuses on enhancing the results of Paludism detection.

Motivation and Proposed Solutions

The motivation for our project arises from the critical need to improve healthcare accessibility and diagnostic accuracy in Algeria and beyond. The aforementioned limitations in the healthcare system hinder effective disease management and treatment, particularly for conditions like malaria, which remain prevalent.

Additionally, numerous efforts are made each year in research projects, particularly in our LINFI laboratory, to improve healthcare. However, the results of these research efforts often remain underutilized and are lost among the multitude of publications. Through this project, we aim to benefit researchers and professionals by making these works accessible via our platform.

By leveraging AI, there is an opportunity to develop a robust and scalable platform that can support:

- Healthcare professionals in diagnosing and managing diseases more effectively.
- Researchers in sharing and adding new datasets, papers and models.
- Promoting and making research projects realized more visible.

Consequently, The success of our work in this context will provide a strong foundation for adapting and enhancing these solutions to meet the specific needs of the Algerian healthcare landscape. In which our project will bring two key contributions to the field of AI-powered healthcare solutions:

- **Development of an AI-Powered Healthcare Platform:** A specialized digital platform tailored for the Algerian context will be developed, granting access to a meticulously curated collection of healthcare-focused academic papers, datasets, and AI applications. Users will have the ability to store their applications, with the added functionality of managing multiple versions of models within each application. Our platform will host several applications, already realized by LINFI members, including the bone age assessment [74], pneumonia detection [50], and diabetic retinopathy detection [16]. Furthermore, our platform will contain over 100 research papers most of which are recently published (between 2022 and 2024). Moreover, our platform will facilitate comprehensive testing of each model, offering an unparalleled solution for research, and resource access within the healthcare sector.

- **Development of a CNN Model for Paludism Diagnosis:** A new Artificial Intelligence model will be developed and compared to various Deep Learning models specifically designed for Paludism diagnosis. We will meticulously analyze their architectures, methodologies, algorithms, and outcomes to identify a solid foundation. Building upon this, we will enhance our approach by experimenting with different loss functions and adjusting hyperparameters to assess their impact on performance. This iterative process will lead us to the optimal model, utilizing a hybrid dataset comprised of images from a public dataset from Kaggle and those collected from seven cities in Algeria with the collaboration of radiologist paramedical specialists. Our proposed model must demonstrate remarkable performance across multiple metrics, including accuracy, precision, F1-score, specificity, recall, sensitivity, and Area Under Curve (AUC).

These contributions collectively aim to enhance healthcare delivery in Algeria, leveraging AI to provide accurate diagnostics and facilitate effective medical research and collaboration.

Thesis Outline

The remainder of this dissertation is organized as follows:

Chapter 1: Medical Background

This chapter provides an overview of the essential medical background necessary for understanding diagnostic processes. It begins with a basic definition of healthcare, followed by an overview of healthcare practices, including medical records management, diagnosis based on blood tests, and medical imaging diagnosis. The chapter then focuses on diagnosis based on medical imaging, discussing its modalities, including invasive and non-invasive techniques. Several challenging issues related to medical diagnosis are also addressed. Additionally, the healthcare situation in Algeria is examined, and E-Health platforms for medical assessment are explored, with an emphasis on the role of AI in E-Health. Finally, Paludism (malaria) is presented as a case study, including an overview of microscopic images, the definition of Paludism, its life cycle, and its diagnostic methods.

Chapter 2: Theoretical and Technical Background

This chapter introduces the fundamental concepts of AI, including Machine Learning (ML) and its various types, as well as Deep Learning (DL). It then discusses the differences between ML and DL and explores artificial neural networks. The focus then shifts to CNNs, covering their definition, architecture, and layer configuration, and mentioning variations in CNN architectures. Finally, the chapter reviews related works on the diagnosis of diseases using microscopic images.

Chapter 3: AI-Powered Healthcare Platform

This chapter provides an overview of the key components and functionalities of our AI-powered healthcare platform. It outlines the actors, primary use cases, and user interactions for searching, testing AI models, managing resources, and administering accounts. Emphasizing scalability, security, and performance, the chapter discusses the technical implementation, including the MVC-based architecture and the backend's capability to handle diverse data types. The platform realization is also presented through key interface screenshots.

Chapter 4: Paludism diagnosis proposed approach

This chapter outlines and explains the various components involved in implementing the diagnostic model. It begins with a discussion of the general approach taken during the study, followed by a detailed description of the dataset used, including its characteristics and sources. The chapter then covers the preprocessing steps required to prepare the image data for analysis. Subsequently, it presents the proposed approach, detailing the specific techniques and algorithms employed. Hardware and software specifications necessary for the model are also discussed. The chapter proceeds with a description of the training experiments conducted to fine-tune the model. Finally, it discusses the results obtained from these experiments, analyzing their implications and effectiveness.

General Conclusion and Perspectives

This section concludes the main objectives achieved in this thesis and outlines potential avenues for future research and development.

Chapter 1

Medical Background

1.1 Introduction

Healthcare is a vital sector focused on maintaining and improving the health of individuals. Within this field, medical imaging plays a crucial role by providing visual representations of the interior of the body, enabling healthcare professionals to diagnose and monitor various conditions.

This chapter offers an overview of the essential medical background necessary for understanding diagnostic processes. We will start with a basic definition of healthcare, followed by an overview of healthcare practices, including medical records management, diagnosis based on blood tests, and medical imaging diagnosis. We will then focus on diagnosis based on medical imaging, discussing its modalities, including invasive and non-invasive techniques. Following this, we will address several challenging issues related to medical diagnosis. We will then examine the healthcare situation in Algeria and explore E-Health platforms for medical assessment, emphasizing the role of AI in E-Health. Finally, we will take the Paludism (malaria) disease as a case study, including an overview of microscopic images, the definition of Paludism, its life cycle, and its diagnosis methods.

1.2 HealthCare definition

Healthcare is "The prevention, treatment, and management of illness and the preservation of mental and physical well-being through the services offered by the medical and allied health professions" [42] In the dictionary of healthcare.

1.3 Overview on healthcare practices

Healthcare practices contain a broad range of activities aimed at maintaining and improving health, preventing diseases, and managing illnesses. In the following subsections more details will be illustrating about those advancements in this practices:

1.3.1 Medical records management

Utilizing patients' medical records is crucial for providing personalized and effective care, offering a range of essential functions. It provides a full patient history, facilitates precise medication management, enables the creation of tailored care plans, aids in managing chronic or complex diseases, facilitates seamless coordination of care between healthcare providers, and supports proactive preventive care measures. By allowing all pertinent information into decision-making processes, healthcare providers can ensure the delivery of high-quality, personalized care that meets the unique needs of each individual patient [6]. One of the most important techniques that allows a continuous tracking of patients' health:

- **Telemedicine:** facilitates remote consultations and treatment, making healthcare more accessible, especially for individuals in remote or underserved areas [19].
- **Electronic Health Records:** streamline the storage, retrieval, and sharing of patient information, enhancing the coordination and efficiency of care [32].

1.3.2 Diagnosis through blood analysis

Blood analysis is essential for diagnosing a wide range of conditions, from infections to chronic diseases, providing critical information about a patient's health status. This process includes various tests that measure components such as red and white blood cells, hemoglobin, platelets, and biochemical markers like glucose, cholesterol, and electrolytes. Blood tests can detect infections, anemia, clotting disorders, and metabolic or genetic conditions. Hormone levels, organ function, and immune system status are also assessed through these tests. By providing precise and quantifiable data, medical blood tests play a critical role in diagnosing, monitoring, and managing patient health effectively [59].

1.3.3 Medical imaging diagnosis

Medical imaging including techniques like X-rays, MRI, CT scans, Ultrasound, Biopsy and microscopic images offers detailed internal views of the human body, significantly aiding in accurate diagnoses. These imaging methods allow doctors to see detailed pictures of organs, bones, tissues, and blood cells helping them to detect and diagnose a wide range of conditions, from broken bones and tumors to heart disease and infections. The images provide critical information that can guide treatment decisions and monitor the progress of the pathology [29].

Despite, the diversity of healthcare practices, incorporating patient management, various diagnostic methods, and remote monitoring. The emergence of advanced medical imaging techniques and its modality including x-rays, MRI, and microscopic images, ... etc has revolutionized diagnostics, which it provides a highly precise diagnoses.

1.4 Diagnosis based on medical imaging

Here we focus on this type of clinical practicing involves using advanced techniques to visualize the inside of the human body, and it's the most precise type of diagnosing as mentioning in the last section. There are several categories, but two important ones are as follows:

1.4.1 Invasive imaging techniques

This involves putting medical tools or substances into the body, usually through cuts, punctures, or natural openings, to reach internal areas or perform medical tests or treatments using biobsy, angiography, and Endoscopy, ... etc. These procedures can have risks like bleeding, infection, or damage to nearby tissues. Figure 1.1 illustrates an invasive type.

Figure 1.1: Invasive imaging techniques

Some of its use modalities will be mentioning with details in the following items:

- **Biopsy:** Involves taking a small sample of tissue from the body for examination under a microscope or other tests. It is used to diagnose various conditions, including cancers, infections, and inflammatory diseases [48].
- **Angiography:** Uses contrast agents and X-rays to visualize blood vessels, often involving catheter insertion into arteries or veins [62].
- **Endoscopy:** Utilizes a flexible tube with a camera to examine internal organs, often inserted through natural body openings or small incisions [73].
- **Microscopic Imaging:** Involves examining tissue samples under a microscope to identify cellular abnormalities, infections, or diseases [20].

1.4.2 Non-invasive imaging techniques

This refers to medical procedures or tests that don't need instruments or substances to be inserted into the body and don't involve breaking the skin or mucous membranes. These methods are usually safer, less painful, and have fewer risks and complications compared to invasive procedures such as X-rays, Computed Tomography, Magnetic Resonance Imaging [70]. Figure 1.2 illustrates a non invasive type.

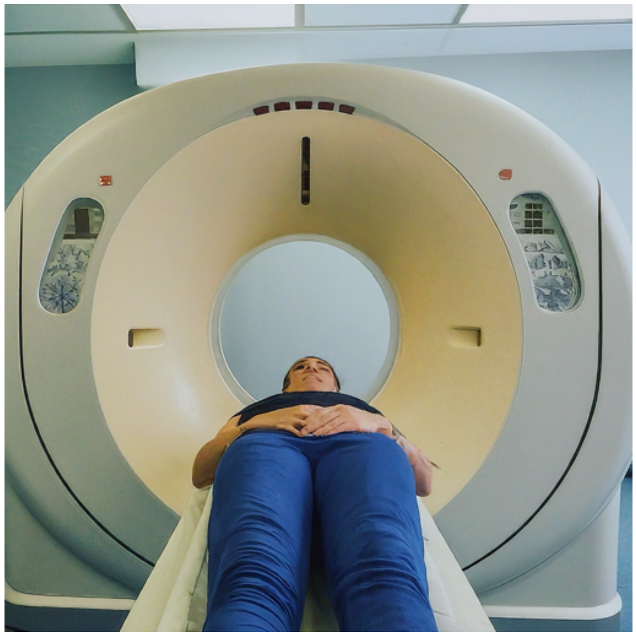

Figure 1.2: Non invasive imaging techniques

Some of its modalities will be defined as follows:

- **X-rays:** use electromagnetic radiation to create images of the inside of the body, particularly useful for examining bones and detecting fractures or infections [10].
- **Ultrasound:** This technique uses high-frequency sound waves to produce images of organs and tissues [40].
- **Magnetic Resonance Imaging (MRI):** uses strong magnetic fields and radio waves to generate detailed images of organs and tissues, particularly effective for soft tissue evaluation [13].
- **Computed Tomography (CT) Scans:** use X-rays and computer processing to create detailed cross-sectional images of the body, helping to diagnose conditions such as cancers, cardiovascular diseases, and internal injuries [22].
- **Positron Emission Tomography (PET) Scans:** involve the use of radioactive tracers to visualize metabolic processes in the body, often used in oncology to detect cancer and monitor its progression [5].
- **Fluoroscopy:** Real-time X-ray imaging that may involve the administration of contrast agents [31].

Based on the medical imaging acquired from various modalities (invasive and non-invasive techniques), disease diagnosis can be achieved through different methods by classifying these images, segmenting the images to focus on regions of interest such as tumors or organs, or using the images to predict potential risks. All of those newest diagnosis techniques using images back from several significant challenges.

1.5 Challenging issues related to medical diagnosis

Despite advances in medical imaging and diagnostic techniques, several challenges persist in achieving accurate and timely diagnoses. These challenges can be categorized into technical, human, and systemic issues [45]:

- **Technical Challenges:** Variability in image quality, influenced by equipment differences, operator skill, and patient factors like movement and body size, poses a significant challenge in medical imaging. Limitations in resolution and clarity of certain imaging modalities can hinder the detection of small or subtle abnormalities. Additionally, the presence of artifacts or noise in images can obscure critical diagnostic details, complicating accurate diagnosis.
- **Human Factors:** Variability in the expertise and experience of radiologists and biologists can lead to diagnostic errors, as can cognitive biases that influence their interpretation, potentially resulting in misdiagnoses or overlooked critical findings. While telemedicine offers a way to overcome some barriers, it faces its own challenges. Moreover, it relies heavily on the manual interpretation of medical imaging which is time-consuming and prone to human error like high workload and fatigue among healthcare professionals. This can negatively impact diagnostic accuracy, further complicating the diagnostic process.
- **Systemic Issues:** Limited access to advanced imaging technologies in low-resource settings creates disparities in diagnostic capabilities, while difficulty integrating imaging results with other medical data, such as lab results and patient history, hampers comprehensive diagnosis. Additionally, the high cost of imaging procedures and variable insurance coverage can restrict patient access to essential diagnostic tests.

Given these challenges, there is a clear need for an E-Health platform empowered by AI. In Algeria, where diagnostic methods are manually intensive and often take a long time delayed, the integration of AI can significantly enhance diagnostic accuracy and efficiency. In which AI can automate image analysis, reducing the cognitive load on doctors and providing precise, reliable diagnoses even when visual differences between healthy and abnormal conditions are subtle. This approach not only speeds up the diagnostic process but also mitigates human error, making it an invaluable tool in modern healthcare.

1.6 Healthcare situation in Algeria

According to Rezki et al. [52] a nation's health is closely linked to its overall development. In Algeria, efforts have been made to improve health through various programs aligned with global initiatives. However, challenges remain. Following independence, Algeria's population grew rapidly, putting a strain on healthcare services. Despite advancements, the growing population continues to outpace available healthcare resources.

A strong national healthcare system is essential to meet increasing health demands. Individual health is crucial for a flowered society, not just as a right but as a necessity for a productive population. Investing in citizens' health is key for any nation seeking economic and social prosperity.

The COVID-19 pandemic highlighted weaknesses in healthcare systems worldwide, underscoring the importance of robust healthcare. Balancing population growth with health development is an ongoing challenge worldwide, but especially for countries like Algeria.

Algeria's healthcare system provides basic services widely but struggles with equitable and advanced care. There is a shortage of specialists, particularly in remote areas, causing long travel or wait times for treatment [9, 18]. Public facilities often face limited equipment, medication, and supplies, affecting the quality of care. Urban areas have better-equipped facilities and more specialists compared to rural areas, where resources are infrequent. The high cost of private care creates a two-tiered system, making high-quality care accessible mainly to those who can afford it [18]. These issues challenge the delivery of quality care across all age groups, from prenatal to elder care [52].

1.7 E-Health platforms for medical assessment

This section talks about several examples of applications in medicine field, which in 1977, AI made its debut in the field of medicine with the introduction of MYCIN, a renowned computer-based consultation system. MYCIN was specifically developed to aid physicians in diagnosing and selecting therapies for patients with bacterial infections [69].

Today, AI applications in healthcare have involved to become even more efficient, offering a myriad of advanced capabilities and it can be broadly categorized into two major categories: general use and specialized use.

General-use platforms including: Enlitic's range of AI technologies seamlessly integrates with current workflows, enabling healthcare providers to improve clinical processes, boost efficiency, and extend their capabilities [51], Merative for clinical decision support and healthcare analytics which Francisco Partners has finalized its acquisition of Watson Health's data analytics tools [47], Regard for automating clinical tasks and Developing AR functionalities for an ECTMS and assess their influence on user experience [33], Google Vertex AI provides two options: AutoML and custom training. AutoML eliminates the need for data science or coding expertise and boasts quicker training times than custom training. It leverages a pre-trained algorithm and refines it using the user's dataset. On the other hand, custom training necessitates familiarity with TensorFlow or scikit-learn models and entails some level of data science proficiency [8], Care.ai for AI-assisted virtual care, primary care physicians are perfectly positioned to guide the healthcare AI revolution. They can play a pivotal role in advancing AI in healthcare by collaborating with technologists to ensure the relevance and human-centeredness of AI applications, employing quality improvement methodologies in AI deployments, and championing for inclusive and ethical AI practices initiatives that address, rather than exacerbate, health disparities [38]. Finally, the most used software Kaggle, Established in 2010 by Anthony Goldbloom and Jeremy Howard, and later acquired by Google in 2017, this online platform strives to assist professionals and learners in achieving their data science objectives through its robust set of tools and resources.

On the other hand, specialized platforms including: Freenome for early cancer detection, it's a privately-owned biotechnology company, has signed an agreement with Siemens Healthineers to work together on multiomics and radiomic diagnostics for breast cancer. The collaboration aims to identify effective markers for early detection of breast cancer through blood samples, complementing current imaging technologies [65]. Iterative Health for detecting GI illness, offers a systematic guide for the iterative medical decision-making process, presenting a clear framework and detailing the key iterative stages of model-based decision-making [34], VirtuSense for predictive fall prevention, introduces a novel single-camera 3D motion capture device equipped with gait analysis functionalities among its array of features. However, the Gait Analysis System utilizing the application device has yet to undergo formal validation [66]

However, None of the existing platforms possess the comprehensive capabilities of our revolutionary platform, which is specifically designed to cater to the unique needs of doctors and researchers. It serves as a centralized hub for accessing a diverse range of new research papers, datasets, and models, providing an unparalleled resource for professionals in the healthcare field.

1.8 AI for E-Health

AI needs the reproducing of human intelligence through machines or systems, with the goal of developing machines that can engage in reasoning, learning, planning, and prediction, reflecting human cognitive capacities and behaviors [56]. Modern healthcare is undergoing a transformative boost thanks to AI. AI's capabilities in prediction, comprehension, learning, and action are revolutionizing the field. From identifying hidden connections within genetic codes to guiding surgical robots, AI empowers healthcare professionals to detect subtle patterns that might otherwise go unnoticed by the human eye [58].

AI is revolutionizing healthcare by powering three ranges of innovative applications [7] which are: patient-oriented AI, Clinician-oriented AI, and administrative and Operational-oriented AI. In Patient Care like Pneumonia Detection in Pediatrics [50], Paediatric Bone Age Assessment from Hand X-ray Using [74], Diabetic Retinopathy Detection [16], Vital Sign Predictions Using Long-Short-Term Memory Networks [15], and the Detection of Fractures in Cervical Spine [53]. In clinician-oriented AI applications such as Clinical Decision Support Systems (CDSS) assist in diagnosing diseases and recommending treatment options, while predictive analytics identify potential patient outcomes based on historical data. In administrative and operational-oriented AI, applications like Hospital Resource Management optimize scheduling, manage bed allocations, and predict patient admission rates, and AI-driven Supply Chain Management ensures the efficient delivery and availability of medical supplies.

In this context, there is an emerging vision involving the integration of these applications, which creates a new need: AI-powered platforms in the healthcare field. These AI-powered platforms aim to provide a unified and comprehensive approach to patient care, streamlining various processes and improving overall efficiency. By integrating multiple AI applications into a single platform, healthcare providers can benefit from enhanced diagnostic accuracy, personalized treatment plans, and real-time monitoring of patient health. Moreover, such platforms can facilitate better communication and collaboration among healthcare professionals, ultimately leading to improved patient outcomes. As the healthcare industry continues to integrate AI technology, the development and implementation of these integrated platforms will play a crucial role in shaping the future of patient care.

There are several examples of artificial intelligence applications in healthcare such as:

- **AI-assisted robotic surgery:** Utilizes intelligent instruments for enhanced precision, control, and flexibility in complex procedures. Figure 1.3 shows an example of an AI-assisted robotic.

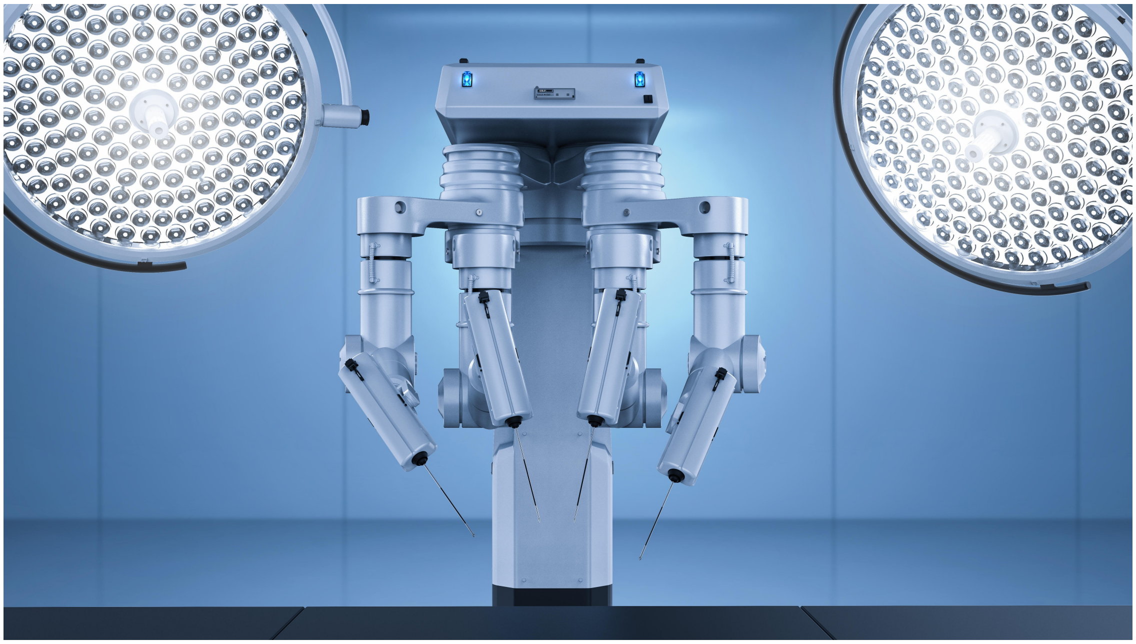

Figure 1.3: AI-assisted robotic surgery example.

- **AI in medical diagnosis:** AI is revolutionizing medical image diagnosis, with blood image analysis being a prime example. AI algorithms can analyze these complex images with remarkable accuracy, assisting doctors in identifying abnormalities and diagnosing blood-related diseases. Figure 1.4 shows an example of blood analysis imaging.

Figure 1.4: Example of blood image analysis

1.9 Case study : Paludism Pathology

In this section, we examine Paludism as a case study of an AI application in healthcare using medical imaging techniques.

Paludism remains one of the most prevalent and deadly diseases worldwide, particularly in tropical and subtropical regions. Traditional diagnostic methods involve microscopic examination of blood smears to identify malaria parasites, a process that is labor-intensive and requires highly trained technicians. However, AI-driven medical imaging techniques offer a transformative approach to diagnosing and managing malaria more efficiently and accurately.

1.9.1 Microscopic image overview

Microscopic imaging is a critical tool in medical diagnosis, allowing for the examination of cells and tissues at a high magnification to detect and analyze diseases at the cellular level. This technique is essential in various medical fields, particularly in pathology, microbiology, and histology.

- **Pathology:** In pathology, microscopic imaging is used to examine tissue samples (biopsies) to diagnose diseases such as cancer. Pathologists look for abnormal cell shapes, sizes, and arrangements that may indicate malignancy. This detailed examination helps determine the type and stage of cancer, guiding treatment decisions [54].
- **Microbiology:** In microbiology, microscopic imaging is employed to identify microorganisms such as bacteria, viruses, fungi, and parasites. Stains and dyes are often used to highlight specific structures within these organisms, aiding in their identification. This is crucial for diagnosing infections and determining the appropriate antimicrobial treatment [21].
- **Histology:** Histological analysis involves the study of tissue architecture and cellular detail. Microscopic imaging allows for the visualization of different tissue components and their organization, which is important in diagnosing a wide range of conditions, from inflammatory diseases to degenerative disorders [54].

1.9.2 Paludism definition

Paludism, also known as Malaria, is a life-threatening mosquito-borne disease caused by parasites of the Plasmodium genus. It is transmitted to humans through the bite of infected female Anopheles mosquitoes [12, 14]. Malaria remains a significant public health challenge, particularly in tropical and subtropical regions, affecting millions of people worldwide each year. Symptoms typically include fever, chills, and flu-like illness, which can progress to severe complications if left untreated. Effective prevention measures include the usage of insecticide-treated bed nets, indoor residual spraying, and antimalarial medications. Despite ongoing efforts to control and eliminate the disease, malaria continues to pose a considerable burden on global health systems and economies. Figure 1.5 shows the malaria infection by female mosquitoes [24].

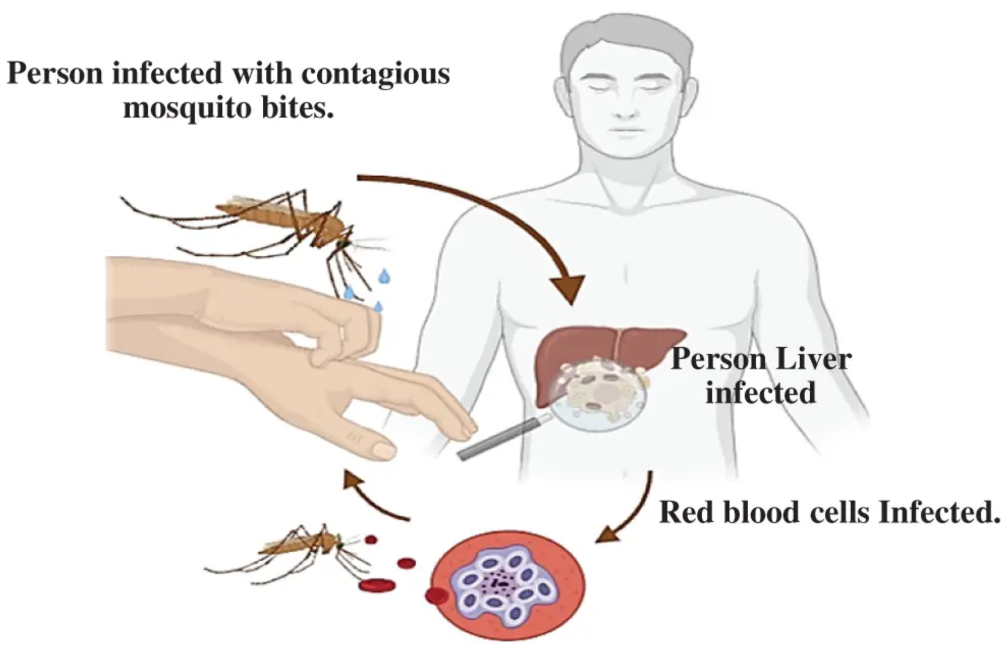

Figure 1.5: The transmission of malaria by female mosquitoes [24].

1.9.3 Paludism life cycle

According to [64] the life cycle of species plasmodium (SPP) involves two hosts: humans and female Anopheles mosquitoes . When an infected mosquito bites a human, it injects sporozoites into the bloodstream. These sporozoites travel to the liver, where they mature and multiply, releasing merozoites into the bloodstream. Merozoites infect red blood cells, causing cycles of replication and rupture, leading to fever and anemia. Some parasites develop into sexual stages (gametocytes) that are ingested by mosquitoes during feeding. In the mosquito, gametocytes mature into zygotes, then ookinetes, and finally, sporozoites, which are transmitted to humans through mosquito bites, completing the cycle. Figure 1.6 illustrates the life cycle of Paludism disease.

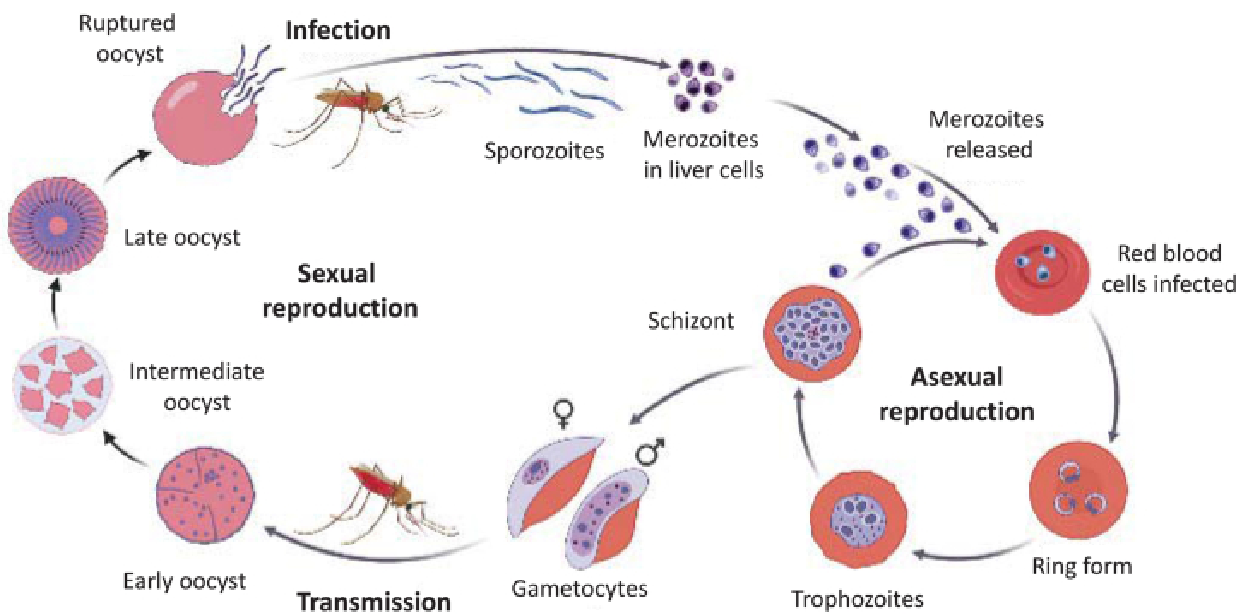

Figure 1.6: life cycle of plasmodium [64]

1.9.4 Paludism diagnosis methods

The primary and widely used method for diagnosing malaria is examining thick and thin blood smears under a microscope [64]. Although there are alternative methods such as Serodiagnostic assays and Molecular methods, none match the efficiency of microscopic examination. Figure 1.7 illustrates the Paludism detection methods.

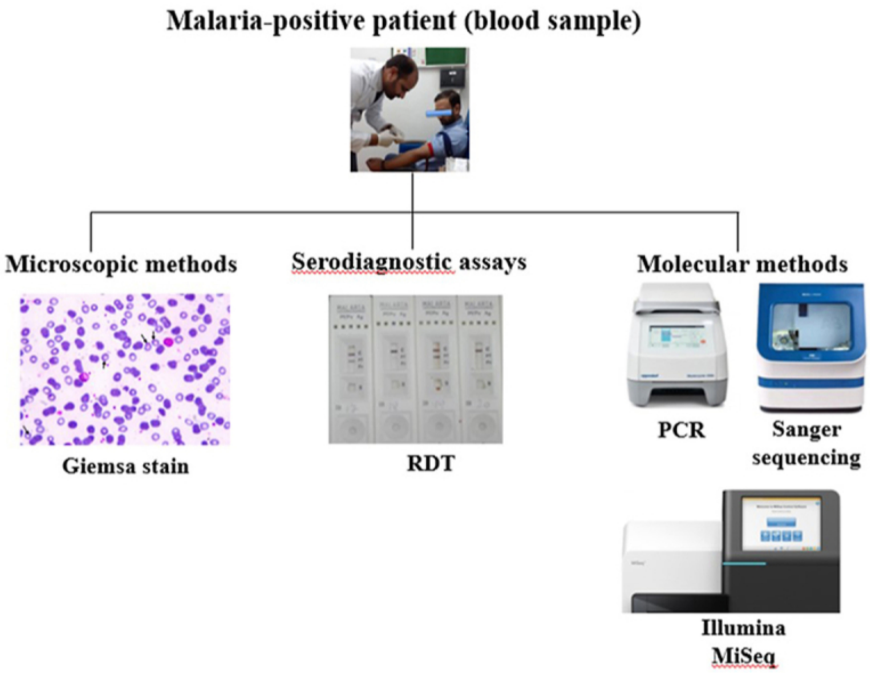

Figure 1.7: Paludism diagnosis methods [64].

As a result, Malaria detection through microscopic images involves analyzing three key characteristics that vary with the type of parasite present. Firstly, distinct morphological features are observed (the appearance of trophozoites, skizonte, gamcytocyte) in infected red blood cells, which differ between species P. falciparum, P. vivax, P. ovale, and P. malariae. Secondly, parasite density varies, with some species, like P. falciparum, often exhibiting higher levels of parasitemia. Lastly, clinical manifestations differ among species, with implications for disease severity and complications. Understanding these variations is essential for accurate diagnosis and effective treatment of malaria infections. but the first key is the most important and the presence of one of those characteristics is enough.

1.10 Conclusion

In this chapter, we provided a comprehensive overview of the essential medical background necessary for understanding diagnostic processes. We began with a basic definition of healthcare and moved on to discuss various healthcare practices, including medical records management, diagnosis based on blood tests, and medical imaging diagnosis. We explored the modalities of medical imaging, covering both invasive and non-invasive techniques. Several challenging issues related to medical diagnosis were addressed, followed by an examination of the healthcare situation in Algeria. We also discussed the potential of E-Health platforms for medical assessment and the role of AI in enhancing these platforms. Lastly, we took Paludism (malaria) as a case study, providing an overview of microscopic images, the definition of Paludism, its life cycle, and its diagnosis methods.

Chapter 2

Theoretical and Technical Background

2.1 Introduction

Artificial Intelligence (AI) is one of the most important fields in Computer Science. Its aim is to create intelligent machines capable of reasoning, learning, planning, and prediction, mimicking human cognitive abilities. This domain covers various aspects such as search algorithms, knowledge graphs, natural language processing, expert systems, evolutionary algorithms, Machine Learning (ML), and Deep Learning (DL) [56].

In this chapter, we start by introducing the fundamental concepts of AI, including ML and its various types. This sets the stage for delving into the more specialized area of DL. We discuss the differences between ML and DL and explore artificial neural networks. We then focus on Convolutional Neural Networks (CNNs) as a technique based on the nature of its use, which is generally images. We cover CNNs' definition, architecture, and layer configuration, and mention variations in CNN architectures. Finally, we review related works on the diagnosis of diseases using microscopic images.

2.2 Artificial Intelligence

Artificial Intelligence (AI) is a branch of computer science [61] that deals with the creation of intelligent machines that can perform tasks that typically require human intelligence. In the medical field, AI is utilized to analyze complex medical data, assist in diagnosis, personalized treatment plans, and improve patient outcomes. AI algorithms can process vast amounts of medical data quickly and accurately, aiding healthcare professionals in making informed decisions. From medical imaging interpretation to patient monitoring, AI has the potential to revolutionize healthcare by enhancing the efficiency, accuracy, and accessibility of medical services.

2.3 Machine learning

ML is the most important part of AI. It addresses tasks like prediction, forecasting, and classification by analyzing data and creating algorithms. ML eliminates the need to manually code all the rules governing a particular environment, making it a powerful tool for problem-solving.

2.4 Types of Learning

Ayodele et al [4] outlines four types of learning, each requiring specific input data:

- **Unsupervised Learning**

  This approach utilizes where the algorithm analyzes the data to uncover inherent structures and relationships.

  K-Nearest Neighbour (KNN) algorithm is an example algorithm of this approach . Figure 2.1 shows an example of unsupervised learning in ML.

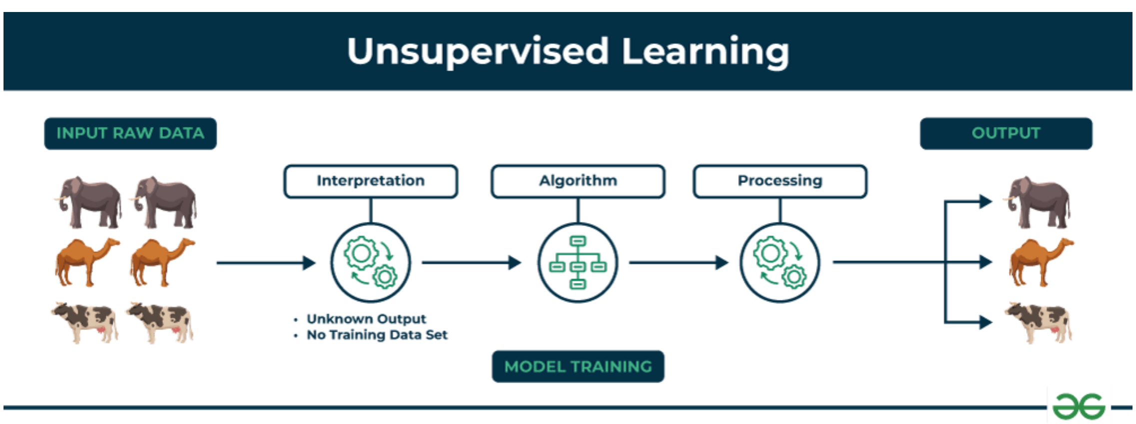

Figure 2.1: Unsupervised Learning in ML.

- **Semi-supervised Learning**

  Semi-supervised learning can utilize a small set of labeled data examples to learn and then generalize to the rest of the dataset without external guidance.

Expectation Maximization (EM) algorithm is an example algorithm of this type. Figure 2.2 shows an example of unsupervised learning in ML.

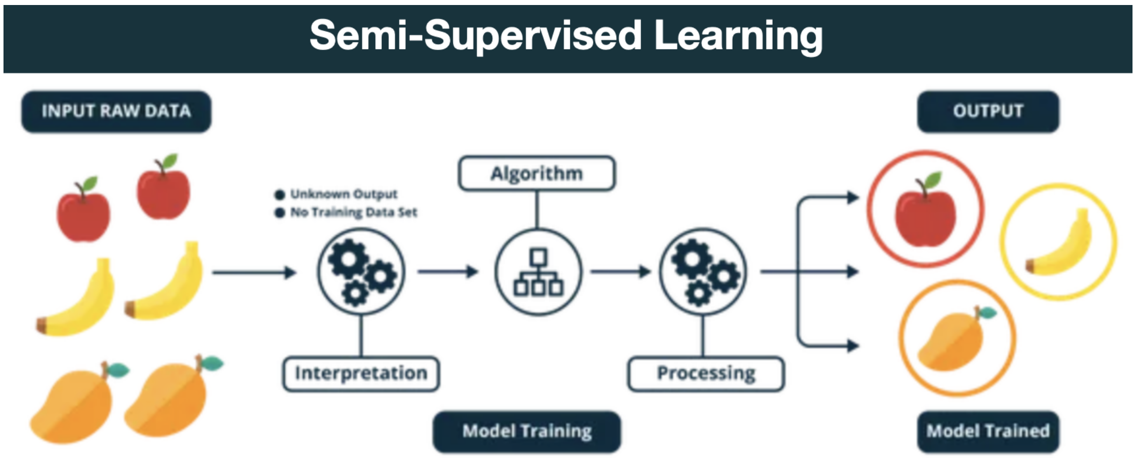

Figure 2.2: Semi-Supervised Learning in ML.

- **Reinforcement Learning**

  Reinforcement Learning is an advanced learning method where an agent explores an unfamiliar environment, taking random actions to discern which are beneficial and which are detrimental based on rewards or penalties received. The goal of the agent is to maximize long-term rewards through optimization. Figure 2.3 shows an example of reinforcement learning in ML.

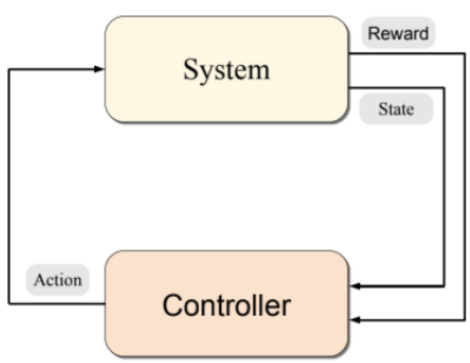

Figure 2.3: Reinforcement Learning in ML [68].

- **Supervised Learning**

  The simplest way to learn something new is through Supervised Learning, which utilizes labeled datasets for specific outputs. This approach trains algorithms to accurately classify data or predict outcomes. In our work, we've employed Supervised Learning. Examples of such algorithms include Support Vector Machines (SVM) and Random Decision Forests. Figure 2.4 shows an example of supervised learning in ML.

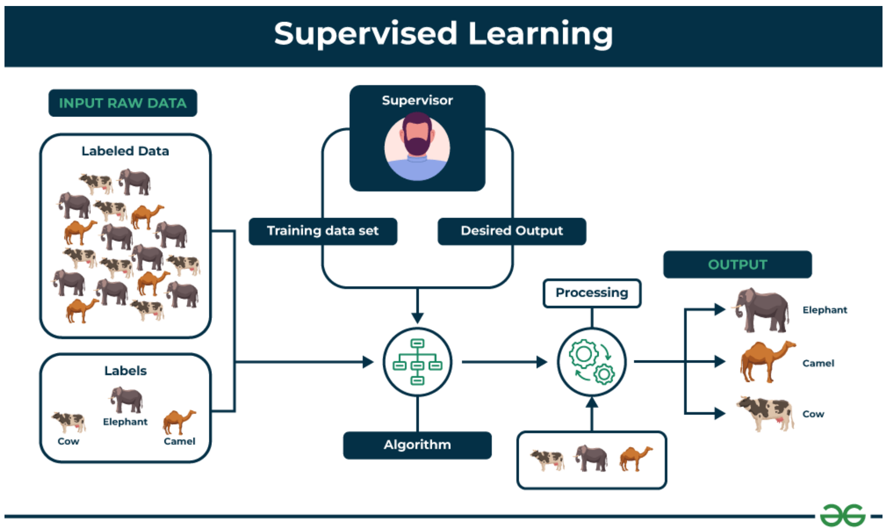

Figure 2.4: Supervised Learning in ML.

In supervised learning, two main tasks can be achieved: Regression and classification.

- **Regression** This task involves predicting a value as an output. The output can be of any type, such as string, numeric, or date,...etc.
- **Classification** Here, the goal is to categorize input data into two or more classes. Rather than making predictions, each input data point is assigned to the class it belongs to.

Figure 2.5 shows the difference between the two tasks of supervised learning classification and regression.

2.5 Deep Learning

DL is a subset of ML that uses neural networks with many layers (hence "deep") to learn from data [72]. Unlike traditional ML, which often requires manual feature extraction, DL algo-

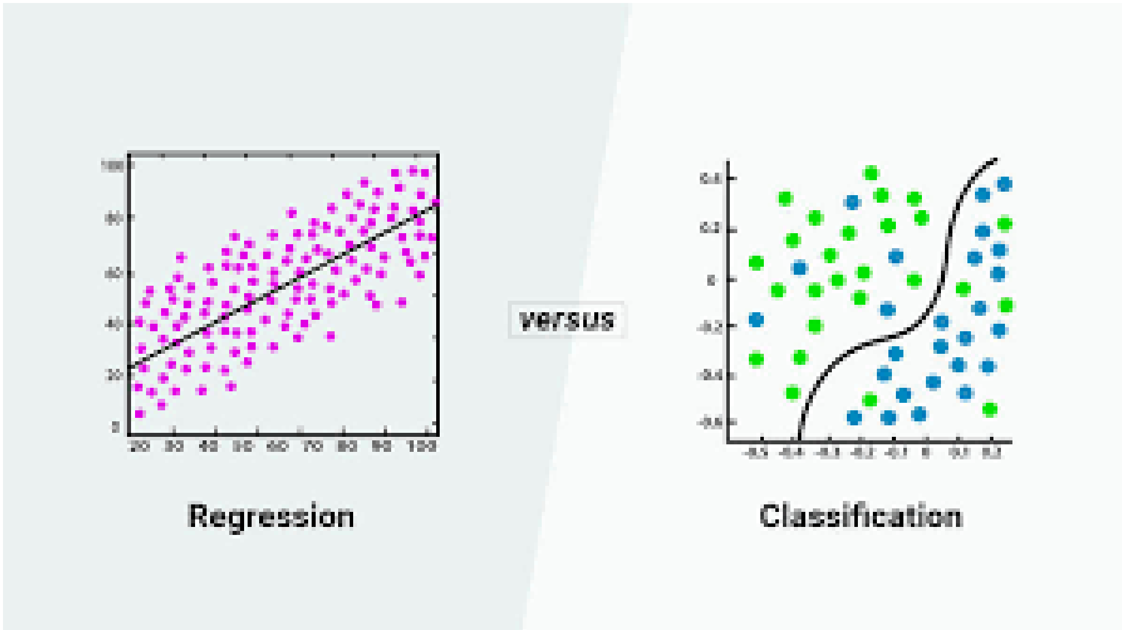

Figure 2.5: Classification and Regression.

rithms can automatically discover intricate patterns and representations within the data. It's like teaching a machine to learn abstract concepts by building increasingly complex layers of understanding. So, while all Deep Learning (DL) is Machine Learning (ML), not all Machine Learning (ML) is Deep Learning (DL). Its ability to extract intricate patterns from large datasets has led to breakthroughs in Pneumonia Detection in Pediatrics [50], Paediatric Bone Age Assessment from Hand X-ray Using [74], Diabetic Retinopathy Detection [16], Vital Sign Predictions Using Long-Short-Term Memory Networks [15], and the Detection of Fractures in Cervical Spine [53].

2.5.1 The differences between the Machine Learning and the Deep Learning

The distinction between ML and DL lies in the algorithms they employ [71]. ML encompasses a diverse range of algorithms such as SVM, Linear Regression, Decision Trees, and Random Forests, each with its unique characteristics. These approaches typically do not demand as much data as DL methods. As a result, ML is a good choice for simpler tasks, smaller datasets, or when interpretability is crucial but the DL is ideal for complex tasks involving unstructured data, where large amounts of data are available.

On the other hand, DL primarily relies on a single algorithm known as Neural Networks.

While there are various types of NNs, the fundamental concept remains consistent across them. Figure 2.6 shows the difference between the ML and the DL.

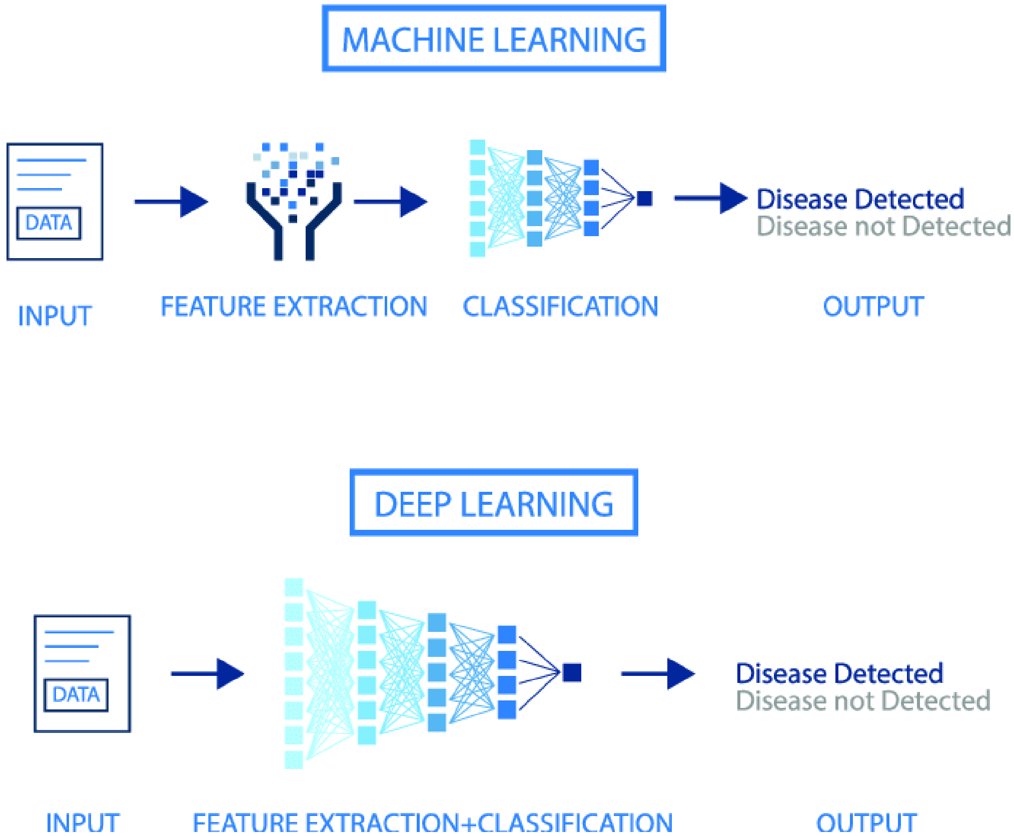

Figure 2.6: The difference between the ML and the DL.

2.5.2 Artificial Neural Networks

In order to comprehend Artificial Neural Networks, it is advisable to introduce fundamental concepts of biological neural networks. Consequently, alterations are generated within the model of ANNs.

2.5.2.1 Biological neuron:

Neurons, the fundamental units of neural tissue, possess the remarkable ability to receive, process, and transmit signals, giving rise to the intricate nervous system. This system serves as our interface with the environment, enabling actions, sensations, and thoughts [35].

The potency of neurons stems from their non-linear nature. If neurons merely performed linear combinations of inputs, the computational power of groups of neurons or entire brain regions would not yield the remarkable outcomes observed.

Signals are received by neurons via dendrites from neighboring cells, and within the nucleus, these signals are linearly combined. If this combination exceeds a certain threshold, the neuron fires, transmitting a signal to subsequent neurons. This process of neuron activation is known as firing.

The Myelin sheath plays a crucial role in modulating the intensity of the signal, either enhancing or diminishing its voltage. This modulation impacts the significance of the signal upon its reception by other neurons. Figure 2.7 illustrates the biological neuron architecture.

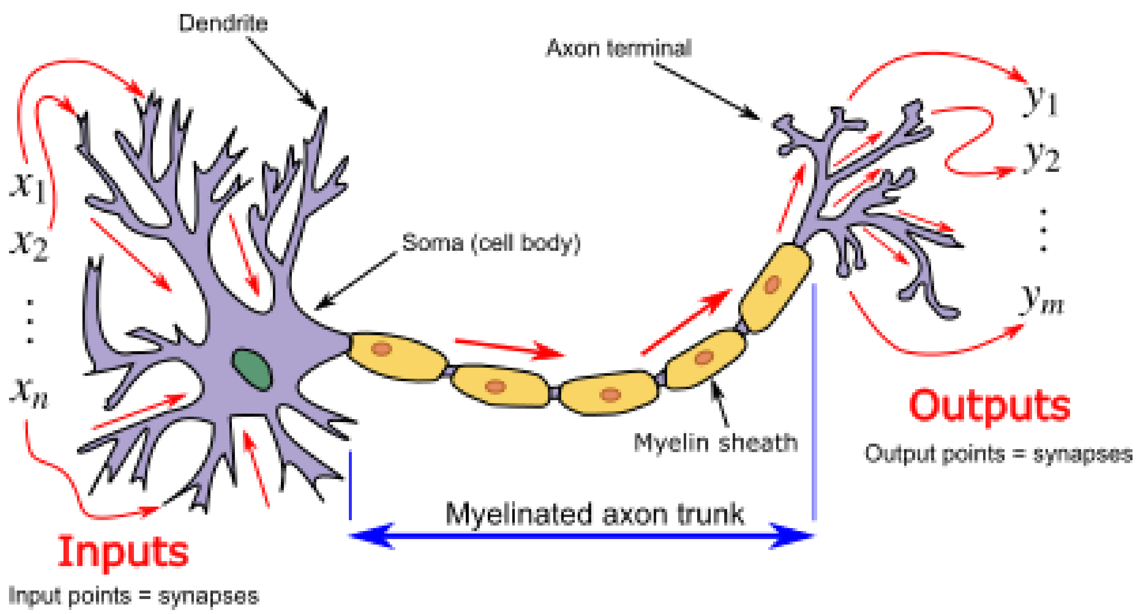

Figure 2.7: Biological Neuron.

2.5.2.2 Artificial Neuron

The artificial neuron depicted in Figure 2.8 serves a similar function to its biological counterpart, acting as a basic processor. Each artificial neuron in the input layer receives multiple variables, with each input associated with a weight representing its connection value.

An activation function processes the sum of the input variables and their weights. The resulting sum is then forwarded to the output layer, where it is compared to a threshold value.

Based on this comparison, the output layer generates a response.

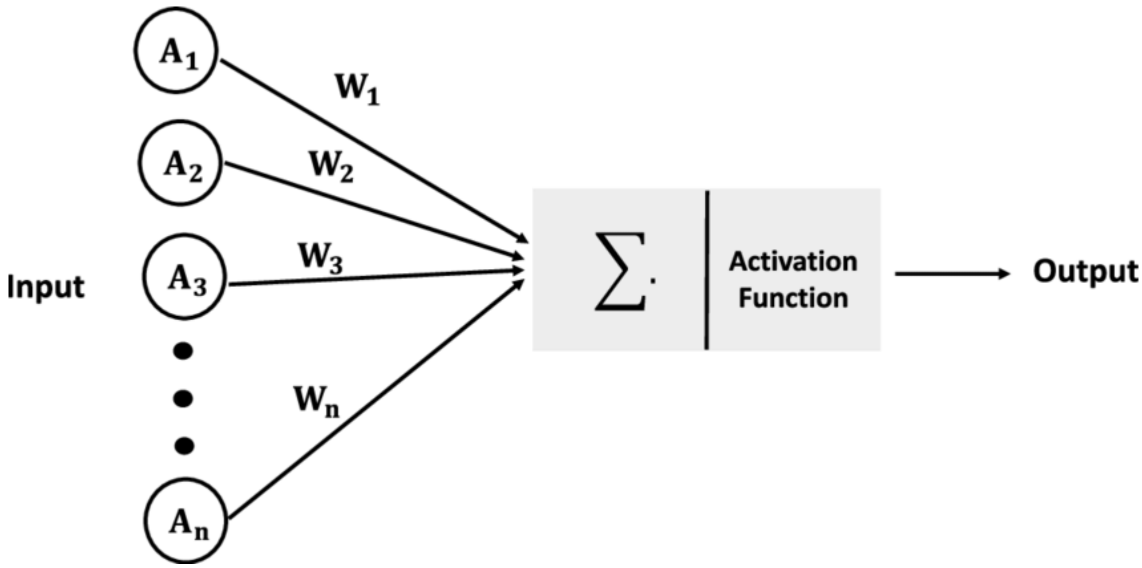

Figure 2.8: The artificial neuron structure.

2.5.2.3 Artificial Neural Network:

The Artificial Neural Network comprises three types of neuron layers: the input layer, a hidden layer (often depicted as a black box), which aids in identifying intricate patterns within the input, and an output layer [26]. Figure 2.9 illustrates the three layers. The size of the output layer varies depending on the task at hand. For predicting income values, there might be one output neuron. However, for classification tasks, the number of output layer neurons corresponds to the number of classes being classified.

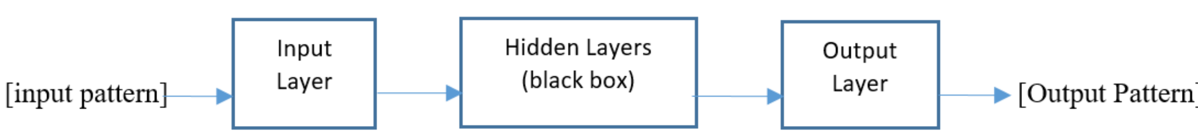

Figure 2.9: A Typical Neural Network [26]

Activation Function: The activation function determines whether a neuron should be activated or not [60]. It evaluates the importance of the neuron's input in the prediction process, typically through simple mathematical operations.

There exist various forms of activation functions, each suited for specific contexts. Below are some of the most commonly used ones.

- **Rectified Linear Unit Function:** RELU is indeed a widely used activation function in NNs. It efficiently transforms all input values to positive numbers by outputting zero for negative inputs and retaining positive inputs unchanged. Figure 2.10 illustrates the curve of RELU activation function.
  it calculates using the following equation 2.1:

$$Relu(z) = max(0, z) \tag{2.1}$$

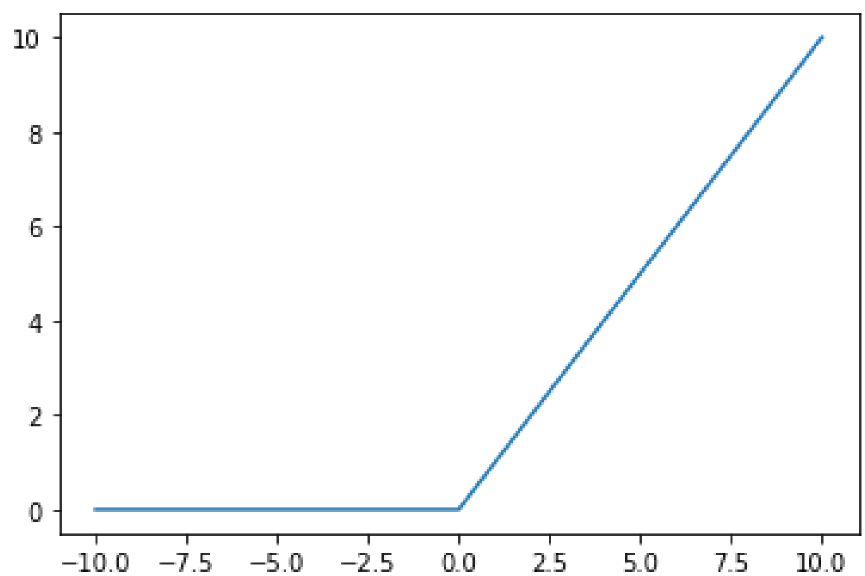

Figure 2.10: RELU Function curve.

- **Exponential Linear Unit Function:** It's an activation function created to achieve faster convergence of the cost function toward zero compared to traditional activation functions such as RELU. Additionally, it aims to produce more accurate results. Figure 2.11 illustrates the curve of ELU activation function.
  it calculates using the following equation 2.2:

$$\mathrm{ELU}(x) = \begin{cases} x & \text{if } x \geq 0, \\ \alpha(\exp(x) - 1) & \text{if } x < 0. \end{cases} \tag{2.2}$$

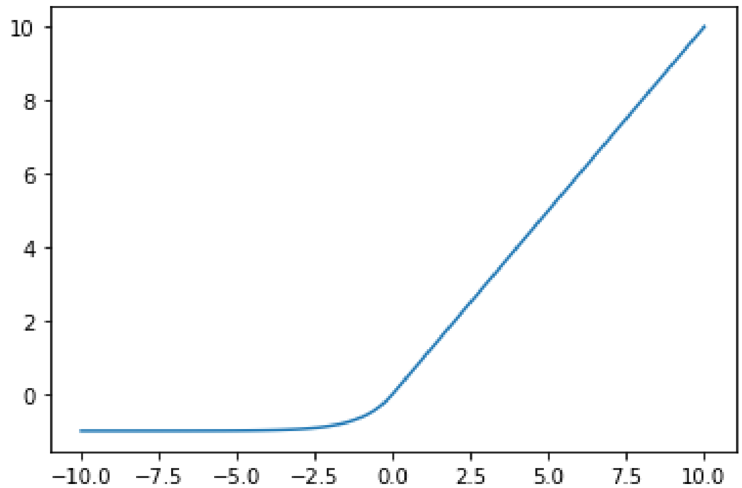

Figure 2.11: ELU Function curve.

- **Sigmoid:** The Sigmoid activation function transforms the input into a value ranging between 0.0 and 1.0. Figure 2.12 illustrates the curve of the Sigmoid activation function. It calculates using the following equation 2.3:

$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{2.3}$$

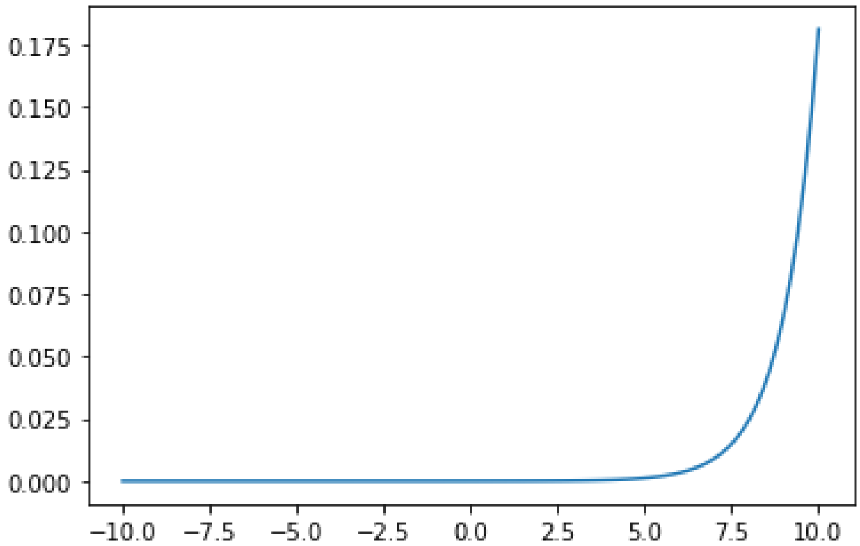

Figure 2.12: Sigmoid Function curve.

- **Softmax:** The Softmax activation function converts a set of numerical values into a set of probabilities, with each probability corresponding to a specific class. This function is frequently employed in ML for NNs tasked with classification, generating N output values, one for each class. Softmax normalizes the inputs, transforming them from weighted sums into probabilities, where the sum of all probabilities equals one. Each output value produced by the Softmax function signifies the probability of belonging to a particular class. Figure 2.13 illustrates the curve of Softmax activation function.
  it calculates using the following equation 2.4:

$$\sigma(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad \text{for } i = 1, 2, \ldots, K \tag{2.4}$$

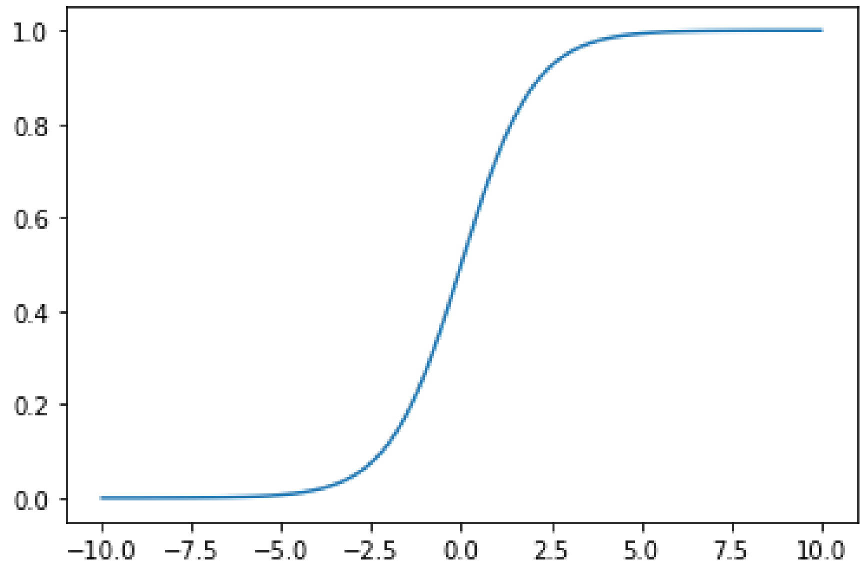

Figure 2.13: Softmax Function curve.

2.6 Convolutional Neural Network

DL has revolutionized numerous scientific fields, offering significant computational power for in-depth analysis of incoming data. Among the most notable advancements has been in Computer Vision, where operations on visual input aim to replicate human sight. Over the years, various technologies have been developed to enhance the efficiency of analysis processes. Dense Neural Network (DNN)s have been a prominent choice, but their architecture has proven to be inadequate for Computer Vision tasks.

2.6.1 CNN definition

Convolutional Neural Networks have emerged as a solution to the computational demands posed by DNNs, particularly in analyzing large images. The inspiration for CNNs stems from studies on the human visual cortex, including research on the visual cortex of cats, which shares similarities with humans. These studies revealed that visual signals traverse various brain regions, each performing distinct types of processing. Similarly, CNNs [2]. The signal is processed through multiple layers, with each layer extracting the most significant features from the input.

2.6.2 CNN Architecture

The architecture of CNNs is typically straightforward, as outlined by Albawi et al [2]:

• Input Layer: Receives images.

• Convolutional Layers: During training, the input image is divided into virtual regions, each analyzed by a filter (kernel). These filters iterate over the regions and determine the weights to represent crucial information. But how are those weights calculated?, the answer to this question represents the true power of CNN. The network automatically calculates these weights by minimizing the loss between input and predictions, and it will give the true weights.

• Flatten Layer: Receives the output matrix from the final convolutional layer and flattens it into a one-dimensional vector.

• Dense Network: Receives the one-dimensional vector and performs necessary computations.

2.6.2.1 How Convolution Works:

The convolution operation plays a pivotal role in CNNs, enabling the calculation of weights necessary to identify specific features within an image.

In convolution, the original image serves as the initial input, along with the current filter. Each filter in the feature map (a set of filters for the current convolutional layer) iterates over the image. Convolution entails a series of sum operations, where each element of the image matrix is multiplied by the corresponding element of the filter matrix. Figure 2.14 illustrates how the filter operates in the convolution layer.

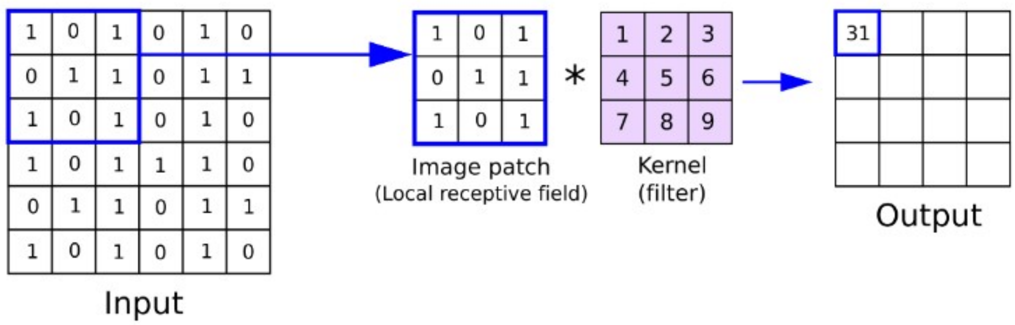

Figure 2.14: Calculation process of a filter in the convolutional layer.

2.6.2.2 Filter:

The filter plays a crucial role in convolutional operations. Its composition dictates the specific characteristics that will be detected within the image. When the values are concentrated solely in the columnar structure of the filter, it will accentuate the vertical lines present in the input. Conversely, emphasis on row values will highlight horizontal lines instead. The incorporation of multiple convolutional layers is essential due to the escalating complexity of shapes discerned by the NN in correlation with the network's depth.

2.6.2.3 Padding:

The resultant matrix from the convolution process exhibits a reduced dimension compared to the initial matrix. This phenomenon may result in a reduction of pertinent data, consequently impacting the overall performance negatively. To mitigate this issue, the padding technique is employed. Padding involves encasing the original image with a border of zeros. Figure 2.15 illustrate the padding technique of adding zeros to an image.

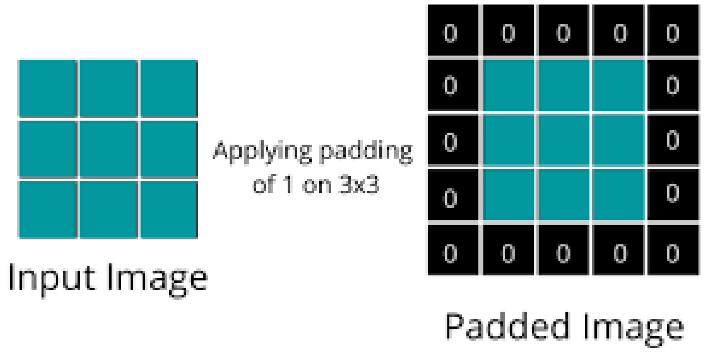

Figure 2.15: Example of adding zeros padding to an image.

2.6.2.4 Stride:

The conventional option dictates that the filter will exclusively shift by one position incrementally. However, this limitation can be circumvented. Should the need arise, the filter's movement can be adjusted to traverse multiple positions by modifying the stride hyper-parameter. As illustrated in Figure 2.16, the stride parameter governs the manner in which the filter performs convolution across the input image.

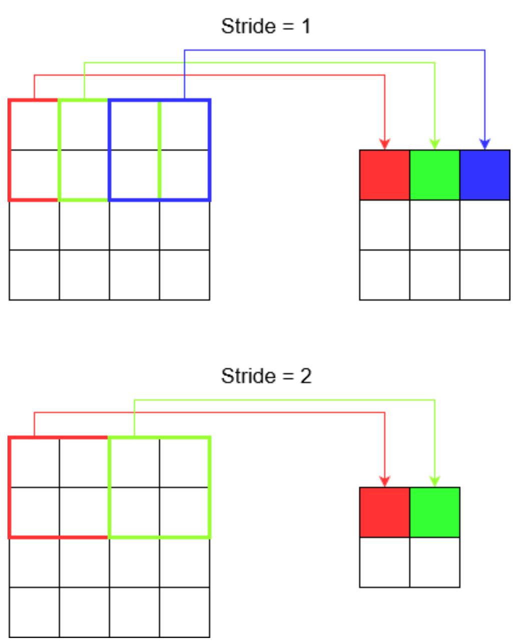

Figure 2.16: Stride in CNN.

2.6.2.5 The Pooling Layers:

The objective of CNNs is to effectively handle images in order to facilitate the process of identifying the most significant features present in the image while maintaining a low computational cost in terms of weight. The Pooling layer plays a crucial role in diminishing the volume of information transferred to subsequent layers by keeping the most crucial data. Through a series of operations carried out on the images, the Pooling Layer systematically extracts pertinent features, thereby reducing the dimensions of the input image at each stage. Figure 2.17 illustrates the technique of max-pooling layer how selects the highest achievable value within the feature map.

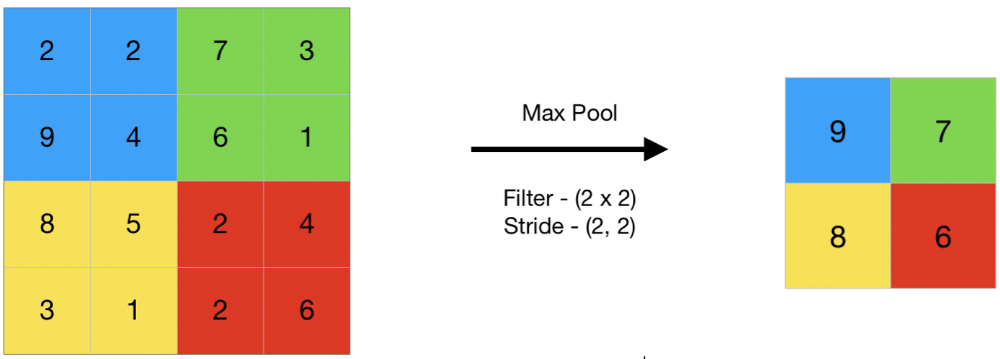

Figure 2.17: A practical example of the max-pooling layer.

There are three types of pooling layers as follows:

- **Max:** The maximum value within the iteration window is regarded as the most crucial information.
- **Average:** The average operation is utilized to mitigate the information among pixels, aiming to decrease information while still consider all values within the iteration window.
- **Global:** Within each feature map, the average value is computed, contributing to a reduction in connections with the final layers. The effectiveness of this layer is contingent upon the reduction in weights.

2.6.3 CNN layers configuration

The procedural flow of the Convolutional Neural Network (CNN) initiates with the examination of the input image by the initial convolutional layer, aimed at identifying fundamental features within the image. Typically, larger filters are employed at this stage to capture overarching information. Subsequent layers are tasked with detecting more intricate information, leading to an escalation in the amount of information acquired. Consequently, a reduction in size occurs progressively at each level, culminating in the formation of a dense representation of the input. Illustrated in Figure 2.18, the latter segment of the CNN framework encompasses a DNN for the purpose of classification. At this juncture, the volume of information furnished to the DNN holds significant importance. Owing to the dense interconnections, the quantity of weights may surge significantly. Hence, CNN endeavors to diminish the width and height dimensions while augmenting the depth of the feature maps.

The efficacy of the GlobalAveragePooling layer is evident in certain scenarios as it obviates the necessity of the entire DNN section, relying solely on a singular Dense Layer for output. Figure 2.18 illustrates a general architecture for CNN.

2.6.4 Variation of CNN architectures

Over years, numerous robust CNN architectures have been introduced. The inception of LENET [36] marked a significant milestone as one of the earliest CNN models proposed for recognizing handwritten digits. ALEXNET [27] emerged as a large-scale CNN architecture utilized in the realm of computer vision, while the Network in Network design [37] proved to be well-suited for handling uncomplicated datasets. In addition to these foundational CNN models, a series of other influential architectures were developed: (i) VGG Net [63], renowned for its widespread adoption attributed to its compact convolutional kernels and straightforward design, (ii) GoogleNet [67], which represented the pioneering intricate architecture in the field, and (iii) Resnet [25], featuring a crucial element of residual network architecture in the form of identity skip connections within the residual blocks. Resnet facilitates the training of deeply layered CNN architectures with ease, and the integration of its capabilities with GoogleNet led to the

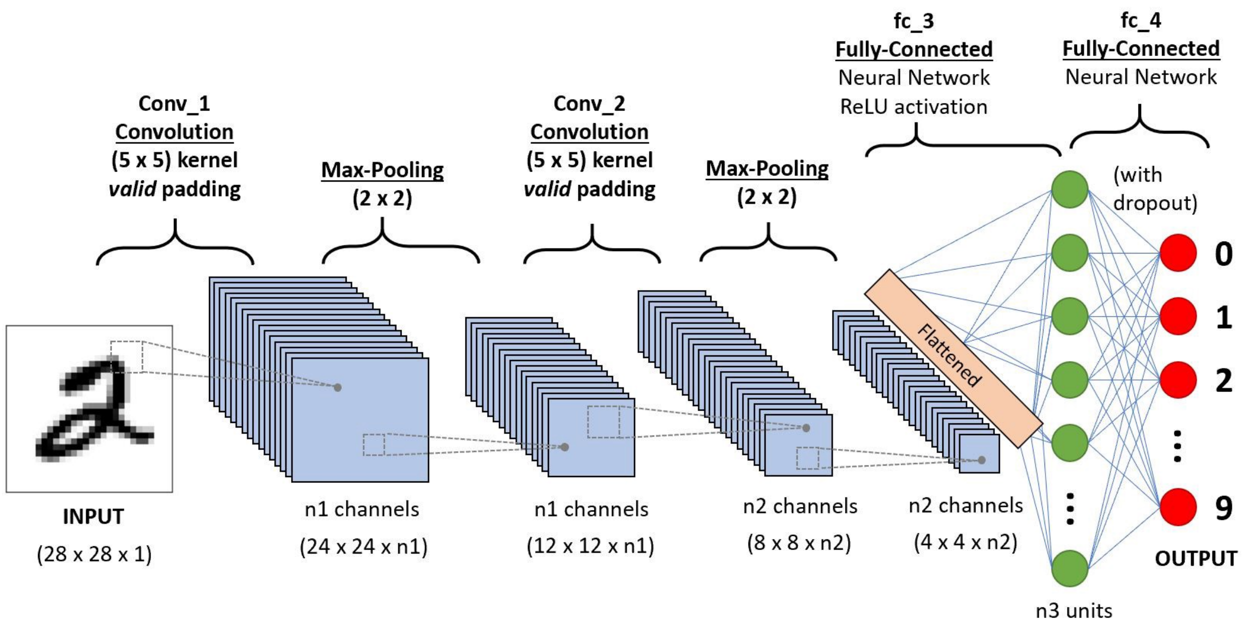

Figure 2.18: Convolutional Neural Network Architecture [23].

inception of a novel architecture termed ResNet. Through the utilization of skip connections, researchers have detected a novel approach to enhance the training process, consequently reducing the overall computational load. The fundamental concept of skip connection serves as the cornerstone of the DenseNet [28] architecture, enabling intricate connections between layers to be effectively complemented.

2.7 Related works of Paludism diagnosis model

Prior research in the field of image detection using DL models provides valuable insights into the methodologies, challenges, and achievements in this context. Several studies have explored different approaches to microscopic image detection with different diseases, using diverse datasets, model architectures, and evaluation metrics. This table 2.1 shows the different and the most relevant works related to classify microscopic images using DL.

For exploring deeply on details of these works we'll talk about them as follows: R Liu Et al proposed an AI-based object detection system for malaria diagnosis from smartphone thin-blood-smear images using a classifier based on CNN to diagnose conditions using images of blood smears, effectively minimizing errors caused by false positive cells. The findings indicate that AIDMAN effectively manages interference, achieving a diagnostic accuracy rate of 98.44% [39]. T Jameela Et al collected images of infected and non-infected erythrocytes, then fed them into CNN models such as ResNet50, ResNet34, VGG-16, and VGG-19, all trained on the same dataset. Transfer learning and fine-tuning techniques were applied, and the results were compared. The VGG-19 model demonstrated the best overall performance among the evaluated parameters and dataset, and they got 0.97, 1.9341, 0.9641, 0.9796 of accuracy, F1-Score, Specificity, and Sensitivity respectively [30]. Then, the study of Essra Hassan Et al The Malaria Convolutinal Neural Network model proposed in this study utilizes transfer learning with three different pre-trained models to classify malaria cell images. The study introduces an effective model for feature extraction and classification from images. Results are compared across various loss functions, including hinge, squared hinge, binary cross-entropy, and categorical cross-entropy, to assess the overall performance of the model, Fine-tuning of weights and dataset augmentation techniques are employed to address overfitting issues. Performance evaluation of the proposed method is conducted using GPU for malaria detection. The proposed model achieves scores of 0.9929, 0.9848, 0.9859, 0.9924, 0.0152, 0.0141, 0.0071, 0.9890, 0.9894, and 0.9780 in terms of specificity, sensitivity, precision, accuracy, F1-score, and Matthews Correlation Coefficient (MCC), respectively [24]. Also, Maqsood et al introduce a tailored CNN model that surpasses all examined DL models. Their approach utilizes binary filtering and image augmentation techniques to enhance the visibility of RBC features before model training. By employing image augmentation techniques, their customized CNN model achieves generalization and mitigates overfitting. Experimental assessments are conducted on the widely-used NIH Malaria Dataset, demonstrating that their proposed algorithm achieves a 96.82% accuracy rate in detecting malaria from microscopic blood smears [41]. Nakasi Et al assess and compare the performance of three pre-trained DL architectures, namely faster R-CNN, SSD, and RetinaNet, on a dataset of thick blood smear images using the Tensorflow object detection API. Employing data augmentation techniques to enhance the performance of the meta architectures, they achieve a peak accuracy of 93.03% with Faster R-CNN, which yields the best results among the evaluated models[44]. Meanwhile, Sarkar et al [55] proposed a shallow CNN architecture designed for malaria diagnosis using thin blood smear RBC slide images. Despite achieving comparable classification accuracy to VGG-16 and ResNet-50 models, their approach significantly reduces computational runtime. Sedik El al propose a CNN model for Efficient Data-Augmented Detection of COVID-19 Infections [57]. Zamora Et al work on Unsupervised online clustering and detection algorithms using crowdsourced data for malaria diagnosis [11]. Rajaraman Et al used Pre-trained CNNs as feature extractors toward improved malaria parasite detection in thin blood smear images [49]. Mehanian Et al propose a CNN model for Malaria Diagnosis and they got 95% of sensitivity [43]. And finally, Puntonet Et al [3] introduced traditional cell segmentation techniques relying on object detection algorithms.

	Methodology	Accuracy	Precision	F1-Score	Specificity	Recall	Sensitivity	AUC	Year
[39]	CNN	0.9844	N/A	N/A	N/A	N/A	N/A	N/A	2023
[30]	CNN	0.9720	N/A	1.9399	0.9641	N/A	0.9796	N/A	2022
[24]	VGG19	0.9890	0.9859	0.9894	0.9929	N/A	0.9848	N/A	2022
[41]	CNN	0.9682	N/A	N/A	0.9778	N/A	0.9633	N/A	2021
[44]	Faster-RCNN	93.03%	N/A	N/A	N/A	N/A	N/A	N/A	2020
[55]	VGG19	96.15%	N/A	N/A	97.53%	N/A	94.82%	N/A	2020
[57]	CNN	97.99%	N/A	N/A	N/A	N/A	N/A	N/A	2020
[11]	SVM	N/A	N/A	N/A	N/A	N/A	94%	N/A	2019
[49]	CNN	98.60%	N/A	N/A	99.2%	N/A	98.10%	99.90%	2018
[43]	CNN	N/A	N/A	N/A	N/A	N/A	95%	90%	2017
[3]	SVM	86.11%	N/A	N/A	N/A	N/A	N/A	N/A	2015

Table 2.1: Related works

2.8 Conclusion

This chapter introduced the fundamental concepts of AI, including ML and its various types. We laid the groundwork for understanding the more specialized area of DL by discussing the differences between ML and DL and exploring artificial neural networks. Our focus then shifted to CNNs, which are particularly suited for image analysis. We covered the definition, architecture, and layer configuration of CNNs, and mentioned variations in CNN architectures. Finally, we reviewed related works on the diagnosis of diseases using microscopic images.

Chapter 3

Towards AI-Powered Platform for E-Health

3.1 Introduction

In recent years, the digitization of healthcare has become crucial for improving medical practices globally. As previously discussed, our primary objective is to develop a specialized AI-powered healthcare platform to contribute to the improvement of the Algerian healthcare system. This platform aims to empower healthcare researchers and professionals by enhancing their access to essential resources and advanced tools related to healthcare. Additionally, it seeks to bridge the gap between academic research and clinical practice, enabling practitioners to benefit from the latest scientific advancements.

In this chapter, we will begin by analyzing the requirements and design considerations for the platform, ensuring it meets our objective. Following this, we will delve into the implementation details by presenting the platform architecture and design and showcasing various features and functionalities through interface screenshots.

3.2 Requirements Analysis

In this section, we will conduct a thorough analysis of the requirements for our AI-powered healthcare platform, focusing on the specific needs of healthcare professionals and researchers. Our goal is to create an online medical platform that enhances research capabilities and resource accessibility. This platform will provide healthcare professionals and researchers with access to a curated collection of academic papers, datasets, and AI applications. Figure 3.1 illustrates the final vision of the platform, highlighting the different resources exposed in it and its potential users

This platform aims to offer the ability to access pre-trained AI models and the option to test them. It should be accessible from any device via a web interface for visitors, with additional functionalities reserved for subscribed members. These users will be able to upload and manage datasets, models, and research papers, which will be hosted on a server.

By carefully considering the requirements and design principles, we aim to create a robust and scalable solution that addresses the unique demands of healthcare professionals and researchers in Algeria.

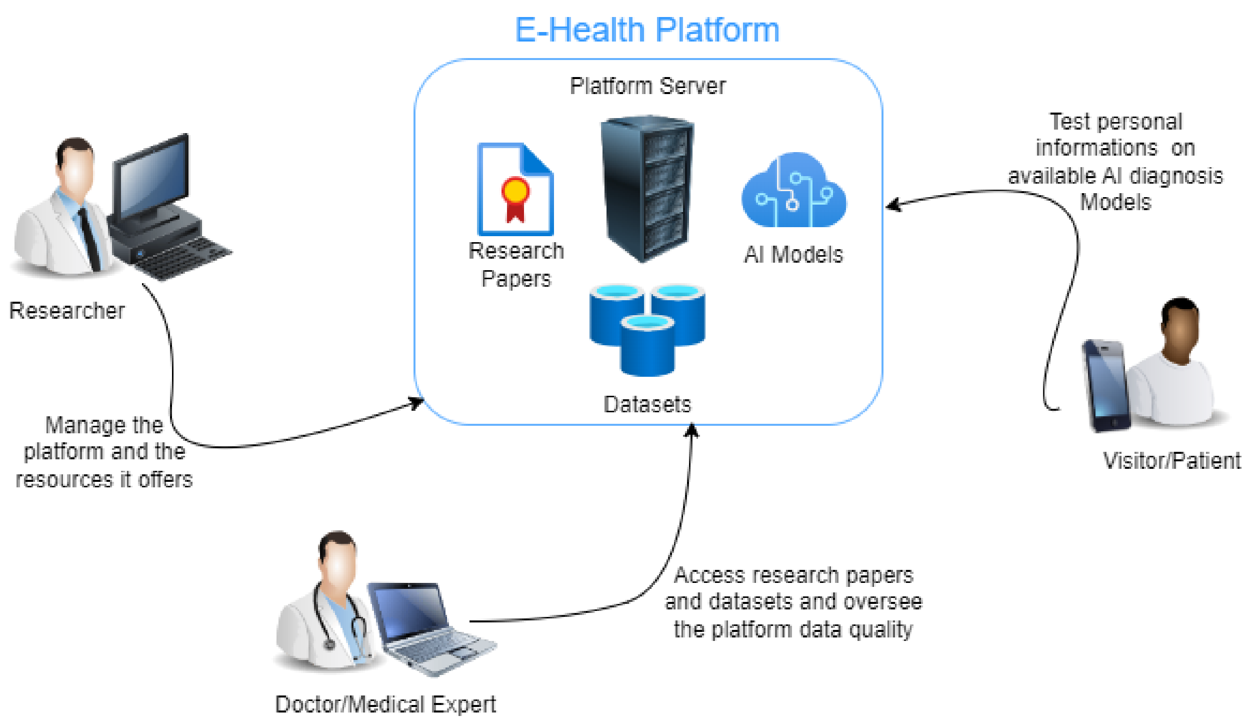

Figure 3.1: General overview of the Platform

3.2.1 Potential Users and Their Roles

In designing our AI-powered healthcare platform, it is essential to consider the diverse range of users who will interact with its functionalities and the different actors.

It is important to clarify the subtle difference between "user" and "actor," as these terms are sometimes confused. A "user" refers to an individual interested in utilizing or benefiting from the platform, while an "actor" specifies a role played by an external entity interacting with the system. Users interact with the system by playing different roles (actors). A single user can interact with the system under different roles at different times, as a role can be played by multiple users depending on the context of system usage. This distinction helps ensure a clear understanding of the interactions and requirements within the platform.

3.2.1.1 Users

The following are the primary categories of users who will interact with our platform, each utilizing its functionalities to achieve their specific goals:

- ***Researchers:*** Conduct research activities using datasets and AI models.
- ***Students:*** Explore and experiment with AI models and medical data.
- ***Teachers:*** Use the platform for educational purposes and to demonstrate AI applications in medical fields.
- ***Doctors:*** Use AI models to assist in diagnosis and analysis of medical images and data.
- ***Biologists:*** Apply AI models in biological and medical research.

3.2.1.2 Actors

The following actors represent the diverse roles and responsibilities for users interacting with our platform:

- ***Visitor:*** Unregistered users who can access limited functionalities such as viewing information and uploading images for AI analysis.
- ***Affiliate user:*** Users who already have an account on our platform. By logging in, they gain access to download datasets and view research papers.
- ***Researcher:*** Registered users with extended privileges, including uploading datasets, models, and research papers.
- ***Administrator:*** Users with full control over the platform, responsible for managing users, datasets, and models, and ensuring system security.

The UML Use Case Diagram provides an overview of the interactions between different actors and the system, highlighting their roles and the functionalities they can access. The General Use Case Diagram (see Figure 3.2) encompasses interactions for non-administrator roles.

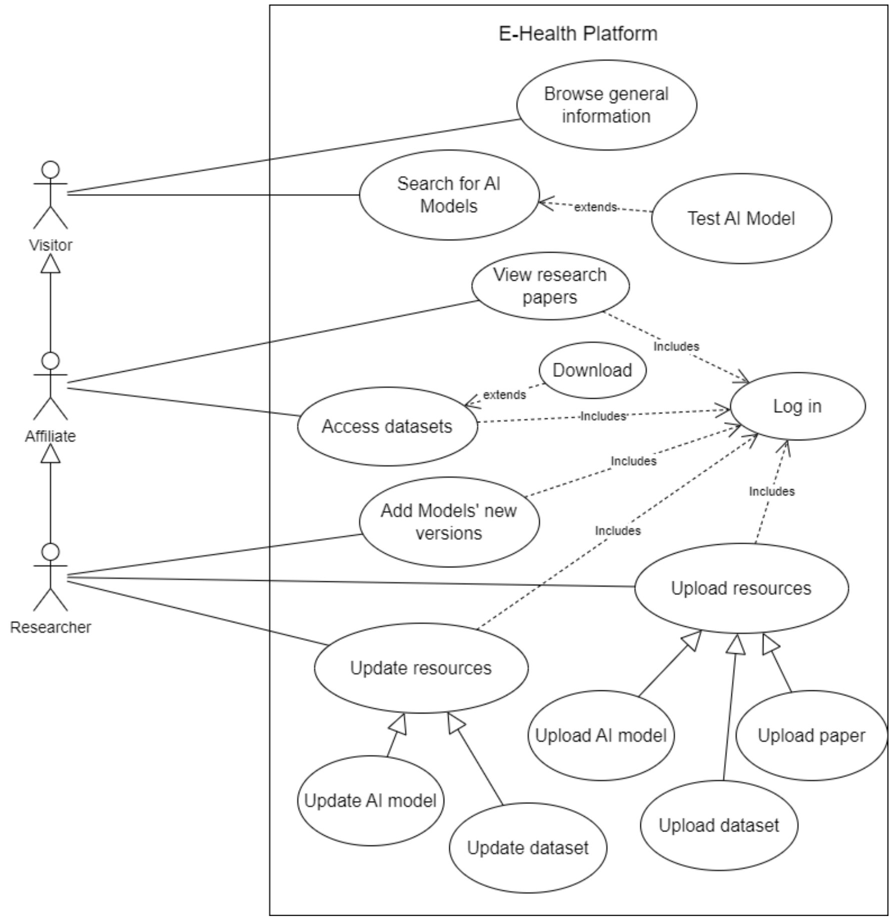

Figure 3.2: General Use Case Diagram

Whereas, the Administrator Use Case Diagram (see Figure 3.3) focuses specifically on administrative functionalities and system management.

3.2.2 Principle Use Cases' Descriptions

In this section, we delve into detailed descriptions of key use cases that outline essential functionalities of the platform:

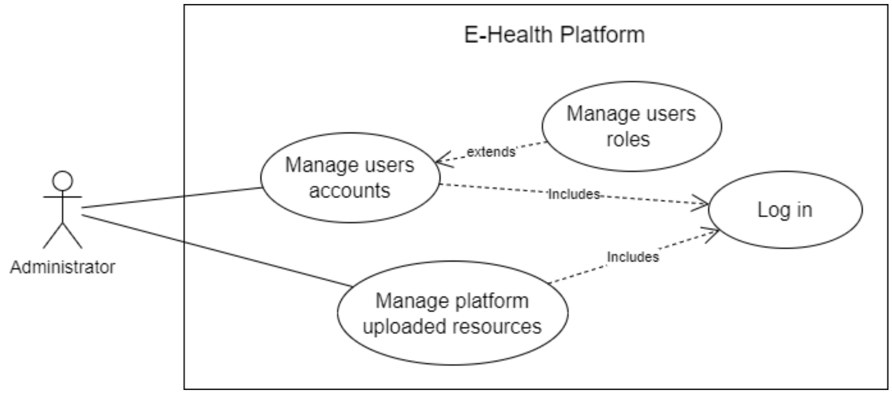

Figure 3.3: Administrator Use Case Diagram

3.2.2.1 Search (and Test) uploaded AI-models:

To facilitate the effective utilization of AI models, this use case outlines the process by which users can search for and test the AI models available on the platform.

- ***Functional requirements:*** Any user can search for available AI models on the platform, and their descriptions. He can also upload medical images (or data) to test an AI model and receive its results.
- ***Involved actors:*** Visitor, Affiliate user, Researcher.
- ***Main scenario:*** The following steps outline the process for searching and testing AI models:
  1. The user logs into the platform (if not a visitor).
  2. The user navigates to the section for browsing available AI models.
  3. The user searches for a specific AI model or browses through the list of available models.
  4. The user views the description and details of the selected AI model.
  5. The user decides to test the model and navigates to the section for uploading medical images.
  6. The user uploads a medical image or dataset to be analyzed.
  7. The platform processes the uploaded image using the selected AI model.
  8. The platform displays the results of the AI model's analysis to the user.

The Figure 3.4 depicts these steps for a visitor.

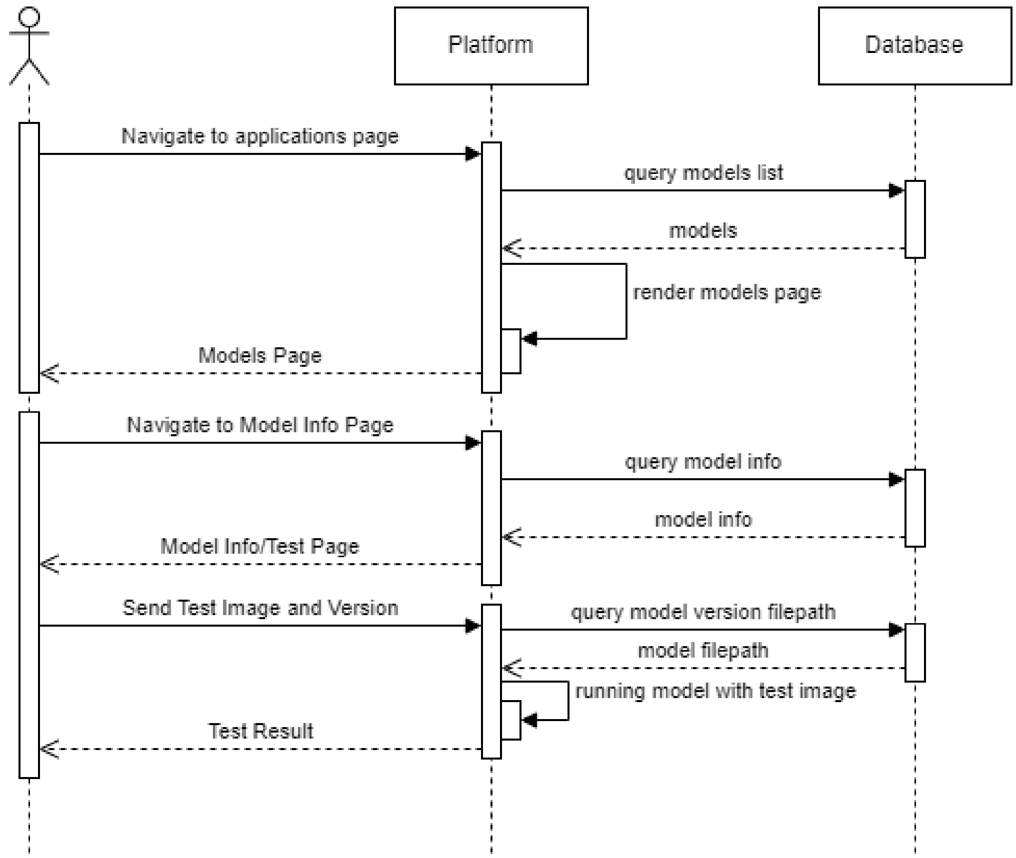

Figure 3.4: Searching and testing AI model Scenario by a visitor

3.2.2.2 View (and download) resources

This use case describes the steps involved for registered users to browse, view details, and download resources available on the platform, such as datasets and research papers.

- ***Functional requirements:*** Registered users can browse and access available resources such as datasets and research papers. They can download these resources for further analysis and study.
- ***Involved actors:*** Affiliate users and Researchers.
- ***Main scenario:*** The following steps outline the process for viewing and downloading resources from the platform:
  1. The user logs into the platform.
  2. The user navigates to the section for browsing available resources.
  3. The user searches for a specific resource or browses through categories.

4. The user views the details and metadata of the selected resource, including its description, format, and usage terms.
5. The user decides to download the resource.
6. The platform verifies user permissions and initiates the download process.
7. The user receives the downloaded resource for local use.

3.2.2.3 Upload AI models

This use case outlines the process for researchers to upload their AI models to the platform, ensuring that each model is accompanied by the necessary metadata.

- ***Functional requirements:*** Researchers can upload AI models to the platform. They should provide descriptions and relevant metadata for each model.
- ***Involved actors:*** Researcher.
- ***Scenario:*** The following steps outline the process for uploading a new AI model on the platform:
  1. The user logs into the platform.
  2. The user navigates to the section for uploading AI models.
  3. The user fills out the required information for the AI model, including the title and description.
  4. The user uploads the AI model file.
  5. The platform adds the AI model to its repository.

Figure 3.5 illustrates these steps by a sequence diagram. While Figure 3.6 outlines the process of updating an existing model on the platform.

3.2.2.4 Manage user accounts

This use case describes the process by which administrators manage user accounts, including the addition of new users and the modification of user roles and details.

- ***Functional requirements:*** Administrators have the capability to manage user accounts, which includes adding and modifying user roles.

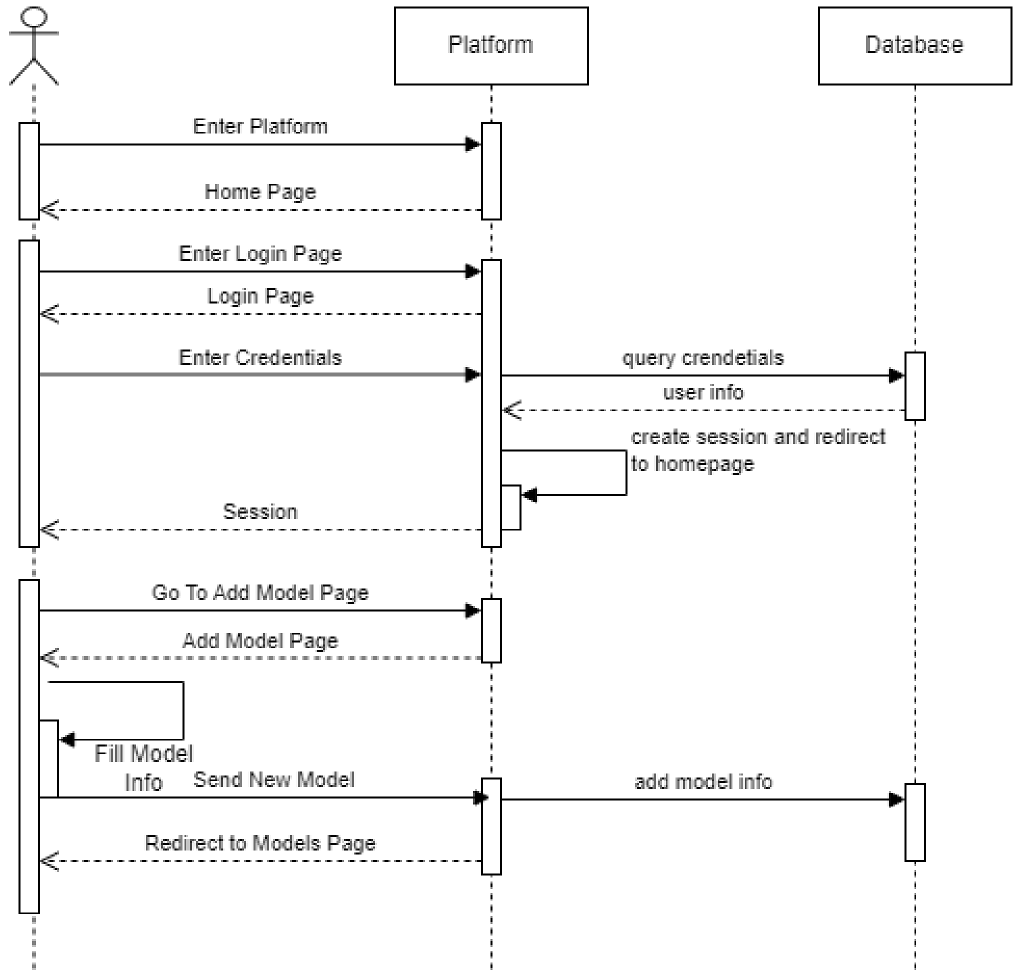

Figure 3.5: Model Upload Scenario

- ***Involved actors:*** Administrator.
- ***Main scenario:*** The following steps outline the process for managing user accounts on the platform:
  1. The administrator logs into the platform.
  2. The administrator navigates to the user management section.
  3. The administrator views the list of existing user accounts.
  4. The administrator adds a new user by entering the necessary information and assigning a role.
  5. The administrator modifies the role or details of an existing user account as needed.
  6. The platform updates the user database to reflect these changes.

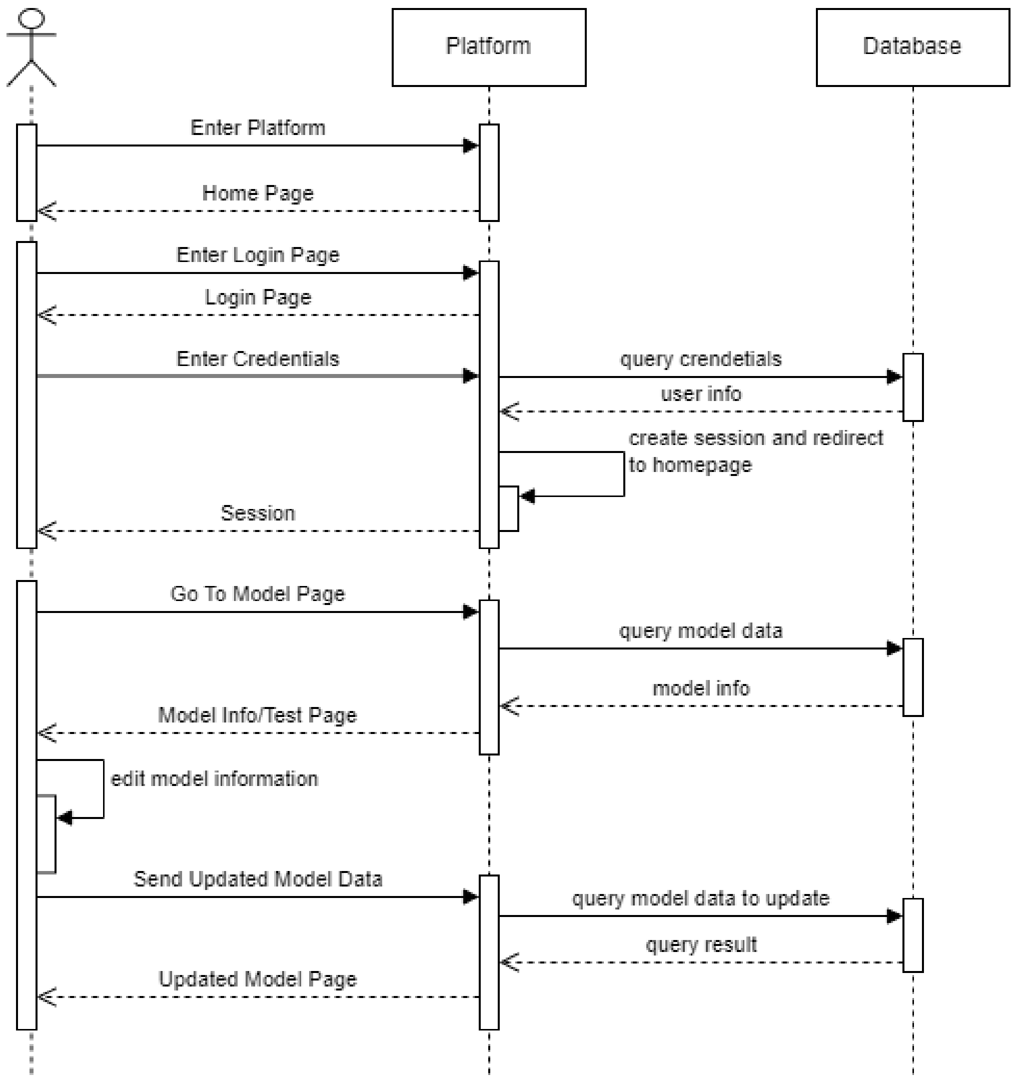

Figure 3.6: Model Update Scenario

3.2.3 Design considerations

Having outlined the primary use cases and their detailed scenarios, we now turn our attention to the design considerations that are fundamental to the development of our AI-powered healthcare platform. It is not enough to simply identify the functional requirements, we must also address the non-functional requirements that ensure the platform's overall effectiveness and usability.

These considerations encompass various aspects such as security, scalability, and performance, each of which is detailed below:

3.2.3.1 Security

- Data Encryption: Some user data, including passwords, should be encrypted during transmission and storage.
- Access Control: Implement robust access control mechanisms to ensure only authorized users can access specific functionalities and data.
- Regular Audits: Conduct regular security audits to identify and address vulnerabilities.

3.2.3.2 Scalability

- Modular Architecture: Design the system with a modular architecture to allow easy integration of new features and components.

3.2.3.3 Performance

- Response Time: Ensure that the platform can handle image uploads and return AI analysis results promptly, with minimal latency.
- Resource Optimization: Optimize the usage of server resources to handle multiple requests efficiently.
- Monitoring and Alerts: Implement performance monitoring tools to track system performance and set up alerts for any issues that may arise.

3.3 Platform Conception

Having outlined the functional and non-functional requirements, we now transition to the platform's design. This section will delve into the architectural design of our platform, emphasizing its adherence to the Model-View-Controller (MVC) architecture. This approach ensures a clear separation of concerns, enhancing maintainability and scalability.

We will first outline the overall platform architecture, followed by a detailed presentation of the database structure which underpins the platform's functionality. Lastly, we will explore the sitemap, illustrating the navigational flow and user access points within the platform.

3.3.1 Platform Architecture

The architecture of our AI-powered healthcare platform is divided into three main components: the user browser interface, the Application Server, and the storage back-end which is called Data Server. This structure ensures a robust, scalable, and efficient system that meets both functional and non-functional requirements. These components are illustrated in Figure 3.7 and explained below:

3.3.1.1 User browser interface

The user browser interface serves as the entry point for users, providing an intuitive and user-friendly environment to interact with the platform. This component includes the front-end application where users can browse AI models, upload medical images, download resources, and more.

3.3.1.2 Application Server

The core of the platform is the application server, which handles the business logic and manages communication between the user interface and the storage back-end. It consists of several key modules:

- ***Router:*** Directs incoming requests to the appropriate handler based on the URL and

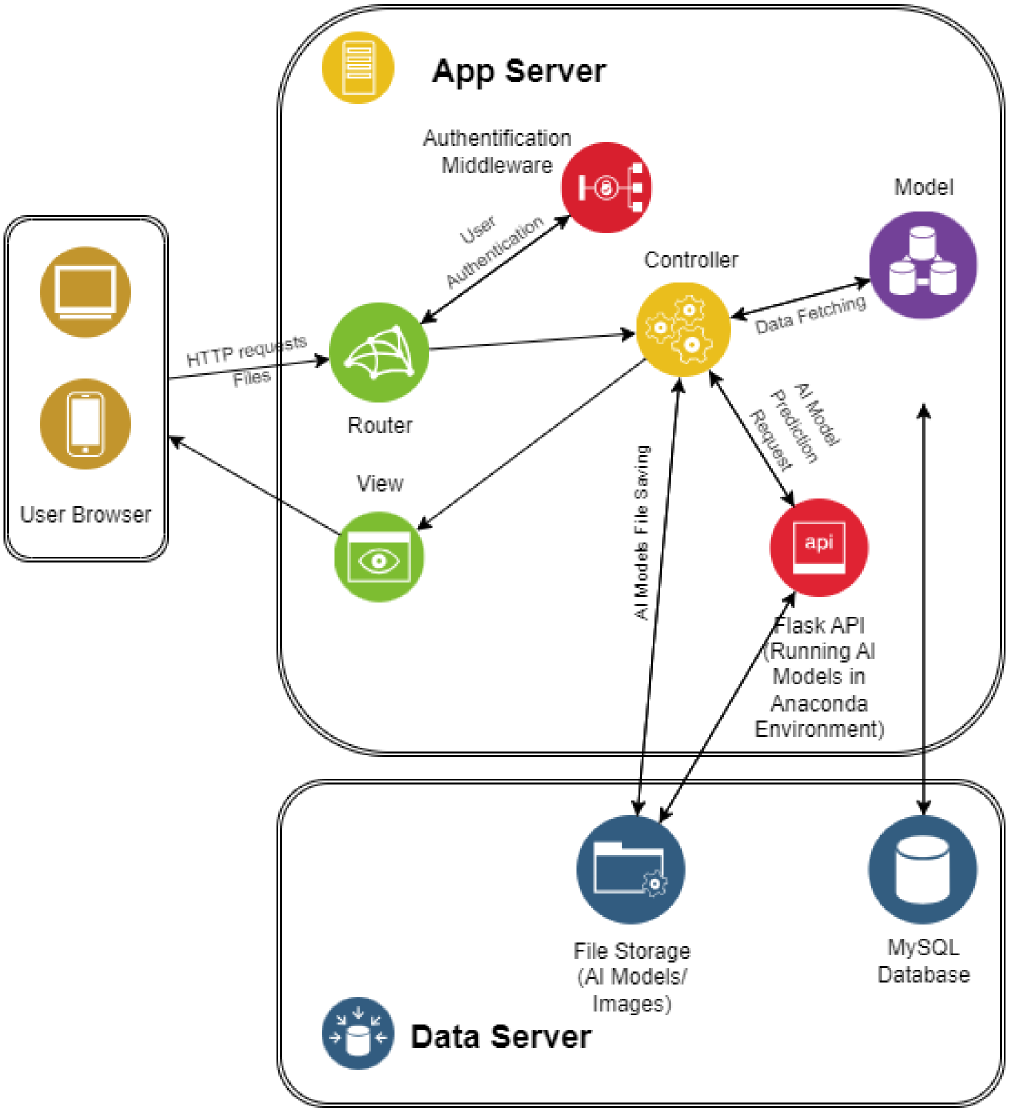

Figure 3.7: Platform Architecture

HTTP method.

- ***Authentication Middleware:*** Ensures secure access to the platform by verifying user credentials and managing sessions.
- ***Controller:*** Implements the application logic, processing requests from the user interface and invoking the necessary operations.
- ***Model:*** Defines the data structures and relationships, acting as an interface between the controller and the database.
- ***Flask API:*** Hosts the AI models and manages their execution, providing results back to the controller for display to the user.

- ***View:*** Renders the user interface, generating the HTML, CSS, and JavaScript needed to display data and interact with users.

3.3.1.3 Storage Back-end (Data Server)

The storage back-end is responsible for persisting data and files, comprising two main components:

- ***MySQL Database:*** Stores structured data such as user information, AI model metadata, and resource descriptions. The structure of our Database is illustrated in Figure 3.8 through an Entity-Relationship diagram.
- ***File Storage:*** Manages unstructured data including AI model files and datasets, ensuring they are accessible for processing and retrieval.

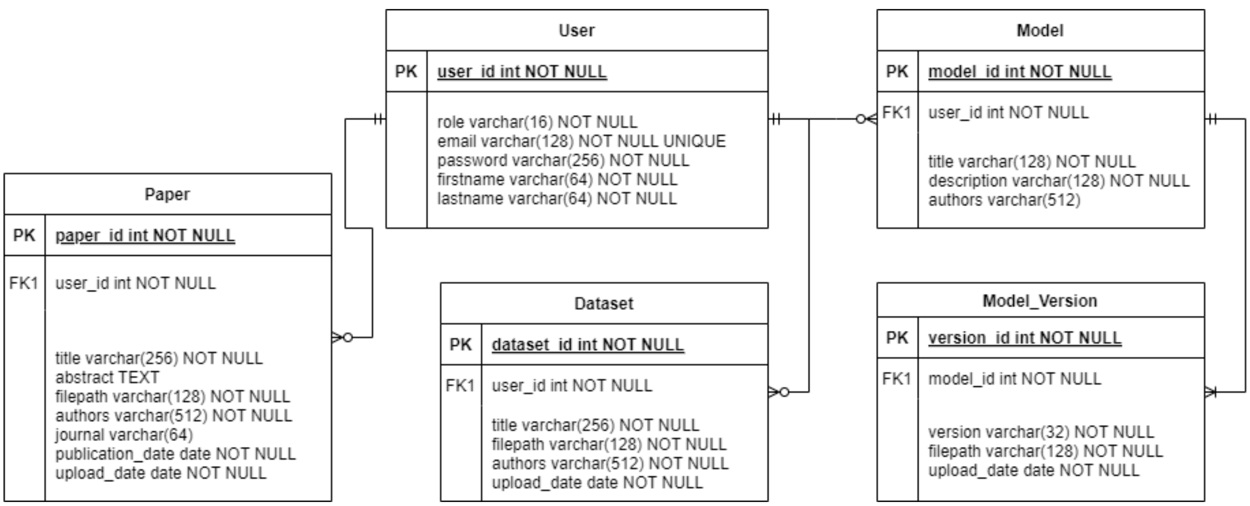

Figure 3.8: Database Entity-Relation Diagram

3.3.2 Sitemap

The following sitemap (see Figure 3.9) illustrates the structure of our platform, outlining the primary sections and their hierarchical relationships. This visual representation helps to understand the organization of pages and the navigation flow.

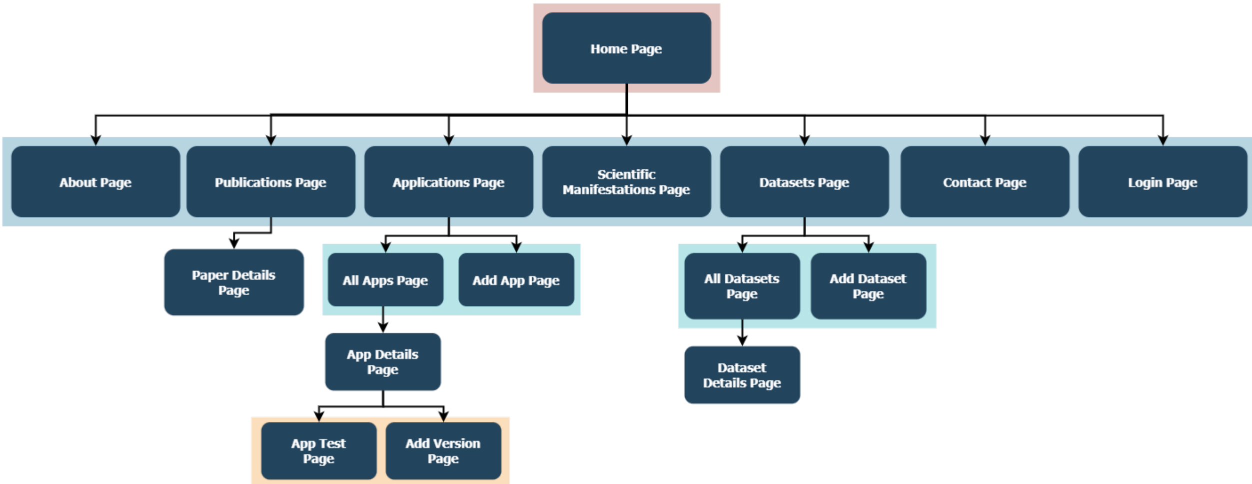

Figure 3.9: Platform Sitemap

3.4 Platform Realization

In this section, we present the technical implementation details of our AI-powered healthcare platform, highlighting the languages and tools. We conclude by exposing the key interfaces developed.

3.4.1 Used languages and tools:

The platform is built using a combination of modern technologies and frameworks:

- ***HTML:*** Hypertext Markup Language (HTML) is the standard markup language for creating web pages and web applications. It was developed by Tim Berners-Lee in the early 1990s as part of the creation of the World Wide Web (WWW).
- ***CSS:*** Cascading Style Sheets (CSS) is a style sheet language used to describe the presentation and design of a document written in HTML or XML. CSS controls the layout, colors, fonts, and overall appearance of web pages, enhancing the user experience. It was created by Håkon Wium Lie and Bert Bos while working with the World Wide Web Consortium (W3C) in 1996.
- ***JavaScript:*** is a programming language commonly used to create interactive effects and dynamic content on websites. It was created by Brendan Eich while he was working at

Netscape Communications Corporation. He developed the language in just 10 days in May 1995.

- ***Node JS:*** is an open-source, cross-platform JavaScript runtime environment that executes JavaScript code outside of a web browser, primarily on the server side. It was created by Ryan Dahl in 2009. It enables developers to use JavaScript for server-side scripting, allowing them to build scalable network applications with a single programming language.
- ***MySQL:*** is a widely used free and open-source relational database management system (RDBMS). Its name is a combination of "My", the name of co-founder Michael Widenius's daughter My, and "SQL", the acronym for Structured Query Language. It is ideal for both small and large applications.
- ***Flask:*** Flask is a micro web framework written in Python. It is classified as a microframework because it does not require particular tools or libraries. It has no database abstraction layer, form validation, or any other components where pre-existing third-party libraries provide common functions.
- **Visual Studio Code (*VSCode*):** is a free, open-source code editor developed by Microsoft. It provides features like debugging, syntax highlighting, and version control integration, making it a popular choice among developers for writing and managing code.

3.4.2 Interfaces' screenshots

We have developed a wide range of pages and features within the platform, each designed to meet the unique needs of healthcare professionals. For doctors, researchers, and laboratories, the login process is simple and efficient, allowing them to access the platform with ease. The user-friendly interfaces make it easy to add new projects, papers, datasets, and model versions. Each part of the platform is thoughtfully designed to improve the user experience and encourage collaboration among healthcare professionals and researchers. By focusing on these details, we aim to support their work, make it easier for them to share information and develop new ideas together, and make them easier to access for public visitors. The following figures represent screenshots from different pages from our platform:

Figure 3.10 illustrates the home page view of the platform.

Figure 3.10: Home Page

Figure 3.11 presents the "About" page overview, While, Figure 3.12 showcases the team members section within the "About" page.

The "Published Papers" page and "AI Applications" page are respectively shown in Figure 3.13 and Figure 3.14. The page for uploading a new model is depicted in Figure 3.15, while Figure 3.16 displays the AI application testing interface.

Figure 3.17 provides an of the datasets page, Figure 3.18 shows the interface for uploading a new dataset, and Figure 3.19 displays detailed information and download options for a specific dataset.

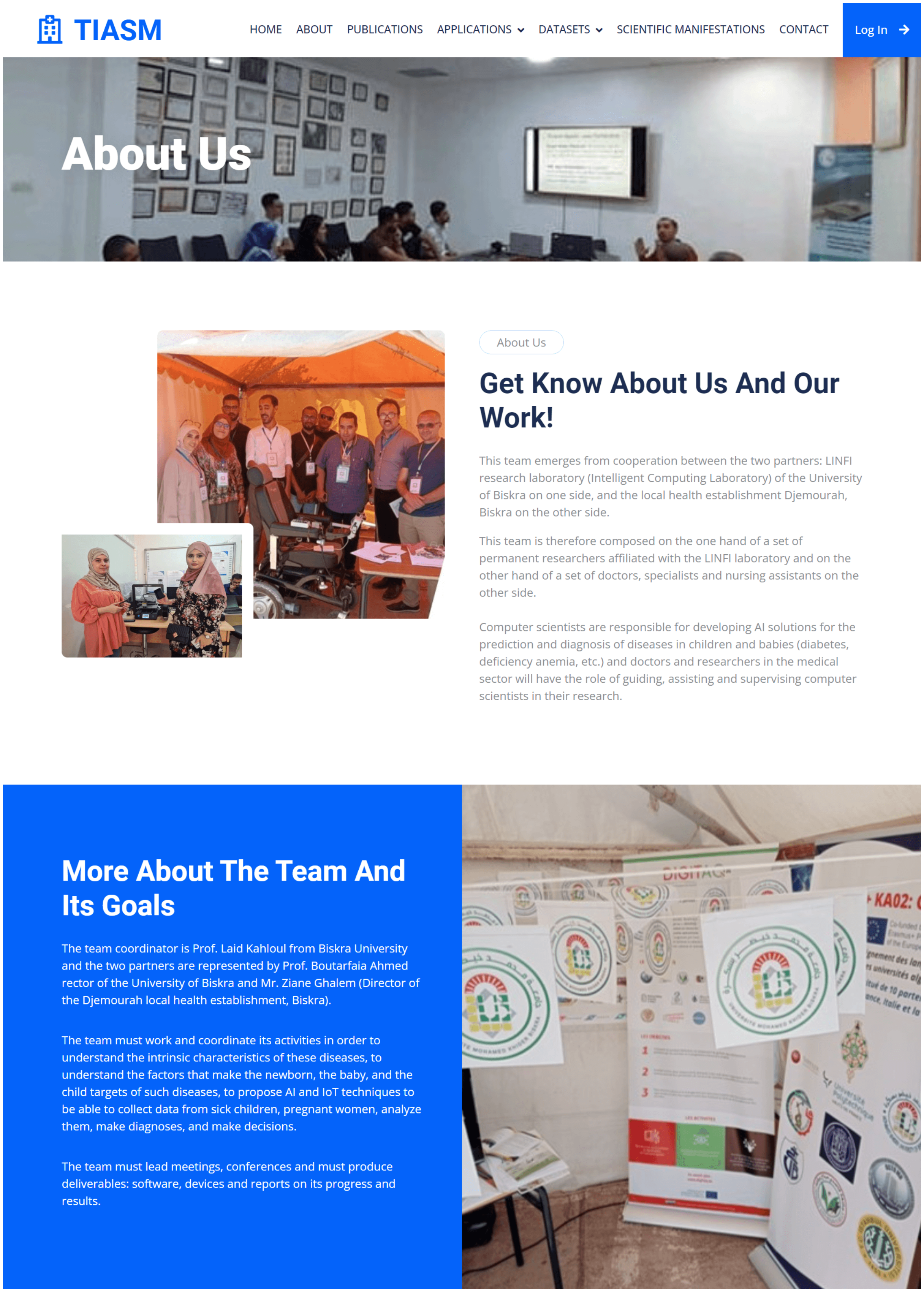

Figure 3.11: About Page

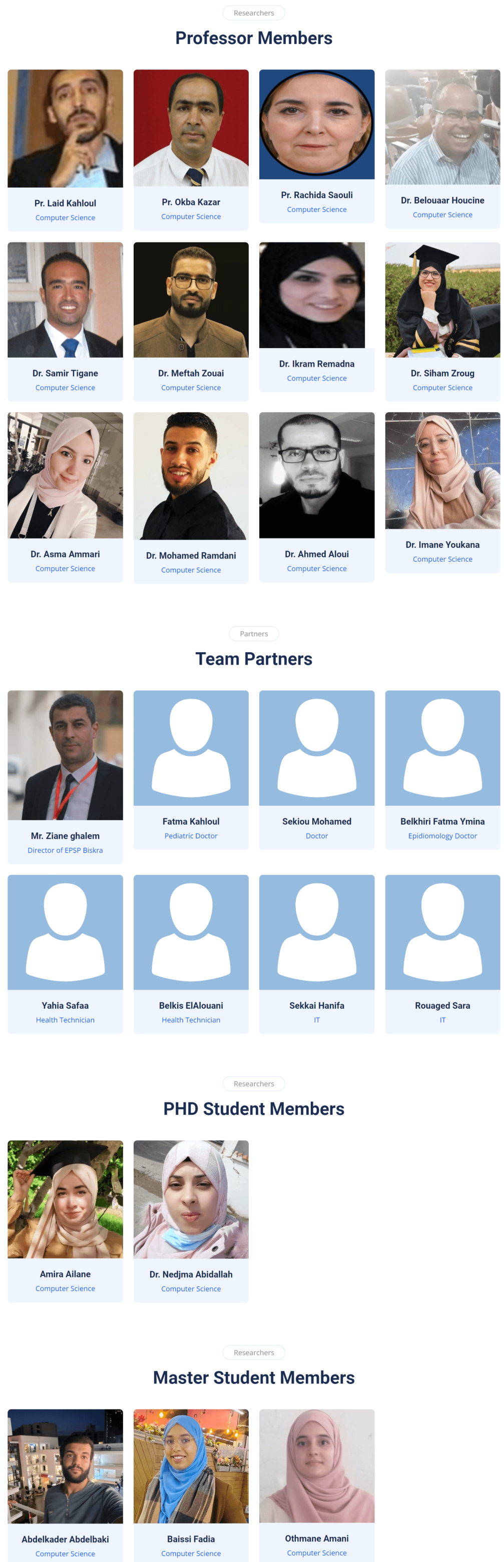

Figure 3.12: About Page Team Members

Figure 3.13: Publications Page

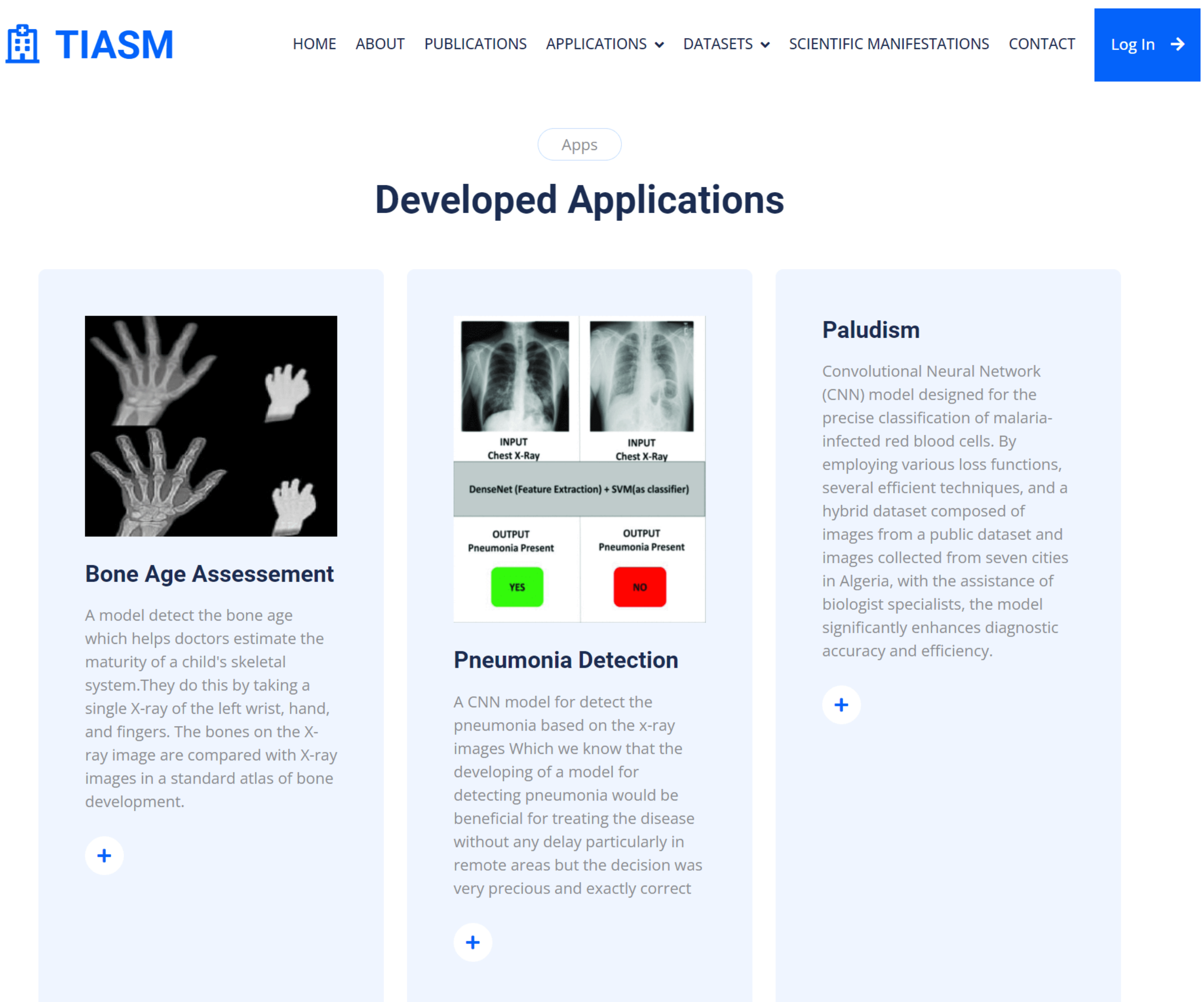

Figure 3.14: Apps Page

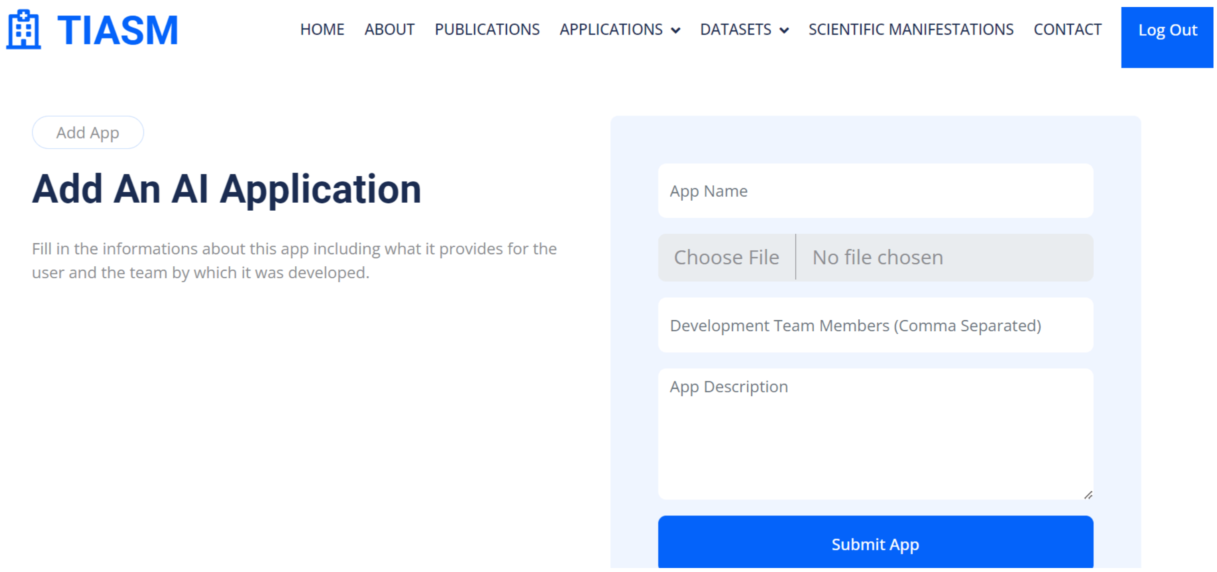

Figure 3.15: Add App Page

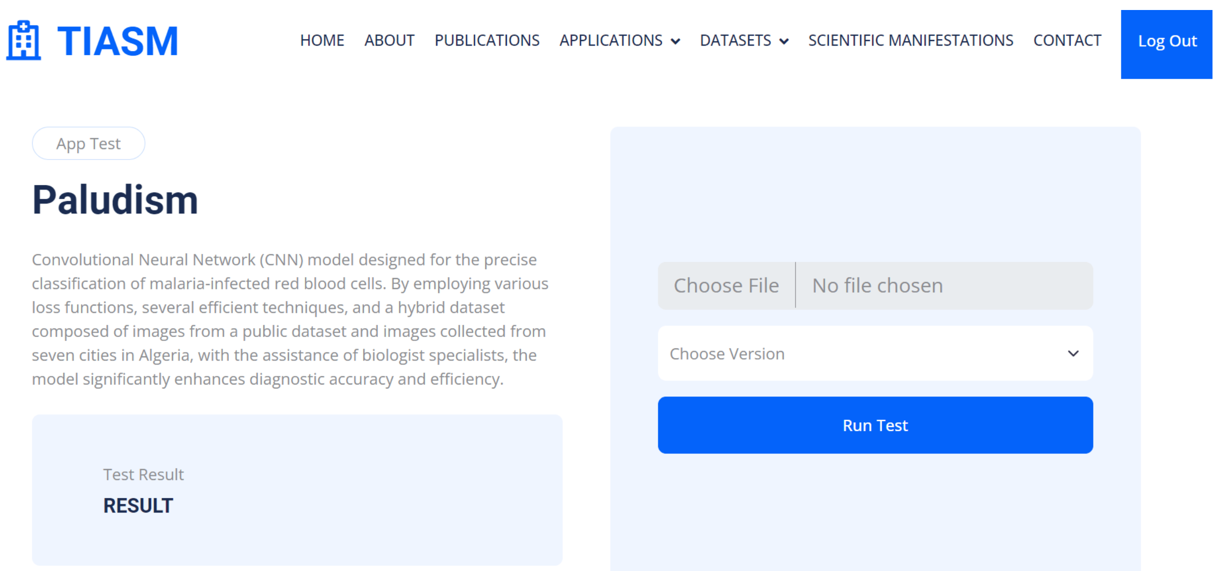

Figure 3.16: Test App Page

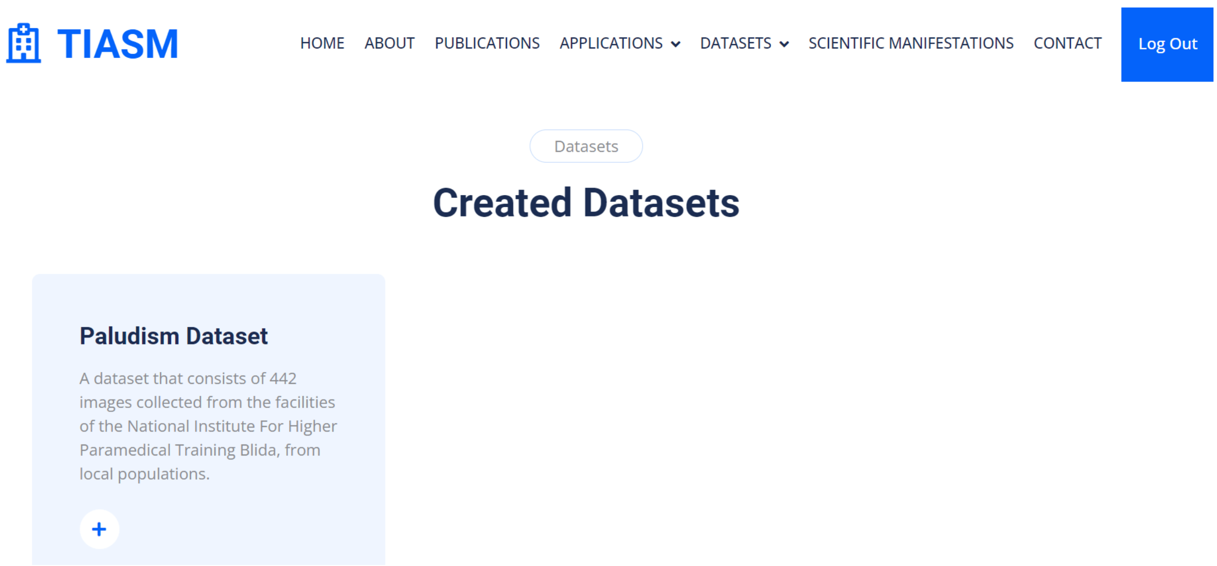

Figure 3.17: Datasets Page

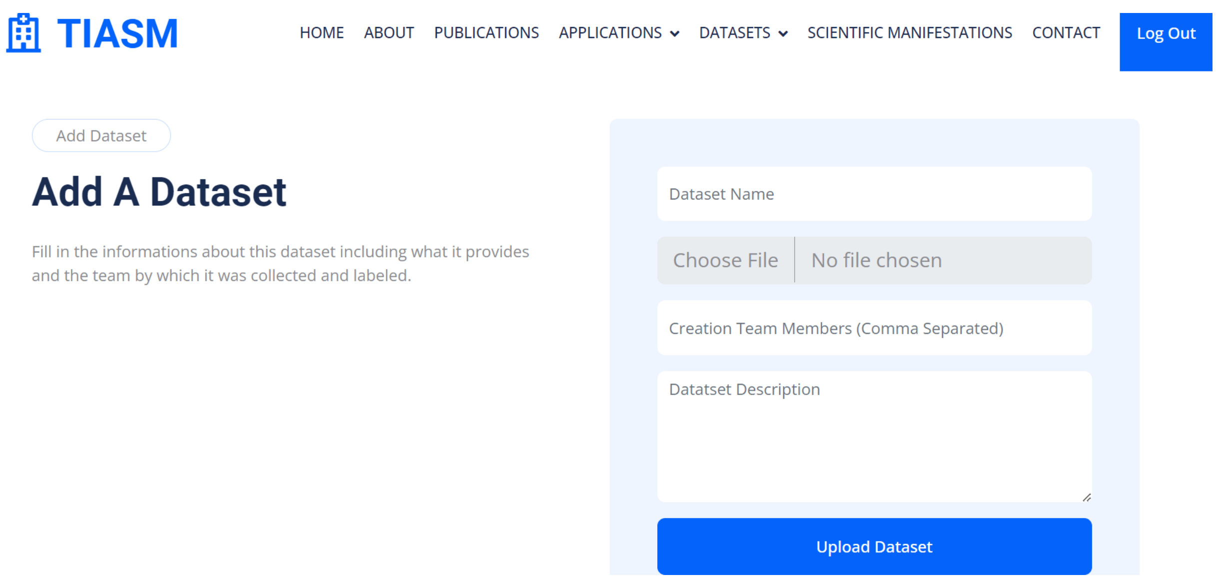

Figure 3.18: Add Dataset Page

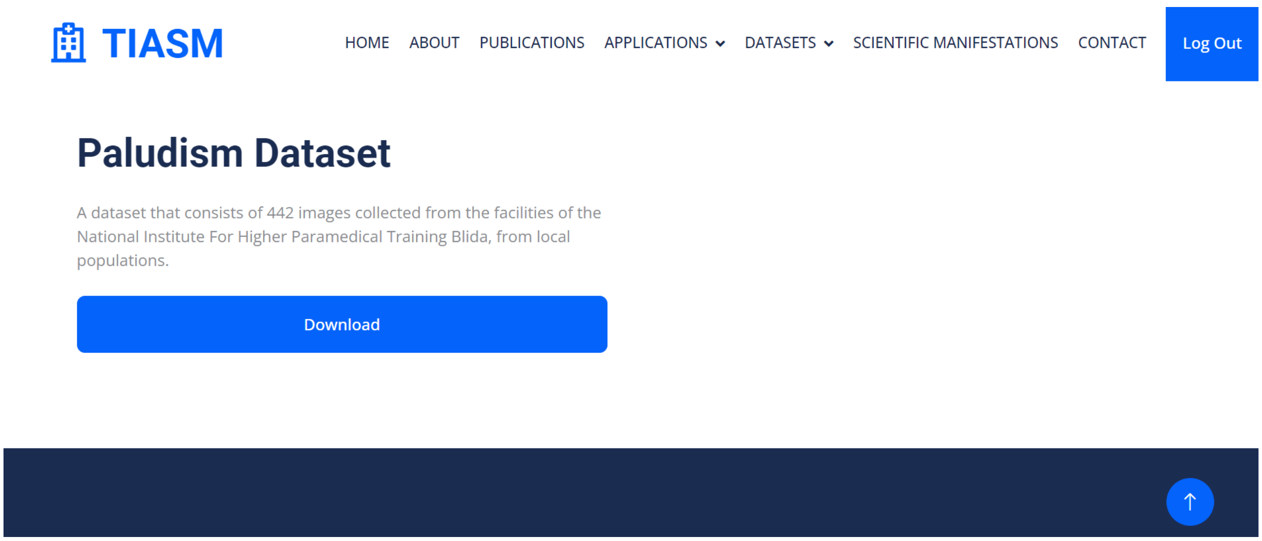

Figure 3.19: Download Dataset Page

3.5 Conclusion

In conclusion, this chapter has provided a comprehensive overview of the key components and functionalities of our AI-powered healthcare platform. We began by outlining the actors of the platform, the primary use cases, and then detailing how users interact with the platform to search, test AI models, manage resources, and administer user accounts. Emphasizing both functional and non-functional requirements, we highlighted the importance of scalability, security, and performance in ensuring the platform's robustness.

Moving forward, we delved into the technical implementation, discussing the architecture based on the Model-View-Controller (MVC) paradigm. The platform's backend, including the application server and storage backend, was explored in detail, showcasing its capability to handle diverse data types and interactions seamlessly. Finally, we presented the platform realization, illustrating key interfaces through screenshots.

In the next chapter, we will present the development of a specific AI model for malaria detection, which constitutes the second objective of our project.

Chapter 4

Paludism Diagnosis Proposed Approach

4.1 Introduction

The integration of AI into the process of healthcare diagnosis imaging type represents a transformative milestone, where AI algorithms emerge as indispensable allies to healthcare providers in navigating the complexities of disease detection and patient management. Leveraging the power of advanced ML and DL methodologies, these AI systems have the ability to analyze vast and diverse datasets.

In this chapter, we will outline and explain the various components involved in the implementation of our model. We begin with a discussion of the general approach taken in our study. This is followed by a detailed description of the dataset used, including its characteristics and sources. Next, we will cover the image data preprocessing steps necessary to prepare the dataset for analysis. We then present the proposed approach, detailing the specific techniques and algorithms employed. Model requirements, including hardware and software specifications, are also discussed. Following this, we will describe the training experimentations conducted to fine-tune the model. Finally, we will discuss the results obtained from these experimentations, analyzing their implications and effectiveness.

4.2 General approach

The proposed approach for classifying malaria-infected red blood cells involves a systematic process that begins with dataset preparation and preprocessing to enhance image quality. This is followed by data augmentation to increase dataset diversity, and the initiation of a CNN for feature extraction. The CNN model is then trained on the dataset, which is split into 80% for training and 20% for testing and validation. After training, the model undergoes fine-tuning to optimize its performance, and is subsequently used for identifying malaria parasites. Finally, the model's performance is evaluated using standard metrics to ensure accuracy and reliability. The Paludism detection proposed system visualized in Figure. 4.1 which it illustrates the sequential steps of our proposed system.

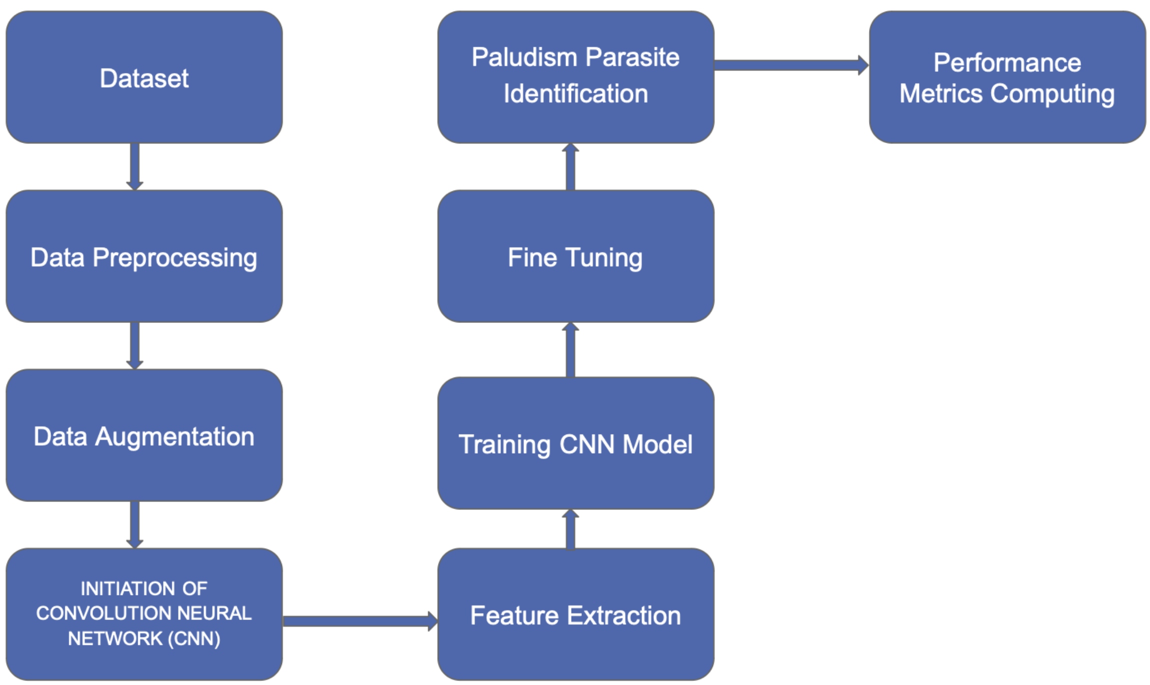

Figure 4.1: Proposed System for Malaria Diagnosis

4.3 Dataset Description

In our study on malaria detection using a CNN model, our dataset is sourced from two distinct locations. The first part comprises 27,116 images obtained from online repositories [17], while the second part consists of 442 images collected from the facilities of the National Institute For Higher Paramedical Training Blida with the goal of addressing these limitations and eventually applying the model to local populations. These images are categorized into two classes: **uninfected** and **parasitized**. Fig. 4.2 shows an example of two images (thus, two classes) obtained from the Higher Paramedical Training Center, hence belonging to our local data set.

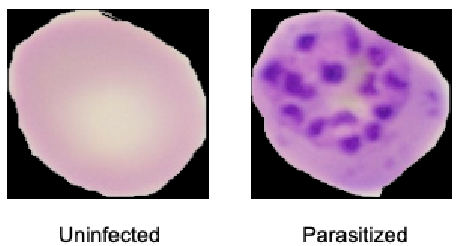

Figure 4.2: Example of data set of classes

To summarize, our dataset contains an equal distribution of 13779 images for each class, ensuring a balanced representation of both uninfected and parasitized samples. This balanced class distribution is crucial for training our CNN model effectively and minimizing bias in our results.

4.4 Image Data Preprocessing

In preparing the dataset for training our CNN model for Paludism diagnosis, we implemented several data preprocessing and augmentation techniques to enhance the quality and diversity of our data. Initially, we performed standard preprocessing steps, including resizing all images to a consistent size of 100x100 pixels and normalizing pixel values to a standardized range [0, 1]. Additionally, we carefully inspected the dataset for any corrupted or low-quality images and removed them to ensure data integrity.

To address the class imbalance and increase the diversity of our training data, we employed data augmentation techniques such as rotation, flipping, zooming, and shifting. By randomly applying these transformations to our images, we generated new samples that simulate variations in image orientation, scale, and position. This augmentation process not only increased the size of our dataset but also introduced robustness to our CNN model by exposing it to a wider range of image variations.

Furthermore, given the sensitive nature of medical image data, we paid special attention to maintaining the integrity and authenticity of our dataset throughout the preprocessing and augmentation process. We ensured that all data manipulations were performed transparently and ethically, with careful consideration of patient privacy and consent.

Overall, the combination of preprocessing and augmentation techniques employed in our dataset preparation phase played a crucial role in improving the performance and generalization ability of our CNN model for malaria detection.

4.5 Proposed approach

The proposed CNN architecture for malaria detection is designed to effectively capture and learn discriminative features from microscopic images of blood smears. The architecture consists of four Conv2D layers, each followed by a RELU activation function to introduce non-linearity. The number of filters in these convolutional layers is gradually increased from 50 to 90, then decreased to 10, and finally to 5, allowing the model to learn hierarchical representations of the input images. Following the convolutional layers, three dense layers are incorporated with RELU activation functions, facilitating the aggregation and refinement of learned features. The final dense layer employs a sigmoid activation function to produce binary predictions indicating the likelihood of each class (infected or uninfected). This architecture is tailored to the specific characteristics of Paludism-infected blood smear images, aiming to achieve high accuracy and robustness in detecting the presence of malaria parasites. Additionally, the simplicity of the architecture makes it computationally efficient and suitable for deployment in resource-constrained environments. To compare the performance of our basic CNN model, we experiment with different loss functions during model compilation. We consider standard loss functions such as binary cross-entropy and sparse categorical cross-entropy. By evaluating the performance of our model architectures across multiple loss functions, we aim to gain insights into their respective strengths and weaknesses in the context of malaria detection. Through empirical analysis and comparative experiments, we seek to identify the most effective combination of model architecture and loss function for accurate and reliable detection of malaria parasites in microscopic images of blood smears. Fig. 4.3 shows the Proposed CNN Architecture.

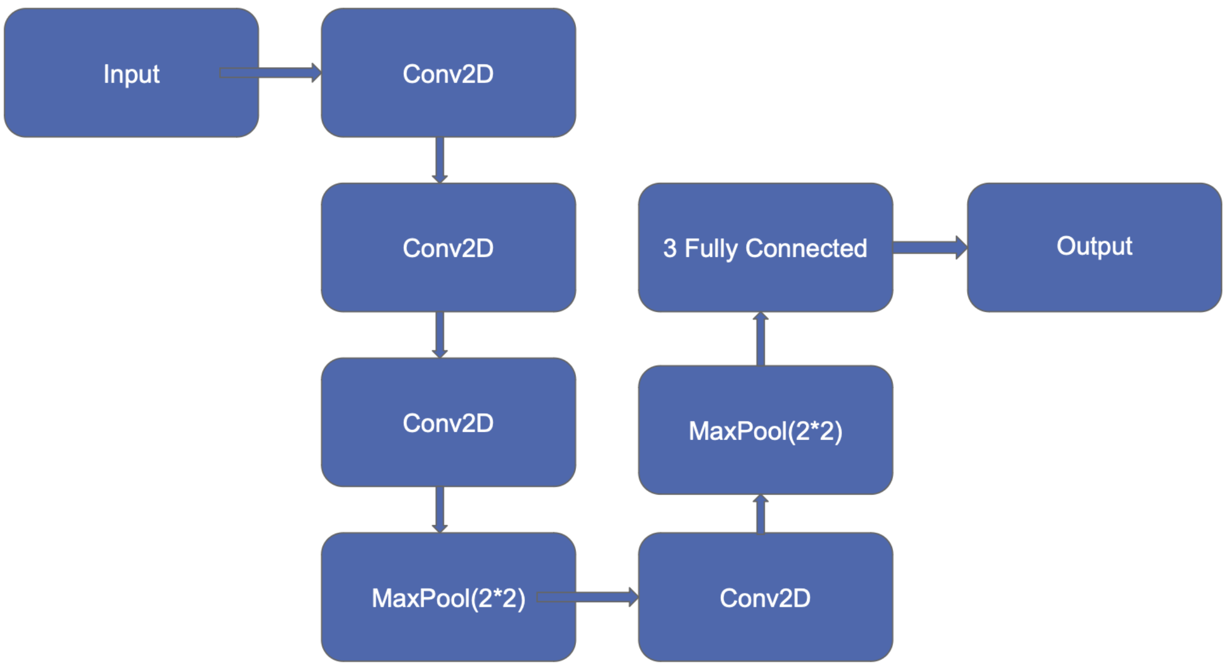

Figure 4.3: Proposed CNN Architecture

4.6 Model requirements

There is many essential requirements for the implementation of our mode. This includes both software and hardware specifications, detailing the necessary tools, libraries, frameworks, and computational resources required to develop, train, and test the model.

4.6.1 Software requirements

The proposed model require several necessities for the implementation. This includes the specific programming languages, libraries, and frameworks used, as well as any other relevant software tools essential for developing, training, and testing the model.

- **Python:** Python is a versatile, general-purpose, interpreted, and high-level computing programming language, developed by Guido van Rossum and originally published in 1991.
- **TensorFlow:** is an open-source framework developed by Google to perform machine learning, deep learning, and other statistical and predictive analytics workloads.
- **Keras:** is an interface for the TensorFlow library, and is an open-source software library suitable for artificial neural networks.
- **NumPy:** its creator is Travis Oliphant. It is a Python fundamental scientific computing library used for working with arrays. It also has functions used in the linear algebra domain, fourier transform, and matrices.
- **Matplotlib:** is a python library available as a component of NumPy to make plots, it is a resource for a big data numerical treatment. Matplotlib has an object-oriented API to establish plots in Python applications.
- **Kaggle:** is a website that allows users to find and publish data set and share ideas, learn new information, and find a lot of coding tricks, as well as observe different examples of real-world data science applications.
- **Spyder:** is a cross-platform which is an open-source integrated development environment (IDE) for scientific programming in the Python language.
- **Jupyter:** is an open-source web application that allows you to create and share documents containing live code, equations, visualizations, and narrative text. It is widely used for data analysis, scientific research, machine learning, and computational journalism.
- **Anaconda:** is a distribution of the Python and R programming languages used for data science and machine learning tasks. It includes a collection of open-source packages and libraries for scientific computing, data analysis, and visualization. Anaconda was created by Continuum Analytics, now known as Anaconda, Inc.
- **Github:** is a web-based platform for version control using Git. It allows developers to col-

laborate on projects, track changes to code, and manage software development projects. GitHub was founded by Chris Wanstrath, P. J. Hyett, Tom Preston-Werner, and Scott Chacon in 2008.

4.6.2 Hardware requirements

In the other hand, several hardware necessities are required also. The model was implemented on a Virtual Machine (VM) created on a VMware ESXI server, located in our laboratory LINFI. The specifications of this virtual machine include 16 Go of RAM, a processor with 8 vCPUs, and storage of 500GB. These resources, along with sufficient storage capacity and reliable network connectivity, provided the necessary computational power and environment to efficiently develop, train, and evaluate our model.

4.7 Training and Experimentation

During the training phase, K-Fold cross-validation was utilized with k=3, following a methodology similar to that described in existing literature such as the research conducted by Nizar Ahmed Et al. on the classification of various subtypes of leukemia from microscopic blood cell images using CNN [1]. This methodology enabled a systematic assessment of model performance while reducing the likelihood of overfitting. Throughout the experimental process, different hyperparameters were investigated, including batch size and number of epochs, and the optimizer in order to enhance model effectiveness. After multiple iterations, it was determined that a batch size of 16, 140 epochs and RMSProp optimizer produced the most favorable outcomes in terms of both accuracy and convergence. This outcome highlights the significance of hyperparameter optimization in achieving peak performance in tasks related to DL. By employing cross-validation techniques and refining hyperparameters, the objective was to establish the reliability and applicability of the models across various datasets and folds, thereby strengthening the credibility of the results and implications.

4.8 Results and discussion

The most Probabilistic loss functions used are binary cross entropy and categorical cross-entropy. In the following items we will define them and give the equations of them:

- **Binary Cross-Entropy Loss Function**

  This function records the number of errors and the accuracy of its estimations for every category. It accomplishes this by averaging the mistakes in the two categories [24]. Equation 4.1 illustrates the formula of calculating binary cross entropy loss function. It is calculated as follows:

$$\text{loss} = -\frac{1}{\text{output size}} \sum_{i=1}^{\text{output size}} y_i \cdot \log \hat{y}_i + (1 - y_i) \cdot \log (1 - \hat{y}_i) \tag{4.1}$$

- **Categorical Cross entropy Loss Function**

  The computation of the difference between two probability distributions is its main goal. This function is applied to a multi-class classification job that combines the Softmax activation function with categorical cross-entropy [24]. Equation 4.2 illustrates the formula of calculating category cross entropy loss function. It is calculated as follows:

$$\text{Loss} = - \sum_{i=1}^{\text{output size}} y_i \log \hat{y}_i \tag{4.2}$$

In the following charts, we present the results obtained from our various experiments comparing the performance of our CNN model with different loss functions and hyperparameters. These experiments were conducted to evaluate the effectiveness of different loss functions in optimizing the performance of our model for malaria detection. Through rigorous experimentation and analysis, we aim to identify the most suitable loss function for achieving accurate and reliable malaria detection using our CNN model. The results presented in these charts offer valuable insights into the impact of binary cross entropy loss function on the overall performance of our model. Figure. 4.4 shows the obtained results in the training phase with Categorical Cross-entropy Loss Function. Figure. 4.5 shows the obtained results in the training phase with Binary Cross-entropy Loss Function.

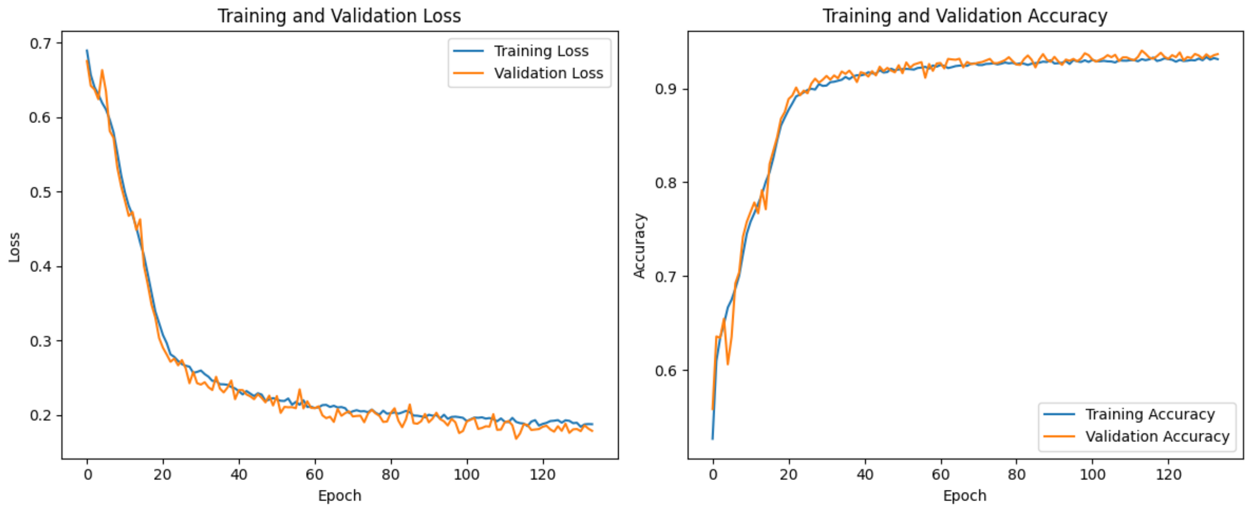

Figure 4.4: Training Results with categorical cross-entropy loss function

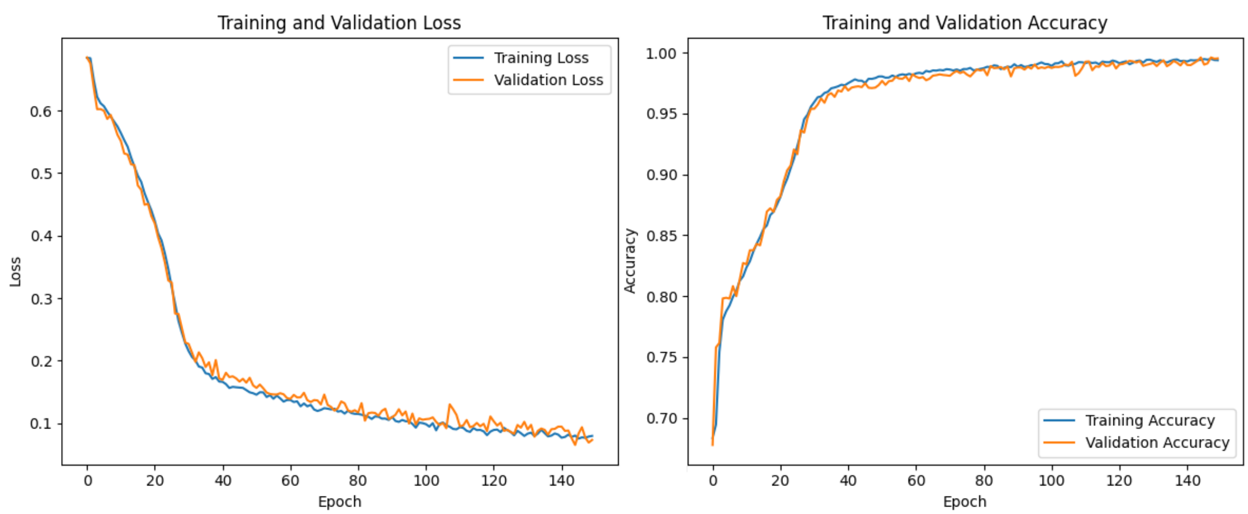

Figure 4.5: Training Results with binary cross entropy loss function

Moreover, we evaluated the performance of our CNN model in predicting the presence of hard-to-detect malaria parasite cells in microscopic images of blood smears. The tables provide a comprehensive overview of key performance metrics, including accuracy, precision, specificity, F1-score recall, sensitivity, and AUC, obtained across different loss functions. Through meticulous analysis, we identified instances where our model successfully detected these challenging cells, resulting in true positive predictions. These accurate predictions demonstrate the robustness and efficacy of our model in identifying subtle and hard-to-detect malaria parasite cells, showcasing its potential for enhancing malaria diagnosis accuracy in real-world clinical settings. By highlighting these successful predictions, we underscore the practical utility and clinical relevance of our CNN model in improving malaria detection outcomes and ultimately advancing patient care. Table. 4.1 shows testing results with loss functions.

Metric	Method	Results
Categorical Cross Entropy	CNN	Accuracy: 0.9372 Precision: 0.9358 F1-Score: 0.9394 Specificity: 0.9348 Recall: 0.9397 Sensitivity: 0.92 AUC: 0.91
Binary Cross Entropy	**CNN**	**Accuracy: 0.9975** **Precision: 0.9893** **F1-Score: 0.9975** **Specificity: 0.9892** **Recall: 1.000** **Sensitivity: 0.98** **AUC: 0.9985**

Table 4.1: Testing Results across Loss Functions

Figure 4.6 illustrates more details in the confusion matrix about results obtained using binary cross entropy loss function.

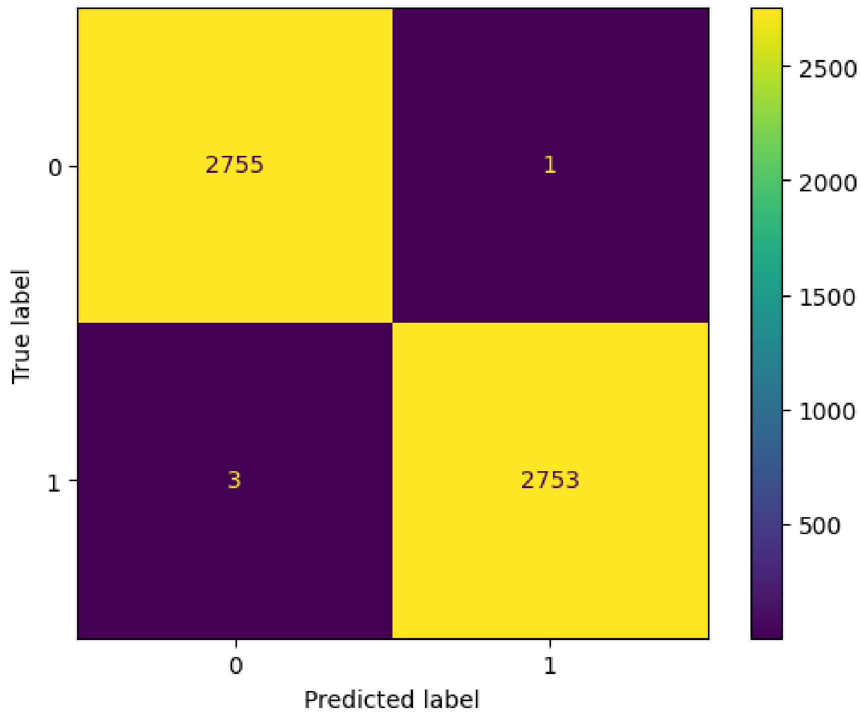

Figure 4.6: Confusion matrix with binary cross entropy loss function

Finally, this is a comparison between the best results obtained in our study with those of the best previous research over 2022-2024. Table. 4.2 shows a comparison of results between our work and related works.

CNN	Accuracy	Precision	F1-Score	Specificity	recall	sensitivity	AUC
[39]	0.9844	N/A	N/A	N/A	N/A	N/A	N/A
[30]	0.9720	N/A	1.9399	0.9641	N/A	0.9796	N/A
[24]	0.9890	0.9859	0.9894	0.9929	N/A	0.9848	N/A
Proposed Model	**0.9975**	**0.9893**	**0.9975**	**0.9892**	**1.000**	**0.98**	**0.9985**

Table 4.2: Comparison between our results and best previous research over 2022-2024.

4.9 Conclusion

In this chapter, we outlined and explained the various components involved in the implementation of our model. We began by discussing the general approach taken in our study, followed by a detailed description of the dataset used, including its characteristics and sources. We covered the image data preprocessing steps necessary to prepare the dataset for analysis and presented the proposed approach, detailing the specific techniques and algorithms employed. We also discussed the model requirements, including hardware and software specifications. The chapter then described the training experimentations conducted to fine-tune the model. Finally, we discussed the results obtained from these experimentations, analyzing their implications and effectiveness in achieving our research objectives.

General Conclusion and Perspectives

Through this project realisation journey, we have identified the critical need for innovative digital and smart solutions to overcome the existing healthcare system's limitations in Algeria and in the whole world, such as inadequate infrastructure, resource distribution and the difficult saving of medical data. Though, we developed an AI-Powred Healthcare platform. The proposed platform served multiple functions, including supporting healthcare professionals in diagnostics, enabling researchers to share and collaborate on new models, and making research efforts more visible and beneficial. Additionally, it offers the capability to test each model like pneumonia detection, bone age assessment and retinopathy diabetic. This initiative platform not only aims to improve healthcare delivery within Algeria but also to contribute valuable insights and tools to the global medical community.

Furthermore, the enhancement of diagnostic accuracy of malaria (Paludism) diagnosis through the development of a specialized CNN model, using various deep learning techniques and a hybrid dataset composed of a public dataset and a dataset created from seven cities in a collaboration work between us and students of paramedical institutions. We evaluated the model's performance using different loss functions (binary cross-entropy, categorical cross-entropy) and fine-tuned the obtained weights while augmenting the combined dataset to prevent overfitting. The proposed model achieved outstanding results in accuracy, precision, F1-score, specificity, recall, sensitivity, and AUC, with values of 0.9975, 0.9893, 0.9975, 0.9892, 0.9994, 0.98, and 0.9985, respectively using the binary cross-entropy loss function.

The project holds significant potential for further development and expansion. Here are several key perspectives for the future:

- **Dataset Creation Tool** One of our future goals is to develop a tool that allows doctors to create and contribute to datasets easily. This tool will enable medical professionals to upload patient data securely.
- **Model Code Integration** Adding a feature that allows researchers to upload the code of their AI models along with the datasets. This will facilitate better reproduction, and further development of these models by other researchers.
- **Multi-Application Projects** Another perspective is to expand the platform to support projects that encompass multiple applications from different research groups. This will enable comprehensive projects that address various aspects of healthcare, providing a holistic approach to solving complex medical challenges.
- **Continuous Improvement of AI Models** Offering continuously refine and improve the AI models hosted on the platform. This involves regular updates based on the latest research, feedback from users, and performance evaluations.
- **Collaboration with International Researchers** Offer an establishment of collaborations with international researchers and institutions to enhance the platform's capabilities and reach.
- **User Training and Support** To maximize the platform's effectiveness, we will provide training and support for healthcare professionals and researchers. This will include tutorials, workshops, and documentation to help users effectively utilize the platform's features and contribute to its development.

In summary, the project represents a significant step towards the offering of digital technologies to improve healthcare delivery in Algeria and beyond. By focusing on accessibility, collaboration, and continuous improvement, the aim is to create a platform that not only addresses current challenges but also paves the way for future advancements in medical research and practice.

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