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Theme

Discriminative appraoch based on deep learning model for covid-19 detection from (chest X-ray or CT-scan) images and cough audios

Supported in: 19 - 06 - 2021 In front of jury:

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University Year: 2020/2021

Dedications

Thanks to Allah first-then the efforts of my loved ones who helped me a lot with their advice and efforts when we were going to offer this job. Dedicate this work to my dear mother,

To my Father.

To my all brothers and sisters

To all my best friends

To my Supervisor teacher Kholladi nedjoua

To all my colleagues.

Khammes Abdallah

Dedications

Thanks to Allah first-then the efforts of my loved ones who helped me a lot with their advice and efforts when we were going to offer this job. Dedicate this work to my dear mother,

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To all my colleagues.

Hassani Abde nour

Acknowledge

Thanks to ALLAH Almighty who gave us

the strengts to complete this work.

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Dr.« Kholladi Houda Nedjoua »

for his wonderful advice

and to follow up our work.

Thanks also to all the professors and friends

for their support and patience.

Abstract

COVID-19, also known as the Corona virus, has partially paralyzed the world in almost all respects, more than 177 million people worldwide are infected with it, and it has caused the deaths of more than 4 million people, early symptoms of the virus include difficulty breathing, fever and fatigue More than 60% of people suffer from a dry cough.

In the past decades, the field of computer vision, deep learning and automated....has shown great improvement and is now being applied in many fields such as security, medicine, self-driving cars... the rapid spread of this pandemic prompted us to stir our minds, find solutions and exploit the available technology to benefit from it to reduce the impact of the pandemic.

That's why we proposed two methods, the first is a machine learning-based COVID-19 cough classifier that is able to distinguish between a positive COVID-19 cough from a healthy and negative COVID-19 cough recorded on a smartphone, and this helps with social distancing and reduce the number of going to the hospital, and the second method is complementary to the first, which is a deep convolutional neural network in order to detect COVID-19 using chest x-ray images, and this is to help doctors make the right decisions in the diagnosis.

After several tests and different methods of using CNN models (VGG16, Resnet50)..., we can say that we have reached the desired result, which amounted to 83.4% for the first method and 96.88% for the second method.

ملخص

أدى COVID-19 ، المعروف أيضًا باسم الفيروس كورونا ، إلى شلل جزئي للعالم من جميع النواحي تقريبا، أكثر من 177 مليون شخص في جميع أنحاء العالم مصابين به، وتسبب في وفاة أكثر من 4 مليون شخص، تشمل الأعراض المبكرة للفيروس صعوبة في التنفس والحمى والإرهاق وأكثر من 60٪ من الناس يعانون من السعال الجاف.

في العقود الماضية ، أظهر مجال الرؤية الحاسوبية والتعلم العميق والآلي .... تحسنًا كبيرًا ويتم تطبيقه الآن في العديد من المجالات مثل الأمن والطب والسيارات ذاتية القيادة ... الانتشار السريع لهذا الوباء دفعنا إلى إثارة عقولنا وإيجاد الحلول واستغلال التكنولوجيا المتاحة للاستفادة منها للحد من تأثير الوباء.

لهذا اقترحنا طريقتين، الاولى هي عبارة عن مصنفًا للسعال يعتمد على التعلم الآلي لـ COVID-19 قادر على التمييز بين السعال الإيجابي لـ COVID-19 من سعال COVID-19 السلبي والصحي المسجل على الهاتف الذكي، وهذا يساعد في التباعد الاجتماعي وتقليل من كثرة الذهاب الى المستشفيات، اما الطريقة الثانية فهي مكملة للاولة وهي عبارة عن شبكة عصبية تلافيفية عميقة من أجل اكتشاف COVID-19 باستخدام الأشعة السينية للصدر الصور x-ray، وهذا لمساعدة الاطباء في اتخاذ القرارة الصحيحة في التشخيص.

بعد عدة اختبارات وطرق مختلفة لاستخدام موديلات (VGG16 ،CNN Resnet50) ... يمكننا القول إننا وصلنا إلى النتيجة المرجوة والتي بلغت 83.4٪ للطريقة الأولى و 96.88٪ للطريقة الثانية.

Résumé

COVID-19, également connu sous le nom de virus Corona, a partiellement paralysé le monde à presque tous égards, plus de 100 millions de personnes dans le monde en sont infectées et il a causé la mort de plus de 200 millions de personnes, premiers symptômes du virus notamment des difficultés respiratoires, de la fièvre et de la fatigue Plus de 60 % des personnes souffrent d'une toux sèche.

Au cours des dernières décennies, le domaine de la vision par ordinateur, de l'apprentissage en profondeur et de la machine... a montré de grandes améliorations et est maintenant appliqué dans de nombreux domaines tels que la sécurité, la médecine, les voitures autonomes... la propagation rapide de cette épidémie nous a incités à exciter nos esprits, à trouver des solutions et à exploiter la technologie disponible pour en tirer parti pour réduire L'impact de l'épidémie.

C'est pourquoi nous avons suggéré deux méthodes, la première est un classificateur de toux COVID-19 basé sur l'apprentissage automatique qui est capable de distinguer une toux COVID-19 positive d'une toux COVID-19 saine et négative enregistrée sur un smartphone, et cela aide à la socialisation.

distanciation et réduire le nombre de personnes se rendant à l'hôpital. Hôpitaux, et la deuxième méthode est complémentaire à la première, qui est un réseau de neurones convolutifs profonds afin de détecter le COVID-19 à l'aide d'images radiographiques thoraciques, et ceci pour aider les médecins à prendre la bonne décision dans le diagnostic. Après plusieurs tests et différentes méthodes d'utilisation des modèles CNN (VGG16, Resnet50)...on peut dire que nous avons atteint le résultat souhaité qui est de 83,4% pour la première méthode et 96,88% pour la seconde méthode.

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GLOSSARY

CAD: Computer Aided Diagnostic

AI: Artificial Intelligence.

ML: Machine Learning.

DL: Deep Learning.

CNN: Convolutional Neural Network.

RNN: Recurrent Neural Network

ANN: Artificial Neural Network

MRD: mild respiratory disease .

MRI :Magnetic Resonance Imaging.

CT: Computerized Tomography.

CV: Computer Vision.

ARDS: acute respiratory disease syndrome

CAD: Computer Aided Detection

SVM: support vector machine.

PCR : polymerase chain reaction

GPU : graphics processing unit

KNN: K-Nearest Neighbor.

Introduction

General Introduction

A shocking impacts on the health status of people has been resulted from the COVID-19 pandemic which has been conducted a loads of issues in daily life all over the world: social, economic, healthcare, isolation, lockdown,....etc. On the 24th of May 2020, statistics have shown more than 5 million people have been contaminated with the virus and more than 300 thousand death cases reported in the worldwide.

In spite of efforts have been anticipated in worldwide to halt COVID-19 transmission, the syndrome coronavirus type 2 (SARS-CoV-2) that has a severe and an acute respiratory syndrome form has affected more than 30 million persons and produced almost 1 million deaths by the end of September 2020 **[29], [30]**

After the rapid global trigger, the majority of countries have equipped their healthcare systems to deal with the pandemic. While extremely attention, international and national planning programs have faced social, institutional and education, political, environmental,industrial and technological challenges **[31], [32].** A significant heterogeneity in the research papers and medications have launched a recent axe, to seek for appropriate diagnostic and elaborating new protocol to limit the speedy propagation of the virus. **[32], [33].**

A wide range of strategies to manage this situation sounds to base on a triad of detection methods: (i) techniques deeply sensitive and specific like gold standard method, (ii) accessibility of care tests which are used as quick and fast responsive for large population screening, and iii) virus detection and surveillance via serology attempts. **[34]**

Recently, Real-Time reverse transcription Polymerase Chain Reaction (RT-PCR) is the most extensively in use as screening tool for the diagnosis and the detection of COVID-19 **[38].** For the reason that RT-PCR has a low sensitivity, radiological images are also known as standards for indicating the status of disease and diagnostic reasons in patients with symptoms of respiratory diseases. Despite the fact the CT scans is primordial and precise standard, as primary test chest digital X-ray system are widely used due to its speed, low cost, produce lower radiation and more accessible **[39] [40]**.

Chapter 01: introduction

The diagnosis of COVID-19 is of vital demand. Several studies have been conducted to decide whether the chest X-ray and computed tomography (CT) scans of patients indicate COVID-19. While these efforts resulted in successful classification systems, the design of a portable and cost-effective COVID-19 diagnosis system has not been addressed yet.

The memory requirements of the current state-of-the-art COVID-19 diagnosis systems are not suitable for embedded systems due to the required large memory size of these systems (e.g., hundreds of megabytes). Thus, the current work is motivated to design a similar system with minimal memory requirements.

1. Introduction

The first case of coronavirus disease 2019 (COVID-19) infection pneumonia was detected in Wuhan, China, Coronavirus disease (COVID-19) is a serious infectious disease that causes severe respiratory illness .

With the absence of specific treatment/vaccines for the coronavirus COVID-19, the most appropriate approach to control this infection is to quarantine people and isolate symptomatic people and suspected or infected cases . In order to discover the infected, Real-time polymerase chain reaction (RT-PCR) remains the standard test of COVID-19 pneumonia but standby time for viral detection with RT-PCR tests, incomplete sampling techniques, variations in viral load, and false-negative rates of a test depending on the kit sensitivity can delay the diagnosis.

The rapid development of technology in this era requires us to introduce computer vision , deep learning or other for this pandemic to benefit from it in prevention or treatment.

2. Overview

The 2020 corona virus pandemic spread in Algeria starting from February 25, 2020, and the first person to be tested positive for corona virus disease was an Italian citizen. Then, other cases infected with Covid-19 were revealed, and the total confirmed cases in Algeria amounted to 125,102 cases, including 3,254 deaths, and this is May 13, 2021.

Algeria has taken several measures in order to limit its spread, which is an increase in the recovery beds and the preparation of medical equipment such as ventilators and others, with the possibility of importing the necessary supplies from other countries. Despite all of this, it was not able to contain this epidemic, and this is for several reasons, including frequent visits to hospitals to check on themselves, and this helps the spread of the virus, as it led to a crisis of shortage of recovery beds And vowed in some medicines and others.

In order to improve living conditions and contribute to reducing the spread of this deadly virus, we decided to introduce modern technologies to benefit from this by creating an application that allows a person to test himself while he is at home, which leads to reducing its spread, and we also trained a model that can detect Corona 19 Based on the chest x-ray, one of the reasons that made us dispense with CT scans for calculating x-rays is that CT scans are very expensive for the patient and there is a shortage of their equipment, so we used

x-rays at the expense of CT scans.

2.1 background and Motivation

- **Background**

The world has suffered from the massive outbreak of the Coronavirus, or COVID-19, which was first detected in December 2019 in Wuhan, China. The main signs of COVID-19 are a high temperature, a dry cough, a cold, shortness of breath, a combination of loss of smell and chest tightness. In order to prevent it, you should take some simple precautions, such as physical distancing, wearing a mask, keeping rooms well ventilated, avoiding crowds, cleaning your hands, and coughing into a bent elbow or tissue.

One of the reasons that made us enter this aspect and work on it is

1) The massive and rapid spread of it Although a lot is known about the spread of COVID-19, a lot of knowledge is still developing.
2) The urgent need to find a quick solution that limits the spread of the virus.
3) Benefiting from the development of technology in these recent years and exploiting it in this circumstance.

In the end, we say that we entered this field because he is the one who attracted us to him, due to his global resonance and the many fears from him.

- **motivation**

The motives behind working on such an issue are first of all humanitarian reasons. Among the main reasons is the early detection of the disease and the reduction of its spread. The second motive is purely scientific, the great technological competition makes us excited to enter the competition as well as how to introduce technology into most areas of the daily life of the individual and society in order to reduce the suffering and the dangers surrounding it. The field is also very interesting, we hope everyone will see it and have an idea of what is happening in the world of technology.

2.1.1) Covid 19 pneumonia detection from CT-scans images.

X-rays are a type of radiation. Many people know that it is used to diagnose bone fractures or to examine teeth.

Healthcare professionals can benefit from X-rays using an X-ray generating device. When the patient is placed in the device, a carefully selected dose of x-rays passes through the target area of the body. Thicker and denser parts of the body, such as bones, allow fewer x-rays to pass, while thinner and smoother parts allow more of them to pass. When the X-rays go out on the other side of the body, a specialized detector detects the pattern on which they are exhaled. This will give a picture of the structures within the body and their changes.[1]

To assess COVID-19, chest X-rays are taken of a person's chest to look at the lung tissue. This test is used for patients suffering from respiratory symptoms caused by COVID-19. X-rays are also used to monitor disease progression and make decisions about treatment and follow-up, [2] such as hospitalizing a patient or sending a patient with severe symptoms for a CT scan.

There are many studies in this field, including:

Kassania et al. [3] compared popular deep learning-based feature extraction frameworks for automatic COVID-19 classification. They tested the combination of different deep learning networks combined with machine learning methods for classification. Experimental results show that the DenseNet121 feature extractor with the bagging tree classifier achieved the best performance with 99% classification accuracy.

Fei et al. [4] developed a deep learning- (DL-) based segmentation system with a human-in-the-loop (HITL) strategy to assist radiologists for infection region segmentation. By comparing the automatically divided infection area and the manually divided area, the average similarity coefficient is about 91.6%.

Maghdid et al. [5] used the deep learning method and transfer learning strategies to diagnose COVID-19 automatically. The structure is a combination of CNN structure and an improved AlexNet structure. The improved architecture accuracy reaches 94.10% on the X-rays and CT slice dataset.

2.1.2) Covid 19 pneumonia detection from cough audios.

Pneumonia kills over 1,800,000 children annually throughout the world. Pneumonia is a very common lungs disease and requires efficient diagnosis at initial stage for proper treatment [6].

Respiratory sounds carry significant information about the condition of respiratory system. Respiratory sounds are often affected by sounds emanating from heart and other organs thus making the analysis task more complex, Also, a cough is a symptom of over thirty non-COVID-19 related medical conditions. This makes the diagnosis of a COVID-19 infection by cough alone an extremely challenging multidisciplinary problem. We address this problem by investigating the distinctness of pathomorphological alterations in the respiratory system induced by COVID-19 infection when compared to other respiratory infections. [7]

Several studies have been conducted to classify and detect lung-related diseases using AI

- **Liu et al.**[8] proposed a classification algorithm of lung sounds based on multilayer perceptron network and Hilbert-Huang transform features for non-invasive diagnosis of pulmonary diseases. The algorithm was tested using the R.A.L.E. database with a multi-layer perceptron classifier and achieved an averaged classification accuracy of 95.84%.
- **Aykanat et al.**[9] proposed a non-invasive classification method of recorded respiratory sounds using an electronic stethoscope. They recorded with this device 17,930 lung sounds from 1,630 subjects. Their results showed that by using convolutional neural network (CNN) and support vector machine (SVM), they could accurately classify respiratory sounds.
- **Azam et al.** [10] presented a scheme to detect respiratory patterns that are irregular due to respiratory diseases. They used 255 breath cycles captured using a smartphone under natural setting. Their experiments showed an accuracy around 75% using SVM for asthmatic inspiratory cycles and complete respiratory sounds

2.1.3) Covid 19 pneumonia progression estimation

There is a serious concern over the variation of case fatality of COVID-19 patients that reflects the preparedness of the medical care system in response to the surge of pneumonia patients. We aimed to quantify the disease spectrum of COVID-19 on which we are based to develop a key indicator on the probability of progression from pneumonia to acute respiratory disease syndrome (ARDS) for fatal COVID-19. The retrospective cohort on 12 countries that have already experienced the epidemic of COVID-19 with available open data on the conformed cases with detailed information on mild respiratory disease (MRD), pneumonia, ARDS, and deaths were used. The pooled estimates from three countries with detailed information were 73% from MRD to pneumonia and 27% from MRD to recovery and the case-fatality rate of ARDS was 43%. The progression from pneumonia to ARDS varied from 3% to 63%. These key estimates were highly associated with the case fatality rates reported for each country with a statistically significant positive relationship (adjusted R^2 = 95%). Such a quantitative model provides key messages for the optimal medical resources allocation to a spectrum of patients requiring quarantine and isolation at home, isolation wards, and intensive care unit in order to reduce deaths from COVID-19.

2.2 Contribution

We want to contribute to the preventive work carried out by the World Health Organization and others, albeit with a very simple matter, in order to limit the spread of this epidemic and contribute to scientific research to create a competitive environment in which the human nation benefits in terms of the facilities it provides.

2.3 Related work

Researchers are generating an unprecedented amount of data around COVID-19, with new and important studies coming out every day. Here's a look at some of COVID-19 research:

- Researchers at Massachusetts Institute of Technology (MIT) developed an artificial intelligence (AI) model able to detect asymptomatic COVID-19 cases by identifying differences in the sounds of coughs between healthy and infected people. The model is built on previous research the group developed to identify conditions like pneumonia, asthma and even Alzheimer's disease. It is actually the Alzheimer's model that was adapted for the COVID-19 algorithms. In a crowdsourcing effort, the team collected forced-cough recordings via a website, making it the largest audio dataset for COVID-19 by 70,000 records. [11]

- Harry Coppock, Alex Gaskell, Panagiotis Tzirakis, Alice Baird, Lyn Jones and Björn Schuller wrote in an article titled 'End-to-end convolutional neural network enables COVID-19 detection from breath and cough audio'[12]
- Piyush Bagad, Aman Dalmia, Jigar Doshi, ArshaNagrani, Parag Bhamare, Amrita Mahale, Saurabh Rane, Neeraj Agarwal and Rahul Panicker wrote in an article titled 'Evidence of COVID-19 Signature in Cough Sounds'[13]
- Chloë Brown,Jagmohan Chauhan, Andreas Grammenos, Jing Han, ApinanHasthanasombat, Dimitris Spathis, Tong Xia, Pietro Cicuta and Cecilia Mascolo wrote in an article titled 'Exploring Automatic Diagnosis of COVID-19 from Crowdsourced Respiratory Sound Data'[14]

2.4 Thesis organization

Regarding the problematic has been tackled in this dissertation topic, an in-depth study has presented several chapters:

Chapter1: Introduction

This chapter devotes an overview highlighting the outbreak of pandemic of Covid-19, then two things are important to ask about: why this case of study is treated ? and what are the important works has been admitted in this research are?, the response of those questions are clearly presented in Background and Motivation, also this work shows evidently contributions can be ameliorated the previous models using background studies cases;

Chapter2: State of the Art

This chapter visualize a deep study on Corona virus Disease 2019 Pneumonia with showing two different modalities in Chest X-rays images scans for COVID-19 pneumonia screening and cough audio for COVID-19 pneumonia screening, after that two important should be exposed are Computer-aided Diagnosis (CAD) and Computer-aided Detection(CAD) using in medical imaging or medical data in general; then anomaly detection as this work will use an AI based model, so this title should be handled, as last AI based Application for COVID-19 Detection.

As this dissertation has tackled two different modalities of data, a discriminated separation between chapters of those modalities;

Chapter3: Automated Model for COVID-19 Detection from Chest X-rays scans images

Chapter4 Automated Model for COVID-19 Detection from Recorded Cough

Chapter 5 Proposed Model for COVID-19 Detection from Recorded Cough and Chest X-rays scans images

Conclusion

In this section, we discussed Background and Motivation and this title is divided intoCOVID-19 pneumonia Detection from CT-scans imagesandCOVID-19 pneumonia Detection from Cough audios, COVID-19 pneumonia progression estimation, In addition to Contributions and Contributions, proposed a deep learning framework for the classification of COVID-19, other pneumonia, and no pneumonia

Chapter 02: background

In December 2019 the SARS-CoV-2 zoonotic virus, originating from the Phinolophus bat, was transmitted to humans, for the first time recorded. The Huanan Seafood Wholesale Market in Wuhan City, Hubei Province, China, was the epicenter of the coronavirus disease (COVID-19) outbreak caused by SARS-CoV-2, which rapidly spread worldwide and was declared a pandemic by WHO on 11th March 2020 .

1. Introduction:

The proverb says “an image is worth a thousand of words". This is why the media, commercial advertising, and educational schools use images to describe events, people, goods, etc... Images often have a simpler meaning than long sentences, and when a word or verbal meaning is added, it almost becomes an all-encompassing meaning of describing or reading a particular scene. and because of it, computers nowadays can learn, evolve and repair automatically. In the recent years, the fast evolution of digital devices (digital cameras, scanners ...) has led to the huge needs in the number of images and sounds that the user wants to access, identify and extract their features in order to understand their meaning. The fields concerned with that are computer vision, image processing, Computer-aided Detection and machine learning (and deep learning)and we will also address the knowledge of the covid 2019 disease pneumonia. In this chapter, the aim of this chapter is to introduce the aforementioned fields and give an overview on them.

2. Computer vision:

The word vision means for the human being is the ability of seeing, the human eye can process huge amount of data without noticing and then the data being processed by the brain, computer vision is the science that is trying to imitate the human eye ability by the computer, if possible, means makes it capable of intelligently identifying objects and extracting features from a digital image, it can be one image or sequence, manipulate their data with ease [15].

2.1 Computer Vision Hierarchy

Computer vision is divided into three basic categories that are as following:

- **Low-level vision:** includes process image for feature extraction. For example, low level vision gives us the boundaries of the objects in the figure1.
- **Intermediate-level vision:** includes object recognition and 3D scene Interpretation. For example, intermediate level vision tells us that there is a person and a ball in the figure1.

- **High-level vision:** Also known as image captioning, includes conceptual description of a scene like activity, intention and behavior. For example, in the figure1 the high level vision tells us that there is a person who is willing to kick the ball.

Figure II 1 An image of a person who wants to kick the ball.

2.2 Examples of CV Applications

- **Robotics Application**: One of the computer vision contributions is the industry field e.g. robotic arm.

Figure II 2 Computer vision in robotics

- **Medicine Application**: Vision-guided robotics surgery. Detecting cancerous tumors and other diseases early

Figure II 3Computer vision in medicine

- **Security Application**: One of the important fields is security and it represents in Surveillance cameras, as because of CV the Surveillance cameras can identify the humans and many other objects. Security does not represent only by Surveillance cameras, it can be in other forms such as biometrics (iris, finger print, face recognition).

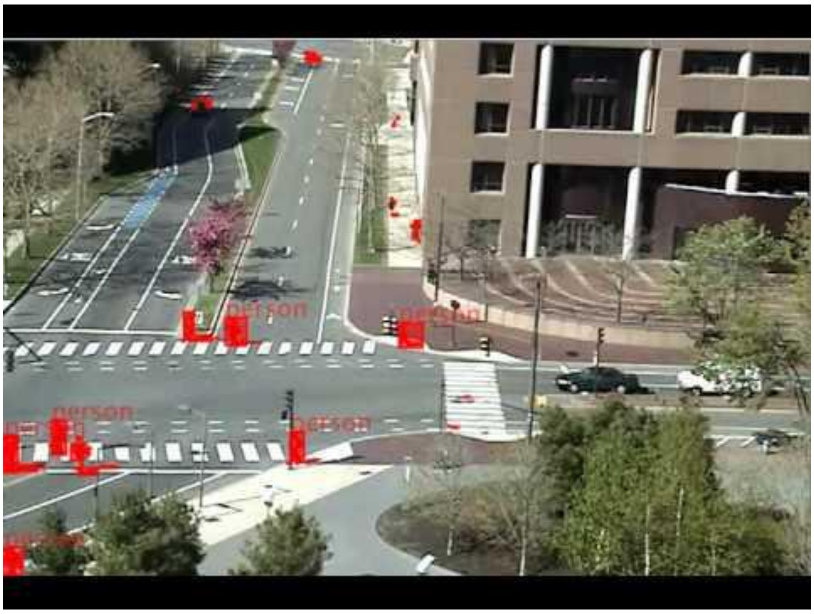


Figure II 4 Computer vision in security

- **Transportation Application:** Clearly the role of computer vision in smart vehicles due to its ability to identify what is on their space, and smart enough to not hit a single thing.

Figure II 5 Computer vision in transportation

3. Image processing

Before talking about image processing we have to identify the image first.

The image is composed of a group of pixels, each pixel is reachable by a two-dimensional function, F (x, y), where x and y are (planar) locative coordinates. Pixel is the most used term to refer to the smallest element in an image, also known as PEL, each pixel corresponds to any value in an 8-bit grayscale image, the pixel value is between 0 and 255.

The field of digital image processing refers to processing digital images by means of a digital computer [16], in order to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be image, characteristics or features associated with that image.

There are two types of methods used for image processing namely, analog and digital image processing. But we focused on digital image processing according to his relation and our needs in this field and because digital image processing has dominated over analog image processing with the passage of time due to its wider range of applications [16].

3.1 Digital image processing.

The digital image processing deals with developing a digital system that performs operations on a digital image.

3.2 Applications of Digital Image Processing.

Almost in every field, digital image processing puts a live effect on things and is growing over time with new technologies. From its wide applications we mention:

- **Image sharpening**

It refers to the process in which we can modify the look and sense of an image. It basically manipulates the images and achieves the desired output. It includes conversion, sharpening, blurring, detecting edges, retrieval, and recognition of images. The principal objective of sharpening is to highlight fine detail in an image or to enhance detail that has been blurred, either in error or as a natural effect of a particular method of image acquisition.

- **Video processing**

Video processing covers most of the image processing methods. What makes video processing different from still image processing is that video imagery contains a significant amount of temporal correlation (redundancy) between the frames. One may attempt to process video imagery as a sequence of still images, where each frame is processed independently. However, some tasks such as motion estimation or the analysis of a time-varying scene obviously cannot be performed on the basis of a single image [17].

4. Computer-aided Detection

They are systems that help doctors interpret medical images. Aiming to help medical professionals identify lesions and diseases, early attempts were made to computerized analysis of medical images, such as diagnosing primary bone tumors and detecting abnormalities on mammograms.

Related technologies are improving diagnosis for many other types of medical images including virtual colonography and angiography, as well as automated quantification of image-derived scales. Accepting and integrating computer-aided diagnostic technology with the practice of electronic radiology is currently a challenge.

It is also very useful in providing some basic information i.e. getting a 'second opinion' and helping expert observers make the final decision. [18]

4.1 General CAD description

Various medical imaging modalities such as magnetic resonance imaging (MRI), computed tomography (X-ray images), and positron emission tomography (PET) have played an important role in medical diagnosis as they provide an inside look at the anatomical and functional aspect of a patient's condition, thus guiding medical decisions for radiologists. . With the widespread use of these imaging technologies, the past two decades have seen a rapid development of image-based computer-aided diagnostic systems that are tools that assist clinicians in the interpretation and analysis of medical images for various tasks. Some typical applications of CAD systems include segmentation of organs and lesions, anomaly detection, and many others.

Over the last two years, various CAD systems have addressed issues such as diagnosis of Alzheimer's disease, segmentation of the multiple sclerosis lesion, detection of enlarged perivascular spaces in the basal ganglia, etc. An effective CAD system can improve radiologist's decisions. [18]

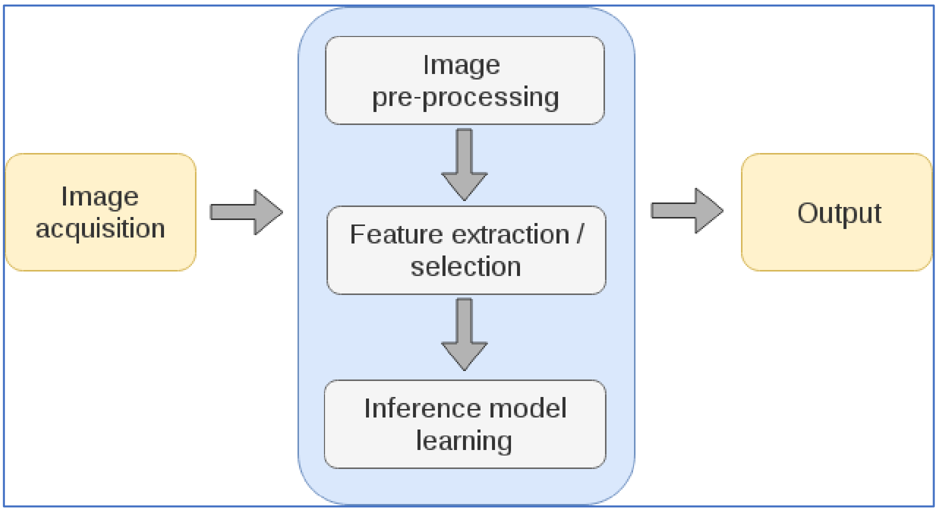


Figure II 6 A typical image-based CAD system pipeline

Image-based CAD systems are designed to apply an automated model to selected input images to produce output that matches the problem. As shown, a typical CAD system entails the following steps - image pre-processing, feature extraction/selection, and model inference learning (usually using a machine learning algorithm). Demonstrates a CAD system with multimodal neuroimaging data input and outputs a probability map that highlights suspicious areas found by the system.

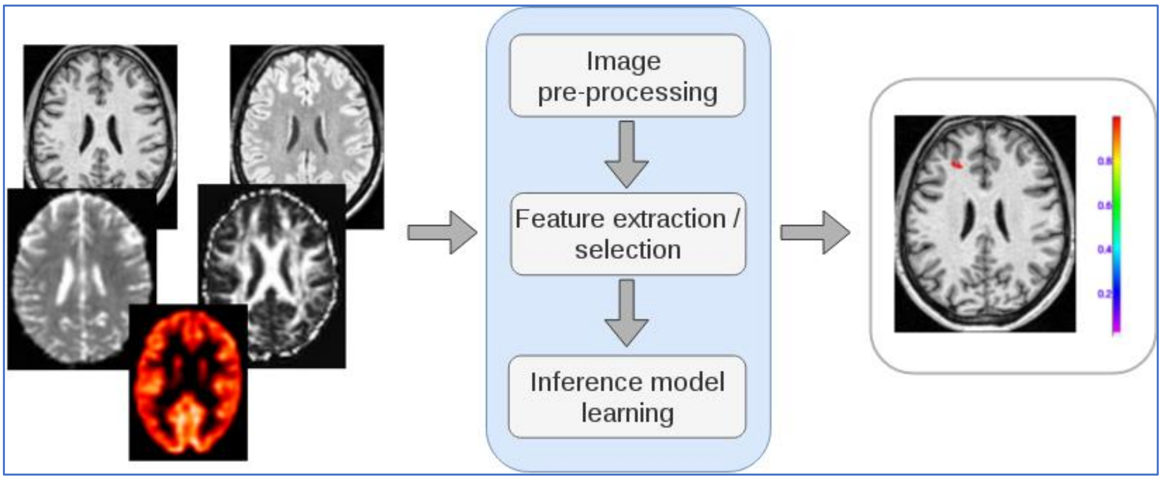


Figure II 7 A simplified picture of the work CAD Neuroimaging System.

The image shows a CAD system for neuroimaging:

- **Input:** Multimodal neuroimaging data.
- **Output:** a probability map that highlights suspicious areas detected by the CAD system.

4.2 Computer-aided Detection (CAD)

CAD also has potential future applications in digital pathology with the advent of full-slide imaging and machine learning algorithms.

CAD is a multidisciplinary technology that combines artificial intelligence and computer vision with radiological image processing and pathology. The typical application is for COVID-19 detections. For example, some hospitals use CAD to support preventive medical examinations in colon polyps and lung cancer (coronavirus).

Although CAD has been used in clinical settings for more than 40 years, CAD does not usually replace a physician or other professional, but rather plays a supporting role for radiologists in general, leaving the expert responsible for the ultimate interpretation of the medical image[18]. However, the goal of some CAD systems is to detect early signs of abnormalities in patients that human professionals cannot guess, as in diabetic retinopathy, and architectural abnormalities on mammograms.

5. Coronavirus disease 2019 pneumonia

COVID-19 is a respiratory disease caused by the new coronavirus (SARS-CoV-2), which has resulted in complications of pneumonia and other serious symptoms and significant deaths. It has spread rapidly since it was identified, and the lack of knowledge has made it difficult to treat and prevent its continued spread. That's why we'll highlight highlights that may help clinicians recognize, manage, and prevent this disease. [1]

5.1 Computed tomography for covid-19 pneumonia screening.

Although the PCR test for Covid-19 remains the gold standard diagnostic method, several reports have highlighted the role of computed tomography as a valuable tool for diagnosing Covid-19, which is one of the most prevalent medical imaging methodologies, and it uses a series of X-ray images. To produce a cross-sectional image of the human body organs, as shown . In addition to its functionality and simplicity, a X-ray images can quickly detect an abnormal lung and enable an early-stage imaging diagnosis of the disease. [19]

On the other hand, a study of 81 patients in Wuhan, China, indicated that pneumonia associated with Covid-19, which is a feature of severe symptoms of the disease, may be manifested by abnormal X-ray images, even at an early stage without symptoms. Patients showed a multifocal unilateral (clouding glass) opacity on a lung X-ray images in the early stages of the infection. As the disease progressed, opacities became more widespread and observed in both lungs. X-ray images have proven valuable in many patients who have false-negative results for the PCR test. A X-ray images, which was conducted on a group of Chinese patients suspected of being infected with the Coronavirus, whose first PCR test result was negative[20], revealed that a large proportion of positive cases according to the X-ray images had contracted the disease based on the following positive results of the instantaneous polymerase chain reaction (PCR). .Moreover, nearly 40% of cases showed improvement in X-ray images follow-up examinations before the negative result indicated by the PCR, indicating that X-ray images may also be an early indicator of disease severity.

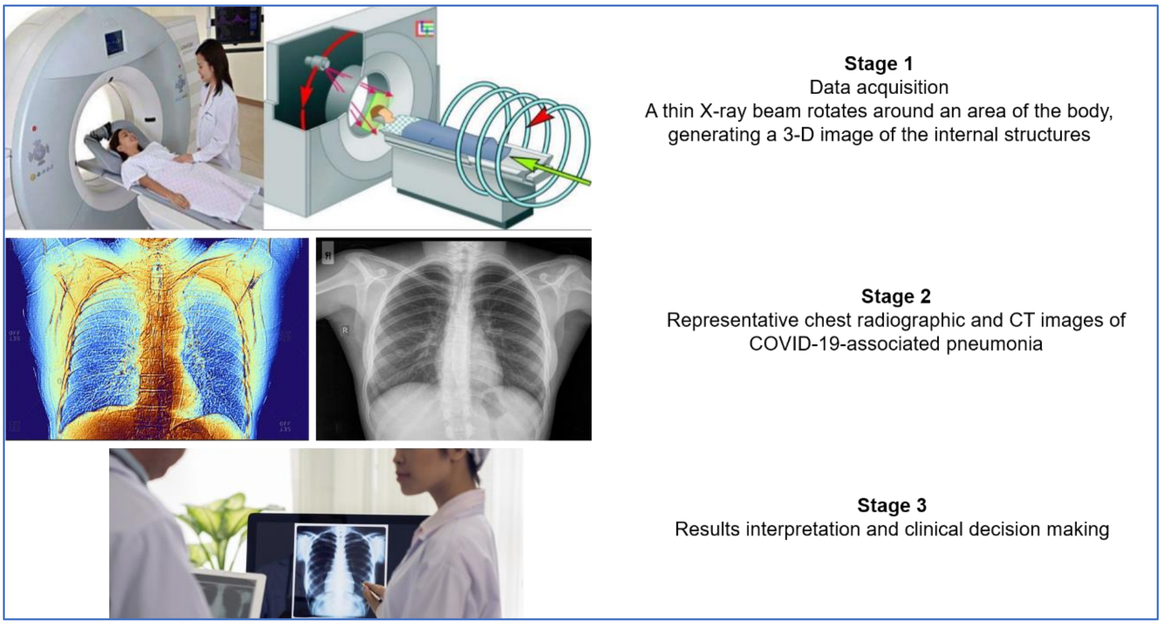


Figure II 8 Computed tomography-based diagnosis of COVID-19 cases

5.2 Cough audio.

A smoker's cough is often confused with the cough that people with Coronavirus suffer, but there are significant differences in these symptoms. [21]

The main difference is that the smoker's cough is related to time, and it usually occurs in the morning immediately after waking up. At the same time, the person with the Coronavirus is accompanied by coughing almost all day long, regardless of time.

It is noteworthy that researchers in the United States have developed a new artificial intelligence algorithm that can identify people infected with the "Covid-19" epidemic through the sound of their coughing.

They said that the human ear could not pick up the vital difference in the sound of an asymptomatic Covid patient's cough.

Chest diseases specialists also warned against confusing infection with the emerging Coronavirus with seasonal diseases that appear at the beginning of spring, such as allergies, asthma, and conjunctivitis. [22]

6. Machine learning and deep learning.

6.1 Machine learning

Machine learning (ML) is one of the fields of computer science that can provide meaning to data with the aid of certain computer systems in order to imitate the human ability to do so. In simple words, ML is a type of artificial intelligence that extracts patterns from raw data using an algorithm or method. The main focus of machine learning is to allow computer systems to learn from experience without the human intervention. [23]

6.2 How machines learn:

Although a machine learning model may apply a mix of different techniques, the methods for learning can typically be categorized as three general types:

- **Supervised learning:** it requires labeled dataset for its learning algorithms among with the desired output. Takes too much time to process the data given in order to reach the wanted result. For example, pictures of dogs labeled “dog” will help the algorithm identify the rules to classify pictures of dogs. [24]

- **Unsupervised learning:** it requires dataset as well for its learning algorithms, however, no need its data to be labeled, does not have an output result, therefore, its algorithms needs to extract patterns from the input data for predicting the outputs. For example, the recommendation system of an e-commerce website where the learning algorithm discovers similar items often bought together. [24]

6.3 Deep Learning:

Deep learning is a kind of machine learning (ML) in artificial intelligence (AI) that contains systems enables computers to learn from experience and understand the world as it actually are. Deep learning is inspired by artificial neural networks, the artificial neural networks known as ANN are inspired by human biological neural networks. For better comprehending, let us first look at a neural network and how it works. [22]

6.4 Neural network:

An ANN is formed from hundreds of artificial neurons or processing elements connected with coefficients (weights), designed in a way to simulate the way in which the human brain processes information. ANNs gather their knowledge by detecting the patterns and relationships in data and learn (or are trained) through experience [24].

A neural network always have:

- **Input layer:** It can be pixels of an image.
- **Hidden layer:** Commonly known as weights which are learned while the neural network is trained.
- **Output layer:** Final layer mainly gives you a prediction of the input you fed into your network.

So, the neural network is an approximation function in which the network tries to learn the parameters (weights) in hidden layers which when multiplied with the input gives you a predicted output close to the desired output. the following figure is an example.

Deep Learning is based on stacking multiple such hidden layers between the input and the output layer, hence the name Deep learning.

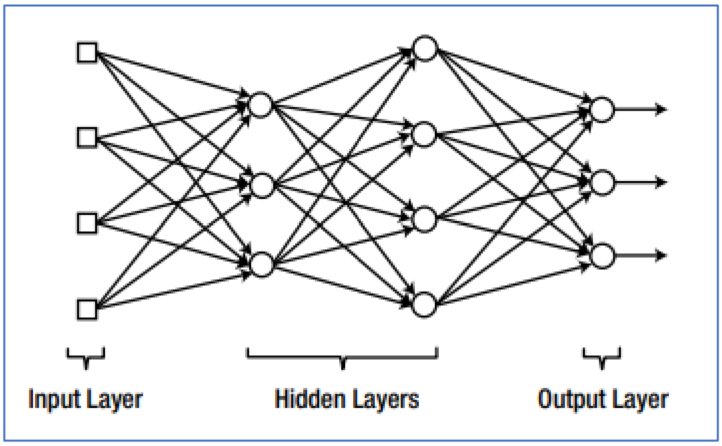


Figure II 9 Neural network

6.5 Types of Deep neural networks.

There are various types of deep neural networks, each of which has a specific use case. From one point of view, they can be categorized into supervised or unsupervised. The type of network to use is also depending on the nature of the task in hand.

6.5.1) ANN

A network is a distributed computing system processing architecture designed to simulate the way the human brain consisting of processing and analyzing elements, containing each processing element on a single output connection (“output”) into different numbers and combinations. ANNs have self-learning capabilities if they had a big amount of data in order to produce better results than before [18].

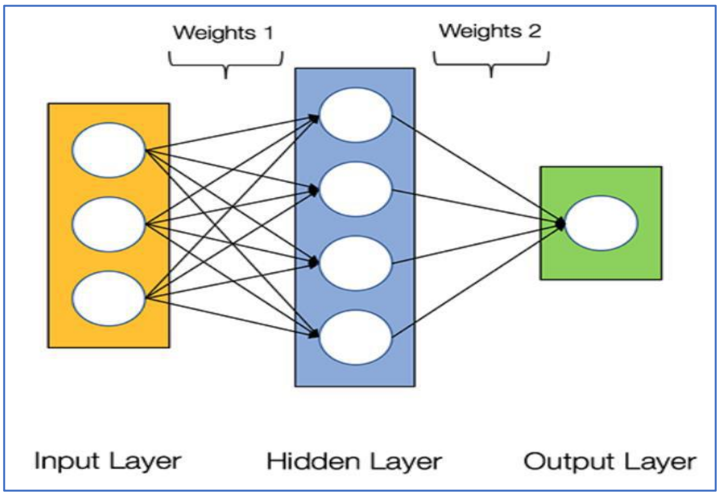


Figure II 10 ANN architecture

6.5.1.1)Types of ANN :

- **Feedforward:**

In a forward ANN feed, the information flow be heading only straight forward and does not contain any feedback loops, as it appears from its name, from the input layer to the hidden layer and finally to the output layer, This type is also referred to as bottom-up or top-down. [20].

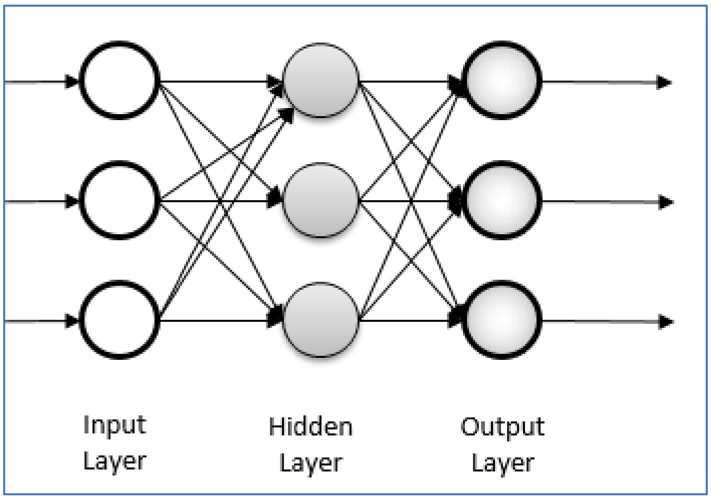


Figure II 11 ANN feedforward architecture.

- **Feedback:**

In the feedback ANNs, unlike the feedforward, it has the ability to go backward because of the feedback loops. Such type of neural networks are mainly for memory retention such as in the case of recurrent neural networks.

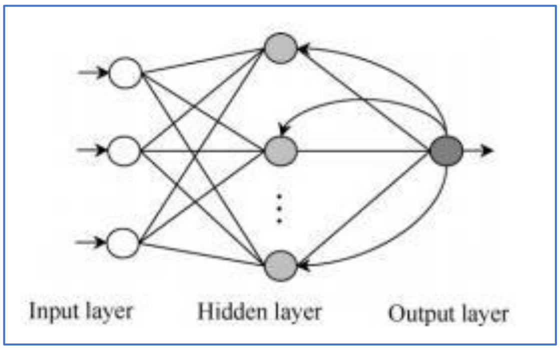


Figure II 12 ANN feedback architecture

6.5.1.2)Ann architecture:

As we had explained above, ANN compose from three parts, input, hidden and output layers, each layer is basically neural, each neuron from the ANN architecture calculated by the formula below:

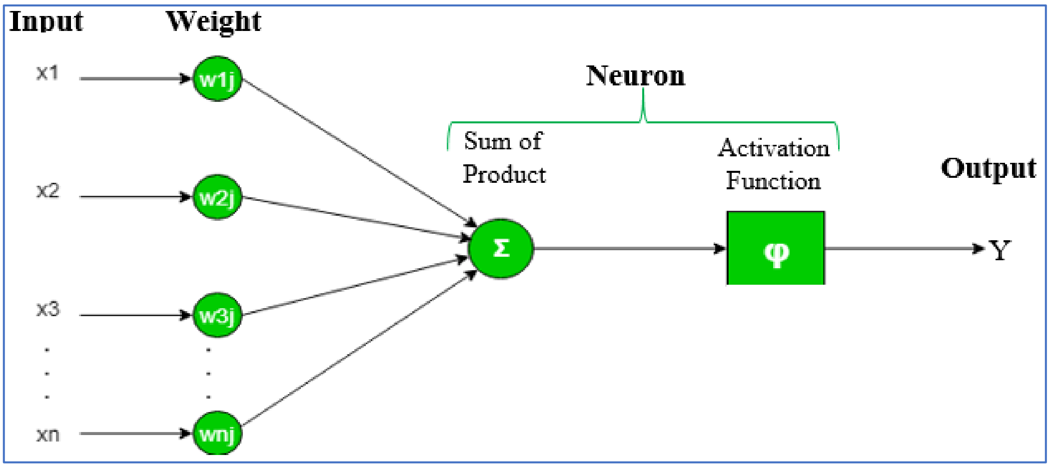


Figure II 13 simple ANN architecture

- Sum of products :**S =** $\Sigma(\boldsymbol{W}i \times \boldsymbol{X}i)\boldsymbol{ni}=\mathbf{0}$
- Activation function: There are several mathematical functions. **(F)**
- Output: **Y = F(S).**

6.5.1.3) Activation function:

Activation function simply is a mathematical equations that control the neuron output whether it should be activated or not, it has many types, we mention:

- **Binary step function:**

The binary step function is a threshold-based activation function. If the input value is above or below a certain threshold, the neuron is activated and sends exactly the same signal to the next layer.

$$f(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases}$$

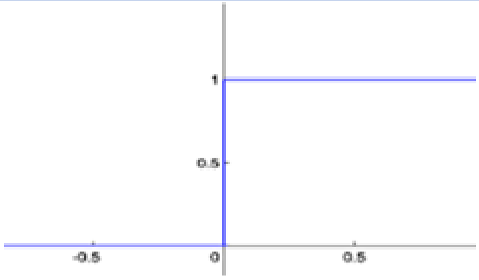


Figure II 14 Graphic binary step function.

The problem with the binary step function is that it does not allow multi-value outputs for example, it cannot support classifying the inputs into one of several categories.

- **Rectified Linear Unit (ReLU) Function:**

One of the most popular AFs in DL models, the rectified linear unit (ReLU) function, is a fast-learning AF that promises to deliver state-of-the-art performance with stellar results. Compared to other AFs like the sigmoid and tanh functions, the ReLU function offers much better performance and generalization in deep learning. The function is a nearly linear function that retains the properties of linear models, which makes them easy to optimize with gradient-descent methods.

The ReLU function performs a threshold operation on each input element where all values less than zero are set to zero. Thus, the ReLU is represented as:

$$\mathrm{f(x)} = \begin{cases} 0, & x < 0 \\ \mathrm{x}, & x \geq 0 \end{cases}$$

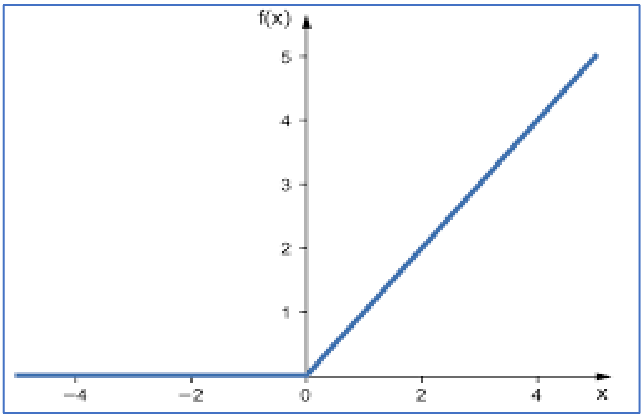


Figure II 15 graphic representation of ReLU function

- **Sigmoid activation function**:

The function is often called the logistic function or sigmoid. It is called the sigmoid because it is S-shaped. This function can be seen as squashing the value of its argument onto the range. What we mean by this is that the sigmoid takes any real number, and outputs numbers between 0 and 1. Because of this, the sigmoid output can be interpreted as a probability, which we will use to make stochastic predictions.

$$f(x) = \frac{1}{1 + e^{-x}}$$

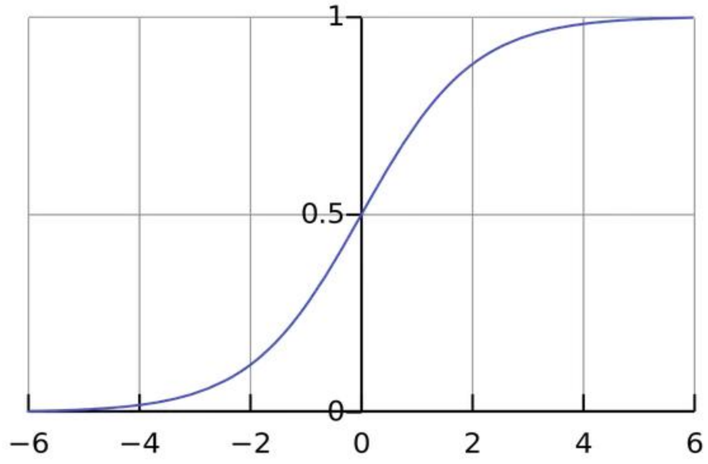


Figure II 16 graphic sigmoid function

- **Softmax Function:**

The softmax function is another type of AF used in neural networks to compute probability distribution from a vector of real numbers. This function generates an output that ranges between values 0 and 1 and with the sum of the probabilities being equal to 1. The softmax function is calculated as follows:

$$\mathrm{F(Xi)} = \frac{\mathrm{e^{Xi}}}{\sum_j \mathrm{e^{Xj}}}$$

7. Back propagation:

Back-propagation is the essence of neural net training. It is the practice of fine-tuning the weights of a neural net based on the error rate (i.e. loss). Proper tuning of the weights ensures lower error rates, making the model reliable by increasing its generalization. It updates the weights with high efficiency. It is usually used in the supervised networks. [20]

If the expected result Y is not the same as the required result d, then the weight should be adjusted according to the following statement of prediction error

Prediction error statement:

$$E = \frac{1}{2}(\text{desired} - \text{predicted})^2$$

To find the error rate to change the weight, we calculate the error derivation by weight.

We must deduce the relationship of error by weight, judging from the error equation for calculation the derivation.

Desired = constant, predicted = F(S)

$$E = \frac{1}{2}(\text{desired} - F(S))^2$$

$$E = \frac{1}{2}(\text{desired} - F(W1 * X1 + W2 * X2 + b))^2 , \; S = W1 * X1 + W2 * X2 + b$$

We found the direct relationship between error and weight, in this way we can calculate the derivation between them, But in this form the derivation will be complicated, therefore we will use chain rule.

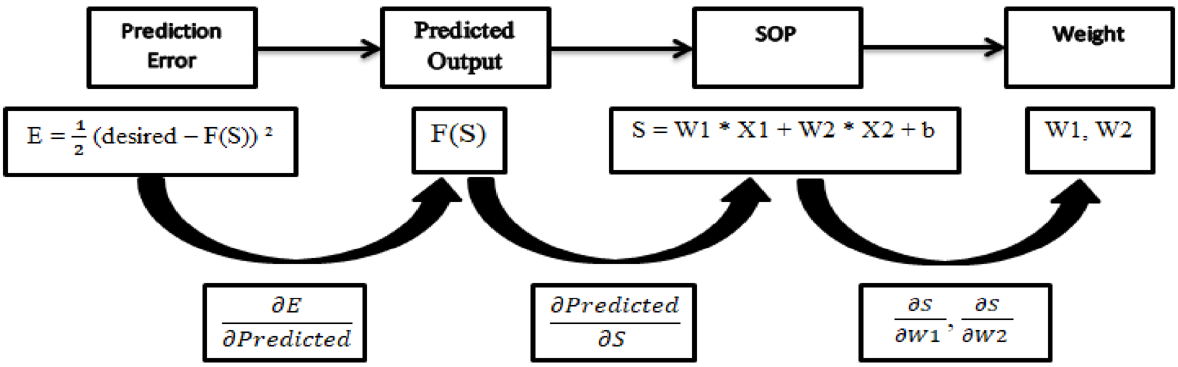


Figure II 17 chine rule

$$\frac{\partial E}{\partial W1} = \frac{\partial E}{\partial Predicted} * \frac{\partial Predicted}{\partial S} * \frac{\partial S}{\partial W1}$$

$$\frac{\partial E}{\partial W2} = \frac{\partial E}{\partial Predicted} * \frac{\partial Predicted}{\partial S} * \frac{\partial S}{\partial W2}$$

- **Interpreting derivatives Signal:**

There are two useful pieces of information that we conclude from the calculated derivatives.

Table II 1 Derivatives relation between weight and error

if signal derivatives positive	**if signal derivatives negative**
decreasing weight <=> decreasing error	decreasing weight <=> increasing error
increasing weight <=> increasing error	increasing weight <=> decreasing error

- **Weights update:**

Each weight will be updated based on its derivative according to this equation:

$$\boldsymbol{W}new = \boldsymbol{W}old - n \times \frac{\partial E}{\partial Wi}$$

We continue updating weights according to the derivatives and we re-train the network for reaching an acceptable error value.

8. Convolutional Neural Network

Convolutional Neural Networks (CNNs), the most representative models of deep learning, they are able to exploit the basic properties underlying natural signals. CNN used primarily to classify images, identify faces, many other aspects of visual data. [20]

8.1 CNN Layers:

There are three layers in a convolutional neural network, earlier and later layers, for the earlier layers is usually composed from convolutional and pooling layers, and for the later layers we have fully connected. Each one of these layers has different parameters and functionalities. [25]

8.1.1 Convolution Layer:

The convolution layers are basically specialized in extracting low level features such as the edges, it normally goes by taking a filter of a specified size (a rule of thumb is 3x3 or 5x5…etc.) and scroll it across the image from top left to bottom right For each point on the image, the value is calculated based on the filter, we combine them into a single matric. When building the network, we randomly specify values for the weights, which are continuously updating themselves as the network is trained (back propagation), the figure11 shows how the process goes. [25]

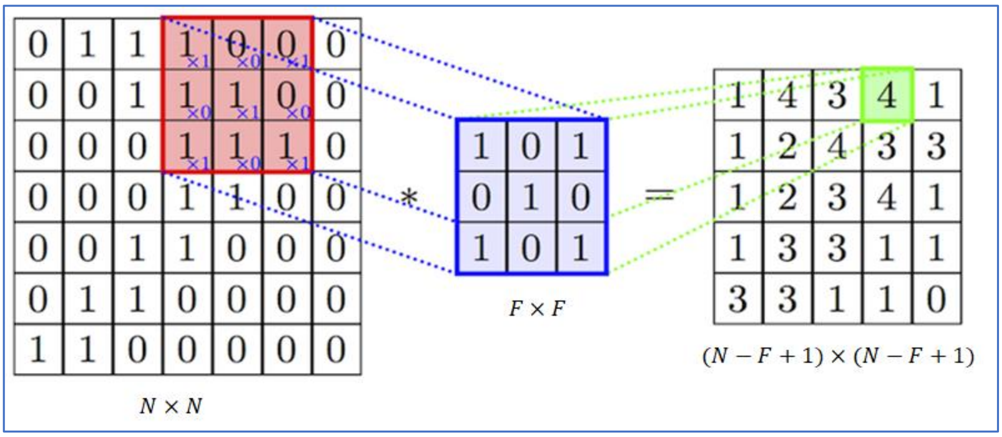


Figure II 18 filter process.

When performing the convolutional neural network on the image. Image edge features will be ignored, in order this ignorance not to happen, we can use padding.

- **Padding:**

Padding essentially makes the feature produced by the filter kernels the same size as the original image. This is very useful for CNN in order not to waste or reduce the output.

Padding size can be calculated:

E.g. Size image the prediction: $M \times M$, Size image: $N \times N$, Size filter: $F \times F$.

Padding size $=(M - N + F - 1) \times (M - N + F - 1)$.

8.1.2 Pooling Layer:

Pooling layers are similar to convolutional layers, however they perform a specific function which is reducing the amount of data in order to minimize the parameter of the next layer however, it makes the network invariant to translations in shape, size and scale. Pooling is two kinds, average and max pooling, which takes the maximum value in a certain filter region, or average pooling, which takes the average value in a filter region. The next figure shows how to do this. [25]

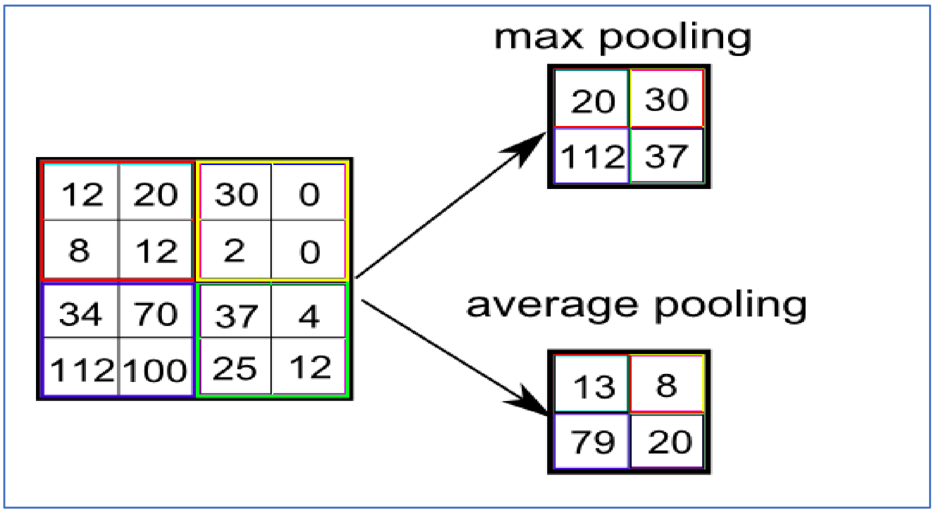


Figure II 19 Average and max pooling

8.1.3 Fully-connected Layer (FC Layer):

Fully connected layers are literally fully connected layers as depicted in figure19. This layer takes input from all neurons in the previous layer and uses them to flatten the results before the classification layer (softmax).

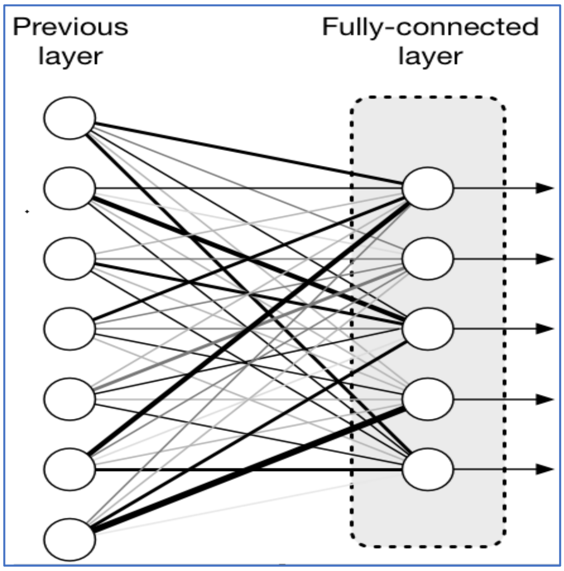


Figure II 20 Fully connected layer

8.2 MODELS OF CNN

Several models of CNN appeared in the ImageNet competition Large Scale Visual Recognition Challenge (ILSVRC) in order to solve image classification problems and object recognition, we will see in this section the Imagenet definition and some of the models.

8.3 VGG16:

VGG16 is a convolutional neural network model proposed by K. Simonyan and A. Zisserman from the University of Oxford in the paper "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.

VGG16 is a convolution neural net (CNN) architecture which was used to win ILSVR (Imagenet) competition in 2014. It is considered to be one of the excellent vision model architecture till date. ... It follows this arrangement of convolution and max pool layers consistently throughout the whole architecture.

This network is characterized by its simplicity, using only 3×3 convolutional layers stacked on top of each other in increasing depth. Reducing volume size is handled by max pooling. Two fully-connected layers, each with 4,096 nodes are then followed by a softmax classifier (above). The "16" stand for the number of weight layers in the network.

- **Architecture:**

VGG16 is a convolution neural net (CNN) architecture which was used to win ILSVR (Imagenet) competition in 2014. It is considered to be one of the excellent vision model architecture till now. Most unique thing about VGG16 is that instead of having a large number of hyper-parameter they focused on having convolution layers of 3x3 filter with a stride 1 and always used same padding and max pooling layer of 2x2 filter of stride 2. It follows this arrangement of convolution and max pool layers consistently throughout the whole architecture. In the end it has 2 fully connected layers (FC) followed by a softmax for output. The 16 in VGG16 refers to it has 16 layers that have weights. This network is a pretty large network and it has about 138 million (approx) parameters.

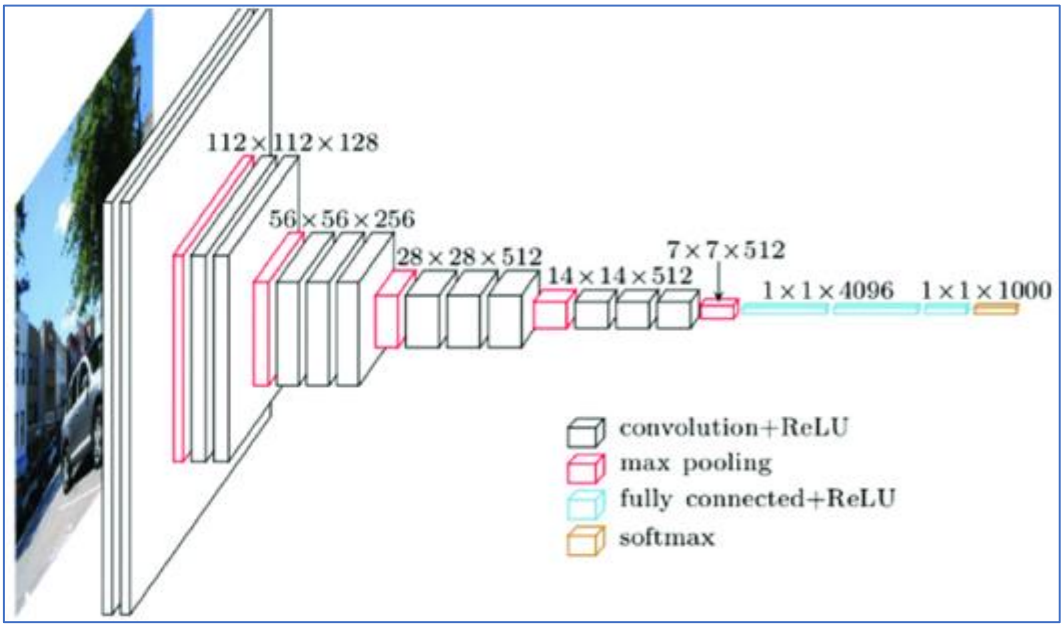


Figure II 21 VGG16 Architecture

8.4 RESNET 50

The search for more speed and accuracy led to the emergence of many different types of neural networks that are used for specific purposes. For example CNN and RNN. While continuing to increase the number of network layers been noticed that very deep networks shows increasing training error. This can be due to reasons such as problems in initialization of the network, optimization function, or due to one of the most famous problem i.e. vanishing gradient problem.

- **Vanishing gradient problem:**

It is a problem that is encountered while training artificial neural networks that involved gradient based learning and back-propagation. We know that in back-propagation, we use gradients to update the weights in a network. But sometimes what happens is that gradient becomes vanishingly small, effectively preventing the weights to change values. This leads to network to stop training as same values are propagated over and over again and no useful work is done.

To solve such problems, Residual neural networks are introduced, which was proposed in 2015 by researchers at Microsoft Research introduced a new architecture called Residual Network.

- **Residual Block:**

This architecture introduced the concept called Residual Network. In this network we use a technique called skip connections. The skip connection skips training from a few layers and connects directly to the output. The below image shows basic residual block.

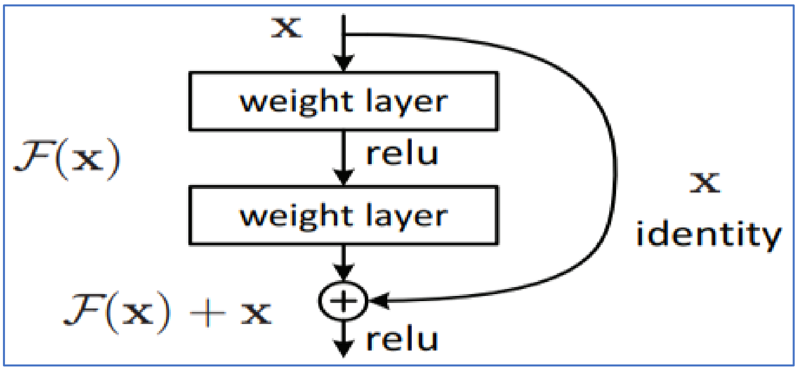


Figure II 22 skip connections

The approach behind this network is instead of layers learn the underlying mapping, we allow network fit the residual mapping. So, instead of say H(x), initial mapping, let the network fit, F(x) := H(x) – x which gives H(x) := F(x)+x.

The advantage of adding this type of skip connection is because if any layer hurt the performance of architecture then it will be skipped by regularization. So, this results in training very deep neural network without the problems caused by vanishing/exploding gradient.

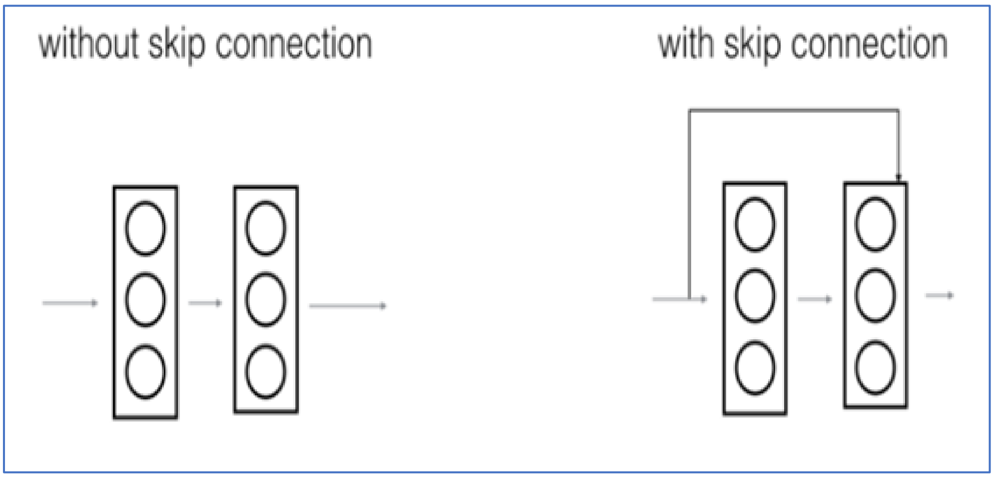


Figure II 23 Skip connection image from deep learning

There can be some scenarios where the output x from the layer and the entry of identity F(X) is different dimensions, we add some process so that the entry is changed or configured to the required dimensions. We will create **W**s until we multiply it by X to become the same size.

Example:

If size X is 128×1 and size of F(X) is 256×1, then the size of WS is 256×128, when multiplying **X** by **Ws**, it produces an X size equal to F (X).

$$Ws \times X = (256 \times 128) \times (128 \times 1) = 256 \times 1$$

During training, the algorithm will test and adjust for Ws.

The following graphic summarizes Resnet architecture.

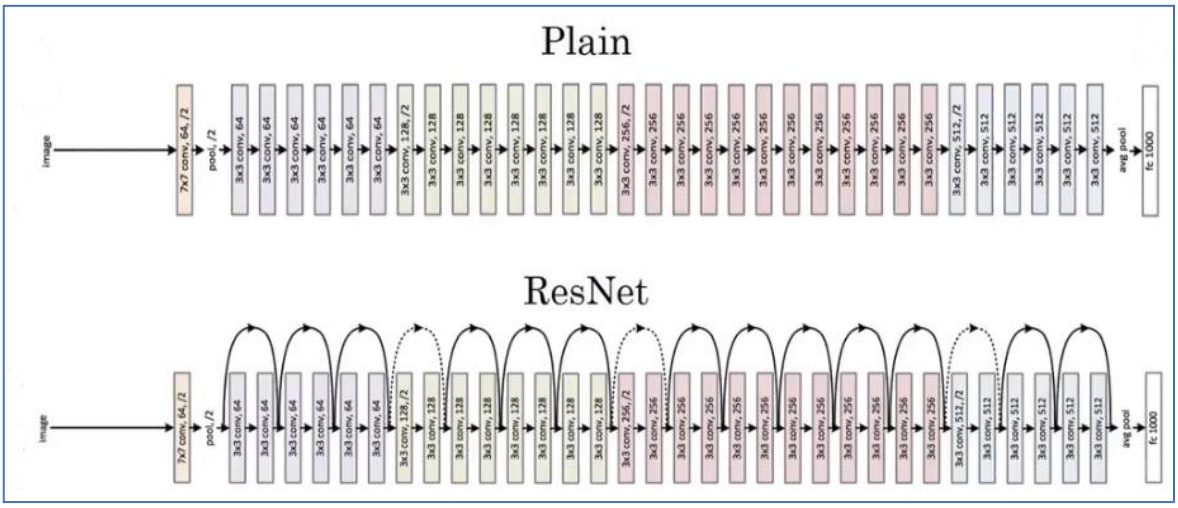


Figure II 24 Resnet architecture

8.5 Training and pre-training

8.5.1 Training from scratch:

After creating or downloading a model, all the weights will be trained according to our needs using back-propagation (mentioned above in ANN), however this training takes a lot of time knowing that this training requires very large databases in order to obtain better results.

8.5.2 Training by used transfer learning:

In computer vision, transfer learning is usually expressed through the use of pre-trained models. A pre-trained model is a model that was trained on a large benchmark dataset to solve a problem similar to the one that we want to solve. Accordingly, due to the computational cost of training such models, it is common practice to import and use models from published literature (e.g. VGG, Inception and Resnet).

8.6 Transfer learning types:

When you are repurposing a pre-trained model for your own needs, you start by removing the original classifier, then you add a new classifier that fits your purpose, and finally you have to fine-tune your model according to one of three strategies:

- **Train the entire model:**

In this case, you use the architecture of the pre-trained model and train it according to your dataset. You're learning the model from scratch, so you'll need a large dataset (and a lot of computational power).

- **Train some layers and leave the others frozen:**

As you remember, lower layers refer to general features (problem independent), while higher layers refer to specific features (problem dependent). Here, we play with that dichotomy by choosing how much we want to adjust the weights of the network (a frozen layer does not change during training). Usually, if you've a small dataset and a large number of parameters, you'll leave more layers frozen to avoid over fitting. By contrast, if the dataset is large and the number of parameters is small, you can improve your model by training more layers to the new task since over fitting is not an issue.

- **Freeze the convolutional base:**

This case corresponds to an extreme situation of the train/freeze trade-off. The main idea is to keep the convolutional base in its original form and then use its outputs to feed the classifier. You're using the pre-trained model as a fixed feature extraction mechanism, which can be useful if you're short on computational power, your dataset is small, and/or pre-trained model solves a problem very similar to the one you want to solve.

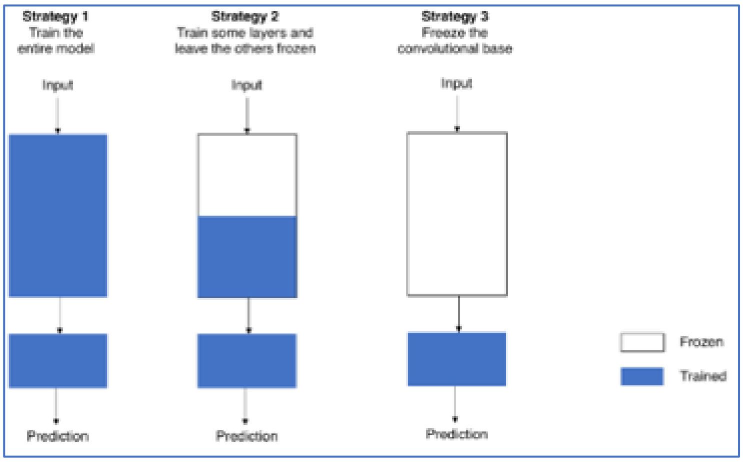


Figure II 25 Fine-turning strategies

9. deep learning in Medical image

Medical imaging is the operation of producing visual images of inner structures of the body for medicinal and scientific study and treatment, as well as a visible view of the function of interior tissues. This process creates a data bank of the stable structure and function of the organs to make it easy to recognize the anomalies. This process pursues disorder identification and management.

Deep learning algorithms, in particular convolutional networks, are rapidly becoming a preferred methodology for analyzing medical images. Although deep learning models have been very successful in medical image analysis, small size medical data sets remain the main hurdle in this field and will continue to be a challenge for us. One of the tasks performed by deep learning is to analyze and interpret medical images, and extract useful information in order to help diagnose and plan treatment.

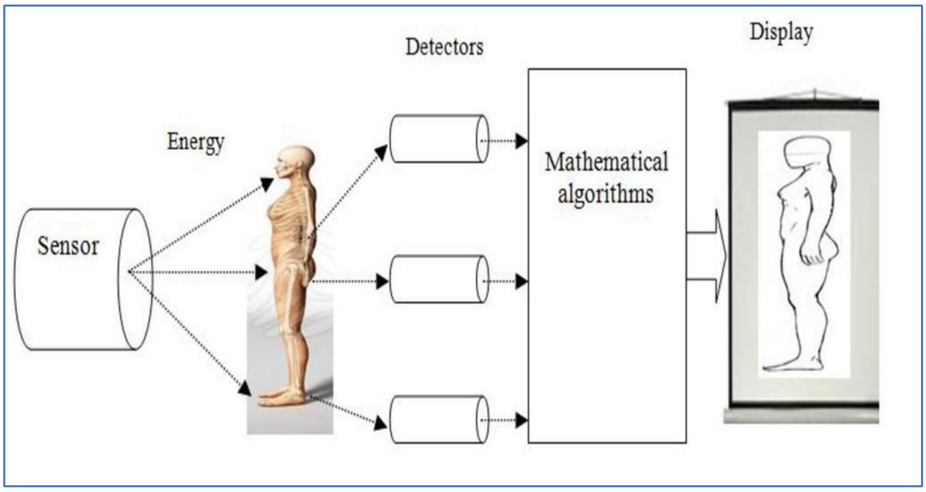


Figure II 26 medical imaging

10. Multi-state disease progression.

COVID-19 is a respiratory disease caused by the novel coronavirus (SARS-CoV-2) and causes substantial morbidity and mortality[2]. It has spread rapidly since it was recognized, and its lack of knowledge has made it difficult to treat and prevent its continuous spread. That is why we will highlight the salient points that may assist clinicians in recognizing, managing, and preventing this disease.

To date, more than 1000 studies addressing various aspects of COVID-19 are registered on ClinicalTrials.gov, including more than 600 interventional studies and randomized clinical trials (RCTs) [26].

We will demonstrate a future observational study using data from a French multicentre database, OutcomeReaTM. Data from 10 French ICUs on admission features and diagnosis, daily disease severity, iatrogenic events, nosocomial infections, vital state, and, since the COVID-19 pandemic, several specific clinical and biological data for COVID-19 patients, were prospectively recorded. Details on data collection and quality are described elsewhere **[11]**.

From a population of 423 recorded COVID-19 patients in the OutcomeReaTM database, 35 patients were excluded since their state was missing at admission and six others were excluded since COVID-19 was hospital acquired. Thus, 382 patients were included in the final analysis. Overall, 297 were male (77.7%) and their median age was 60.5 (52–70) years. The median duration from first symptoms to ICU admission was 10 (7–12) days, and the median number of days in the hospital before ICU admission was 2 (1–4) days. The patients' characteristics and drugs administered at ICU admission are depicted. The initial oxygenation state at ICU admission was non-invasive oxygenation for 243 (63.6%) patients, invasive ventilation for 116 (30.4%) patients, and ECMO for 23 (6.0%) patients. One hundred and twenty-five (32.7%) patients died before day 60.

After conducting a study and extracting the results, they found that transitions could be associated with well-known risk factors (i.e., age, Charlson score, SOFA score, inflammatory parameters). Moreover, corticosteroids seemed to decrease the risk of being invasively ventilated, and IL-antagonists to increase the chance of being successfully extubated. Using a G-computation approach, we also estimated the beneficial effect of corticosteroid and IL-antagonist therapy on day-60 mortality. The day-60 predicted estimate of mortality was 33.4% without immune-modulatory therapy and 27.3% with the combination of corticosteroids and IL-antagonists.

Using a multistate model based on prospectively collected data from 10 ICUs, they observed that the day-60 outcome in COVID-19 patients is highly dependent upon the first ventilation state upon ICU admission. Moreover, they illustrated that corticosteroids and IL-antagonists may influence the intubation duration and, when administered together, may favorably impact the 60-day mortality.

11. Anomaly detection

Anomaly detection (also known as exogenous analysis) is a step in data mining that identifies data points, events, and/or observations that deviate from the normal behavior of a data set. It is considered an unexpected change in these data patterns, or an event that does not conform to the expected data pattern. In other words, an anomaly is a deviation from the usual work. [11]

Anomaly detection plays an essential role in powerful distributed software systems. Anomalies can be detected:

- Enhance communication about system behavior
- Improved root cause analysis
- Minimize threats to the software ecosystem.

Conclusion

In this section, we discussedCOVID-19 has led to complications such as acute respiratory disorder, heart problems, and secondary infections in a relatively high proportion of patients and thus significant mortality. Early detection and commencement of treatment in severe cases is key to reducing mortality

Chapter 03:

Automated Model for COVID-19 Detection from CT scans images

Introduction

This work proposes an automated diagnosis of COVID-19 infection from CT scans of the patients using deep learning technique. The proposed model, ReCOV-101, uses full chest CT scans to detect varying degrees of COVID-19 infection. To improve the detection accuracy, the CT-scans were preprocessed by employing segmentation and interpolation. The proposed scheme is based on the residual network that takes advantage of skip connection, allowing the model to go deeper. The model was trained on a single enterprise-level GPU. It can easily be provided on a network's edge, reducing communication with the cloud, often required for larger neural network

1. Overview

The world has been enduring the formidable outbreak of Coronavirus or COVID-19 which was first detected in December 2019. It is a potential zoonotic disease with the estimated mortality rate of 2%-5% . According to the scientific brief of the WHO, the modes of transmission of COVID-19 involve respiratory droplets the size of greater than 5-10 µm. This also involves potential airborne transmission . So, the growth factor of this disease is also very high with the estimation of 13.32 M confirmed cases and 0.856 M deaths worldwide as of May 13, 2021 . Fig 1 shows the time-series graph of the total confirmed COVID-19 cases and deaths all over the world.

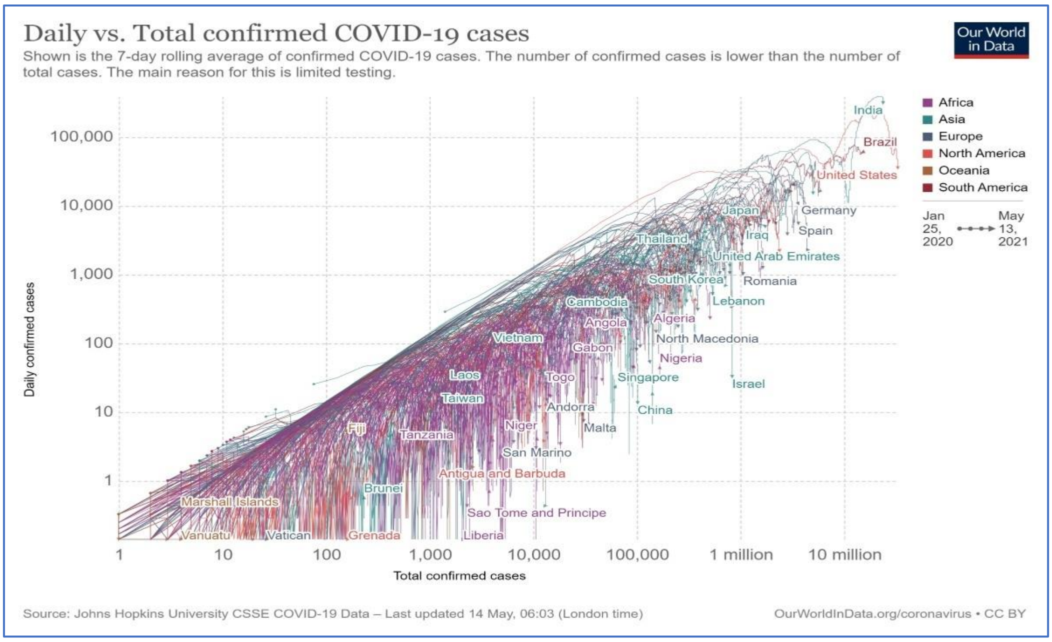


Figure III 1 Time-series graph of world-wide total confirmed cases and deaths due to COVID-19

Chest x-ray is a relatively accessible, inexpensive, fast imaging modality that might be valuable in the prognostication of patients with COVID-19. We aimed to develop and evaluate an artificial intelligence system using chest x-rays and clinical data to predict disease severity and progression in patients with COVID-19.

2. Related work

In one work, a convolutional neural network (CNN) model was used to identify Covid-19 patients with the help of CT scans. There are many other researches working to detect the presence of Covid-19 virus in human lungs with the help of computerized tomography, and a multi-tasking model has been developed under self-supervised artificial intelligence to diagnose Covid-19 virus in human lung. With the help of CT scans with an accuracy of 89%, automatic segmentation and determination of the volume of the lungs are performed. Describes a fully automated framework for detecting coronavirus and infected lungs from chest CT images and distinguishing it from other lung diseases. However, CXR images are better than any other method in detecting Covid-19 due to their promising results combined with the availability of CXR devices and their low maintenance cost. There has been a lot of work that researchers have done in the field of detecting patients for Covid-19 using CXR images. [8]

In one such work, translational learning was used with the Inception-v3 network to classify pneumonia patients and normal Covid-19 patients using CXR images. In another work, another used DenseNet with the ChexNet architecture to separate normal people, patients with bacterial and viral pneumonia, and patients with Covid-19. Sequential Xception and ResNet50 v2 can also be used to detect viral pneumonia and Covid-19 patients.

The lack of a large number of image data for COVID-19 patients is a challenge faced by most researchers working in this field. CovidGAN has been developed to artificially generate data, which in turn will help improve Covid-19 detection. Apart from using single modern deep learning models, one work has been developing a custom architecture called the CovidNet architecture to classify Covid-19 patients, healthy subjects, and pneumonia patients. This custom grid, designed using a lightweight drop-and-drop and extend (PEPX) design pattern, demonstrated a classification accuracy of 94%—a result that outperformed lab tests. [9]

Most of the work on detecting Covid-19 from CXR images has used single deep learning models for example. DenseNet, ResNet, Xception, etc. None of the works attempted to combine models to double their classification ability. Various work done on Ensemble Learning with Deep Neural Networks shows that aggregated learning methods are superior in prediction over individual models.

The weighted average of the output probabilities was introduced as the aggregation method. It was found to be better than the unweighted average. The relative performance of different group methods with convolutional neural networks such as unweighted mean, majority voting, optimal Bayes classifier and super-learner were also compared. In this paper, we proposed a novel method to synthesize three of the latest CNN models DenseNet201, Resnet50V2, and Inceptionv3 to classify Covid-19 + five patients from CXR images.

3. Experiment setup

3.1) Implementation

We have used Google Colab GPU (Tesla K80 12GB GDDR5 VRAM), Python 3.7 andTensorFlow 2.2.0. For the implementation of CNN, the deep learning library of TensorFlow 2.2.0 is used, and the training and the testing procedures are done in the Google Colab platform.

3.2) Dataset

The dataset of this work has been collected from Kaggle repository , which contains Chest X-Ray scans of Covid-19 affected, normal and pneumonia. This collected dataset is not meant to claim the diagnostic ability of any Deep Learning model but to research about various possibleways of efficiently detecting Coronavirus infections using computer vision techniques. The collected dataset consists of 6432 total chest X-ray images. This data set is further divided into training (i.e., 5467) and validation (i.e., 965) set of normal, covid, and pneumonia. In the training set, 1345 is normal, 490 are covid. In the validation phase, 238 samples of a normal case, 86 covid were considered for this analysis. At the time of the drafting of this paper, we had 576 PA (Posteroanterior) View scans of Covid-19 affected patients. The scans were scaled down 128×128 to aid the fast training of our model. The PA view scans were deemed to be consistent with our covid dataset. Table 1 displays the data distribution for training and testing the data , fig2 picture showing dividing pictures for use in a model .

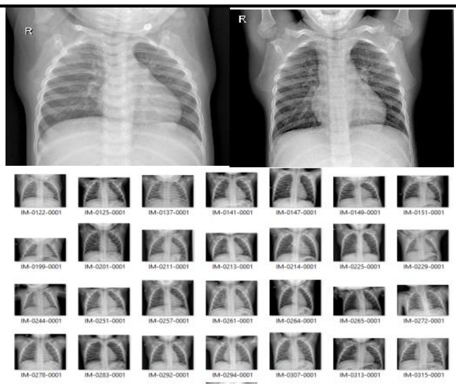
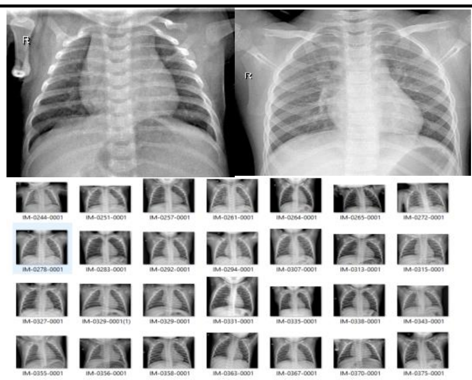
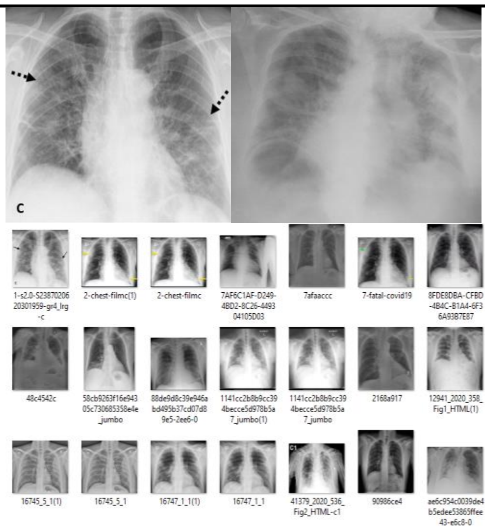
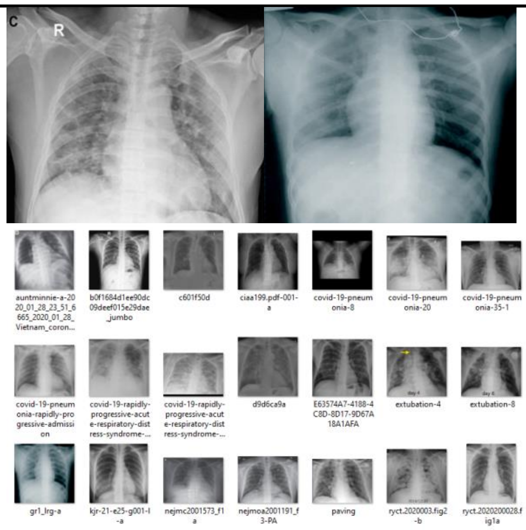
	Train	**Tests**
Healthy Person		
Covid-19 Infected Patient		

Table III 1 Dataset Distribution

3.3) Methods

The proposed model for automated diagnosis of COVID-19 cases is illustrated in Fig. 2. The model aims to classify a given chest X-ray image into normal or COVID-19 category which includes two vital stages: preprocessing (normalization and augmentation) and classification using pre-trained CNN architectures. The description of each stage is detailed in the subsequent sections.

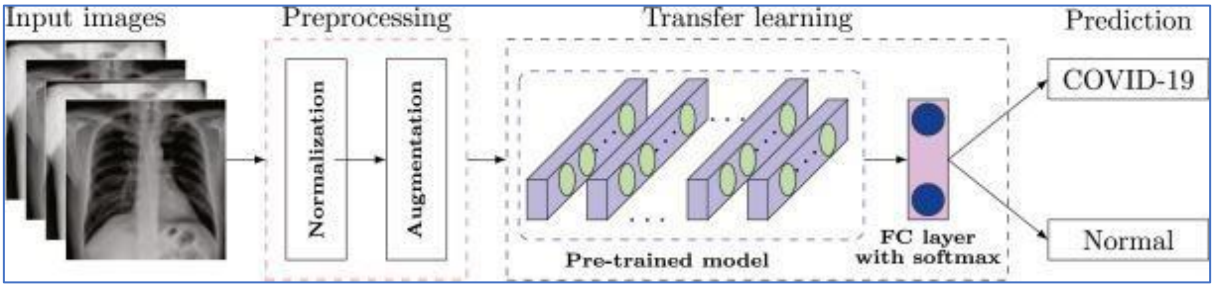


Figure III 2 Overview of the proposed automated COVID-19 diagnosis method using frontal-view chest X-ray images.

3.4) Preprocessing

3.4.1) Normalization

Data normalization is an essential step and is generally used to maintain numerical stability in CNN architectures. It provides quick learning for her. Therefore, in this study, the pixel values of the input images were normalized between the range 0-1. The images used in the studied data sets are gray scale images and re-scaling was achieved by multiplying 1/255 by the pixel values.

The collages are first normalized and resized to 224_224 shaped images.then the images are mixed and divided into training and test data, where the test volume is 20% and the rest for training purposes. Thus, the training data contains 771 images where there are 438 images for class 0 and 333 images for class 1. The test data contains 235 images where there are 100 images for class 0 and 135 images for class 1.

However, if there are two or more images of the same patient, it is ensured that these images are tagged as either training data or test data - but not in both. If the same patient images are kept in the training and test data, there is a possibility that the results are very promising due to patient interference. With this, image folders are ready to train the model followed by testing the effectiveness of the trained model.

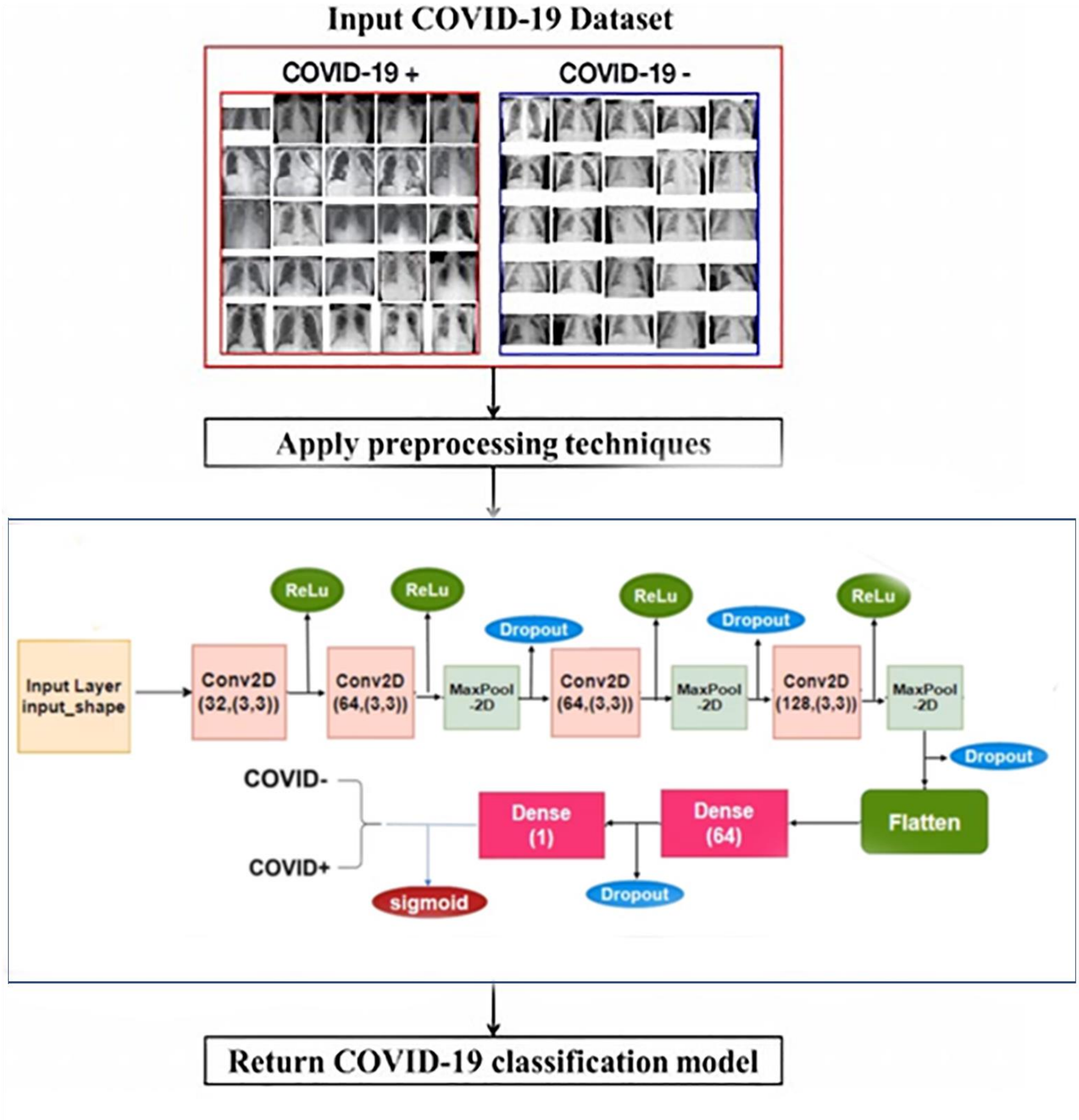


Figure III 3 Block diagram of training process of the CNN-based COVID-19 classi¯cation model

3.4.2) Features extraction

CNN is the most commonly used architecture where the image is inserted into the input layer, which propagates through multiple hidden layers and finally produces the prediction probability through the output layer. These hidden layers consist of a series of convolutional layers followed by assembly layers that attempt to discover and learn very complex features and patterns belonging to images of a particular class. This is the reason for the tremendous success of CNN models in the field of computer vision and its various applications. Although CNN performs great in the task of classifying images, there are some limitations to this.

First, to make more accurate predictions, the CNN model needs to be trained on a large data set to satisfy our arguments. However, so far, large data sets are not publicly available, in our work, instead of using a CNN model to predict COVID cases, we used it to extract robust features, and then the obtained feature vector is passed to a two-stage FS technology followed by SVM classification Classifier-based for cross-sectional input images..

The proposed CNN model considers images of size 224x224 in the input layer. The input layer is followed by a Convolutional layer, a Batch Normalization layer and a Maxpooling layer. This set of layers is repeated four times with various number of filters having a size of (3 x 3). All neurons in these layers have the ReLU (Rectified Linear Unit) as their activation functions. The final Convolution layer consists of 8 filters of size (3 x 3) followed by fully connected layers having ReLU activation. For all these layers, stride of size (1x1) is used in Convolutional layers and stride of size (2x2) is used in Maxpooling layers. An overview of this architecture is shown in Table 1. From the last Convolutional layer, a total of 800 features are generated from each image sample. Total parameters of this architecture are 66,079, where trainable parameters are 65,727 and the rest 352 are non-trainable parameters.

3.4.3) Feature selection

Performing feature extraction may create some redundant and inappropriate features in the feature space. It is essential to eliminate redundant and irrelevant feature attributes as removing them not only helps enhance overall classification accuracy but also reduces computational overhead. This is usually performed by FS technology. Fixed service is defined as the procedure for selecting a subset of the set of candidate features that shows the best performance under some rating system. The different FS-based algorithms mentioned in the literature can be categorized into three groups namely: filter base, shell-based methods, and embedded methods. Filtering methods use a statistical or probabilistic approach to scoring/ranking feature attributes and on the basis of an assigned score, feature attributes are either selected or removed before entering into the classification model. Sheath methods are often used in coalition with an ML algorithm, in which the effect of feature attributes is validated by learning algorithms, which in turn select optimal feature sets to increase classification accuracy. In contrast, the embedded model integrates FS within a specific ML-based algorithm. In the proposed work, we used a two-stage approach to select the most relevant features from the feature set produced by CNN so that a near-perfect CT image-based COVID-19 classification system could be designed. The adopted approach is detailed in the following subsections.

3.4.4) Classifier Architectures

CNN models have proven to get superior results in a wide variety of medical image processing applications. However, training these models from scratch will be challenging to predict COVID-19 cases due to the limited availability of X-ray samples. Applying pre-trained models using the Transfer Learning (TL) concept can be useful in such circumstances. In TL, the knowledge gained through a DL model trained from a large data set is used to solve a task related to a relatively smaller data set. This helps eliminate the need for large data set and longer learning time as required by learning methods trained from the start. In this study, eight pre-trained models such as AlexNet, VGG-16, GoogleNet, MobileNet-V2, SqueezeNet, ResNet-34 and ResNet-50, and Inception-V3 was used to classify COVID-19 from normal cases. These networks have been very successful in a wide range of computer vision problems and medical image analysis, and were therefore selected in this study to differentiate COVID-19 infection from normal cases. It isnoteworthy here that these models were originally trained on a large-scaled classification dataset called ImageNet and were later tuned to chest X-ray images. The last layer was removed in these models and a new fully connected (FC) layer was introduced with a two-layer output size representing two different classes (normal and COVID-19). In these resulting models, only the final FC layer is trained, while the other layers are initialized with pre-trained weights. Hyperparameters play a major role in fine-tuning these DL models and have been kept constant to derive a fair comparison.

ResNet-34 is a residual deep network designed based on the concept of residual learning [39]. It consists of one free-standing wrapping layer and 16 residual gaps followed by one FC layer. This network essentially overcomes the degradation problem by introducing residual connections. **ResNet-50** is another variant of ResNet consisting of the same number of remaining block as ResNet-34, but the structure of the remaining block is different [24]. The ResNet-50 model replaces each remaining two-layer block of ResNet-34 with a three-layer bottleneck block that uses 1×1 convolutions.

GoogleNet is a 22-layer deep architecture containing 5 million parameters which is significantly superior to the parameters used in AlexNet and VGG models [19]. The starting module is the basic building block of this model which helps in data processing using multiple filters at the same time.

Inception-V3 is a variant of Inception-V2 and avoids representational bottlenecks [19]. It has more efficient calculations using analysis techniques and achieves a lower error rate in contrast to the previous variants. This network contains 42 layers with an input image size of 299 x 299.

MobileNet-V2 is built on the ideas of MobileNet-V1 that uses a deep detachable wrap as efficient building blocks. But this version introduces a new layer unit, the inverted residual with a linear bottleneck [19]. It is a compact and cost-effective architecture that helps in achieving high performance with limited resources. It has 19 remaining bottleneck layers. The main purpose of this research is to identify the best DL model for COVID-19 screening that can move researchers forward to develop more effective AI-based solutions.

4. Evaluation

4.1 Evaluation dataset

The dataset used in this work was obtained from the Kaggle “COVID-19 Radiography Database”. The database from this repository consists of 219 positive COVID-19 images, 1,341 normal images, and 1,345 viral pneumonia images.. By adding another 152 positive COVID-19 images from other similar sources, the total number of images for this category was increased to 371. Our experiments were performed using CXR radiographs of COVID-19 positive cases and normal images from the dataset. All images have been resized from 1024 x 1024 to 100 x 100 pixels, which greatly reduces the extracted feature set and enhances computational speed. All results mentioned in the work were achieved using the original data set. Representative radiographs of both patients with COVID-19 and normal conditions are given in the figure. 6, respectively. Starting from the numbers of individual images from the different categories, it can be seen that the data set is unbalanced, we have generated 3 subsets from the full data set for evaluation. Changed split ratio between COVID-19 and non-COVID-19 CXR images by either increasing or decreasing non-COVID-19 CXR images to make subsets containing 30% COVID-19-70% non-COVID-19 images, 50% COVID-19-images 50% non-COVID-19, the complete dataset containing all COVID-19 and non-COVID-19 CXR images. It should be noted here that this split was only for evaluation, and the final model was trained on the original data set.

4.2 Evaluation method

All tests were performed on Google Colaboratory, allowing execution of python code in browser, on Google Cloud Servers running on a Intel(R) Xeon(R) CPU @ 2.30 GHz, having 20 physical cores paired with a K80 GPU and RAM capacity up to 36 GB. A maximum of 108 GB of disk space was available, out of which 33 GB was used for the experiments.

Pillow library, a fork of Python Imaging Library was used for extracting features from the lung CXRs. All the algorithms were developed using Python 3.6.7 as the language and NumPy, Pandas, and Scikit-learn libraries.

5. Experiment Result

5.1) Code Explaining

Before everything, The library and packages necessary to start work must be called, as shown in the following figure:

```
import tensorflow.keras
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Dense, Activation, Flatten, Conv2D, MaxPool2D, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.losses import binary_crossentropy
from tensorflow.keras import metrics
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report, confusion_matrix, plot_confusion_matrix, ConfusionMatrixDisp
import numpy as np
```

Figure III 4 Importing library

Firstly, we started with the code of image enhancement to:

- Denoise a grayscale image with median filter
- Loading our data

  And then we called the database and put it in a variable, As in the following figure:

```
# Create path

train_loc = '/content/drive/My Drive/our_DATA/train/'
test_loc = '/content/drive/My Drive/our_DATA/val/'
```

Figure III 5 load our data

We resize the images to 224 x 224 fixed pixels while ignoring the aspect ratio, so that it has the same size as the input layer of the model we're going to train.

```
# resize images

trdata = ImageDataGenerator(rescale= 1./255,
                            shear_range = 0.2,
                            zoom_range = 0.2,
                            horizontal_flip = True,
)

traindata = trdata.flow_from_directory(directory = train_loc, target_size = (224,224))

tsdata = ImageDataGenerator(rescale= 1./255,
                            shear_range = 0.2,
                            zoom_range = 0.2,
                            horizontal_flip = True,
)

testdata = tsdata.flow_from_directory(directory = test_loc, target_size = (224,224))
```

Figure III 6 Resize images

This figure shows the code for creating a model by going through several layers to the end.

```
# define input image
input_shape = (224,224,3)
# create the Network
# Input layer
img_imput = Input(shape  = input_shape, name = 'img_input')

# Convo layers
x = Conv2D(32, (3,3) , padding = 'same' , activation='relu', name = 'layer_1') (img_imput)
x = Conv2D(64, (3,3) , padding = 'same' , activation='relu', name = 'layer_2') (x)
x = MaxPool2D((2,2), strides=(2,2), name = 'layer_3') (x)
x = Dropout(0.25)(x)

x = Conv2D(64, (3,3) , padding = 'same' , activation='relu', name = 'layer_4') (x)
x = MaxPool2D((2,2), strides=(2,2), name = 'layer_5') (x)
x = Dropout(0.25)(x)

x = Conv2D(128, (3,3) , padding = 'same' , activation='relu', name = 'layer_6') (x)
x = MaxPool2D((2,2), strides=(2,2), name = 'layer_7') (x)
x = Dropout(0.25)(x)

x = Flatten(name = 'layer_8')(x)
x= Dense(64, name = 'layer_9')(x)
x = Dropout(0.5) (x)
x = Dense(2, activation='sigmoid', name='predictions')(x)
```

Figure III 7 Resnet model for segmentation

The figure shows creating the form and giving it a name:

```
# Generate the model
model = Model(inputs = img_imput, outputs =x , name='CNN_COVID_19')
```

Figure III 8 Generate the model

Print the network structure

```
# Print network structure
model.summary()
```

Figure III 9 Print network structure

The result of print network structure shown in figure III.10 :

```
Model: "CNN_COVID_19"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
img_input (InputLayer)       [(None, 224, 224, 3)]     0
_________________________________________________________________
layer_1 (Conv2D)             (None, 224, 224, 32)      896
_________________________________________________________________
layer_2 (Conv2D)             (None, 224, 224, 64)      18496
_________________________________________________________________
layer_3 (MaxPooling2D)       (None, 112, 112, 64)      0
_________________________________________________________________
dropout (Dropout)            (None, 112, 112, 64)      0
_________________________________________________________________
layer_4 (Conv2D)             (None, 112, 112, 64)      36928
_________________________________________________________________
layer_5 (MaxPooling2D)       (None, 56, 56, 64)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 56, 56, 64)        0
_________________________________________________________________
layer_6 (Conv2D)             (None, 56, 56, 128)       73856
_________________________________________________________________
layer_7 (MaxPooling2D)       (None, 28, 28, 128)       0
_________________________________________________________________
dropout_2 (Dropout)          (None, 28, 28, 128)       0
_________________________________________________________________
layer_8 (Flatten)            (None, 100352)            0
_________________________________________________________________
layer_9 (Dense)              (None, 64)                6422592
_________________________________________________________________
dropout_3 (Dropout)          (None, 64)                0
_________________________________________________________________
predictions (Dense)          (None, 2)                 130
=================================================================
Total params: 6,552,898
Trainable params: 6,552,898
Non-trainable params: 0
```

Figure III 10 The result of print network structure

After that we compiling the model and start the training and the test

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

```
# start Train/Test
batch_size = 32
hist = model.fit(traindata, steps_per_epoch = traindata.samples//batch_size,
                 validation_data = testdata,validation_steps = testdata.samples//batch_size,
                 epochs = 20
                 )
```

Figure III 11 Code of compiling the model and start train and test

```
Epoch 1/20
18/18 [==============================] - 440s 23s/step - loss: 0.8687 - accuracy: 0.6781 - val_loss: 0.4404 - val_accuracy: 0.8750
Epoch 2/20
18/18 [==============================] - 27s 1s/step - loss: 0.2500 - accuracy: 0.9085 - val_loss: 0.1360 - val_accuracy: 0.9688
Epoch 3/20
18/18 [==============================] - 27s 1s/step - loss: 0.1341 - accuracy: 0.9381 - val_loss: 0.1234 - val_accuracy: 0.9375
Epoch 4/20
18/18 [==============================] - 27s 1s/step - loss: 0.0542 - accuracy: 0.9795 - val_loss: 0.0519 - val_accuracy: 0.9792
Epoch 5/20
18/18 [==============================] - 27s 1s/step - loss: 0.0719 - accuracy: 0.9833 - val_loss: 0.1628 - val_accuracy: 0.9688
Epoch 6/20
18/18 [==============================] - 27s 1s/step - loss: 0.0830 - accuracy: 0.9803 - val_loss: 0.1406 - val_accuracy: 0.9583
Epoch 7/20
18/18 [==============================] - 27s 1s/step - loss: 0.0622 - accuracy: 0.9825 - val_loss: 0.0874 - val_accuracy: 0.9688
Epoch 8/20
18/18 [==============================] - 27s 1s/step - loss: 0.0564 - accuracy: 0.9802 - val_loss: 0.0970 - val_accuracy: 0.9896
Epoch 9/20
18/18 [==============================] - 27s 1s/step - loss: 0.0420 - accuracy: 0.9900 - val_loss: 0.0180 - val_accuracy: 1.0000
Epoch 10/20
18/18 [==============================] - 26s 1s/step - loss: 0.0476 - accuracy: 0.9861 - val_loss: 0.1541 - val_accuracy: 0.9688
Epoch 11/20
18/18 [==============================] - 27s 1s/step - loss: 0.0552 - accuracy: 0.9914 - val_loss: 0.0500 - val_accuracy: 1.0000
Epoch 12/20
18/18 [==============================] - 27s 1s/step - loss: 0.0293 - accuracy: 0.9904 - val_loss: 0.0347 - val_accuracy: 0.9896
Epoch 13/20
18/18 [==============================] - 27s 1s/step - loss: 0.0308 - accuracy: 0.9931 - val_loss: 0.0428 - val_accuracy: 0.9896
Epoch 14/20
18/18 [==============================] - 27s 1s/step - loss: 0.0424 - accuracy: 0.9889 - val_loss: 0.0893 - val_accuracy: 0.9792
Epoch 15/20
18/18 [==============================] - 27s 1s/step - loss: 0.0295 - accuracy: 0.9948 - val_loss: 0.0647 - val_accuracy: 0.9896
Epoch 16/20
18/18 [==============================] - 27s 1s/step - loss: 0.0505 - accuracy: 0.9920 - val_loss: 0.0289 - val_accuracy: 1.0000
Epoch 17/20
18/18 [==============================] - 27s 1s/step - loss: 0.0368 - accuracy: 0.9861 - val_loss: 0.0443 - val_accuracy: 0.9792
Epoch 18/20
18/18 [==============================] - 27s 2s/step - loss: 0.0327 - accuracy: 0.9942 - val_loss: 0.0757 - val_accuracy: 0.9688
Epoch 19/20
18/18 [==============================] - 26s 1s/step - loss: 0.0169 - accuracy: 0.9980 - val_loss: 0.0543 - val_accuracy: 0.9792
Epoch 20/20
18/18 [==============================] - 27s 1s/step - loss: 0.0169 - accuracy: 0.9968 - val_loss: 0.1094 - val_accuracy: 0.9688
```

Figure III 12 sown the execute training

5.2 Results

We used the VGG16 and Resnet50 pre-trained models on Imagenet and used them in different ways, once with no changes, again with just softmax training and keeping the previous layers frozen, and again with the last convolution layer training with softmax and keeping the previous layers frozen, the last time that In it, we made transformers to create our model and train it from scratch, and then compared the results extracted, and they were as follows:

	Trained	**Number Weight trained**	**Training time (m)**
VGG16	**Softmax**	**4,098**	**44 m**
	Last layer +Softmax	**2,363,906**	**86m**
Resnet50	**Softmax**	**4,098**	**33 m**
	Last layer +Softmax	**8,194**	**65 m**
Our models	**CNN-Covid19**	**6,552898**	**215m**

The following table summarizes the results of detection accuracy for each one:

	Training	**Accuracy**
VGG16	**Softmax**	**70.25%**
	Last layer+ Softmax	**86.57%**
ResNet50	**Softmax**	**67.20%**
	Last layer+ Softmax	**83.83%**
Our models	**CNN-Covid19**	**96.88%**

Table III 2 Accuracy

We noticed that fine-tuning VGG16 (modified in the last layer + soft-max) and fine-tuning Resnet50 (adjusted in the last layer + soft-max) gave an acceptable result. And by virtue of man always looking for the best, so we decided to try and create a model and train all its layers and weights, and it gave us better results as shown in the previous table.

5.3 Discussion

The study of chest X-ray images for accurate prediction of COVID-19 infection has attracted significant interest since the release of the data set developed by Cohen. Subsequently, several attempts were made to develop a reliable diagnostic model using DL techniques. The concept of TL has been widely used with CNN-based networks.

However, most previous methods have been evaluated using a limited amount of data. Moreover, in some cases, the data is unbalanced.

The results obtained showed that our proposed algorithm is effective, although our solution is effective, it sometimes errs, so we tried several ways to achieve the last result. Comparing VGG16 and ResNet50 models and ours, our model outperformed them as possible because all of their layers were trained and weighted, and our result was acceptable.

CNN models gave good results (83.73% for VGG16 and 73.18% for ResNet50), however, we wanted to increase the accuracy much more. That's why we created a model and trained all its layers and weighted to give us a good result.

In the end, our proposed solution reached our desired goal by detecting the infected disease with an accuracy of up to 96.88%

Conclusion

In this section, we discussedAutomated Model for COVID-19 Detection from CT scans images and Overview, Related work, Dataset, Methods, Deployed Pipeline, Evaluation and Results, Results.

there are several methods for the diagnosis of COVID-19. The standard procedure for testing is the real-time reverse transcription-polymerase chain reaction (rRT-PCR). Along with this laboratory testing, scans of the chest area in the form of X-rays and CT scans are proven to help its diagnosis

Chapter 04:

Automated Model for COVID-19 Detection from Recorded Cough

Introduction

researchers have found that people who are asymptomatic for Covid-19 may differ from healthy individuals in the way that they cough. These differences are not decipherable to the human ear. But it turns out that they can be picked up by artificial intelligence.

1. Overview

Pneumonia kills more than 1,800,000 children annually worldwide. Pneumonia is a very common disease of the lungs and requires an effective diagnosis at the initial stage for appropriate treatment.

The main signs of COVID-19 are a high temperature, a different cough, a cold, shortness of breath, a combination of loss of smell and chest tightness. The digital world is growing day by day. In this context, a digital stethoscope can read all these symptoms and diagnose respiratory diseases. In this study, we mainly focus on literature reviews on how SARS-CoV-2 is spread and in-depth analysis of the diagnosis of COVID-19 from human respiratory sounds such as cough, wheezing, and wheezing by analyzing respiratory sound parameters.

Respiratory sounds carry important information about the state of the respiratory system. Respiratory sounds are often affected by sounds from the heart and other organs, which makes the task of analysis more complicated, and coughing is a symptom of more than thirty medical conditions not linked to COVID-19. This makes diagnosing COVID-19 infection by coughing alone a very challenging multidisciplinary problem. We address this issue by investigating the differentiation of the pathological changes in the respiratory tract caused by COVID-19 infection when compared to other respiratory diseases.

2. Related work :

Several thesis and articles have appeared on how to classify a patient's cough. We'll take a look at some of these articles.

- Filipe Barata, Peter Tinschert, Frank Rassouli, Claudia Steurer-Stey , Elgar Fleisch, Milo Alan Puhan, Martin Brutsche, David Kotz and Tobias Kowatsch wrote in an article titled "Automatic Recognition, Segmentation, and Sex Assignment of Nocturnal Asthmatic Coughs and Cough Epochs in Smartphone Audio Recordings: Observational Field Study"

In this articale they used the convolutional neural network model that they developed in their work for automatic cough recognition. They also used techniques (such as group learning, minibatch balancing, and thresholding) to address the imbalance in the data set. They evaluated the workbook in a classification task and a segmentation task. The cough recognition classifier served as the basis for the cough segmentation classifier from continuous audio recordings. Compare the number of cases of spontaneous coughing and coughing with the cough shown in humans and the number of coughing period. They used Gaussian mixture models to construct a classifier of cough and cough period signals based on sex. [11]

They recorded audio data from 94 adults with asthma (overall: median 43 years; female: 57%; males 43%). The audio data was recorded by each participant in their everyday environment using a smartphone placed next to their bed; The recordings were made over the course of 28 nights. Out of 704,697 sounds, they identified 30,304 sounds as coughing. After several exercises and experiments of the Gaussian mixture model, the result of gender classification based on the era of cough has reached an accuracy of 83%.

- Shivani Yadav, KausthubhaNk, DipanjanGope, Uma Maheswari Krishnaswamy and Prasanta Kumar Ghosh wrote in an article titled "Comparison of Cough, Wheeze and Sustained Phonation for Automatic Classification Between Healthy Subjects and Asthmatic Patients"

In this work, they consider the task of automatic classification of asthmatic patients and healthy subjects using acoustic stimuli. Coughing and wheezing were used as acoustic stimuli for the classification task. In this work they focus on the continuous sounds, /a:/, /i:/, /u:/, /eɪ/, /oƱ/ and compare their classification performance with coughing and wheezing. Classification experiments in 35 asthmatic patients and 36 healthy subjects showed that the continuous vowel /i:/ achieves the highest classification accuracy of 80.79% among five vowels. However, it was found to be higher and lower than the classification accuracy of 78.72% and 90.25% obtained using cough and wheezing, respectively. This indicates that for a speech-based classification of asthma, /i:/ would be a better choice compared to the other vowels considered in this work. However, when non-verbal sounds are included in the classification, wheezing is a better choice than /i:/.[12]

3. Experiment setup

3.1) Implementation

We have used Google Colab GPU (Tesla K80 12GB GDDR5 VRAM), Python 3.7 andTensorFlow 2.2.0. For the implementation of CNN, the deep learning library of TensorFlow 2.2.0 is used, and the training and the testing procedures are done in the Google Colab platform.

3.2) Dataset

Data description The data contains 34 patients tested for COVID-19, 16 positive cases, and 18 negative cases. The information available for each patient can be categorized into four categories: general information (age and gender), symptoms (sore throat, shortness of breath, runny nose, loss of smell or taste, fever, fatigue, diarrhea, cough, body aches, no symptoms), diseases Respiratory (sinus, COPD, bronchitis, asthma and others), voice features (3 cough sounds per patient). In total, the data contained 97 cough sounds (some patients did not provide all three cough recordings). Despite the lack of database, we will continue to experiment.

	The number of coughing sounds			
	Male		**Female**	
	Age over 35	**Age less than 35**	**Age over 35**	**Age less than 35**
negative	13	20	5	10
positive	15	14	7	13
total summation	28	34	12	23

Table IV 1 Dataset

3.3) Method

This study demonstrates the feasibility of an alternative form of COVID-19 detection, harnessing digital technology through the use of acoustic biomarkers and deep learning. Specifically, we show that a deep neural network-based model can be trained to detect asymptomatic and asymptomatic COVID-19 cases using audio recordings of breathing and coughing, and then classify the cough sound as a patient or not.

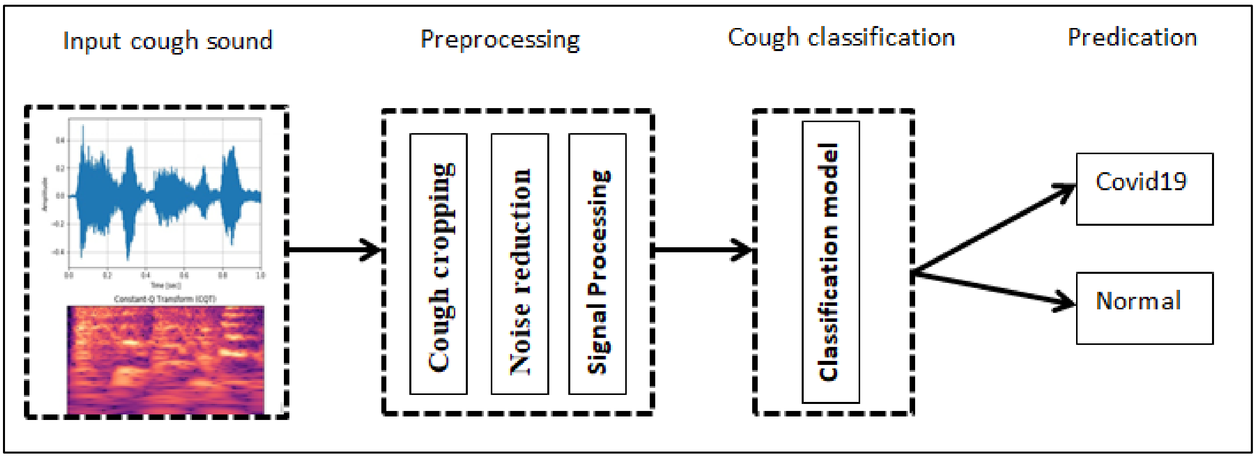


Figure IV 1 Overview of the proposed automated COVID-19 diagnosis method using frontal-view cough

3.4) Preprocessing :

Sound data preprocessing Our cough classification framework consists of the subsequent parts discussed in the following subsections:

- **Input audio file** : audio file with the following properties: wav format, single channel, 16 kHz sample rate and 256 kbps bitrate
- **Cough cropping** : detects which parts of the provided audio file contain cough. Subsequently, it cuts the file into two distinct audio files, with cough and with other sounds which are assumed to be noise,
- **Noise reduction** : uses the provided audio file with noise to suppress the noise in the cough audio file,
- **Signal Processing** : converts the audio file into the set of features used for classification,
- **Classification model** : classifies the provided features as a Covid-19 Cough or Non-Covid-19 Cough.

3.5) feature extraction and feature selection:

Feature extraction is an important step toward classifying cough sounds. However, generating a classification model from a high dimensional dataset takes time and may converge to a local minimum due to the large search space. Therefore, selecting a miniature set of relevant features in an audio sample can significantly improve performance creating a classification model. There are several techniques for feature selection including Shannon Entropy (SH), Fisher Score, Mel-Frequency Cepstral Coefficients, and ZCR Crossing Rate (ZCR). However, the MFCC method has gained popularity due to its efficiency in analyzing speech and sound signals in general, and thus was chosen in the analysis of cough sounds. The selection of features during the preprocessing of cough sounds is twofold: first, dimensionality reduction to classify the feature matrix, and secondly, the extraction of the most common information found in the cough sound. Before the feature can be extracted, any noise from the cough sound must be filtered out. The quality and performance of the classification process strongly depends on how well the feature extraction process is.

4. Evaluation and Results:

4.1) Evaluation dataset

Contrary to the popular opinion that analyzing secondary data is easy or quick, you often use the same methodologies in primary research and rely on existing data that may not be ideal for you. To make an informed decision about data usage, we can go through the following points to improve our database:

- Study design.
- Data collection methods.
- Data file format.
- Data set documentation including variable names and descriptions.
- Data quality including reliability and validity.
- Extent of missing data.
- Availability of a contact person.

4.2) Evaluation method :

We use the following metrics for assessing the proposed method

Accuracy:

Accuracy is defined as 'the degree to which the result of a measurement conforms to the correct value or a standard' and essentially refers to how close a measurement is to its agreed value.

And it too Proportion of correct classifications from overall number of cases.

$$\text{Accuracy} = \frac{\textit{Correct prediction}}{\textit{total correct prediction}}$$

5. Experiment Result

5.1) Code Explaining:

Before everything, The library and packages necessary to start work must be called, as shown in the following figure:

```
import librosa
import os
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
```

Figure IV 2 Importing library

We load the database and put it in a variable as shown in the following figure:

```
audio = "/content/drive/MyDrive/COVID-19-train-audio-master/not-covid19-coughs/PMID-32095775/# 30 Chesty and wet cough-d2wkdrScerU.mp3"
y, sr = librosa.load(audio, mono=True, duration=1)
```

Figure IV 3 load our dataset

Extract the features of all the sounds in the database and put them in a variable:

```
chroma_stft = librosa.feature.chroma_stft(y=y, sr=sr)
spec_cent = librosa.feature.spectral_centroid(y=y, sr=sr)
spec_bw = librosa.feature.spectral_bandwidth(y=y, sr=sr)
rolloff = librosa.feature.spectral_rolloff(y=y, sr=sr)
zcr = librosa.feature.zero_crossing_rate(y)
mfcc = librosa.feature.mfcc(y=y, sr=sr)
```

Figure IV 4 Extract features

It inserts the variables that carry the extracted features, and then returns the average of the array's elements. and put it in the same variable.:

```
chroma_stft = np.mean(chroma_stft)
spec_cent = np.mean(spec_cent)
spec_bw = np.mean(spec_bw)
rolloff = np.mean(rolloff)
zcr = np.mean(zcr)
mfcc = np.mean(mfcc)
```

Figure IV 5 average extracted features

Training the model on the extracted features:

```
dt = pd.read_csv("feature.csv")  # the dataset
# print(dt.head(0))
train, test = train_test_split(dt)

# print(train.shape)
# print(test.shape)

train_X = train[["chroma_stft", "spec_cent", "spec_bw", "rolloff", "zcr", "mfcc"]]
train_y = train.prognosis

test_X = test[["chroma_stft", "spec_cent", "spec_bw", "rolloff", "zcr", "mfcc"]]
test_y = test.prognosis

# knn
model = KNeighborsClassifier(n_neighbors=3)
model.fit(train_X, train_y)

val = np.array([chroma_stft, spec_cent, spec_bw, rolloff, zcr, mfcc])
val = val.reshape(1, -1)
prediction = model.predict(val)
print(prediction)
```

Figure IV 6 average extracted features

5.2) Results

In order to determine the value of k in which the classification is better, we decided to test and evaluate the model using accuracy scales with each of the variables 3,5,7 or 10 for K. The following figure illustrates this.

```
K=3
model = KNeighborsClassifier(n_neighbors=K)
model.fit(train_X, train_y)

val = np.array([chroma_stft, spec_cent, spec_bw, rolloff, zcr, mfcc])
val = val.reshape(1, -1)
prediction = model.predict(val)
test_y=print(prediction)
print(metrics.accuracy_score(test_X, test_y))
```

Figure IV 7 accuracy extraction code

After running the script on all the selected values of K, the evaluation result appears in the following table:

Number K	Accuracy
3	62.1%
5	73.8%
7	83.4%
10	75.6%

Table IV 2 Accuracy

5.3) Discussion

Cough is one of the most important symptoms in clinical trials of the respiratory system, while objective indicators of cough severity are severely absent. It cannot be measured accurately due to technical conditions.

We wanted to enter the adventure and try in this field, despite the difficulties we faced due to the lack of database and the lack of information on the disease, which is unstable and is still developing.

For this, we used functions found in library Liberosa to help us extract the features from the cough sound and then enter these features into the KNN model in order to train it to classify the cough between a sick person or not.

After training the model several times and each time we change the value of k until we reach an acceptable result, which is 83.4%.

Conclusion

COVID-19 is a large-scale contagious respiratory disease that has spread across the world in 2020. Therefore, a low-cost, fast, and easily available solution is needed to provide a COVID-19 diagnosis to curb the outbreak. According to recent studies, one of the main symptoms of COVID-19 is coughing. The goal of this research effort is to develop a method for the automatic diagnosis of COVID-19 by detecting cough during recorded conversations.

Chapter 05:
Proposed Model for COVID-19 Detection from Recorded Cough

1. Proposed Method for COVID-19 Detection from Cough or chest x-ray:

In this dissertation, the main point and interesting issue treated which has considerated COVID-19 pandemic triage for a high influx of patients with typically moderate-to-severe clinical suspected symptoms of COVID-19 pneumonia. The extremely use of PCR for extent and morphology of pneumonia permitted a clear observation and agreement for clinical management, however the limited service of healthcare offered by our country interlock the diagnostic and the given response in the desired time, which lead to an increase in the number of PCR test answer that significantly augmented when they transfer it to restricted laboratory agreed by the government. This centralization of required test answer has yielded the process of prognostic diagnostic very slow which can drive to the increase of contagious Covid-19 cases, as result it will contribute for repetitive peak. As the current status of Algerians hospitals, reanimation services have very limited places for comatose cases, systematically this will conduct a very tough situation.

The major source of conflict for using PCR based protocol was the frequency and the load requested in compare the number of centers approved by the state for elaborating the test.

As citizens in first position and developers, This project has explored the amount of research realized in this axe to seek a solution to diminish the pandemic in Algeria with , more than testing kit becomes unavailable due to the high demand, challenges remain an open key in research field. In addition, the high false negative rates ,the sensitivity of elaborating the test delays in processing, unpredictability in test techniques, and sometimes the precision reported as low as 60–70%.[Pasteur institute,2021]

As the initial surveillance activities in this pandemic, the application proposed of this work propose an AI model based infection control measures in healthcare establishments to delineate Covid-19 indications from two data: {Cough as preliminary test, X-rays as second checking up }.

This prospective study, conducted among healthcare services and citizens patient with laboratory-confirmed coronavirus infection (COVID-19) receiving care, it has the following main objectives:

1. Better understand the extent of human-to-human transmission among citizens contact, by estimating the probability of first test infections 1 through recorded cough using mobile for initial checking-up;

2.Process the cough recorded and give an initial rate as suspect Covid-19 patient or Normal case;

3.Once the patient is suspected by Covid-19, it should be requested for taking X-rays scan;

4.Analyze the x-rays scan and process it via X-rays based AI model;

5. Characterize the range of clinical scan with delineating infection and infectious risk factors in x-rays;

6. To assess the effectiveness of the model based AI for infection control measures, many metrics provided;

7. Evaluate the effectiveness of infection percentage within true and false positive scans visually.

The no obvious reasons (e.g. age, disease extent historic pathology, etc.). Such observation emphasizes the need to define the clinical indications from a recorded cough as the first position examination and x-rays scan imaging modality as confirmation examination result. In fact, weakly defined criteria may unfairly raise the number of X-rays scans after recorded cough, with potential damaging effects on the workflow and healthcare safety.

In order to evaluate the clinical implications of Covid-19 based on two data: recorded cough and imaging modalities{X-rays}, the sensitivity, the specificity, and the prognostic value will be compared in the following sections with previous models illustrated with references. The level of precision for the proposed pipeline have improved in accuracy with previous findings Ref.[9, 16, 17, 19].

2. Proposed Pipeline:

In this paper we dealt with the main points and an interesting topic that was taken into consideration especially in the COVID-19 pandemic is the large influx of patients to the hospital which helps its spread, because patients and non-patients want to prevent it. Vaccine or other treatment.

The use of PCR for the extent and morphology of pneumonia has allowed clear observation and agreement on clinical management, yet the limited healthcare service provided by our country is intertwined between diagnosis and response given in the required time, resulting in an exponential increase in the number of PCR test answers Double when transferred to government approved restricted laboratory.

Given the current situation of Algerian hospitals, resuscitation services have very limited places for comatose cases, and this will systematically lead to a very difficult situation. As a result, you will contribute to reaching the peak due to the large number of wounded in one hall.

After all these conditions we live in, we believe that we can bring technology into the working life of this deadly disease. We divided our work into two methods, the first is the examination by coughing, and the second is by treating an x-ray image of the chest, the following image illustrates this:

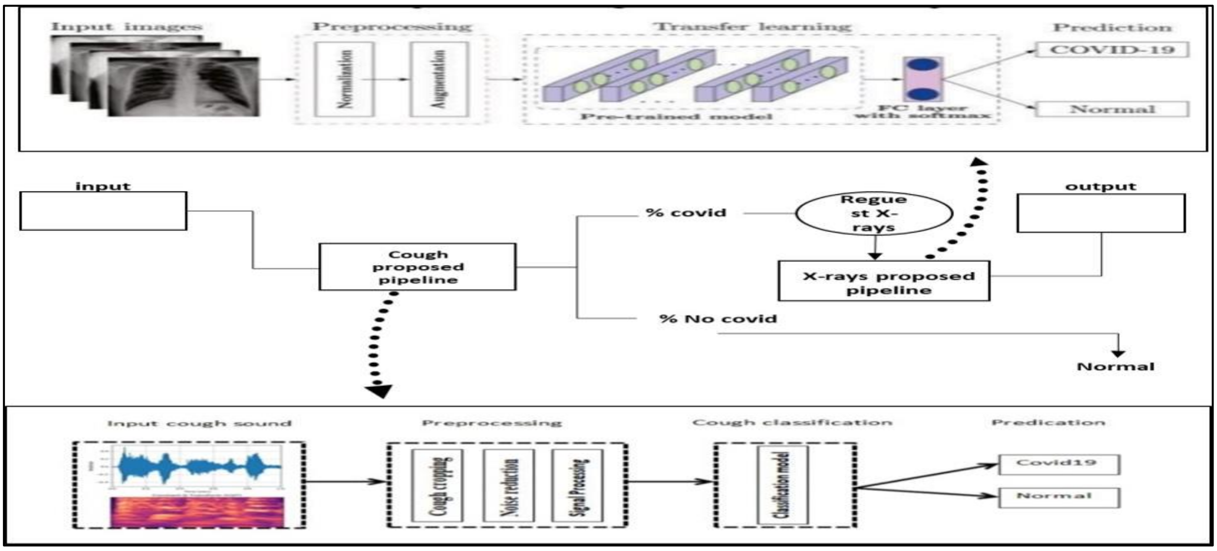


Figure V 1 Proposed Pipeline

2.1 The first method:

We used deep learning and machine learning and used many experiments on a set of models, and after a period of training and testing, we came to an acceptable result for detecting COVID-19 through the cough of a sick person. This step gives us a service, which is to reduce the proportion of people who will come to the hospital, through A person who can test himself while he is at home, this is by coughing the patient three times on the application in his phone, and waits some time for his cough to be Processing and the result is either above the threshold or below, if the prediction rate is above the threshold, he will be called to Hospital, this is to complete treatment.

2.2 The second method:

we used deep learning, machine learning and some of the cnn models that we mentioned in the previous chapter in detail, after the patient has completed the test and the result shows that he must go to the nearest hospital to complete the treatment, for this we decided to add another idea to help doctors diagnose patients and reduce it time, using Models trained on x-ray images of many patients with COVID-19, you can find this in the previous section for more understanding.

In the end, we see that we have reached the desired goal, which is that the first method is based on the diagnostic test for the disease that contributes to not many people coming to the hospital, and the second is to help doctors diagnose the patient.

3. Evaluation of Proposed Pipeline :

3.1 Confusion Matrix

The Confusion matrix is the easiest and intuitive metrics used for finding the accuracy of the model. The main used is for Classification problem where the output can be of two or many types of classes.

CM is a table with two dimensions (“Predicted” and “Actual”), and groups of “classes” in both dimensions. Our Predicted ones are rows and Actual classifications are columns. CM in itself is not a performance measure as such, but almost all of the performance metrics are based on Confusion Matrix and the numbers inside it. [27]

Predicted Class

True class

	P	**N**
P	True positives (TP)	False positives (FP)
N	False négatives (FN)	True négatives (TN)

Figure V 2 Confusion matrix

3.1.1 Confusion matrix Terms

- **False Negatives (FN):** False negatives are the cases when the actual class of the datapoint was 1 (True) and the predicted is 0 (False). False is because the model has predicted incorrectly and negative because the class predicted was a negative one (0).

- **True Positives (TP):** True positives are the cases when the actual class of the data point was 1 (True) and the predicted is also 1 (True)

- **False Positives (FP):** False positives are the cases when the actual class of the datapoint was 0 (False) and the predicted is 1 (True). False is because the model has predicted incorrectly and positive because the class predicted was a positive one (1)

- **True Negatives (TN):** True negatives are the cases when the actual class of the datapoint was 0 (False) and the predicted is also 0(False). [27]

3.1.2 Classifier Evaluation Metrics

3.1.2.1 Accuracy

Accuracy in classification problems is the number of correct predictions made by the model over all kinds predictions made.[27]

Predicted Class

+

True class

	P	**N**
P	True positives (TP)	False positives (FP)
N	False négatives (FN)	True négatives (TN)

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN}$$

Figure V 3 Accuracy Formula

When to use Accuracy?

Accuracy is a good measure when the target variable classes in the data are nearly balanced.

When NOT to use Accuracy

Accuracy should NEVER be used as a measure when the target variable classes in the data are a majority of one class. [27]

3.1.2.2 Precision

Precision is a measure based on CM that tells us what proportion of patients that we diagnosed as having corona and actually had corona. The predicted positives (People predicted as coronavirus are TP and FP) and the people actually having a corona are TP. [27]

Predicted Class

True class		**P**	**N**
	P	True positives (TP)	False positives (FP)
	N	False négatives (FN)	True négatives (TN)

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

Figure V 4 Precision Formula

3.1.2.3 Recall

Recall is a measure that tells us what proportion of patients that actually had corona was diagnosed by the algorithm as having corona. The actual positives (People having corona are TP and FN) and the people diagnosed by the model having a corona are TP. (Note: FN is included because the Person actually had a corona even though the model predicted otherwise). [27]

Predicted Class

True class		**P**	**N**
	P	True positives (TP)	False négatives (FN)
	N	False positives (FP)	True négatives (TN)

$$\textbf{Recall} = \frac{TP}{TP+FN}$$

Figure V 5 Recall Formula

3.1.2.4 Specificity

Specificity is a measure that tells us what proportion of patients that did NOT have corona , were predicted by the model as non-coronavirus. The actual negatives (People actually NOT having corona are FP and TN) and the people diagnosed by us not having caorona are TN. (Note: FP is included because the Person did NOT actually have corona even though the model predicted Specificity is the exact opposite of Recall. [27]

Predicted Class

		P	**N**
True class	**P**	True positives (TP)	False négatives (FN)
	N	False positives (FP)	True négatives (TN)

$$\textbf{Specificity} = \frac{TN}{TN+FP}$$

Figure V 6 Specificity Formula

3.1.2.5 Dice score

The Dice similarity coefficient, also known as the Sorensen–Dice index or simply Dice co-efficient, is a statistical tool which measures the similarity between two sets of data. This index has become arguably the most broadly used tool in the validation of image segmentation algorithms created with AI

$$Dice = \frac{2 \times TP}{(TP + FP) + (TP + FN)}$$

Figure V 7 Dice Formula

3.1.2.6 The F1 score

The F1 Score is a number between 0 and 1 and is the harmonic mean of precision and recall. [28]

$$F_1 = 2 * \frac{precision * recall}{precision + recall}$$

Figure V 8 F1 score Formula

3.2 X-rays :

We script in figure V.9 a code for testing and evaluate the model with Confusion Matrix

```
# Confusion Matrix  & Pres  & Recall   & F1-Score

target_names = ['COVID+', 'COVID-']
label_names = [0,1]

Y_pred = model.predict_generator(testdata)
y_pred = np.argmax(Y_pred ,  axis = 1)  #max high level pred

cm = confusion_matrix(testdata.classes, y_pred, labels = label_names)


print('Confusion Matrix')
print(confusion_matrix(testdata.classes, y_pred))

print('classification_Report')
print(classification_report(testdata.classes, y_pred, target_names=target_names))

disp = ConfusionMatrixDisplay(confusion_matrix= cm, display_labels=target_names)
disp = disp.plot(cmap=plt.cm.Blues, values_format = 'g')
plt.show()
```

Figure V 9 Confusion Matrix

After running the script the result of the evaluation appear in figure V.10

```
Confusion Matrix
[[30 29]
 [29 30]]
classification_Report
              precision    recall  f1-score   support

      COVID+       0.51      0.51      0.51        59
      COVID-       0.51      0.51      0.51        59

    accuracy                           0.51       118
   macro avg       0.51      0.51      0.51       118
weighted avg       0.51      0.51      0.51       118
```

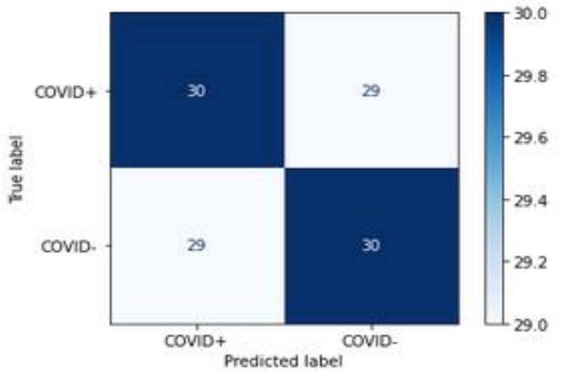


Figure V 10 Result of Confusion Matrix

The following table presents the results of the two articles mentioned in the previous chapter and the results obtained by us.

	Accuracy
Article 1	89.00%
Article 2	94.00%
Our method	96.88%

Table V 1 Accuracy of X-rays

3.3 cough :

The following table presents the results of the two articles mentioned in the previous chapter and the results obtained by us.

	Accuracy
Article 1	83.00%
Article 2	80.00%
Our method	83.4%

Table V 2 Accuracy of cough

4. Performance of Proposed Model

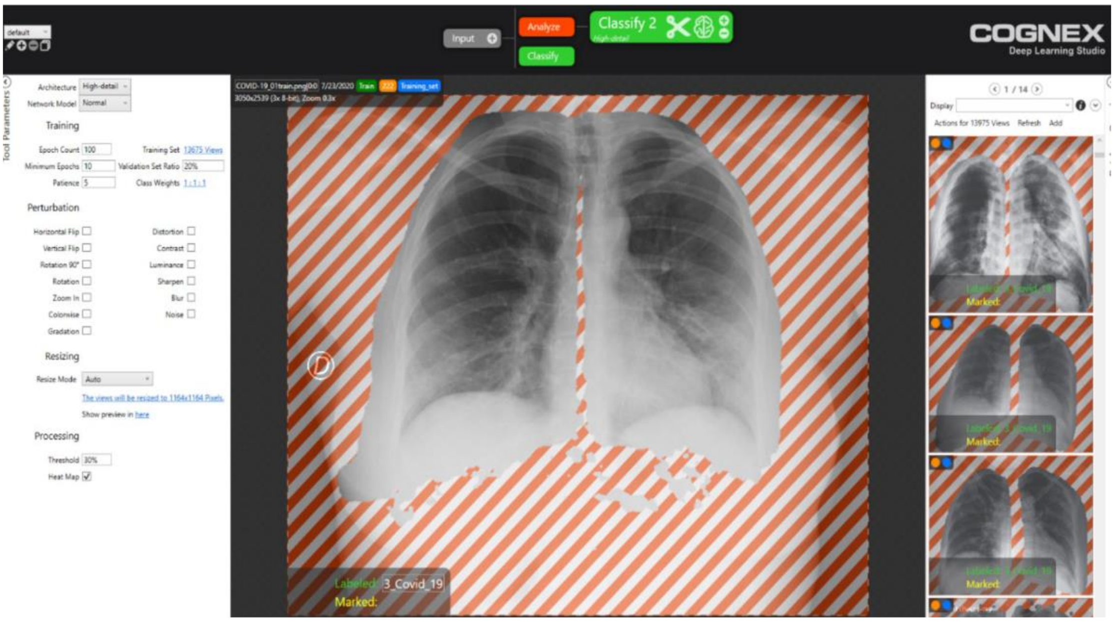


Figure V 11 The main interface

5. Results and discussion

After the emergence of the Corona epidemic and its terrible spread, several research and commercial institutions set out to find solutions to limit its spread or find a treatment for it.

That is why we have introduced deep machine learning and benefited from it in this field, by creating two methods mentioned above in detail. The first is to detect the epidemic from the sound of coughing, and the second is to detect and diagnose the disease from a image chest x-ray.

After doing several exercises and implementing different methods to test the results obtained in order to improve the discovery of the first or second method.

In the end, we can say that the results obtained were acceptable, which amounted to 83.4% for the detection of corona from the sound of coughing, and for the detection of the disease from the X-ray image, it reached 96.88%

6. Loss function and Accuracy Function

Figure V.12 represents training Loss Function over Epoch:

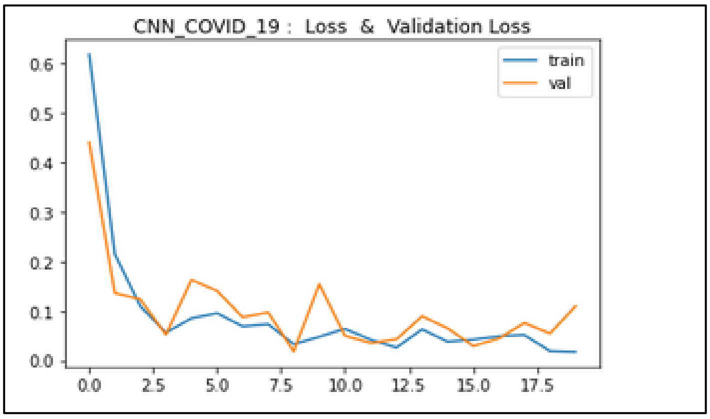


Figure V 12 Loss & Validation loss

Figure V.13 represents training Accuracy Function over Epoch:

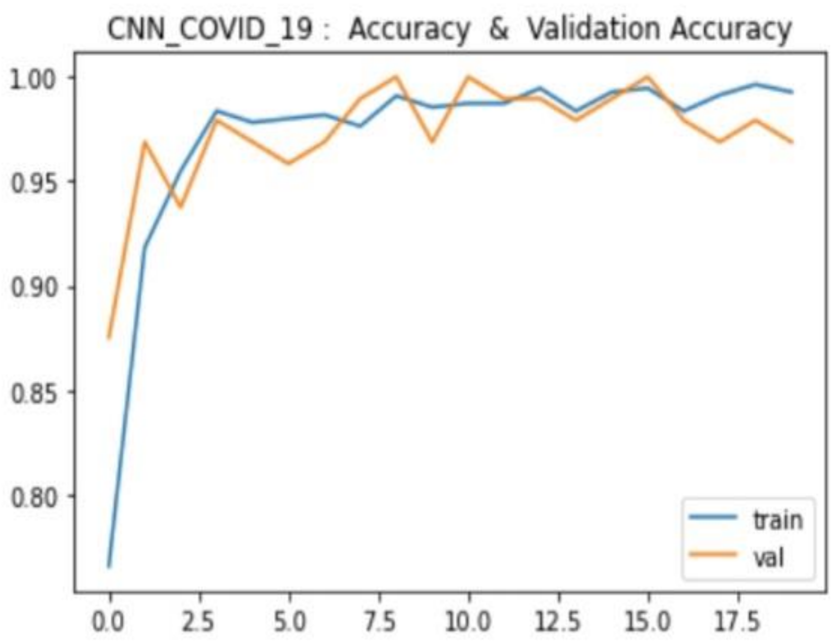


Figure V 13 Accuracy & Validation Accuracy

Conclusion

The limitations of this study include scattered sample size of the patients with positive cough record findings and short follow up period. In addition, the audio recorded between cough obtained was not uniform in all patients which may have led to undiagnosed abnormalities. And the lack of correlation between cough recorded and cough findings.

General Conclusion

Coronavirus disease 2019 (COVID-19) has recently become an unprecedented public health crisis worldwide **[Alimadadi A ,2020].** Unknown respiratory disease has affected many patients and has appeared in Wuhan, Hubei Province, China by the late of month of December 2019.

At the end of December 2019, patients with a previously unknown respiratory disease were identified in Wuhan, Hubei Province, China **[36]**. In January 25, 2020, the diagnosis of COVID-19, with the confirmation of more than 1975 patients since the hospitalization of first patient was on December 12, 2019. A new coronavirus named severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) has discovered and resulted COVID-19**[37] [36].**

The proposed framework has built up by including recorded audios from dataset XXX which consecutively take as input an audio then it has been processed and analyzed by a model based AI to classify this audio with illustrating a probability of having Covid-19, then if the patient recorded cough demonstrates high probability so this patient will be considered as suspect case, the checking up requires more precision, the system will demand a Chest X-rays image scan, another process will have part to diagnostic this patient ,the proposed system work as follows:

Phase 1: Request an audio record, Apply the model based AI to analyze the recorded audio, after a probability shows the percentage of covid-19 infection;

Training phase has.............audios, Testing phase has ....audios;

Phase 2:If the probability of audio show high level of disease, Chest X-rays image processing model should been processed

Training phase has.............audios, Testing phase has ....audios; The modification of model was elaborated in Preprocessing phase, The results of this system were externally validated in .... patients images scans and tested on .... patients images scans

This retrospective study was approved by the following datasets: ....for coughs and ....for images scans. Informed consent samples were tested as cross validation test.

General conclusion

Limitation of this work

This study has been deviated from axe point to another regarding to several issues have faced us for working on the first problematic. This last has devoted to collect Algerian data, to see and observe a local parameters and obtain insights study on own data, also this study helps well the healthcare service to attain peaks as we know the low level of hospitals and reanimation rooms. A lot of obstacles have been part for not having this work to take place, we cite some of them:

-This study to be realized in high standards needs means and time throughout many barriers limit the progress of the proposed aim work;

- The correlation and confusion has appeared in this new form of virus which result a variety of symptoms, meanwhile there is a derivation asymptomatic;
- The sensitivity of finding volunteer to incorporate for building Algerian Dataset ,I can refer this issue whether to the sensibility of this disease and its rapid speed for propagation or distrust to building a local Computer Aided for Diagnostic.
- The cooperation has been supported by government to find solution for current pandemic as Algerians citizens life has low level in healthcare service.
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Future work and Perspective

In this dissertation, as final year Msc students, tend to reveal the potential of Deep Learning models for the challenging recent topic of COVID-19 detection on Chest X-rays images and the newest research axe which is cough. We as well emphasize that two different modalities of data with larger and more diverse datasets compared in State of the art of each modalities and show the efficiency of this system. In order to evaluate and perform the methods using in both models with a more realistic manner if we tend to rely on Computer Aided for Diagnosis in Algeria.

As a future research path, we intend to build a local dataset images and recorded coughs from all over cities in Algeria centers, regarding to attempt covering our healthcare sector, ethnic groups dedicated for volunteering tasks and acquisition data and thus, properly to validate the proposed CAD.

Bibliography

[1]: Aykanat M, Kılıç Ö, Kurt B, Saryal S. Classification of lung sounds using convolutional neural networks. *EURASIP J Image Video Process*

[2] *:* Azam MA, Shahzadi A, Khalid A, Anwar SM, Naeem U. Smartphone based human breath analysis from respiratory sounds. In: *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. Honolulu, HI: IEEE;

[3]: Liu YX, Yang Y, Chen YH. Lung sound classification based on Hilbert-Huang transform features and multilayer perceptron network. In: *2017 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC)*. Kuala Lumpur: IEEE;

[4] [Khaoula DRID, Oumkalthoum ZOUAOUI]"Object detection and recognition from images," University of KasdiMerbah Ouargla, Ouargla.

[5] [Li Liu, Wanli Ouyang, Xiaogang Wang, Paul Fieguth, Jie Chen, Xinwang Liu, Matti Pietikäinen]"Deep Learning for Generic Object Detection," International Journal of Computer Vision,

[6] [VěraKůrková, Yannis Manolopoulos, Barbara Hammer, LazarosIliadis, IliasMaglogiannis]Artificial Neural Networks and Machine Learning – ICANN: International Conference on Artificial Neural Networks, Rhodes, Greece, Proceedings, Part I, Springer International Publishing .

[7] A Guide to Convolutional Neural Networks for Computer Vision, Morgan & Claypool .

[8] An, J. and Cho, S. Variational autoencoder based anomaly detection using reconstruction probability. SNU Data Mining Center, Tech. Rep.

[9] E. E.-D. Hemdan, M. A. Shouman, and M. E. Karar, “COVIDX-net: a framework of deep learning classifiers to diagnose COVID-19 in X-ray images,” 2020, https://arxiv.org/abs/2003.11055. View at: Google Scholar

[10] https://arxiv.org/abs/2009.08790

[11] https://ieeexplore.ieee.org/abstract/document/9414576

[12] https://innovations.bmj.com/content/7/2/356.abstract

[13] https://www.biospace.com/article/a-roundup-of-new-covid-19-research/

[14] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7318970/

[15] https://www.tandfonline.com/doi/full/10.1080/19466315.2021.1880966

[16] https://www.who.int/health-topics/coronavirus#tab=tab_1

[17] Kurt Demaagd, Anthony Oliver, Nathan Oostendorp, Katherine Scott, Practical Computer Vision with SimpleCV: The Simple Way to Make Technology See, O'Reilly Media.

[18] Mohammed Sunasra , Performance Metrics for Classification problems in Machine Learning, https://medium.com/thalus-ai/performance-metrics-for-classificationproblems- in-machine-learning-part-i-b085d432082b

[19] Munawar, A., Vinayavekhin, P., and De Magistris, G. Limiting the reconstruction capability of generative neural network using negative learning. arXiv preprint arXiv:1708.08985.

[20] Munawar, A., Vinayavekhin, P., and De Magistris, G. Spatio-temporal anomaly detection for industrial robots through prediction in unsupervised feature space. In Applications of Computer Vision (WACV), IEEE WinterConference on, pages 1017–1025. IEEE.

[21] Rafel C Gonzalvez, Richard E Woods, Digital Image processing, prantice hall.

[22] Rahul Agarwal , The 5 Classification Evaluation metrics every Data Scientist must know,

[23] S. Fei, Y. Gao, J. Wang, and W. Shi, “Lung infection quantification of COVID-19 in CT images with deep learning,” 2020, https://arxiv.org/abs/2003.04655. View at: Google Scholar

[24] S. H. Kassania, P. H. Kassasnib, and J. Michal, “Automatic detection of coronavirus disease (COVID-19) in X-ray and CT images: a machine learning

based approach," 2020, https://arxiv.org/abs/2004.10641. View at: Google Scholar

[25] Salman Khan, Hossein Rahmani, Syed Afaq Ali Shah, Mohammed Bennamoun

[26] tekalp, A. Murat, Digital video processing, Prantice Hall.

[27] Xu, H., Chen, W., Zhao, N., Li, Z., Bu, J., Li, Z., Liu, Y., Zhao, Y., Pei, D., Feng, Y., et al. Unsupervised anomaly detection via variational autoencoder for seasonal kpis in web applications. In Proceedings of the 2018 World WideWeb Conference on World Wide Web, pages 187–196. International World WideWebConferences Steering Committee.

[28] Zhao S, Lin Q, Ran J, Musa SS, Yang G, Wang W, Lou Y, Gao D,Yang L, He D (2020) Preliminary estimation of the basic reproduction number of novel coronavirus (2019-nCoV) in China, from2019 to 2020: a data-driven analysis in the early phase of the outbreak. Int J Infect Dis 92:214–217

[29] **[Postom JT,2020]**Poston JT, Patel BK, Davis AM. Management of Critically Ill Adults With COVID-19. JAMA 2020.

[30] **[WHO,2020]** World Health Organization: Director-General's opening remarks at the media briefing on COVID-19 - 29 June 2020. 2020 [cited April 1, 2020]; Updated March 11, 2020]. Available from: https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200629-covid-19-sitrep-161.pdf?sfvrsn=74fde64e_2;

[31] **[LID,2020]**The Lancet Infectious D. Challenges of coronavirus disease 2019. Lancet Infect Dis 2020: 20(3): 261.

[32] **[Blazic I,2020].**Blazic I, Brkljacic B, Frija G. The use of imaging in COVID-19-results of a global survey by the International Society of Radiology. Eur Radiol 2020.

[33] **[Sverzellati N,2021]** Sverzellati N, Ryerson CJ, Milanese G, et al. Chest x-ray or CT for COVID-19 pneumonia? Comparative study in a simulated triage setting. Eur Respir J 2021; in press (https://doi.org/10.1183/13993003.04188-2020).

[34] **[Huergo,,2021]**Huergo, Maria Ana Cristina and Thanh, Nguyen Thi Kim, journal of "Analyst",title ="Current advances in the detection of COVID-19 and evaluation of the

humoral response", publisher ="The Royal Society of Chemistry", doi ="10.1039/D0AN01686A", url ="http://dx.doi.org/10.1039/D0AN01686A",2021.

[35] **[Alimadadi A ,2020]**Alimadadi A, Aryal S, Manandhar I, Munroe PB, Joe B, Cheng X ,(2020) Artificial intelligence andmachine learning to fight COVID-19. American Physiological Society Bethesda, MD.

[36] **[Wu F, Zhao S,2020]**Wu F, Zhao S, Yu B, Chen Y-M, Wang W, Song Z-G, Hu Y, Tao Z-W, Tian J-H, Pei Y-Y (2020) A new coronavirus associated with human respiratory disease in China. Nature 579(7798):265–269

[37] **[ChinazziM,,2020]**ChinazziM, Davis JT, Ajelli M, Gioannini C, LitvinovaM, Merler S, y Piontti AP, Mu K, Rossi L, Sun K (2020) The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. Science 368 (6489):395–400

[38] **[Pereira RM, 2020]**Pereira RM, Bertolini D, Teixeira LO, Silla CN Jr, Costa YM (2020) COVID-19 identification in chest X-ray images on flat and hierarchical classification scenarios. Comput Methods Prog Biomed 194:105532

[39] **[Robson B , 2020]**Robson B (2020) Computers and viral diseases. Preliminary bioinformatics studies on the design of a synthetic vaccine and a preventative peptidomimetic antagonist against the SARS-CoV-2 (2019-nCoV, COVID-19) coronavirus. Comput Biol Med 119:103670

[40] **[Ozturk T, 2020]**Ozturk T, Talo M, Yildirim EA, Baloglu UB, Yildirim O, Acharya UR (2020) Automated detection of COVID-19 cases using deep neural networks with X-ray images. Comput BiolMed 121:103792