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About:

Deep Learning Applied to Chest Medical Images Classification

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بسم الله الرحمن الرحيم

Dedication

I dedicate this work to:

- *My entire family, my father and my mother, this work wouldn't have been establishes without her love and encouragements over the years.*
- *My grand ma, for her love.*
- *My brother Tarek, for his love and support.*
- *To all of my friends and people who constantly believed in me*

Thanks

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Abstract

Lung disease is common throughout the world. Especially these include pneumonia, covid, tuberculosis, and lung opacity; so an early and precise diagnosis of lung disease is important. For this reason, Computer Aided Diagnostic (CAD) systems using X-Rays medical images are often used to assist healthcare professionals to make more and more accurate decisions, for this purpose, many image processing and machine learning models have been proposed and developed, like deep learning techniques include convolution neural networks (CNN), Visual Geometry Group-based Neural Networks (VGG), and Residual Neural Networks (ResNet). In this work, we used three models based on ResNet50, VGG16, and VGG19 that were pre-trained using ImageNet database. As implementation tools, Jupyter Notebook, Tensorflow, and Keras are used. The three models were applied to the chest X-ray database collected from two different sources on the Kaggle repository using transfer learning. A step of pre-processing was applied to the radiography database using histogram equalization. Finally, the best accuracies results are as follows: for the case based on ResNet50 model, the best validation accuracy values were 94.5% and 93.2%, and in the case based on VGG16 model, the accuracies were 93.2% and 89.7%, and in the case based on VGG19 model the accuracies were 95.2% and 91%.

Keywords: CAD, COVID, lung opacity, pneumonia, tuberculosis, convolution neural network, deep learning, transfer learning, VGG, ResNet.

List of abbreviations

AI	Artificial intelligence
ANN	Artificial neural network
BNN	Biological neural network
CAD	Computer-Aided detection and diagnosis
CADE	Computer-Aided detection
CADX	Computer-Aided diagnosis
CNN	Convolution neural network
ML	Machine learning
ReLU	Rectified linear unit
ResNet	Residual neural network
VGG	Visual Geometry group
DL	Deep learning
CT	Computed tomography
MRI	Magnetic resonance imaging
PET	Position emission tomography
RBF	Radial basis function
TB	Tuberculosis
TP	True positive
FP	False positive

FN	False negative
TN	True negative
RBF	Radial basis function
ROI	Region of interest

Summary

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General Introduction

The lung is a vital organ in the human physiological structure, and illnesses in the lung severely can influence health conditions. This work investigates the classification of lung abnormalities, such as pneumonia, covid, tuberculosis, and lung opacity using visual geometry group based neural networks (VGG), and residual neural networks (ResNet50) deep learning techniques. Pneumonia is a seasonal infectious lung disease that can lead to life-threatening complications for children (age <5 years) and elderly individuals (age > 60 years) if not diagnosed and treated early.

Since late December 2019, a novel coronavirus disease 2019 (COVID-19) has been causing serious lung damage and breathing problems. In addition, pneumonia, a form of lung disease can be due to the causative virus of COVID-19 or may be caused by other viral or bacterial infections [38]. Hence, early detection of lung diseases has become more important than ever.

Tuberculosis (TB) is a chronic bacterial disease infecting the lungs, kidneys, spine and/or brain [1]. TB is an airborne mycobacterium that can be spread from person to person, such as when an infected person coughs or sneezes. It can also cause an infection after a period of latency in a person who was infected at an earlier time. Lung opacity represents the result of a decrease in the ratio of gas to soft tissue (blood, lung parenchyma and stroma) in the lung.

In clinics, all this diseases are diagnosed with a variety of imaging modalities, including chest X-Ray, CT, and MRI. While chest X-Ray radiographs are the most cost-effective diagnostic tool for lung diseases detection, the diagnosis of these diseases from chest X-Rays necessitate highly skilled radiologists as these images are often overlapping with each other.

Computer-Aided-Diagnosis (CAD) procedure overcomes these problems by employing Machine Learning (ML) and Deep-Learning (DL) for automated detection of lung diseases. More recently, DL has been widely researched due to its general applicability to problems involving automated feature extraction and classification [39-40]. Convolutional Neural Network (CNN) based assessments are widely used in image classification and object detection [41]. CNNs involve spatial filters that automatically gather information of the structure embedded in the image. Unlike conventional image classification methods existing in ML, CNNs are run on images directly, a pixel-based approach, as there is no need for image pre-processing subroutines [42].

In this work, a DL framework is proposed to identify lung diseases in X-Ray radiographs using a well-known DL approach called ResNet50. Initial experimental investigation with model based on ResNet50 on chosen test images (80 normal, 80 covid, 80 lung opacity, 80 tuberculosis and 80 pneumonia X-Rays) of dimension 224 × 224 × 3 yielded a validation accuracy of 94.5%, 93.2%. After implementing modifications in the final stage of the DL structure, the proposed model based on VGG16 and the model based on VGG19 technique is tested on the same dataset and a validation accuracy of 93.2%, 89.7% and 95.2%, 91% respectively. This solution can put up decreasing medical costs with the enlargement of computer science for health and medical science projects.

Chapter 1: Computer-Aided detection and diagnosis in medical imaging of chest diseases

I. Introduction

Lung diseases, also known as respiratory diseases or pulmonary disorders, are conditions that affect the normal functioning of the lungs. These diseases can affect the airways, lung tissue, blood vessels, or the respiratory system as a whole. Lung diseases can range from acute infections to chronic conditions, and they can have various causes, including infections, environmental factors, genetic predisposition, autoimmune reactions, and exposure to harmful substances.

Medical imaging refers to the use of various technologies and techniques to visualize the internal structures and functions of the human body for diagnostic purposes. It plays a crucial role in the detection, diagnosis, and monitoring of various diseases and conditions. Medical images provide valuable information to healthcare professionals, aiding in the identification and characterization of abnormalities or changes in the body.

CAD stands for Computer-Aided Design or Computer-Aided Drafting. It is a technology that uses computer software to assist in the creation, modification, analysis, and optimization of designs and drawings. CAD software is commonly used in various industries, including architecture, engineering, manufacturing, and construction.

CAD systems in medical imaging work by analyzing image data and applying pattern recognition, machine learning, or artificial intelligence techniques to detect and highlight areas that may indicate the presence of a particular condition or disease. The CAD software can flag suspicious regions, provide quantitative measurements, or generate additional image enhancements to aid in the diagnostic process.

Image processing has a wide range of applications, including medical imaging, satellite imaging, surveillance systems, facial recognition, digital photography, computer vision, and many others. It plays a crucial role in analyzing and interpreting visual data, enabling better understanding, decision-making, and automation in various domains.

In this chapter we present chest diseases, the deferent medical images, introduces CAD, in the end defined digital image and image processing.

II. Chest diseases

1. Pneumonia

1.1. Definition

Pneumonia is an infection in one or both lungs caused by bacteria, viruses, fungi, allergic reaction or chemical irritants. When these germs reach your lungs, your immune system sends cells to attack the germs. These cells cause the alveoli (air sacs) to become inflamed and to fill up with mucus and other liquids. This leads to breathing difficulty, fever, cough and fatigue.[1]

1.2. The type of pneumonia

The body typically protects the lungs from infection by filtering germs out of the air we breathe. Pneumonia occurs when germs such as bacteria, viruses, or fungi manage to enter the lungs and your immune system attempts to combat the infection. The main types of pneumonia are:

- ✓ **Bacterial pneumonia**: such streptococcus pneumonia, which usually occurs when the body is weakened in some way
- ✓ **Viral pneumonia**: caused by viruses such as influenza (flu)
- ✓ **Mycoplasma pneumonia**: caused by the bacterium mycoplasma pneumonia
- ✓ **Fungal pneumonia:** caused by the inhalation of fungi spores

Other pneumonias may be caused by infections due to inhaling food, liquid, gases or allergic reactions.[1]

1.3. The symptoms of pneumonia

The symptoms of pneumonia vary depending on the severity of your condition. Immediate medical attention is necessary if you have any of the following symptoms [1]:

- ✓ Cough with bloody or discolored mucus
- ✓ Chest pain
- ✓ High fever
- ✓ Shaking and chills
- ✓ Shortness of breath that worsens with activity
- ✓ Loss of energy and exhaustion
- ✓ Loss of appetite
- ✓ Rapid pulse
- ✓ Nausea
- ✓ Vomiting
- ✓ Diarrhea

- ✓ Confused mental state or delirium
- ✓ Muscle pain or weakness

2. Tuberculosis

2.1. Definition

Tuberculosis (TB) is a chronic bacterial disease infecting the lungs, kidneys, spine and/or brain. TB is an airborne mycobacterium that can be spread from person to person, such as when an infected person coughs or sneezes. It can also cause an infection after a period of latency in a person who was infected at an earlier time. Without treatment, TB can cause serious complications in other parts of the body or even be fatal. Treatment requires months of adherence to several antibiotics, but most cases can be cured. Drug-resistant TB is much more difficult to cure and treatment takes much longer (nine to 18 months).[1]

2.2. The symptoms of TB

Tuberculosis consists of three stages: exposure, latent TB infection (when the patient does not yet exhibit symptoms of the disease) and TB disease (when the person has signs and symptoms of an active infection). The symptoms of active TB or NTM may progress slowly and resemble those of other lung conditions or medical conditions. It is important that you contact your physician for a diagnosis early, as leaving the condition untreated may cause severe damage to the lungs or respiratory failure. Symptoms include [1]:

- ✓ A persistent cough
- ✓ Coughing blood or sputum
- ✓ Chest pain
- ✓ High fever
- ✓ Chills or night sweats
- ✓ Shortness of breath (dyspnea)
- ✓ Loss of energy and exhaustion
- ✓ Loss of appetite and unintended weight loss
- ✓ Poor growth in children

3. Lung cancer

3.1. Definition

Lung cancer forms in tissues of the lung, usually in the cells lining air passages. It starts from a single cell, but usually includes millions of cells by the time it can be seen by an X-ray. Cancer cells lose their previous function in the body. Instead they grow faster than regular cells. They cause the body to weaken and prevent organs from working. The two main types of lung cancer are small cell lung cancer, which spreads quickly and non-small cell lung cancer, which is more common and spreads slowly. More than 225,000 Americans are diagnosed with lung cancer each year. Treatment depends on the type and stage of lung cancer and may include one or more treatments, including surgery, chemotherapy, radiation therapy or targeted drug therapy.[1]

3.2. The types of lung cancer

There are two major types of lung cancer [1] :

- ❖ Non-small cell lung cancer accounts for 85 to 90 percent of lung cancers. The main types of non-small cell lung cancer are:
  - ✓ Squamous cell carcinoma (also called epidermis carcinoma) often begins in the bronchi near the middle of the lungs.
  - ✓ Adenocarcinoma usually begins along the outer edges of the lungs. It is the most common type of lung cancer in people who have never smoked.
  - ✓ Large cell carcinomas are a group of cancers with large, abnormal-looking cells related to hormone secreting glands. These tumors may begin anywhere in the lungs and grow quickly.
- ❖ Small cell lung cancer is sometimes called oat cell cancer. It grows rapidly and spreads to other organs. There are two types:
  - ✓ Limited. Cancer is generally found in one lung. There may be cancer in nearby lymph nodes on the same side of the chest.
  - ✓ Extensive. Cancer has spread beyond the primary tumor in the lung into other parts of the body.

3.3. The symptoms of lung cancer

Lung cancer may not cause any symptoms and may be found on a routine chest X-ray or low-dose chest CT scan. Signs and symptoms of lung cancer may include [1]:

- ✓ Cough that doesn't go away and worsens over time
- ✓ Trouble breathing
- ✓ Chest pain
- ✓ Wheezing
- ✓ Coughing up blood or rust-colored mucus
- ✓ Hoarseness
- ✓ Loss of appetite
- ✓ Weight loss for no known reason
- ✓ Feeling very tired
- ✓ Pneumonia or bronchitis
- ✓ Shoulder pain
- ✓ Bone pain
- ✓ Yellowing of skin and eyes (jaundice)
- ✓ Headache, seizures, or confusion
- ✓ Enlarged lymph nodes in the neck

4. Corona virus

4.1. Definition

Coronaviruses form a family of various viruses (Corona viridian) that can also infect both man and animal. Their name means "crown virus" and comes from the fact that they all have a crown-like appearance when viewed under a microscope. The coronaviruses were first identified in humans in the 1960s. It is viruses that cause emerging diseases, i. e. new infections due to modifications or mutations of the virus. Human coronaviruses cause respiratory infections, ranging from a mild cold to severe lung disease, sometimes fatal. They may also be accompanied by disorders [43].

4.2. The symptoms of corona virus

Symptoms of COVID-19 are similar to those of other colds and flu, and the main symptoms of coronavirus compared to other diseases include [43]:

- ✓ Fever.
- ✓ Inflammation of the throat.
- ✓ Cough.
- ✓ Tired.
- ✓ Inflammation of the lungs.

5. Lung opacity

5.1. Definition

Lung opacity refers to an abnormal or hazy appearance of the lung tissue on imaging studies, such as chest X-rays or computed tomography (CT) scans. It is a radiological finding that indicates a change in the density or structure of the lungs [44].

5.2. The symptoms of lung opacity

Symptoms of lung opacity may vary depending on the underlying cause. However, if the underlying condition is significant, the following symptoms may be present:

- ✓ Difficulty breathing or a feeling of breathlessness, especially during physical activity or exertion.
- ✓ Persistent cough that may produce phlegm or blood in some cases.
- ✓ Sharp or dull pain in the chest, which may worsen with deep breathing or coughing.
- ✓ Elevated body temperature, often accompanied by other signs of infection.

III. The medical image

1. Medical imaging

Medical imaging is the visualization of body parts, tissues, or organs, for used in the clinical diagnosis, treatment, and surveillance of diseases. Whereas, Medical image processing deals with the development of problem-specific approaches to improving raw medical image data for selective visualization as well as more in-depth analysis. There are various needs for the medical image processing:

- Hospitals and radiology centers handling several terabytes of medical images
- Medical images are very complex to manipulate
- The nature of diseases can be diagnosed by providing solutions that:

They Are close to the intelligence of doctors a tactical plan for mega data in medical imaging, is to dynamically integrate medical images, information in vitro diagnosis, genetic information, and electronic profile. It offers the ability to support personalized decision-making by analyzing data from a large number of patients with similar conditions[2].

2. Modalities of medical images

The rapid development of the medical and healthcare sector directly on the diagnosis, prevention, and treatment of diseases related to the quality of life of every citizen. Medical imaging is a key tool in clinical practice, where generalized analytical methods such as image pretreatment, extraction, segmentation, recording, and classification of features are applied.

Many radiological and pathological images in digital format are generated by the hospital's and medical centers sophisticated imaging devices. Techniques of anatomical imaging such as ultrasound (US), computed tomography (CT), and magnetic imaging Resonance Imaging (MRI) are used daily worldwide chickens tests on human beings.

All of the above imaging techniques are of extreme importance in many areas such as computer-assisted diagnosis, pathology monitoring, processing, and modification of processing. Information extracted from images may include:

Functional descriptions, geometric models of anatomical structures, and diagnostic evaluation. Different solutions such as Picture Archive and Communication Systems (PACS) and specialized image database systems address the problem of medical data archiving image collections. The classification results obtained may also serve several clinical applications such as disease growth monitoring and therapy. The main contribution of this research is to examine the accuracy of the classification and retrieval of liver images by machine learning ultrasound algorithms.

Among all types of medical imaging, ultrasound imaging is still one of the most popular techniques due to its non-ionization and low cost. Digital Imaging and Communication in Medicine (DICOM) Standard is used globally to store, exchange and transmit medical images. The DICOM standard integrates protocols for imaging techniques such as X-ray, ultrasound tomography (CT), resonance imaging magnetic resonance imaging (MRI), and radiotherapy[2].

2.1. X-ray

X-ray technology is the oldest and most commonly used form of imaging. X-rays use ionizing radiation to produce images of a person's internal structure by sending X-rays through the body, which are absorbed in different quantities depending on the density of the material. In addition, other devices included 'X-ray type' include: mammography, interventional radiology, computer radiography, radiography, and computed tomography (CT). Radiation therapy is a type of device that also uses X-rays, gamma rays, electron beams, or protons to treat cancer (Figure 1). Radiographic images are generally used to assess [2]:

- Broken bones
- Cavities
- Swallowed objects
- The lungs
- Blood vessels
- Breasts (mammography)

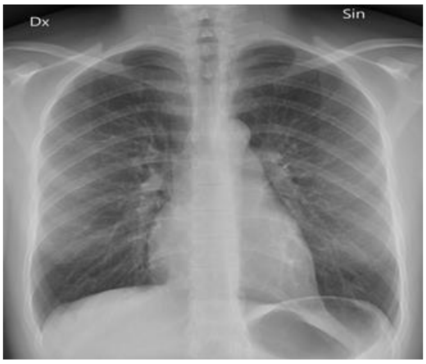

Figure 1: Chest X-Rays [46]

2.2. Ultrasound

Diagnostic ultrasound, also known as medical ultrasound or ultrasound graphing, uses high-frequency sound waves to create images of the inside of the body (Figure 2). The ultrasound machine sends sound waves into the body and can convert the sound echoes back to images. Ultrasound technology can also produce audible sounds of blood flow, allowing health professionals health to use both sound and visuals to assess the health of the patient. Ultrasound is often used to assess[2]:

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

Figure 2: Ultrasound [47]

2.3. Computed tomography (CT)

Computed tomography (CT), also known as computed tomography (CT), is a medical imaging method that joins multiple X-ray projections taken from different angles to make detailed cross-sectional images of areas inside the body CT scans allow doctors to obtain 3D views of very specific parts of the body, such as soft tissues, pelvis, vessels blood, lungs, brain, heart, abdomen, and bones. CT scan is also often a diagnostic method for many cancers, such as liver, lung and pancreatic cancers (Figure 3). CT is often used to assess [2]:

- ❖ Presence, size, and location of tumors
- ❖ Organs of the pelvis, chest, and abdomen
- ❖ Colon health (colonization by T. C.)
- ❖ Vascular status/blood flow
- ❖ Pulmonary embolism (scan angiography)
- ❖ Abdominal aortic aneurysms (angiography by scan)
- ❖ Bone damage
- ❖ Heart tissue
- ❖ Traumatic injuries
- ❖ Cardiovascular disease

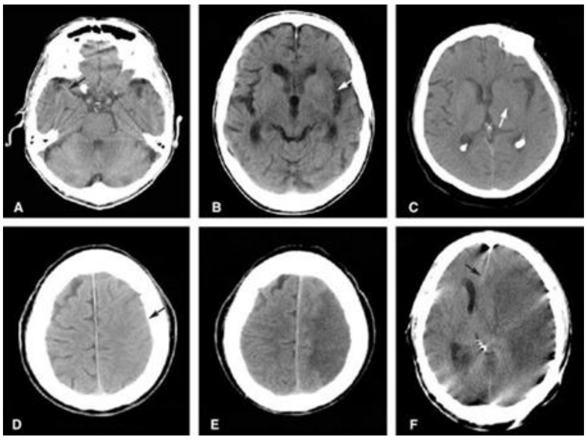

Figure 3: Computed tomography [48]

2.4. Magnetic resonance imaging (MRI)

Magnetic Resonance Imaging (MRI) is a medical imaging technology that uses radio waves and a magnetic field to produce detailed images of organs and tissues. MRI is very effective in diagnosing several conditions by showing the difference between normal and soft tissues in the body. MRI is often used to assess[2]:

- Blood vessels
- Abnormal tissue
- Breasts
- Bones and joints
- Organs of the pelvis, chest, and abdomen (heart, liver, kidney, spleen)
- Injuries to the spine
- Tendons and ligament tears

2.5. Position emission tomography

Positron Emission Tomography (PET) is a nuclear imaging technique that provides physicians with information on how tissues and organs are operated. PET is often used in combination with computed tomography and uses a scanner and a small amount of radiopharmaceuticals injected into the vein of a patient to help make detailed, computerized pictures of areas inside the body (Figure 4). The PET is often used to assess [2]:

- Neurological diseases such as Alzheimer's disease and multiple sclerosis
- Cancer
- Effectiveness of treatment

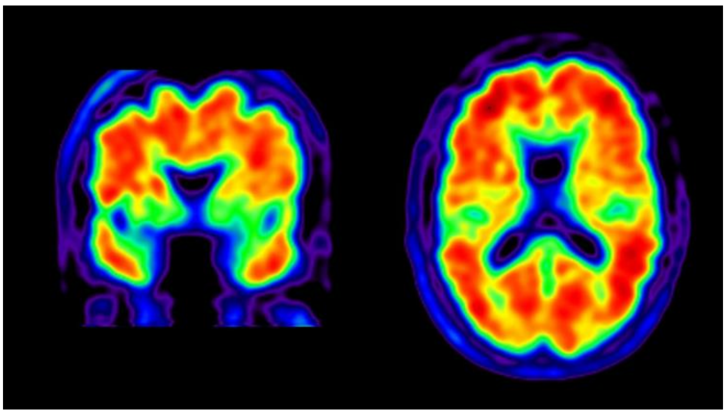

Figure 4: Position emission tomography [49]

IV. Computer-Aided Detection and Diagnosis technology

1. CAD in medical imaging

CAD is a technology which includes multiple elements like concepts of artificial intelligence (AI), computer vision, and medical image processing. The main application of CAD system is finding abnormality in human body. Among all these, detection of tumor is the typical application because if it misses in basic screening, it leads to cancer (Figure 5). The word CAD is often commonly used for both computer-aided detection and computer-aided diagnosis[3]:

- ✓ **Computer-Aided Detection (CADe):** Marks different picture areas that may appear irregular, intended to reduce the possibility of overlooking interesting pathologies.
- ✓ **Computer-Aided Diagnosis (CADx):** assists a doctor in evaluating and classifying pathology in medical imaging.

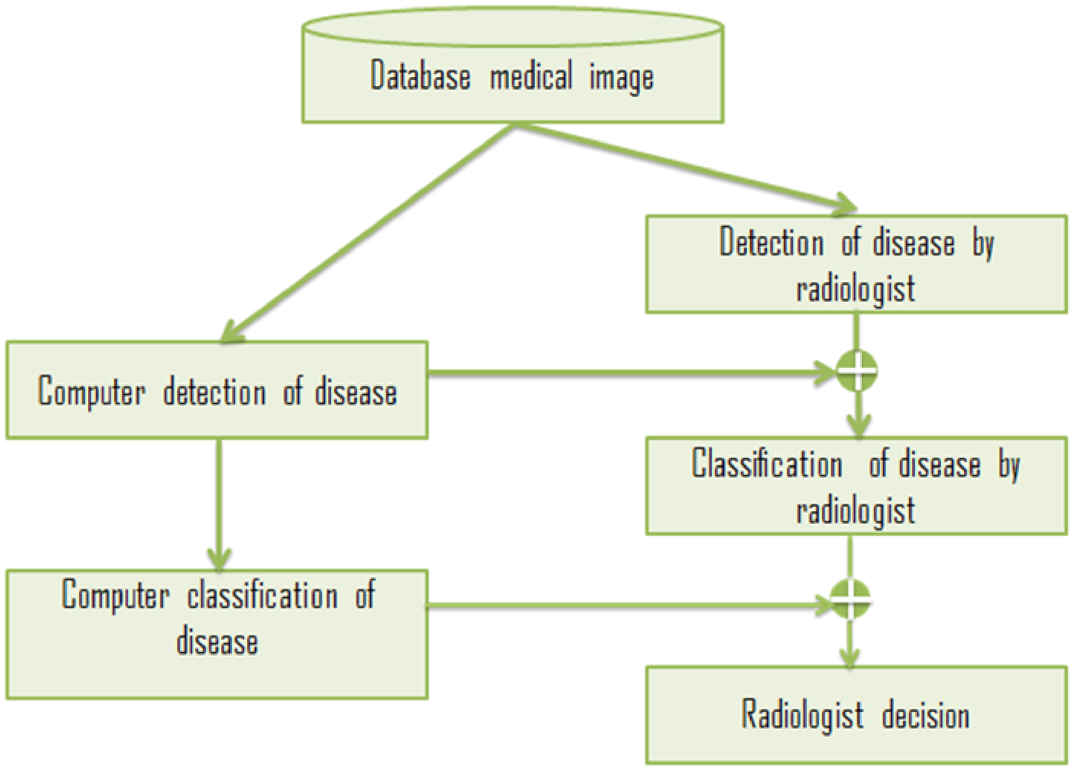

Figure 5: Computer-Aided diagnosis of medical images

2. Applications of CAD system

CAD is used in the diagnosis of breast cancer, lung cancer, colon cancer, prostate cancer, bone metastases, coronary artery disease, congenital heart defect, pathological brain detection, Alzheimer's disease, and diabetic retinopathy[3]

3. The work flow of CAD

The work flow of CAD present in Figure 6 [3].

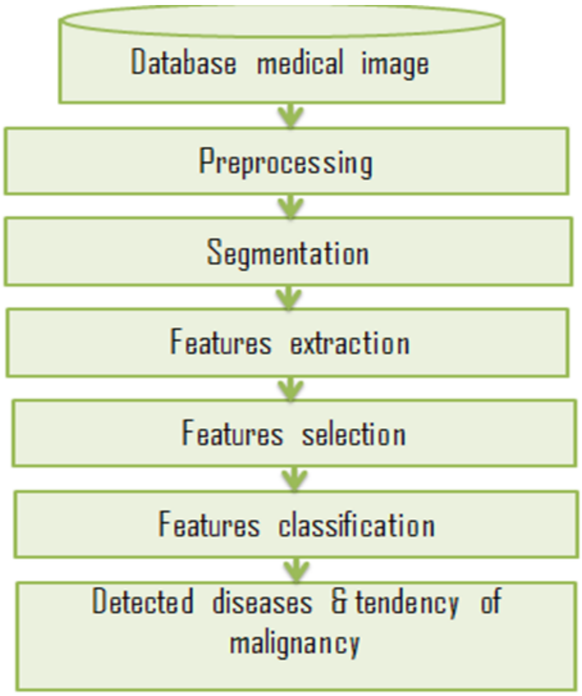

Figure 6: General scheme of CAD

3.1. Pre processing

- ❖ Reduction of background artifacts (bugs in images)
- ❖ Removal of noise
- ❖ Filtering
- ❖ Enhancing the quality of the image by leveling and increased contrast for clearing the images

3.2. Segmentation

- ❖ Disparity of different structures in the image, e.g., mass, micro calcification, and tissue
- ❖ Finding the ground truth from anatomic databank

3.3. Features extraction

Detected region of interest is analyzed individually for special feature (characteristics)[3]:

- ❖ Size, location, and border
- ❖ Gray levels analyzed in ROI
- ❖ Texture of the ROI
- ❖ Patterns found in ROI
- ❖ Architectural distortion of the ROI

3.4. Features selection

Feature selection is also known as Variable selection or Attribute selection. Essentially, it is the selection of a subset of features from a larger pool of available features. In other terms, it is the process of selecting the most important/relevant features for further classification process. There are two major types of algorithms for feature selection: wrapper methods, and filter methods[4]:

- ❖ Wrapper Feature Selection Methods,
- ❖ Filter Feature Selection Methods.

3.5. Features classification

After analysis of structure, every ROI is evaluated individually for scoring of the probability value for true positive (TP), false positive (FP), false negative (FN) and true negative (TN). The following procedures are examples of classification algorithms[3]:

- ❖ Nearest-neighbor rule (e.g., k-nearest neighbors')
- ❖ Minimum distance classifier
- ❖ Cascade classifier
- ❖ Naive Bayesian classifier
- ❖ Artificial neural network
- ❖ Radial basis function network (RBF)

V. Artificial vision

1. Image processing

Modern technology has made it possible to manipulate multidimensional signals means of systems ranging from simple digital circuits to parallel computers perfected. The discipline of image processing is broad, encompassing signal processing and image-specific techniques. Its applications range from medicine to entertainment, including geological processing and remote sensing. One image can be considered as a function f (x, y) of two variables x and y as in electrical engineering and computer science, it is a two-dimensional signal [36].

2. The Digital Image

In the real world, a picture can be a photograph, a painting, or even a dream, but in the world of computers, it's a set of points called "pixels." This image is commonly called digital image and formally defined as an array pixels whose values specify the luminous intensity of the flux on the image element represented by this pixel. As mentioned earlier, the digital image is a function of two variables x and y that are responsible for the distribution (positions2) of the pixels of the image.

Positions and values are positive scalars whose range depends on characteristics of the digitization unit. The value of each pixel can be between 0 and 255. Three different types of digital images can be illustrated [45]:

- ✓ Image in black and white.
- ✓ Image of value in grey.
- ✓ Color picture.

3. Acquisition of images

Before starting an image processing procedure, an image must be captured and converted into digital form. This process is called image acquisition; its aim is to transforming a vision of the real world into a digital image. However, a good understanding of the process of image formation is necessary in the analysis quantitative of all required images. So that an object in the three-dimensional world becomes a digital image in the memory of a computer, you have to go through three steps:

- ❖ Becoming visible: by interacting with light or more generally with radiation electromagnetic, an object becomes visible. The light captured by a camera system is determined by the optical properties of the material from which the article is manufactured and by illumination.

- ❖ Projection: The optical system collects the light rays reflected by objects and projects the three-dimensional world onto a two-dimensional image plane.
- ❖ Digitization: The continuous image on the image plane must be converted to image points on a discreet grid. In addition, the intensity at each point must be represented by an appropriate finite number of gray scale values (Quartation) [37].

4. Characteristics of a digital image

The image is a structured set of information characterized by the following parameters:

4.1. Size

It's the size of the picture. The latter is presented in the form of a matrix whose elements are numerical values representative of light intensities (pixels).Number of rows in this matrix multiplied by the number of columns gives us the number total number of pixels in an image.

4.2. Resolution

It is the clarity or finesse of details achieved by a monitor or printer in the production of images. On computer monitors, the resolution is expressed as the number of pixels per unit of measurement (inch or centimeter).The word resolution is also used for denote the total number of pixels that can be displayed horizontally or vertically on a The larger the monitor number, the better the resolution.

4.3. Noise

A noise (parasite) in an image is considered a phenomenon of sudden variation of the intensity of a pixel in relation to its neighbors; it comes from the illumination of optical and electronic devices of the sensor.

4.4. Histogram

The gray scale or color histogram of an image is a function that gives the frequency of occurrence of each level of grey (color) in the image. It makes it possible to provide a large amount of information on the distribution of grey levels (color) in the case of an image that is too bright or too dark.

It can be used to enhance the quality of an image (Image Enhancement) by introducing some changes, in order to be able to extract the relevant information from it (Figure 7).

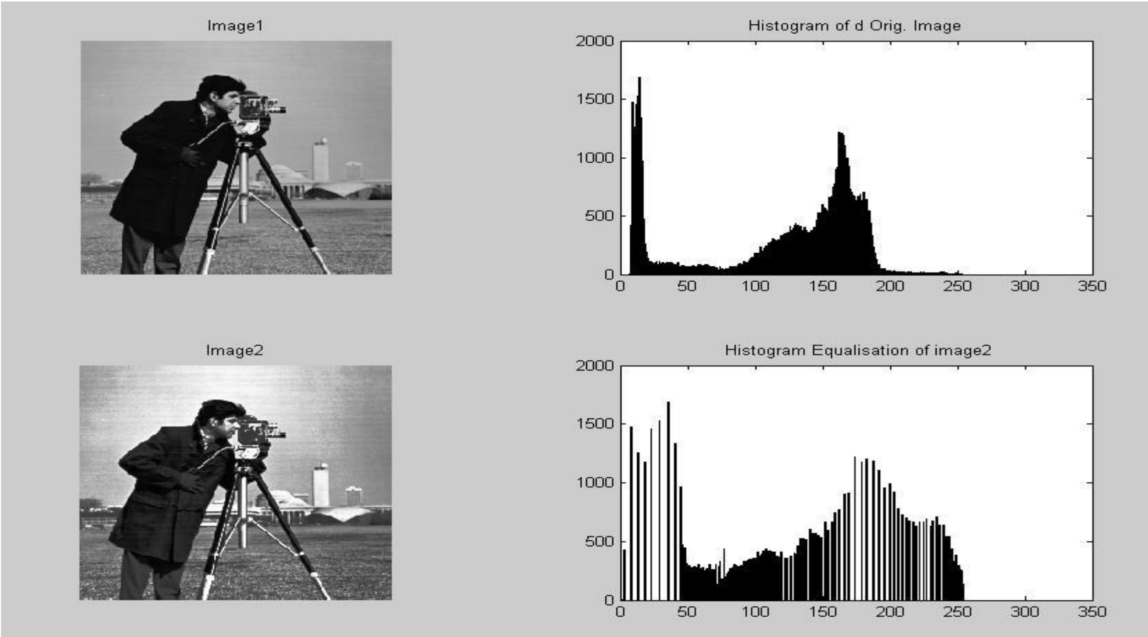

Figure 7: The image with her histogram [50]

To reduce the quantification error, to compare two images obtained under different illumination, or to measure some properties on an image, we change often the histogram.

4.5. Luminance

It is the degree of brightness of the points in the picture .It is also defined as the quotient of the luminous intensity of a surface by the apparent area of that surface, for a distant observer, the word luminance is substituted or word brilliance, which corresponds to the brightness of an object .Good luminance, is characterized by:

- ✓ Bright (bright) images.
- ✓ Good contrast: avoid images or the gram of contrast tends towards white or black; these images cause loss of detail in dark or bright areas.
- ✓ Absence of parasites.

4.6. Grayscale images

The grayscale is the value of light intensity at a point. The color of a pixel can take on values ranging from black to white, passing through a finite number of intermediate levels. To represent images in grayscale, we can assign a value corresponding to the amount of light reflected by each pixel in the image. This value can be between 0 and 255, for example. Each pixel is no longer represented by a bit, but by a byte. To achieve this, the hardware used to display the image must be capable of producing the corresponding grayscale.

The number of grayscale depends on the number of bits used to describe the "color" of each pixel in the image. The higher this number, the more levels are possible (Figure 8).

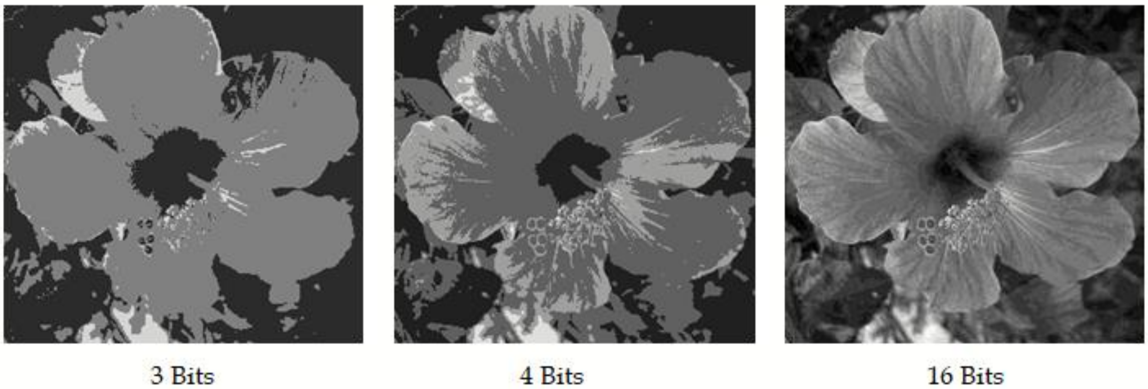

Figure 8: Grayscale images [51]

4.7. color Images

Although it is sometimes useful to be able to represent black and white images, the multimedia applications most often use color images. Representation color is done in the same way as monochrome images with however a few peculiarities. Indeed, it is first necessary to choose a model of representation. On can represent colors using their primary components. Emitting systems (Computer screens, etc.) are based on the principle of additive synthesis: colors consist of a mix of red, green and blue (R.V.B. model) (Figure 9).

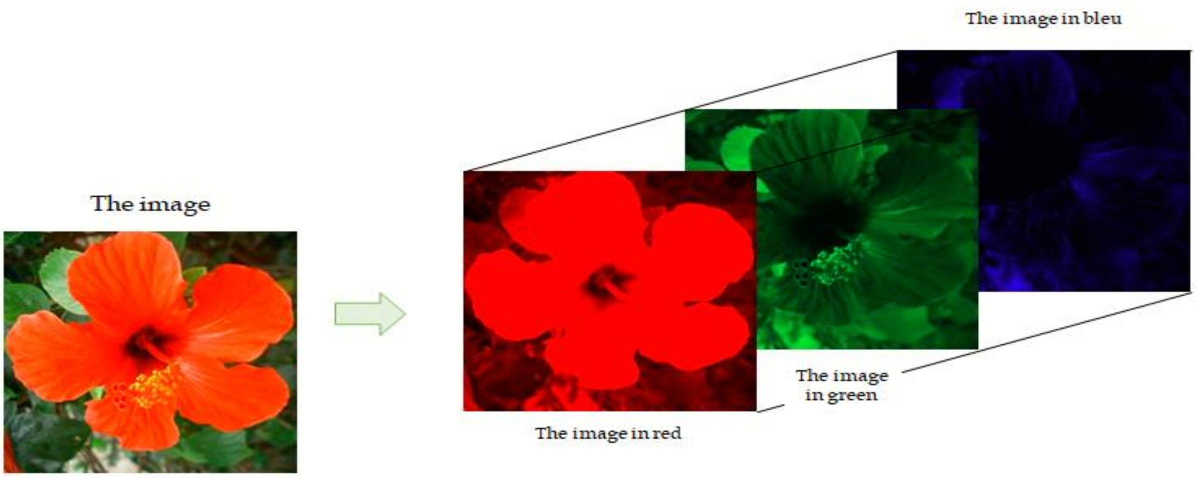

Figure 9: Images in color [51]

4.8. Contrast

It is the marked opposition between two regions of an image, more precisely between the dark areas and light areas of this image. The contrast is defined according to the luminance's of two image areas. If L1 and L2 are the degrees of brightness respectively two adjacent areas A1 and A2 of an image, the contrast C is defined by the ratio.

$$C = \frac{(L_1 + L_2)}{(L_1 + L_2)}$$

4.9. Histogram equalization

Histogram equalization is a widely utilized technique for enhancing contrast in image processing. It is valued for its simplicity and effectiveness. This method involves modifying the dynamic range and contrast of an image by adjusting its intensity histogram to achieve the desired shape.

Step 1: histogram calculation $h(i) \quad i \epsilon [0,255]$

Step 2: histogram normalization $h_n(i) = \frac{h(i)}{nb} \quad i \epsilon [0,255]$

(nb: number of pixels in the image)

Step 3: Normalized probability density $C(i) = \sum_{j=0}^{i} h_n(i) \quad i \epsilon [0,255]$

Step 4: Image grayscale transformation $j'(x, y) = C\big(f(x, y)\big) * 255$

VI. Conclusion

In this chapter, we provide an overview of various chest diseases, including their definitions, types, and symptoms. Furthermore, we explore the common medical imaging techniques employed to detect these diseases. Specifically, we delve into computer-aided diagnosis, which serves as a system for identifying chest diseases from medical images.

Moreover, we define digital images and discuss the concept of image processing. We lay the foundation for understanding how digital images are manipulated and analyzed.

Moving forward, the next chapter will delve into the fundamental principles of artificial intelligence. We will explore key concepts and principles that underpin the field of AI, including machine learning, neural networks, and other pertinent techniques.

Chapter 2: Artificial intelligence

I. Introduction

Artificial Intelligence (AI) refers to the development and implementation of computer systems that can perform tasks and make decisions that typically require human intelligence. AI aims to replicate and augment human cognitive abilities, such as learning, reasoning, problem-solving, perception, and decision-making, using algorithms and data.

AI algorithms can analyze medical images, such as X-rays, MRIs, and CT scans, to assist in the detection and diagnosis of various conditions. Deep learning techniques enable AI systems to recognize patterns and anomalies in images, helping radiologists and other healthcare professionals make more accurate interpretations.

ANN stands for Artificial Neural Network. An Artificial Neural Network is a computational model inspired by the structure and functioning of biological neural networks, such as the human brain. It is a type of machine learning algorithm that is capable of learning from and making predictions or decisions based on input data.

In the context of artificial intelligence and machine learning, CNN stands for Convolutional Neural Network. A Convolutional Neural Network is a type of deep learning model specifically designed for analyzing visual data, such as images and videos. It is inspired by the structure and functionality of the human visual cortex, which is responsible for processing visual information in the brain.

CNNs are highly effective in tasks related to computer vision, including image classification, object detection, image segmentation, and image generation. They have revolutionized the field of computer vision and have achieved remarkable performance on various benchmark datasets.

In this chapter we defined the artificial intelligence and her application in medicine .We moved to the definition of machine learning and her methods, next we showed the difference between biological neural networks and artificial neural networks. We defined deep learning and showed the difference between it and machine learning. And finally we present CNN and there different layers.

II. Artificial intelligence

1. Definition

Artificial intelligence (AI) is a wide-ranging branch of computer science concerned with building smart machines capable of performing tasks that typically require human intelligence. AI is an interdisciplinary science with multiple approaches, but advancements in machine learning and deep learning are creating a paradigm shift in virtually every sector of the tech industry.

Artificial intelligence allows machines to model, and even improves upon, the capabilities of the human mind. From the development of self-driving cars to the proliferation of smart assistants like Siri and Alexa, AI is a growing part of everyday life. As a result, many tech companies across various industries are investing in artificially intelligent technologies[5].

2. Types of artificial intelligence

Artificial intelligence can be categorized into one of four types[5].

- **Reactive AI** uses algorithms to optimize outputs based on a set of inputs. Chess-playing AIs, for example, are reactive systems that optimize the best strategy to win the game. Reactive AI tends to be fairly static, unable to learn or adapt to novel situations. Thus, it will produce the same output given identical inputs.
- **Limited memory AI** can adapt to past experience or update itself based on new observations or data. Often, the amount of updating is limited (hence the name), and the length of memory is relatively short. Autonomous vehicles, for example, can "read the road" and adapt to novel situations, even "learning" from past experience.
- **Theory-of-mind AI** is fully-adaptive and have an extensive ability to learn and retain past experiences. These types of AI include advanced chat-bots that could pass the Turing Test, fooling a person into believing the AI was a human being. While advanced and impressive, these AI are not self-aware.
- **Self-aware AI**, as the name suggests, become sentient and aware of their own existence. Still in the realm of science fiction, some experts believe that an AI will never become conscious or "alive".

3. Application of artificial intelligence in medicine

There are numerous ways AI can positively impact the practice of medicine, whether it's through speeding up the pace of research or helping clinicians make better decisions. Here are some examples of how AI could be used[6]:

3.1. AI in disease detection and diagnosis

Unlike humans, AI never needs to sleep. Machine learning models could be used to observe the vital signs of patients receiving critical care and alert clinicians if certain risk factors increase. While medical devices like heart monitors can track vital signs, AI can collect the data from those devices and look for more complex conditions, such as sepsis. One IBM client has developed a predictive AI model for premature babies that are 75% accurate in detecting severe sepsis[6].

3.2. Personalized disease treatment

Precision medicine could become easier to support with virtual AI assistance. Because AI models can learn and retain preferences, AI has the potential to provide customized real-time recommendations to patients around the clock. Rather than having to repeat information with a new person each time, a healthcare system could offer patients around-the-clock access to an AI-powered virtual assistant that could answer questions based on the patient's medical history, preferences and personal needs[6].

3.3. AI in medical imaging

AI is already playing a prominent role in medical imaging. Research has indicated that AI powered by artificial neural networks can be just as effective as human radiologists at detecting signs of breast cancer as well as other conditions. In addition to helping clinicians spot early signs of disease, AI can also help make the staggering number of medical images that clinicians have to keep track of more manageable by detecting vital pieces of a patient's history and presenting the relevant images to them[6].

III. Machine learning

1. Definition

In principle, machines, computers and programs only function the way you have previously configured them: "if case A occurs, trigger B". However, our expectations of modern computer systems are increasing and the programs cannot foresee every conceivable case and impose a solution on the computer. It is therefore necessary for the software to make autonomous decisions and react appropriately to unknown situations. But algorithms must be available to allow programs to learn. This means that it must first be fed with data and that it can then make associations "Learn"[7].

2. Machine learning methods

There're two known methods in machine learning: supervised learning and unsupervised learning. I will focus on the first methods in the following:

2.1. Supervised machine learning

Supervised learning, also known as supervised machine learning, is defined by its use of labeled datasets to train algorithms to classify data or predict outcomes accurately. As input data is fed into the model, the model adjusts its weights until it has been fitted appropriately. 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 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 bays, linear regression, logistic regression, random forest, and support vector machine (SVM)[7].

❖ **Mathematical presentation:**

Annotated examples of data are given: (x1, y1), (x2, y2), (x3, y3) … and we predict the output on new data: x* y*.

2.2. 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. This method's ability to discover similarities and differences in information make it ideal for exploratory data analysis, cross-selling strategies, customer segmentation, and image and pattern recognition (Figure 10). 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, and probabilistic clustering methods[7].

❖ **Mathematical presentation:**

Only raw observations of random variables are given: x1, x2, x3, x4…. and we expect the deduction of the relation: xi yi.

2.3. Reinforcement Learning

Reinforcement Learning is a feedback-based machine learning technique. Agents must explore the environment and perform actions based on their actions. Reinforcement learning is like training a puppy to do tricks in exchange for treats [58].

2.4. Semi-supervised Learning

Semi-supervised Learning is an intermediate technique for both supervised and unsupervised learning. It performs actions on datasets having few labels as well as unlabeled data [58].

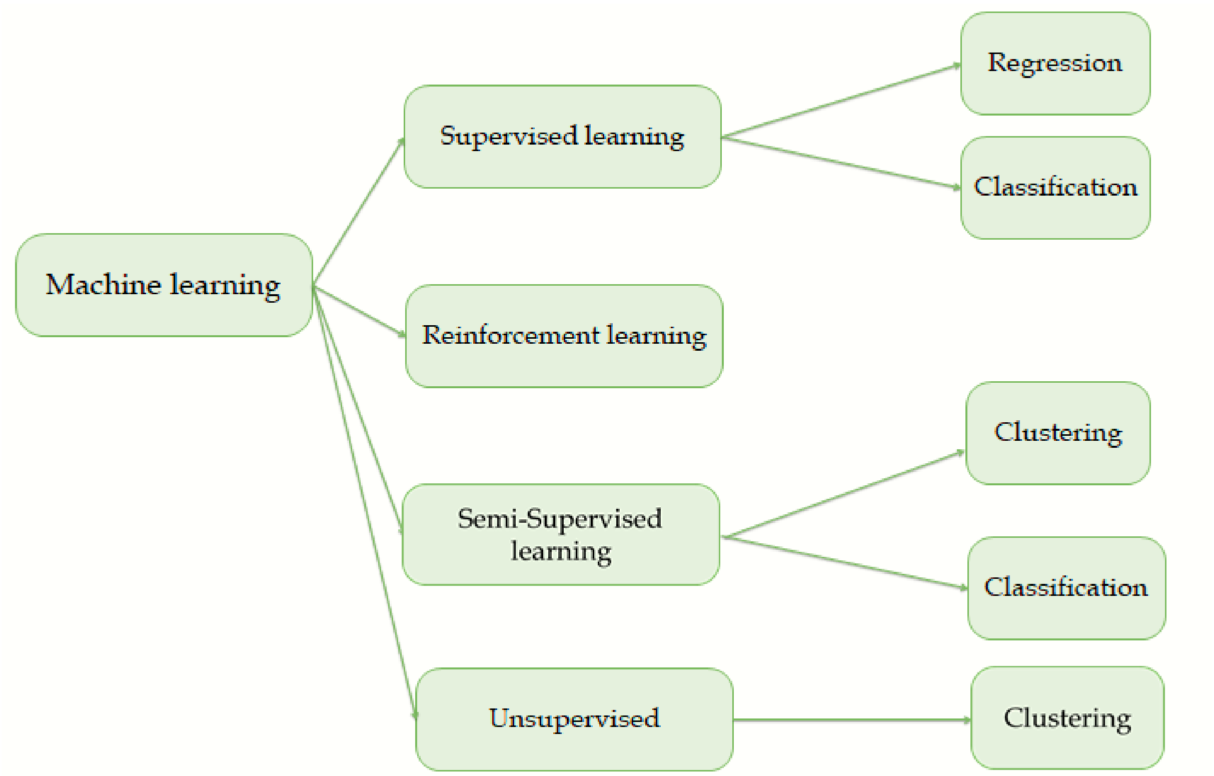

Figure 10: Fundamental approaches in machine learning

IV. Neural Networks

1. Biological Neural Networks

A nerve cell (neuron) is a biological specific cell that processes information. There are large numbers of neurons, about 1011 with various interconnections, about 1015 according to estimation (Figure 11)[8].

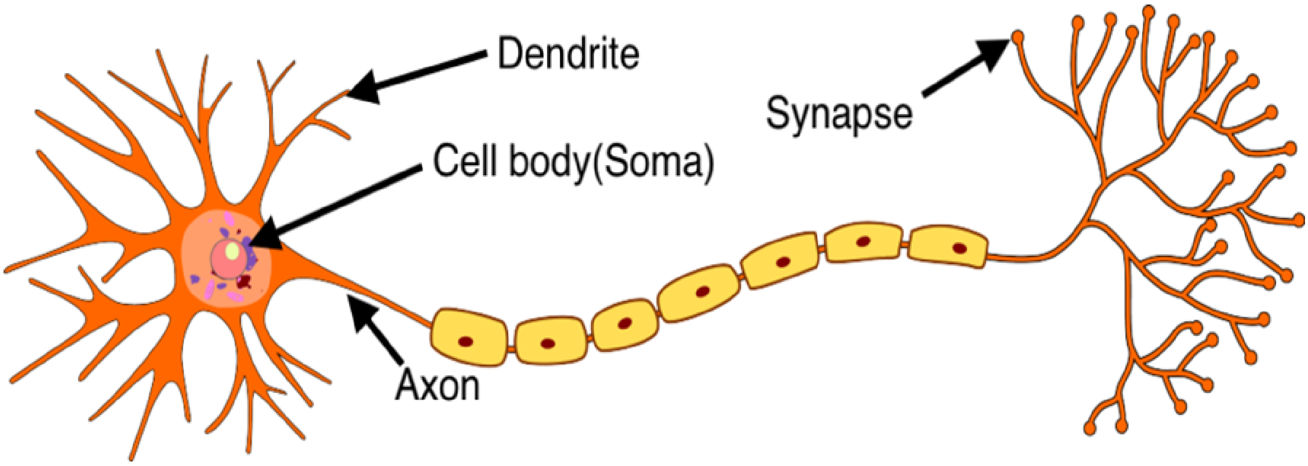

Figure 11: the biological neuron [52]

❖ The cell body

It contains the nucleus of the neuron and performs the biochemical transformations necessary for the synthesis of enzymes and other molecules that ensure the life of neurons. Its shape is pyramidal or spherical in most cases; it often depends on its position in the brain. This cell body is a few microns in diameter.

❖ The dendrites

Each neuron has a hair of dendrites. These are thin tubular extensions, a few tenths of microns in diameter and a few tens of microns in length. They are the main receptors of the neuron which are used to pick up the signals which reach it.

❖ The axon

The axon, which is strictly speaking the nerve fiber, serves as a means of transport for the signals emitted by the neuron. It differs from dendrites by its shape and the properties of its outer membrane. Indeed, it is generally longer than the dendrites, and branches out at its end, where it communicates with other neurons, while the ramifications of the dendrites occur rather near the cell body.

- **Synapses**

It's the link between the axon and other neuronal dendrites.

2. Artificial Neural Network

2.1. History of ANN

The history of ANNs is summarized as follows:

1957: proposal of the perceptron by Frank Rosenblatt

1967: demonstration by Marvin Minsky that the perceptron is unable to process non-linearly separable data, disinterested in neural approaches.

1986: Rumelhart, Hinton and Williams demonstrate the use of gradient propagation for training the multilayer perceptron.

1995-2005: development of SVM, loss of interest for neural networks.

2006: first deep architectures of neural networks.

2012: Object Recognition (Toronto, ImageNet) and Speech (Microsoft) demonstrate the potential of disruptive deep learning technology.

2014: explosion of private investments in machine learning, in particular in deep learning[8].

2.2. Definition

Neural networks, also known as artificial neural networks (ANNs) or simulated neural networks (SNNs) are a subset of machine learning and are at the heart of deep learning algorithms. Their name and structure are inspired by the human brain, mimicking the way that biological neurons signal to one another.

Similar to the biological one, the artificial neuron consists of the following[9]:

- One or more incoming connections, with the task of collecting numerical signals from other neurons; each connection is assigned a weight that will be used to consider each signal sent.
- One or more output connections that carry the signal for the other neurons.
- An activation function determines the numerical value of the output signal on the basis of the signals received from the input connections with other neurons, and suitably collected from the weights associated with each picked-up signal and the activation threshold of the neuron itself.

The following figure represents the artificial neuron (Figure 12):

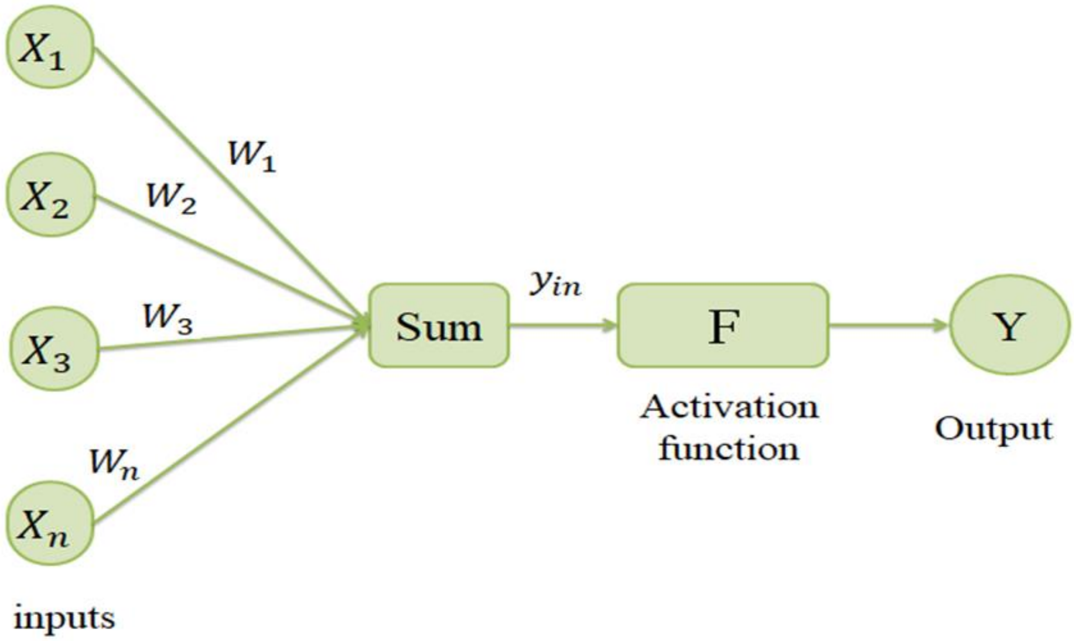

Figure 12: General model of ANN

$$\text{Inputs } (X_1, X_2, X_3, \dots \dots \dots, X_n)$$
$$\text{Weights } (W_1, W_2, W_3, \dots \dots \dots \dots., W_n)$$

The net input can be determined as follows, for the general artificial neural network model above:

$$y_{in} = X_1 * W_1 + X_2 * W_2 + X_3 * W_3 + \cdots X_n * W_n \dots (1)$$

$$\text{Input} \quad y_{in} = \sum(X_i * W_i) \; \dots. (2)$$

The output can be determined with the activation function applied to the net input.

$$Y = f(y_{in}) \dots (3)$$

Output = function (net input calculated)

3. ANN VS BNN

Consider the terminology-based similarities between artificial neuron network (ANN) and the biological neuron network (BNN), before looking at the differences[8].

Table1: similarities between BNN and ANN

Biological Neural Network (BNN)	Artificial Neural Network (ANN)
Soma	Node
Dendrites	Input
Synapse	Weights or Interconnections
Axon	Output

4. Activation Functions

An artificial neuron calculates a "weighted sum" of its input, adds a bias and then decides whether the neuron should be activated or not (Figure 13).

$$Y = \sum(weight * input + bias) \quad .... (4)$$

There is a set of activation functions that differs in complexity and output:

- ✓ **Rectified linear unit (ReLU)** this function converges faster optimizes and produces the desired value faster. It is by far the most popular activation function used in hidden layers (Figure 13)

$$f(z) = max(0, z) .... (5)$$

- ✓ **Sigmoid** takes a real value as input and outputs another value between 0 and 1 it's easy to work with and has all the nice properties of activation functions: it's non-linear, continuously differentiable, monotonic, and has a fixed output range (Figure 13).

$$f(z) = \frac{1}{1+e^{z}} ..... (6)$$

- ✓ **Softmax** used in the output layer because it reduces dimensions and can represent a categorical distribution (Figure 13).

$$\sigma(z)_j = \frac{e^{z_i}}{\sum_{k=1}^{k} e^{z_k}} \qquad for\ j = 1, \dots \dots \dots \dots, k \ .... (7)$$

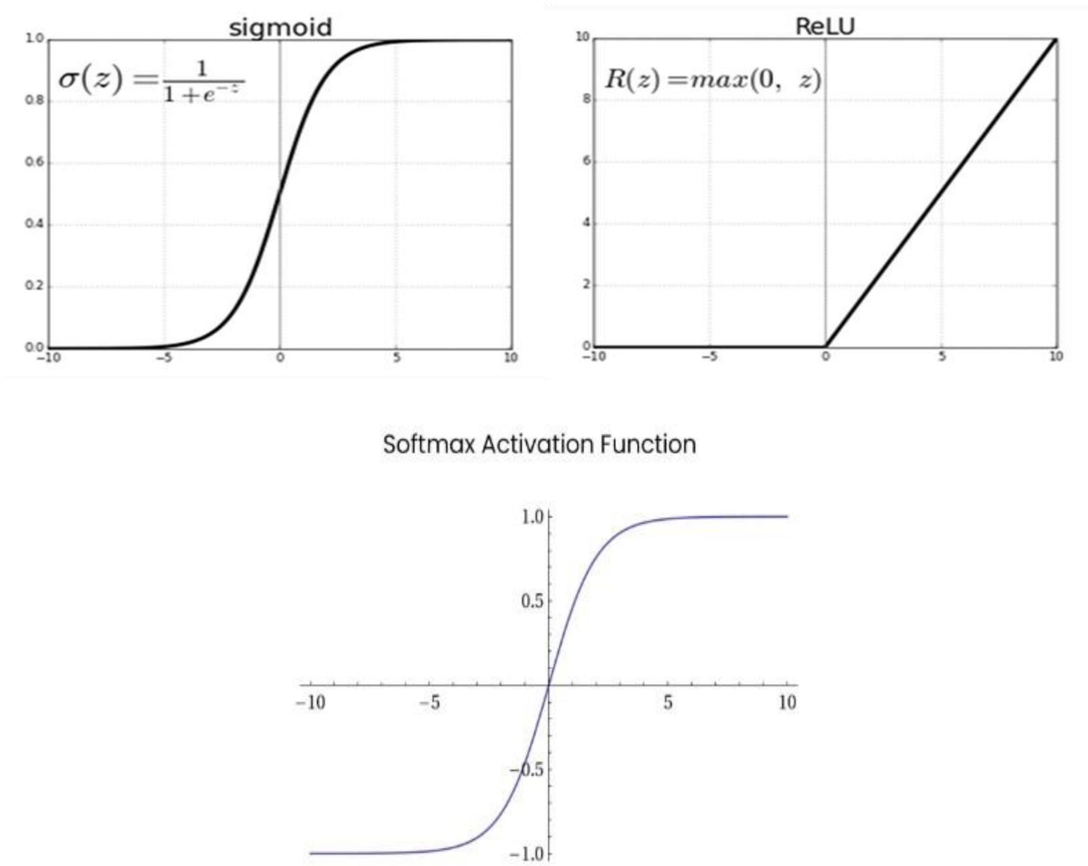

Figure 13: ReLU vs Sigmoid vs Softmax [53][54]

5. Optimizers

Optimizers are algorithms or methods used to change the attributes of your neural network such as weights and learning rate in order to reduce the losses.

5.1. Gradient Descent

Gradient descent is a basic optimization algorithm that calculates the gradients of the neural network's parameters (weights and biases) for each observation in the dataset. It then updates the parameters by taking steps proportional to the negative gradients, aiming to minimize the loss function.

5.2. Stochastic Gradient Descent (SGD)

SGD is a variant of gradient descent where the weights and biases are updated after each observation in the dataset. Instead of calculating the gradients for the entire dataset, SGD estimates the gradients using a randomly selected subset of observations, making it computationally efficient for large datasets.

5.3. Adam (Adaptive Moment Estimation)

Adam is an optimization algorithm that combines the ideas of adaptive learning rates and momentum. It maintains exponentially weighted averages of past gradients and squared gradients, allowing it to adaptively adjust the learning rate for each parameter. Adam is known for its efficiency and often achieves faster convergence compared to other optimizers.

5.4. RMSprop

RMSprop is another optimization algorithm that addresses the issues of oscillations in certain directions. It calculates the exponentially weighted average of past squared gradients and uses it to normalize the gradients during the parameter updates. By reducing the oscillations, RMSprop enables the algorithm to take larger steps in the horizontal direction, which can lead to faster convergence.

6. Construction of a neural network

The processing nodes that form the neural network resemble the neurons of the human brain. A node is connected to different nodes in several layers which are found above and below. The function of these nodes is to move the data to through the network in one direction only.

7. Layers of a neural network

An artificial neural network is organized into three types of layers (figure 14):

- ❖ **Input layer** this layer receives the data, no calculation is performed. The nodes here transmit just the information at the hidden layer.

- ❖ **Hidden layers** nodes in this layer are not exposed to the outside world. The hidden layer performs all sorts of calculations on the features input through the input layer and transfers the result to the output layer.

- ❖ **Output layer** this layer sends the information learned by the network to the outside world.

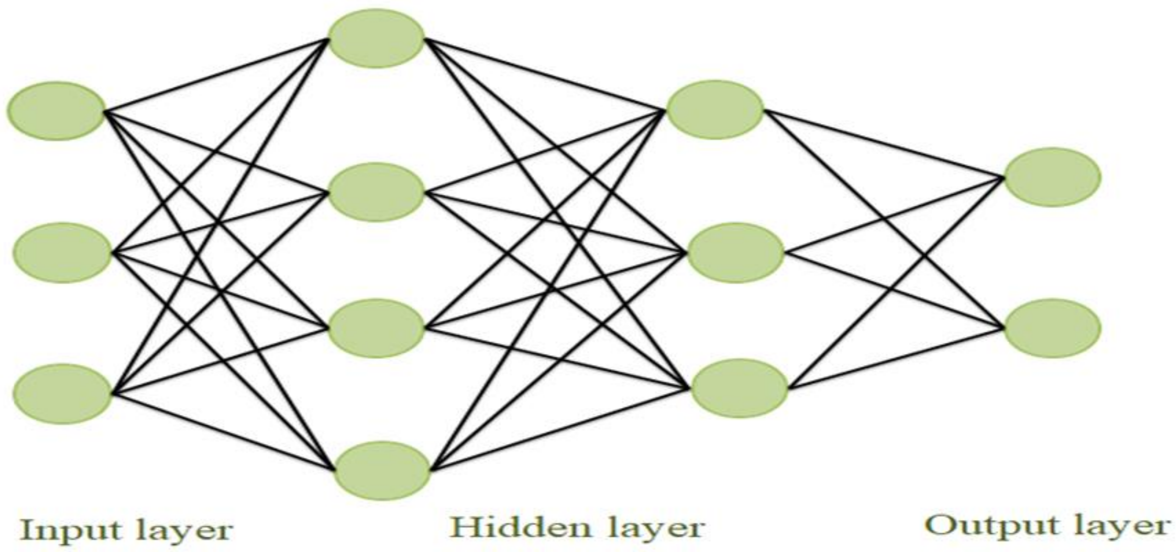

Figure 14: Architecture of neural network

V. Deep learning
1. Definition

Deep learning is a subfield of machine learning which consists of a set of algorithms capable of imitating the functioning of the human brain thanks to artificial neural networks. . These networks are composed of tens or even hundreds of layers of neurons.

The higher the number of layers, the more the network is qualified as "deep". Learning depth is the most powerful technique in machine learning, especially in the image classification. It is used in[57]:

- ✓ Language processing
- ✓ Image recognition
- ✓ Autonomous cars
- ✓ Medical diagnosis
- ✓ Chabot's
- ✓ The robots…

Figure 15 shows the correlation between artificial intelligence, machine learning and deep learning.

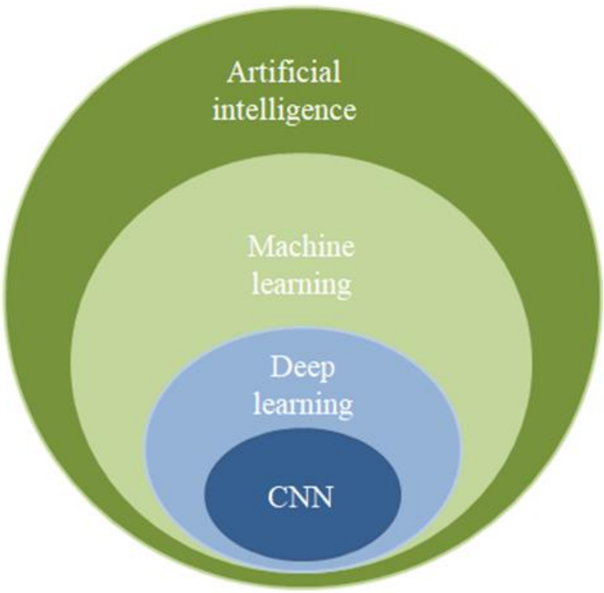

Figure 15: Correlation between IA, ML and DL

2. The difference between ML and DL

Table 2: ML versus DL

Machine learning	Deep learning
Originated around 1960s	Originated around 1970s
A practice getting machines to make decisions without being programmed	The process of using Artificial Neural Networks to solve complex problems
A subset of AI and Data Science	A subset of Machine Learning ,AI and Data Science
Aim is to make machines learn through data so that they can solve problems	Aim is to build Neural Networks that automatically discover patterns for feature detection

3. Convolutional neural networks

To reiterate from the Neural Networks Learn Hub article, neural networks are a subset of machine learning, and they are at the heart of deep learning algorithms. They are comprised of node layers, containing an input layer, one or more hidden layers, and an output layer. Each node connects to another and has an associated weight and threshold. If the output of any individual node is above the specified threshold value, that node is activated, sending data to the next layer of the network. Otherwise, no data is passed along to the next layer of the network.

While we primarily focused on feed forward networks in that article, there are various types of neural nets, which are used for different use cases and data types. For example, recurrent neural networks are commonly used for natural language processing and speech recognition whereas convolutional neural networks (ConvNets or CNNs) are more often utilized for classification and computer vision tasks. Prior to CNNs, manual, time-consuming feature extraction methods were used to identify objects in images. However, convolutional neural networks now provide a more scalable approach to image classification and object recognition tasks, leveraging principles from linear algebra, specifically matrix multiplication, to identify patterns within an image. That said, they can be computationally demanding, requiring graphical processing units (GPUs) to train models [56].

4. The different layers of a CNN

There are four types of layers for a convolutional neural network: the convolution layer, the pooling layer, the ReLU correction layer and the fully-connected layer. I will explain how these different layers work (Figure 16).

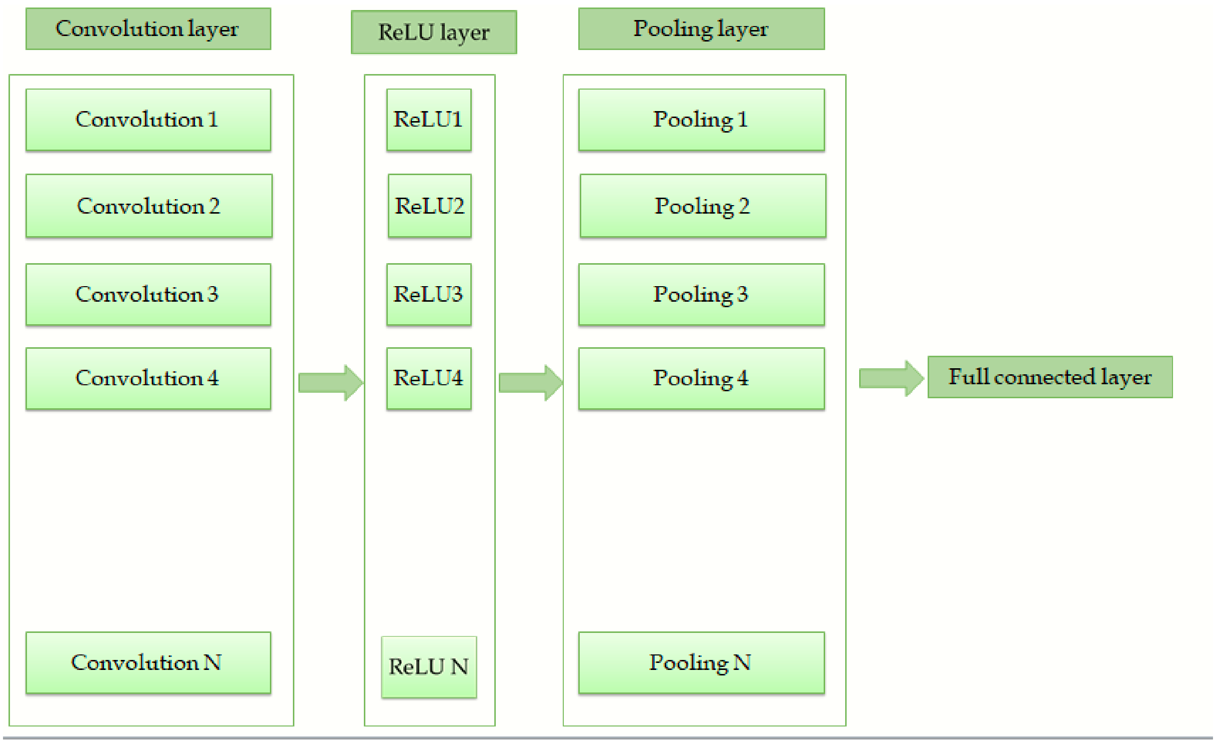

Figure 16: CNN Layers

4.1. Convolutional Layer

The convolutional layer is the key component of CNNs and always constitutes at least their first layer.

Its purpose is to identify the presence of a set of features in the images received as input. To do this, we perform convolution filtering: the principle is to "drag" a window representing the feature on the image, and calculate the convolution product between the feature and each portion of the scanned image (Figure 17). A feature is then seen as a filter.

I a digital image, h a function of $[x_1, x_2] * [y_1, y_2]$ real values

The convolution of I by h definite by:

$$(I * h)[x.y] = \sum_{i=x_1}^{x_2} \sum_{j=y_1}^{y_2} h[i-j].I[x-i, y-j] \ldots.. (8)$$

The convolution layer therefore receives as input several images and calculates the convolution of each of them with each filter. The filters correspond exactly to the features that we want to find in the images.

We obtain for each pair (image, filter) an activation map, or feature map, which tells us where the features are in the image: the higher the value, the more the corresponding place in the image looks like the feature.

Unlike traditional methods, features are not pre-defined according to a particular formalism (for example SIFT), but learned by the network during the training phase. The filter cores designate the weights of the convolution layer. These weights are initialized and then updated by back propagation of the gradient.

This is the strength of CNNs: these are capable of determining the discriminating elements of an image on their own, by adapting to the problem posed. For example, if the question is to distinguish cats from dogs, the automatically defined features can describe the shape of the ears or legs[10].

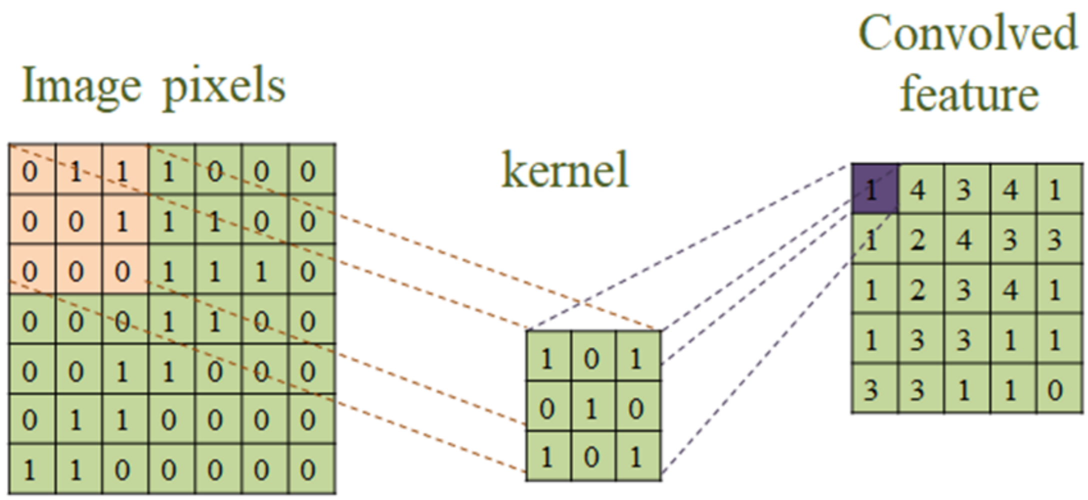

Figure 17: Convolution filter

4.2. Pooling Layer

Pooling layers, also known as down sampling, conducts dimensionality reduction, reducing the number of parameters in the input. Similar to the convolutional layer, the pooling operation sweeps a filter across the entire input, but the difference is that this filter does not have any weights. Instead, the kernel applies an aggregation function to the values within the receptive field, populating the output array. There are two main types of pooling[11]:

- **Max pooling:** As the filter moves across the input, it selects the pixel with the maximum value to send to the output array. As an aside, this approach tends to be used more often compared to average pooling (Figure 18).
- **Average pooling:** As the filter moves across the input, it calculates the average value within the receptive field to send to the output array.

While a lot of information is lost in the pooling layer, it also has a number of benefits to the CNN. They help to reduce complexity, improve efficiency, and limit risk of over fitting.

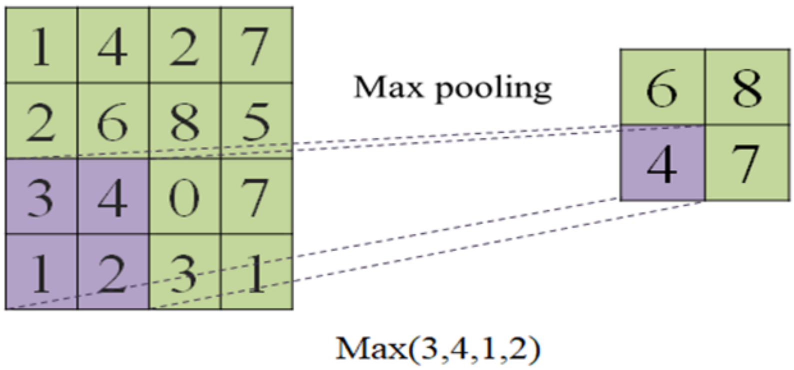

Figure 18: The Pooling operation

4.3. The ReLU correction layer

ReLU (Rectified Linear Units) designates the real non-linear function defined by ReLU(x) = max (0, x), (Figure 19).

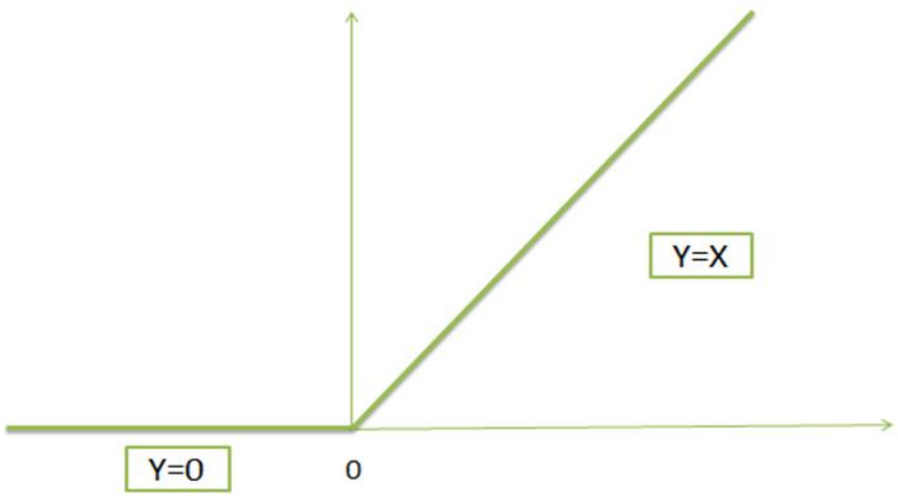

Figure 19: ReLU function

The ReLU correction layer therefore replaces all negative values received as inputs with zeros. It plays the role of activation function (Figure 20).

Figure 20: ReLU applied

4.4. Fully-Connected Layer

The name of the full-connected layer aptly describes itself. As mentioned earlier, the pixel values of the input image are not directly connected to the output layer in partially connected layers. However, in the fully-connected layer, each node in the output layer connects directly to a node in the previous layer (Figure 21)[11].

This layer performs the task of classification based on the features extracted through the previous layers and their different filters. While convolutional and pooling layers tend to use ReLu functions, FC layers usually leverage a softmax activation function to classify inputs appropriately, producing a probability from 0 to 1(Figure 22).

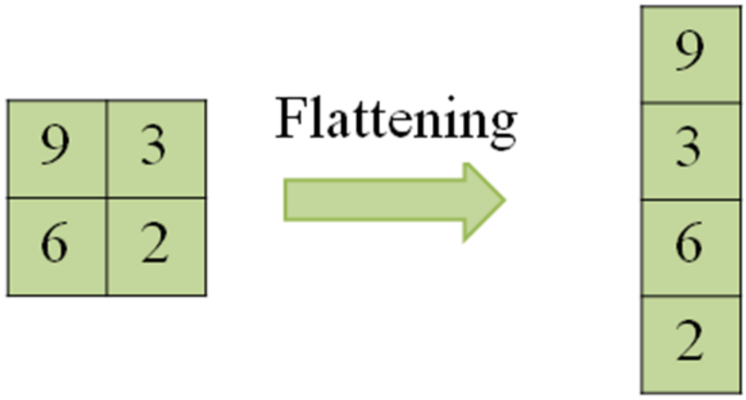

Figure 21: Flattening operation

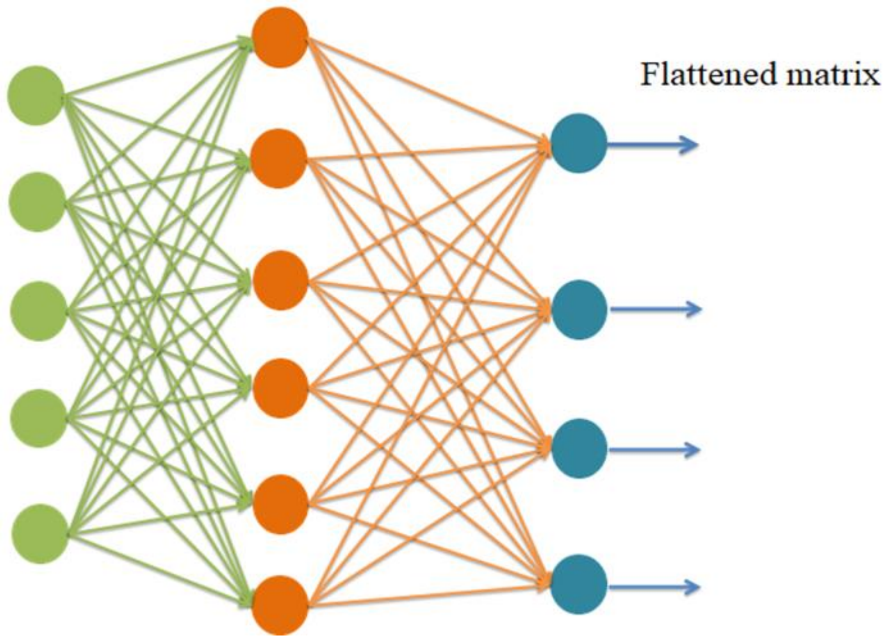

Figure 22: Fully-Connected layer

5. Architecture of a convolutional neural network

Over the last 10 years, several CNN architectures have been presented. Model architecture is a critical factor in improving the performance of different applications. Various modifications have been achieved in CNN architecture from 1989 until today.

Such modifications include structural reformulation, regularization, parameter optimizations, etc. Conversely, it should be noted that the key upgrade in CNN performance occurred largely due to the processing-unit reorganization, as well as the development of novel blocks. In particular, the most novel developments in CNN architectures were performed on the use of network depth. In this section, we review the most popular CNN architectures, beginning from the AlexNet model in 2012 and ending at the High-resolution (HR) model in 2020. Studying these architectures features (such as input size, depth, and robustness) is the key to help researchers to choose the suitable architecture for their target task (Figure 23)[12].

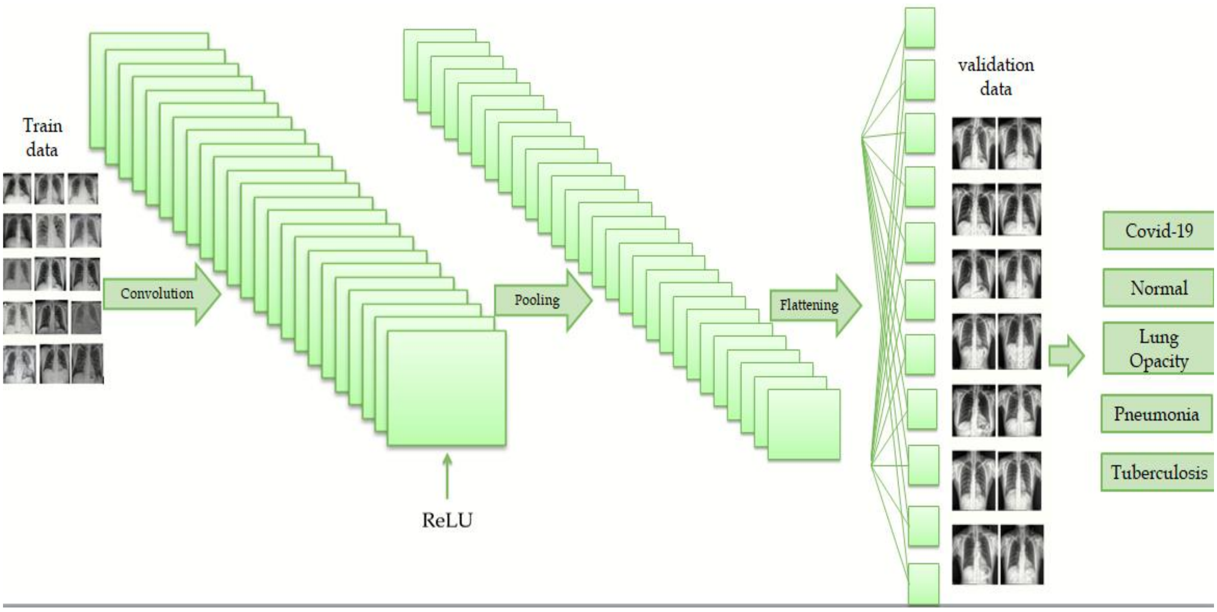

Figure 23: Convolutional Neural Networks

6. CNN known models

We now have all the tools to understand the architecture of a convolutional neural network. There are several in the literature whose effectiveness varies according to the task because they do not all have the same number of convolutions (nor the same structure).

These include:

- LeNet is one of the earliest and simplest CNN architectures, introduced in 1998 by Yann LeCun.
- AlexNet was introduced in 2012 and played a crucial role in popularizing deep learning.

- ZFNet is an improvement upon the AlexNet architecture, introduced in 2013 by Matthew Zeiler and Rob Fergus.
- GoogLeNet, also known as Inception v1, was introduced by Google researchers in 2014.
- VGGNet, proposed by the Visual Geometry Group at the University of Oxford in 2014, is known for its simplicity and depth.
- ResNet, introduced in 2015, stands for "Residual Network" and addresses the problem of vanishing gradients in very deep neural networks.

7. Transfer learning

Transfer learning is a powerful technique in machine learning and neural networks where a model trained on one task is utilized as a starting point for a related task. Instead of training a model from scratch on the second task, transfer learning leverages the knowledge and learned representations acquired during the training of the initial model.

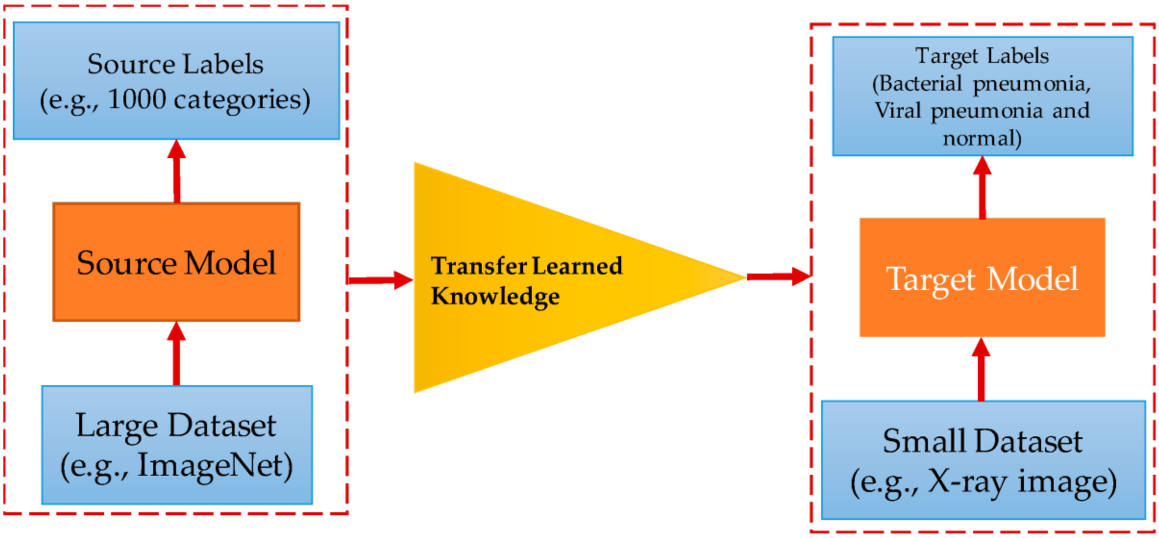

Figure 24: Transfer Learning [59]

VI. Conclusion

In this chapter we presented the keys principal of artificial intelligence represented by machine learning, deep learning, ANN and finally CNN and there defiant layers. In the next chapter we will present Overview of recent studies related to the current study.

Chapter 3: State of Art

I. Introduction

Convolutional Neural Networks (CNNs) have achieved remarkable success in various computer vision tasks and have become the state of the art models in the field. CNNs have revolutionized image classification, object detection, image segmentation, and many other visual recognition tasks. In this introduction, we will explore the state of the art advancements in CNN architectures and techniques.

In recent years, CNN architectures have achieved remarkable results in various challenging tasks such as image classification, object detection, semantic segmentation, and instance segmentation. Their performance continues to improve with ongoing research and development in the field.

By leveraging the power of CNNs and their state-of-the-art architectures, researchers and practitioners can tackle complex computer vision problems with high accuracy, pushing the boundaries of what is possible in visual recognition tasks.

In this chapter we present the state of the art advancement in CNN architecture and techniques.

II. Related works

In spite of launching the first CAD system for detecting lung nodules or affected lung cells in the late 1980s, those efforts were not enough. This is because there were many inadequate computational resources for the implementation of advanced image processing techniques at that time. Lung disease detection using basic image processing techniques is also time consuming. After the successful invention of GPU and CNN, the performance of CAD (for lung disease diagnosing) and decision support arrangement got a high boost. Many studies propose many various deep learning models in order to detect lung diseases the all fourth present in Table 3.

Table 3: Overview of recent studies related to the current study

Model's description	Model's performance	Model's Dataset
VGG 16[13]	Accuracy: 75%	278 positive and 66 negative COVID 19 X-rays and 39 positive And 30 negative images.
ResNet[14]	Accuracy: 86.7%	618 CT samples
Perform segmentation of COVID-19 infection regions from CT scans using deep learning model named as VB-Net[15]	Dice similarity coefficient: 91.6%	249 CT images in training and 300 in validation.

Employ Details Relation Extraction Neural network (DRE-Net) to obtain the image level predictions of corona19 virus form healthy and bacterial pneumonia[16]	Accuracy: 94%	CT scans images (88 patients of COVID-19, 101 patients of bacterial pneumonia, and 86 healthy persons)
2D CNN network [17]	Accuracy: 98%	224 images in two categories covid and normal images from GitHub datasets.
CovXNets [18]	COVID/Normal: Accuracy: 97.4%,COVID/Viral pneumonia: Accuracy: 97.4%, COVID/ Bacterial pneumonia: Accuracy: 94.7% COVID/normal/Viral/Bacterial pneumonia: Accuracy: 90.2%	305 images for each category
nCOVnet[19]	Accuracy: 97.62%	127 COVID-19 positive patients' X-ray images for training, on contrary, 31COVID-19 positive patients' X-ray images for testing.

VGG 19[20]	Accuracy: 91%	360 images of COVID-19 patients, 16 images of SARS and 18 images Of Streptococcus pneumonia.
Naive Bayes[21]	Accuracy: 92.6%	3500 COVID-19, 2400 normal chest scans
DenseNet-201[22]	Accuracy: 94.76%	62 patients
Inception FO-MPA[23]	Inception: Accuracy: 98.7% FO-PA: Accuracy: 99.6% accuracy	Dataset 1 200 COVID-19 images 1675 negative images Dataset 2 219 COVID-19 images 1341 negative images
COVIDX-Net[24]	Accuracy : 86.74%	Dataset 1 200 COVID-19 images 1675 negative images Dataset 2219 COVID-19 images 1341 negative images
ResNet50[24]	Accuracy : 98%	The dataset used in this work is very small, consisting of only 25 COVID-19 cases, and 25 normal X-ray images.

VGG 16[25]	Accuracy : 95.88%	The dataset used in this work is very small, consisting of only 25 COVID-19 cases, and 25 normal X-ray images.
Inception V3[26]	Accuracy : 92.35%	Dataset 112 X Ray scans for COVID-19 112 healthy scans and 112 scans for common bacterial Pneumonia.
DenseNet[26]	Accuracy :63.56%	Dataset X Ray chest images 430 COVID-19, 326 pneumonia and normal 374.
New- DenseNet[26]	Accuracy :85%	Dataset X Ray chest images 430 COVID-19, 326 pneumonia and normal 374.
Inception V3[26]	Accuracy :84.51%	Dataset X Ray chest images 430 COVID-19, 326 pneumonia and normal 374.
DenseNet[26]	Accuracy :60%	Dataset CT chest images 1252 COVID-19, 1230 normal.

New- DenseNet[26]	Accuracy :95.98%	Dataset CT chest images 1252 COVID-19, 1230 normal.
ResNet50[27]	Accuracy : 98.0%	Dataset 50 COVID-19 and 50 normal cases chest X-ray images.
InceptionV3[27]	Accuracy : 97.0%	Dataset 50 COVID-19 and 50 normal cases chest X-ray images.
Inception-ResNetV2[27]	Accuracy : 87%	Dataset 50 COVID-19 and 50 normal cases chest X-ray images.
COVID-Net[28]	Accuracy : 83.5%	The dataset was composed of 5941 chest X-ray images in total, among them 1203 were normal, 931 bacterial pneumonia, 660 Viral pneumonia and 45 COVID-19.
CoroNet[29]	Accuracy :99%	The dataset consists of 1203 normal, 660 bacterial Pneumonia and 931 viral Pneumonia cases. We collected a total of 1300 images.

III. Conclusion

In this chapter we present the state of the art advancement in CNN architecture and techniques. In the next chapter we will present Tools and libraries, Exploited datasets and pre-trained models, Implementation and training.

Chapter 4: Experiments and realization

I. Introduction

In the field of machine learning and deep learning, there are several essential components involved in developing and training models. This includes tools and libraries, exploited datasets and pre-trained models, as well as implementation and training techniques.

In these chapter present Tools and Libraries, Exploited Datasets and Pre-trained Models, Implementation and Training.

II. Tools and libraries

1. Python

Python is an easy to learn, powerful programming language. It has efficient high-level data structures and a simple but effective approach to object-oriented programming. Python’s elegant syntax and dynamic typing, together with its interpreted nature, make it an ideal language for scripting and rapid application development in many areas on most platforms (Figure 24)[30].

Figure 25: python logo [55]

2. Google Colaboratory

Colaboratory, or “Colab” for short, is a product from Google Research. Colab allows anybody to write and execute arbitrary python code through the browser, and is especially well suited to machine learning, data analysis and education. More technically, Colab is a hosted Jupyter notebook service that requires no setup to use, while providing free access to computing resources including GPUs (Figure 25)[31].

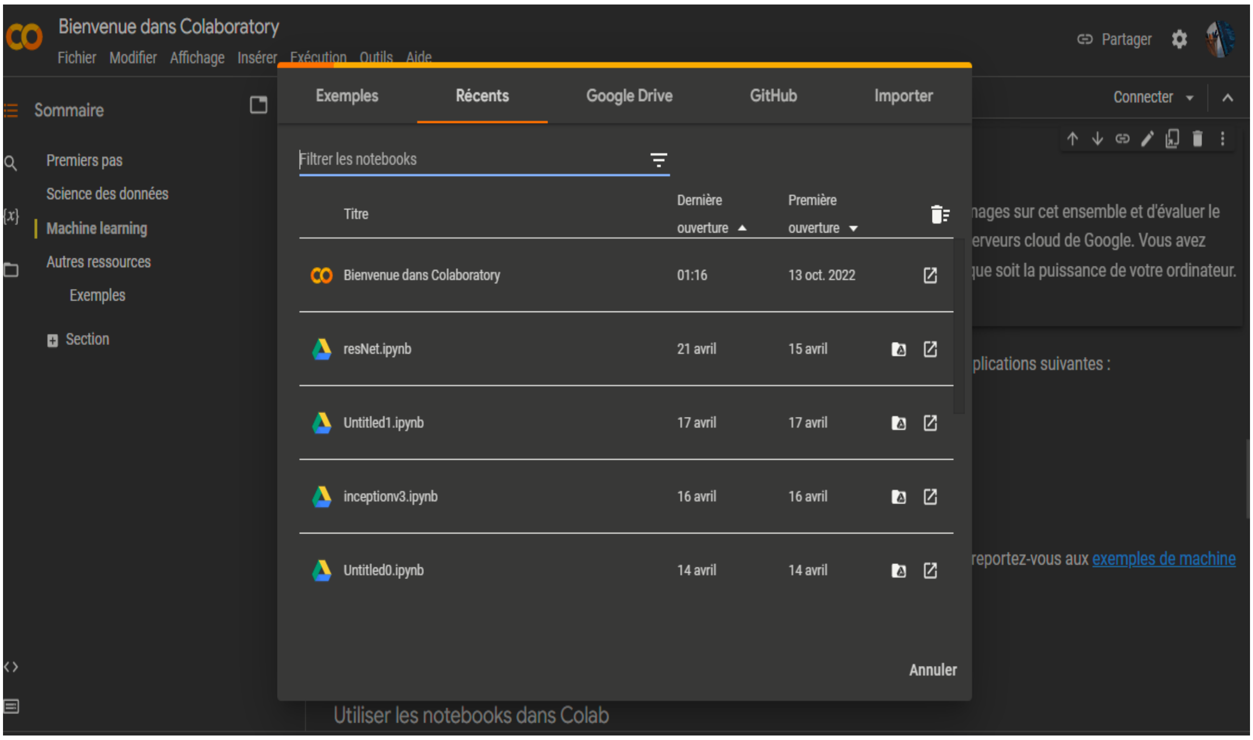

Figure 26: Google Colab[31]

3. Anaconda

Anaconda was founded in 2012 by Peter Wang and Travis Oliphant out of the need to bring Python into business data analytics, which was rapidly transforming as a result of emerging technology trends. Additionally, the open-source community lacked an entity that could organize and collectivize it to maximize its impact. Since that time, the Python ecosystem has significantly expanded, with Python being the most popular programming language used today. Alongside this expansion, Anaconda has provided value to students learning Python and data science, individual practitioners, small teams, and enterprise businesses. We aim to meet every user where they are in their data science journey. Anaconda now has over 300 full-time employees based in the United States, Canada, Germany, United Kingdom, Australia, India, and Japan. We are proud to serve over 35 million users worldwide (Figure 26)[32].

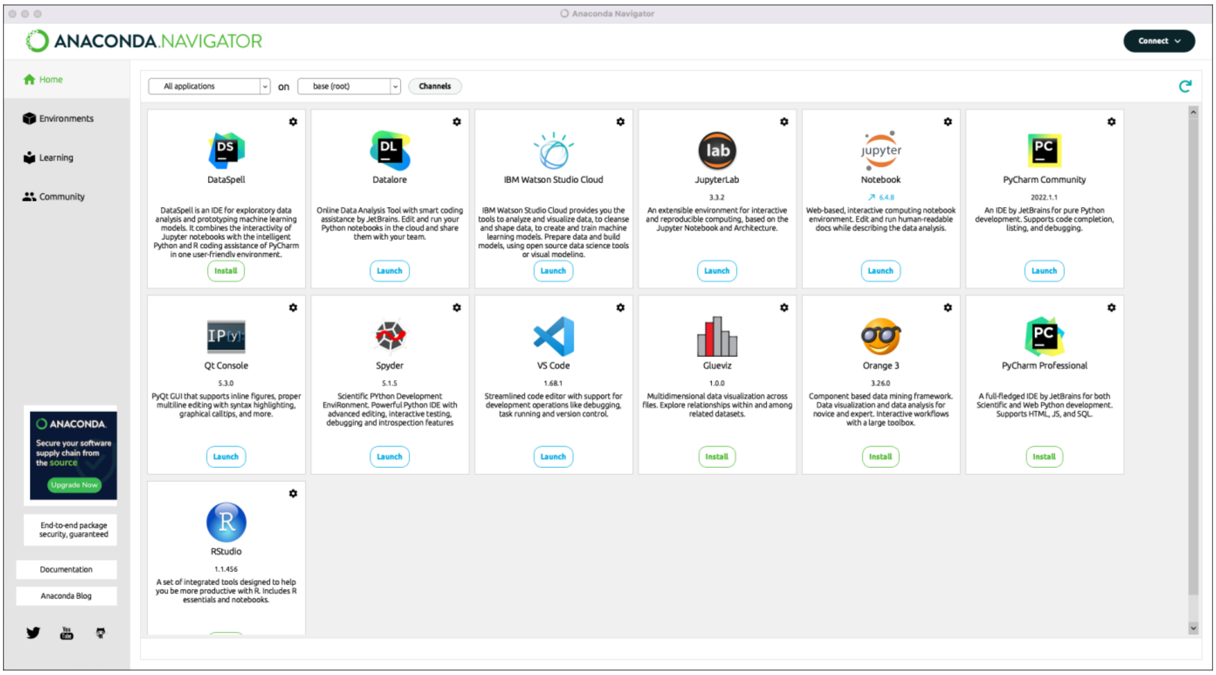

Figure 27: Anaconda navigator[32]

4. Jupyter Notebook

The Jupyter Notebook is an open-source web application that allows you to create and share documents that contain live code, equations, visualizations and narrative text. Uses include: data cleaning and transformation, numerical simulation, statistical modeling, data visualization, machine learning, and much more (Figure 27)[33].

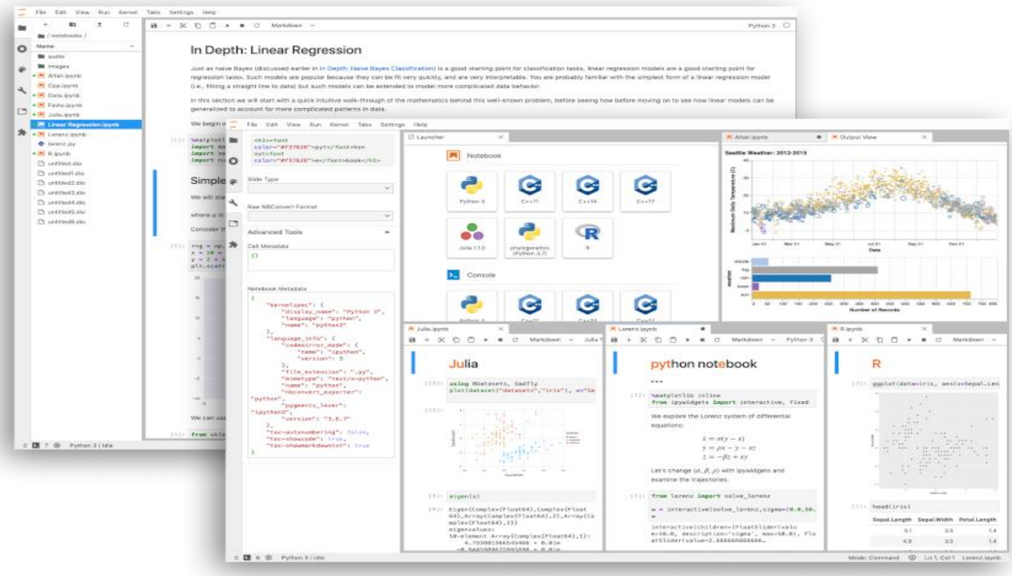

Figure 28: jupyter notebook[33]

5. TensorFlow

TensorFlow is an end-to-end open source platform for machine learning. It has a comprehensive, flexible ecosystem of tools, libraries and community resources that lets researchers push the state-of-the-art in ML and developers easily build and deploy ML powered applications (Figure 28)[34].

Figure 29: TensorFlow [34]

6. Keras

Keras is a deep learning API written in Python, running on top of the machine learning platform TensorFlow. It was developed with a focus on enabling fast experimentation. Being able to go from idea to result as fast as possible is key to doing good research (Figure 29)[35].

Figure 30: Keras[35]

7. Flask

Flask is a web application framework written in Python. It was developed by Armin Ronacher, who led a team of international Python enthusiasts called Poocco. Flask is based on the Werkzeg WSGI toolkit and the Jinja2 template engine. Both is Pocco projects (Figure 30)[13].

Figure 31: Flask [13]

III. Exploited datasets and pre-trained models

1. Datasets

Table 4: Dataset summary

Disease	No.of images
Covid-19	400
Normal	400
Lung opacity	400
Pneumonia viral	400
Tuberculosis	400

Deep learning is all about data which serves as fuel in these learning. Our data Contains 2000 Chest X-ray with five classes. Covid-19, Normal, Lung opacity Pneumonia viral and Tuberculosis. Covid-19, Normal, Lung opacity, Pneumonia viral Chest X-ray images were obtained from Kaggle repository "COVID-19 Radiography Database". Tuberculosis Chest X-ray images were obtained from

Kaggle repository" Tuberculosis Chest X-rays (Shenzhen)".we then resized all the images to the dimension of 224x224 pixels. Table 1 show the summary of the prepared dataset (Figure 33) below shows some samples of chest X-ray images from prepared dataset.

In order to make the images clearer we did image processing represented in histogram equalization (Figure 32) (Figure 33).

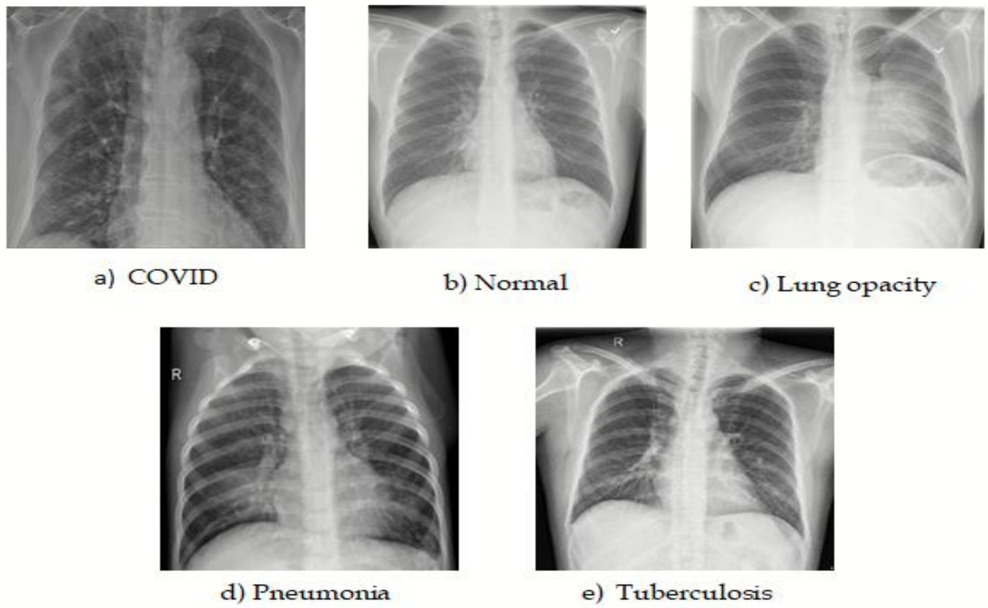

Figure 32: Samples of chest x-ray images without preprocessing

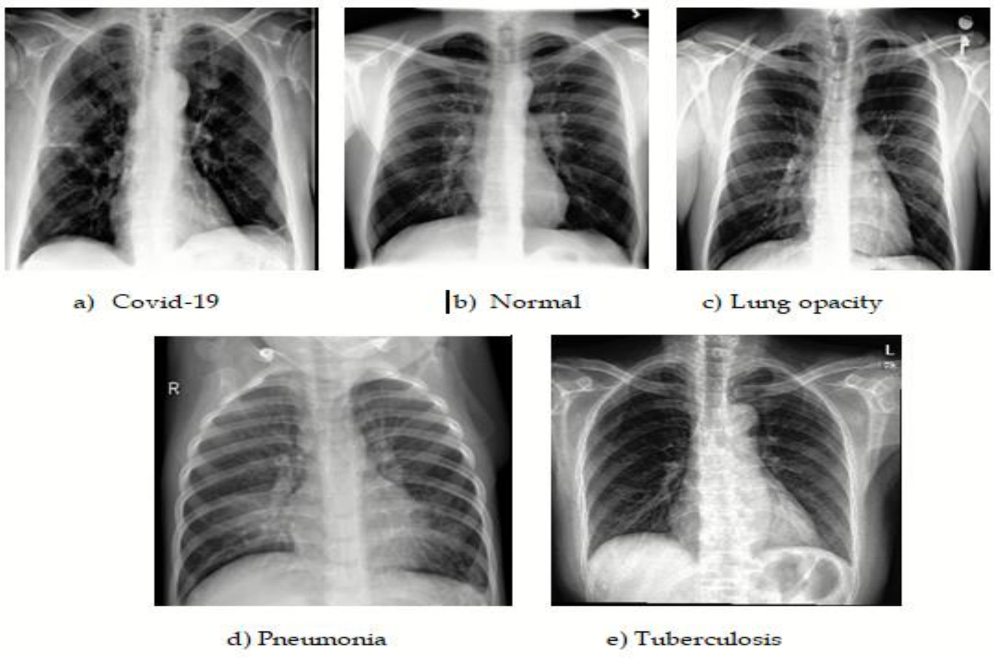

Figure 33: Samples of chest x-ray images from prepared dataset with preprocessing

2. Model architecture and development

Pre-trained models are models that have been already trained on some sort of data with different number of classes. A pre-trained model may not be 100% accurate in any application, but it saves huge efforts required to re-invent the wheel.

For building the following CAD, we proposed three model bases on three pre-trained models from the wide range of pre-trained models that are available in Keras: ResNet50, VGG16 and VGG19.

- The Residual Network architecture brought a simple but novel idea: not only use the output of each constitutional layer, but also combine the output of the layer with the original input. In the following diagram, we observe a simplified view of one of the ResNet modules; it clearly shows the sum operation at the end of the Convolutional layer stack, and a final ReLU operation (figure 34).

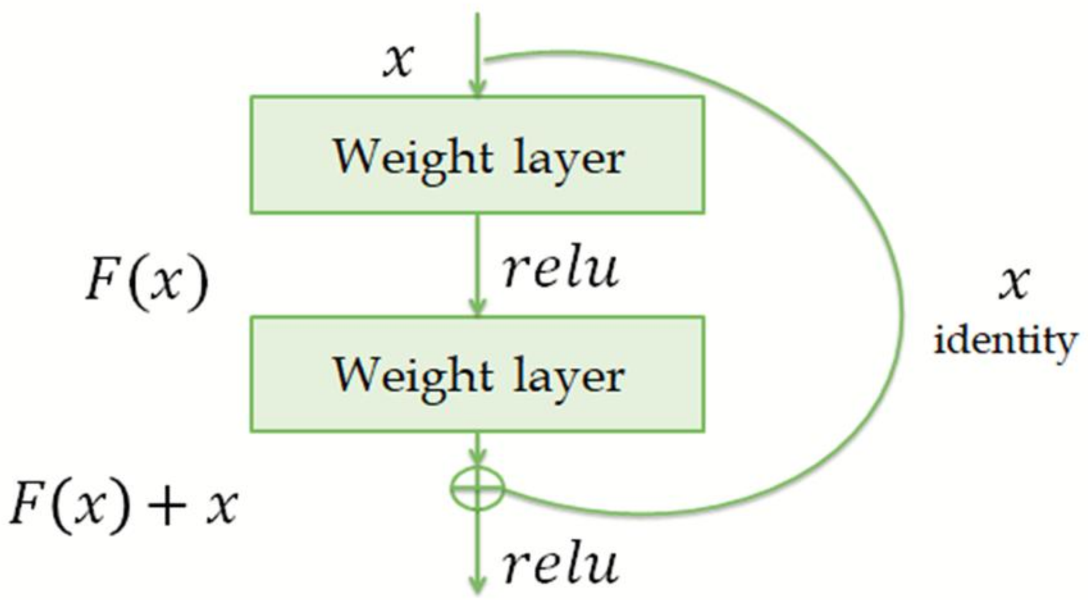

Figure 34: ResNet architecture

In the model number one we used ResNet50 as base model .Our first model has 439,486,341 parameters in total out of which 415,898,629 trainable and 23,587,712 are non-trainable parameters and output shape of model are show in Table 5.

Table 5: Details of model one architecture

Layer (type)	Output Shape	Param #
ResNet50 (model)	7 x 7 x 2048	393, 587,712
flattent (Flattent)	100352	0
dense(Dense)	4096	41045888
dense_1(Dense)	1024	4195328
dense _2(Dense)	512	524800
dense_3(Dense)	256	131328
dense_4(Dense)	5	1285
Total parameters : 439, 486,341		
Traitable Parameters : 415, 898,629		
Non-Traitable parameters : 23, 587,712		

- VGG16 is convolutional neural network mode that's used for image recognition. It's unique in that has only 16 layered that have weights as opposed to relying on a large number of hyper parameters. It's considered one of best vision model architecture (Figure 35).

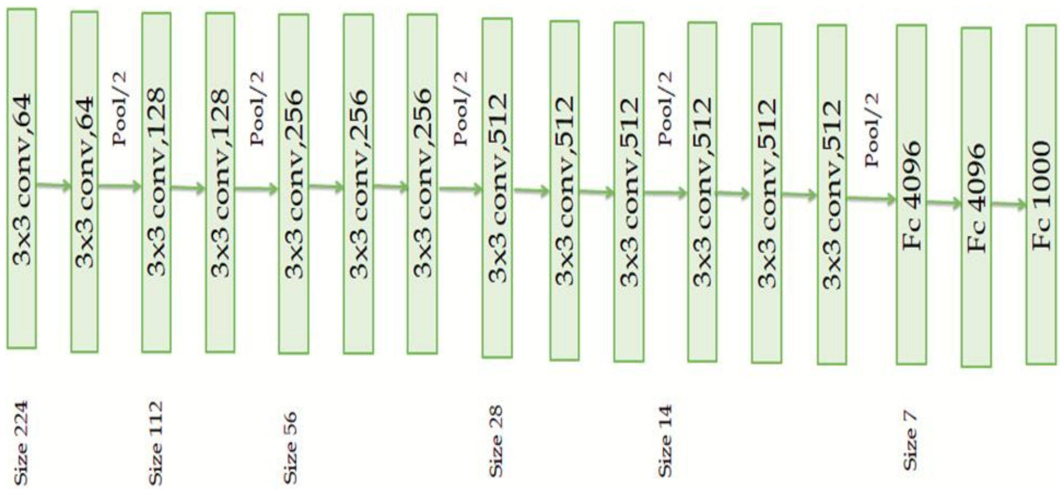

Figure 35: VGG16 architecture

In the model two we used VGG16 as base model. This model has 121,938,245 parameters in total out of which 107,223,557 trainable and 14,714,688 are non-trainable parameters and output shape of this second model are show in table 6.

Table 6: Details of model number two architecture

Layer (type)	Output Shape	Param #
VGG16 (model)	7 x 7 x 512	14, 714,688
flattent (Flattent)	25088	0
dense(Dense)	4096	10, 764,544
dense_1(Dense)	1024	41,95328
dense_2(Dense)	256	262,400
dense_3(Dense)	5	1285
Total Parameters : 121, 938,245		
Traitable Parameters : 107, 223,557		
Non-Traitable parameters : 14, 714,688		

❖ VGG19 is convolution neural network mode that's used for image. It's has 19 layers (Figure 36).

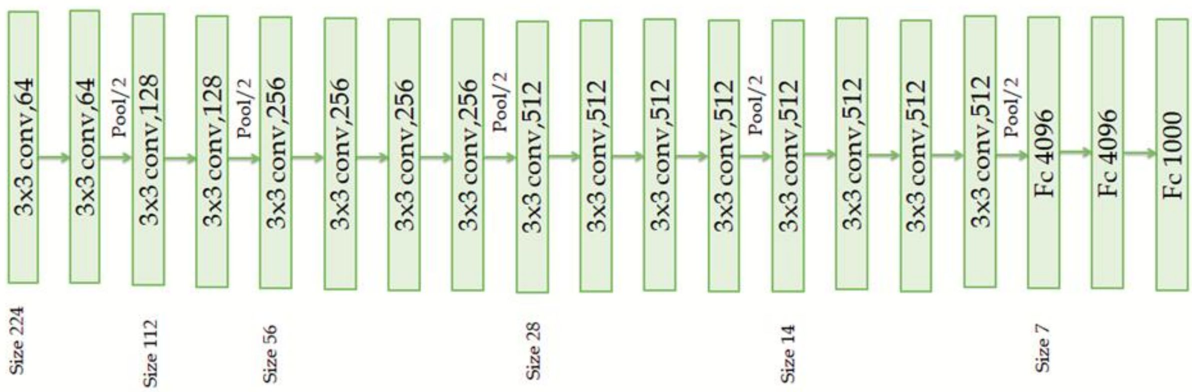

Figure 36: VGG19 architecture

In the model number three we used VGG19 as base model. This model has 127,247,941 parameters in total out of which 107,223,557 trainable 20,024,384 are non-trainable parameters and output shape of this last model is show in Table 7.

Table 7: Details of model number three architecture

Layer (type)	Output Shape	Param #
VGG19 (model)	7 x 7 x 512	20, 024,384
flattent (Flattent)	25088	0
dense(Dense)	4096	10, 764,544
dense_1(Dense)	1024	41,95328
dense_2(Dense)	256	262,400
dense_3(Dense)	5	1285
Total Parameters : 127, 247,941		
Traitable Parameters : 107, 223,557		
Non-Traitable parameters : 20, 024,384		

We used transfer learning to overcome the problem of over fitting as the training data not sufficient.

3. Implementation and training

We implemented three models to detect lung diseases from chest x-ray images. The three models are the main multi class model which id trained to classify chest x-ray images into five categories: Covid-19, Normal, lung opacity, Pneumonia and Tuberculosis.

The three proposed models was implemented in Keras on top of Tensorflow 2.0.The models was pre-trained on ImageNet (transfer learning) dataset and then retrained end to end .To the three models on prepared dataset using SGD optimizer and Adam optimizer with learning rate of 0.001, batch size 64 and epoch value of 100. All the experiment and training was done on Google colaboratery .the plots of accuracy and loss on the training and validation sets over training epochs of first model, second model and the last model are show in (Figure 37) and (Figure 38).

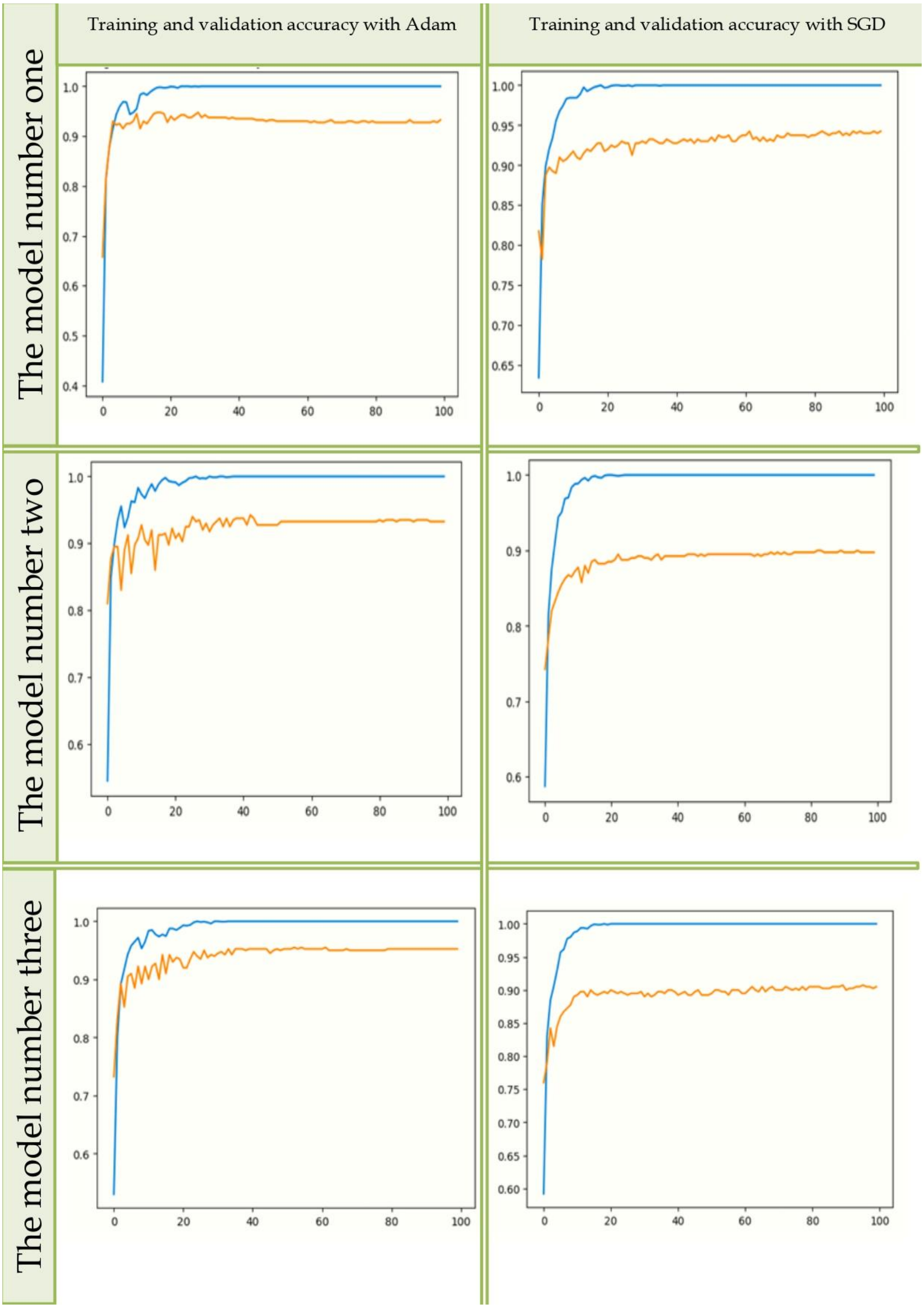

Figure 37: Plots of accuracy on training and validation using Adam and SGD optimizer

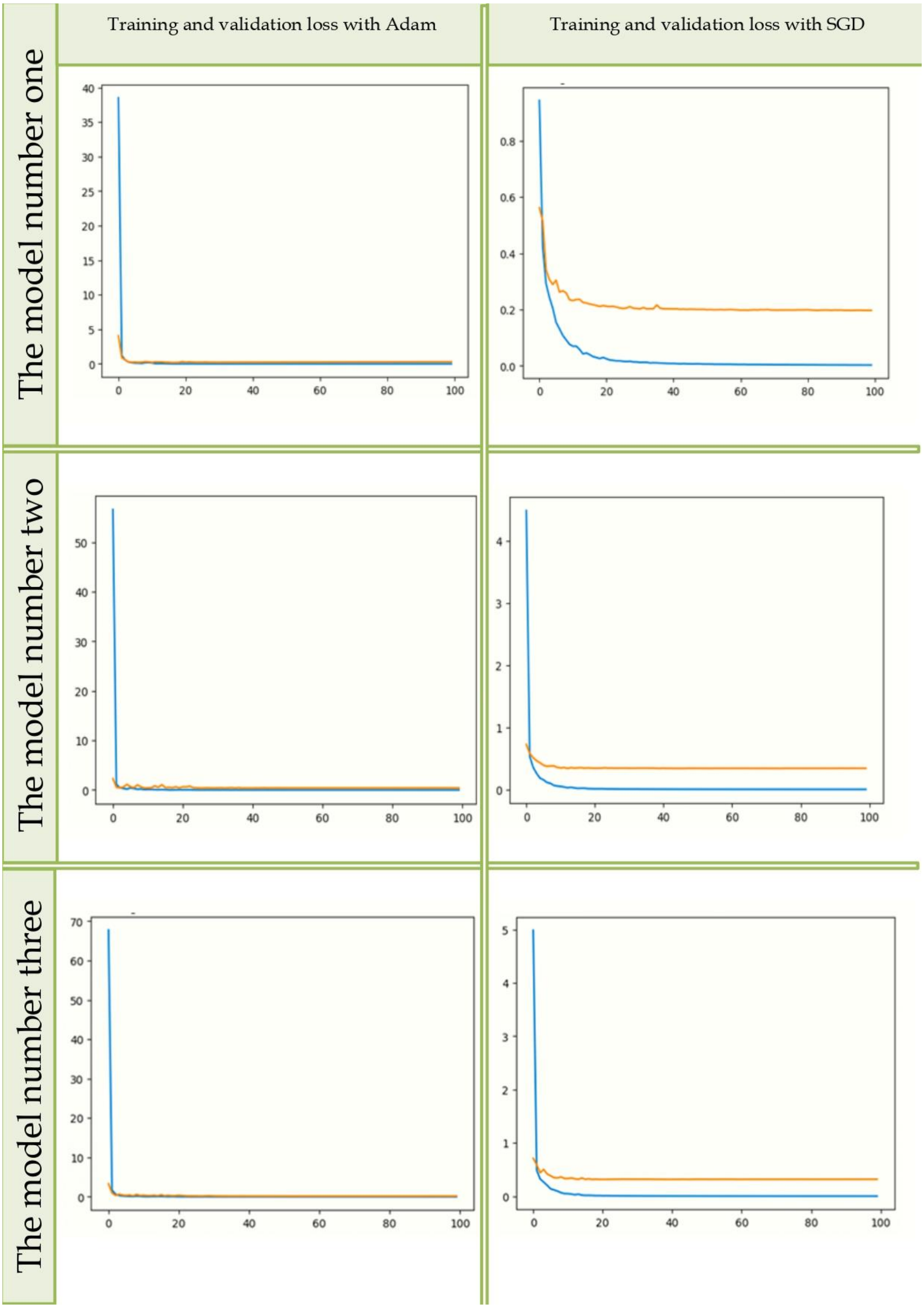

Figure 38: Plots of loss on training and validation using Adam and SGD optimizer

4. Results

The performance of the three models proposed is presented in the form of Confusion matrix (CM) in (Figure 39). Overall Accuracy, precision, recall and F-measure computed for each class by formulae given below are summarized in Table 8, Table 9 Table 10 and Table 11.

$$Accuracy = \frac{No.of\ images\ correctly\ classified}{Total\ No.of\ images} \ldots\ldots. (9)$$

$$Precision = \frac{Sum\ o\ f\ all\ True\ Positives\ (TP)}{Sum\ o\ f\ all\ True\ Positives\ (TP) + All\ False\ Positives\ (FP)} \ldots\ldots (10)$$

$$Recall = \frac{Sum\ o\ f\ all\ True\ Positives\ (TP)}{Sum\ o\ f\ all\ True\ Positives\ (TP) + All\ False\ Negatives\ (FN)} \ldots\ldots\ldots (11)$$

$$F - measure = \frac{2 * Precision * Recall}{Precision + Recall} \ldots\ldots\ldots\ldots. (12)$$

$$Specificity = \frac{Sum\ o\ f\ all\ Truen\ Negative\ (TN)}{Sum\ o\ f\ all\ True\ Negative\ (TN) + All\ False\ Negative\ (FN)} \ldots\ldots\ldots\ldots (13)$$

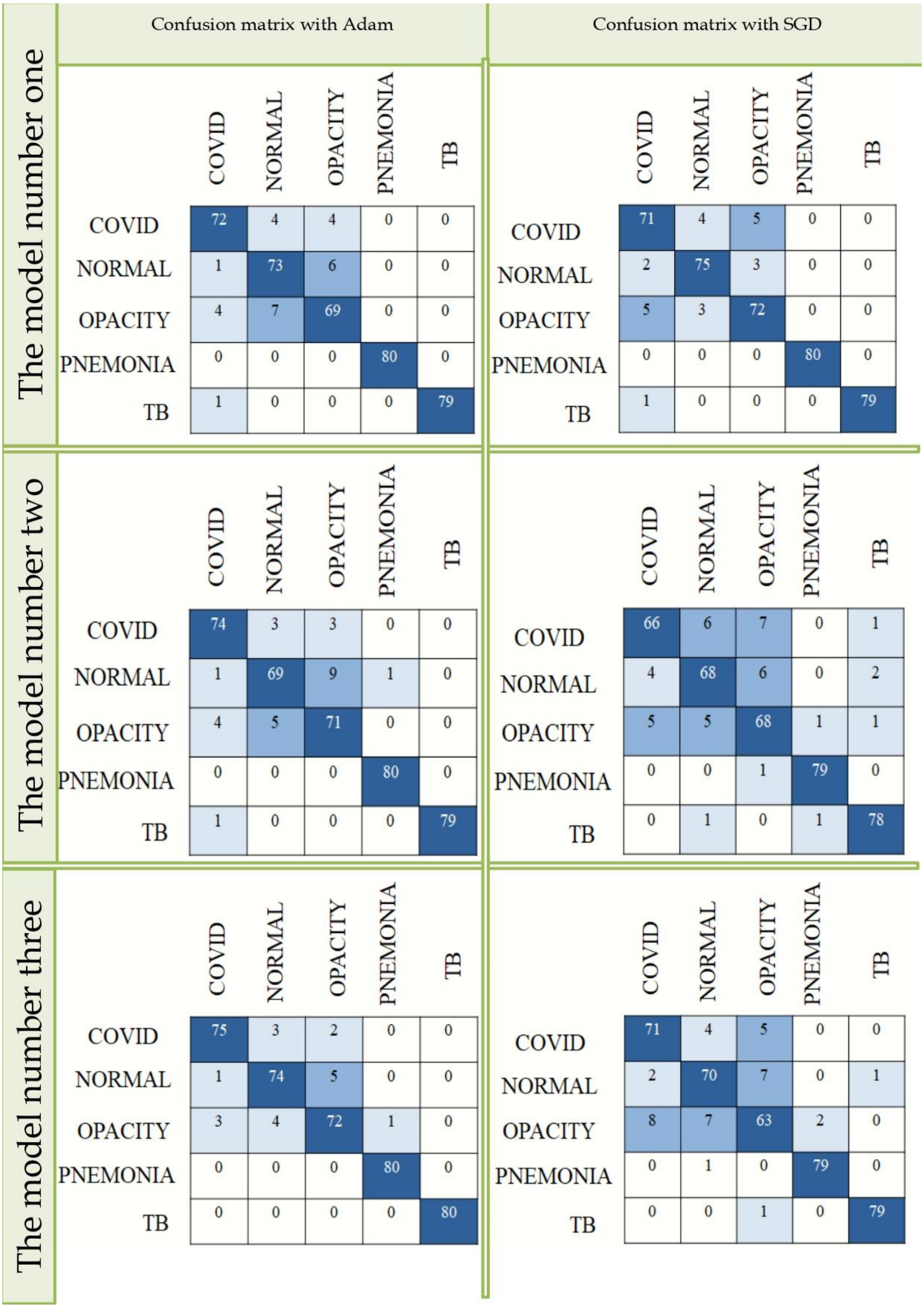

Figure 39: Confusion matrices of the three models using Adam and SGD optimizer

Table 8: Performance of the model number one

Class	Precision (%)		Recall (%)		Specificity (%)		F-measure (%)	
Optimizer	With Adam	With SGD	With Adam	With SGD	With Adam	With SGD	With Adam	With SGD
COVID	92.3%	89.8%	90%	88.7%	97.5%	97.1%	91.1%	89.2%
NORMAL	86.9%	91.4%	91.2%	93.7%	97.7%	98.4%	88.9%	92.5%
OPACITY	87.3%	90%	86.2%	90%	96.5%	97.5%	86.7%	90%
PNEMONIA	100%	100%	100%	100%	100%	100%	100%	100%
TB	100%	100%	98.7%	98.7%	99.6%	99.6%	99.3%	99.3%

Table 9: Performance of the model number two

Class	Precision (%)		Recall (%)		Specificity (%)		F-measure (%)	
Optimizer	With Adam	With SGD	With Adam	With SGD	With Adam	With SGD	With Adam	With SGD
COVID	92.5%	88%	92.5%	82.5%	98.1%	95.6%	92.5%	85.1%
NORMAL	89.6%	86%	86.2%	85%	96.5%	96.2%	87.8%	85.4%
OPACITY	86.5%	82.9%	88.7%	85%	97.1%	96.2%	87.5%	83.9%
PNEMONIA	98.7%	97.5%	100%	98.7%	100%	99.6%	99.3%	98%
TB	100%	95.1%	98.7%	97.5%	99.6%	99.3%	99.3%	96.2%

Table 10: Performance of the model number three

Class	Precision (%)		Recall (%)		Specificity (%)		F-measure (%)	
Optimizer	With Adam	With SGD	With Adam	With SGD	With Adam	With SGD	With Adam	With SGD
COVID	94.9%	87.6%	93.7%	87.5%	98.4%	97.1%	94.2%	86.3%
NORMAL	91.3%	85.3%	92.5%	87.5%	97.8%	96.8%	91.8%	86.3%
OPACITY	90%	82.8%	90%	78.7%	97.8%	94.7%	90%	80.6%
PNEMONIA	97.5%	97.5%	100%	98.7%	100%	99.6%	98.7%	98%
TB	100%	98.7%	100%	98.7%	100%	99.6%	100%	98.7%

Table 11: Overall accuracy of the three models

	Overall accuracy (%)	
The models	With Adam optimizer	With SGD optimizer
Model one	93.2%	94.2%
Model two	93.2%	89.7%
Model three	95.2%	90.5%

The aforementioned performance metrics are the top metrics used to measure the performance of classification algorithms. The model one proposed with Adam and optimized achieved an average accuracy of 93.2%, while as average accuracy, precision, recall and F-measure (F1-Score) for COVID class are 92.3%, 90%, 97.5% and 91.1% respectively. With SGD and optimized achieved an average accuracy of 94.2%, while as average accuracy, precision, recall and F-measure (F1-Score) for COVID class are 89.8%,88.7%, 97.1% and 89.2% respectively.

The model two proposed with Adam optimized achieved an average accuracy of 93.2%, while as average accuracy, precision, recall and F-measure (F1-Score) for OPACITY class are 86.5%, 88.7%, 97.1% and 87.5% respectively. With SGD optimized achieved an average accuracy of 89.7%, while as average accuracy, precision, recall and F-measure (F1-Score) for OPACITY class are 82.9%, 85%, 96.2% and 83.9% respectively.

The last model proposed with Adam optimized achieved an average accuracy of 95.2%, while as average accuracy, precision, recall and F-measure (F1-Score) for

PNEMONIA class are 97,5%, 100%, 100% and 98,7% respectively. With SGD optimized achieved an average accuracy of 90.5%, while as average accuracy, precision, recall and F-measure (F1-Score) for PNEMONIA class are 97.5%, 98.7%, 99.6% and 98% respectively. The class wise performance of the three models with Adam and SGD is presented in Table 8, Table 9, Table10 and Table 11.

5. Discussion

In this study, we proposed three models based on ResNet50, VGG16 andVGG19 architectures to detect lung diseases cases from chest X-ray image. Our model number one achieved an accuracy of 93.2% with SGD, 94.2% with Adam, In the model number two achieved an accuracy of 89.7% with SGD, 93.5% with Adam, In the model three accuracy 95.2% with Adam and 90.5% with SGD, the results obtained by our proposed models are superior compared to other studies in the literature [13][14][20], Image preprocessing has helped us to raise the performance of the three models. The promising and encouraging results of deep learning models in detection of lung diseases from radiography images indicate that deep learning has a greater role to play in fighting this pandemic in near future. Some limitation of this study can be overcome with more in depth analysis which is possible once more patient data (both symptomatic and asymptomatic patients) becomes available.

IV. Conclusion

In this chapter, we have presented the development tools, the architectures of the exploited pre-trained models and datasets. For implementing the models ,model three based on VGG19 revealed the most efficient among the selected models, and even though it is known that the deepest the neural network, the more preformat it is. We came to conclude that a deep neural network has also its limits.

General Conclusion and perspectives

As the lung diseases pandemic are increasing daily, many countries are facing shortage of resources. During this health emergency, it is important that not even a single positive case goes unidentified. With this thing in mind, we proposed a deep learning approach to detect lung diseases from chest radiography images. The proposed methods are a convolutional neural network. The models have been trained and tested on a small dataset of few hundred images prepared by obtaining chest X-ray images of various pneumonia cases, lung opacity cases, tuberculosis cases and COVID-19 cases from different publically available databases. The three models are computationally less expensive and achieved promising results on the prepared dataset. The performance can further be improved once more training data becomes available.

In the future, we look forward to improving the performance of the three models and adding other models, and adding other diseases, to make the system comprehensive for all lung diseases.

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