Fast Detection of Covid-19 using Deep Learning

Project report submitted in partial fulfilment for the degree of Bachelor of Technology
in

“Computer Science and Engineering”

by

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Candidate's Declaration

I hereby declare that the work presented in this report entitled **"**Fast Detection of COVID-19 using Deep Learning**"** in partial fulfilment of the requirements for the award of the degree of **Bachelor of Technology** in **Computer Science and Engineering** submitted in the department of Computer Science & Engineering and Information Technology**,** Jaypee University of Information Technology Waknaghat is an authentic record of my work carried out over a period from January 2021 to May 2021 under the supervision of Dr. Pradeep Kumar Gupta (Associate Professor, Computer Science & Engineering and Information Technology (CSE&IT)).

The matter embodied in the report has not been submitted for the award of any other degree or diploma.

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This to certify that the above statement made by the candidates is true to the best of my knowledge.

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Associate Professor

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Acknowledgment

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List of Abbreviations

ROC = Receiver operating characteristics

CNN = Convolutional Neural Network

AUC = Area Under Curve

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Abstract

Most part of the world has witnessed a pandemic caused by the novel coronavirus or SARS-COV-2. Many countries have tried shutting down mass gatherings and citizens have tried staying indoors because of the exponentially increasing number of cases of this disease. But after all that, this sort of increase in the number of patients is overwhelming the healthcare systems across the world. There are limited testing kits, it is not feasible for such a large number of patients with respiratory illness to be tested using conventional techniques (RT-PCR). Healthcare needs advancement in technology for enhancing testing methodologies and deep learning has proved its benefits by automating the analysis of medical images. With the use of deep learning algorithms, the project aims to develop an algorithm for COVID-19 detection which is faster and more precise than existing methodologies of testing, explicitly, the project uses VGG-19 network which when applied onto the images of lungs, features like shadowy patches are detected in the X-ray images.

CHAPTER 1 : INTRODUCTION

1.1 Introduction

The coronavirus, which originally appeared in Wuhan City, China in December 2019, spread rapidly around the world and became a pandemic. It has had an overwhelming effect on our daily lives, general well-being, and the global economy. In order to prevent the further spread of this scourge and to treat affected patients quickly, it is important to identify the positive cases as ahead of schedule as could reasonably be expected. As there are no specific mechanized toolboxes available analytical instruments for helpers have grown. Deep learning is one of the most effective Artificial Intelligence strategies for powerful and accurate COVID-19 screening to analyze chest X-ray images. The coronavirus affects an individual's respiratory system and causes white patchy shadows in the lungs that can be seen by lung X-ray images. Late findings using techniques of radiology imaging indicate that such images provide exceptional COVID-19 infection information. For the precise detection of this infection, the use of cutting-edge computerized reasoning (AI) procedures combined with radiological imaging may be beneficial and can also be effective in conquering the problem of the absence of particular doctors in remote cities. Another model for COVID-19 identification using chest X-ray images is provided in this report. The proposed model is designed to provide the binary classification (COVID and No-Findings) of the disease with correct diagnostics.

There are a few desirable conditions for the use of X-Ray over conventional scientific tests:

1. Convenient X-Ray scanners, not at all like CT scans, often empower research within a seclusion ward itself thus reducing the need of extra Personal Protective

Equipment (PPE), a very unusual and valuable advantage in this case. It also eliminates the risk of pollution received from the clinic.

2. Transferring specialized X-Ray images would not require any transportation from the point of diagnosis to the point of examination, thereby rendering the indicative process very brisk.

3. X-Ray imaging is much more unrestricted and financially savvy than the normal demonstrative experiments.

In the modern world, radiographs are deciphered by non-radiologists by and large. In addition, given the oddity of the virus, a large percentage of radiologists themselves may not be familiar with all of the disease's subtleties and may be insufficient to accommodate them. Capacity to conduct extremely reliable analysis. The key commitment of this work is to propose a new paradigm focused on a deep neural framework for the extremely detailed detection of COVID-19 contamination from patients' chest X-Ray images.

Real-time reverse transcription-polymerase chain reaction is the most general and popular research method used for COVID-19 diagnosis (RT-PCR). For example, radiological imaging of the chest, registered tomography (CT) and X-ray play an important role in the early diagnosis and treatment of this disease[1]. Regardless of if unfavorable findings are produced, side effects can be detected by observation due to the low RT-PCR affectability of 60 percent-70 percent. CT is a sensitive technique for the detection of COVID-19 pneumonia, which can be treated as an RT-PCR screening apparatus. As of late, the use of AI techniques for programmed determination in the clinical area has achieved renown by being a subordinate device for clinicians. Deep learning, which is a well-known computerized reasoning (AI) research area, allows models to start and finish to produce assured results using input data. It’s procedures have been solicited in numerous issues, as in, arrhythmia detection, skin cancer classification [3], breast cancer detection [4], brain disease classification [5], pneumonia detection from chest X-ray images [6], fundus image segmentation [7], and lung segmentation [8].

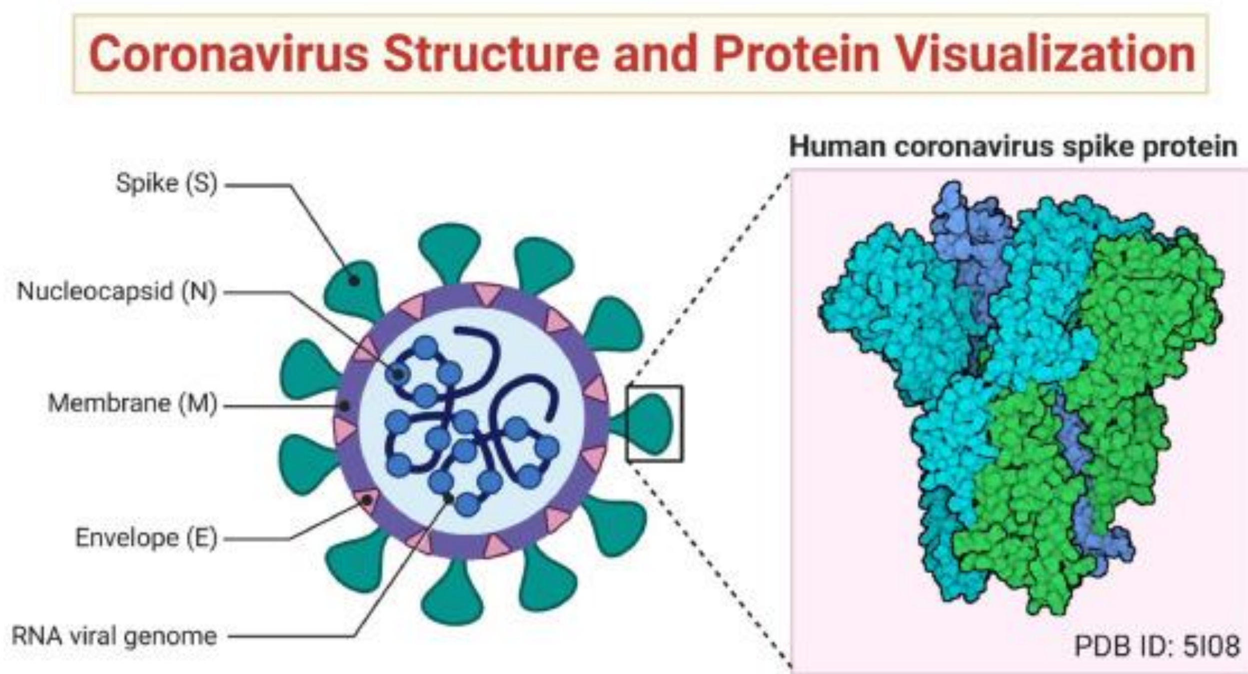

Fig. 1 Coronavirus Structure and Protein Visualization

The meteoric rise of the COVID-19 scourge has required the need for skill in this area. This has raised interest for the development of mechanized position systems that depend on Ai applications. Because of the specific amount of radiologists, it is a shifting assignment to send primary clinicians to every treatment center. Easy, reliable, and strong AI systems may be productive along those same lines to overcome this problem and provide patients with momentous assistance. The AI developments in radiology can be helpful in gaining accurate evaluation, considering the fact that radiologists take on a prominent place due to their tremendous presence in this area. AI methods, for example, missing a range of available RT-PCR testing kits, test prices, and keeping up time of test results, may also be useful in filtering out hindrances.

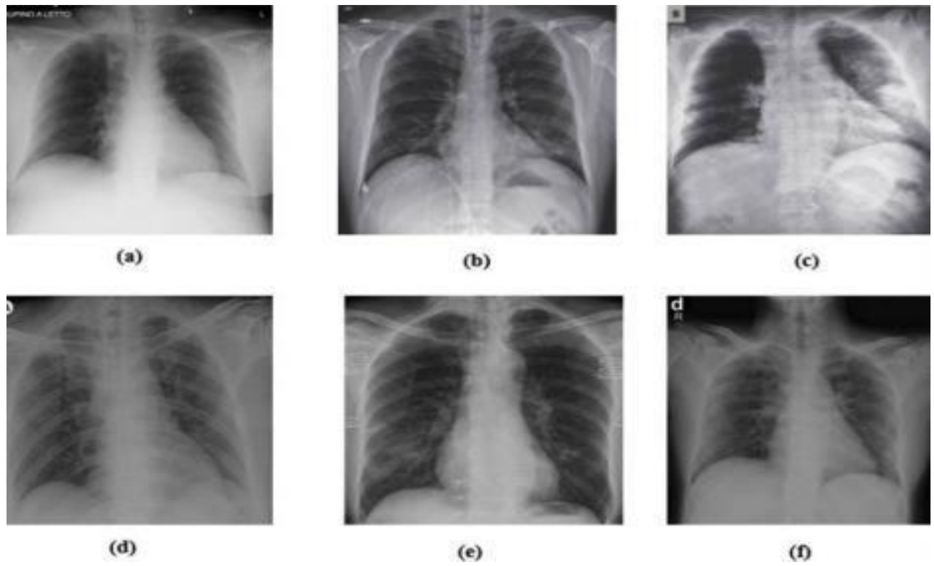

Fig. 2: Some X-ray images from dataset

1.2 Origin of the challenge

In patients of this disease, a terrific rise in impacted urban areas occurred outside the Hubei area during the second half of this January 2020 in consideration of the population growth. Following an accelerated growth until January 23, 2020, the burst extended to

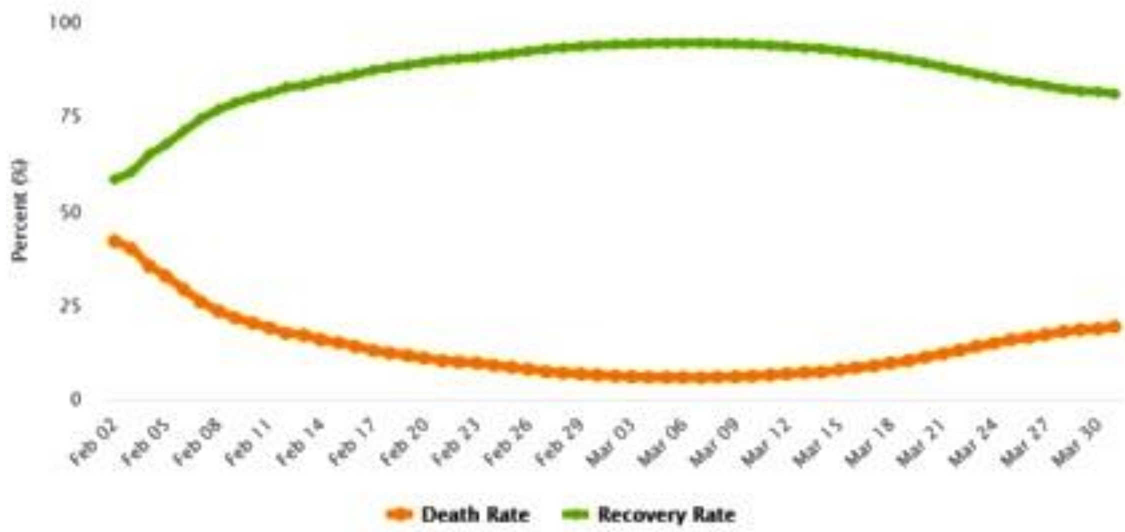

Fig 3. Death and recovery rate of COVID-19

numerous countries, taking widespread account of it around the world. The proximity of human exposure through particles, and touch has been confirmed by data from classes of infected relatives and clinical specialists. There is really no strong evidence of intra - uterine infection up to this point.

Evaluations show that COVID-19 has a 3-day middle incubation period, Symptomless propagation with promise. Towards the end of January 2020, more than 10000 cases of COVID-19 pollution across China were recorded by WHO[30].Medically examined reports and laboratory-affirmed cases were included in official records because chest CT results are diagnosis and Care Programme of 2019 New Coronavirus Pneumonia proposed as the major evidence for scientifically affirmed cases by National Health and Health Commission of China in 2020. As of February 19, 2020, this increased to a total of 74,280 affirmed cases in China and 924 approved cases in 24 countries elsewhere outside of China, and a total in about 2009 transfers. Sustainable prediction and regulation forecasts must include early detection, inference, fast diagnosis, and separation to round horizontal transmission to manage COVID-19, as well as decreasing optional infection among near contacts and workers of clinical services.

1.3 Problem Statement

Many innovative screening algorithms have been proposed to classify potential cases of COVID-19 following the recent unexpected increase of COVID-19 infections across the globe. CNNs are proves to be working well in the research field for X-ray image classification for Covid, but there are limitations to CNN which are yet to be addressed. Not enough RT-PCR tools are available in these nations. It takes too long to get the COVID-19 outcomes in hand, even though there are, and determine whether or not to quarantine an individual. In comparison, only restricted open-source programs that utilize chest X-ray files are accessible for use [9].

CHAPTER 2 : LITERATURE SURVEY

Chinese healthcare facilities had poor research units at the outset of the pandemic, that are now producing a high incidence of fraudulent negative outcomes, but specialists are advised to make a decision based on the results of clinical and chest CT. In nations such as Turkey, where a limited number of test sets were available at the onset of the pandemic, CT is commonly used for COVID-19 identification.

Clinicians in imaging inquiries of COVID-19 have noted tremendous revelations. Kong et al.[10] observed the right airspace opacity in a person with COVID-19. Yoon et al.[13] detailed that in the lower left lung region, one of every 3 participants examined reported single nodular obscuration. Alternatively, with in two lungs, the remaining two contained 4 to 5 volatile opacities.

In certain patients, Zhao et al. [11] not only discovered ground-glass opacities (GGO) or blended GGO, but also detected coalescence and vascular expansion in the injury. As daily CT outlines of COVID-19 cases, Li and Xia [12] declared GGO and unification, interlobular septal thickening and airflow bronchogram indicator, even without vascular growth. Another experience is fringe primary or multifocal GGO affecting the 2 lungs in half of 75% of patients [25]. In comparison, Chung et al. and Zu et al. [1] find that there could be modified lung opacities for 33 percent of chest CTs. Chest X-ray photographs taken on days 1, 4, 5 and 7 for a 50-year-old COVID-19 patient with pneumonia are provided in Figure 3, and explanation of all these images is also provided.

[22],[23] and [24] highlight the major development of AI for healthcare demands caused by the efficient use of deep-learning and machine-learning techniques.

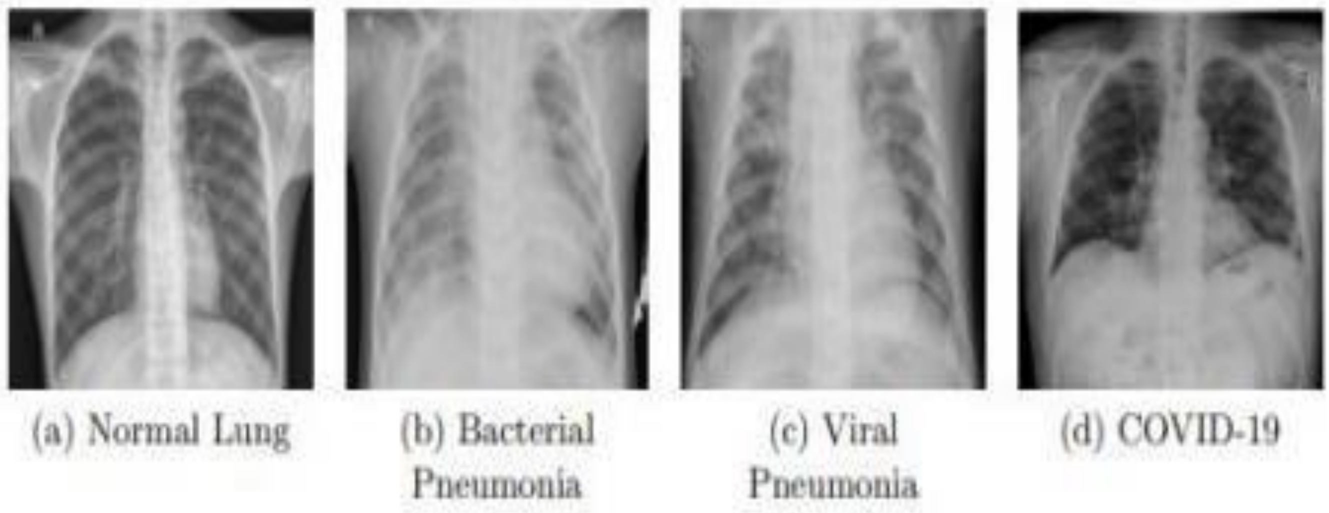

Figure 4: Chest X-ray images of a COVID-19 patient throughout a 7 days period [26]

Since about late, the use of AI strategies for automated diagnosis with in clinical sector has expanded in popularity by being an assist system for clinicians. Deep learning, a common field of artificial intelligence (AI) science allows models to start and end to produce assured outcomes using input data without any need for feature extraction in manual way. Many other challenges, such asbreast cancer diagnosis, arrhythmia identification, skin-cancer recognition, brain disease classification, pneumonia0detection from chest X-ray images, and lung segmentation, have been successfully extended to deep learning procedures.

Capsule Networks (CapsNets) [14], an alternate approach are capable of collecting location info in images by way of general agreement routing, wherein capsules seek to achieve collective agreement on the nature of detected things. This agreement optimizes data through aspects and portions of objects and can thus identify their relationships without even a large dataset. For detection of COVID-19 using X-ray photographs, a Capsule Network-based structure known is suggested. The obtained accuracy is of 95.7 percent, percent precision, 95.8 percent precision, and 0.97 Area Under the Curve (AUC).The pre train method is opposite to Reference [19], whose pre training is done on the basis of realistic photographs (ImageNet dataset). Instinctively, in contrast to the situation whereby realistic images have been used for this role, pre training focused around an X-ray dataset of just a similar description is supposed to lead to improved transfer learning.

The rapid ascent of the COVID-19 pandemic has needed the prerequisite for mastery in this area. This has increased excitement for designing computerized exploration systems that draw on AI techniques. Due to the fixed number of radiologists [18], it is a provocative decision to send master clinicians to any other emergency hospital. As a result, easy, reliable and fast AI models may be helpful in defeating this problem and provide people with convenient support. The AI advances in radiology can be helpful in getting reliable analysis, given the fact how radiologists presume a crucial role due to their tremendous presence in this industry. In addition, in taking out downsides, AI approaches can be worthwhile, such as insufficient numbers of reachable RT-PCR test packages, tests expenditure, and hold time for test results.

Several radiology photographs for COVD-19 detection have been commonly used recently. To study COVID-19 in X-ray images, Hemdan et al. used deep learning models and suggested a COVIDX-Net model with seven CNN models. A remarkable design for COVID19 identification (COVID-Net) was suggested by Wang and Wong, which had 92.4 percent accuracy in organizing standard non-COVID pneumonia and COVID-19 groups.

Using 224 confirmed COVID-19 cases data, Ioannis et al. built up the deep learning model. Their method produces distinct advancement rates of 98.75 percent and 93.48 percent for two and three classes. Using chest X-ray images together with the ResNet50 model, Narin et al. obtained a 98 percent COVID-19 discovery accuracy. The outlines of various CNN models were organized by Sethy and Behera using X-ray images with the assist vector machine (SVM) classifier. Their analysis indicates that the best execution was provided by the ResNet50 method using SVM classifier. Finally, there are also a few late COVID-19 identification research studies using various deep learning models with CT images.

A deep learning approach for the configured conclusion of COVID-19 is advocated in this research. Without using any parts extraction strategies, the suggested model has a top to bottom engineering, and refined chest X-ray images are required to preserve the outcome. This model is formulated with 125 X-ray images of the chest, that are not in a conventional structure and have been acquired.In recovered people diagnostic tests undertaken after 5-13 days were also found positive.The findings show the ability that even recovering patients can continue spreading the virus. More analytical techniques for evaluation are also required. A helplessness to understand the beginnings of the disease is one of the most important disadvantages of chest medical imaging tests, since they do not provide sufficient adequacy in GGO identification. In just about any event, concentrations which are not detectable to the human eye can be clustered across trained deep learning techniques and help in serving solutions for it.

CHAPTER 3 : SYSTEM DEVELOPMENT

3.1 About the Dataset

In this study, a COVID-19 X-ray images database created by Cohen JP [53] utilizing pictures from different open access sources was used. This database is continually refreshed with pictures shared by analysts from various districts. At present, there are 306 X-ray pictures determined to have COVID-19 in the database and 162 images with non COVID-19 patients. Fig. 2 shows four COVID-19 cases from the database and the discoveries of the specialists.

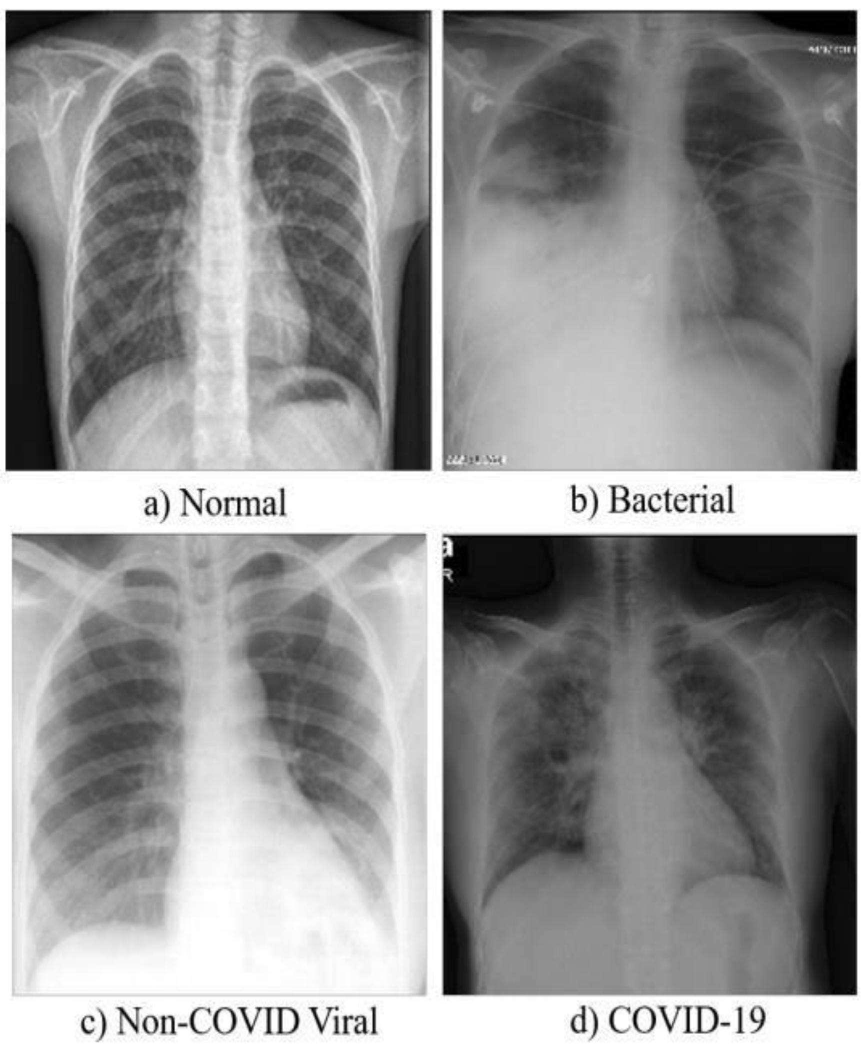

Fig 5. Labels available in the dataset

Table 1. The complete dataset out of which 468 images of COVID-19 patients has been used.

Type	Genus or Species	Image Count
Viral	COVID-19 (SARSr-CoV-2)	468
	SARS (SARSr-CoV-1)	16
	MERS-CoV	10
	Varicella	5
	Influenza	4
	Herpes	3
Bacterial	*Streptococcus* spp.	13
	Klebsiella spp.	9
	Escherichia coli	4
	Nocardia spp.	4
	Mycoplasma spp.	5
	Legionella spp.	7
	Unknown	2
	Chlamydophila spp.	1
	Staphylococcus spp.	1
Fungal	*Pneumocystis* spp.	24
	Aspergillosis spp.	2
Lipoid	Not applicable	8
Aspiration	Not applicable	1
Unknown	Unknown	59

3.2. The Proposed Method

3.2.1 The Central Pillar: Deep learning in medical analyses

Currently, deep neural networks are the top of the line Ai techniques across a variety of regions, from image analysis to real language preparation, and thus are widely transmitted throughout the academic community and industry. When everything is said and done, these advances have an extraordinary value for clinical predictive analytics, medical diagnostics and medicare overall to be progressively thought out.
In clinical practice and educational activities, medical image analysis plays an important role. The traditional strategy has hit its roof on operation. Other than that, a lot of cost, time and effort can be spent on removing and selecting grouping characteristics when using them. A growing AI strategy that has shown the ability for different classification tasks is the deep neural network.

A few of the key specifics and capabilities of a Capsule Network and how it builds on traditional industry standard networks primarily by solving its drawbacks and applying new approaches to CNNs.

Thus, this project specifically focuses on how to apply the capsule nets system, put together calculation with respect to a chest X-ray dataset to characterize pneumonia. Although the typical form of clinical diagnosis for COVID-19 involves specialized equipment and has limited sensitivity comparatively. In one of the other side, computed tomography (CT) analyses and X-ray images show unique symptoms related to that same condition. Overlapping with several other infections relating to lungs makes it very difficult to detect COVID-19 in humans. A sudden burst of concern in designing strategies for diagnoses focused mostly on Deep Neural Network (DNN), specifically based on CNNs, to promote the detection of true positive samples of COVID-19 has boomed. Nonetheless, CNNs are likely to encounter loss of spatial information and involve the need of enormous data. Proposed is an alternate simulation system focused on capsule networks, which is prepared to handle not so large datasets that are of major interest due to the unexpected and accelerated appearance of COVID-19. Our findings are based on an X-ray dataset, indicate that model has advantages over the existing versions based on CNN.

Following a new dataset built with an extra dataset of X-ray images to theoretically and further expand the diagnostic capability of the model. This is contradictory to current COVID-19 detection research, when pre-training is carried out on the basis of natural pictures, pre-training and transfer learning have been used.

In particular, Transfer learning is an increasingly beneficial order technique on a limited dataset contrasted with a SVM with powerful free basic excerpts and capsule network located fast and rotated binary (ORB). In scooping up movement, it is important to retrain unique indicators on another analytical dataset to enhance performance. A legitimate network sophistication that coordinates the scale of the dataset seems to be the next critical aspect.

3.2.2 Some drawbacks of conventional CNN

All possible variations in the testing images must be considered for a CNN has to be precise so that it studies on almost all of them-that is why there has been image augmentation-that rearranges, rotates, inverts, crops, zooms, and makes a lot of several other adjustments on data to create any possible permutations, which when fed into network make it learn better. This is a costly affair for computing and demands volumes of information. This really is the dilemma of invariance. Translational invariance can be handled by CNNs, but really not rotational invariance.

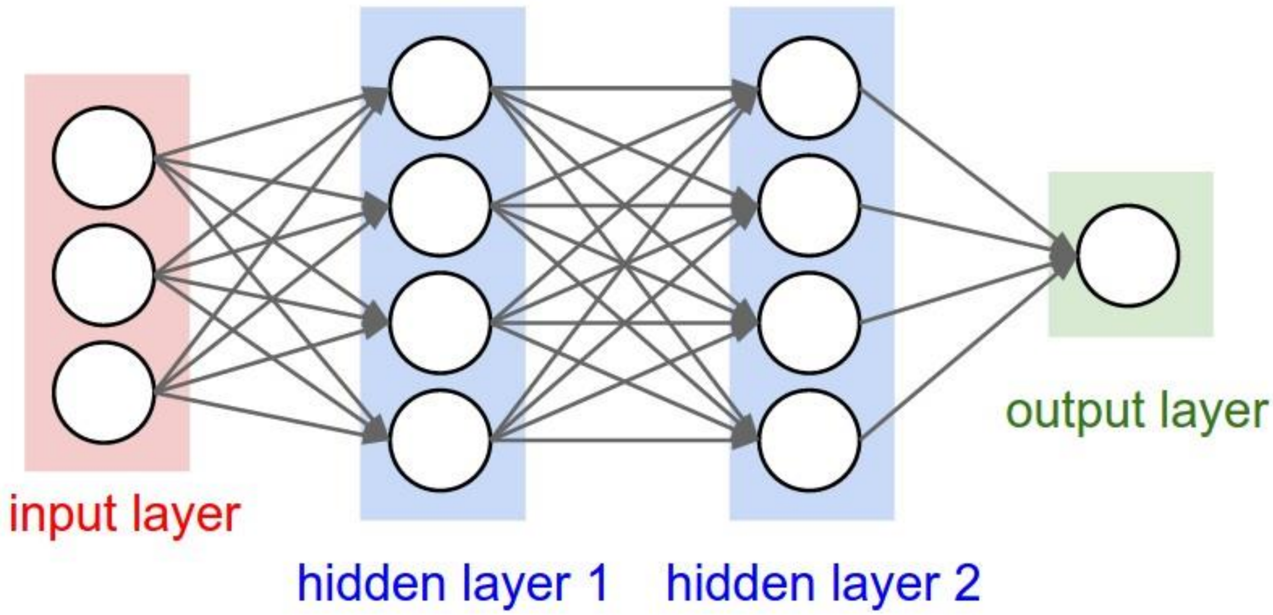

Fig. 6. A simple neural network with 2 hidden layers

If you teach an individual to recognise the pictures of cats in which all the cats look to their left, request to identify a cat in a picture in which cat faces to the opposite, it would be recognizable by persons. A CNN is unable to grasp this concept (except if it is trained such images of cats looking both ways). A picture having a eyes below the lips and an lips below the eye will not be identified by CapsNet as a human face unlike CNN. Max -pooling layers in CNN run within 2 layers as a courier that passes activation details between layers. This informs the layers about something like a subject's existence, but not really the spatial relationship in between components. For generating translational invariance, the MaxPooling layer slices off the whole information, the potential of a network to identify an entity even anywhere it lies throughout the photograph. Maxpooling therefore does not have "'ViewPoint Invariance", the power to make the system susceptible to perspective shifts.

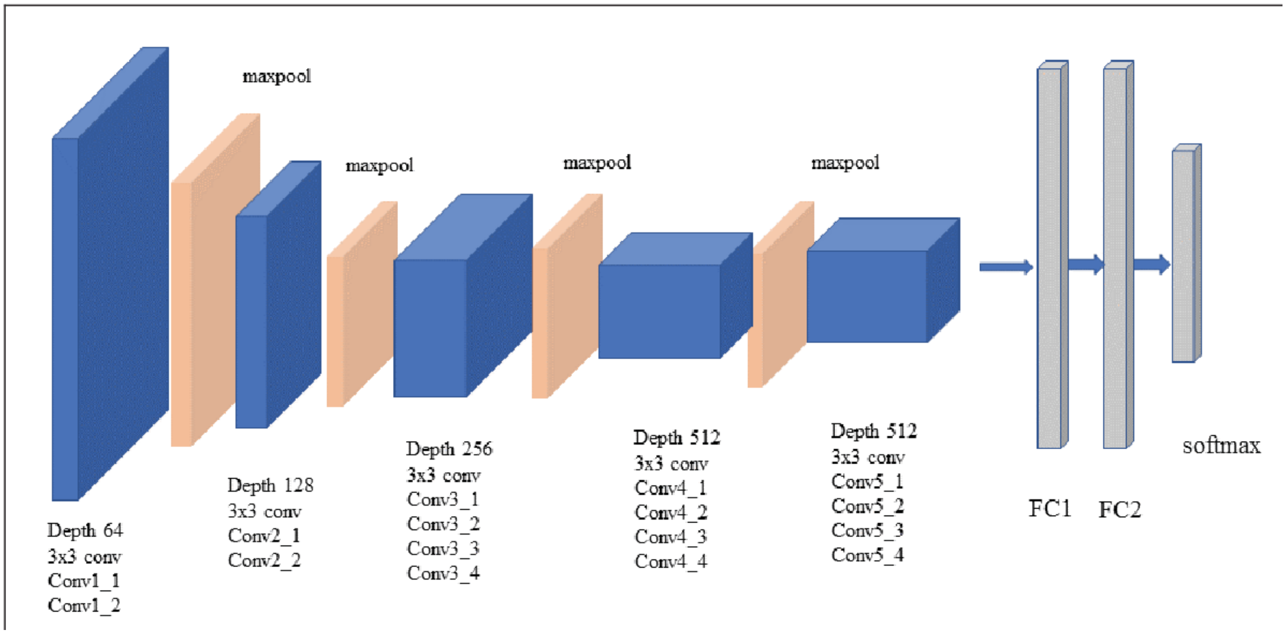

Fig 7. VGG-19 architecture

3.2.3 Proposed Model and Algorithm

The proposed model depends on the working of deep learning-based CNN known as VGG-19. The applied parameters in this model are tabulated in Table 1 which consist of 24 layers. The first layer indicates the input layer and is fixed with the size of 224 x 224 x 3 pixels which makes it a RGB image. The next 18 layers are the combination of Convolution+ReLU and Max Pooling layers. These layers are part of the pre-trained VGG19 Model proposed in [35] and trained on the ImageNet dataset. ImageNet contains around 15 million annotated images from 22,000 different categories and VGG19 was able to achieve 92.7% accuracy on ImageNet. Therefore, we used the VGG19 model as depicted in Fig. 5 for feature extraction as a base model. Then we have applied a transfer learning model using the proposed 5 different layers and trained the proposed model on the COVID-19 dataset which is shown in Fig. 4. These 5 layers are an integral part of the head model where the first layer acts as an Average Pooling 2D layer with pool size of (4,4). In average pooling, the average value of all the pixels in the batch is selected unlike max pooling where the maximum value is selected. Next, we use a flatten layer whose role is to apply a flattening transformation on the tensor converting the two-dimensional matrix of features into a vector that can be fed into a fully connected neural network classifier. Once, we have the transformed vector we then input it into a fully dense connected layer with a size of 64 units and a ReLU activation function. Then, we apply dropout with a threshold of 0.5. The dropout layer simply ignores some units (neurons) taking in consideration the threshold value which we provided. Finally, we have an output layer having just two units. Now, the model is optimized using the Adam optimizer [36]. Adaptive moment estimation or Adam is an optimization algorithm which is used in place of vanilla stochastic gradient descent. The proposed algorithm

'VGG-19' is based on transfer learning model. The description of notations used in the Algorithm 1 is provided here, δ1 and δ2 refers to the training data set and testing data set respectively. μ, is the learning rate indicating how quickly a model adapts to the problem. Typically, it values nearby zero. ϵ is the total number of iterations the CNN model is trained for also known as epochs. β is another configurable hyper-parameter generally having values in the form of 2n. We can tune these three hyper-parameters (μ, ϵ, and β) based on step 1 to 3 of Algorithm 1 in a sort of hit and trial fashion to achieve the best accuracy with the given data set. The algorithm outputs weights stored in the form of a '.h5' file which are further used for prediction on a completely random X-ray image.

3.2.5 Inferences

The remarks upon the performance of model are as follows:

- The model worked remarkably for the combined class task in identifying COVID-19 instances.
- It efficient in understanding the results of COVID-19.
- It shows the adequacy for understanding of translational and rotational invariance successfully.
- Performs better than a shallow CNN on a similar task
- Issues found with shallow CNNs have been resolved for more accurate and precise predictions for COVID-19 detection through X-ray images of patients.
- VGG-19 networks are an emerging method that outperforms various fields of conventional tasks that were previously done by a little weaker algorithms.

CHAPTER 4 : PERFORMANCE ANALYSIS

For evaluating the trained VGG-19 network model we have used confusion matrix. The confusion matrix is calculated by first calculating the True Positive (TP) , True Negative (TN), False Positive (FP) and False Negative (FN). After calculating these parameters we use the following formulas to calculate different derivatives such as True Positive Rate (TPR), Specificity (SPC), Precision (PPV), Negative Predictive Value (NPV) , False Positive Rate (FPR), False Discovery Rate (FDR), False Negative Rate (FNR), Accuracy (ACC) and F1 Score.

Table 2: Formulas used to calculate result with the values obtained from the confusion matrix.

TPR = TP / (TP + FN)
SPC = TN / (FP + TN)
PPV = TP / (TP + FP)
NPV = TN / (TN + FN)
FPR = FP / (FP + TN)
FDR = FP / (FP + TP)
FNR = FN / (FN + TP)
ACC = (TP + TN) / (P + N)
F1 = 2TP / (2TP + FP + FN)

Table 3: Confusion matrix

	True COVID-19 Positive	True COVID-19 Negative
Predicted COVID-19 Positive	TP = 300	FP = 6
Predicted COVID-19 Negative	FN = 12	TN = 150

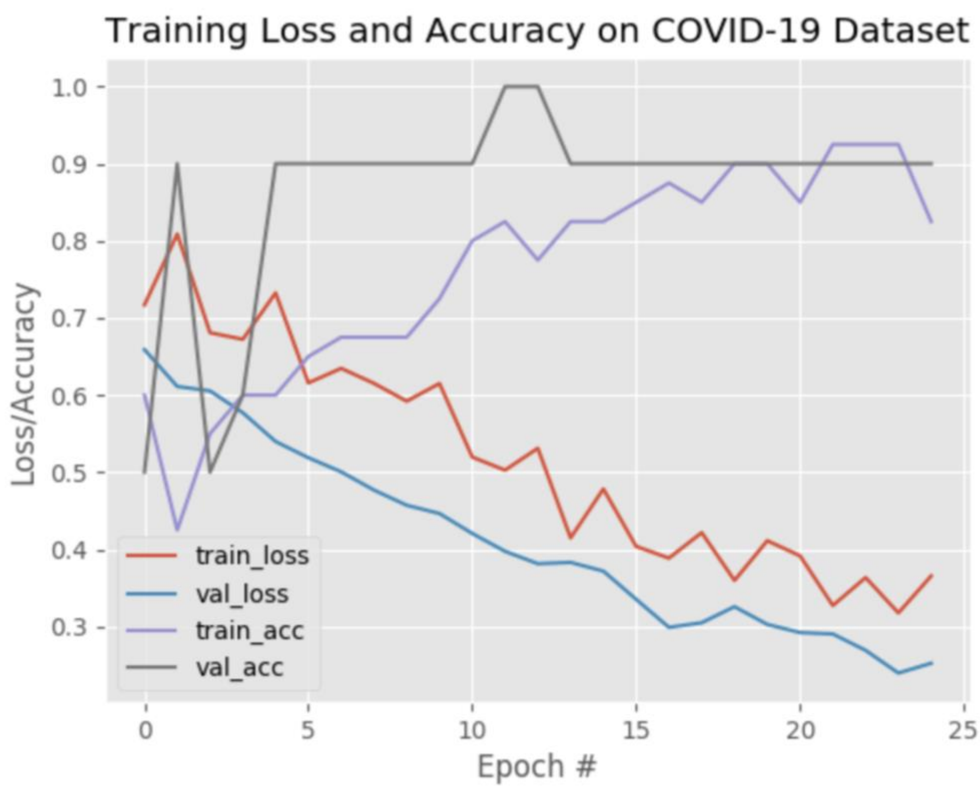

Fig. 8 Training loss and accuracy

Table 4: Result values calculated using the confusion matrix

Measure	Value
Sensitivity	0.9615
Specificity	0.9615
Precision	0.9804
Negative Predictive Value	0.9259
False Positive Rate	0.0385
False Discovery Rate	0.0196
False Negative Rate	0.0385
Accuracy	0.9615
F1 Score	0.9709

4.1 Observation

Using the confusion matrix the accuracy of our model is calculated to be 96.15% with 98.04% precision and 97.09 F1 Score. Sensitivity is the probability that a person having

COVID-19 is diagnosed with COVID-19 correctly. In medical Imaging our main aim is to have a high sensitivity to not miss the true positive patients which could become a carrier of the disease if tested falsely. Whereas specificity is the probability that a non COVID-19 patient is tested as a non COVID-19 patient. Which is also very essential in medical imaging since in a scenario where the model has a very low specificity, a large number of false positive patients i.e. healthy patients diagnosed with COVID-19 will be admitted to the hospital where they would be at a risk of getting the disease transmitted from the other patients.

CONCLUSION

A deep learning-based model in this study has been introduced to differentiate and organize COVID-19 cases from X-ray images. To reduce the need for manual inspection of images, the model is entirely automated with a start to finish framework. Multi-class undertakings with an accuracy of 96 percent can be conducted independently by our created system. The discussion of the proposed process has been well assessed and a larger database is suitable for testing. In distant communities in countries affected by COVID-19, this structure can also be used to overcome a radiology deficiency. Similarly, other chest-related diseases, which include tuberculosis and pneumonia, can also be analyzed using these methods. The use of a specific amount of COVID-19 Xray photos is a limitation of the research.

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APPENDICES

Appendix A: Appendix

Multiple extensions to sources of the script are described below to provide the viewer additional information which might be needed but were not contained in the key chapters of this thesis.

A.1 Dataset Collection

A public open dataset of chest X-ray and CT images of patients which are positive or suspected of COVID-19 or other viral and bacterial pneumonias. It has data collected from public sources as well as through indirect collection from hospitals and physicians.

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