

DEEP LEARNING BASED AUTOMATIC DETECTION OF COVID-19 USING CHEST X-RAY AND CT-SCAN

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ABSTRACT: The COVID-19 pandemic, which has spread to more than 150 nations worldwide, is negatively affecting many people's well-being and quality of life. The capacity to quickly identify infected individuals and place them under particular supervision is one of the most important weapons in the fight against COVID-19. One of the quickest methods to detect these illnesses in a patient is probably through the discipline of radiography and radiologic imaging. According to a preliminary investigation, chest radiographs of people who have COVID-19 infections have been demonstrated to have distinctive abnormalities. In this work, we examine the viability of detecting COVID-19 in chest X-rays using machine learning methods. In the beginning, we gather 9000 instances of chest X-rays and CT scans from public sources. The presence of COVID-19 illness was visible in the images, according to a board-certified radiologist. Although this is a positive development, additional research on a large number of COVID-19 images is necessary to evaluate accuracy rates with more accuracy. Implementations of models and datasets.

Keywords: CNN, Resnet-50, VGG 16, convex net.

I. INTRODUCTION

Lung disease is one of the least widespread health problems in the globe. There are three main types of lung disease: those affecting the tissues themselves, those affecting the blood flow, and those affecting the airways. Asthma, cystic fibrosis, chronic pulmonary obstructive disorder (COPD), influenza (TB), bronchitis, etc., all affect the airways and make it difficult for the body to take in oxygen and other gases. Diseases of the circulatory system, such as lung embolism and pulmonary hypertension, cause problems with blood flow because of clotting in the blood arteries. Lungs. Lung diseases like sarcoidosis and pulmonary fibrosis, for example, are caused by inflammation of lung tissue, which therefore limits lung expansion. Additional lung illnesses include lung tumours, pneumo-thorax, pneumonia, which is and acute respiratory distress syndrome. One of the rapidly spreading viral infections, coronavirus disease (COVID-19) has impacted a sizable fraction of the world's population without discrimination based on gender or ethnicity. The COVID-19 infection severely compromises lung function by damaging the respiratory tract and causing a layer of lung lesions. In December of 2019, a case of COVID-19 is discovered in Wuhan, China.

The virus was termed "severe acute respiratory crisis coronavirus 2 (SARS-COV-2)" by the Worldwide Committee on Virus Taxonomy (ICTV) and "COVID-19" by the World Health Organisation.

COVID-19 symptoms include dry cough, fatigue, mild to moderate respiratory illness, loss of taste sensitivity, and fever. Droplets as small as a micron are expelled from the airways and lips of a person infected with COVID-19 when they sneeze, cough, or even talk. Serious illnesses are more common in those with preexisting health disorders such diabetes, chronic respiratory ailments, cardio-vascular diseases, and cancer. Older adults with several health problems are more likely to get an illness than younger people. Antigen tests may be used to determine whether or not a person has been infected with COVID-19, while antibody testing can be used to determine whether or not a patient has been exposed to that virus. Since polymerase chain reaction (PCR) is used in a significant portion of COVID-19 antigen testing, these analyses are often referred to as PCR analyses. The nasopharyngeal swab is used to obtain a clinical specimen, which is then frozen, sent to the laboratories for RNA isolation, and finally subjected to quantitative transcription by reverse PCR. The inability of governments throughout the globe to stem from the propagation of COVID-19 in humans may be attributed to a number of

causes. A) there has not been enough technology to screen for COVID-19 in a population of one million individuals; B) there are no vaccines or pharmaceutical treatments available at this time. India, on the other hand, had 1,854,250 tests performed, or 1,344 per million people. Due to a shortage of COVID-19 testing kits, fewer tests are conducted per million persons. The respiratory system, among others, has been hit hard by the COVID-19 epidemic. This demonstrates that chest radiography's diagnostic imaging qualities are useful for the rapid detection of COVID-19. CT (computed Tomography) scanning and X-rays are two examples of medical imaging modalities that may be used to get chest imaging features. CT scans provide advantages over x-rays in many areas, including the ability to produce a three-dimensional picture of internal organs and the ease with which illness and its location may be examined. X-rays only provide a 2-dimensional image of an organ, which is only helpful for examining thick tissues. In addition, every nation has access to the same high-quality CT scan equipment. Therefore, to find COVID-19, researchers are focusing on chest CT scans. A skilled radiologist must supervise the quick and precise detection of COVID-19 utilising a chest computed tomography (CT) scan. Healthcare professionals have a significant portion of the responsibility for providing early and effective care for COVID-19 disease. However, a significant obstacle is the dearth of readily available standard COVID-19 detection kits.

In order to diagnose COVID-19 utilising an imaging modality without the need for human intervention, an automated diagnostic model is therefore necessary. The proposed study's objective is to automatically locate and detect COVID-19 in a chest CT scan. A innovative three-stage wavelet-enhanced data augmentation, illness detection, and anomaly localization approach is used to accomplish this. The scientific community can only access a tiny number of CT images of COVID-19 illness online. The pre-processed images are divided into three phases employing stationary wavelets in order to avoid the requirement for large data bases to be trained and overfitting problems. After that, each of these images is subjected to a shear, turning, and translation operation. Using transfer learning-based approaches, phase 2 of CT scan classification divides scans into COVID and NONCOVID groups. Also employed is ResNet50, a model with four extra, more sophisticated convolutional layers. Following that, the best training model is chosen by comparing it to a set of transfer learning model benchmarks. The characteristic map and activator layers of the best machine learning model are used in the third stage to identify the abnormality in chest CT images of COVID-19-positive patients. The contributions of the anticipated work are listed in the following manner: We compare the performances of four trained transferable learning models in order to address the issue of COVID-19 detection by CT scan with a constrained dataset. We also examine the feature maps in the deeper layer utilising the suggested method with innovative data augmentation.

II.LITERATURE SURVEY

Many researchers have done a wide range of work to further this topic.

[1] A real-time and chest CT comparison of the 2019 coronavirus illness (COVID-19) in ChinaAs stated, there were 1,014. Background As a crucial addition to research on reverse transcription polymerase chain reaction (RT-PCR), computed tomography (CT) is used to identify coronavirus illness 2019 (COVID-19).in order to compare the covid-19 diagnosis accuracy of RT-PCR and chest CT.Tools and Methods Chest CT and RT-PCR tests were conducted on 1014 Wuhan, China residents on January 6 and February 6, 2020. RT-PCR, the gold standard, was compared to chest computed tomography (CT) for the detection of COVID-19. the variable nature of RT-PCR results, which might be either positive or negative.

[2]Using deep learning on medical images to detect treatable conditions and make diagnoses. The use of decision-making algorithms in medical imaging is plagued by issues of reliability and interpretability.To screen for common, curable, and potentially blinding retinal illnesses, we develop a diagnostic tool using deep learning architecture in this study.Our approach utilises transfer learning, a technique which allows a neural network to be trained with far less input than is required by traditional methods. We apply our technology to a dataset of optical coherence tomography, or OCT, pictures and show that it can accurately diagnose age-related macular edoema as well as human professionals.We also give a more accurate and clear evaluation by emphasising the locations identified by the neutral network. The results of a chest X-ray.

Because of its simplicity to use and superior classification performance, the closest neighbour (KNN) algorithm is widely employed in data mining and statistics.Although experts set the value of k, typical KNN algorithms cannot apply this value for all test samples. Earlier systems used the time-consuming cross validation procedure to assign various k values to various test samples.The findings of this study suggest that by employing an instructional cycle in the KNN classification, it is feasible to learn several optimal k values for various test/new samples.To be more precise, the kTree method uses a unique sparse reconstruction model to identify the best k

metrics for each training sample, and then it uses those metrics to build a decision tree (referred to as a KTree) from the training data.

[4] In the past several years, there has been a significant rise in the use of artificial intelligence (AI) and the internet of things (IOT), two quickly developing technologies with numerous potential medical applications. However, radiologists are getting overburdened due to the rising popularity of PET scans. Given the magnitude of the problem, studies into a novel approach called as "computer aided diagnosis" are underway in an effort to find a solution. The Smart Lung Cancer Detecting and stage Classifier (SLD-SC) presented here is a hybrid approach to PET scans. A detector may be used to identify the stage.

[5] Several state-of-the-art models in computer vision have been developed thanks to deep learning, and they all need huge troves of labelled data. To construct data-sets with specified properties, such as tiny object regions and high occlusion levels, however, gathering, annotating real-world photos is often too time- and resource-intensive and inflexible. Within the paradigm of parallel vision, this research suggests an approach for building fictitious settings and automatically generating digital images complete with precise annotations. The ParallelEye virtual dataset was developed for use in different computer vision tools. We then show that using the DPM (Deformable pieces model) + faster R-CNN receivers in Parallel Eye greatly improves model performance.

[6] Classifying documents and texts has become more important in the study of machine learning. Widespread use in fields including business, ham/spam filtering, healthcare, internet shopping, social media sentiment, consumer product sentiment, etc. has led to the development of a number of techniques for accurately predicting the category or classifying every new text or document under examination. Since news stories in today's newspapers often convey a range of moods a inclination towards a good or negative attitude, the substance of the news may be actively used to access the influence on the reader. This work aims to predict if a news article's sentiment is positive or negative using two popular native Gaussian Text Categorization techniques.

[7] "Coronavirus disorders 2019 (COVID-19): Role of chest radiography in diagnostics and management," by L.M. Xia and Y. Li, has been tentatively scheduled for publication in the June 2020 issue of the American Journal of Roentgenology (vol.214, no.6), pages 1280-1286. Our research aimed to determine how well chest x-rays performed in the identification and treatment of 2019 coronavirus illness (COVID-19) and how often radiologists made inaccurate diagnoses. The CT characteristics of COVID-19 are given and compared to the CT characteristics of all other viruses in order to educate radiologists with probable CT patterns. The new coronavirus SARS-CoV-2 (Severe Acute Respiratory disorder Coronavirus 2) is responsible for an epidemic of pneumonia, according to the World Committee in Taxonomy of Viruses.[3]. The sickness caused by the virus has been given the name coronavirus disease (COVID-19).

[8] "Covid-19: Automatically recognising from X-ray images via transfer learning with a convolutional neural network," will be published in 2020. Reference: preprint at arXiv: 2003.11617. Automatic coronavirus illness diagnosis was performed in this work using a database of chest x-ray pictures from patients with community-acquired pneumonia caused by bacteria, previously confirmed cases of covid-19 disease, and non-infected controls. The purpose of this research is to evaluate newly suggested architectures for cutting-edge convolutional neural networks to classify medical images. In particular, the strategy of "transfer learning" was implemented. Transfer learning has been shown to have remarkable success when used to the challenging problem of anomaly identification in very tiny medical picture data-sets. Two datasets were utilised in this study. First, a trove of X-rays totaling 1427, with 224 showing verified cases of Covid-19 illnesses.

[9] Detecting COVID-19 in x-ray images using keras, TensorFLOW, and sophisticated learning is available at: <https://www.pyimagesearch.com/2020>. Wuhan, an area in China, was the site of the first 2019 discovery of COVID-19 in December, and the virus has since spread throughout the world.

No effective therapy for COVID-19 has ever been identified as of yet. Yet the possibility of death in individuals can be progressively forecasted before the illness develops to the critically sick. The rapid spread of the coronavirus infection astonished the globe and has had a major effect on the lives of billions of people. Deep learning for measuring COVID-19 infection with CT images has not been investigated. There is currently no clinically-viable method of automatically estimating infection burden in COVID-19 patients.

[10] COVID-net, a custom-built deep convolutional neural network for identifying COVID-19 cases in chest X-rays by 2020 (preprint 2003.09871, arXiv). The 2019 coronavirus diseases (COVID-19) pandemic has had devastating effects on global health due to its origins in the severe abrupt airway syndrome coronavirus 2 (SARS-CoV-2) infection of humans. Population. In the fight against COVID-19, it is crucial to conduct thorough patient screenings so that infected people may get prompt medical attention and isolation measures. The majority of

COVID-19 patients are detected by the use of reverse transcription-polymerase chain reaction (RT-PCR) testing, which may detect SARS-CoV-2 ribonucleic acid (RNA) in respiratory specimens (collected through a variety of procedures).

[11] To the editors and reviewers of IEEE Access, a note on "Medical healthcare big data classification employing the kNN classification algorithm," volume 8, issue 11, November 2019, pages 28808-28819. The rapid development of IT has allowed for the intelligent development of medical informatization. Big data in medicine provides access to vital information, which in turn makes possible cutting-edge healthcare. Categorising large data in the health industry is crucial for intelligentization of health-related information. The KNN (K-Nearest Neighbour) classification algorithm's rising popularity may be attributed to how easily it can be implemented. However, the KNN algorithm's classification performance degrades noticeably when the sample length and the feature attributes are large. In this paper, we assess the upgraded KNN technique.

[12] To cite this paper: "Facial mood classification based on SVM, KNN, et MLP classifiers," in Innovative science and engineering conference proceedings (2019), pages 70–75, Zakho-Duhok, Iraq. To cite this article: "Facial expression recognition with SVM, KNN, and, MLP classifiers," Proc. Int. Conf. Applied Sciences and Engineering, Zakho-Duhok, Iraq, 2019, pp. 70-75 (2019). Identification of facial expressions (FER) has been, by all accounts, a game-changer in the world of image processing. Since the 1990s, publications about FER have been popular in the academic literature. Typically, FER consists of three stages: face detection, extracted features, and classification. This paper demonstrates a method for automatically recognising the eight most common facial emotions, including neutral, happy, angry, shocked, and disgusted.

[13] The article is titled "Dendritic neuron model with successful training procedures for classifications, approximates, and prediction," and it tackles the aforementioned topic. Journal of Neural Engineering, Volume 30, Issue 2, February 2019, Pages 601-614. The enhanced the piezoelectric in (K,Na)NbO₃ perovskite-based free of lead, piezoelectrics is temperature sensitive, which is one of the technical challenges inhibiting their use in practical applications. Based on these findings, a formula was developed that displays a piezoelectric strain constant d_{33}^* of up to 600 pm/V throughout a large temperature range of up to 100 °C while still being frequency-insensitive. The high performance achieved by combining strong piezoelectric technology and superb stability is supported by a diffused period transition (DPT), which is associated with the transition from ferroelectric to relaxation or behaviour generated by high piezoelectric power and outstanding stability. This was discovered through the measurement of electrical properties and the observation of nano structures.

[14] In the November 2019 issue of IEEE Access, volume 7, number 11, a piece titled "Recognising pong Motions Using Inertial Data via Machine Learning Classification Algorithms" was published. As the Internet of Things (IoT) and other sensing technologies have advanced, new perspectives on individuals and their surroundings have developed. Many of the sensors included in commercial wearable sensing systems are well-suited to tasks like recording movements and behavioural analysis. This study proposes a technique for commercial smart watch-based ping-pong motion detection. We use an IoT-based data collecting system to track the watch's acceleration, angle of rotation, and magnetic induction. Using the properties of the recovered data, experiments were conducted using powerful machine learning algorithms.

[15] Analysing a "Ladle furnace temperature forecasting system based on enormous amounts of data corresponds to the random forest," Predicting the temperature of the gaseous steel in the ladle furnace is the primary focus of the study. The majority of existing temperature prediction models use a small data set. Their accuracy is currently too low for any kind of useful manufacturing. Thankfully, the massive sample size is based on the real manufacturing procedure. However, due to the large size of the data set, developing a model for the temperature of liquid steel is difficult. In this research, the probabilistic forest approach is favoured above other regression methods because of its high power, minimal complexity, and rapid construction. It employs sample subsets and a straightforward sub-model learning technique, and it is built on a parallel ensemble architecture.

III. DETECTION OF COVID-19 USING CHEST X-RAY AND CT- SCAN IMAGES.

A. Preparation of dataset:

Given that both CAT scans and X rays may aid in the detection of COVID-19, we accessed our suggested structures using both. The recently released COVID-19 dataset for CT and X-ray imaging is rather small compared to other public deep learning datasets.



Figure 1: Healthy person chest X:ray.

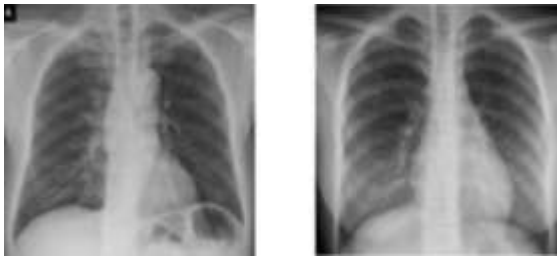


Figure 2: Chest X-ray in case of COVID-19

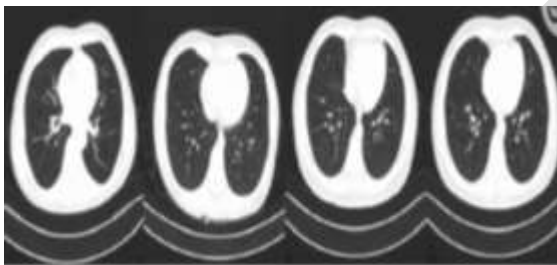


Figure 3:Healthy person CT-scan.

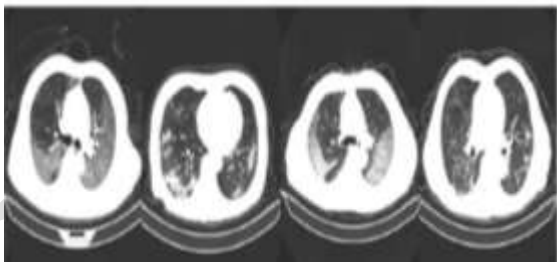


Figure 4:CT-Scan of COVID-19 effected person.

B. Pre-processing:

Getting the photos into the right dimensions and shape for training the model is a priority.

C. System architecture:



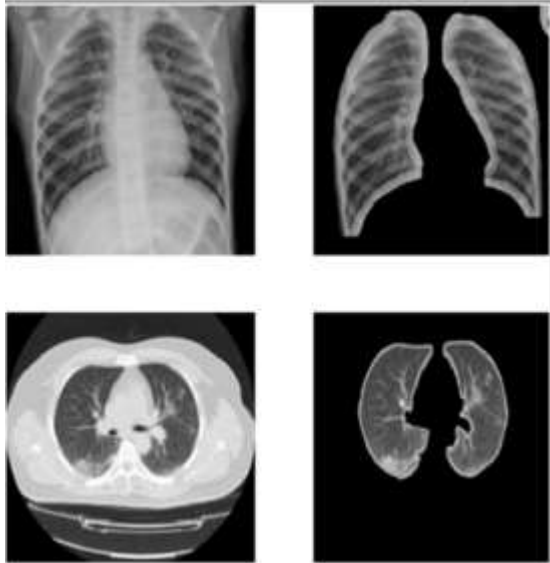
Figure 5: System Architecture

D. Image resizing:

The data set has to be standardised since it was gathered using a wide variety of scanners and locations, and their output sizes may vary. picture scaling is used to generalise every picture in the dataset to a single dimension, which helps the CNN model's classification performance.

E. Image segmentation:

Among the many methods of image processing, image segmentation is essential for increasing the model's accuracy and reliability. The lung region is the region of interest (ROI) for COVID-19 identification during segmentation. To reduce computing complexity, it isolates the lung region from the rest of the image data used in medical diagnostics. Figure depicts examples of photos used for segmentation.

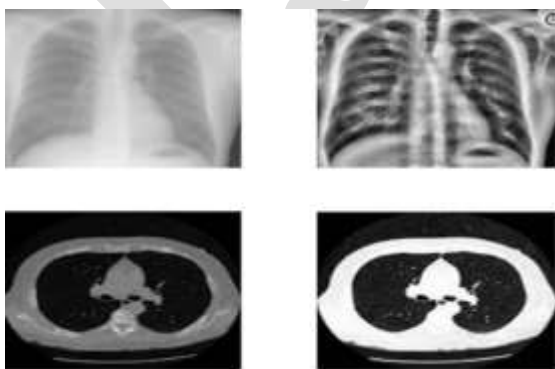


Lung images Segmentation Lung Images.

Figure 6 : Samples for segmentation.

F. Image enhancement:

Image enhancement is essential in the medical field for better patient diagnosis based on improved visual quality of medical pictures. Histogram equalising is an enhancement technique for balancing the intensity of a picture across all of its pixels. Strong constriction in white area may sometimes wipe out information contained by white pixels. Using adaptive histogram equalisation (AHE), the intensity values are only spread out throughout the specific region of the picture. It may lead to an overamplification of background noise in the uniform zones[14]. The overemphasis of noise caused by AHE is reduced by contrasts limitation adaptive graphic equalisation, or CLAHE. It enhances the picture by avoiding noise from being enhanced together with the contrast[15]. This limit is adjusted by the user.Author: Alaa S.



Lung images Enhanced lung mages.

Figure 7: Samples for Enhancement.

3.1PRE TRAINED CNN MODELS:

A. VGG-16:

The input to the network is a 224 by 224 by 3 pixel picture. The first two tiers include 64 channels, each with the same padding and a filter size of 3 by 3. Both 128- and 3-layer pools are present after a stride(2,2) maximum. The next layer is a stride(2,2) maximum-pooling layer. Both of the subsequent convolutional layers consist of 256 filters, each measuring 3 by 3. First, a max pool layer is followed by two sets that include three convolutional layers. Each has the same padding and dimension of (3,3) and includes 512 filters. Then, the two-convolutional-layer stack is fed this picture. When we stacked the greatest possible pool and layers of convolution, we got a feature map with a dimension of 7,7,512. We then flatten this result to get a (1,25088) feature vector. The following 3 levels are also interconnected. In the ILSVRC Challenge, the first layer makes use of the most recent function vector of size (1, 4096), while the second layer generates a vector of value(1,4096), and the third layer generates 1000 classes.

B. CONVEXNET:

Beck and Sengupta's work formulates the training in a neural network as a convex optimisation issue, which may be tackled using descent gradient or sub gradient approaches. They show that many types of neural networks, such as feed forward and convolutional networks, may be employed with their approach. The core principle of the technique is to use a convex approximation of the concave objective function that emerges during the training of the neural networks. The trained network is guaranteed to be close to optimum since this method finds the global minimum of the goal function. Though it has much potential, convex optimisation when creating neural networks is deceptively complex.

C. RESNET-50

Using an image net dataset that kaiming created, a 50-layer network was trained. He et al. It is possible to enhance results by stacking convolutional and pooling layers, however doing so beyond a certain point decreases model performance. The problem was addressed by adding shortcut connections, which made it possible to arbitrarily remove one or more layers of affecting the model's computational difficulty or the total number of parameters. The foundation of the design was the 34-layer weighted RESNET-34 network. It provided a novel approach to overcoming the vanishing gradient issue in CNNs by exploiting the connections as a short cut to including more convolutional layers. When a conventional network is transformed into a residual network through a short cut connection, the link "skips over" a layer or layers.

D. CNN

The convolutional neural system (CNN) is a popular implementation of the deeper neural network architecture. Computer vision is a subfield of artificial intelligence that allows computers to process and make sense of visual data. When it comes to machine learning, artificial neural networks perform well. Neural networks are used in a wide variety of data sets, including those including pictures, music, and text. In order to forecast the word order, we use a recurrent neural network, more precisely, a long short-term memory (LSTM) network, and in order to categorise pictures, we use a convolutional neural network, more precisely, a long short-term memory (LSTM) network. The purpose of this blog is to serve as CNN's skeletal framework. A typical neural networks consists of three subnetworks: Three layers: input, concealed, and output.

3.2 EVALUATION METRICS:

The effectiveness of the suggested methodology is assessed using four assessment measures. These are what they are:

Precision: The percentage of positive predictions that fall into the positive category is known as precision.

$$\text{Precision} = \text{TP} / \text{TP} + \text{FP}$$

Recall: Recall is the portion of the dataset's positive cases that are correctly predicted to be positive.

$$\text{Recall} = \text{TP} / \text{TP} + \text{FN}$$

Accuracy: The percentage of all forecasts that are accurate is known as accuracy.

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

IV. Results and Analysis:

This task makes use of a computer with an I3 Intel CPU, 8 GB of RAM, and a hard disc with a capacity of 160 GB. In this work, the COVID-19 is detected using a software-based method that combines state-of-the-art image

processing + computer vision methods. Python was used as the analysing language for the various security features. The proposed system uses image processing to authenticate the COVID-19 input picture. Multiple techniques are used to process the input picture, and all retrieved features are thoroughly examined. The results have already been decided.

MODEL PERFORMANCE DATASET:

MODEL	Accuracy	Precision	recall
VGG 16	0.5399	0.4926	0.9845
CONVEXNET	0.8212	0.541	0.8699
CNN	0.8917	0.5159	0.8992
RESNET-50	0.9528	0.585	0.9968

Table 1: Compared to other models' performances on the Covid-19 mixed-dataset screening task, RESNET-50 stands out as having higher precision, efficacy, and recall.

Displaying output:

All algorithms' results are visible to the user. Each feature's extracted picture and other relevant data are shown in a separate window inside py cham. In addition to the data, the current state of each component is also shown. Whether or not a person has been infected with COVID-19 may be determined by looking at the aggregate amount of distinctive characteristics that have passed for the COVID-19 output picture. All of PyCharm's Python source code makes use of the Pandas, Numpy, Matplotlib that and the school libraries.



Figure8: Showing home page.



Figure9: Initially no image is displayed and user is asked to insert image.



Figure10:Chest X-ray in case of COVID-19



Figure11:Chest X-ray in case of a healthy person.



Figure 12:CT-scan of COVID-19 effected person.



Figure13: CT-Scan in case of healthy per

RESULT ANALYSIS: Model Accuracy on Dataset:

Model	Loss	Accuracy	Validation Loss	Validation Accuracy
VGG-16	0.7471	0.5399	7.3819	0.2519
CONVEXNET	0.1355	0.9512	0.4349	0.7942
CNN	0.0214	0.9917	0.6135	0.8937
RESNET-50	0.3767	0.9428	0.7113	0.8936

Table 2: Using a variety of datasets, the best-performing models had little validation loss and high accuracy.

Model Confusion Matrix on Dataset:

Confusion Matrix		Actual Situation			
Model Classification	Covid-19 Chest X-Ray	COVID-19 Chest X-Ray category that are correctly classified as COVID-19	COVID-19 Chest X-Ray category that are wrongly classified as COVID-19	COVID-19 Chest X-Ray category that are wrongly classified as COVID-19	COVID-19 Chest X-Ray category that are wrongly classified as COVID-19
		COVID-Negative Chest X-Ray category that are wrongly classified as COVID-19	COVID-Negative Chest X-Ray category that are correctly classified as COVID-19	COVID-Negative Chest X-Ray category that are wrongly classified as COVID-19	COVID-Negative Chest X-Ray category that are wrongly classified as COVID-19
	Covid-19 CT-Scan	COVID-19 CT Scan category that are wrongly classified as COVID-19	COVID-19 CT Scan category that are wrongly classified as COVID-19	COVID-19 CT Scan category that are correctly classified as COVID-19	COVID-19 CT Scan category that are wrongly classified as COVID-19
		COVID-Negative CT Scan category that are wrongly classified as COVID-19	COVID-Negative CT Scan category that are wrongly classified as COVID-19	COVID-Negative CT Scan category that are wrongly classified as COVID-19	COVID-Negative CT Scan category that are correctly classified as COVID-19

Table 3: We compared the results of the confusion matrix with our current investigation on patients who tested positive and negative for covid-19 using chest X-ray and computed tomography scans.

Parameter Setting:

Parameter	Value
Epochs	3,3,3,30
Optimizer	RESNET-50, CONVEXNET, VGG-16, CNN
Learning Rate	0.00001, 0.0001, 0.001, 0.1, 1
Drop Out	0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9

Table 4: Using the COVID-19 dataset, the conv laers, epochs=4, optimizer=RESNET50, CONVEXNET, VGG-16, CNN, and a variety of learning rates and drop out, we calculated the average accuracy of the initial version of the model

Chest X Ray and CT Scan image dataset.

Category	Total Number of Images	Number of Images Selected In Study	Train	Validation	Test
Covid-19 Chest X-Ray	2537	1051	984	543	543
Covid-Negative Chest X-Ray	2394	1027	960	576	576
Covid-19 CT-Scan	2501	1078	972	584	584
Covid-Negative CT-Scan	2501	1059	953	593	593
Total	9933	4215	2969	2296	2296

Table 5: The sum of all chest x-ray and CT scan pictures used in the covid-19 detection training set.

4.3 PERFORMANCE ANALYSIS:

The following charts show the training and test achievement of all models for each epoch. Models trained on RESNET-50 improved their accuracy by 98%, whereas VGG16, CNN, and CONVEXNET all achieved 84%.

MODEL GRAPHS:

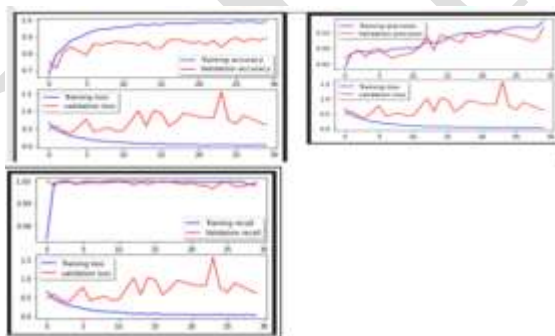


Figure 14: Performance analysis Graphs of CNN

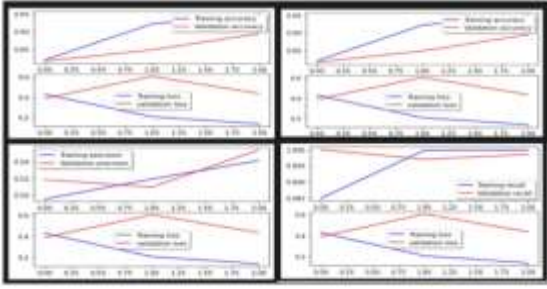


Figure 15:Performance analysis Graphs of CONVEXNET

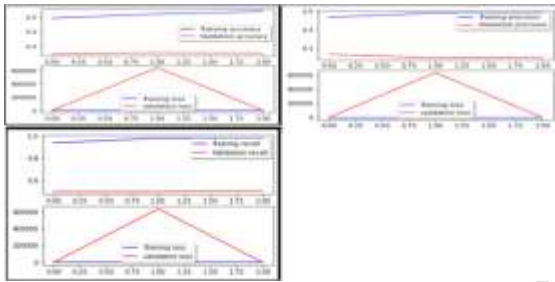


Figure 16:Performance analysis Graphs of VGG-16.

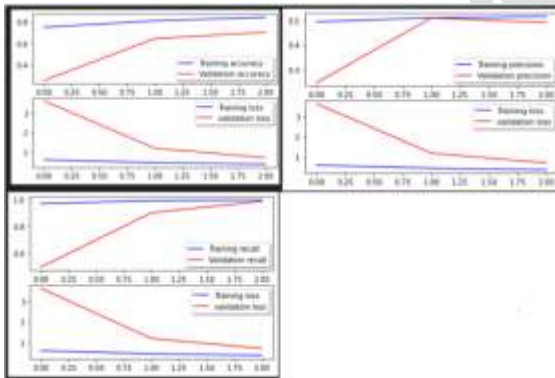


Figure 17:Performance analysis Graphs of RESNET-50

4.4 Performance of confusion matrix:To evaluate the overall performance of all of them during the modelling stage in the test set, we may use the matrix of uncertainty shown in the image below. RESNET-50 was the best in properly identifying COVID-19 and non-COVID-19 patients, whereas VGG-16 performed the worst, with the highest number of misclassified samples.

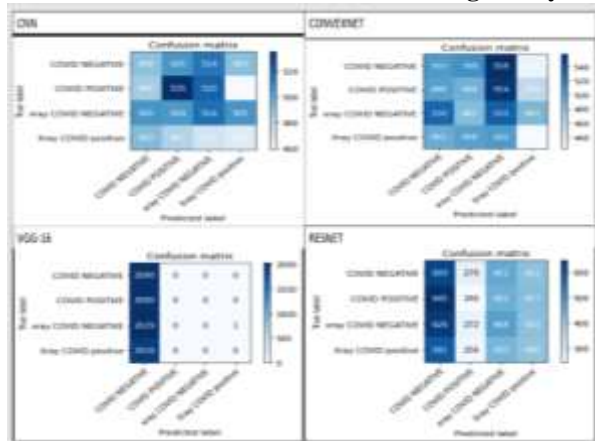


Figure18: Confusion matrices of all models applied to the mixed test dataset.

V.CONCLUSION:

Using these tools, we were able to perfect our method for analysing CT scan of X-ray pictures to determine the probability that they belonged to a person infected with COVID-19. The time and resources spent using this programme are minimised. This programme may readily be expanded to deal with a flood of tests, as is common during epidemics. Early detection allows for quicker treatment and reduces the risk of widespread illness.

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