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On: Tuesday 28 jun 2022

Breast cancer detection using CNN

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Dédicace

To my parents To the persons I owe everything to. To the persons whom I stood tongueless to express how grateful I am for everything they did for me and for making me who I am today. May God Bless You Beyond Any Known Measure

To my brother and sisters to the strongest bond of my life.The source of joy, happiness, strength and will.To the people who defended me and were my shield whenever I needed them.

To my classmates To my friends whom I shared every moment of joy and sorrow. To my friends whom I spent my journey with. May God Be Before You To Guide You

Abstract

Breast cancer is extremely common among women. The use of manual diagnostic techniques has proven to be time-consuming, subjective, and challenging. Because deep learning techniques are transforming the field of medical image analysis, we proposed convolutional neural networks (CNNs) for breast mass detection in this study to reduce processing overhead. This feature is built into the CNN architecture.Once detected, our approach classifies the mass region as benign or malignant Abnormalities on mammograms (MG). according to the proposed model, MG. images have been gathereIt went through several phases of preparation.And then extract the breast area from the MG image's background. The test data set reveals the model's performance.

To be: 90% detection accuracy.

Résumé

Le cancer du sein est extrêmement fréquent chez les femmes. L'utilisation de techniques de diagnostic manuel s'est avérée chronophage, subjective et difficile. Parce que les techniques d'apprentissage en profondeur transforment le domaine de l'analyse d'images médicales, nous avons proposé des réseaux de neurones convolutifs (CNN) pour la détection de la masse mammaire dans cette étude afin de réduire les frais généraux de traitement. Cette fonctionnalité est intégrée à l'architecture CNN. Une fois détectée, notre approche classe la région de masse en tant qu'anomalies bénignes ou malignes sur les mammographies (MG). selon le modèle proposé, MG. images ont été recueillies Il est passé par plusieurs phases de préparation. Ensuite, extrayez la zone du sein de l'arrière-plan de l'image MG. L'ensemble de données de test révèle les performances du modèle.

Être : 90% de précision de détection.

ملخص

سرطان الثدي منتشر للغاية بين النساء. لقد ثبت أن استخدام تقنيات التشخيص اليدوي يستغرق وقتًا طويلاً ، وذاتيًا ، وصعبًا. نظرًا لأن تقنيات التعلم العميق تعمل على تغيير مجال تحليل الصور الطبية ، فقد اقترحنا الشبكات العصبية التلافيفية (CNN) للكشف عن كتلة الثدي في هذه الدراسة لتقليل النفقات العامة للمعالجة. تم دمج هذه الميزة في بنية CNN ، وبمجرد اكتشافها ، يصنف نهجنا منطقة الكتلة على أنها تشوهات حميدة أو خبيثة في تصوير الثدي بالأشعة السينية (MG). وفقًا للنموذج المقترح MG. تم التقاط الصور وقد مرت بعدة مراحل من التحضير. ثم قم باستخراج منطقة الثدي من خلفية صورة MG. تكشف مجموعة بيانات الاختبار عن أداء النموذج.ليكون:90% دقة الكشف

TABLE OF CONTENTS

List of Figures

List of Tables

GENERAL INTRODUCTION

In order to properly analyze information, new processes and technologies are currently required in the medical area. This is owing to technical advancements that have raised the level of expertise in computer science. This allowed for the development of more powerful machines, as well as the execution of complex algorithms and the testing of novel concepts. Approaches to Artificial Intelligence (AI) that were previously inconceivable. Artificial intelligence is used in a variety of sectors, including medical (natural language processing, expert systems, speech recognition, etc.). Medicine, like many other professions, has benefited from the computer revolution, particularly artificial intelligence. in this situation, In general, information technology has become an indispensable instrument in modern medical practice.Signal analysis and medical imaging are commonly used as diagnostic aids.Neural Networks (RN), Algorithms, and Other Artificial Intelligence Technologies Alginate (GA) is a substance that is often utilized in medicinal applications to enhance blood flow. Medical diagnostic support system performance.

The World Health Organization has issued a warning about the dangers of breast cancer, which has spread throughout the world and is difficult to identify in the early stages since there are no visual signs and no discomfort. And it would be tough to detect such a thing.

Our research aims to develop a diagnostic assistance system for classifying (or recognizing) positive and negative breast cancer images. To accomplish so, we'll classify photographs using an automated method.This method is based on python deep learning (DL) modeling approaches, which is based on the image data .To classify images, we'll start with the most fundamental phase, which is the categorization that determines whether or not a person is unwell. We do this by utilizing a database that contains Breast cancer (78,786 photographs) and normal breasts (198,738 photos) are the two forms of breast cancer in our database.

There are 277,524 photos in all. This method shortens the processing time and improves error detection. We're utilizing a deep learning system that employs a variety of algorithms. Medical picture classification. The constructions were utilized for Deep Learning (DL) Networks are a type of deep learning network.There are two types of data in the database.

This thesis is divided into three chapters: Chapter one discusses medical imaging and breast cancer, chapter two discusses machine learning and deep learning, and chapter three discusses machine learning, deep learning, convolutional neural networks, and singularity are terms used to describe recent studies relevant to humans. Then we move on to the last chapter, the considered system, where we will show it, and the results of using a convolutional neural network are described in detail.

CHAPITRE I

MEDICAL IMAGING

AND

BREAST CANCER

Chapter 1 : Medical imaging and Breast cancer

1-Introduction

Medical imaging was once used solely for diagnostic purposes, but with the advancement of CAD technology and 3D printing, health care is undergoing a metamorphosis. Medical imaging is the technique and practice of imaging the interior of a body for clinical assessment and medical intervention, as well as visual representation of the function of specific organs or tissues. The goal of medical imaging is to reveal hidden inner structures beneath the skin and bones, as well as to detect and treat disease[1]. Medical imaging also builds a database of normal anatomy and physiology, which can be used to spot abnormalities. Medical imaging, which encompasses MRI techniques, x-ray radiography, medical ultrasound imaging, flexible imaging, endoscopy, touch imaging, thermal imaging, medical imaging, and nuclear medicine imaging techniques, is a subset of biological imaging. SPECT and positron emission tomography are examples of functional imaging techniques. Other procedures that create data that can be shown as a graph include EEG, MEG, ECG, and other recording and measurement techniques[2]. As a result, medical imaging has made it easier for doctors to diagnose and treat disorders. This subject is constantly evolving in order to improve and simplify accuracy in medicine, and medical imaging, in particular, is utilizing artificial intelligence to diagnose crit.
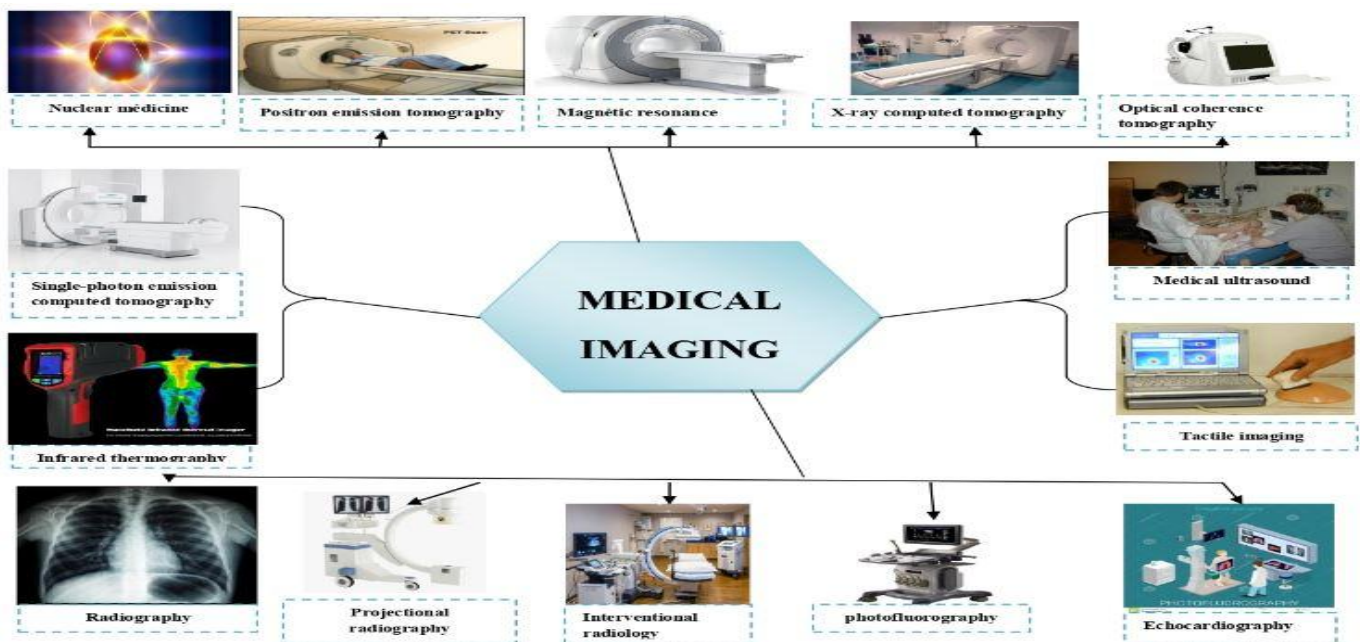
Figure 1.1: The different medical imaging modalities.

2- The history of medical imaging

The concept of medical imaging began in 1895 with the invention of the x-ray by a German professor of physics, Wilhelm Rontgen. The concept of x-ray is based on the principle of passing ionizing radiation through the body and having the images projected on a photosensitive plate placed behind it. The concept of this technology is to take a serial series of images of slices of the body and to then put them back together with a computer to visualize internal structures of the body. Medical imaging has improved immensely since the firstx-raysweretakenover120yearsago.

There is much more accuracy in diagnosing a medical problem and because of these advances, there is also much less need to perform exploratory surgery[3].

radiogr aphy (J. Hall-Edward s, 1896)
ultraso nograp hy (I. Edler, C. Hertz, 1953)
CT tomogr aphy (A. Cormac k, G. Hounsfi eld, 1972)
endosc opy (B. Hirscho witz, since 70ties)
Endosc opic capsule (Given Imagin g, 2001)

angiogr aphy (E. Moniz, 1927)
Termog raphy (since 60thies , XX c.)
PET tomogr aphy (M. Ter-Pogossi an et.al., 1973)
MRI tomogra phy (P. Lauterbu r, P. Mansfiel d, 1973 since 80ties)
CT+MRI, PET+MRI (Gen. Electric, 2010)

Figure 1.2: The history of medical imaging[4].

3. Medical imaging modaltos

3.1. Ionizing radiation:

Ionizing radiation is a physical phenomenon based on directing high energy particles (photons) to an obmmject. In medical sector this phenomenon is used to create images, both anatomical (X-ray, CT) and physiological, or functional, images (Nuclear Medicine – PET and SPECT)[5].
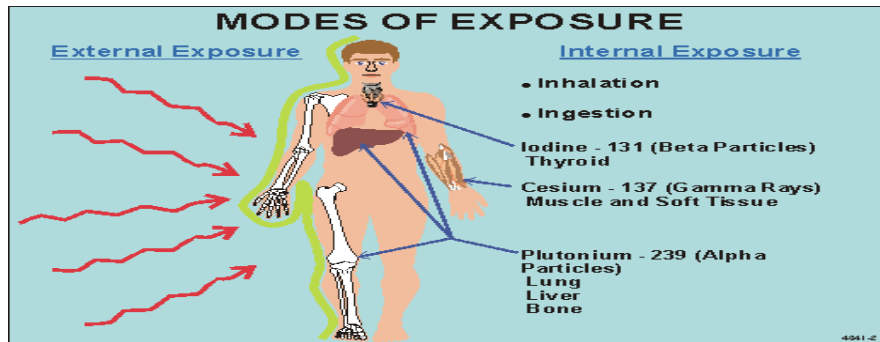
Figure 1.3: Ways materials contaminated with ionized radiation enter the body[6].

3.2. X-ray images

X-rays images are the oldest and most commonly used medical imaging technique. X-rays were discovered in 1895 and first used to image human tissue in 1896. X-rays use ionizing radiation to produce images of a person's internal structure by sending beams through the body. The   digestive   system.

Angiography uses X-rays in combination with a contrast agent in order to visualize blood vessels, particularly the coronary arteries[7].

Figure 1.4: human lung X-ray image[8].

3.3. Computedtomography (CT)

Also commonly referred to as a CT scan, Computed Tomography is an imaging technique that combines multiple X-ray images taken from different angles. This produces detailed cross-sectional internal images. The first CT scanner for medical use dates from 1972.Cardiology.Technological improvements in CT such as dose modulation acquisition techniques and iterative reconstruction algorithms dramatically reduce the required X-Ray dose, improve hospital efficiency and clinical effectiveness and reduce costs[9].

Figure 1.5: Computed tomography (CT) [10].

3.4.Molecularimag

Molecular Imaging is a diagnostic technology that allows doctors to see metabolic processes in patients by giving them modest doses of radioactive medicines. Clinical pictures can be improved by combining molecular imaging with CT or MRI images. The first SPECT and PET scanners were invented in 1976, and have gone through five generations to reach the current market[11].
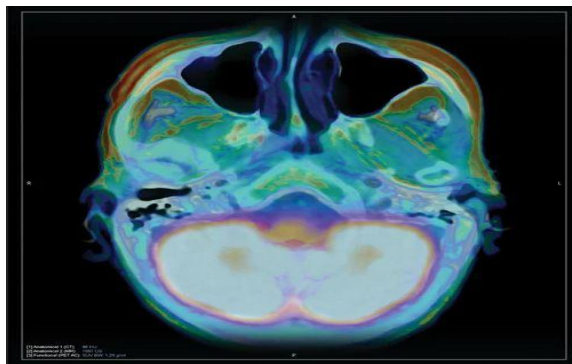
Figure 1.6: Examination of the tension area of the brain by computerized tomography[12].

3.5.Magneticresonanceimaging (MRI)

Magnetic Resonance Imaging (MRI) is a technique for obtaining detailed images of organs and tissues that employs radio waves and a magnetic field. In 1973, the first magnetic

resonance image was captured, and in 1977, the first MRI scanner for medical imaging was created [13].

The type of radiation used in this imaging technology produces images of soft tissues only, leaving the bones out. By demonstrating the contrast between normal and diseased tissues, this trait has proven to be extremely useful in detecting a variety of illnesses[14]. MRI is frequently used to assess patients:

- Blood vessels
- Breasts
- Rgans

Figure 1.7: Magnetic Resonance Imaging (MRI) of the Bones, Joints, and Soft Tissues[15].

3.6.Ultrasound

Ultrasound can be used for therapy and muscle stimulation, or as a diagnostic tool in medical imaging with the help of an ultrasonographer. The ultrasound equipment transmits sound waves into the body and can convert the echoes, or returned sound, into a picture. Ultrasound technology may also provide audible blood flow sounds, allowing medical personnel to examine a patient's health using both sounds and pictures[16].Ultrasound is often used to evaluate:

- Pregnancy
- Abnormalities in the heart and blood vessels
- Organs in the pelvis and abdomen
- Symptoms of pain, swelling and infection

Figure 1.8: Ultrasound to image the inside of the abdomen[17].

4.Breast cancer

4.1. Introduction

Breast cancer was the most often diagnosed cancer in 2020. In 2020, incident breast cancer cases accounted for 11.7 percent of all new cancer diagnoses and 6.9% of all cancer-related deaths worldwide. Among all malignancies in women, breast cancer has the greatest fatality rate[18]. While industrialized nations have an 88 percent higher breast cancer incidence rate than developing countries, developing countries have a 17 percent higher mortality rate than countries with a higher Human Development Index (HDI). While the death rate for breast cancer in wealthy countries is 12.8 per 100,000, it is higher in underdeveloped countries, at 15 per 100,000 [19].The stage of breast cancer when it is diagnosed is a significant influence in death. In developed nations, regular mammograms are used to detect breast cancer in its early stages in women over a specific age or with a family history of the disease. Only 5% of global resources are spent on breast cancer screening in underdeveloped countries. Due to a lack of resources in these countries, mammograms are significantly less common, and breast self-examinations and clinical breast examinations are far more common[20].Breast self-examinations have a sensitivity rate of 20% and are not linked to mortality rates. Breast exams are frequently accompanied by a mammogram because mammography has a sensitivity of 63-95 percent. According to a Ugandan study, just four mammography machines are available for every 6-7 million women in the country[21]. As a result of this unmet demand, more late-stage breast cancer diagnoses are made, resulting in greater mortality rates. According to Da Costa Vieira et al., countries with a lower HDI had a lower rate of early diagnosis than those with a higher HDI [22].Imaging-detected lumps or lesions in the breast are usually followed by a biopsy of the

tissue sample to determine the cancer's stage and subtype. Excisional biopsy, incisional biopsy, core biopsy, and fine needle aspiration biopsy are the four types of biopsy that can be performed. Histopathology is performed on tissue taken by one of these biopsy procedures, and it is stained with hematoxylin and eosin (H&E).Pathologists examine H&E-stained tissue slices under a microscope to see if the tissue is malignant and, if so, what stage of cancer growth it is in. These tissues are sometimes from non-cancerous benign tumors like adenosis or fibroadenoma. On the other hand, benign lesions with proliferative and atypical nuclei on histology have been associated to an increased risk of cancer[23].However, in low-resource areas, obtainingquick diagnosis and treatment is difficult due to a shortage of skilled pathologists.
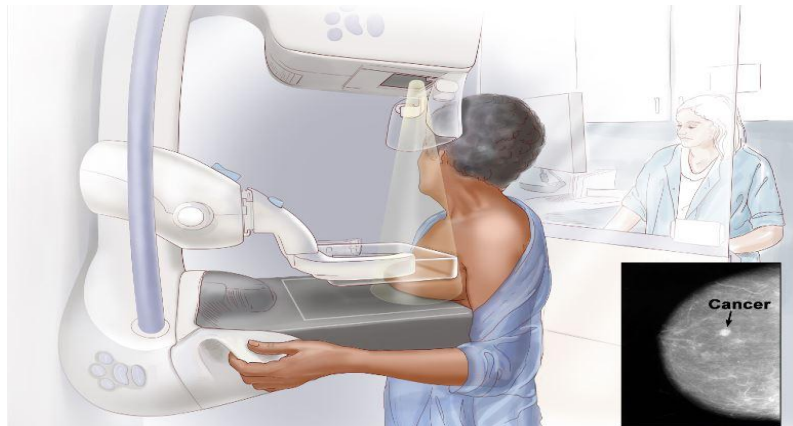
Figure 1.9: Mammography, which uses X-rays to take pictures of breast tissue [24].

5. Breast tumor classification

Breast cancer is divided into two categories. The first is Benign Tumor, which is non-cancerous, and the second is Malignant Tumor, which is also known as Cancerous Tumor.

5.1.BenignTumor:

Benign breast tumors are described as clusters of comparable cells that do not adhere to a regular pattern.

Cells divide and grow, resulting in a mass of cells that do not divide and grow microscopically.

It has the look of a cancerous tumor[25].These are all positive traits tumor:

- Computed tomography or magnetic resonance imaging are used to detect the majority of benign cancers.

- Slowly grows, does not penetrate nearby tissues or expand to other organs, and frequently has a border or edge visible on CT images.

- Because it can impose pressure on other tissues and structures within the skull, it can be life-threatening, hence the word "benign" might be misleading.

5.2.MalignantTumor:

Precancerous cells are found in malignant breast tumors, which generally lack defined boundaries. they really are

It is deemed life-threatening due to its rapid growth[26].A malignant tumor has the following characteristics:

- Cancer that spreads quickly to other parts of the brain and spine.

- These are usually more significant and often fatal threats to life.
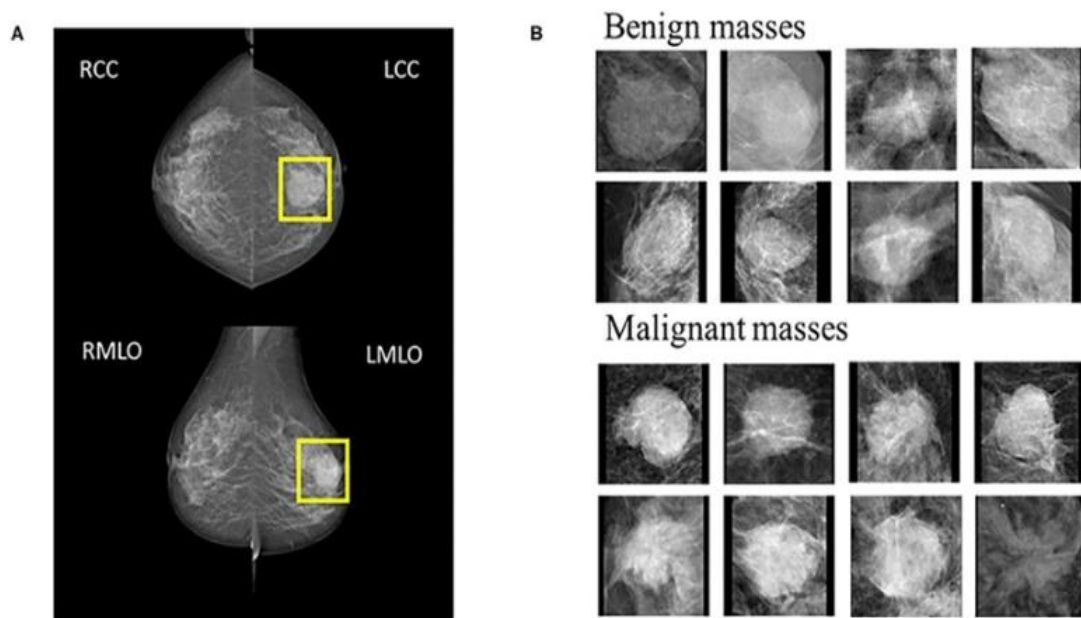
Figure 1.10: The difference between benign and malignant for the breast[27].

6.Objective

Our thesis' major goal is to create a model that can predict whether or not an image contains a tumor. A data set consists of a collection of files. Because the collection of breast cancer data is insufficient and too large, the key goal is to work on a medical image. We aimed to create a model that could do all of the fundamental and necessary activities for tumor detection and treatment.

We suggested an efficient and successful technique for segmentation and diagnosis of breast cancer without the use of humans, based on both classical classifiers and convolutional neural networks (CNNs).

7 Conclusion

Medical imaging is an essential branch of medicine, and it has enabled physicians and experts to more effectively diagnose and treat diseases. It has accelerated in recent years, as we can see. We introduced the medical imaging examination in this chapter.

Its different qualities and types (magnetic resonance imaging, x-rays, etc.) in general. There are techniques added to the medical field in order to speed up and facilitate and with the provision of more accurate results in the diagnosis of diseases, the most important of which is the deep learning technology, which contributed to the diagnosis of diseases. He mentioned different types from the neural network.

CHAPTER 2

DEEP LEARNING

AND

CNN.

Chapter 2 : Deep learning and CNN

1- Introduction

Artificial intelligence (AI) is becoming more and more important in a variety of fields, as it includes a wide range of technologies that mimic human intelligence. As machine learning (ML) and deep learning (DL), which allow devices to continue to think and develop based on the data they receive, these are the technologies that contribute to this development. The importance of artificial intelligence has grown increasingly, especially in the medical field, as many medical centers depend on it to discover, treat and diagnose diseases, which saves millions of lives.

2.Machine learning

2.1Definition

Machine learning is a branch of artificial intelligence (AI) and computer science which focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy.

Machine learning uses a variety of algorithms that iteratively learn from data to improve, describe data, and predict outcomes. As the algorithms ingest training data, it is then possible to produce more precise models based on that data. A machine learning model is the output generated when you train your machine learning algorithm with data[28].

Figure 2.1: The most important areas of machine learning[29].

3.Machine learning methods

Machine learning classifiers fall into three primary categories:

3.1. Supervised machine learning

Supervised learning, also known as supervised machine learning, is defined by its use of labeled datasets to train algorithms that to classify data or predict outcomes accurately. As input data is fed into the model, it adjusts its weights until the model has been fitted appropriately[30]. This occurs as part of the cross validation process to ensure that the model avoids over fitting or under fitting. Supervised learning helps organizations solve for a variety of real-world problems at scale, such as classifying spam in a separate folder from your inbox. Some methods used in supervised learning include neural networks, naïve bayes, linear regression, logistic regression, random forest, support vector machine (SVM), and more.
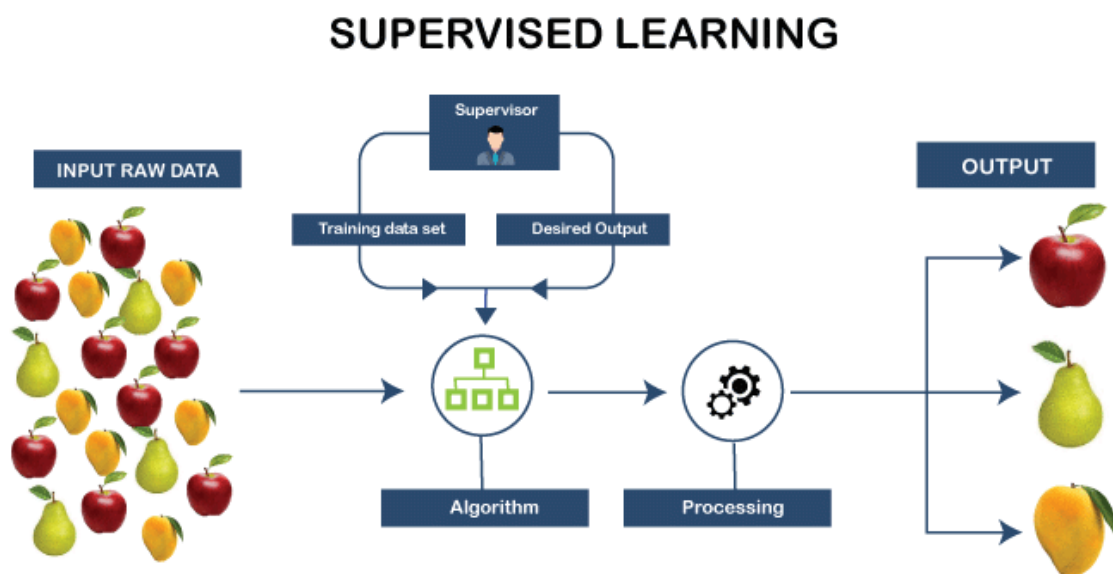
Figure 2.2: Dive into Supervised Machine Learning[31].

3.2. Unsupervised machine learning

Unsupervised learning, also known as unsupervised machine learning, uses machine learning algorithms to analyze and cluster unlabeled datasets. These algorithms discover hidden patterns or data groupings without the need for human intervention. Its ability to discover similarities and differences in information make it the ideal solution for exploratory data analysis, cross-selling strategies, customer segmentation, image and pattern recognition. It's also

used to reduce the number of features in a model through the process of dimensionality reduction; principal component analysis (PCA) and singular value decomposition (SVD) are two common approaches for this. Other algorithms used in unsupervised learning include neural networks, k-means clustering, probabilistic clustering methods, and more[32].
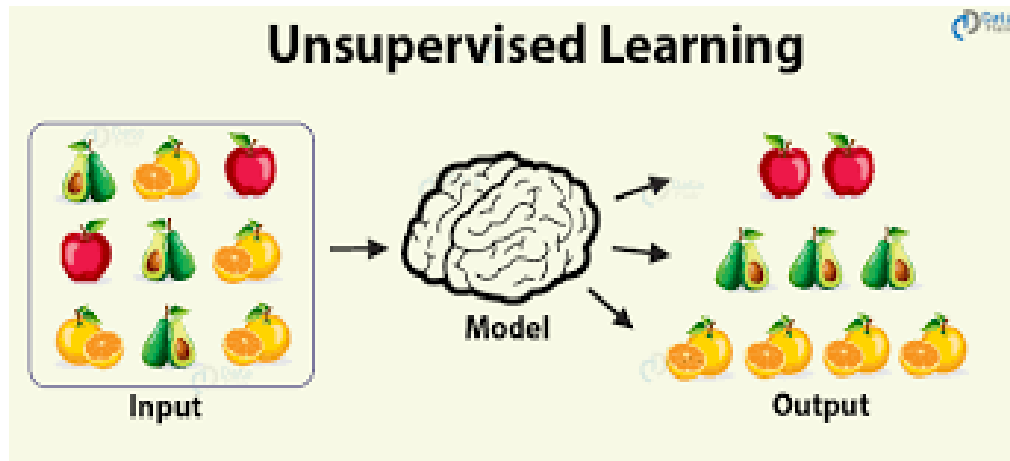
Figure 2.3: Unsupervised machine learning process[33].

3.3. Reinforcementlearning

One of the most common applications of reinforcement learning is in robotics or game playing. Take the example of the need to train a robot to navigate a set of stairs. The robot changes its approach to navigating the terrain based on the outcome of its actions. When the robot falls, the data is recalibrated so the steps are navigated differently until the robot is trained by trial and error to understand how to climb stairs. In other words, the robot learns based on a successful sequence of actions. The learning algorithm has to be able to discover an association between the goal of climbing stairs successfully without falling and the sequence of events that lead to the outcome. Reinforcement learning is also the algorithm that is being used for self-driving cars. Even with this complex scenario, the algorithm can be optimized over time to find ways to adapt to the state where actions are rewarded.

One of the easiest ways to think about reinforcement learning is the way an animal is trained to take actions based on rewards[34].
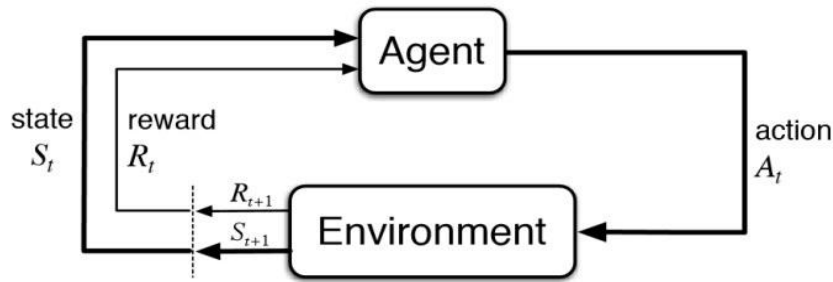
Figure 2.4: Basic Diagram of Reinforcement Learning[35].

4. Machine Learning Classifiers

A classification technique is used to evaluate our suggested model. even the building This is the cancer-detection model. It is made up of six classic machine learning algorithms. We employ these several types of classifiers to justify our model. A classic machine learning algorithm Logistic K-Nearest Neighbor,Multilayer Perceptron, Naive Bayes, Random Forest, Vector Support, Regression From our proposed model, a machine to get tumor detection accuracy**.**

4.1. K-NearestNeighbor

For supervised learning, KNN is one of the most basic classification algorithms. In feature space, the goal is to find the test data's closest match. Objects are typically categorised by majority vote based on the labels of their k closest neighbors. If k is equal to one The class of the object closest to it is used to classify it. If there are simply a few people, k must be an odd integer and there are two classes. There are situations, though, when k is an unusual letter. If you're doing multi-class categorization, you'll need to use an integer. After that, we'll vectorize each image. We utilized the most common distance function for KNN in place of fixed-length using real numbers. It is the Euclidean distance between two points x and y, and it may be calculated[36].
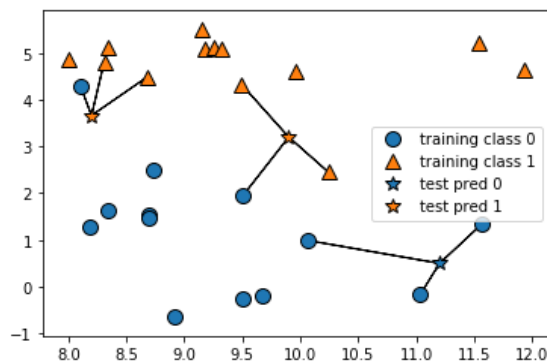
Figure 2.5: K-nearest neighbor of machine learning foundation [37].

4.2. LogisticRegression

The logistic regression, like all regression studies, is a predictive analysis. To describe data and explain the relationship between one dependent binary variable and one or more nominal, ordinal, interval, or ratio-level independent variables, logistic regression is utilized. Logistic regression, like linear regression, uses an equation as its representation. Weights or coefficient values (referred to as y) are used to mix input values (x) linearly. (Beta) is a Greek capital letter that is used to forecast an output value (y). A significant distinction from linear The output value being modeled is a binary value (0 or 1) rather than a number. a number value The logistic regression equationis as follow[38].
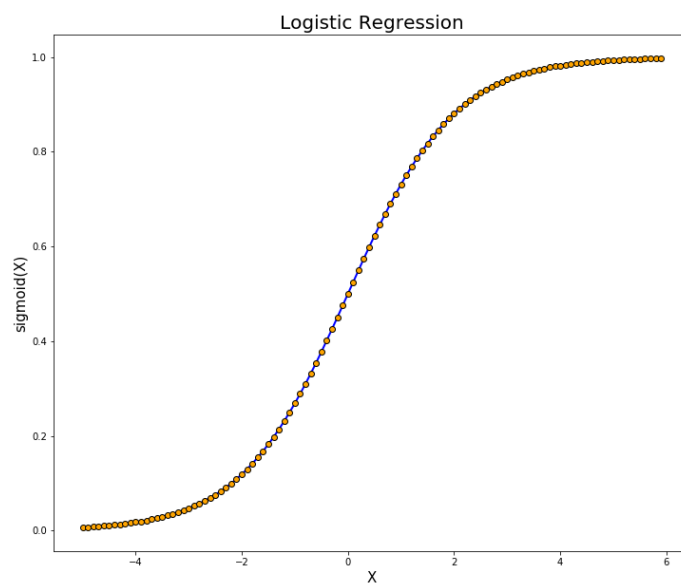
Figure 2.6: Simply illustratelogisticregression[39].

4.3 Artificial Neural Network

Artificial neural networks are used in deep learning, and they are modeled after networks found in the human brain. Deep learning is a type of machine learning that uses numerous layers of neural networks[40].

A three-layer artificial neural network is common. Layers are made up of a number of interconnected nodes. The following is a description of the three layers of ANN:
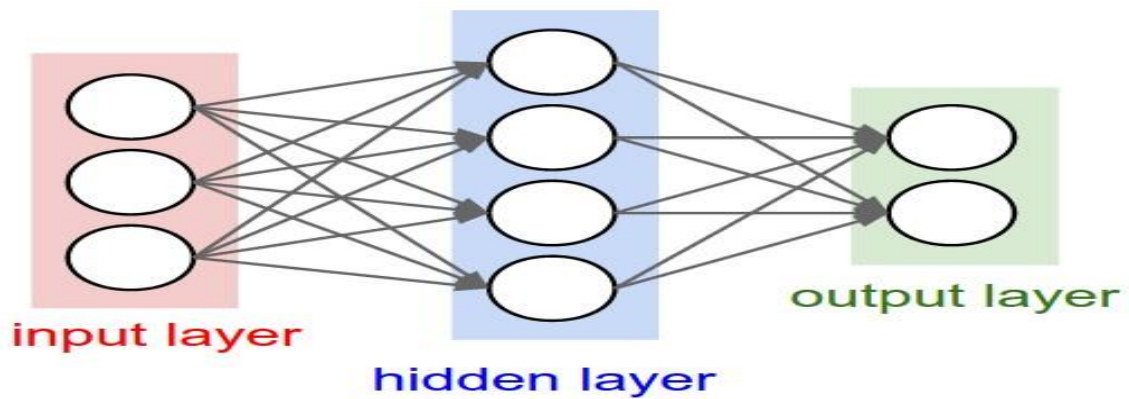
Figure 2.7: Asimple Artificial Neural Network[41].

Input Layer

This layer is made up of neurons that receive and transmit information to the following layer. Features or features in the data set must be equal to the number of layers in the input layer.

Hidden Layer

Simply put, hidden layers are layers of mathematical functions, each of which is meant to create an output specific to the desired outcome. Squashing functions, for example, are certain types of hidden layers. Because they take an input and create an output value between 0 and 1, the range for defining probability, these functions are especially useful when the algorithm's desired output is a probability

Output Layer

The projected feature, or class in a classification issue, is the output layer, which varies depending on the type of developed model. The information transmitted from the hidden layer is used by the output layer to generate the output.

4.4. Support Vector Machine (SVM)

Support vector machines are supervised learning models that examine data for classification and regression analysis and have associated learning algorithms. Given a set of training scenarios, each of them was classified as belonging to one of two groups, The SVM training method creates a model that allocates new instances of one of the previously mentioned classes. It is a non-probabilistic binary linear classifier[42] because it can only classify one of two classes. SVM is a type of machine learning algorithm.
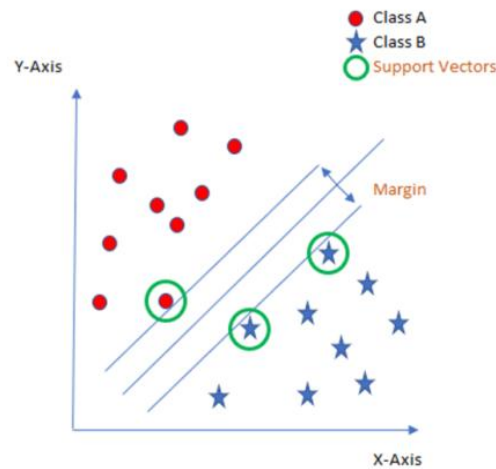
Figure 2.8: Determine Support Vector Machine[43].

4.5. Metrics

Accuracy is a metric for evaluating machine learning classification models. Accuracy is expressed as a percentage of the model's correct predictions. Usually, the accuracy is calculated as [44].

$$\mathbf{accuracy} = \frac{\mathbf{number\,of\,correct\,predictions}}{\mathbf{total\,number\,of\,predictions}} \qquad (\,45\,)$$

For binary classification, accuracy can also be evaluated as positive or negative[46].

$$\mathbf{accuracy} = \frac{\mathbf{TP+TN}}{\mathbf{TP+TN+FP+FN}} \qquad (\,47\,)$$

True Positives are represented by TP, True Negatives are represented by TN, False Positives are represented by FP, and False Negatives are represented by FN. Precision is defined as the number of true positives divided by the number of true positives plus the number of false positives[48].

$$\mathbf{precision} = \frac{\mathbf{TP}}{\mathbf{TP+FP}} \qquad (49\,)$$

5. Deep learning

A subset of machine learning algorithms is known as deep learning. Deep learning's success has spawned a slew of pattern recognition applications, but it necessitates a massive

amount of data. Artificial intelligence (AI), also known as deep learning, has the potential to change the healthcare industry. Early studies of deep learning applied to the detection or classification of lesions indicated that it outperformed existing techniques or even a radiologist in many cases. Deep learning-based medical image analysis has the potential to increase the accuracy and efficiency of many diagnostic and treatment processes, leading to the introduction of new research and development projects in CAD. Despite the optimism around this new era of machine learning, the research and implementation of CAD or AI technology is still a work in progress[50].
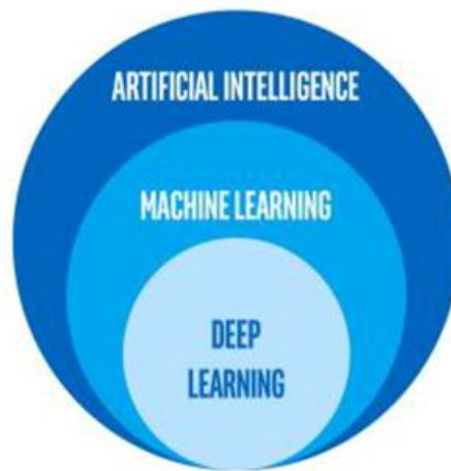
Figure 2.9: Artificial intelligence Vs machine learning Vs deep learning[51].

5.1. Types of Neural Networks

Artificial neural networks come in a variety of shapes and sizes. These networks are based on mathematical operations and a set of parameters that must be met in order to determine the result. The following are some of the most well-known neural networks[52].

5.1.1 Feedforward Neural Network

A Feedforward artificial neural network is one in which data flows in one way between the input and output nodes, as the name implies. Data will not cycle backwards through the same tiers of nodes as it flows forward. The one-way transfer of data makes Feedforward neural networks relatively straightforward, despite the fact that there may be many distinct layers with many different nodes. Artificial neural network models that feed forward are typically employed to solve simple categorization tasks. Models will outperform typical machine learning models, but they will not achieve the level of abstraction found in deep learning models[53].

5.1.2 Radial Basis Function Neural Network

The radial basis function (RBF) An input layer, a layer with radial basis function nodes with variable parameters, and an output layer are the most common layers in neural networks. Models can be used to accomplish categorization, time series regression, and system control. The absolute value between a center point and a given point is calculated using radial basis functions. A radial basis function measures the distance between an input and a learned classification in classification. The input is classed as such if it is the most similar to a specific tag. System control, such as systems that handle power restoration after a power outage, is a typical use for radial basis function neural networks. The artificial neural network can recognize the priority order for power restoration and repair[54].

5.1.3 Recurrent Neural Network

The Recurrent Neural Network is based on the notion of preserving a layer's output and feeding it back into the input to help forecast the layer's outcome. Long Short Term Memory is another name for this[55].

5.1.4 Convolutional Neural Network

Convolutional neural networks are comparable to feed forward neural networks in that the weights and biases of the neurons are learnable.

5.1.5 Modular Neural Network

A modular neural network is made up of many networks that work independently and execute distinct tasks. During the calculation process, the various networks do not really interact or notify each other. They operate separately to get the desired result[56].

6. Convolutional Neural Network (CNN)

CNNs are used to look for patterns in images. This is accomplished by saturating an image with noise and looking for[57]. In the few front layers of CNNs, the network can recognize lines and corners. However, as we go further into our neural net, we can transfer these patterns down and begin to identify more complicated traits. CNNs are exceptionally good at recognizing objects in images because of this property[58]. CNNs are used in the proposed system to detect breast cancer in images of breast tissue. The convolutional layer, the pooling layer, and the fully connected layer are the three main layers of the CNN architecture. The output of neurons associated with local areas is calculated in the first layer. The standard product of the weights and the area is used to determine each one. Filters for image entries are often 3 x 3, 5 x 5, or 8 × 8 pixels in size. These filters use a sliding window on the image to scan the image while

learning repeated patterns that exist in any part of the region. picture. The step is the distance between two filters. If the step's meta-parameter is smaller than the filter dimension, convolution is extended to nested windows. A graphic representation of Neural Networks.
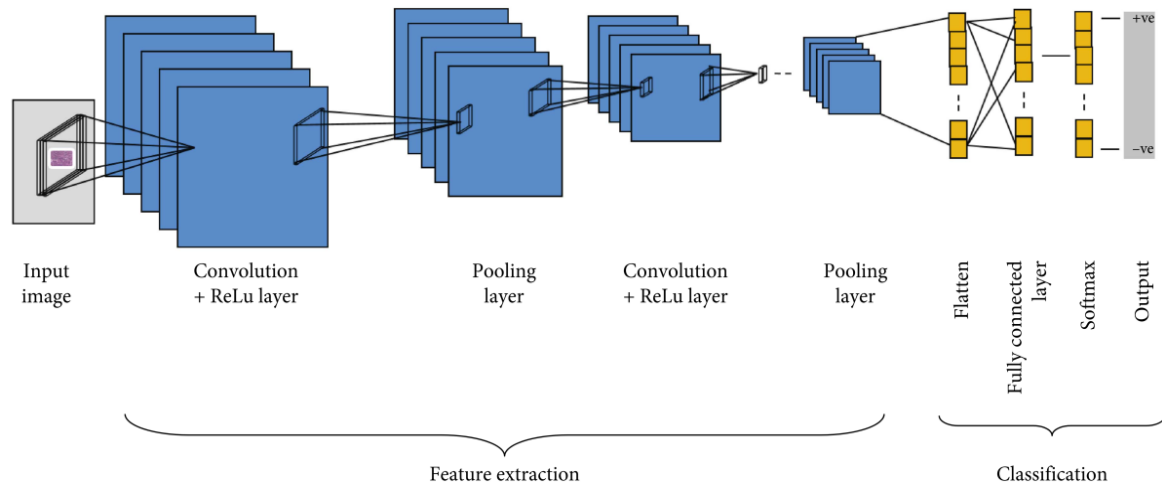
Figure 2.10: Automatic breast cancer diagnosis using a model CNN architecture[59].

6.1 Input layer:

The input picture is transformed over into the network of the shape [32x32x3] in the first layer of the CNN calculation. This matrice contains the pixel estimation for a picture of 32 width, 32 height, and three shading channels. RGB [60].

6.2 Convolutionallayer:

Convolutional layer is the significant layer in the convolutional neural organizations. This layer processes the yield of the neurons associated with the information. Every neuron is allotted a weight. The dot product of the loads of the neurons and the information is determined in this layer[61].

6.3 Pooling Layer :

The features of images with precise positions are brought out by convolutional layers. The feature maps will be altered if the placements vary even slightly for whatever reason. To solve this issue, downsampling must be performed at the output of each convolutional layer[62] Downsampling can be done with convolutional layers by shifting the phase of the convolution over the image.

A pooling layer[63] is a more acceptable and common solution. The outcomes will be more accurate as a result of this procedure.

7. Why CNN is different than simple Neural Network:

The architecture of convolutional neural networks differs from that of ordinary neural networks[64]. An input is transformed by a sequence of hidden layers in a regular neural network.Every layer is made up of a group of neurons, with each layer fully connected to all neurons in the layer before it and each layer's neurons operating independently and not sharing information. any interconnections between them Last but not least, there is a fully connected layer, which isTheforecasts are represented by the output layer. Scalability is a problem with regular neural networks. to see the whole picture.

Convolutional Neural Networks are a unique type of neural network. The layers are first grouped in three dimensions: width, height, and depth. Furthermore, the neurons in one layer do not link to all of the neurons in the following layer, but only a small portion of it. Finally, the conclusion The output will be condensed into a single vector of probability scores sorted by depth. dimension.

Moreover, CNNs perform convolution operation in case of matrix multiplication.
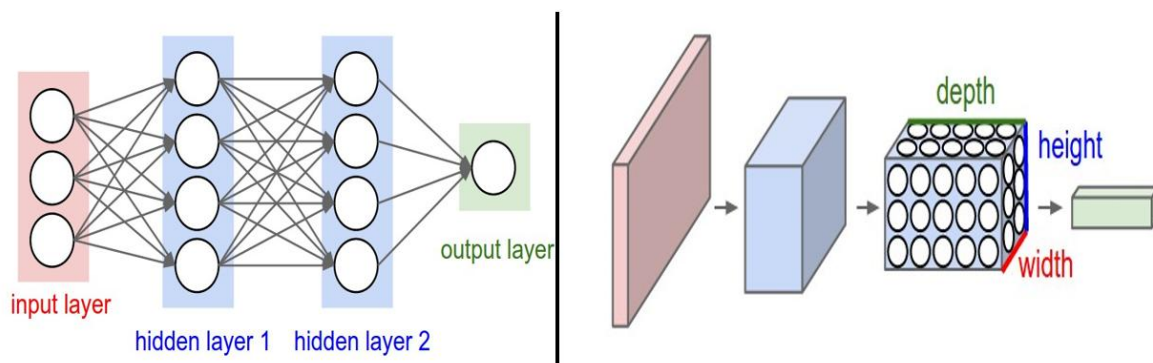
Figure 2.11: A simple neural network and A Convolutional Neural Network[65].

The left side shows a standard three-layer neural network. On the other hand, the right side of the image depicts a CNN that arranges its neurons in three dimensions (width, height, and depth) [66]. Each CNN layer converts the 3D input volume into the 3D neural output volume. activation. The image is held by the red input layer in this example, so its width and height are the same. The image size will be three (red, green, blue), and the depth will be three (red, green, blue).

8. The Convolution Operation

Convolutional Neural Networks conduct the convolution operation, which is a mathematical procedure. Convolution is a mathematical technique that forms a third function by combining two functions (f and g). The f and convolution operation The letter g is represented by the symbol f*g.

One is moved and reversed. This operation is an integral transform of a specific type [67]:

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau)g(t - \tau)d\tau \qquad (68)$$

The convolution operation is made up of three components.[69]

Input image: It is the image that is given as an input.

Feature detector: The feature detector is often referred to as a "kernel" or a " filter".

Sometimes a 5*5 or a 7*7 matrix is used as a feature detector.

Feature map: An activation map is another name for a feature map. It's termed a feature map since it's a map of where a specific type of feature can be found in an image.
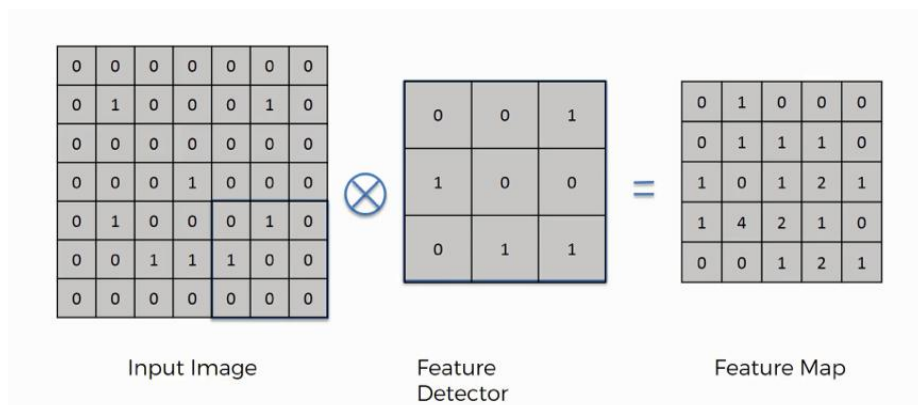
Figure 2.12: Convolution Operation[70].

Function of Regularization

Regularization is a technique used in machine learning to avoid overfitting. By adding a penalty to the loss function, regularization prevents over-fitting. By including this penalty, the model is trained to avoid learning interdependent sets of data. Dropout and Batch Normalization are the two most common regularization procedures.

Dropout

Dropout is a regularization method for neural networks that aids in decreasing interdependent learning among neurons. Dropout forces a neural network to learn more robust features that can be used with a variety of inputs. Dropout briefly destroys some neurons during the forward pass. If we set the dropout to 20%, for example, 1 out of every 5 neurons will be inactivated during the forward pass. Any weight updates will not be made during the reverse pass.

(a) Standard Neural Net   (b) After applying dropout.
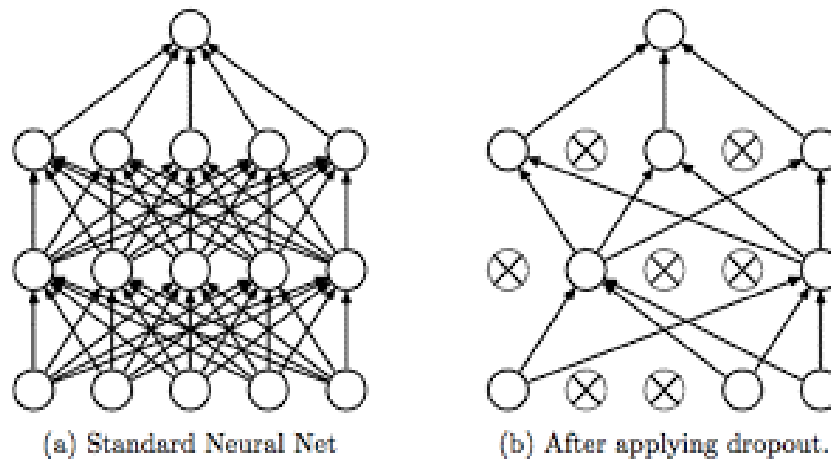
Figure 2.13: Network before and after Dropout[71].

Batch Normalization

Batch normalization is a technique for reducing the internal covariate shift in neural networks, allowing larger learning rates to be used.

The approach, in theory, adds an extra phase between the layers, in which the The output of the previous layer is normalized. BN also inhibits minor alterations to the system. parameters to amplify, allowing for larger learning rates and thereby making the network more effective. There are two algorithms that make up batch normalization (BN). The first algorithm transforms a layer's original input, x, into a shifted and normalized value, y. The overall training of a batch-normalized network is the second [72].
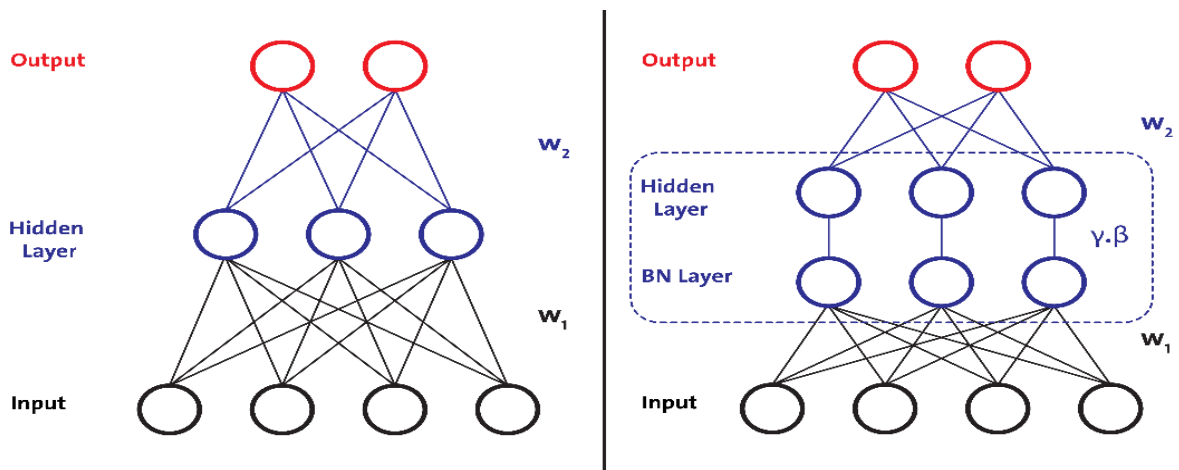
Figure 2.14: A Neural Network before and after Batch Normalization [73].

9.Conclusion

Automated breast cancer detection using MRI and CT scans: a performance analysis In our work, we use basic image processing algorithms based on diverse hard and soft computing. Furthermore, in order to integrate a depth learning method in our work, we implemented CNN for breast cancer diagnosis. We compare the usual result to see which one is the best. With a CNN score, Precision (SVM) is used. Furthermore, our work demonstrates an universal technique. Detecting cancer and extracting its different characteristics.

CHAPTRE 3

SYSTEM

ARCHITECTURE,

IMPLEMENTATION

AND RESULTS

Chapter 3 System Architecture, Implementation and Results

1. Introduction

This chapter is devoted to presenting the structure of three models and its implementation to train them, then we will discuss the results obtained and before that we will learn about the tools used.

2. Development and environment tools

In our project, we used various tools, frameworks, libraries, and software to create machine learning and deep learning models that we can consider a good choice because of the benefits they provide. We will mention all these tools and libraries in this chapter.

2.1 Python

Is an easy to learn language and it is the best way to work with deep learning algorithms. The simple and intuitive structure lets you focus on learning the basics of deep learning, rather than spending hours correcting crazy translator mistakes in other languages.

We will use the Python programming language for all examples in Deep Learning for Computer Vision[74].

2.2 Keras

It is a programming interface for the construction and training of high-level deep learning networks written in Python language that we will mainly use the Keras library. Keras supports both TensorFlow and Theano, making it easy to quickly build and train networks[75].

2.3 TensorFlow

It is an open-source machine learning platform designed by Google to develop and run machine learning and deep learning applications. It is a toolkit for easily solving very complex mathematical problems. TensorFlow is therefore a complete platform that facilitates the creation and publication of ML models[76].

2.4 Colab

Its a tool for teaching and researching machine learning, created as Part of a Google research project. Creating and running Jupyter Notebook on Colab is very easy and free. You can save your laptop to Google Drive or GitHub and even train yourdeep learning on GPU[77].

2.5 The dataset

The dataset we are using for today's post is for Invasive Ductal Carcinoma (IDC), the most common of all breast cancer.The dataset was originally curated by Janowczyk and Madabhushi and Roa et al. but is available in public domain on Kaggle's website.The original dataset consisted of 162 slide images scanned at 40x.

Slide images are naturally massive (in terms of spatial dimensions), so in order to make them easier to work with, a total of 277,524 patches of 50×50 pixels were extracted, including:

- 198,738 negativeexamples (no cancer)
- 78,786 positive examples (indicating cancer was found in the patch)
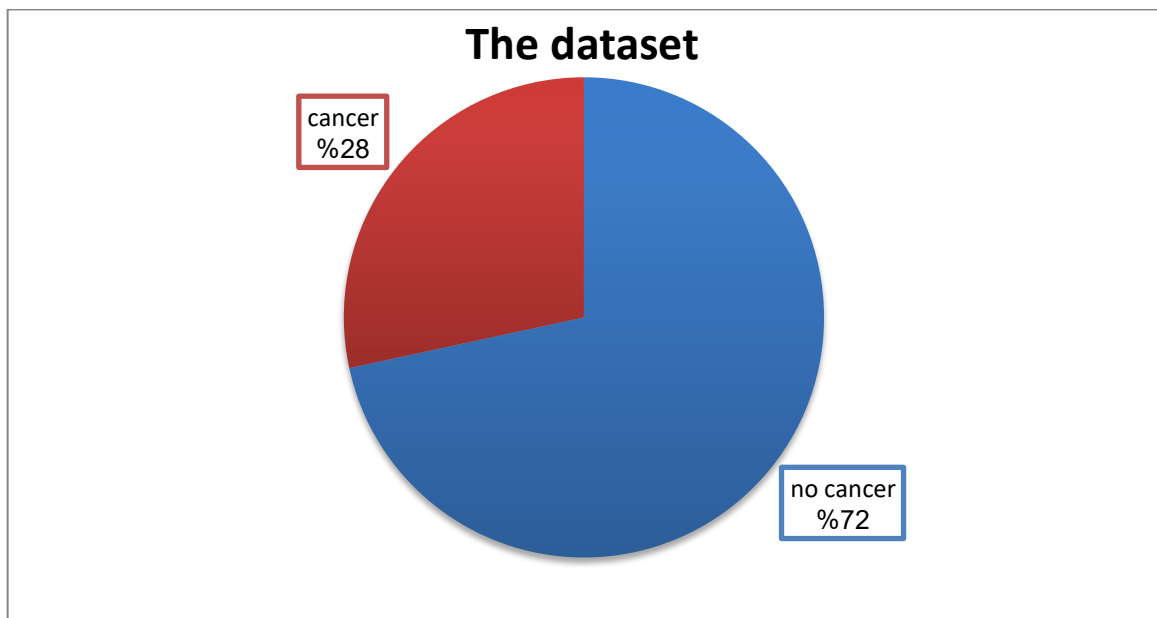
Figure 3. 1: Dataset Classes

There is clearly an imbalance in the class data with over 2x the number of negative data points than positive data points.

Each image in the dataset has a specific filename structure. An example of an image filename in the dataset can be seen below:

10253_idx5_x1351_y1101_class0.png

We can interpret this filename as:

- Patient ID: 10253_idx5
- x-coordinate of the crop: 1,351
- y-coordinate of the crop: 1,101
- Class label: 0 (0 indicates no IDC while 1 indicates IDC)[78].
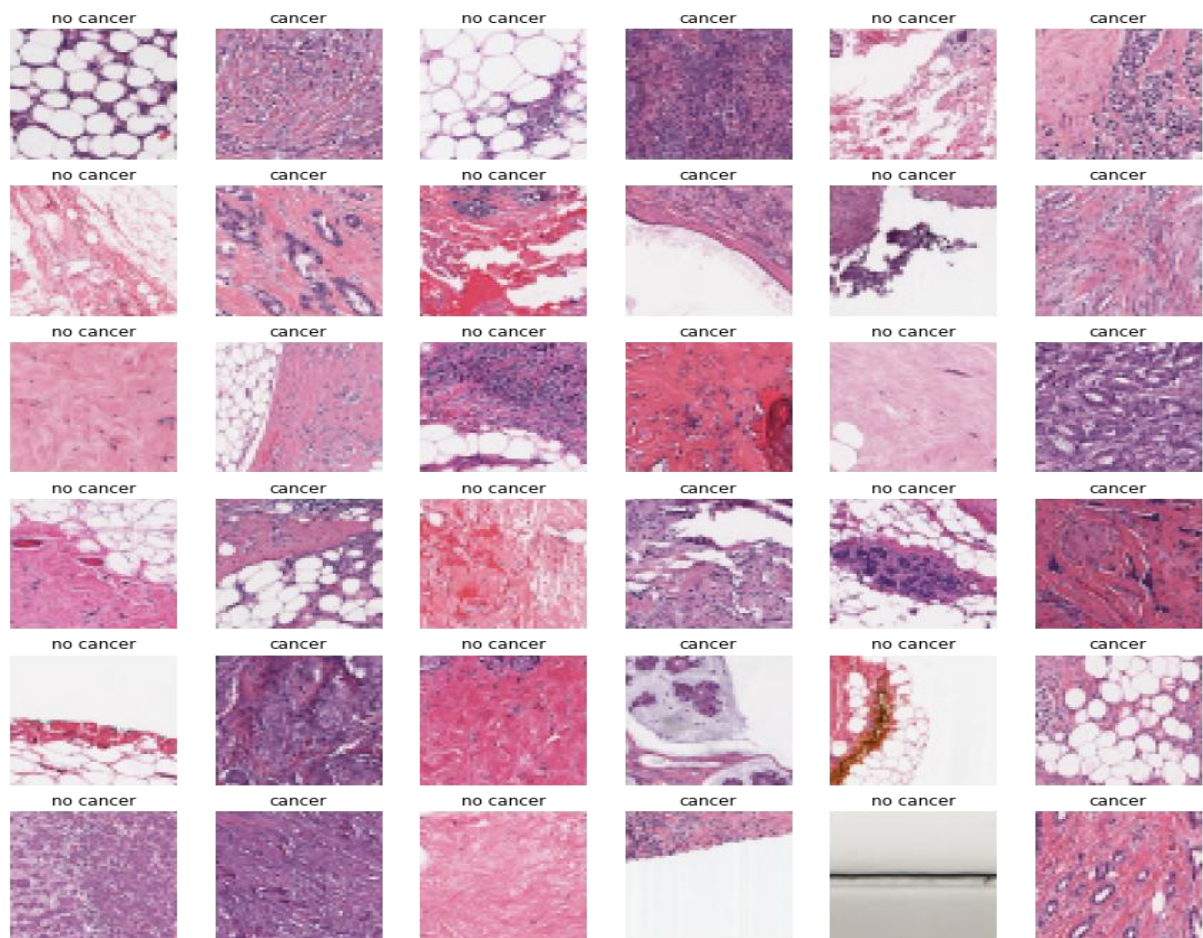
Figure 3. 2: Samples of database images used [79].

3.Image Classification

The complete image classification pipeline can be formalized as follows:

- Our input is a training dataset that consists of 277,524 images, each labeled with one of 2 different classes.
- Then, we use this training set to train a classifier to learn what every one of the classes looks like.

In the end, we evaluate the quality of the classifier by asking it to predict labels for a new set of images that it has never seen before. We will then compare the true labels of these images to the ones predicted by the classifier.

From there we'll create a Python script to split the input dataset into three sets:
- A training set
- A validation set
- A testing set
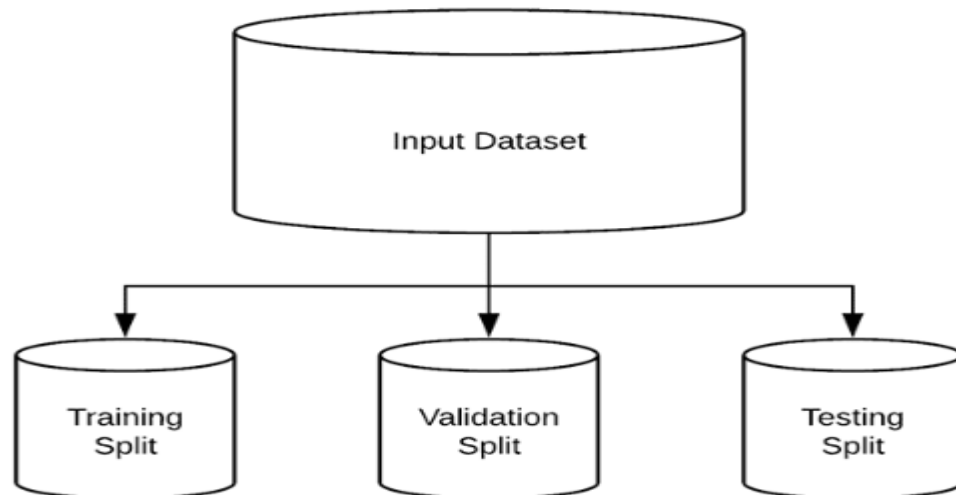
Figure 3. 3: Splitting The Dataset[80].

Data augmentation, a frame of regularization, is critical for about all profound learning tests to help with demonstrate generalization. The strategy intentionally perturbs preparing illustrations, changing their appearance somewhat, some time recently passing them into the organize for preparing. This partially alleviates they have to be accumulate more preparing information, in spite of the fact that more preparing data will seldom harmed your show. First, our configuration contains the path to the original input dataset downloaded from Kaggle

From there we specify the base path to where we're going to store our image files after creating the training, testing, and validation splits. We derive paths to training, validation, and testing output directories.

4. Model training and validation

We notice that there are two main processes that encompass our design has :

Training: This is the most important process because we are going to create our model using precise configurations.

- The Dataset: it is a data base of images listed in classes.
- Cnn and parameters: this is our algorithm for creating a convolution neural network that will be configured with parameters,

Testing : In the Test process we find:

- The image: this is the input for the tests. These are several images or just one.
- The model: it is a file generated in our training.

4.1 The models used in our study
To train our model, we will use the model.fit () method that works well after the successful building of model architecture. With the help of 50 batch sizes, we got 90% accuracy on training sets and acquired stability after 30 epochs.

Define the number of training epochs, initial learning rate, and batch size..

4.2 CNN model building
This section describes the models and methodology used in this chapter. The dataset is loaded from the kaggle dataset. Then we have split the dataset into training and testing set. Each

pixel in the image is flattened, so its value is between 0 and 1. The data is trained on the CNN model.

The CNN models are directly derived from the Sklearn library. the performance generally depends on the depth of the network architecture. Training a deep network requires high computing power and long training time.We build a CNN model to classify the images into their respective categories.

The architecture of our model have multi layer:

What is a Conv2D Layer?

Keras Conv2D is a 2D Convolution Layer, this layer creates a convolution kernel that is wind with layers input which helps produce a tensor of outputs.
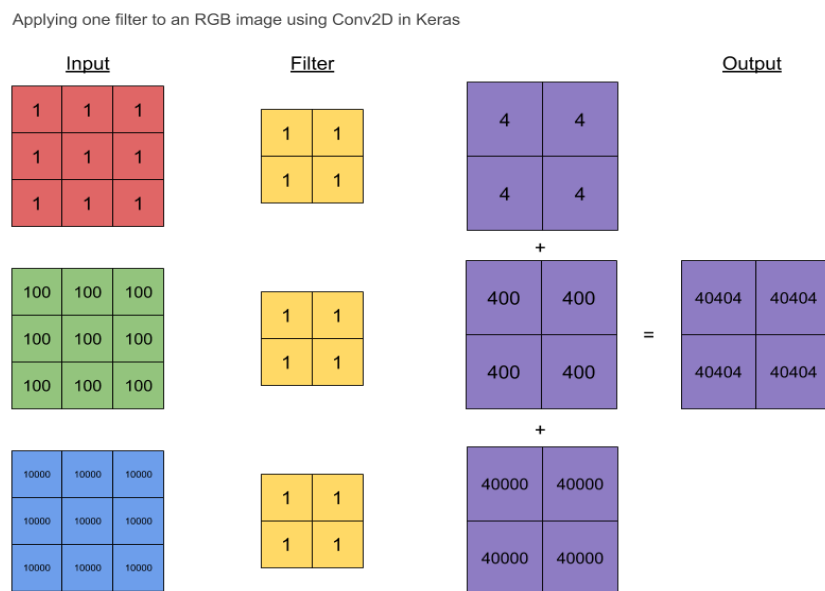
Figure 3. 4: Applying One Filter To An RGB Image Using Conv2d In Keras[81].

What is a Maxpooling2d Layer?

Maxpooling operation for 2D spatial data. Down samples the input along its spatial dimensions (height and width) by taking the maximum value over an input window (of size defined by pool size) for each channel of the input. The windowisshifted by stridesalongeach dimension[82].
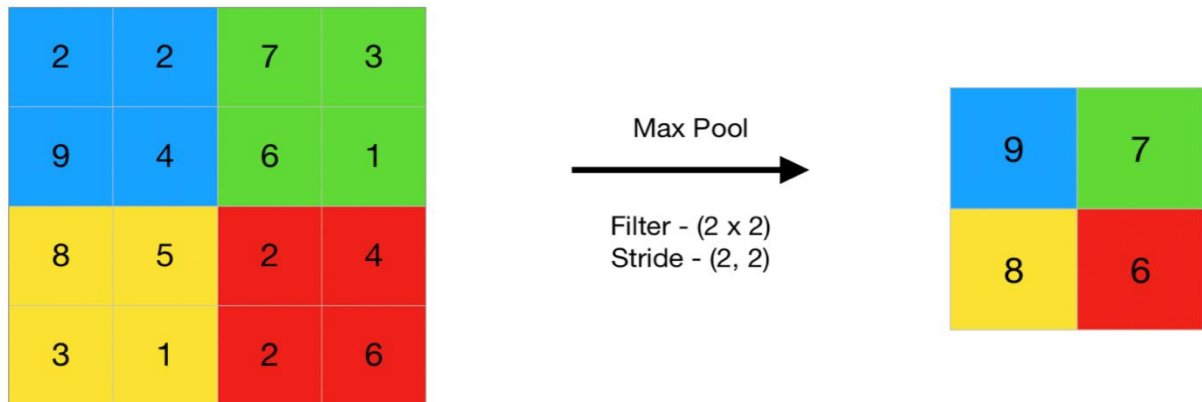
Figure 3. 5: One Filter using maxpooling2d in keras[83].

What is a Dropout Layer in Keras?

The Dropout layer randomly sets input units to 0 with a frequency of rate at each step during training time, which helps prevent overfitting. Inputs not set to 0 are scaled up by 1/(1 - rate) such that the sum over all inputs is unchanged[84].
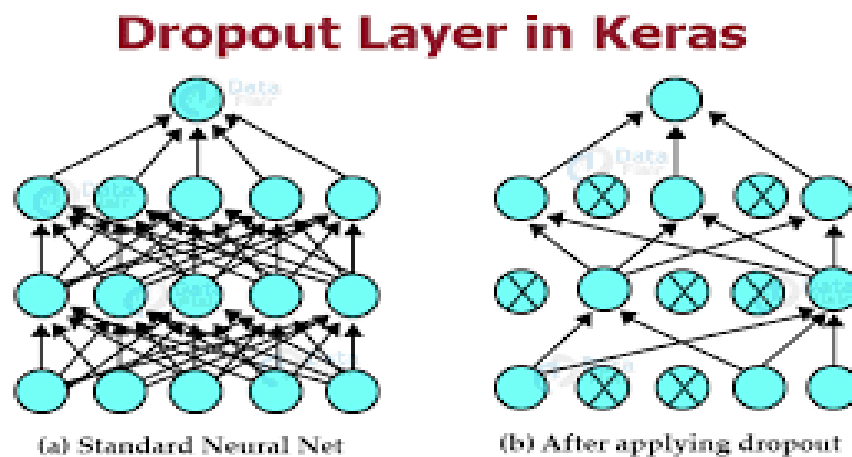
Figure 3. 6: One Filter Using Dropout In Keras[85].

What is a Flatten Layer in Keras?

flatten function flattens the multi-dimensional input tensors into a single dimension, so you can model your input layer and build your neural network model, then pass those data into every single neuron of the model effectively[86].
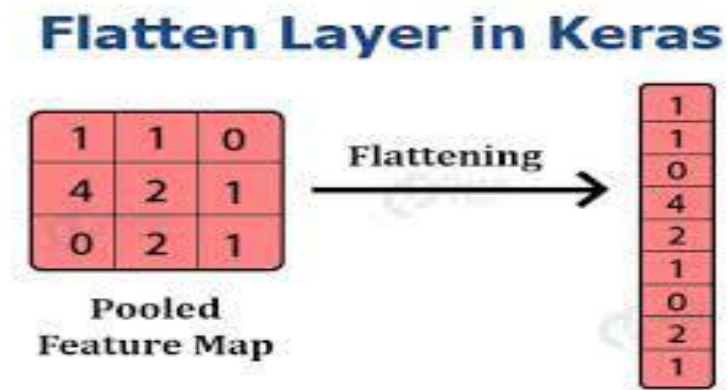
Figure 3. 7: One Flatten Layer In Keras[87].

What is Dense Layer in Keras?

Dense layer is the regular deeply connected neural network layer. It is most common and frequently used layer. Dense layer does the below operation on the input and return the output. output = activation(dot(input, kernel) + bias) [88].
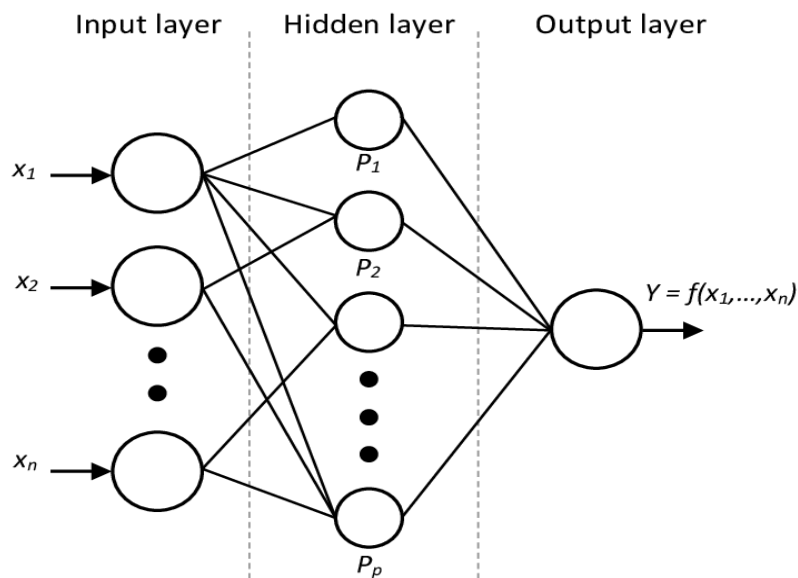
Figure 3. 8: Dense Layer In Keras[89].

Adam:

Adam An optimization algorithm that can be used instead of the classical random gradient descent procedure to update the weights of the iterative network based on the training data, which is easy to implement and efficient in calculation terms**.**

Batch size

```
history = model.fit(X_train, y_train, validation_data = (X_test, y_test), epochs = 30, batch_size = 50)
```

Batch size is one of the most important hyper parameters to tune in deep learning. I prefer to use a larger batch size to train my models as it allows computational speedups from the parallelism of GPUs. However, it is well known that too large of a batch size will lead to poor generalization. On the one extreme, using a batch equal to the entire dataset guarantees convergence to the global optima of the objective function. However this is at the cost of slower convergence to that optima. On the other hand, using smaller batch sizes have been shown to have faster convergence to good results. This is intuitively explained by the fact that smaller batch sizes allow the model to start learning before having to see all the data. The downside of using a smaller batch size is that the model is not guaranteed to converge to the global optima Therefore it is often advised that one starts at a small batch size reaping the benefits of faster training dynamics and steadily grows the batch size through training.

```
Epoch 30/30
1576/1576 [==============================] - 10s 7ms/step - loss: 0.2340 - accuracy: 0.9043 - val_loss: 0.2553 - val_accuracy: 0.9
064
```

5. Output

The foremost common metric for assessing show execution is the accuracy. In any case, when as it were 2% of your dataset is of one course (harmful) and 98% a few other lesson (kind), misclassification scores don't really make sense. You'll be 98% precise and still capture none of the threatening cases which might make a loathsome classifier.

5.1 Confusion Matrix

To extract more information about model performance the confusion matrix is used. The confusion matrix helps us visualize whether the model is "confused" in discriminating between the two classes. As seen in the next figure, it is a 2×2 matrix. The labels of the two rows and columns are *Positive* and *Negative* to reflect the two class labels. In this example the row labels represent the ground-truth labels, while the column labels represent the predicted labels. This could be changed.

The 4 elements of the matrix (the items in red and green) represent the 4 metrics that count the number of correct and incorrect predictions the model made. Each element is given a label that consists of two words:

- True or False
- Positive or Negative

It is True when the prediction is correct (i.e. there is a match between the predicted and ground-truth labels), and False when there is a mismatch between the predicted and ground-truth labels. Positive or Negative refers to the predicted label[90].

Figure 3. 9: Confusion Matrix for Binary Classification[91].

In summary, whenever the prediction is wrong, the first word is False. Otherwise, it is True. The goal is to maximize the metrics with the word True (True Positive and True Negative), and minimize the other two metrics (False Positive and False Negative). The four metrics in the confusion matrix are thus:

- Top-Left (True Positive): How many times did the model correctly classify a Positive sample as Positive.
- Top-Right (False Negative): How many times did the model incorrectly classify a Positive sample as Negative.
- Bottom-Left (False Positive): How many times did the model incorrectly classify a Negative sample as Positive.
- Bottom-Right (True Negative): How many times did the model correctly classify a Negative sample as Negative.

6. Model CNN 1

6.1 Splitting the Data

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(118179, 50, 50, 3) (39393, 50, 50, 3) (118179, 2) (39393, 2)
```

Figure 3. 10: The data has been split.

6.2 Creating the CNN model

```
model=Sequential()
model.add(Conv2D(filters=32,kernel_size=(4,4),input_shape=(50,50,3),activation='relu'))
model.add(MaxPool2D(pool_size=(2,2)))

model.add(MaxPool2D(pool_size=(2,2)))
model.add(Dropout(0.25))

model.add(Conv2D(filters=32,kernel_size=(4,4),activation='relu'))
model.add(MaxPool2D(pool_size=(2,2)))

model.add(MaxPool2D(pool_size=(2,2), strides=(2,2)))
model.add(Dropout(0.25))

model.add(Flatten())

model.add(Dense(128,activation='relu'))
model.add(Dense(2,activation='sigmoid'))

model.compile(loss = 'binary_crossentropy', optimizer ='adam', metrics= ['accuracy'])

model.summary()
```

Figure 3. 11: The architecture of the CNN model.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 47, 47, 32)	1568
max_pooling2d (MaxPooling 2D)	(None, 23, 23, 32)	0
max_pooling2d_1 (MaxPooli ng2	(None, 11, 11, 32)	0
dropout (Dropout)	(None, 11, 11, 32)	0
conv2d_1 (Conv2D)	(None, 8, 8, 32)	16416

max_pooling2d_2 (MaxPooling2 ng2	(None, 4, 4, 32)	0
max_pooling2d_3 (MaxPooling2 ng2	(None, 2, 2, 32)	0
dropout_1 (Dropout)	(None, 2, 2, 32)	0
flatten (Flatten)	(None, 128)	0
dense (Dense)	(None, 128)	16512
dense_1 (Dense)	(None, 2)	258

Table 3-1: Architectureof the CNN model 1.

6.3 Results and discussion
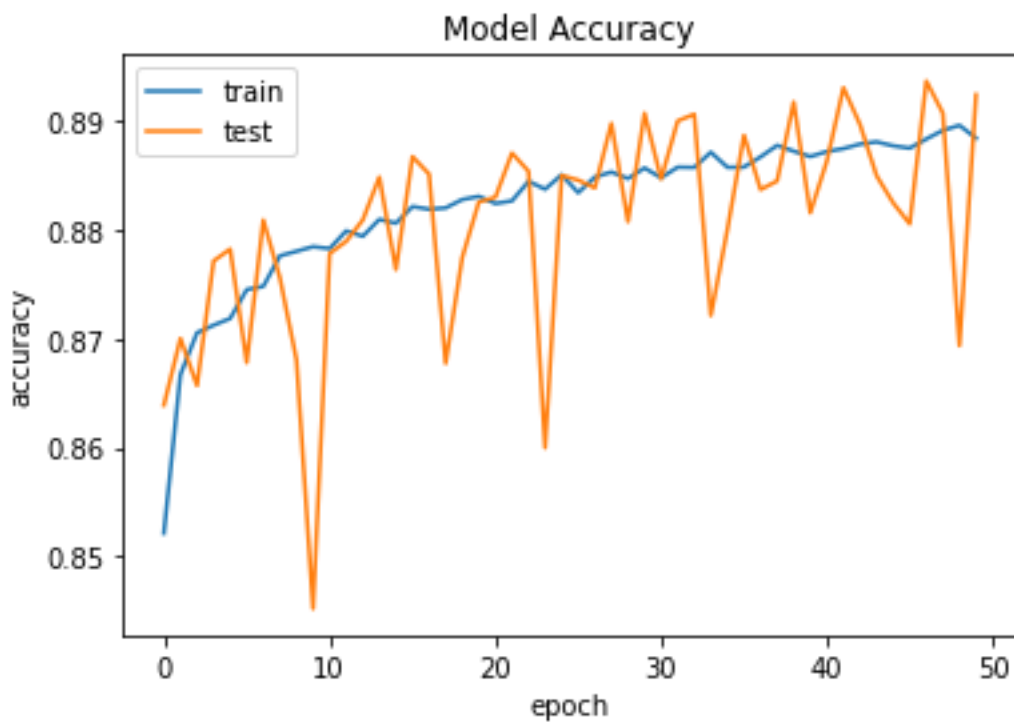
Figure 3. 12: Training And Validation Accuracy (Model 1).

We note in the statement of the model 1 ,First epochs of trainig Started from : accuracy: 0.8521with val_accuracy: 0.8639 , , and the last epochs: accuracy: 0.8884 - val_accuracy: 0.8924 with oscillation in testing and stable in training .
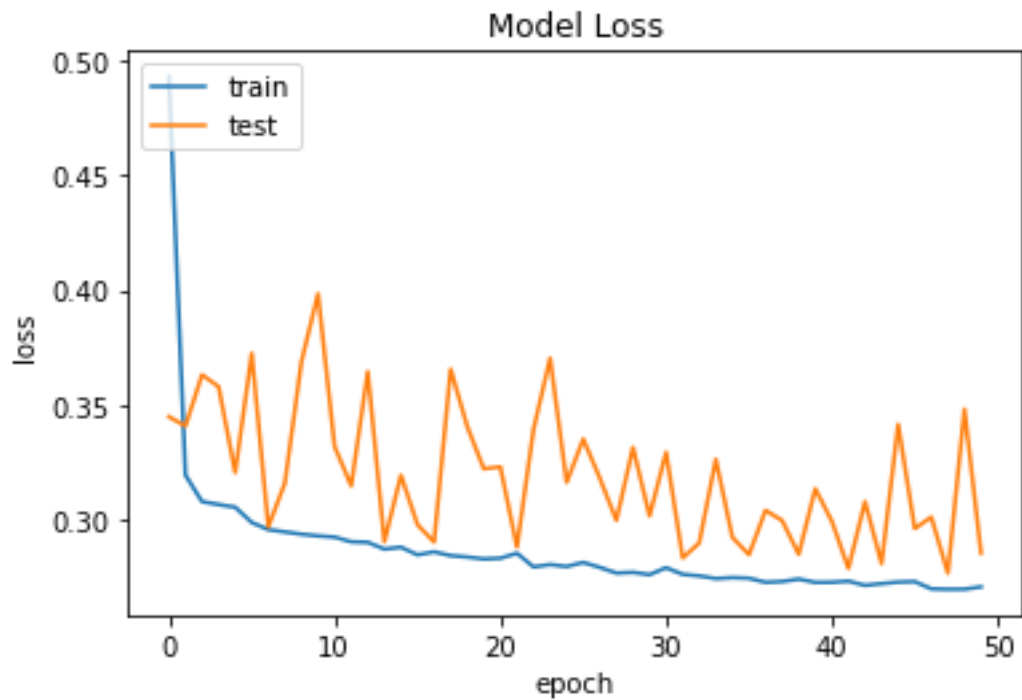
Figure 3. 13: Training And Validation Accuracy (Model 1).

We note in the statement of the model 1 ,First epochs of trainig Started from : loss: 0.4928with val_loss: 0.3448 , , and the last epochs: loss: 0.2708- val_loss: 0.2855with oscillation in testing and stable in training.

6.4 Confusion Matrix

```python
from sklearn.metrics import confusion_matrix
import seaborn as sns

Y_pred = model.predict(X_test)
Y_pred_classes = np.argmax(Y_pred,axis = 1)
Y_true = np.argmax(y_test,axis = 1)

confusion_mtx = confusion_matrix(Y_true, Y_pred_classes)

f,ax = plt.subplots(figsize=(8, 8))
sns.heatmap(confusion_mtx, annot=True, linewidths=0.01,cmap="Greens",linecolor="gray", fmt= '.1f',ax=ax)
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix")
plt.show()
```

Figure 3. 14: Confusion Matrix code For The First Model.
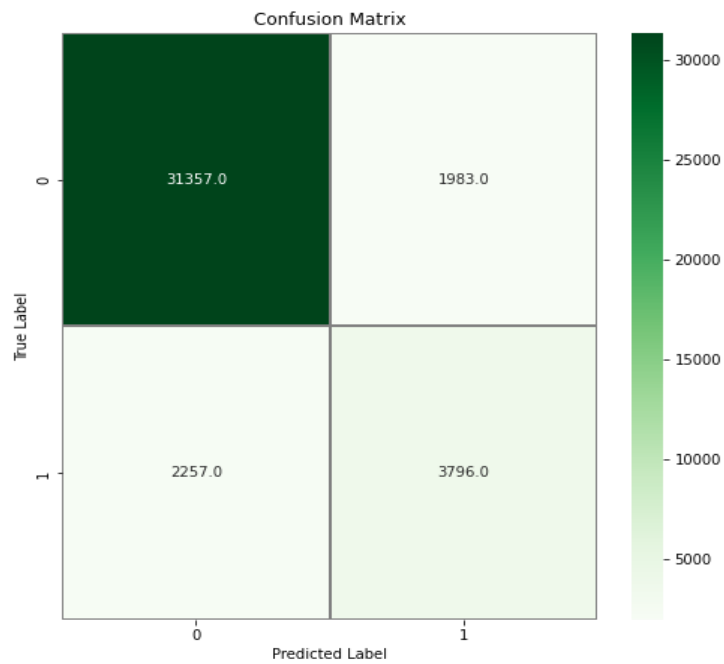
Figure 3. 15: Confusion Matrix For The First Model.

In the Top-Left (True Positive): 31357 times did the model correctly classify a Positive sample as Positive.

- In the Top-Right (False Negative): 1983 time did the model incorrectly classify a Positive sample as Negative.
- In the Bottom-Left (False Positive): 2257 times did the model incorrectly classify a Negative sample as Positive.
- In the Bottom-Right (True Negative): 3796 times did the model correctly classify a Negative sample as Negative.

7. Model CNN 2

7.1 Splitting the Data

```python
from sklearn.model_selection import train_test_split
from keras.utils.np_utils import to_categorical


X_train, X_predict, y_train, y_true = train_test_split(X, y, test_size = 0.3, random_state = 7)


rate = 0.5
num = int(X.shape[0] * rate)

X_test = X_train[num:]
X_train = X_train[:num]


y_test = y_train[num:]
y_train = y_train[:num]


y_train = to_categorical(y_train, 2)
y_test = to_categorical(y_test, 2)
y_true = to_categorical(y_true, 2)


print('X_train shape : {}' .format(X_train.shape))
print('X_test shape : {}' .format(X_test.shape))
print('X_predict shape : {}' .format(X_predict.shape))
print('y_train shape : {}' .format(y_train.shape))
print('y_test shape : {}' .format(y_test.shape))
print('y_true shape : {}' .format(y_true.shape))
```

```
X_train shape : (78786, 50, 50, 3)
X_test shape : (31514, 50, 50, 3)
X_predict shape : (47272, 50, 50, 3)
y_train shape : (78786, 2)
y_test shape : (31514, 2)
y_true shape : (47272, 2)
```

Figure 3. 16: The data has been split.

7.2 Creating the CNN model

```python
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Dropout, Flatten, Dense

model = Sequential()

model.add(Conv2D(32, (3, 3), padding = 'same', activation = 'relu', input_shape = (50, 50, 3)))
model.add(MaxPooling2D(2, 2))
model.add(Dropout(0.25))

model.add(Conv2D(64, (3, 3), padding = 'same', activation = 'relu', input_shape = (50, 50, 3)))
model.add(MaxPooling2D(2, 2))
model.add(Dropout(0.25))

model.add(Conv2D(128, (3, 3), padding = 'same', activation = 'relu', input_shape = (50, 50, 3)))
model.add(MaxPooling2D(2, 2))
model.add(Dropout(0.25))

model.add(Conv2D(128, (3, 3), padding = 'same', activation = 'relu', input_shape = (50, 50, 3)))
model.add(MaxPooling2D(2, 2))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(128, activation = 'relu'))

model.add(Dropout(0.5))
model.add(Dense(2, activation = 'sigmoid'))

model.summary()
```

Figure 3. 17: The architecture of the CNN model.

Layer (type)	Output Shape	Param #
conv2d_2 (Conv2D)	(None, 50, 50, 32)	896
max_pooling2d_4 (MaxPooling2	(None, 25, 25, 32)	0
dropout_2 (Dropout)	(None, 25, 25, 32)	0
conv2d_3 (Conv2D)	(None, 25, 25, 64)	18496

max_pooling2d_5 (MaxPooling2	(None, 12, 12, 64)	0
dropout_3 (Dropout)	(None, 12, 12, 64)	0
conv2d_4 (Conv2D)	(None, 12, 12, 128)	73856
max_pooling2d_6 (MaxPooling2	(None, 6, 6, 128)	0
dropout_4 (Dropout)	(None, 6, 6, 128)	0
conv2d_5 (Conv2D)	(None, 6, 6, 128)	147584
max_pooling2d_7 (MaxPooling2	(None, 3, 3, 128)	0
dropout_5 (Dropout)	(None, 3, 3, 128)	0
flatten_2 (Flatten)	(None, 1152)	0
dense_8 (Dense)	(None, 128)	147584
dropout_6 (Dropout)	(None, 128)	0
dense_9 (Dense)	(None, 2)	258

Table 3-2: Algorithms Of The Model CNN 2.

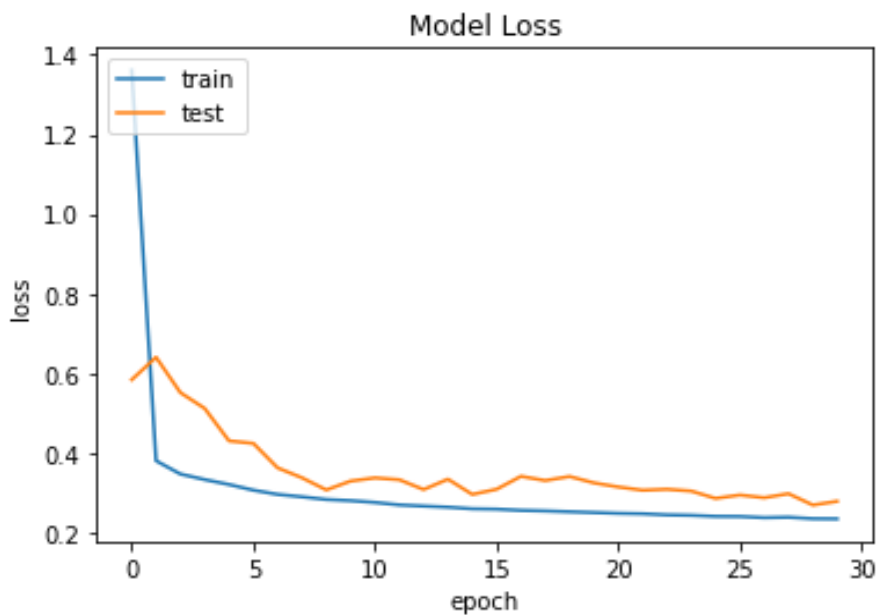## 7.3 Results and discussion
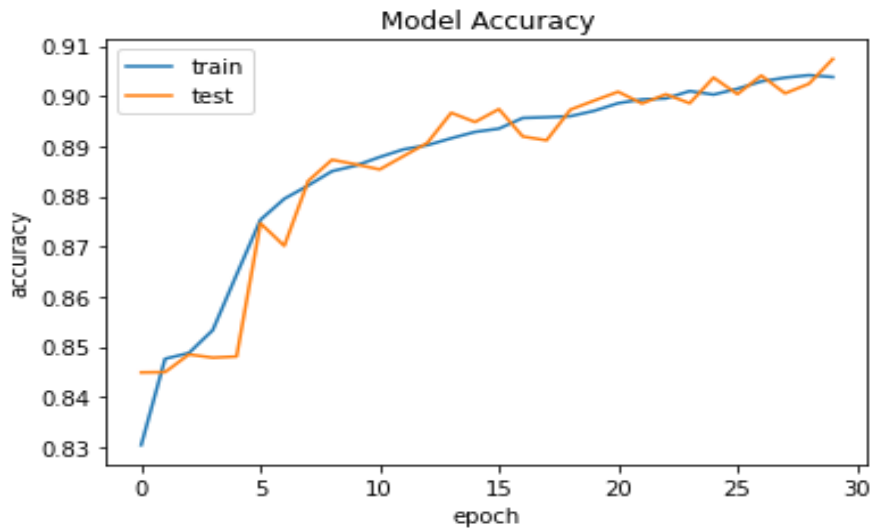
Figure 3. 18: Training And Validation Accuracy (Model 2).

We note in the statement of the model 2 ,First epochs of trainig Started from : accuracy: 0.8120 with val_accuracy: 0.8450, and the last epochs: accuracy: 0.8884 - val_accuracy: 0.8924 with Kind of stable in testing and stable in training

Figure 3. 19: Training And Validation Accuracy (Model 2).

We note in the statement of the model 1 ,First epochs of trainig Started from : loss: 2.3325 with val_loss: 0.4780, and the last epochs: loss0.2300- val_loss: 0.2657 with kind of stable in testing and stable in training.

7.4 Confusion Matrix

```python
from sklearn.metrics import confusion_matrix
import seaborn as sns

Y_pred = model.predict(X_test)
Y_pred_classes = np.argmax(Y_pred,axis = 1)
Y_true = np.argmax(y_test,axis = 1)

confusion_mtx = confusion_matrix(Y_true, Y_pred_classes)

f,ax = plt.subplots(figsize=(8, 8))
sns.heatmap(confusion_mtx, annot=True, linewidths=0.01,cmap="Greens",linecolor="gray", fmt= '.1f',ax=ax)
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.title("Confusion Matrix")
plt.show()
```

Figure 3. 20: Confusion Matrix code For The First Model.
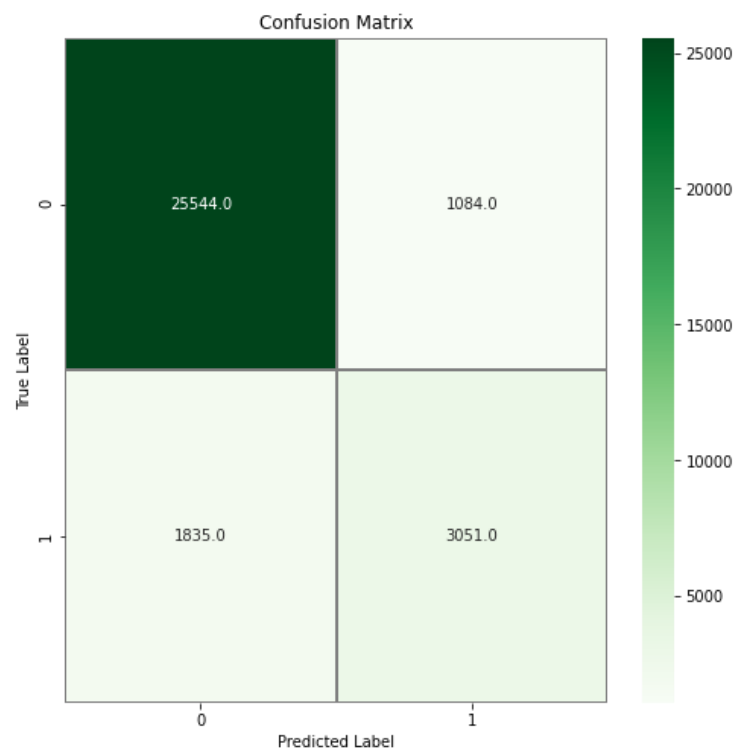
Figure 3. 21: Confusion Matrixe For The Second Model.

- In the Top-Left (True Positive): 25544 times did the model correctly classify a Positive sample as Positive.
- In the Top-Right (False Negative): 1084 time did the model incorrectly classify a Positive sample as Negative.
- In the Bottom-Left (False Positive): 1835 times did the model incorrectly classify a Negative sample as Positive.
- In the Bottom-Right (True Negative): 3051 times did the model correctly classify a Negative sample as Negative.

8. Results

	MODEL CNN 1	MODEL CNN 2
Accuracy	89.24%	90.63%
Time(second)	1224.2	1638.3
Epoch	50	30

Table 3-3 : Results obtained from the application of CNN algorithms.

9. Discussion

In order to show the results obtained for these architectures, we illustrate in the following the results in terms of accuracy and error for each of the model.

9.1 Model CNN 1

While learning at model 1. For 50 iterations the processor took 1224.2s to do 10 iterations (finish the training) with a fixed error rate of 0.0001 and an accuracy of 89.24%.

9.2 Model CNN 2

While learning at model 2. For 30 iterations the processor took 1638.3s to do 30 iterations (finish the training) with a fixed error rate of 0.0001 and an accuracy of 90.63%.

10. Conclusion

According to the figures of the model1, model 2 and architectures, the learning accuracy increases with the number of Epochs, this reflects that at each Epoch the model learns more information. If the accuracy is decreased then we will need more information to train our models and therefore we need to increase the number of epochs and vice versa. Similarly, the learning error decreases with the number of epochs. So we find that in our application, the model 2 result is better than the model 1 result. Also, the deeper the architecture and the easy dataset for learning, Better and more accurate the test result. So, the right choice of the number of dataset and epochs and batch size is very important in the training part because it allows the model to better learn the data and avoid the problem of overfitting or underfitting.

General conclusion

Advances in artificial intelligence, such as machine learning and deep learning, have enabled us to deal with increasingly complex situations and get good results, which is critical in the field of medical imaging, where accuracy can save human lives. Artificial intelligence has a lot of benefits when it comes to research in healthcare. who pledges to improve the healthcare system in the future.

Completing this thesis was, in fact, a truly enriching experience. The latter provided an opportunity to put my new knowledge into practice and to work independently on an exciting and useful research topic in the fields of artificial intelligence and medicine.We can offer the following views:Test the models we used in our app on larger databases.Use of different medical imaging methods.

For optimal efficiency, it is required to parallelize and use a high-performance computing platform in the context of the entire dataset. We did our best to reliably detect tumors, but we ran into several issues in our work where tumors could not be detected. wrongly detected or detected As a result, we'll strive to work on those photographs as well as the overall project. dataset. As a result, we'll try to use different deep learning algorithms in the future. can produce a more precise and superior result

The current study proposes a CNN approach that analyzes regions of IDC tissue in WSIs for the automatic detection of this cancer. Two different CNN structures are described in this study with an appropriate comparison. The proposed system using CNN Model 2 achieves an accuracy of 90%. The architectures were routed through a large dataset of approximately 275,000 RGB image spots of 50×50 pixels. The proposed model has been found to successfully obtain correct results that may reduce human errors in the diagnostic process and reduce the cost of cancer diagnosis. The main limitation of this study is the use of a secondary database such as Kaggle, and future study must be conducted based on primary dataset for greater accuracy of findings regarding breast cancer identification.

In the end, the realization of this thesis was a very enriching experience. The latter was an opportunity to put into practice the knowledge I have acquired, and to work independently on a research project that is interesting and has value in AI and in the medical field.

As perspectives we can propose:

- Test the models used in our application on other larger databases.
- Use of other medical imaging modality (MRI, Ultrasound, …)

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