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A DEEP LEARNING HYBRID APPROACH FOR THE DETECTION OF COVID-19 FROM X-RAY IMAGES USING CNN-LSTM NETWORK MODELS

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Abstract : **.** Corona Virus Infectious Disease (COVID-19) is an infectious disease. The disease of COVID-19 came to the earth in the beginning of 2019. It is breaking out all over the world and affecting a huge number of people all over the world. The World Health Organization (WHO) has declared COVID-19 a pandemic. Doctors' diagnoses. The corona virus (COVID-19) has become one of the most serious and acute diseases in recent times that has spread throughout the world. An automated disease detection framework helps clinicians diagnose disease and provides an accurate, consistent and rapid response and reduces mortality. Therefore, to prevent the spread of COVID-19, an automatic detection system should be adopted as the fastest diagnostic option. This paper aims to present hybrid deep learning approaches for convolutional neural network (CNN) and long-term memory (LSTM) to automatically predict COVID-19 from X-ray images. In this system, CNN is used for deep feature extraction and LSTM is used for detection using the extracted feature. The dataset for this system uses a set of 500 X-ray images, including 200 images of COVID-19. Experimental results show that the proposed system achieved 97% accuracy, 95% specificity, and 98% sensitivity. The system achieved the desired results.

Index-Terms - COVID-19, Deep learning, Chest X-ray, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Images.

I. INTRODUCTION

The global coronavirus epidemic has locked down the entire process of every sector. According to the latest estimates from the World Health Organization, more than seven million people have been infected and nearly 414,060 have died (as of June 10, 2020) [1]. The healthcare system has failed even in developed countries due to the lack of intensive care units (ICU). Patients with more severe disease from COVID-19 are placed in the intensive care unit. The strain that began spreading in Wuhan, China was identified as two different coronaviruses, SARS and Middle East Respiratory Syndrome (MERS) [2]. Symptoms of different types of COVID-19 diseases can vary from common cold to fever, shortness of breath and acute respiratory symptoms [3]. Compared to SARS, the coronavirus affects the respiratory tract as well as the kidneys and liver [4]. Early detection of coronavirus plays an important role in controlling COVID-19 due to its high infectivity. According to Chinese government guidelines, the diagnosis of coronavirus must be confirmed by gene sequencing of respiratory or blood samples as the main indicator of reverse transcription polymerase chain reaction (RT-PCR) [5]. The RT-PCR process takes 4-6 hours to results, which takes a long time compared to the rapid spread of COVID-19. In addition to inefficiency, there is a serious shortage of RT-PCR test kits. Therefore, many infected cases cannot be detected in time and tend to unknowingly infect others. If this disease is detected at an early stage, the incidence of COVID-19 is reduced [7]. Efforts have been made to find alternative testing methods to mitigate the inefficiencies and shortcomings of current COVID-19 tests. Another imaging method is to diagnose COVID-19 infections using radiological images such as X-rays or computed tomography (CT). Previous work shows that abnormalities in the form of ground opacities have been observed in radiological images in patients with COVID-19 [8]. The researchers claim that a chest radiology-based system could be an important method to identify, quantify and track COVID-19 events [9]. Today, many scientists around the world are working to fight against COVID-19. Many researchers are demonstrating different ways to detect COVID-19 using X-rays. Recently, computer vision [10], machine learning [13] and deep learning [14], [15] have been used to automatically diagnose various diseases of the human body, thus providing intelligent health care [16]. The deep learning method is used as feature extraction, which improves the classification accuracy [18]. Detection of tumor shape and area in lungs, X-ray suppression, diagnosis of diabetic retinopathy, prostate segmentation, diagnosis of skin lesions, examination of myocardium in coronary CT are examples of the contribution of deep learning [19], [20]. Therefore, the purpose of this paper is to propose a deep learning-based system combining CNN-LSTM network to automatically detect COVID-19 based on X-ray images. The system designed for feature extraction uses CNN and LSTM to classify COVID-19 based on these features. The combination of 2D CNN and LSTM localization functions greatly improves the classification. The dataset used in this work is collected from several sources and pre-processing is done to reduce noise.

II. RELATED WORKS

With the outbreak of COVID-19, more efforts have been made to develop deep learning methods to diagnose COVID-19 from clinical images, including computed tomography (CT) and chest X-rays. This literature details recently developed systems that apply deep learning techniques to the field of COVID-19 detection. Rahimzadeh et al. [21] developed a coupled CNN to classify COVID-19 cases based on Xception and ResNet50V2 models using chest X-rays. The developed system used material containing 180 images of COVID-19 patients, 6,054 images of pneumonia patients, and 8,851 images of normal people. In this work, 633 images of each phase were selected for training and eight phases were used. The test result gave 99.56 percent accuracy and 80.53 percent recovery of COVID-19 cases. Alqudah et al. [22] used artificial intelligence techniques to develop a system to detect COVID-19 from a chest X-ray image. The images used were classified using various machine learning techniques such as Support Vector Machine (SVM), CNN and Random Forest (RF). The system has an accuracy of 95.2%, a specificity of 100% and a sensitivity of 93.3%. Loey et al. [23] applied a deep learning Generative Adversarial Network (GAN) to diagnose COVID-19 based on a chest X-ray image. The system used three pre-trained models called Alexnet, Googlenet and Restnet18 to detect the coronavirus. The collected data includes 69 images of cases of COVID-19, 79 images of cases of bacterial pneumonia, 79 images of cases of viral pneumonia and 79 images of normal cases. Googlenet was selected as the leading deep learning technique with 80.6 percent test accuracy in the four-class scenario, Alex network with 85.2 percent test accuracy in the three-class scenario, and. For COVID-19, the system achieved an accuracy of 98.3. Apostolopoulos et al. [25] presented a transfer learning strategy with CNN to automatically diagnose COVID-19 cases by extracting key features from a chest X-ray image. The system used five CNN variants called VGG19, Inception, Mobile Net, caption and Inception-ResNetV2 to classify the COVID-19 images. In the developed system, the material contains 224 images of COVID-19 patients, 700 images of pneumonia patients and 504 images of normal patients. The dataset is partitioned using the concept of tenfold cross-validation for training and evaluation purposes. VGG19 was selected as the basic deep learning model, which has an accuracy of 93.48% a specificity of 92.85 percent, and a sensitivity of 98.75 percent in the developed system. Bandyopadhyay et al. [26] proposed a new model combining LSTM-GRU to automatically classify confirmed, published, negative and fatal COVID-19 cases. The developed system achieved 87% accuracy for the confirmed case, 67.8% accuracy for the negative case, 62%accuracy for the dead case, and 40.5% accuracy for the published case for the COVID-19 version. Khan et al. [27] presented a deep learning network to automatically predict COVID-19 cases based on chest X-ray. In the development system, the dataset contains 284 images of COVID-19 cases, 330 images of pneumonia bacterial cases, 327 images of pneumonia virus cases and 310 images of normal cases. The proposed system achieved 89.5 percent accuracy, 97 percent precision, and 100 percent recall for COVID-19 cases. Kumar et al. [28] presented a deep learning methodology to classify patients infected with COVID-19 using chest X-rays. The formula used nine pre-trained models for feature extraction and a support vector machine for classification. They compiled two datasets containing 158 X-rays from both COVID-19 and non-COVID-19 patients.

III. METHODOLOGY

A general system for detecting COVID-19 requires several steps, shown in Figure 1. Initially, raw X-rays pass through a preprocessing pipeline. In the preprocessing process, data resizing, blending, normalization and upscaling were performed. The pre-processed dataset is then split into a training set and a test set. Next, we trained the CNN and CNN-LSTM architecture using the workflow training data. After each epoch, the training accuracy and losses are found in the proposed system. At the same time, 5-fold cross-validation also achieves validation accuracy and loss. The performance is measured by a number of evaluation measures such as confusion matrix, accuracy, specificity, sensitivity and f1 score of the proposed system.

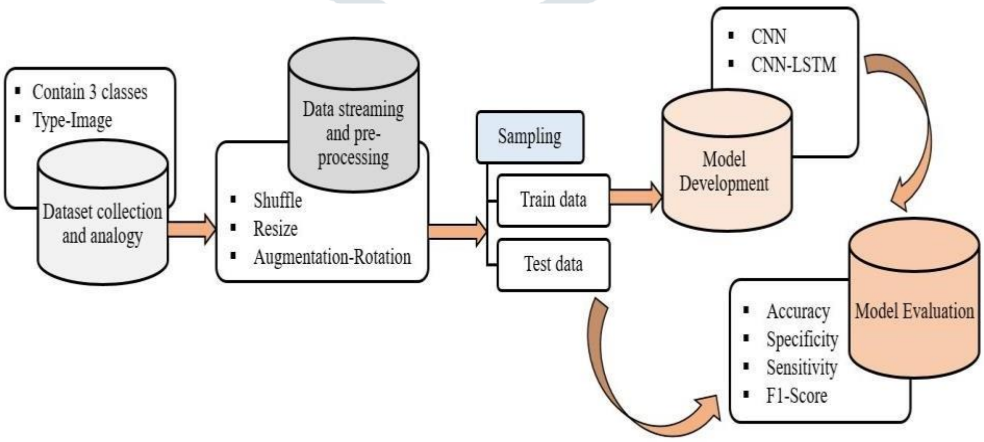


Fig. 1. The overall system architecture of the proposed COVID-19 detection system

3.1 Development of Hybrid Network

The proposed architecture is formed with the combination of CNN and LSTM network which is briefly described as follows.

3.1.1 Convolutional Neural Network

A special type of multilayer perceptron is a convolutional neural network. However, a simple neural network cannot learn complex features, but a deep architectural network can. CNNs have shown excellent performance in many applications [33], [34] such as image classification, object detection, and medical image analysis. The basic idea of CNN is that it can obtain local features from the inputs of higher layers and feed them to lower layers for more complex features. A CNN consists of a convolution layer, a pooling layer, and a fully connected (FC) layer. A typical CNN architecture with these layers is illustrated in Figure 3.

Table 1. The partitioning description of used dataset

Data/Cases	COVID-19	Normal	Pneumonia	Overall
Training	119	119	119	357
Testing	30	24	20	74
Overall	141	140	140	421

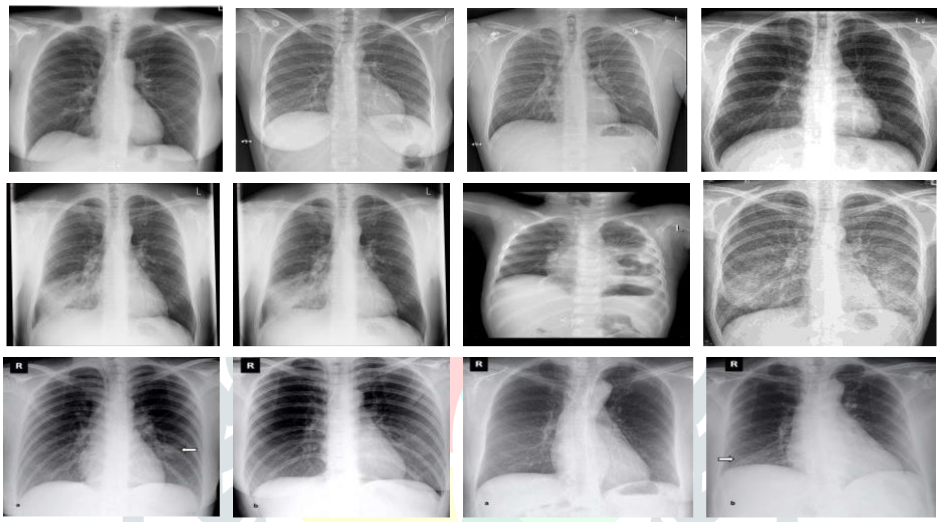


Fig. 2. The images in the first row show 4 sample images COVID-19 cases. The images in thesecond row are 4 sample images of pneumonia cases and the third row are 4 sample images ofnormal cases.

The convolutional layer includes a set of kernels [35] for determining a tensor of featuremaps. These kernels convolve entire input using "stride(s)" so that the dimensions of the output volume become integers [36]. The input volume's dimensions reduce after the convolutional layer for the striding process. Therefore, zero-padding [37] is re- quired to pad the input volume with zeros to maintain the dimension of the input volume with low-level features. The operation of convolution layer is given as:

$$F\ (i,) = (I*K)\ (i, j) = \ \Sigma\Sigma\ I\ (i+m, j+n)\ K\ (m, n) \quad (1)$$

where I refers to the input matrix, K refers to a 2D filter of size m x n,and F refers output of the 2D feature map. The operation of the convolution layer is denoted by I*K.

For increasing the nonlinearity in the feature maps, the rectified linear unit (ReLU) layer is used [38]. ReLU computes the activation by keeping the threshold the input atzero. It is mathematical expression is given as:

$$f(x) = \max\ (0, x) \quad (2)$$

The pooling layer [39] is performed down sampling of the given input dimension to reduce the number of parameters. Max Pooling is the most common method which produces the maximum value in the input region. The fully-connected layer [40] is usedas a classifier to make a decision based on obtained features from convolution and pooling layers. A full CNN architecture is developed with these layers which are discussedabove.

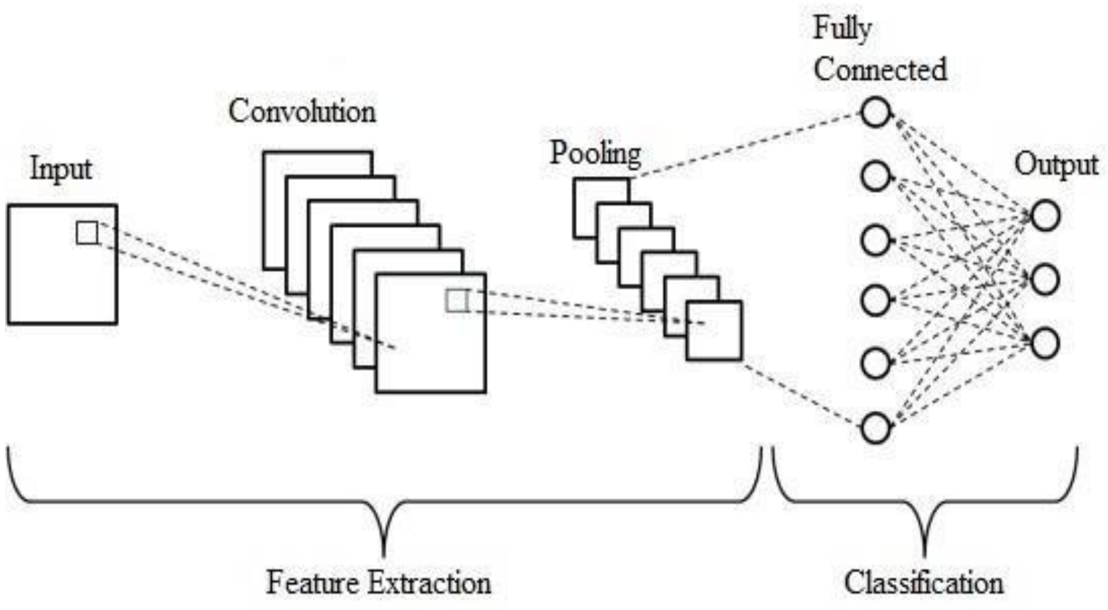


Fig. 3. A typical architecture of the convolutional neural network.

3.1.2 Long Short-Term Memory

Long short-term memory is an improvement from the recurrent neural network (RNN).LSTM proposes memory blocks instead of conventional RNN units to solve vanishingand exploding gradient problem [41]. LSTM added a cell state to save long-term states which is the main difference from RNN. LSTM network can remember and connect theprevious information to the present [42]. The structure of the LSTM network is shownin Fig. 4. The LSTM is combined with three gates such as the input gate, the forget gateand output gate where xt refers the current input, Ct and $Ct{-}1$ refer the new and previous cell state respectively, ht and $ht{-}1$ refer the current and previous output respectively.The principle of the input gate of the LSTM is shown in the following forms.

$$it = \sigma(W\mathrm{i} \cdot [ht{-}1, xt] + b\mathrm{i}) \quad (3)$$

$$\tilde{C}t = \tanh(W\mathrm{i} \cdot [ht{-}1, xt] + b\mathrm{i}) \quad (4)$$

$$C\mathrm{t} = ft\ Ct{-}1 + it\ \tilde{C}t \quad (5)$$

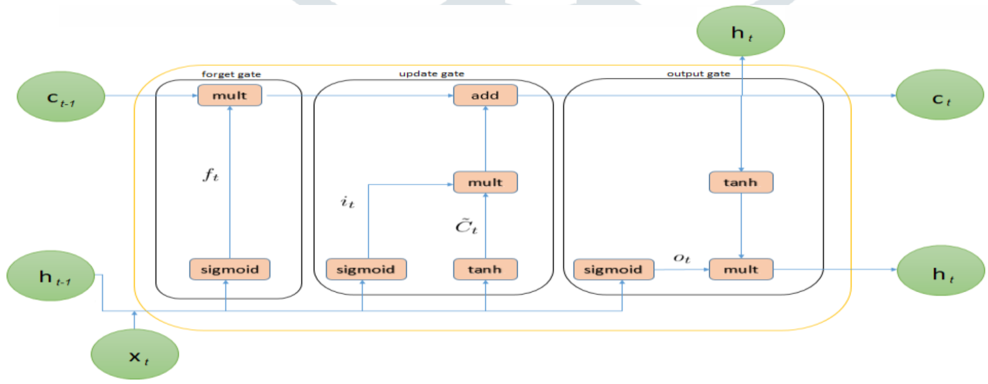


Fig. 4. The internal structure of Long short-term memory.

where (3) is used to pass $ht{-}1$ and xt through the sigmoid layer to decide which portion of information should be added. Subsequently, (4) obtains new information after pass-ing $ht{-}1$ and xt through the tanh layer. The current moment information $\tilde{C}t$ and long- term memory information $Ct{-}1$ into Ct are combined in (5), where it refers to sigmoid output, and $\tilde{C}t$ refers to tanh output. Here, W_i refers to weight matrices and b_i refers to input gate bias of LSTM. Then, the LSTM's forget gate allows the selective passage ofinformation using a sigmoid layer and a dot product. The decision about whether to forget from the previous cell's related information with a certain probability is done using (6) where Wf refers to the weight matrix, bf is the offset, and σ refers to the sigmoid function.

$$ft = \sigma(Wf \cdot [ht{-}1, xt] + bf\ ) \quad (6)$$

The LSTM's output gate determines the states which are required to be continued by the $ht{-}1$ and xt inputs following to (7) and (8). The final output is obtained to multiply with the state decision vectors passing new information C_t through the tanh layer.

$$O_t = \sigma(WO \cdot [\ ht{-}1, xt] + bO\ ) \quad (7)$$

$$h_t = Ot \tanh(Ct) \quad (8)$$

where Wo and bo are the output gate's weighted matrices and the output gate's bias ofLSTM respectively.

3.1.3 Hybrid CNN-LSTM Network Model

In this paper, a combined method was developed to automatically detect the COVID- 19 cases using three types of X-ray images. The structure of this architecture is developed by combining CNN and LSTM networks where CNN is used to extract the com-plex features from images and LSTM is used as a classifier. Fig. 5 illustrates the proposed hybrid network for COVID-19 detection. Each convolution block combined with two or three 2D CNN and one pooling layer; the rectified linear units are activated as an activation function. The convolution kernel is extracted convolution feature by multiplying the superposition matrix in all convolution operations. The maximum-pooled filter of the feature map is used for feature extraction aftera two-dimensional convolution, and the filter's step size is two. In the last part of the architecture, the function map is transferred to the LSTM layer to extract time information. Finally, the fully connected layer of the softmax function is used to predict intothree categories (COVID-19, pneumonia, and normal).

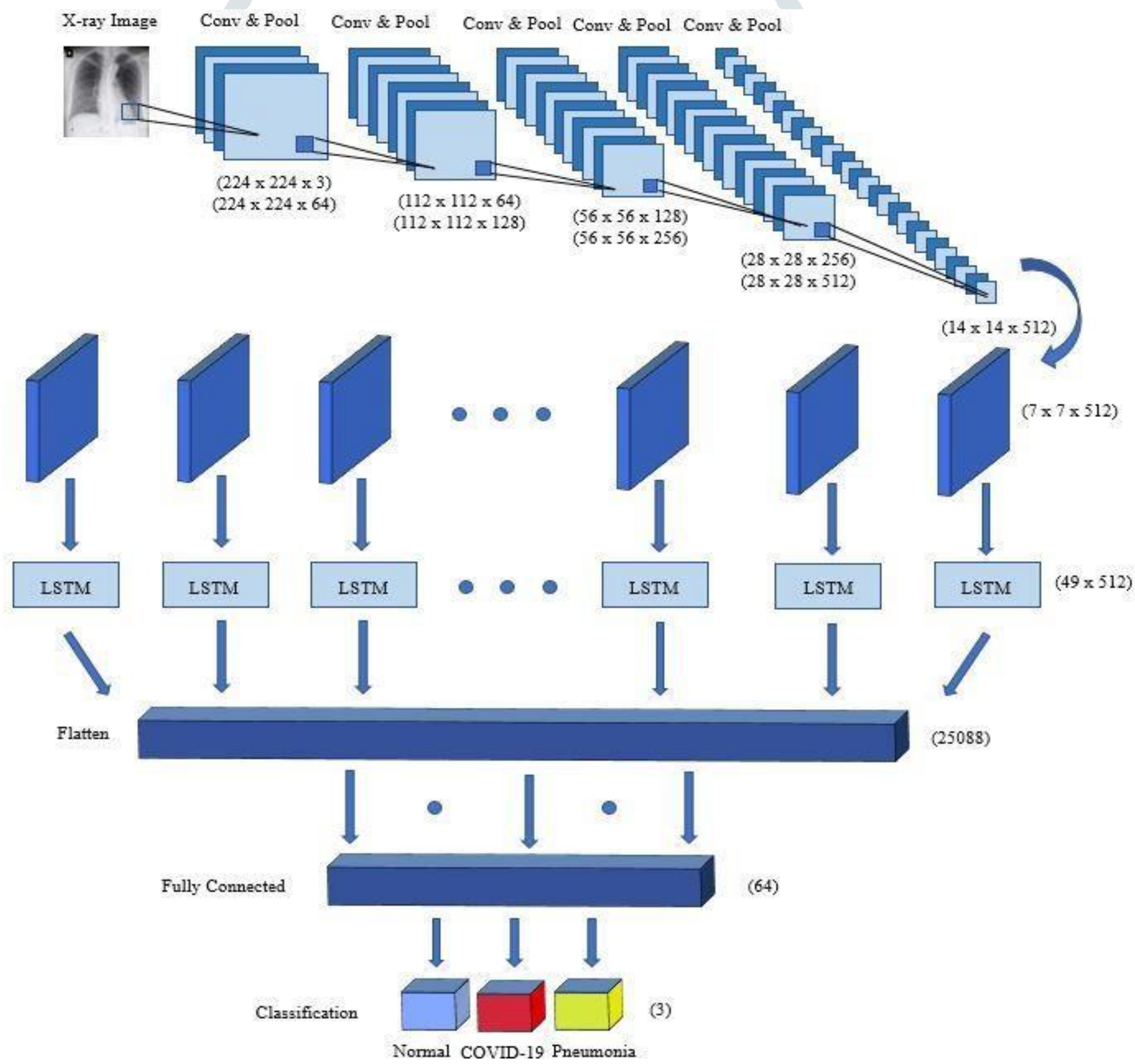


Fig. 5. An illustration of the proposed hybrid network for COVID-19 detection.

The structure of the proposed architecture is shown in Table 2. From Table 2, it is foundthat the Layers 1–17 of the network are convolutional layers, and layer 18 is the LSTMlayer. Finally, a fully connected layer is added for predicting the output. After the pooling layer, the output shape is found (none, 7, 7, 512). The input size of the LSTM layeris (49, 512). After analyzing LSTM time characteristics, finally, the architecture sorts X-ray images through a fully connected layer.

Table 2. The full summary of CNN-LSTM network

Layer	Type	Kernel Size	Stride	Kernel	Input Size
1	Convolution2D	3 × 3	1	64	224 × 224 × 3
2	Convolution2D	3 × 3	1	64	224 × 224 × 64
3	Pool	2 × 2	2	-	224 × 224 × 64
4	Convolution2D	3 × 3	1	128	112 × 112 × 64
5	Convolution2D	3 × 3	1	128	112 × 112 ×128
6	Pooling	2 × 2	2	-	112 × 112 ×128
7	Convolution2D	3 × 3	1	256	56 × 56 ×128
8	Convolution2D	3 × 3	1	256	56 × 56 ×256
9	Pool	2 × 2	2	-	56 × 56 ×256
10	Convolution2D	3 × 3	1	512	28 × 28 ×256
11	Convolution2D	3 × 3	1	512	28 × 28 ×512
12	Convolution2D	3 × 3	1	512	28 × 28 ×512
13	Pool	2 × 2	2	-	28 × 28 ×512
14	Convolution2D	3 × 3	1	512	14 × 14 ×512
15	Convolution2D	3 × 3	1	512	14 × 14 ×512
16	Convolution2D	3 × 3	1	512	14 × 14 ×512
17	Pool	2 × 2	2	-	14 × 14 ×512
18	LSTM	-	-	-	49 × 512
19	FC	-	-	64	25,088
20	Output	-	-	3	74

3.1.4 Performance Evaluation Metrics

The following metrics are used to measure the performance of the proposed system. Itis noted that TP is the correctly predicted COVID-19 cases, FP is the normal or pneumonia cases that were misclassified as COVID-19 by the proposed system, TN is the normal or pneumonia cases that were correctly classified, while the FN refers to COVID-19 cases that were misclassified as normal or pneumonia cases.

$$\text{Accuracy} = (TP + TN)/\,(TN + FP + TP + FN) \tag{9}$$

$$\text{Sensitivity} = TP/\,(TP + FN) \tag{10}$$

$$\text{Specificity} = TN/\,(TN + FP) \tag{11}$$

$$F1 - \text{score} = (2 * TP)/\,(2 * TP + FP + FN) \tag{12}$$

IV. RESULTS AND DISCUSSION

Fig.6 depicts the confusion matrix of the test phase of the proposed CNN-LSTM and the competitive CNN architecture for COVID-19 disease classification. Though both architectures classify all 22 images of COVID-19 perfectly, there are four misclassifiedimages for CNN and two misclassified images for CNN-LSTM among 64 images. It isfound that the proposed CNN-LSTM network outperforms the competitive CNN net- work as it has better, and consistent true positive and true negative values and lesser false-negative and false-positive values. Hence, the proposed system can efficiently classify COVID-19 cases. Moreover, Fig. 7 illustrates the performance evaluation of the CNN classifier graphically with accuracy and cross-entropy (loss) in the training and validation phase. The training and validation accuracy is found at 92% and 95% respectively. Similarly, the training and validation loss are found 0.18 and 0.09 respectively for the CNN architecture. Further, Fig. 8 depicts the performance evaluation of the CNN-LSTM classifier graphically with accuracy and cross-entropy (loss) in the training and validation phase. The training and validation accuracy is found 95% and 98% respectively. Similarly, the training and validation loss are found 0.18 and 0.04 respectively for the CNN-LSTM architecture. The best scores of trainings and validation accuracy were achieved for theCNN-LSTM architecture comparing with the CNN architecture.

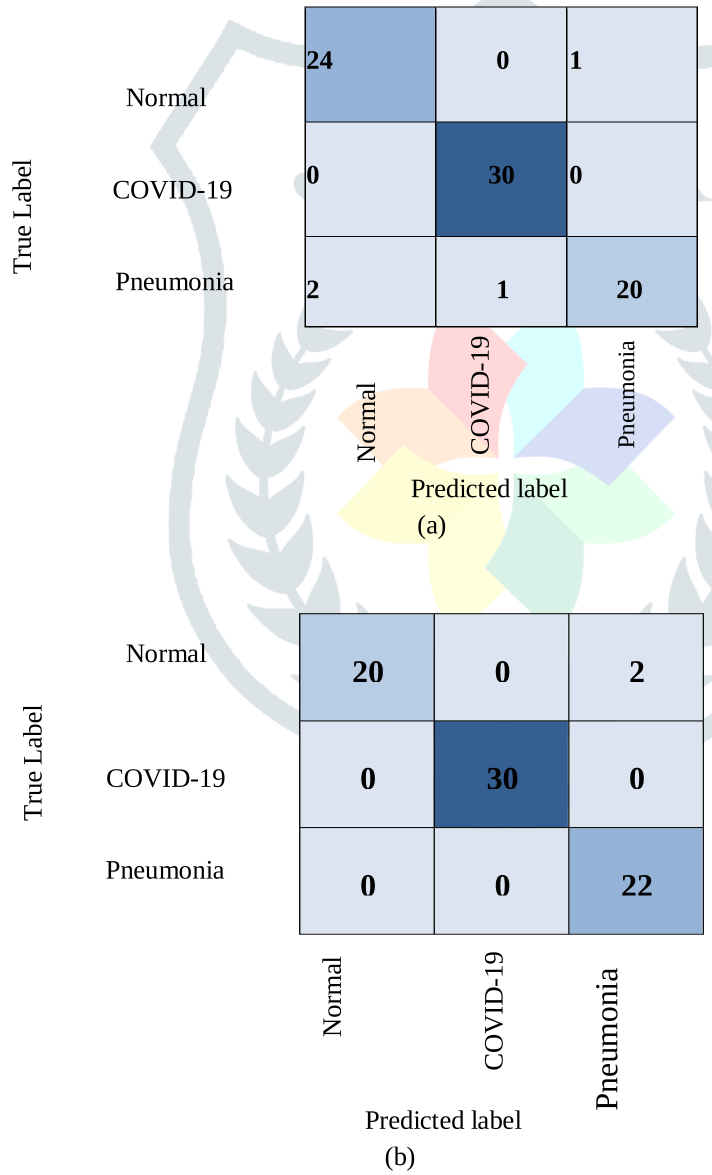
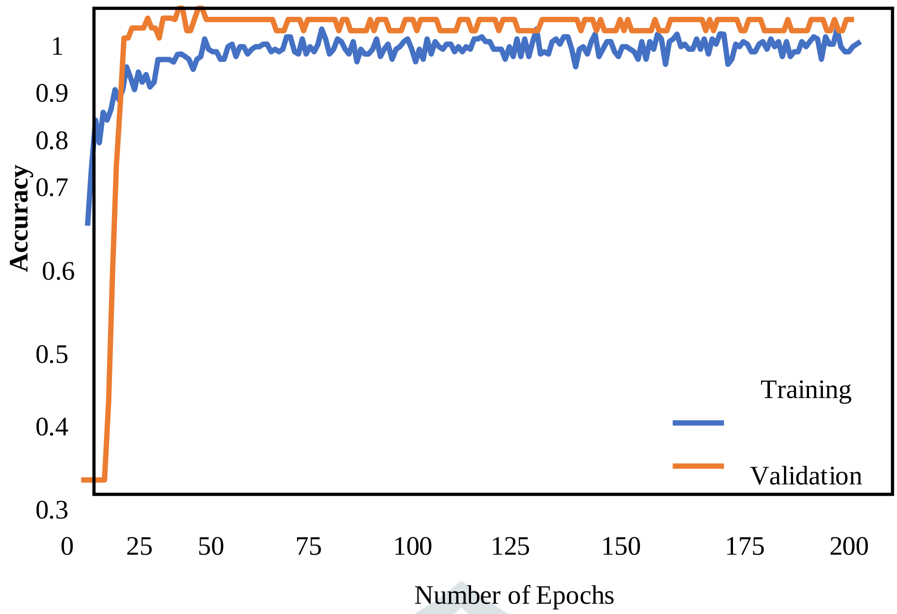
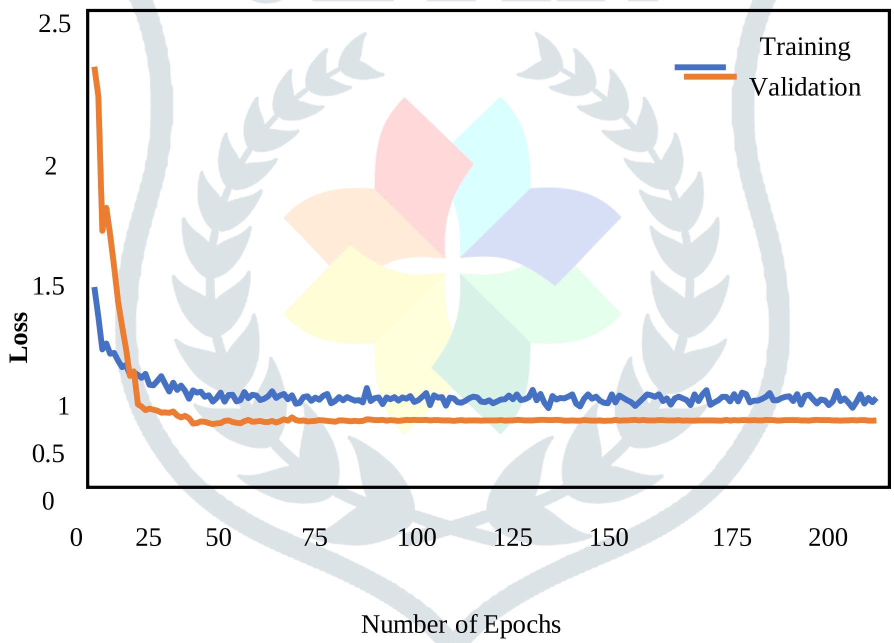


Fig. 6. Confusion matrix of the proposed COVID-19 detection system. (a) CNN (b) CNN-LSTM



(a)



(b)

Fig. 7. Evaluation metrics of COVID-19 detection system based on CNN architecture (a) Accuracy (b) Loss

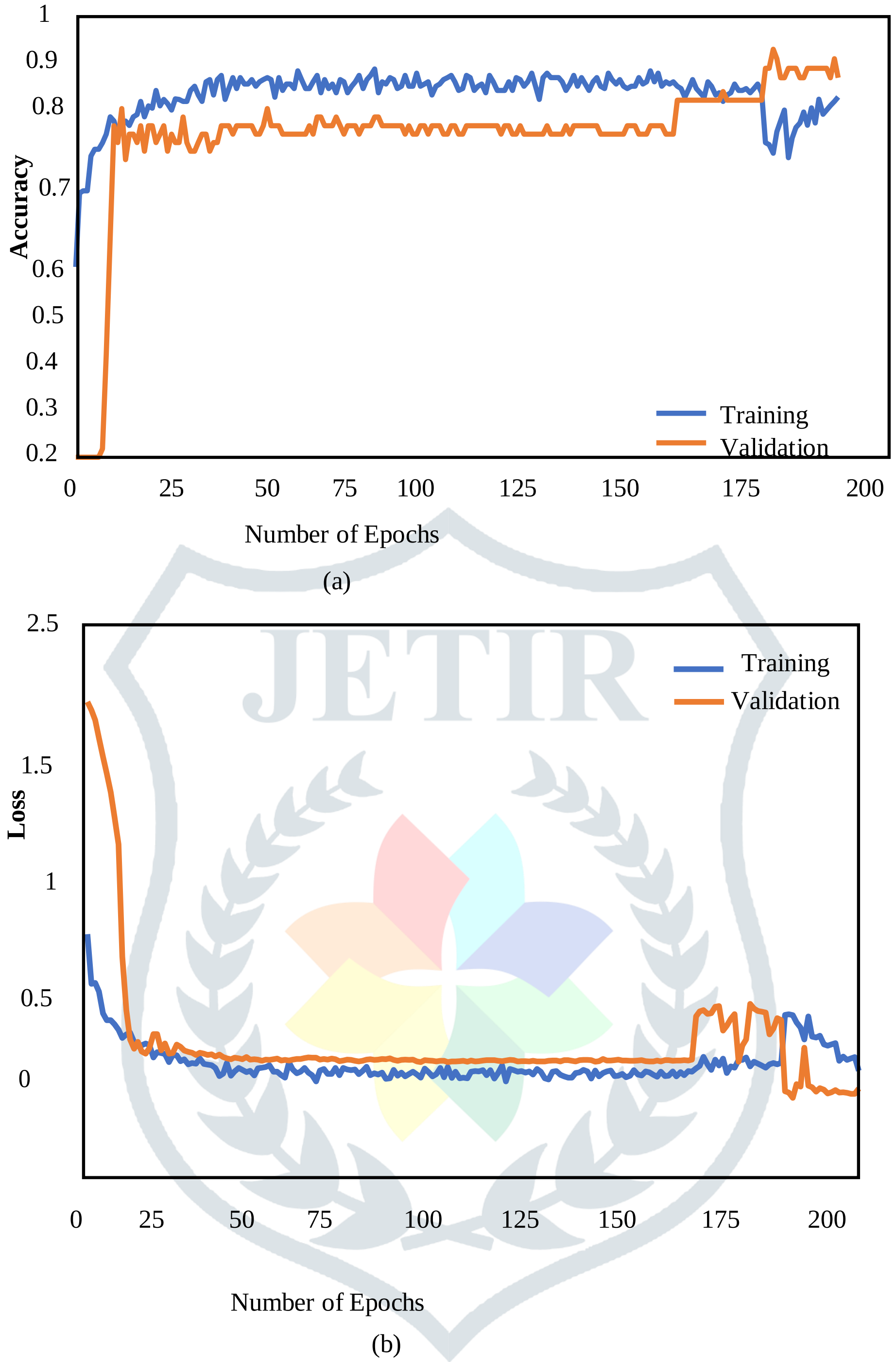


Fig. 8. Evaluation metrics of COVID-19 detection system based on CNN-LSTM architecture (a) Accuracy (b) Loss.

The overall accuracy, specificity, sensitivity, and f1-score for each case of CNN Architecture are summarized in Table 3 and visually shown in Fig. 9. The obtained accuracy is 94% for COVID-19, pneumonia, and normal cases. The specificity is found 96%, 95%, and 91% for COVID-19, pneumonia, and normal cases respectively. The sensitivity has achieved 100%, 86%, and 95% for COVID-19, pneumonia, and normal casesrespectively. The f1-score is obtained 98%, 90%, 93% for COVID-19, pneumonia, and normal cases respectively. While the highest specificity, sensitivity, and f1-score are obtained by COVID-19,

the lower values of sensitivity and f1-score are found in pneumonia case.

Table 3. Performance of the CNN network

Class	Accuracy (%)	Specificity (%)	Sensitivity (%)	F1-Score (%)
COVID-19	0.94	0.96	1.00	0.98
Pneumonia	0.94	0.95	0.86	0.90
Normal	0.94	0.91	0.95	0.93

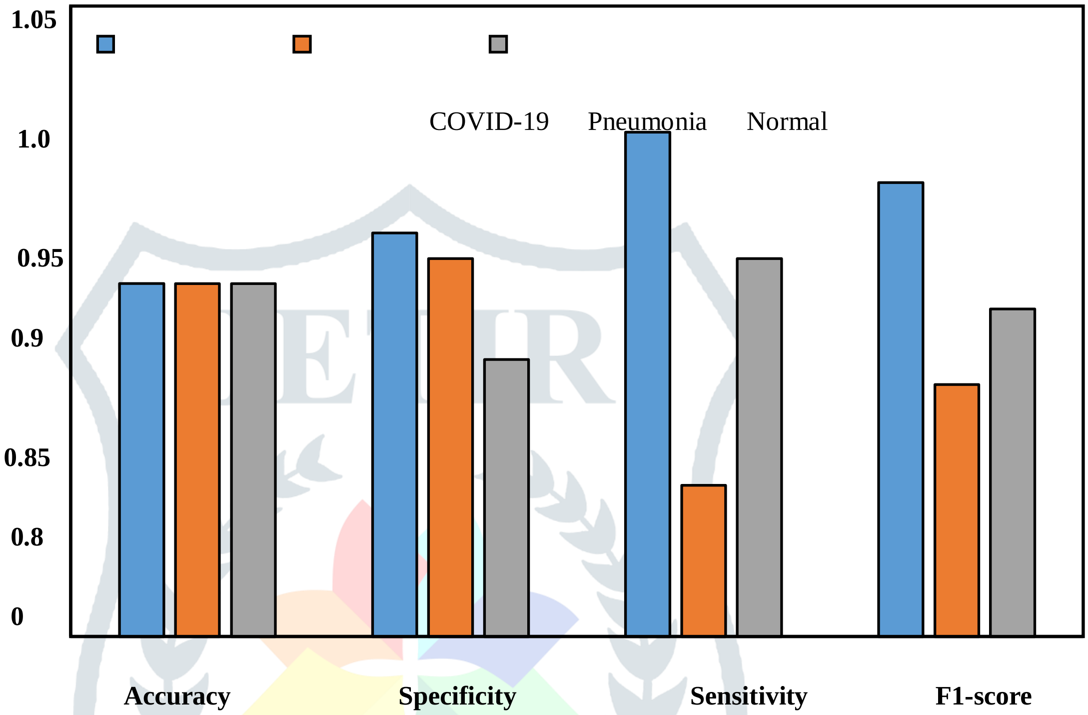


Fig. 9. The graphical representation of the results of the CNN network.

Furthermore, Table 4 and Fig. 10 shows the performance metrics of each class of the developed CNN-LSTM network. The accuracy is 97% for COVID-19, pneumonia, andnormal cases. The specificity is obtained 91%, 100%, and 100% for COVID-19, pneumonia, and normal cases respectively. The sensitivity is achieved 100% for both COVID-19 and pneumonia cases and 90% for normal cases. The f1-score is found 100% for COVID-19 and 95% for both pneumonia, and normal cases. While the maximum sensitivity and f1-score are achieved by COVID-19, the lower values of sensitivity and f1-score are obtained in normal and pneumonia cases respectively.

Table 4. Performance of the CNN-LSTM network

Class	Accuracy (%)	Specificity (%)	Sensitivity (%)	F1-score (%)
COVID-19	0.97	0.91	1.00	1.00
Pneumonia	0.97	1.00	1.00	0.95
Normal	0.97	1.00	0.90	0.95

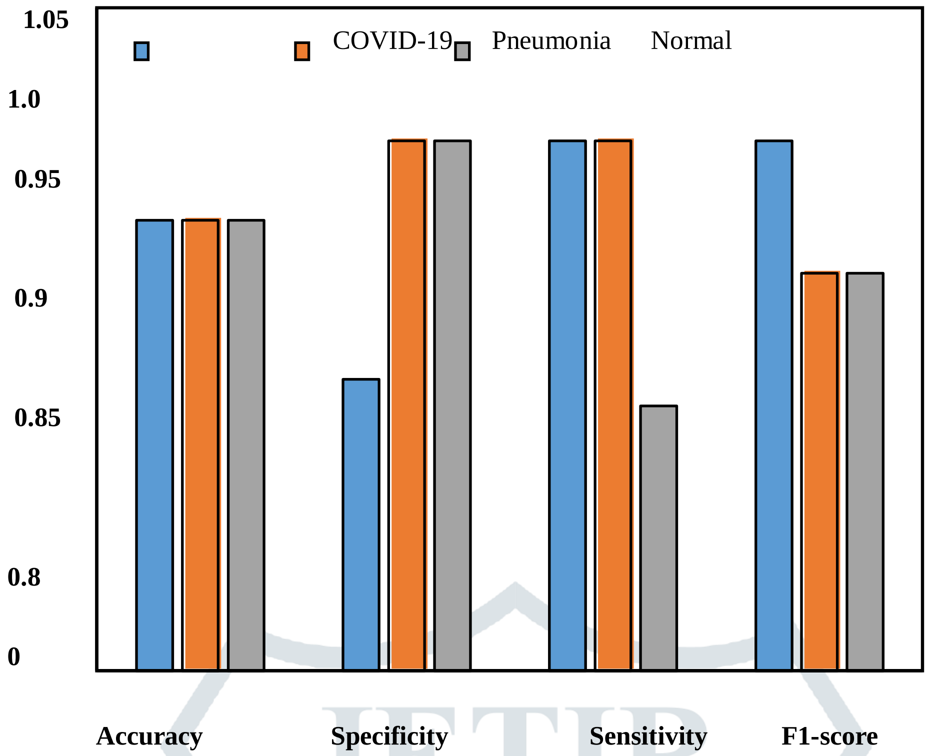


Fig. 10. The graphical representation of the results of the CNN-LSTM network.

From the experimental findings, it is evident that the CNN architecture achieved 94% accuracy, 96% specificity, and 100% sensitivity after experimental verification for theCOVID-19 infected cases. Comparing the outcomes, the proposed CNN-LSTM net- work achieved an overall 97% accuracy, 91% specificity, and 100% sensitivity respectively for the COVID-19 cases. The main purpose of this research is to achieve good results in detecting COVID-19 cases and not detecting false COVID-19 cases. Hence, experimental results reveal that the proposed CNN-LSTM architecture outperforms competitive CNN network.

V. CONCLUSION

The COVID-19 cases are increasing daily, many countries face resource shortages. Hence, it is necessary to identify every single positive case during this health emergency. We introduced a deep CNN-LSTM network for the detection of novel COVID-19 from X-ray images. CNN is used as a feature extractor and the LSTM networkas a classifier for the detection of coronavirus. The developed system obtained an overall 97% accuracy for all cases and 100% accuracy for COVID-19 cases. The proposedCNN-LSTM and competitive CNN architecture are applied both on the same dataset. The extensive experimental results reveal that the proposed architecture outperforms competitive CNN network. In these global COVID-19 pandemics, we hope that the proposed system would able to develop a tool for COVID-19 patients and reduce the workload of the medical diagnosis for COVID-19.

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