A Study and Analysis of COVID-19 Diagnosis and Approach of Deep Learning

Mangai Begum R

Assistant Professor, Department of Information Technology, St. Joseph's College (Autonomous),
Affiliated to Bharathidasan University, Trichy, India.

Summary
The pandemic of Covid-19 (Coronavirus Disease 19) has devastated the world, affected millions of people, and disrupted the world economy. The cause of the Covid19 epidemic has been identified as a new variant known as Severe Acute Respiratory Syndrome Coronavirus 2(SARS-CoV2). It motives irritation of a small air sac referred to as the alveoli. The alveoli make up most of the tissue in the lungs and fill the sac with mucus. Most human beings with Covid19 usually do no longer improve pneumonia. However, chest x-rays of seriously unwell sufferers can be a useful device for medical doctors in diagnosing Covid19—both CT and X-ray exhibit usual patterns of frosted glass (GGO) and consolidation. The introduction of deep getting to know and brand new imaging helps radiologists and medical practitioners discover these unnatural patterns and pick out Covid19-infected chest x-rays. This venture makes use of a new deep studying structure proposed to diagnose Covid19 by the use of chest X-rays. The suggested model in this work aims to predict and forecast the patients at risk and identify the primary COVID-19 risk variables

Keywords:
X-rays of Chest, Deep Learning, Covid-19, Convolutional, Dilation.

1. Introduction

The Covid-19 outbreak has ravaged the worldwide health system. Many countries and organizations have been taken aback by the disease's spread and deadly toll. Researchers suggest the aetiology of SARSCoV2. A new virus variant is known as SARSCoV2, found to be the source of the Covid19 epidemic. Scientists and doctors explore the various methods to prevent the illness from spreading. Lockdown measures have been in effect for several months by governments and organizations. The high number of reported cases makes it challenging for clinicians to recognise covid19. The Covid19 epidemic's third wave appears to be more hazardous than the first and second waves, which is terrible. Containment efforts have been in place for months by governments and groups. Doctors and paramedics have difficulty diagnosing covid19 due to many reported instances. For several months, governments and organisations have imposed lockdown measures. Because of the enormous number of reported instances of covid19, identifying the disease has become a big undertaking for physicians and clinicians. To assess the efficacy of our suggested strategy, we compared it to the performance of a typical integrated neural network (CNN) trained on picture data. SARSCoV2 induces inflammation of the tiny air sacs termed alveoli, which make up the majority of lung tissue and fill the sacs with mucus. Laboratory testing such as transcriptase-RT PCR can aid in the early diagnosis of covid19.

Nevertheless, their low sensitivity [1],[2] means RTPCR assays might miss real positives, leading to false positives and negatives. Most covid19 cases do not proceed to pneumonia; nevertheless, chest x-rays of severely sick patients can assist doctors in detecting covid19. As a result, negative patients' X-ray scans may be investigated further to detect covid19 infection. Although there is no one best method for detecting covid19 disease [3], a combination of RT PCR testing and diagnostic chest radiography (CXR) can help identify positive patients.

Doctors can use artificial intelligence to help them' automate the Covid19 diagnostic process. To date, various deep learning approaches for image classification have been presented. Many criteria, such as the quality of the data and the learning stage, affect the performance of the model [4]. The final part of the study presents Ensemble CovidNet (eCOVNET), a new deep learning architecture for classifying Covid19CXR into viruses and common classes. Two separate networks make up the Ensemble Covid Net. The COVID19 radiology database was used for model training and evaluation [5],[6]. Tulin Ozturk et al. created the underlying functional layer of the network, inspired by COVIDNet [7].

Our goal is to develop a COVID19 prediction utility in response to today's artificial disasters. To limit the spread of the virus, governments rely solely on preventive measures [8]. It is essential to "recognize" all factors in any intervention. Large professional groups study many aspects of the pandemic, providing results that allow society to fit into this knowledge framework. According to

Manuscript received September 5, 2022
Manuscript revised September 20, 2022
https://doi.org/10.22937/IJCSNS.2022.22.9.23

the World Health Organization, India has recorded Omicron variant instances as of December 29, 2021, accounting for 4,444 of the 4,444,578 cases worldwide

2. Background Study

Deep learning has been the preferred image processing approach in recent years, and it has had a significant influence on the area of medical imaging [9]. Many scientists have been working on image processing algorithms in recent months. Deep learning is notoriously data-poor, and the CXR discovery community has profited in recent years from the availability of numerous extensive tagged databases. The automated production of markers from radiation reports enables the majority.

This study classifies workshops using deep learning from chest x-rays based on task picture location prediction (classification and regression), segmentation, placement, image production, and ability domain adaptability. Learn more about standard applications and current and emerging leading technology. The quaternion convolutional neural system was initially introduced [10], and among increased presentation for voice detection, lethal stimulus detection, and sound event discovery in 3D [11], different image processing, and photo colour categorization [12]. Scientific Medical imaging [13] is critical for standardizing early screening access, especially for specific connection and medicine strategies. It allows breathless processes in resource-deprived and overworked environments, perfecting vacuity and vacuity while using equipment commonly available in medical facilities worldwide. As healthcare systems throughout the world struggle to offer rapid treatment and care, screening ground rules have become increasingly important in isolating potentially infected individuals and preventing disease transmission. As a consequence, a group of researchers collaborated to use free databases of CXR images, some of which had metadata about respiratory disorders. COVID Net was one of the earliest concepts for a public network based on COVID 19 data derived from CXR pictures when initially available. Significant visual anomalies such as flat white lines, bands, reticular alterations, and opaque reflectors could be detected on the COVID19 X-ray of the Chest [14]. An outcome, by evaluating the patient's visual anomalies with chest X-ray films for infection, this imaging test may be used as an initial screening technique to diagnose COVID19 viral infection. COVID19 [15] is a virus. Additional imaging techniques, such as CT scans, increase resolution, although chest x-rays are cheap and precise [16],[17]. Therefore, Delays in virus detection can lead to severe lung damage. This virus has a low mortality rate. However, this virus is too contagious to ignore. The lack of 4,444 hospitals to treat thousands of patients daily exacerbates the viral danger. Predicting the viability of an infected person is just as important as detecting the virus early. When resources are scarce, health care facilities can make the most of the 4,444 available resources depending on the patient's condition. On the other hand, deep networks may help estimate survival odds. In this study, we used a clinical dataset containing gender, age, and blood type to conduct a diagnostic analysis of the COVID-19 virus.

SARS-CoV-2 causes inflammation of the alveoli, which are tiny air sacs that make up the bulk of lung tissue and fill the sack with mucus. Laboratory testing like reverse transcription-polymerase chain reaction can help identify covid-19 early (RT-PCR). However, due to their low sensitivity [18], RT-PCR tests might miss real positives, resulting in false positives and negatives. Most instances of covid-19 do not progress to pneumonia; nevertheless, chest radiography of seriously afflicted individuals can aid clinicians in detecting covid-19. Chest x-ray of patients who tested negative for covid-19 could be examined further for infection. Though there is no one-size-fits-all method for detecting covid-19 disease [19], a combination of RT PCR and Chest X-rays (CXRs) diagnosis can help identify positive people.

Artificial intelligence can help doctors automate the Covid-19 diagnosis procedure. Numerous deep learning algorithms have been presented thus far for image classification. Many factors, such as data quality and learning stage, impact the model's performance [9]. Ensemble Covid-Net (eCOVNET), a revolutionary deep learning architecture for categorizing Covid19CXR into viruses and standard classes, is introduced in the study's last portion. Two eCOVNET networks expand at different rates. The model was trained and evaluated using the COVID19 radiography database [20],[21]. Tulin Ozturk et al. developed the network's basic functional layer, which was influenced by COVIDNet [22]. Tulin O et al. created a layer that denotes the basic functions for networks affected by COVIDNet [23]. This study aimed to evaluate the survival of COVID-19 patients using clinical signs. We initially reviewed strategies for detecting COVID-19 using clinical characteristics and imaging data [24]. Researchers developed and tested a randomized machine learning (RF) forest model that included the features of each modality to determine the clinical category of COVID-19. The predictive accuracy of the HF model exceeded 90% when morbidity/symptoms and biochemistry were used as inputs and greater than 95% when both were used.

Relationships between input characteristics were further investigated using Gini admixtures and the most important variables for each modality (age, hypertension, cardiovascular disease, sex, diabetes), DDimer, hsTNI, neutrophils, IL6, LDH found. The RF model achieved a prediction accuracy of over 99% by combining 10 most important multimodal features [25].

The three objectives of the study were as follows:

1. On builds a prediction mortality model utilizing conventional clinical data from the patient's first day.

2. Determine if non-invasive patient features can predict COVID-19-related mortality.

3. The proposed model evaluates the invasive and non-invasive characteristics in predicted mortality. Persistent laboratory tests isolate clinical and demographic features. The researchers design the significant machine learning standards to explore and evaluate the predictive ability of the above functional categories. Machine learning can develop models utilizing X-ray and CT data. Many projects are currently underway in this field. The deep, complex neural networks by the literature studied for COVIDNet [26], Can identify COVID-19 using X-rays of chests and how many persons have been detected by COVID. It is unknown whether that person is affected or to what extent. Not all COVID-19 patients require thorough testing. Early diagnosis of hardest-hit can help guide recommendations and plan the allocation and use of health care resources. Yan et al. employed ML and a predictive method established from the given information of 29 (unique) people in China, as mentioned in the chapter [27], to estimate death risk for infected people. [28] Create an ML system competent in detecting COVID 19 and the chance of creating ARDS. The suggested model is 80 per cent accurate. Coivd patients will be divided into subgroups established on resistant cell counts in the blood, gender, and conveyed signs [29]. Eventually, we readied the model of XG Boost to determine COVID patients from influenza-infected people, with a perceptiveness of 92.6 % and a specificity of 97.8 %. Aside from clinical operations, machine learning may help with illness detection by leveraging photos and text data. Machine learning may use to detect novel coronaviruses. It can also forecast the features of viruses from all around the world. However, machine learning requires a significant amount of data to categorize or predict illnesses. Annotation data is necessary for supervised machine learning algorithms to type text or pictures into numerous categories. Over the last decade, tremendous progress has been made in this field to complete several critical projects. The latest outbreak has piqued the interest of many specialists worldwide [30].

Using Keras, TensorFlow, and Deep Learning architecture, COVID could be identified from Images of X-ray. Simonyan and Zisserman[31] used the VGG16 neural convolutional network to make this model. It has a three-cross-three filter with a stride one convolution layer, a two-cross two filter with two strides, fully connected layers, and a max-pooling for output. Average pooling, flattening, and a thick layer were used in addition to the VGG16 CNN model. There are 138 million (approximately) parameters to deal with in this network.

Table 1: Shows the summary of linked research

Author	***Year***	Techniques	Detection Type
[20]	2021	XGBoost classifier	Mortality risk prediction
[22]	2020	Random Forest	COVID-19 severity classification
[27]	2021	MLP	COVID-19 detection
[29]	2020	MLP	Mortality risk prediction
[30]	2020	Multinomial Naïve Regression status of Logistic and Bayes	Infected people categorization into four classes { ARDS , SARS, COVID-19, Both (COVID-19 and SARS)}
[37]	2020	An collection of NN, boosted conclusion tree grade, SVM, Including	Calculation of Mortality hazard forecast
[32]	2020	CNN	COVID-19 detection

3. Proposed Methodology

To measure its efficacy, we compared the performance of our proposed approach to that of a standard convolutional neural network (CNN) trained on image data.

3.1. Datasets

Generating a new annotated chest X-ray data set is time-consuming and expensive. As a result, researchers must train models using publicly available chest x-rays, specifically chest x-rays (CXR). The rationale for using chest X-rays to train and test models is that they are much cheaper to produce than other chest X-rays, such as CT scans. A publicly available X-ray of the chest database was connected to guide and test the form to achieve research objectives. This work uses the COVID19 radiographic database [32], a publicly available radiographic database created by M.E.H. Chowder, etc. An unbalanced data set can overestimate the training model. Models trained on unbalanced datasets are more likely to classify photos into several categories. To prevent this, 700 299x299 radiographs were retrieved from the COVID database of x-ray [33], one for each class (covid19, virus, and normal). According to the initial 80% of the data, the guiding forms are connected to the remaining 20%.

In this study, diagnosing Covid-19 using CXR can be considered a classification issue. Classification of Covid CXRs from different classes of CXRs can be performed in two phases.

- Phase 1: Preprocessing of the dataset using adaptive histogram equalization technique
- Phase 2: Proposal of a new deep learning architecture for classifying Covid CXR from various classes of CXR.

3.1.1 Phase 1: preprocessing of the dataset using adaptive histogram equalization technique

One of the most important processes in data analysis and forecasting is preprocessing. The photons are randomly distributed in the image, making the CXR more susceptible to noise.

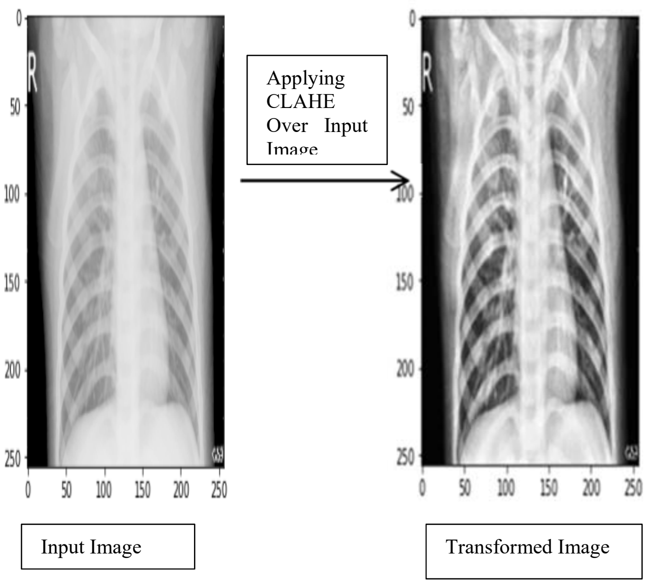

Figure -1 CLAHE Transformed Image

Training a deep learning model with noisy raw inputs can reduce the model's performance. Data preprocessing and feature extraction should be considered when dealing with noise-sensitive images. A variant of adaptive histogram equalization called Contrast Limit Adaptive Histogram Equalization (CLAHE) reduces noise gain in training and test datasets. CLAHE's contrast limiting feature can optically enhance the opacity / grey field of the CXR. These grey spots, known as glass bed opacity, are a common abnormality in patients with pneumonia caused by Covid19. Figure 1 shows the converted sample image

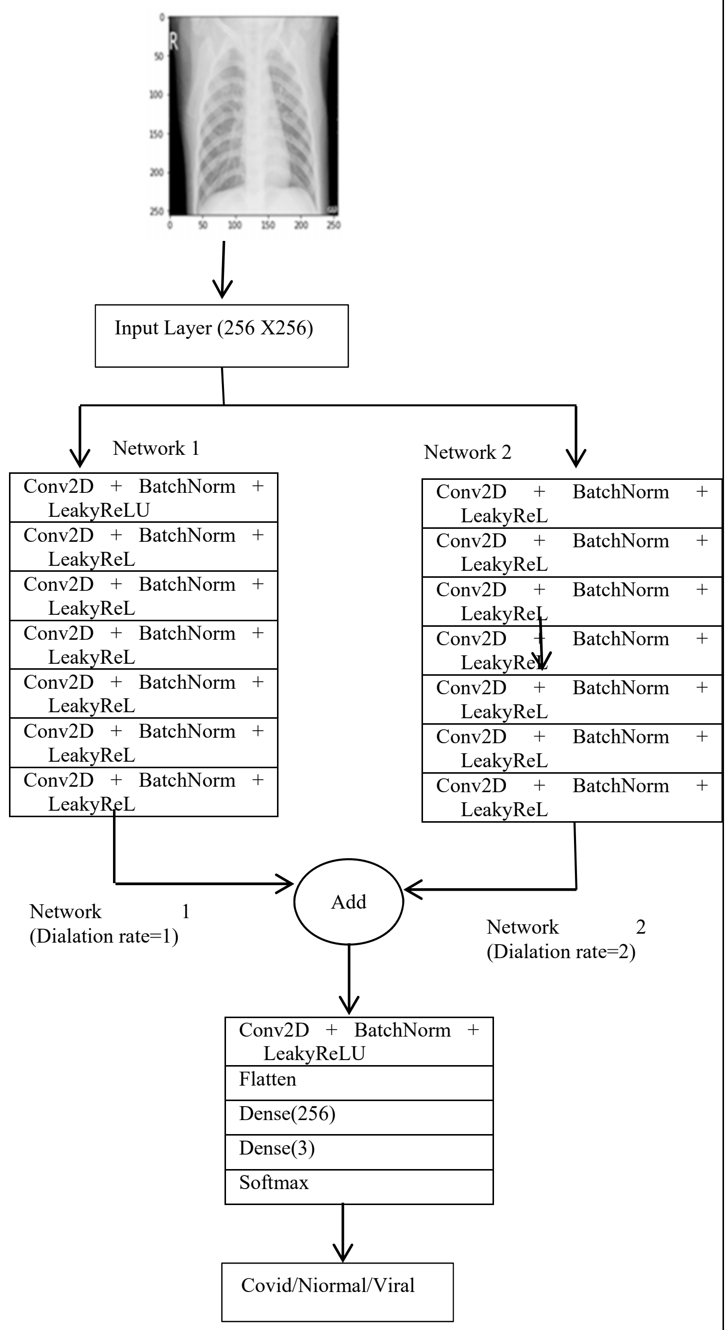

Figure-2 Architecture of e-COVNET

3.1.2 Phase 2: Proposal of a new additional learning architecture to classify CXR of Covid and its different classes

Building new novel deep learning architectures for image classification problems can be challenging. A better approach to solving an image classification could be using existing proven models to develop a new architecture. A new deep learning architecture called ensemble-CovidNet(e-COVNET) is proposed in this study. Very deep networks suffer from vanishing or exploding gradient problems. Hence instead of training a very deep neural network, two different networks can be trained in parallel to reduce the performance degradation [34].

e-COVNET comprises of two networks i) network1 and ii) network 2. It uses a 2D convolution function with batch normalization as a fundamental layer for two networks. e-COVNET uses a batch connection layer that uses Relu and Leaky as the triggers to determine which level is. It is shown in Figure 3.

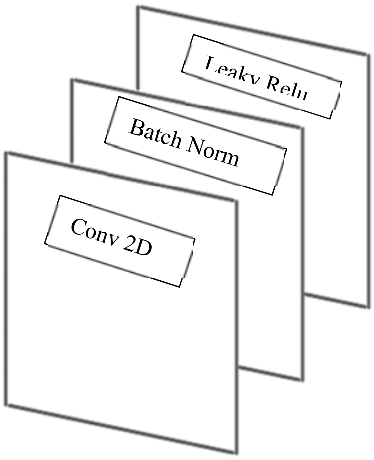

Figure-3 Basic Functional Layer of network 1 and network 2

1. Conv2D: Convolution is a linear operation systematically performed on the input to extract a certain characteristic. The convolution operation on input images with geometrical features that can clearly distinguish one image layer from another is performed by a 2D convolution layer or simply a Conv2D layer.

2. Batch normalization: The distribution of initial random weights significantly impacts the formation of deep neural networks. Using the convolution function, the training data distribution can be changed significantly. When training a complex neural network (CNN) with large data sets, the network encounters the problem of fading and fading magnitudes. Batch normalization is performed to normalize the inputs of each class to solve this problem.

3. Leaky ReLU: Each basic function layer has a LeakyReLU activation function. Since the linear activation function (ReLU) has a multi-convergence ratio, it is used by more deep neural networks than conventional logistic activation functions such as sigmoid and tanh. Equation 1 represents the activation function of the ReLU

$$F(x) = \max(x, 0) \quad (1)$$

However, one of the main disadvantages of ReLU is that it suffers from a dead ReLU problem. ReLU always gives the value 0 for any value less than 0, which inactive the neurons in the next layer. This problem was solved in the LeakyReLU function by inducing a small change in the slope for all input values less than 0. The LeakyReLU function can be represented by equation 2.

$$F(x) = \max(x, 0), \text{ if } x > 0 \text{ or } 0.01 * x, \text{ otherwise} \quad (2)$$

Networks 1 and 2 contain 7 layers of essential functions stacked on top of each other.

Network 1: It is made up of 7 primary functional layers. Each 2D convolution in each base function layer has 16 filters with a 3x3 multiplier. Network extension rate 1 is set to one.

Network 2: Like the network1, seven basic functional layers were placed on top of one another, with each 2D convolution function in the basic functional layer including 16 filters. The 2D convolution layer's kernel shape is 3x3. The rate of dilation is set at 2

Table-2 and table-3 mentioned the layers, parameters present network 1.

Table-2 parameters of Network 1

Nth Layer	*Layer(type)*	Output Shape	No.of Parameters
1	Conv2D	(299, 299, 16)	160
2	Conv2D	(299, 299, 16)	2320
3	Conv2D	(299, 299, 16)	2320
4	Conv2D	(299, 299, 16)	2320
5	Conv2D	(299, 299, 16)	2320
6	Conv2D	(299, 299, 16)	2320
7	Conv2D	(299, 299, 16)	2320

Table-3 parameters of Network 2

Nth Layer	Layer(type)	Output Shape	No.of Parameters
1	Conv2D	(299, 299, 16)	160
2	Conv2D	(299, 299, 16)	2320
3	Conv2D	(299, 299, 16)	2320
4	Conv2D	(299, 299, 16)	2320
5	Conv2D	(299, 299, 16)	2320
6	Conv2D	(299, 299, 16)	2320
7	Conv2D	(299, 299, 16)	2320

Table 4 shows type of layers present in fully connected layer and no. of parameters

Table 4. Fully connected layers

Nth Layer	***Layer(type)***	Output Shape	No.of Parameters
8	Conv2D	(299, 299, 2)	290
9	Flatten	(178802)	0
10	Dense	(1000)	178803000
11	Dense	(128)	128128
12	Dense	(3)	387

The dilation rate factor defines the space between kernel values. The dilated convolution feature of Networt2 is essential for expanding the receptive region and allowing networks to extract several properties from input images [35]. The outputs of networks 1 and 2 are merged using a simple addition function, which is then linked to a convolutional layer [1] with two filters, and finally to a fully connected layer. The convolutional layer's output volume is flattened before connecting to a fully linked layer. The completely linked layer is a two-layer perceptron with 1000 and 128 neurons in each dense layer. The covid, normal, and viral ternary categorization is performed by Network1, Network2, and the fully linked layer. The network's performance diminishes as the depth of the network expands due to the vanishing gradient problem. To tackle the problem, e-COVNET employs a technique that entails concurrently training two networks and then merging the data obtained.

4. Experimental Results and Discussions

4.1 Implementation

Keras API TensorFlow is used to build a custom e-COVNET model as a backend tool. Kaggle's underlying hardware is used to train an extensive resource model. Along with python 3.7, NumPy, OpenCV, matplotlib, sci-kit learn packages were used to investigate the results.the previous phase is multiplied with the predictions, and the training data for the level 2 phase is obtained.

4.2 Ternary Categorization: Normal situation vs Covid vs Viral

To achieve that objective in a ternary classification, the experiment was performed to classify covid19 CXRs into normal and viral CXRs. The trends of training loss and accuracy versus epochs were given in the figure 4 and 5. Since the training dataset was limited to 3900 images the model suffered from little to no over fitting. In order to achieve the purpose of ternary classification, the idea of this test is to categorize CXR covid-19, viral CXR and normal. The figure-4 shows the trends of training loss and accuracy versus epoch. The four standards of precision, exactness, recollect and core of F1 standards are connected to compare models.

80% of X-ray pictures are utilized for training, while 20% are used to verify the results of the training. Figure-4 shows the accuracy arc for training data and validation data. Accuracy curve depicts the relationship between the training data accuracy which is slightly higher than the validation data accuracy rate, which represents the accuracy prediction levels.

Figure-4 Accuracy of e-COVNET model

Figure-5 shows the curve of the validation loss of the e-COVNET model. As seen in Fig. 5, the loss values increase significantly at the start of training and drop considerably at the end. The COVID-19 class has significantly less data than the other classes (Pneumonia and No-Findings). The quick ups and downs are gradually minimised as the proposed deep learning model evaluates all X-ray images for each epoch during training.

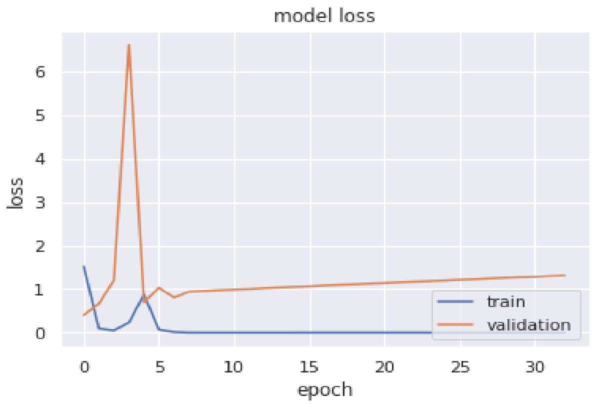

Figure-5 Loss of e-COVNET model

Accuracy: The fraction of correct projections to total forecasts.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

Where TP ,TN, FP and FN represents true positive, true negative, false positivbe and false negative respectively.

Precision: Precision refers to the quantum of data that's transferred by a number in terms of its integers; it shows the closeness of two or further measures to each other. It's self-reliant of accuracy.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

Recall: The recall is the balance of positive examples among the absolute digit of positive specimens. Actually, the whole digit of real negatives is separated by the absolute number of genuine negatives. In our scenario, recall directs to the likelihood of precisely categorizing a pneumonia model.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (5)$$

F-Score: F- Score is a calculate that connects both preciseness and recollect as refereed in specific method

$$\text{Score of F} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

The proposed the e-COVNET model is compared against the existing classifiers in (14) with the results shown in Tables 4 and 5. The average test accuracy of thee-COVNET over significant iterations is shown in Table 4. The accuracy of the pre-trained imagenet models ResNet50[42], Xception[43], MobileNet[44], VGG19[45], ResNetv2[46] and Inception v3[47] was 0.85 percent, 0.94 percent, 0.94 percent, 0.92 percent, 0.93 percent, and 0.91 percent, respectively. As a result, the suggested model beats the known deep learning framework, with an accuracy of 95%.

Table 4 Comparative Measures of Different Classifiers

	Precisio						**F1-Score**		
Model	Covid-19 Infection	Normal Mode	Viral Mode	Infection of Covid-19	Mode of Normal	Mode of Viral	Infection of Covid-19	Mode of Normal	Mode of Viral
e-COVNET(Proposed)	0.962	1.0	1.0	1.0	0.90	0.89	0.98	0.94	0.94
ResNet50	0.83	0.88	0.85	0.97	0.82	0.77	0.90	0.85	0.81
Xception	1.00	0.86	0.97	1.00	0.97	0.84	1.00	0.91	0.90
Mobilenet	1.00	0.86	0.99	0.98	0.99	0.86	0.99	0.92	0.92
VGG19	0.95	0.89	0.91	0.93	0.94	0.88	0.94	0.92	0.89
ResNetv2	1.00	0.84	0.92	0.95	0.94	0.95	0.98	0.89	0.88
Inception v3	0.99	0.85	0.96	0.99	0.96	0.84	0.99	0.90	0.89

Table 5: Average test accuracy detection of the e-COVNET

Model	*Accuracy(%)*
e-COVNET(Proposed)	95
ResNet50[35]	85
Xception[36]	94
MobileNet[37]	94
VGG19[38]	92
ResNetv2[39]	93
Inception v3[40]	91

Conclusion

Python programming was applied to do the analysis. Human coronaviruses are being examined in terms of clinical, epidemiological, transmission, and comparative aspects, as well as the therapy of 2019-nCoV-related illnesses. Finally, we evaluated earlier analysis on COVID-19 finding by computers and created our indepth learning approach for detecting COVID infected patients. But this analysis, the recommended deep convolutional network was connected to categorize X-rays into three types: normal, viral pneumonia, as well as COVID19. By decreasing the time to diagnosis, the suggested approach assists radiologists and clinicians in identifying possibly positive Covid 19 patients with 95 % accuracy. The model performed relatively well over the existing pre-trained model, but suffered from overfitting training data due to the lack of available Covid19 CXR. We can further develop this work to extract more characteristics from the input data, and subsequent recurrent neural networks can be utilized to improve accuracy. This model has the potential to significantly increase your model's performance.

Acknowledgements

This work has not been funded by any research organization

References

[1] J. Kanne, B. Little, J. Chung, B. Elicker and L. Ketai, "Essentials for Radiologists on COVID-19: An Update—Radiology Scientific Expert Panel", Radiology, vol. 296, no. 2, pp. E113-E114, Feb.2020.

[2] X. Xie, Z. Zhong, W. Zhao, C. Zheng, F. Wang and J. Liu, "Chest CT for Typical Coronavirus Disease 2019 (COVID-19) Pneumonia: Relationship to Negative RT-PCR Testing", Radiology, vol. 296, no. 2, pp. E41-E45, Feb.2020.

[3] J. Hadden, A. Tiwari, R. Roy, D. Ruta, "Computer assisted customer churn management: State-of-the-art and future trends", Computers & Operations Research, vol. 34, no. 10, pp. 2902-2917, Oct.2007.

[4] D. Ji, Z. Zhang, Y. Zhao and Q. Zhao, "Research on Classification of COVID-19 Chest X-Ray Image Modal Feature Fusion Based on Deep Learning", Journal of Healthcare Engineering, vol. 2021, pp. 1-12, Aug.2021.

[5] Chowdhury M.E.H, Rahman T, Khandakar A, R. Mazhar, Kadir M.A, Mahbub Z.B, Islam K.R, Khan M.S., Iqbal A, N. Al-Emadi, M.B.I. Reaz, M. T. Islam, "Can AI help in screening Viral and COVID-19 pneumonia?" IEEE Access, Vol. 8, pp. 132665 – 132676, July 2020.

[6] T. Rahman et al., "Exploring the effect of image enhancement techniques on COVID-19 detection using chest X-ray images", Computers in Biology and Medicine, vol. 132, p. 104319, May 2021.

[7] M. Annarumma, S. Withey, R. Bakewell, E. Pesce, V. Goh and G. Montana, "Automated Triaging of Adult Chest Radiographs with Deep Artificial Neural Networks", Radiology, vol. 291, no. 1, pp. 272-272, Jan.2019.

[8] G. Bacellar, M. Chandrappa, R. Kulkarni and S. Dey, "COVID-19 Chest X-Ray Image Classification Using Deep Learning", medRxiv, Preprint Server for Healh Sciences, july 2021. Available: 10.1101/2021.07.15.212606.

[9] L. Wang, Z. Lin and A. Wong, "COVID-Net: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images", Scientific Reports, vol. 10, no. 1, Nov.2020.

[10] X. Zhu, Y. Xu, H. Xu and C. Chen, "Quaternion Convolutional Neural Networks", Computer Vision – ECCV 2018, pp. 645-661, Sep.2018.

[11] D. Comminiello, M. Lella, S. Scardapane and A. Uncini, "Quaternion Convolutional Neural Networks for Detection and Localization of 3D Sound Events," ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 8533-8537,May 2019.

[12] T. Parcollet, M. Morchid and G. Linarès, "Quaternion Convolutional Neural Networks for Heterogeneous Image Processing," ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 8514-8518, Apr.2019.

[13] R. Sadre, B. Sundaram, S. Majumdar and D. Ushizima, "Validating deep learning inference during chest X-ray classification for COVID-19 screening", Scientific Reports, vol. 11, no. 1, Apr.2021.

[14] J. Cleverley, J. Piper and M. Jones, "The role of chest radiography in confirming covid-19 pneumonia", BMJ, p. m2426, July 2020.

[15] G. Rubin et al., "The Role of Chest Imaging in Patient Management during the COVID-19 Pandemic: A Multinational Consensus Statement from the Fleischner Society", Radiology, vol. 296, no. 1, pp. 172-180, Apr. 2020.

[16] X. Wang et al., "A Weakly-Supervised Framework for COVID-19 Classification and Lesion Localization From Chest CT," in IEEE Transactions on Medical Imaging, vol. 39, no. 8, pp. 2615-2625, Aug. 2020

[17] T. Ozturk, M. Talo, E. Yildirim, U. Baloglu, O. Yildirim and U. Rajendra Acharya, "Automated detection of COVID-19 cases using deep neural networks with X-ray images", Computers in Biology and Medicine, vol. 121, p. 103792, June 2020.

[18] W. Li et al., "Using machine learning of clinical data to diagnose COVID-19: a systematic review and meta-analysis", BMC Medical Informatics and Decision Making, vol. 20, no. 1, Sep. 2020.

[19] Y. Chen et al., "An Interpretable Machine Learning Framework for Accurate Severe vs Non-severe COVID-19 Clinical Type Classification", medRxiv, Preprint Server for Healh Sciences, May 2020.

[20] J. Kanne, B. Little, J. Chung, B. Elicker and L. Ketai, "Essentials for Radiologists on COVID-19: An Update—Radiology Scientific Expert Panel", Radiology, vol. 296, no. 2, pp. E113-E114, Feb. 2020.

[21] E. Lee, M. Ng and P. Khong, "COVID-19 pneumonia: what has CT taught us?", The Lancet Infectious Diseases, vol. 20, no. 4, pp. 384-385, Feb.2020.

[22] F. Pan et al., "Time Course of Lung Changes at Chest CT during Recovery from Coronavirus Disease 2019 (COVID-19)", Radiology, vol. 295, no. 3, pp. 715-721, Feb.2020.

[23] M. Mazurowski, M. Buda, A. Saha and M. Bashir, "Deep learning in radiology: An overview of the concepts and a survey of the state of the art with focus on MRI", Journal of Magnetic Resonance Imaging, vol. 49, no. 4, pp. 939-954, Apr.2018.

[24] A. Khanday, S. Rabani, Q. Khan, N. Rouf and M. Mohi Ud Din, "Machine learning based approaches for detecting COVID-19 using clinical text data", International Journal of Information Technology, vol. 12, no. 3, pp. 731-739, June 2020.

[25] Y. Gao et al., "Machine learning based early warning system enables accurate mortality risk prediction for COVID-19", Nature Communications, vol. 11, no. 1, Oct.2020.

[26] Karen Simonyan, Andrew Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition", Connell University, https://arxiv.org/abs/1409.1556v6, Apr. 2015.

[27] M. Mahdavi et al., "A machine learning based exploration of COVID-19 mortality risk", PLOS ONE, vol. 16, no. 7, p. e0252384, Jul.2021.

[28] J. Zhu et al., "Deep-learning artificial intelligence analysis of clinical variables predicts mortality in COVID-19 patients", Journal of the American College of Emergency Physicians Open, vol. 1, no. 6, pp. 1364-1373, Aug.2020.

[29] Rahman, M., Uddin, M., Wadud, M., Akhter, A., Akter, O. "A Study on Epidemiological Characteristics and ML Based Detection of Novel COVID-19".Preprint,Research Gate, March 2020.

[30] L. Lu, "Dying ReLU and Initialization: Theory and Numerical Examples", Communications in Computational Physics, vol. 28, no. 5, pp. 1671-1706, Nov.2020.

[31] A. Bernheim et al., "Chest CT Findings in Coronavirus Disease-19 (COVID-19): Relationship to Duration of Infection", Radiology, vol. 295, no. 3, p. 200463, Feb.2020.

[32] T. Ozturk, M. Talo, E. Yildirim, U. Baloglu, O. Yildirim and U. Rajendra Acharya, "Automated detection of COVID-19 cases using deep neural networks with X-ray images", Computers in Biology and Medicine, vol. 121, p. 103792, June 2020.

[33] E.Allibhai, Building a Convolutional Neural Network (CNN-Conv2D) in Keras[Online].Available:https://towardsdatascience.com/building-a-convolutional-neural-networkCNN-in-keras-329fbbadc5f5[Accessed: 1-May-2020

[34] Sergey Ioffe, Christian Szegedy ,Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift, arXiv:1502.03167 [cs.LG], Feb.2015
[35] Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun, "Deep Residual Learning for Image Recognition" , arXiv preprint, https://arxiv.org/abs/1512.03385,[cs.CV], 2015.
[36] François Chollet, "Xception: Deep Learning with Depthwise Separable Convolutionsm", arXiv Preprint, https://arxiv.org/abs/1610.02357v3, 2015
[37] Wei Wang ,1 Yutao Li , Ting Zou , Xin Wang , Jieyu You , and Yanhong Luo, "A Novel Image Classification Approach via Dense-MobileNet Models", arXiv Preprint, https://doi.org/10.1155/2020/7602384, Volume 2020 |Article ID 7602384,
[38] Xiangyu Zhang, Jianhua Zou, Kaiming He† , and Jian Sun, "Accelerating Very Deep Convolutional Networks for Classification and Detection", arXiv Preprint, https://arxiv.org/abs/1505.06798v2[cs.CV], 2015.
[39] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov and L. -C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2018, pp. 4510-4520, doi: 10.1109/CVPR.2018.00474.
[40] Christian Szegedy et. al, "Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning",arXiv preprint, arXiv:1602.07261v2 [cs.CV] Aug 2020
[41] J. Goyal Jain B. Kishan, "Enhanced Heterogeneous Ensemble Technique for Improving Software Fault Prediction", International Journal on "Technical and Physical Problems of Engineering, Volume 13, Number 4 Pages 63-71, December 2021.
[42] R. Esmaeilzadeh A. Roshan Milani, "Efficient Electric Price Forecasting Using Neural Networks", International Journal onTechnical and Physical Problems of Engineering, Volume 9, Number 3 Pages 30-34, September 2017.

Mangai Begam RAMANUJAM was born in 1974 in Madurai district, Tamil Nadu. She has a bachelor's degree in Businnes Administration and a master's degree in computer science Madras University. Bharathidasan University awarded him a Ph.D. She is currently a Professor at the Department of Information Technology, St.Joseph's College(Autonomous), Tiruchirappalli. She has more than 14 years of teaching experiences. She has organized many national and international conferences. She also delivers the guest lecturers about the data analytics and other emerging technologies in various colleges. His current research interests include Image Processing, Cognitive Science, Big data, data mining and so on