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COVID-19 Diagnosis Using Deep Learning

Field: Electronics
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"Deliberate decision-making and rapid implementation avoid you from taking bad decisions."

My Father BELBEY Ammar Khelifa

"In the blessing of this Morning and God The ever-Opener, and the reader of the slates ."

My Grandmother

COVID-19 is an infectious disease caused by a new virus that has not been previously identified, the disease causes respiratory illness with symptoms such as cough, fever, and in more severe cases, breathing Failure. Even though this virus first started in Wuhan, China in December 2019, more than 174 million of people around the world have been infected and more than 3.75 million of peoples have already died.
The main purpose of this study is getting an accurate and faster detection of COVID-19 patients deep learning-based radiology image analysis method that could provide very satisfying testing accuracy up to 100%.
We apply deep learning method to classify X-ray Images of coronavirus (COVID-19) and due to scarcity of publicly available COVID-19 X-ray samples, we have trained our model with an Available worldwide database.
The contents of this Thesis are organized as the following.
Chapter 01 Gives the reader a brief about COVID-19 and Diagnosis methods from Lab tests to Medical Imaging, Chapter 02 discusses the proposed method and the models used in the implementation.
The experimental setup is discussed in chapter 03 with detailed analysis on results, and conclusions respectively.

Keywords: COVID-19, Deep Learning, CNN, X-Ray, VGG16Net, Diagnosis, Image classification, Convolutional neural networks

تشخيص COVID-19 القائم على التعلم العميق

COVID-19هو مرض معد يسببه فيروس جديد لم يكن معروفا من قبل ، ويسبب المرض مشاكل في الجهاز التنفسي مع أعراض مثل السعال والحمى ، وفي الحالات الأكثر خطورة ، فشل التنفس. على الرغم من أن هذا الفيروس بدأ لأول مرة في ووهان ، الصين في ديسمبر 2019 ، إلا أنه قد أصيب أكثر من 174 مليون شخص حول العالم و أدى إلى أكثر من 3.75 مليون شخص، الغرض الرئيسي من هذه الدراسة هو الحصول على كشف دقيق وسريع لمرضى COVID-19 طريقة تحليل صور الأشعة القائمة على التعلم العميق والتي يمكن أن توفر دقة اختبار مرضية للغاية تصل إلى 100٪.
لقد قمنا بتطبيق تقنية التعلم العميق لتصنيف صور الأشعة السينية لفيروس كورونا (COVID-19) وبسبب ندرة عينات الأشعة السينية المتاحة للجمهور محليا ، قمنا بتدريب نموذجنا باستخدام قاعدة بيانات متاحة عالميا.
تم تنظيم محتويات هذه الرسالة على النحو التالي :
الفصل الأول يقدم للقارئ موجزًا عن COVID-19 وطرق التشخيص من الاختبارات المخبرية إلى التصوير الطبي.
يناقش الفصل الثاني الطريقة المقترحة والنماذج المستخدمة في التنفيذ بينما قمنا بمناقشة الإعداد التجريبي في الفصل الثالث مع تحاليل مفصلة حول النتائج والاستنتاجات على التوالي.

الكلمات المفتاحية : COVID-19 ، التعلم العميق ، CNN ، الأشعة السينية ، VGG16Net ، التشخيص ، تصنيف الصور، الشبكات العصبية الملتفة

Diagnostic du COVID-19 à base d'apprentissage profond

COVID-19 est une maladie infectieuse causée par un nouveau virus qui n'a pas été identifié auparavant, la maladie provoque des problèmes respiratoires avec des symptômes tels que la toux, la fièvre et, dans les cas plus graves, une insuffisance respiratoire. Même si ce virus a commencé à Wuhan, en Chine, décembre 2019, plus de 174 millions de personnes dans le monde ont été infectées et plus de 3,75 millions de personnes sont déjà décédées, L'objectif principal de cette étude est d'obtenir une détection précise et plus rapide de la méthode d'analyse d'images radiologiques basée sur l'apprentissage profond des patients COVID-19 qui pourrait fournir une précision de test très satisfaisante jusqu'à 100%.
Nous appliquons une méthode d'apprentissage en profondeur pour classer les images radiographiques de la pneumonie (COVID-19) et en raison de la rareté des échantillons de rayons X COVID-19 accessibles au public, nous avons formé notre modèle avec une base de données Disponible dans le monde entier.
Le contenu de cette thèse est organisé comme suit :
Chapitre 01 Donne au lecteur un bref aperçu des méthodes COVID-19 et Dignosis, des tests de laboratoire à l'imagerie médicale, Le chapitre 02 traite de la méthode proposée et des modèles utilisés dans la mise en œuvre. Le montage expérimental est discuté dans le chapitre 03 avec une discussion détaillée sur les résultats et les conclusions respectivement.
Mots-clés : COVID-19, Deep Learning, CNN, X-Ray, VGG16Net, Diagnostic, Classification d'images, Réseau de neurones convolutifs

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In addition, I would like to thank my parents for their wise counsel and sympathetic ear. You are always there for me.

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THANK YOU ALL . . .

General Introduction

With the outbreak of an unknown disease in late 2019 in China, some people became infected with the disease in a local market. The disease was completely unknown at first, but specialists diagnosed its symptoms as similar to those of coronavirus infection and flu. The specific cause of this widespread disease was initially unknown, but after the laboratory examination and analysis of positive sputum by real-time polymerase chain reaction (PCR) test, the viral infection was confirmed and eventually named "COVID-19" upon the recommendation of the World Health Organization (WHO).

Over a short period, the COVID-19 epidemic crossed geographical boundaries with a devastating effect on the health, economy, and welfare of the global population.

The early detection of COVID-19 is essential not only for patient care but also for public health by ensuring the patients' isolation and controlling the pandemic, the RT-PCR test was the gold standard for diagnosing COVID-19 but it has limiting aspects with certain features that make it difficult to diagnose the disease. RT-PCR is a very time-consuming, complex, costly, manual process and low sensitivity, several studies have reported the sensitivity of this diagnostic method to be 30% to 60% here comes to the line One of the most important ways to diagnose COVID-19 which is using radiological images, including X-ray and computed tomography (CT) scan. Chest imaging is a quick and easy procedure recommended by medical and health protocols and has been mentioned in several texts as the first tool in screening during epidemics.

Considering the advantages of X-ray tests, we propose the COVID-19 Diag model that uses a convolution of positive COVID-19 and negative COVID-19 chest X-ray images to train a network and detect COVID-19 viruses in early infection stages.

The developed Model uses the VGG16 convolutional neural network (CNN) categorize the chest X-ray images of patients as COVID-19 or NO-COVID-19 starting from training the CNN using a dataset of 1400 CXR images.

This study has Three Chapters.Chapter 01 Giving a brief about COVID-19 and Dignosis methods from Lab tests to Medical Imaging . Chapter 2 highlights the used technology and its advanetages. Chapter 3 describes COVID-19 Diag comprising the two tests with the dataset used in its evaluation and gives also the results and compares them. . . .

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List of Abbreviations

CXR	**C**hest **X** **R**ay
WHO	**W**orld **H**ealth **O**rganization
ILSVRC	**I**mageNet **L**arge **S**cale **V**isual **R**ecognition **C**hallenge
ML	**M**achine **L**earning
DL	**D**eep **L**earning
CNN	**C**onvolutional **N**eural **N**etwork

For My Grandmother, I wanted to tell you that I reached what you wanted me to be ! May ALLAH Bless you...
To My Father who can't wait to see me above in the sky, This work for you and there is more in the Future...
To my Mother the first one who belives in me and the only candle in this Dark hard path...
To my Aunt Thank you for your Motivational speech...
For All my familly and friends thank you all for everything... . . .

Chapter 1

Introduction to COVID-19

1.1 Introduction

With the outbreak of an unknown disease in late 2019 in China, some people became infected with the disease in a local market.

The disease was completely unknown at first, but specialists diagnosed its symptoms as similar to those of coronavirus infection and flu [1].

The specific cause of this widespread disease was initially unknown, but after the laboratory examination and analysis of positive sputum by real-time polymerase chain reaction (PCR) test, the viral infection was confirmed and eventually named "COVID-19" upon the recommendation of the World Health Organization (WHO).

Over a short period, the COVID-19 epidemic crossed geographical boundaries with a devastating effect on the health, economy, and welfare of the global population.

Until June 10, 2021, more than 174 million people worldwide contracted COVID-19, of whom more than 3,750,000 people died officially due to the disease. [1]

The early detection of COVID-19 is essential not only for patient care but also for public health by ensuring the patients' isolation and controlling the pandemic.

Due to the novelty of the disease, ways to fight it were not known in the early days, but researchers considered screening and rapid diagnosis of infected patients and their separation from the community of healthy people as an important measure.

The clinical features of COVID-19 include respiratory symptoms, fever, cough, dyspnea, and pneumonia.

However, these symptoms do not always indicate COVID-19 and are observed in many cases of pneumonia, leading to diagnostic problems for physicians.

1.2 COVID-19 Identification and Detection

While the RT-PCR test is the gold standard for diagnosing COVID-19, it has limiting aspects with certain features that make it difficult to diagnose the disease. RT-PCR is a very time-consuming, complex, costly, and manual process.

One of the drawbacks of this method is the need for a laboratory kit, the provision of which is difficult or even impossible for many countries during crises and epidemics.

Like all diagnostic and laboratory methods in healthcare systems, this method is not error-free and is biased. It requires an expert laboratory technician to sample the nasal and throat mucosa which is a painful method, and this is why many people refuse to undergo nasal swap sampling [2–3].

More importantly, many studies indicated the low sensitivity of the RT-PCR test; several studies have reported the sensitivity of this diagnostic method to be 30% to 60%, indicating a decrease in the accuracy of the diagnosis of COVID-19 in many cases. Some studies also pointed to its false-negative rate and contradictory results [4, 5].

Regarding to the conditions mentioned above the CT scan and X-ray scans comes the field, both use invisible ranges of electro-magnetic spectrum to detect any kind of anomaly used for early detects and have high clinical relevance.

In this study, we found out that the chest X-ray tests are economically affordable and the results are relatively easy to use.

Chest X-ray tests are easily available, have portable versions, and a low risk of radiation. On the other hand, CT scans have high risk of radiation, are expensive, need clinical expertise to handle and are non-portable.

This makes the use of X-ray scans more convenient than CT scans.

1.3 Medical Imaging

Medical imaging refers to techniques and processes used to create images of various parts of the human body for diagnostic and treatment purposes within digital health, it is crucial in every medical setting and at all levels of healthcare.

Use of medical imaging helps physicians to arrive at more accurate diagnoses and appropriate treatment decisions.

Without it, both diagnosis and treatment in digital health can be very difficult to achieve with any level of accuracy.

1.3.1 CT-SCAN

As alternative ways to diagnose COVID-19 most of countries are using radiological images, including X-ray and computed tomography (CT) scan.

Computed tomography (CT) scans use a computer to merge 2-D X-ray images and convert them to a 3-D image. They require highly specialized equipment and are done in hospital by a specialist radiographer. Chest imaging is a quick and easy procedure recommended by medical and health protocols and has been mentioned in several texts as the first tool in screening during epidemics [6].

Compared to RT-PCR, CT-SCAN images have a high sensitivity in diagnosing and detecting cases with COVID-19; however, their specificity is low. This means that CT scan is more accurate in cases of COVID-19, but less accurate in cases of nonviral pneumonia.

The American College of Radiology recommends that CT scans should not be used as the first line of diagnosis. Problems such as the risk of transmission of the disease while using a CT scan device and its high cost can cause serious complications for the patient and healthcare systems, so it is recommended that if medical imaging is needed, the CT scan be replaced with X-ray.

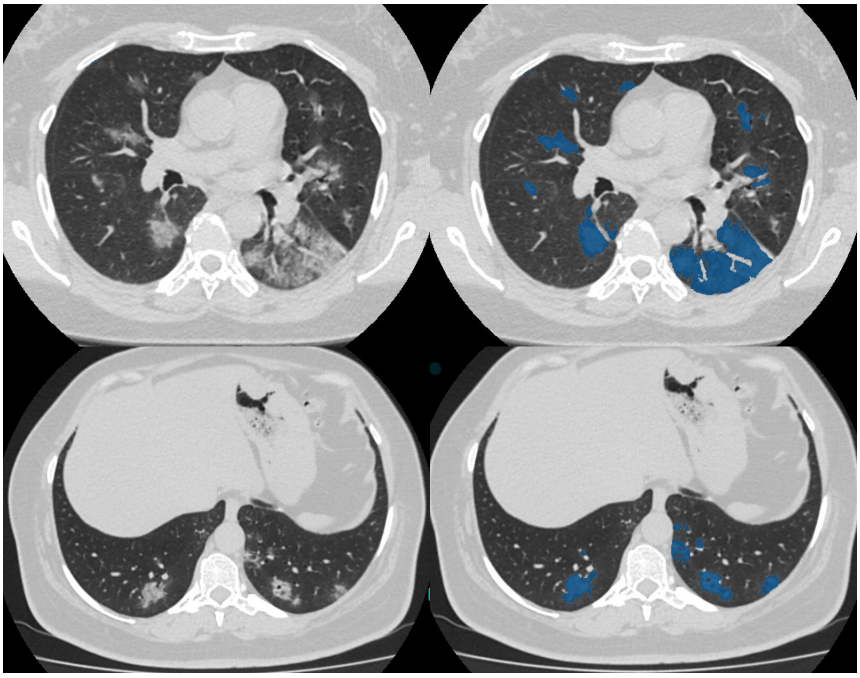

FIGURE 1.1: CT-SCAN image sample

1.3.2 X-RAY

X-rays (radiography) use radiation to produce a 2-D image. Usually done in hospitals, using fixed equipment by a radiographer, they can also be done on portable machines, also it is much more extensive and cost-effective than conventional diagnostic tests.

Transmission of an X-ray digital image does not require transferring from the access point to the analysis point, so the diagnostic process is performed very quickly.

Chest radiography is convenient and fast for medical triaging of patients.

Unlike CT scans, X-ray imaging requires less scarce and expensive equipment, so significant savings can be made in the running costs.

Furthermore, portable CXR devices can be used in isolated rooms to reduce the risk of infection resulting from the use of these devices in hospitals.

Various studies have indicated the failure of CXR imaging in diagnosing COVID-19 and differentiating it from other types of pneumonia.

The radiologist cannot use X-rays to detect pleural effusion and determine the volume involved.

However, regardless of the low accuracy of X-ray diagnosis of COVID-19, it has some strong points.

To overcome the limitations of COVID-19 diagnostic tests using radiological images, various studies have been conducted on the use of deep learning (DL) in the analysis of radiological images as we did in this study.

FIGURE 1.2: X-Ray image sample

1.4 Classification Methods

The classification of image can be divided into the supervised classification and the unsupervised classification according to whether there is the extant category.

The two methods have difference in essence, but they are connected with each other. Below we analyzed the difference and relation of the two methods in general such as the principle, the course and ways of classification.[8]

1.4.1 Unsupervised

Is where the outcomes (groupings of pixels with common characteristics) are based on the software analysis of an image without the user providing sample classes. The computer uses techniques to determine which pixels are related and groups them into classes.

The user can specify which algorism the software will use and the desired number of output classes but otherwise does not aid in the classification process.

However, the user must have knowledge of the area being classified when the groupings of pixels with common characteristics produced by the computer have to be related to actual features on the ground (such as wetlands, developed areas, coniferous forests, etc.).

Unsupervised models are used for many tasks but the main task is:

- **Clustering** which is a data mining technique for grouping unlabeled data based on their similarities or differences.

For example, K-means clustering algorithms assign similar data points into groups, where the K value represents the size of the grouping and granularity.

This technique is helpful for market segmentation, image compression, etc. [See figure 1.3]

1.4.2 Supervised

Based on the idea that a user can select sample pixels in an image that are representative of specific classes and then direct the image processing software to use these training sites as references for the classification of all other pixels in the image.

Training sites (also known as testing sets or input classes) are selected based on the knowledge of the user.

The user also sets the bounds for how similar other pixels must be to group them together.

These bounds are often set based on the spectral characteristics of the training area, plus or minus a certain increment (often based on "brightness" or strength of reflection in specific spectral bands).

The user also designates the number of classes that the image is classified into.

It can be separated into two types of problems when data mining:

- **Classification** problems use an algorithm to accurately assign test data into specific categories, such as separating apples from oranges.

Or, in the real world, supervised learning algorithms can be used to classify spam in a separate folder from your inbox. Linear classifiers, support vector machines, decision trees and random forest are all common types of classification algorithms. .[Figure1.2]

- **Regression** is another method that uses an algorithm to understand the relationship between dependent and independent variables.

Regression models are helpful for predicting numerical values based on different data points, such as sales revenue projections for a given business.

Some popular regression algorithms are linear regression, logistic regression and polynomial regression. [Figure 1.3]

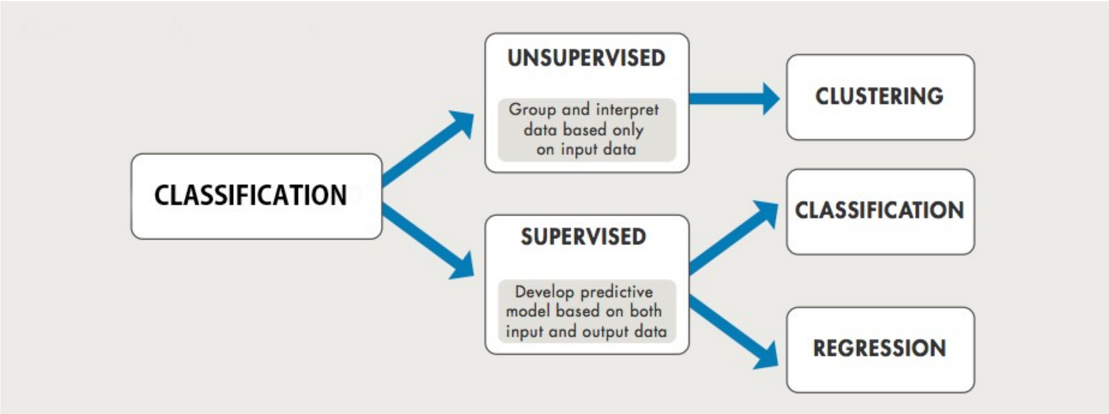

FIGURE 1.3: Classification Methods.

1.5 The Workflow of COVID-19 Detection

The whole system for detection of COVID-19 from chest X-ray images comprised of few important steps—collection of dataset, pre-processing the data, categorization of dataset, training the models and evaluation and analysis of the model.

The complete system architecture of the for detecting COVID-19 with CNN is depicted in [Figure 1.4]. At first the dataset needed for training and validating the model is collected and sorted out.The collected data are then shuffled, resized and normalized to maintain the uniformity. After this step, all the data are categorize according to the classification of the model.Then all the models are trained and validated with the same dataset and same environment.

Lastly the trained models are analyzed based on few important metrics like accuracy, recall, precision, F-1 score, ROC curve.

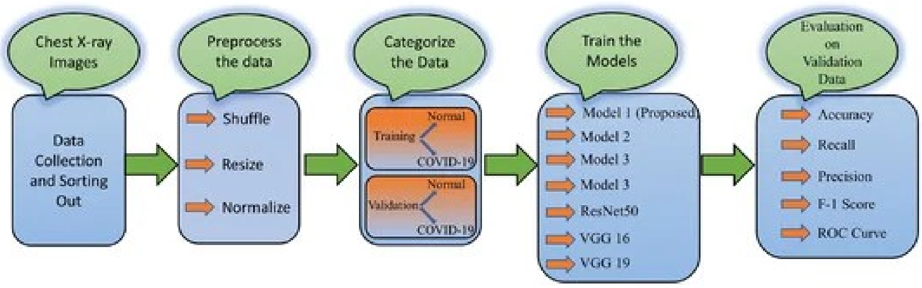

FIGURE 1.4: System Architecture for COVID-19 Detection with CNN.

1.5.1 CNN Modeling

CNN has been playing a great role in classifying images, in particular medical images.

Which opened a new windows of opportunities and made the disease detection much more convenient.

It also successfully detects recent novel Coronavirus with higher accuracy. One of the constraints that researchers encounter is a limited dataset for training their model.

Being a novel disease, the CXR dataset of COVID-19 positive patients is also limited. Therefore, to avoid overfitting, a sequential CNN model is proposed for classifying X-ray images.

Figure 1.3 depicts the proposed CNN model for COVID-19 detection.

This model has 4 main components: (i) input layers (ii) convolutional layers (iii) fully connected layers and (iv) output layers.

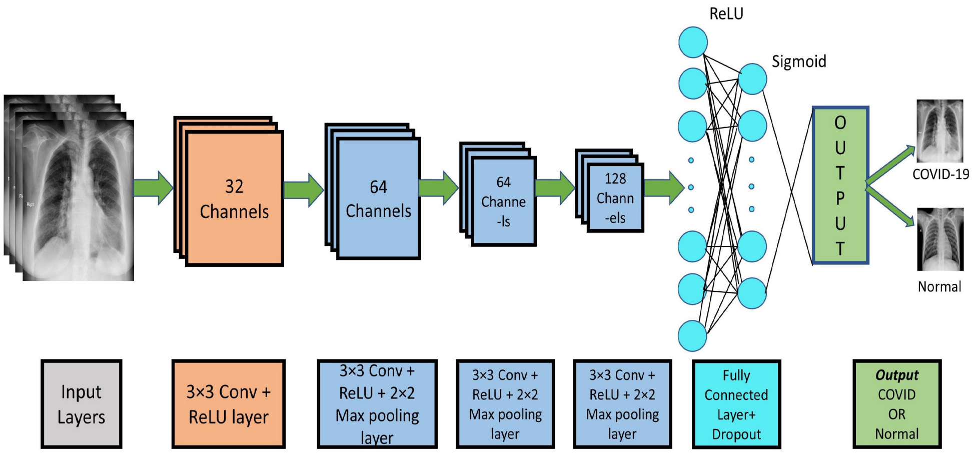

FIGURE 1.5: Main Components of CNN used for COVID-19 Diagnose

1.6 Conclusion

The majority of the literature surrounding imaging for COVID-19 has focused on CT as the primary imaging modality.

However, other imaging modalities such as chest radiography (CXR) and ultrasound are now also being considered.

CXR has shown to be useful as a first-line investigation to screen for COVID-19 because of its practical advantages, in terms of speed and infection control. In China and Italy, alongside RT-PCR and CT, chest X-ray has been used in the screening and monitoring of patients [9]. British hospitals have also started utilising chest X-ray as a first-line tool for triage of COVID-19 patients, owing to the long turnaround times for RT-PCR [10].

The severity of chest radiograph abnormalities was found to peak at 10-12 days from symptom onset, similar to CT findings which peak at 6–11 days [10]. CXR may however provide practical advantages compared to CT such as preventing cross-infection from transport of patients to contaminated CT suites, inefficiencies of subsequent decontamination of CT suites, along with unavailability of CT in many parts of the world.

Additionally, in patients with obvious clinical signs diagnostic of COVID-19, a positive chest radiograph may negate the need for CT, making CXR a viable alternative in terms of cost effectiveness as well [11]. Furthermore, imaging will enable detection of any underlying cardiopulmonary abnormalities as well as establishing baseline pulmonary status. Thus, allowing physicians to assess for risk and wary of any possible secondary complications of COVID-19 such as pulmonary embolism, bacterial pneumonia or possible heart failures [12], [13].

Chapter 2

Deep learning and applications

2.1 Introduction

Machine learning has seen some dramatic developments recently, leading to a lot of interest from industry, academia and popular culture. These are driven by breakthroughs in artificial neural networks, often termed deep learning, a set of techniques and algorithms that enable computers to discover complicated patterns in large data sets.

Feeding the breakthroughs is the increased access to data ("big data"), user-friendly software frameworks, and an explosion of the available compute power, enabling the use of neural networks that are deeper than ever before.

These models nowadays form the state-of-the-art approach to a wide variety of problems in computer vision, language modeling and robotics.

Deep learning rose to its prominent position in computer vision when neural networks started outperforming other methods on several high-profile image analysis benchmarks. Most famously on the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) in 2012 [14] when a deep learning model (a convolutional neural network) halved the second best error rate on the image classification task.

Enabling computers to recognize objects in natural images was until recently thought to be a very difficult task, but by now convolutional neural networks have surpassed even human performance on the ILSVRC, and reached a level where the ILSVRC classification task is essentially solved (i.e. with error rate close to the Bayes rate), Deep learning techniques have become the de facto standard for a wide variety of computer vision problems. They are, however, not limited to image processing and analysis but are outperforming other approaches in areas like natural language processing, speech recognition and synthesis, and in the analysis of unstructured, tabular-type data using entity embeddings.

The use of machine learning in general and deep learning in particular within healthcare is still in its infancy, but there are several strong initiatives across academia, and multiple large companies are pursuing healthcare projects based on machine learning. Not only medical technology companies, but also for example Google Brain, DeepMind, Microsoft, and IBM.

2.2 Machine learning

Machine learning is one of the approaches to artificial intelligence. It is a discipline devoted to data analysis.

The goal of this discipline is to create knowledge automatically from raw data (samples). This knowledge (or model) can then be used to make decisions.

Depending on the nature of the samples (labeled or not), there are three types of learning :

Supervised learning: This approach aims to design a model linking training data to a set of output values (the input data is labeled).

Unsupervised learning: It aims to design a model structuring information. The difference here is that the behaviors (or categories or even classes) of the training data are not known, this is what we are trying to find.

Semi-supervised learning: The input data consists of labeled and unlabeled examples.

This can be very useful when you have two types of data, because it allows not to leave any aside and to use all the information.

2.3 Deep learning

Deep learning is a subfield of machine learning that focuses on algorithms inspired by the structure and function of the brain, called artificial neural networks.

It involves a particular type of mathematical model which can be seen as a composition of simple blocks of a certain type, in a multi-layered structure and where some of these blocks can be adjusted to better predict the end result.

In deep learning, a computer model learns to perform classification tasks directly from images, text or sound.

Deep learning models can achieve peak accuracy, sometimes exceeding performance at a human level. Models are trained using a large mass of labeled data and neural network architectures that contain many layers.

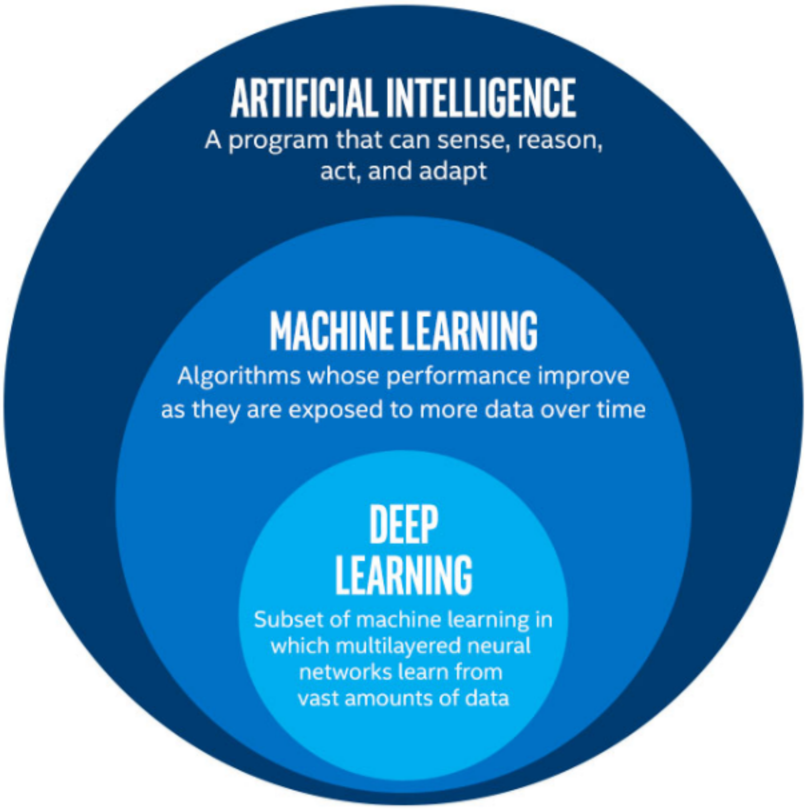

FIGURE 2.1: Relation Between AI and ML and DL

2.3.1 Supervised learning

Is the most used type of learning. It consists in input variables (X) and an output variable (Y), where the supervised learning algorithm will find a mapping function between the predictive variables in input (X) and the variable to be predicted (Y).

The mapping function describing the relationship between (X) and (Y) is called a prediction model. It is called supervised learning because the process of an algorithm drawn from the training set can be thought of as a teacher supervising the learning process. We know the correct answers, the algorithm makes iterative predictions on the learning data and is corrected by the teacher. Learning stops when the algorithm reaches an acceptable level of performance.

Supervised learning is typically done in the context of classification and regression.

2.3.2 Unsupervised learning

Consists of having only input data (X) and no corresponding output variables. Its objective is to model the structure or the underlying distribution in the data to learn more about the data. This is called unsupervised learning because, unlike supervised learning, there is no correct answer and no teacher. The algorithms are left to their own mechanisms for discovering and presenting the interesting structure of the data.

Unsupervised learning includes two categories of algorithms: Grouping, association and dimensionality reduction algorithms.

2.4 Differences between ML& DL and Why Deep Learning ?

The ML algorithms work well for a wide variety of problems. However, they failed to solve some major AI problems such as speech recognition and image recognition. The development of deep learning was driven in part by the failure of traditional algorithms in such AI task. But it was only after larger amounts of data became available, thanks in particular to Big Data and connected objects, and computing machines became more powerful that we could understand the real potential of deep learning.

One of the big differences between Deep Learning and traditional ML algorithms is that it adapts well, the greater the amount of data provided the better the performance of a deep learning algorithm.

Unlike many classic ML algorithms which have an upper bound on the amount of data they can receive sometimes called a "performance plateau", Deep Learning models do not have such limitations (theoretically) and they are even went so far as to exceed human performance in areas such as image processing.

Another difference between traditional ML algorithms and deep learning algorithms is the feature extraction step.

In traditional ML algorithms the feature extraction is done manually, it is a difficult and time consuming step and requires a specialist in the subject while in Deep Learning this step is performed automatically by the algorithm

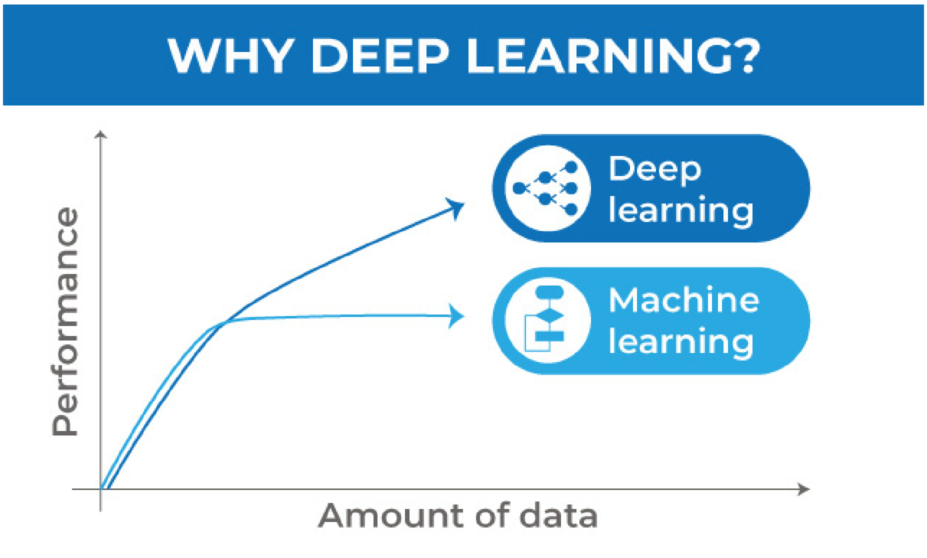

FIGURE 2.2: ML and DL Performance .

2.5 Artificial neural networks (ANN)

The artificial neural network is an information processing system that started around 50 years ago and is still under development.

This system is inspired by the functioning of human neurons. They consist of a large number of linked elementary processors (neuron) working together, each elementary processor calculates a single output based on the information it receives, to perform a given classification task.

The artificial neuron is a nonlinear and bounded algebraic function, whose value depends on parameters called coefficients or weights. The variables of this function are usually called inputs to the neuron, and the value of the function is called its output[12] .

The artificial neuron is therefore a simplified mathematical model of the biological neuron.

The Xi Represent the input vectors

The Wij Are the synaptic weights of the neuron j

Bias bi Input often takes the values -1 or +1 which allows to add flexibility

Sum function Integrates all the inputs and the bias and calculates the output of the neuron

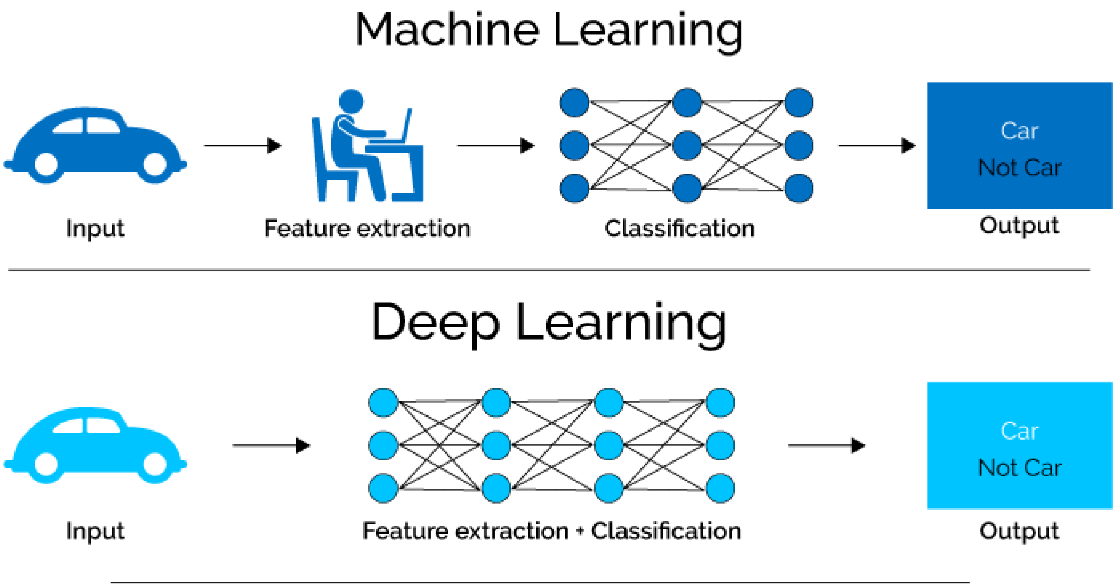

FIGURE 2.3: ML and DL Agorithms .

The activation function f Is the activation function of the neuron. There are many possible forms for the activation function

2.6 Convolutional neural networks

(CNN) The convolutional neuron network is initially proposed by the French researcher Yann LeCun [17], it is a particular type of neuron network which is based on the convolution operation, its main goal is to extract characteristics from a given image.

Convolutional networks are the most efficient structures for classifying or recognizing images .

A network is said to be convolutional when each neuron receives its information not from the entire preceding layer, but only neurons located in its receptive field.

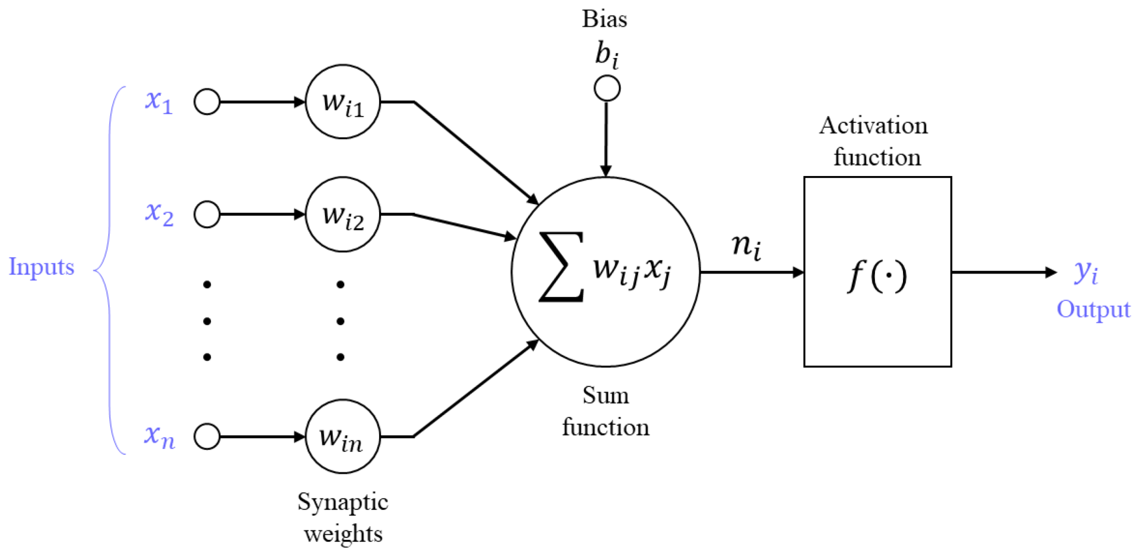

FIGURE 2.4: Artificial neural networks (ANN)

2.6.1 Presentation

Convolutional Neural Networks (CNNs) have two distinct parts. As input, an image is provided in the form of a matrix of pixels, 2 dimensions for a grayscale image.

The color is represented by a third dimension, of depth 3 to represent the fundamental colors [Red, Green, Blue].

The first part of a CNN is the actual convolutional part. It works as a feature extractor from images. An image is passed through a succession of filters, or convolution nuclei, creating new images called convolution cards. Some intermediate filters reduce the image resolution by a local maximum operation.

Finally, the convolution maps are flattened and concatenated into a feature vector, called the CNN code.

This CNN code at the output of the convolutional part is then plugged into the input of a second part, made up of fully connected layers (multilayer perceptron). The role of this part is to combine the characteristics of the CNN code to classify the image.

The output is a final layer with one neuron per category. The numerical values obtained are generally normalized between 0 and 1, of sum 1, to produce a probability distribution over the categories.

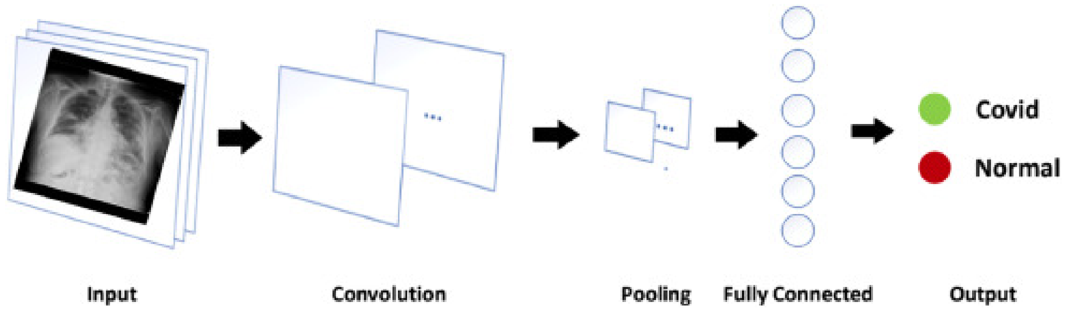

FIGURE 2.5: Convolutional neural networks (CNN)

2.6.2 Convolutional neural network architecture

Convolutional Neural Networks are very similar to ordinary Neural Networks, they are made up of neurons that have learnable weights and biases. Each neuron receives some inputs, performs a dot product and optionally follows it with a non-linearity.

1- The Convolution Layer

When presented with a new image, CNN is not sure whether the features will be present at the edge or the center of the image, so it seeks to find them throughout the image and in any position. By calculating in any the image if a feature is present, we do a filtering. The mathematics we use to do this is called a convolution, from which convolutional neural networks get their name. Convolutional layers are the heart of convolutional networks. They consist of a rectangular grid of neurons having a small receptive field extended across the depth of the input volume. It works as an extractor of characteristics of the images by the filtering operation on the image. To perform this operation on the whole image, we define a neighborhood window of size (s * s) that will move through the whole image. At the very start of the convolution, the window will be positioned at the top left of the image then it will shift a certain number of boxes (called the step) to the right and when it arrives at the end of the image, it will shift down one step and so on until the filter has traveled the entire image.

Three hyper parameters are used to size the volume of the convolution layer:

1.Depth of layer K: Number of convolution nuclei

2.The step S: Controls the overlap of the receptive fields.

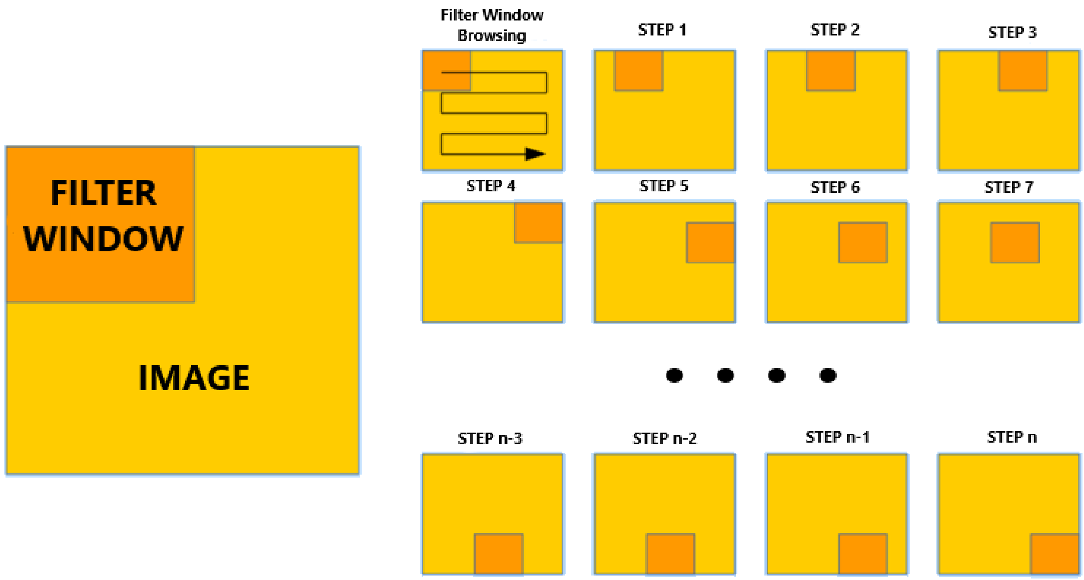

FIGURE 2.6: The Convolution Layer

3.The margin (at 0) or zero padding P: This margin is used to control the dimension spatial output volume.

2- The Pooling Layer

Another very powerful tool used by CNNs is called Pooling.

Which is a method of taking a large image and reducing its size while preserving the most important information it contains. Which is a form of downsampling of the . This type of layer is often placed between two convolution layers, it receives several feature maps as input and applies the pooling operation to each of them.

The two most used methods to apply this operation are the following, either we take the average of the values of the zone (pooling average), or we extract only the highest value (max pooling). We use in this work the one which applies the max operation to the result of each filter.

To do this, we cut the image into regular cells, then we keep the maximum value within each cell.

In practice, small square cells are often used so as not to lose too much information.

The most common form is a pool layer with tiles of size 2 × 2 (width / height) and as an output value the maximum input value its use is to reduce

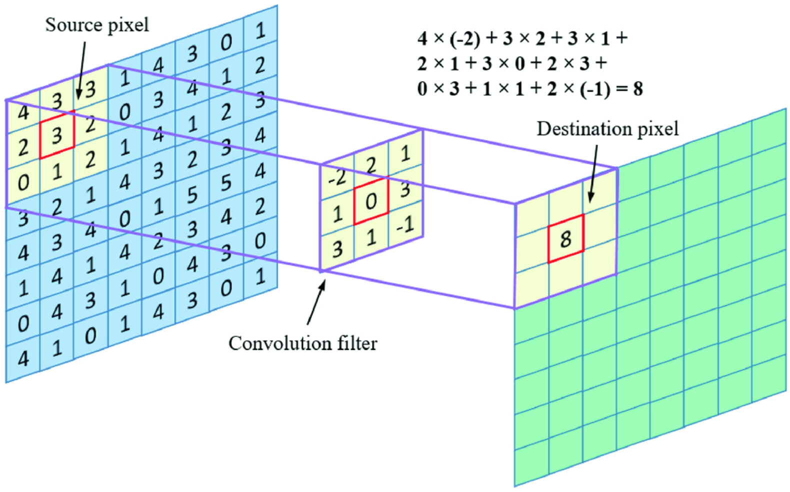

FIGURE 2.7: The Convolution Layer parameters

the amount of weight to be learned which reduces the computation time as well as the probability of over-learning, in this case we speak of "Max-Pool 2x2".

3- Correction layers (Relu)

Often, it is possible to improve the efficiency of the processing by interposing between the processing layers a layer which will perform a mathematical function (activation function) on the output signals.

The ReLU correction layer (short for Rectified Linear Unit) denotes the real non-linear function defined by ReLU(x)=max (0, x)

This function, also called “non-saturating activation function”, increases the nonlinear properties of the decision function and of the whole network without affecting the receptive fields of the convolution layer.

The ReLU correction layer therefore replaces all the negative values received as inputs with zeros. It often plays the role of an activation function, the ReLU correction is preferable, but there are other forms
Correction by hyperbolic tangent: f (x) = tanh (x)
Correction by the saturating hyperbolic tangent: f (x) = | tanh (x) |
Correction by the sigmoid function: f(x) = (1 + e - x) -1

4- Normalization Layer

Many types of normalization layers have been proposed for use in ConvNet architectures, sometimes with the intentions of implementing inhibition schemes observed in the biological brain. However, these layers have

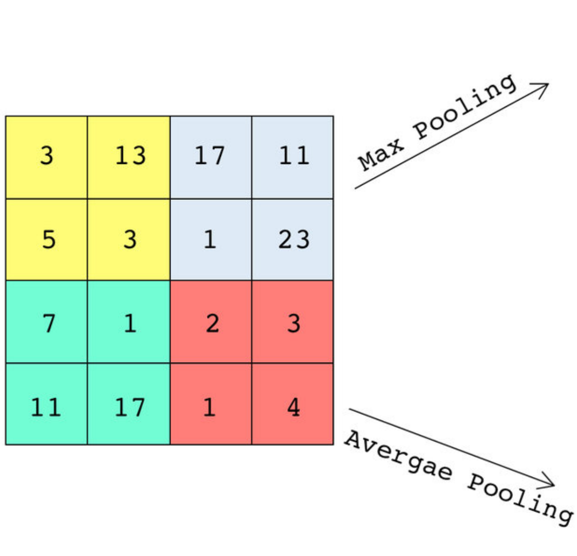

FIGURE 2.8: The Pooling Layer

since fallen out of favor because in practice their contribution has been shown to be minimal, if any.

5- Fully-Connected layer

The fully-connected layer is a perceptron or a MLP (multi-layer perceptron) which is always the last layer of a neural network, convolutional or not - it is therefore not characteristic of a CNN.

After extracting the input features through multiple layers of convolution and max-pooling into a 1D vector, the perceptron takes the extracted features as input and produces a vector of size N, where N is the number of classes in our image classification problem.

Each element of the vector indicates the probability for the input image to belong to a class, the probabilities of belonging to each class are computed using the activation function of type sigmoid or SoftMax.

The FC layer consists in multiplying the input vector by the matrix containing the weights. The fact that each input value is connected with all output values explains the term fully-connected .

6- Batch Normalization

The Batch Normalization technique was recently introduced in 2015 in order to learn CNNs more quickly and efficiently.

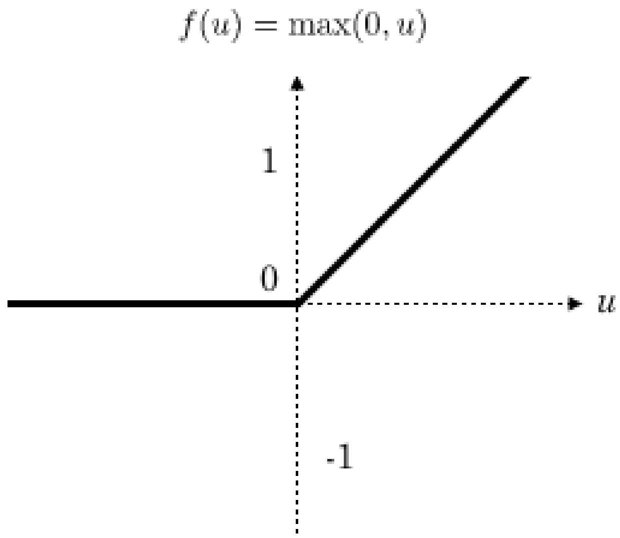

FIGURE 2.9: Correction layers (Relu)

His idea is to normalize the values between 0 and 1 for example. Strictly speaking, Batch Normalization normalizes data by subtracting the average from the data batch and dividing by its average.

This operation will make the network more stable and will also accelerate its learning phase.

From a mathematical point of view, one does not lose information by passing values between -10 and 10 than between -1 and 1. This also makes it possible to reduce the coarse deviations which could have too big an impact on the update of the weights (during the descent of the gradient). In addition, it also makes it possible to make it more generic as a predictor.

In fact, suppose that we have trained a network to detect cats in hundreds of images but that the cats are mostly of a dark color (black, gray).

Without Batch Normalization, this color will have said for value 5. If now the network is confronted with cats whose coat is of a brighter color like orange or white, this value field for these colors going from 50 to 100, the network would be lost and would recognize less the cats of this color.

This example shows the importance of a Batch Normalization layer, after each convolution layer if possible.

2.7 Most Popular Convolutional Neural Networks

There are research teams fully dedicated to developing deep learning architectures for CNN and to training them in huge datasets, so we will take advantage of this and use them instead of creating a new architecture every

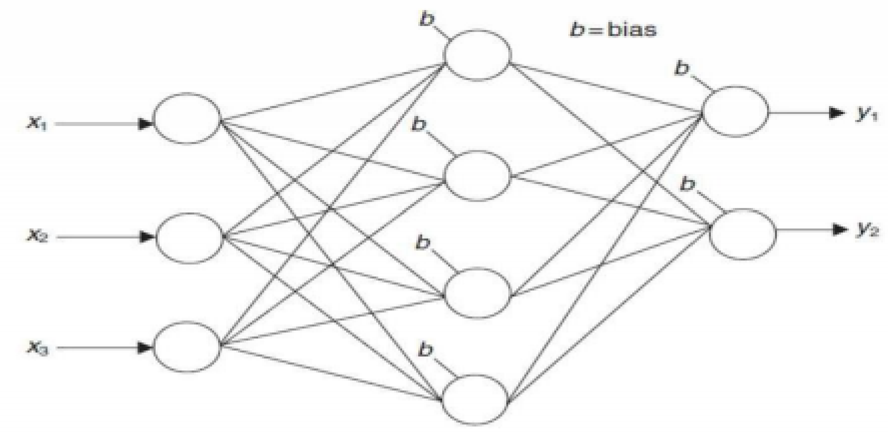

FIGURE 2.10: Fully-Connected layer

time we face a new problem.

This will provide us with stability and precision.

The most common deep learning architectures for CNN today are :

2.7.1 ResNet (2015)

Residual network developed by Kaiming He et al, it was the winner of ILSVRC 2015. It features connection hopping and a strong use of batch normalization It also uses global AVG pooling instead of PMC at the end.

2.7.2 LeNet (1990)

The first successful applications of convolutional networks were developed by Yann LeCun in the 1990s. Among these, the best known is the LeNet architecture used to read postal codes, numbers, etc. [17].

2.7.3 AlexNet (2012)

The first work that popularized convolutional networks in computer vision was AlexNet, developed by Alex Krizhevsky, Ilya Sutskever and Geoff Hinton. This CNN was submitted to the ImageNet base challenge in 2012 and clearly outperformed its competitors. The network had a very similar architecture to LeNet, but was deeper, larger and had convolutional layers stacked on top of each other (previously, it was common to have only one convolutional layer always immediately followed by a pooling layer followed by a pooling layer) [17]

2.7.4 VGG16 and VGG19

This architecture, which was one of the first to appear, was introduced by Simonyan and Zisserman in 2014 with their paper entitled Very Deep Convolutional Networks for Large Scale Image Recognition. The model achieves 92.7% top-5 test accuracy in ImageNet, which is a dataset of over 14 million images belonging to 1000 classes. It was one of the famous model submitted to ILSVRC-2014. It makes the improvement over AlexNet by replacing large kernel-sized filters (11 and 5 in the first and second convolutional layer, respectively) with multiple 3×3 kernel-sized filters one after another. VGG16 was trained for weeks and was using NVIDIA Titan Black GPU's. Besides, to reduce the size of the activation maps obtained, max-pooling blocks are interspersed between the convolutional ones, reducing the size of these activation maps by half. Finally, a classification block is used, consisting of two dense layers of 4096 neurons each, and the last layer, which is the output layer, of 1000 neurons.

2.8 Conclution

Deep Learning and Machine Learning are considered to be the subcategories of Artificial intelligence.

Both Machine Learning and Deep Learning are the special algorithms that can perform certain tasks, distinguished by their own advantages.

In machine learning The develops and studies give computers the ability to solve problems by learning from experiences.

Machine learning models provided experiences in the form of training data, and they are tuned to produce accurate predictions for the training data by an optimization algorithm.

Traditionally, machine learning models are trained to perform useful tasks based on manually designed features extracted from the raw data, or features learned by other simple machine learning models, comparing to deep learning, the computers learn useful representations and features automatically, directly from the raw data, bypassing this manual and difficult step.

By far the most common models in deep learning are various variants of artificial neural networks and specially the convolutional neural networks CNNs which used mostly in medical imaging as powerful way to learn useful representations of images and other structured data.

A CNN is a particular kind of artificial neural network aimed at preserving spatial relationships in the data, with very few connections between the layers. The input to a CNN is arranged in a grid structure and then fed through layers that preserve these relationships, each layer operation operating on a small region of the previous layer, CNNs typically have fully connected layers at the end, which compute the final outputs.

CNNs are able to form highly efficient representation of the input data, well-suited for image-oriented tasks.

Chapter 3

Applications And Results

3.1 Materials and Methods

One of the major applications of DL in radiology practices was the detection of tissue-skeletal abnormalities and the classification of diseases. The convolutional neural network has proven to be one of the most important DL algorithms and the most effective technique in detecting abnormalities and pathologies in chest radiographs [15]. In this model we used DL based Development envirenement to create an accurate system of COVID-19 DIAGNOSIS. The Development envirenement of the model COVID-19 Diag are described further in details.

3.1.1 Python

Python is an interpreted, interactive, object-oriented programming language.

It incorporates modules, exceptions, dynamic typing, very high level dynamic data types, and classes.

It supports multiple programming paradigms beyond object-oriented programming, such as procedural and functional programming.

Python combines remarkable power with very clear syntax. It has interfaces to many system calls and libraries, as well as to various window systems, and is extensible in C or C++. It is also usable as an extension language for applications that need a programmable interface.

Finally, Python is portable: it runs on many Unix variants including Linux and macOS, and on Windows.

What does Python used for ?

- AI and machine learning
- DATA ANALYTICS
- DATA VISUALISATION
- PROGRAMMING APPLICATIONS

3.1.2 TensorFlow

TensorFlow is an open source framework developed by Google researchers to run machine learning, deep learning and other statistical and predictive analytics workloads.

Like similar platforms, it's designed to streamline the process of developing and executing advanced analytics applications for users such as data scientists, statisticians and predictive modelers.

The TensorFlow software handles data sets that are arrayed as computational nodes in graph form.

The edges that connect the nodes in a graph can represent multidimensional vectors or matrices, creating what are known as tensors.

Because TensorFlow programs use a data flow architecture that works with generalized intermediate results of the computations, they are especially open to very large-scale parallel processing applications, with neural networks being a common example.

3.1.3 keras

Keras is an open-source software library that provides a Python interface for artificial neural networks. Keras acts as an interface for the TensorFlow library.

Keras supported multiple backends, including TensorFlow, Microsoft Cognitive Toolkit, Theano, and PlaidML.

Designed to enable fast experimentation with deep neural networks, it focuses on being user-friendly, modular, and extensible.

It was developed as part of the research effort of project ONEIROS (Open-ended Neuro-Electronic Intelligent Robot Operating System), and its primary author and maintainer is François Chollet, a Google engineer. Chollet is also the author of the XCeption deep neural network model.

Keras contains numerous implementations of commonly used neural-network building blocks such as layers, objectives, activation functions, optimizers, and a host of tools to make working with image and text data easier to simplify the coding necessary for writing deep neural network code. The code is hosted on GitHub, and community support forums include the GitHub issues page, and a Slack channel.

In addition to standard neural networks, Keras has support for convolutional and recurrent neural networks.

It supports other common utility layers like dropout, batch normalization, and pooling.

Keras allows users to productize deep models on smartphones (iOS and Android), on the web, or on the Java Virtual Machine. It also allows use of distributed training of deep-learning models on clusters of Graphics processing units (GPU) and tensor processing units.

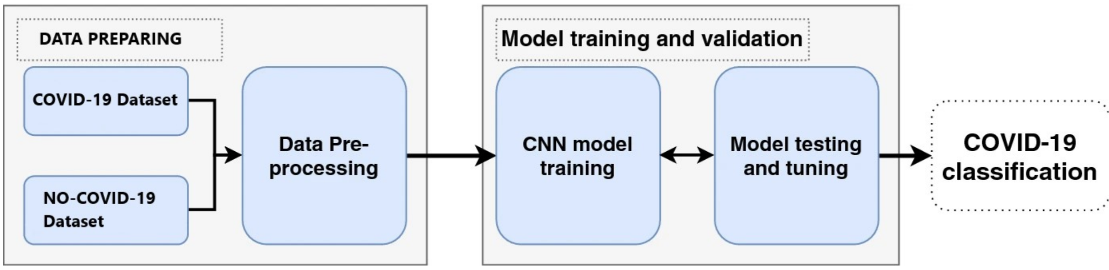

FIGURE 3.1: COVID-19 Diagnosis Model Workflow

3.2 Database and Training Resources

The data augmentation process was implemented by using python programming language with tensorflow and augmentor library.

The dataset contains of 1400 chest X-ray images, 700 images under categories ('NO-COVID-19) and (COVID-19) was splitted as a training and testing set.

We trained the model and tuned it using different learning parameters and training and testing dataset distributions.

We performed tow training-testing data splits on VGG16 CNN architecture: 70–30%, and 80–20%.

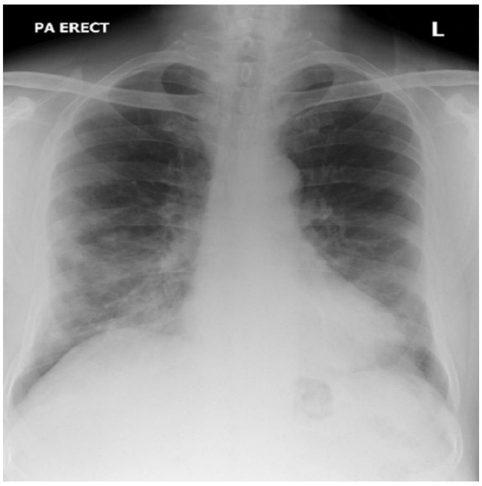

FIGURE 3.2: Dataset COVID-19 random Sample

FIGURE 3.3: Dataset NO-COVID-19 random Sample

3.3 Convolutional Neural Network Used

The proposed COVID-19 Diag model uses the standard VGG16Net with a few modifications.

VGG16 (also called OxfordNet) is a convolutional neural network architecture named after the Visual Geometry Group from Oxford, who developed it. It was used to win the ILSVRC2014 (Large Scale Visual Recognition Challenge 2014)) competition in 2014. It still considered to be an excellent vision model.

VGG-16 is a convolutional neural network that 16 layers deep. The model loads a set of weights pre-trained on ImageNet.

The model achieves 92.7% top-5 test accuracy in ImageNet, which is a dataset of over 14 million images belonging to 1000 classes.

The Keras application library was used to import the pre trained VGG16.The convolutional layers are grouped as a set and after the each set of convolutional layers the max pooling layer was introduced to reduce the dimension of the features.

Using VGG16 CNN needs at first the dataset needed for training and testing the Dataset is collected and sorted out. The collected data are then shuffled, resized and normalized to maintain the uniformity. After this step, all the data are categorize according to the classification of the model **(COVID-19 and NO-COVID-19)** . Then the model were trained and tested with 70–30%, and 80–20% dataset splitting in the same environment.

Lastly the trained models are analyzed based on few important metrics like accuracy, recall, precision, F-1 score.

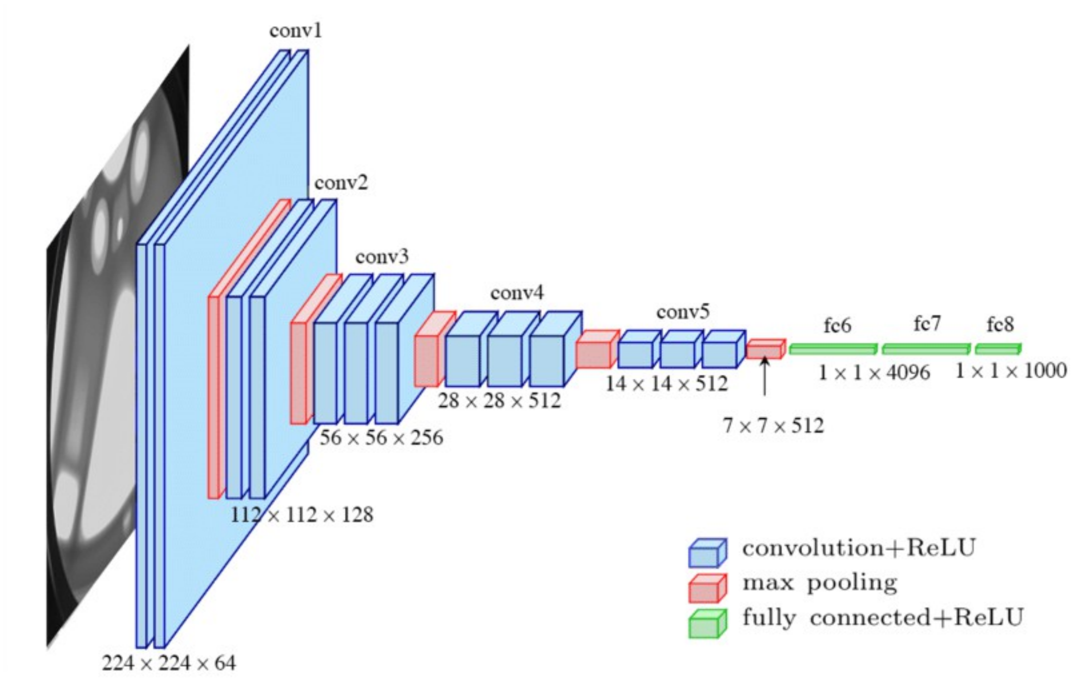

FIGURE 3.4: VGG16 Architecture

3.4 Parameters Evaluations

We used four parameters, true positive (TP), true negative (TN), false positive (FP) and false negative (FN) to evaluate the overall performance of proposed CNN model on four performance metrics: accuracy, precision, recall and F1-score

3.4.1 Accuracy

Accuracy is an essential metric for the evaluation of the results of DL classifiers. It is a summary of the true positive and true negatives divided by the confusion of the matrix components' total values. The most accurate model is an excellent one, but it is imperative to ensure that symmetric sets of data with almost equal false positive values and false negative values.

$$Accuracy(\%) = \frac{TP + TN}{TP + FN + TN + FP} 100\%.$$

FIGURE 3.5: Accuracy

3.4.2 Sensitivity (Recall)

sensitivity is measured as the number of accurate positive predictions divided by the sum of positive. The best sensitivity is 1.0, whereas the worst is 0.0. We calculate sensitivity using following equation:

$$Sensitivity = \frac{TP}{TP + FN}$$

FIGURE 3.6: Sensitivity (Recall)

3.4.3 Precision

Precision is the fraction of the correct positive labelled by our model to all negative labelled. Precision has been calculated as follows

$$Precision = \frac{TP}{TP + FP}$$

FIGURE 3.7: Precision

3.4.4 F1-score

The F-score, also called the F1-score, is a measure of a model's accuracy on a dataset. It is used to evaluate binary classification systems, which classify examples into 'positive' or 'negative'.

The formula for the standard F1-score is the harmonic mean of the precision and recall. A perfect model has an F-score of 1.

$$F1\ Score = 2 \times \left(\frac{Precision \times Recall}{Precision + Recall}\right)$$

FIGURE 3.8: F1-score

3.5 Results And Discussion

We performed tow training-testing data splits on each CNN architecture

We took 80–20% combination of training and testing data (which means we let our system take 80% of dataset as train data and the left 20% will be for testing DATA) as first test . For the Second test We took 70–30% combination of training and testing data (which means we let our system take 70% of dataset as train data and the left 30% will be for testing DATA) and examined their performances in terms of accuracy, precision, recall and F1 score.

In order to ensure that our model generalizes, we perform data augmentation by setting the random image rotation setting to 15 degrees clockwise or counterclockwise. Also We tuned the model using VGG16 with different learning parameters and training and testing dataset distributions.

We set the Epochs to **20** and Batch size to **8**, Then we start and training our Model.

Table 5 shows the detailed performance analysis of COVID-19 Diag model on VGG16 CNN architectures and presents the evaluation metrics for Both tests.

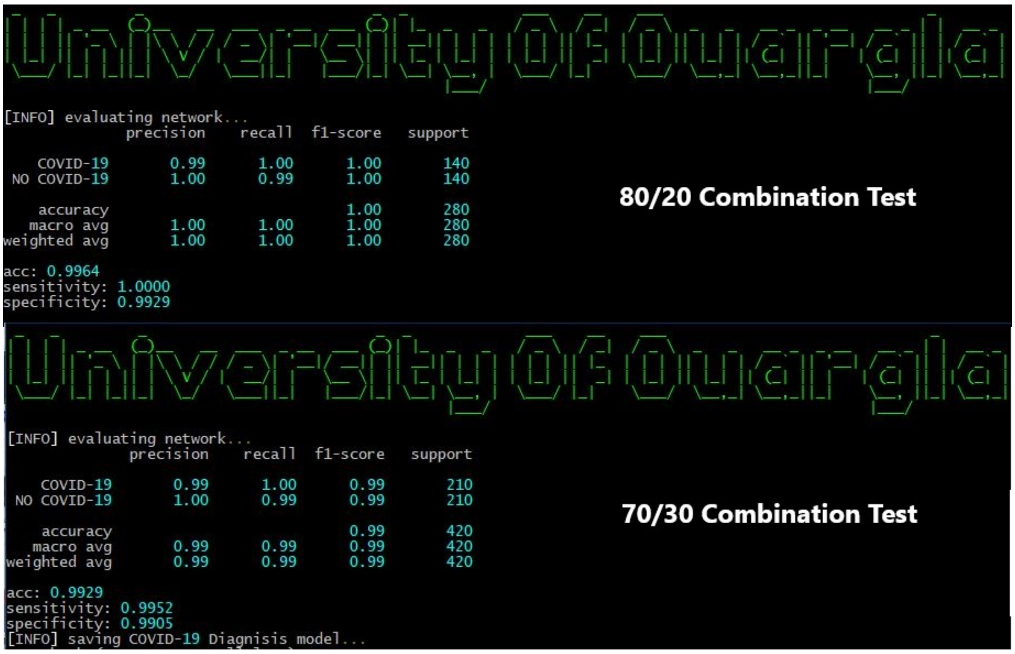

FIGURE 3.9: Combination 80/20 and 70/30 Results

TABLE 3.1: Table:Combination 80/20 and 70/30 Comparison

3.5.1 Model Evaluation

	80–20% combination	70–30% combination
Accuracy	99.64%	99.29%
Precision	100%	99%
F1-score	100%	99%
Recall	100%	99%
Sensitivty	100%	99.52%
specifity	99.29%	99.05%

TABLE 3.1: Combination 80/20 and 70/30 Comparison.

As we can see in Table, We found out that the(80–20%) combination with VGG16 CNN model achieves the highest performance compared to (70–30%) combination.

Explained details and performance analysis next.

Our COVID-19 Diag model produces the best results with a maximum accuracy of **99.64%** at (80–20%) combination while we get **99.29%** at (70–30%) combination.

The model achieves the highest precision of **100%** at (80–20%) combination while we get **99%**at (70–30%) combination and achieves the highest F1-score of **100%** at (80–20%) combination while we get **99%**at (70–30%) combination.

COVID-19 Diag produces maximum recall value of **100%** at (80–20%) combination while we get **99%** at (70–30%) combination, and achieves the highest sensitivty of **100%** at (80–20%) combination while we get **99.52%** at (70–30%) combination..

Also achieves **99.29%** of specifity as its higher value at (80–20%) combination while we get **99.05%**at (70–30%) combination.[See Table 3.1]

It clearly shows that, the best result is achieved by COVID-19 Diag model under (80/20) combination which is trained and tested with Dataset of 700 COVID-19 and 700 NO-COVID-19 chest X-ray images with accuracy and F1-score of 99.64% and 100% respectively.

It performs better than (70/30) combination.

3.5.2 Training History

As the training history plot shows, VGG16 network is giving its perfect results regarding to **Training(Loss/ Accuracy)** when using the first test Combination (80/20) .[See Figure 3.10]

Especially testing loss decreases very rapidly in the beginning, to stabilize when the number of epochs increases Which is perfct for Accuracy .

But when it comes to the second test Combination (70/30) it gives unstable results and low decreasing rate Testing Loss by Epochs which have an impact on the Accuracy value.[See Figure 3.11]

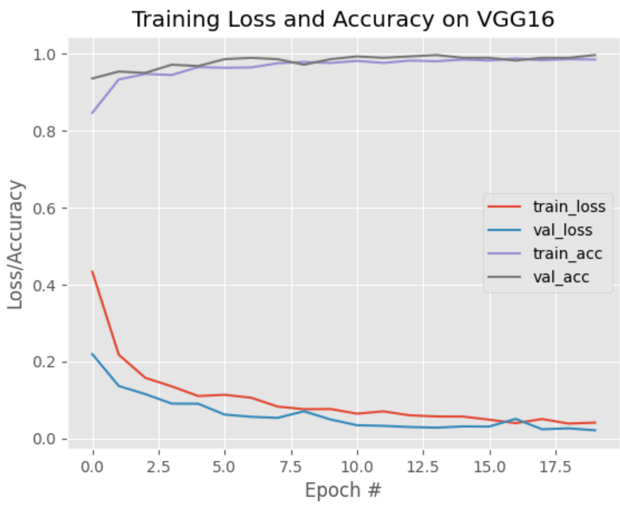

FIGURE 3.10: Training Loss and Accuracy on VGG16 Combination (80/20)

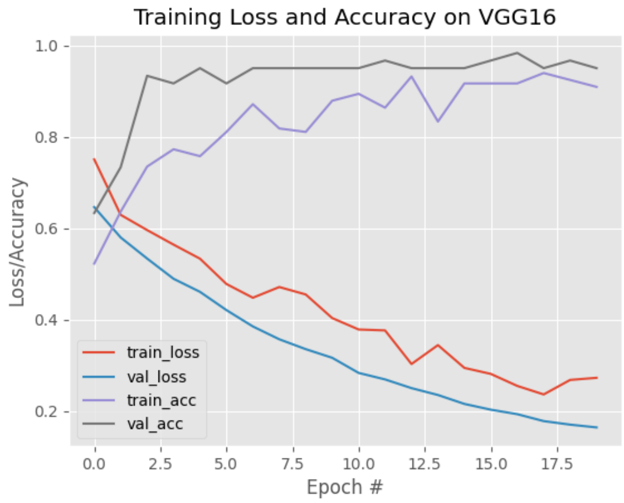

FIGURE 3.11: Training Loss and Accuracy on VGG16 Combination (70/30)

3.5.3 Confusion Matrix

Confusion matrix represents the performance of the classification algorithms. It shows the True Positive (TP), True negative (TN), False positive (FP) and False Negative (FN) of the classification algorithm.

We can see that the Model achives 140 test sample as (True Negative), 139 (True Positive), 1 (False Negative) and 0 (False Positive) When applying the First Combination (80/20).

And 209 test sample as (True Negative), 208 (True Positive), 2 (False Negative) and 1 (False Positive) When applying the Second Combination (70/30).

Next fugures illustrates the confusion matrix of our COVID-19 Diag model under both of Combination.

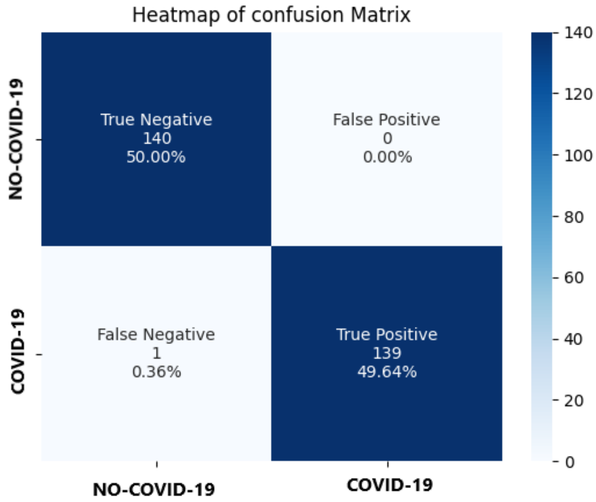

FIGURE 3.12: Confusion matrix on VGG16 of Combination (80/20)

3.6 Conclusion

We conclude from these results that the COVID-19 Diag model achieves better performance on the chest X-ray image dataset of 700 COVID-19 and 700 NO-COVID-19 chest X-ray images (on all evaluation metrics) using the (80/20) Combination on VGG16 CNN

Therefore the performances of VGG-16 improves regarding to the size of Dataset and splitting combination and .

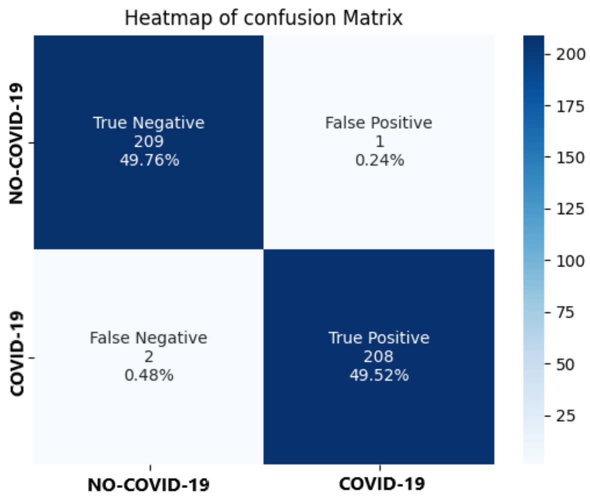

FIGURE 3.13: Confusion matrix on VGG16 of Combination (70/30)

General Conclusion

As discussed before, the early detection and diagnosis of COVID-19 by DL and with the least cost and complications are the basic steps in preventing the disease and the progression of the pandemic.

In the near future, with the incorporation of DL algorithms in the equipment of radiology centers, it will be possible to achieve a faster, cheaper, and safer diagnosis of this disease. The use of these Technologies in fast diagnostic decision-making of COVID-19 can be a powerful tool for radiologists to reduce human error and can assist them to make decisions in critical conditions and at the peak of the disease.

This model gives perfect results comparing with other prominent works in the field and can be improved further with multi-class classification and availability of the larger dataset.

Finally, CNN has great prospects in detecting COVID-19 with very limited time, resources, and costs. Though the proposed model shows promising results, it is not clinically tested. However, with such a higher accuracy the proposed model can surely play an important role in early and fast detection of COVID-19 thus reducing testing time and cost.

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