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Deep Learning Approach to Recognize COVID-19, SARS and Streptococcus Diseases from Chest X-ray Images

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Corona virus disease (COVID-19) became pandemic for the world in the year 2020 and large numbers of people are infected worldwide due to the rapid widespread of this infectious virus. Pathological laboratory testing of a large number of suspects becomes challenging and producing false-negative results. Therefore, this paper aims to develop a deep learning basedapproach for automatic detection of COVID-19 infection using medical X-ray images. The proposed approach is used for the fast detection of COVID-19 along with other similar diseases such as Streptococcus, and severe acute respiratory syndrome (SARS) positive cases. A 2D-convolution neural network (2D-CNN) is used to recognize the graphical features of X-ray image's dataset of COVID-19 positive, Streptococcus and SARSpatients. The proposed approach is tested on the COVID-chest X-Ray dataset. Experiments produced individual accuraciesof COVID-19, Streptococcus, SARS disease and normal persons are 100%, 90.9%, 91.3%, and 94.7% respectively and achieved an overall accuracy of 95.73%. From the experimental results, it is proved that the performance of the proposed approach is better as compared to the mentioned state-of-art methods.

Keywords: CNN, Computed Tomography, Corona virus, Medical Image Processing, Pandemic

Introduction

Corona is a Latin word which means crown and due to crown-like spikes on the surface, it was named so. Corona viruses belong to Coronavirinae sub-family and are a type of positive-sense Ribonucleic Acid (RNA). It is in the Coronaviridae family of the Nidovirales order.[1] Based on their genomic structure, it is divided into four main subgroups i.e. Alpha, Beta, Gamma, and Delta. Only the first two categories i.e. Alpha and Beta infect mammals usually causing respiratory symptoms in humans and gastroenteritis in other animals.[2]

Total numbers of six corona viruses are known till December of 2019 which can infect human beings and other animals such as bats, birds, mice, lion, domestic and wild animals. These viruses of the Corona family can affect lungs, liver, gastrointestinal tract, human's nervous system, etc. HCoV-NL63, HCoV-OC43, HCoV-229E, and HKU1 are four types out of six in which symptoms are like mild common cold-type in immune-competent people.[2–4] Rest two types of corona i.e. severe acute respiratory syndrome Coronavirus (SARS-CoV) and the middle east respiratory syndrome Coronavirus (MERS-CoV) have introduced pandemics of 10% mortality in 2002–2003 and 37% mortality in 2013 respectively. SARS-CoV and MERS-CoV were transmitted from animals to humans.

Corona virus disease 2019 (COVID-19) is a new evolutionary type of Corona virus which was initially named as severe acute respiratory syndrome Corona virus 2 (SARS-CoV-2) from 2019-nCoV on 11th Feb, 2020. This virus was first detected in the month of Dec 2019 in Wuhan City of Hubei Province, China. This disease was renamed as COVID-19[(6)] because it was caused by SARS-CoV-2. Initially, throat swabs collected from the patients to identify disease type with influenza-like-illness. Tests revealed disease identification as SARS-CoV-2 RNA which is a type of viral pneumonia that covers milder illness and even asymptomatic infection. The reports also suggested that this virus spread through community transmission.[1,4] By June 30, 2020, worldwide total number of 10 185 374 COVID-19 positive cases, 5 03 862 numbers of death and 65 32 548 recovered cases were reported.[2] World Health Organization (WHO) declared COVID-19 a pandemic. It is affecting 209 countries and territories around the world and two international conveyances which caused global alarm.[5]

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The diagnosis of COVID-19 is based on epidemiological history, clinical symptoms, and positive CT and X-ray images, as well as positive pathogenic testing.[1] The clinical distinctiveness of COVID-19 includes respiratory symptoms, dry cough, high fever, throat pain, sneezing, dyspnea, and pneumonia.[1] But in some cases, general symptoms of COVID-19 are nonspecific; for example, CT scan or X-ray images of chest of an infected person can show symptoms of normal pneumonia and the pathogenic testing revealed COVID-19 positive because laboratory detection technology supports real-time reverse transcription polymerase chain reaction (RT-PCR) which takes 4–6 hours to get results. The Pathogenic testing procedure takes a long time which is enough in the spreading of the virus. Even till now, there is no such tool available that can automatically quantify the volume of infection for corona virus patients. Apart from prompt and accurate testing, it is also important to stop the epidemic lifetime to take alternative actions. Virus spread can be stopped to break the chain of transmission by closing borders, schools, suspending community services, and commuters. It is known that enough RT-PCR testing kits are not available in developing countries like India, Pakistan, Bangladesh, Nepal, Bhutan, etc which may enhance the infection level of the virus. This huge shortage of testing kits and its result producing speed motivated us to identify alternative testing methods that can produce prompt accurate results, cheaper and easy availability of testing facility than RT-PCR.

Medical image processing[6] or analysis may be an alternative in the detection of this pandemic disease. Medical image analysis played a big part in assisting the doctors in diagnosing the diseases. Clinical medical devices have emerged with a combination of hardware and image processing methods which has a huge jump in medical areas. In view of the large potentiality of this field and based on the literature review[1,6] we chose analysis of X-ray images due to the availability of plenty of X-ray Machines worldwide in the laboratories, less cost of X-ray Machine than Computed Tomography (CT). Another reason for choosing X-ray images is that the availability of dataset[7] of three types of disease those are COVID-19, SARS, and Streptococcus along with normal person chest X-ray images. The flow diagram of the proposed approach is given in Fig. 1.

In summary, the contribution of the paper is given as:

- This paper proposes a deep learning approach to recognize the three types of diseases from X-ray images. In the first step, data augmentation is performed to enhance the synthetic data to better train the network.
- In the second step, 2D-Deep Convolutional Neural Network has been trained to recognize the disease types using the X-Ray images.

Literature Review

The outbreak of person-to-person transmissible pneumonia caused by the 2019-nCov has triggered a global warning. Since the disease is spreading exponentially and also we have limited authorized labs for testing the COVID-19. Some alternative method to diagnose the disease is the need of the hour. Many researchers have proposed deep learning-based models to diagnose the COVID-19 from the chest CT images and X-ray images of patients. Xu *et al.*[8] proposed multiple convolution neural network (CNN) models to classify CT images and calculated the infection probability of COVID-19. They collected 618 numbers of CT samples out of which 219 samples from COVID-19 patients, 224 from patients with influenza-A viral pneumonia, and 175 CT samples from healthy people and used data augmentation methods to increase the sample size. The Accuracy achieved is 86.7%. Another method that uses CT images is proposed by Gozes *et al.*[9] who developed an artificial intelligence (AI) based CT image analysis tool for tracking and detection of COVID-19 here authors used 2-D and 3-D deep learning models. They used popular UNET architecture for segmentation and Resnet-50 model for classification. Resnet-50 network is 50 layers deep and can classify images into 1000 classes moreover authors evaluate the progression of the disease and

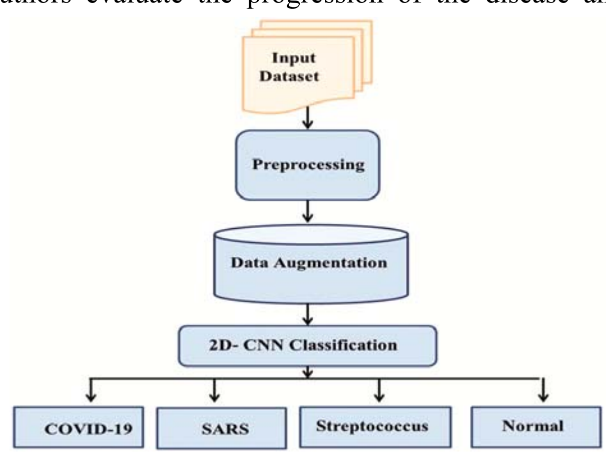

Fig. 1 — shows the flow diagram of the proposed deep learning based approach

generated a corona score based on which they can quantify the disease burden. The Authors used a testing set of 157 international patients (US and China). Another approach to diagnosing the Covid-19 disease from the CT images is proposed by Wang *et al.*[10] who developed an algorithm to diagnose the COVID-19 positive cases by modifying the inception migration learning model followed by external and internal validation. In this work, authors collected 453 CT images of confirmed corona cases along with those previously diagnosed with viral pneumonia. Authors achieved 82.9% accuracy using internal validation with a sensitivity of 84% and specificity of 80.5% however with an external testing dataset they achieved 73.1% accuracy with a sensitivity of 74% and specificity of 67%.

The approaches discussed so far are based on CT-Scan which takes CT scan images as input and then some deep learning model classifies the image into different classes like COVID-19 positive, Common pneumonia, normal, etc. one unique approach to diagnose the Covid-19 infection using smartphone embedded sensors comes from the Maghdid *et al.*[11] who proposed a framework which will work with smartphones. The proposed framework will take various inputs through various sensors of smartphones like CT images of lungs and human tracking video observation through a camera, Temperature through fingerprint sensor, cough voice samples through microphone sensors, etc. and then the proposed framework will work on those inputs to predict the disease.

Researchers also used X-ray images to diagnose the COVID-19 infection. Ghoshal *et al.*[12] proposed one such model which works on X-ray images. In this study, they collected 5941 X-ray images with data augmentation across four classes normal: 1583, bacterial pneumonia: 2786, Covid-19 positive: 68 and COVID-19 Negative: 1504. The Authors used the RESNET-50 V2 model for classification and Bayesian CNN model to estimate the uncertainty with the predication. Actually, in the ambiguous situation, most of the deep learning models are not able to say that “I am not sure” they can either predict YES or NO so authors in this study estimated the uncertainty with the predication using Bayesian CNN and the proposed model can predict with the uncertainty score which gives confidence in the diagnosis. Another approach to diagnosing the COVID-19 infection using X-ray images is given by Narin *et al.*[13] who proposed a model which can automatically predict COVID-19 infection case using Deep CNN model. Authors used InceptionV3, ResNet50 and Inception-ResNetV2 pre-trained models. Authors find that ResNet50 is the best model among the other two pre-training models. They used a small dataset of 50 X-ray images of Covid-19 positive and 50 normal X-ray images. The Authors divided the dataset randomly into two datasets with 80% images for training and 20% images for testing and obtained the highest accuracy of 98% with the ResNet50 model.

Another similar approach Hemdan *et al.*[14] proposed a new deep learning-based framework named COVIDX-Net to automatically diagnose the COVID-19 patients using X-ray images. The proposed framework used seven different architectures of Deep CNN like VGG19, the second version of Google Mobile Net, etc. Each deep neural network was able to classify the patient using an X-ray image into Covid-19 positive and Covid-19 negative classes. Authors have achieved an overall accuracy of 90% with the VGG19 and DenseNet 201 Architectures. This work is an example of binary classification. One another approach which works on three classes and still giving better result is proposed by Apostolopoulos *et al.*[15] who collected 1427 X-ray images across three classes, Covid-19 positive-224, Bacterial Pneumonia-700 and 504 images of normal people for training and testing the system. Authors used different CNN models with transfer learning for classification and found that VGG19 and Mobile Net performs best among other CNN models with an accuracy of 98.75% and 97.40% respectively. When authors further evaluated the two best models they find that VGG19 has better accuracy but Mobile Net gives lesser false-negative cases so in terms of specificity Mobile Net outperforms VGG19.

Another method that uses 7 classes is proposed by Apostolopoulos *et al.*[16] in which they collected 3905 X-ray images of six diseases further they applied data augmentation techniques to increase the data set. They trained Convolution Neural Network and MobileNet from scratch with seven class classifications, they achieved the accuracy of 87.66%, with two class problems Covid-19 positive and Negative they achieved the accuracy of 99.18% with 97.36% sensitivity and 99.42% specificity. Another method using X-ray images to diagnose the Covid-19 infection is proposed by Bukhari *et al.*[17] they collected 278 X-ray images of three groups of Covid-19 Positive, Common Pneumonia, and Normal People further they applied different data augmentation methods like horizontal flip, random zoom, random rotate, random lightning, etc. to increase the dataset. The Authors also used a 50% dropout strategy to avoid over-fitting. The deep learning CNN model ResNet-50 is used to classify the images into three diseases. The overall accuracy achieved is 98.18% with an F1 score of 98.19%.

Proposed Approach

To recognize the types of diseases such as COVID-19, SARS, and Streptococcus diseases from X-ray images, we proposed a deep learning-based approach. In this approach, a 2D-Deep Convolution Neural Network (2D-CNN) is used with hyper-parameter tuning. Since we worked on a recently prepared dataset named COVID-chest X-ray dataset which is small in size, hence we used the data augmentation tool available in Keras library to increase the size of the dataset to train our deep network. Next, the subsequent section discusses pre-processing & feature extraction followed by classifications by 2D-CNN to recognize the types of diseases.

Preprocessing and Feature Extraction

Resizing

For the experimentation, we have collected X-Ray images from the COVID-chest X-Ray dataset. The proposed approach read all types of disease and normal X-Ray images for resizing the initial raw information to a new size (50×50) using the OpenCV library in Python. Then we have converted all X-Ray images in gray scalelevel for further processing. Since we are using deep network, so we don't need to explicitly extract manual features rather we extracted the features by tuning the hyper-parameter of the 2D-CNN network.

2D-CNN based Disease Recognition

After the evolution of 2D convolutional neural network (2D-CNN), it has been widely used for medial image classification problems. For example, Narin *et al.*[13] proposed three convolutional neural network such as ResNet50, InceptionV3 and Inception-ResNetV2 model using X-ray images to detect COVID-19 disease and achieved 98% accuracy. Similarly, Hemdan *et al.*[14] also proposed COVIDX-Net approach to detect COVID-19 disease. In this approach author used seven convolutional neural network such as VGG-19, DenseNet201, ResNetV2, InceptionV3, InceptionResNetV2, Xception and MobileNetV2 among them two CNN model such as VGG-19 and DenseNet201 performed well and both models achieved 90% accuracy to detect COVID-19 disease. In addition to that Apostolopoulos *et al.*[15] also used transfer learning with 2D convolutional neural network to detect COVID-19 disease form X-ray images and achieved best results over mentioned state-of-art methods. A large number of researchers[8–17] also used deep convolutional neural network to detect COVID-19 disease using either X-ray or CT image. Based on the performance of CNN shown by researchers, we have also used 2D-Convolutional Neural Network (2D-CNN) to automatic detection of the COVID-19 disease. Another reason to choose the 2D-CNN model is that, the 2D-CNN model automatically detects and learns the features from the input image data and requires less training overhead.

A 2D Convolutional neural network[18–20] (2D-CNN) is a powerful neural network from Keras Deep Learning library written in python language specially designed for the data that has matrix-like shape such as 2D image recognition. The connectivity design pattern of neurons of the convolution neural network is similar to a biological neural network. CNN is a sequential classifier and contains the different layers in the sequence. The function of a layer is to take data from the previous layer and gives output to the next layer. CNN used mainly four types of layers such as convolution layer, pooling layer, dropout layer, and fully connected layer, and place the layer one over another to make a robust CNN model. The amount of pre-processing required for the input data is least in CNN. In this work, 2D-CNN is used for the recognition of types of diseases. For the network design, two convolution layers were taken, in the first layer, we took 8 filters having a size of 3×3 followed by max-pooling layer having a size of max-pool is 2×2. Next, we took 15 filters in the second convolution layer with filter size 3×3 followed by a max-pooling layer with a pool size of 2×2. We used *relu* activation function for both convolution layers and the value of the padding is the same for both max-pooling layers. After the second max-pooling layer, a flatten layer is used. The architecture of 2D-CNN for types of diseases recognition is given in Fig. 2.

$$\mathrm{CCE} = -\frac{1}{S}\sum_{j=1}^{S}\sum_{m=1}^{C} l_{\mathrm{yi}\in\mathrm{Cm}} \log\mathrm{Prob}_{\mathrm{model}}[_{\mathrm{yi}\in\mathrm{Cm}}] \quad \ldots (1)$$

where 'S' is the number of samples and each sample belongs to a category 'm' out of total 'C' categories.

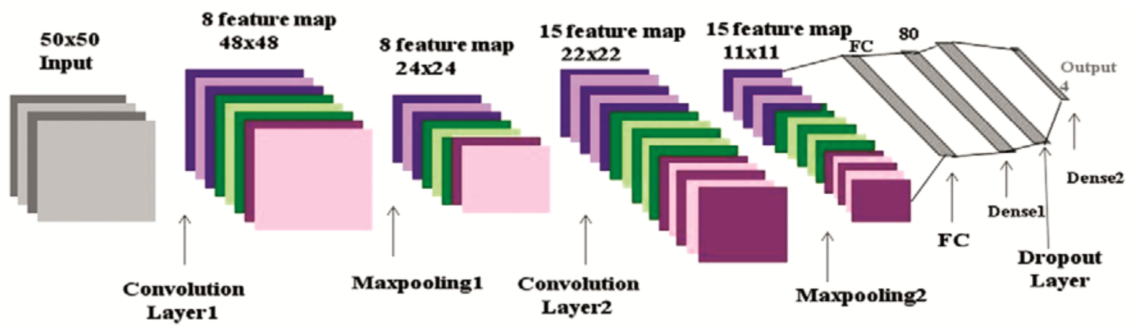

Fig. 2 — 2D-CNN architecture of type of diseases recognition

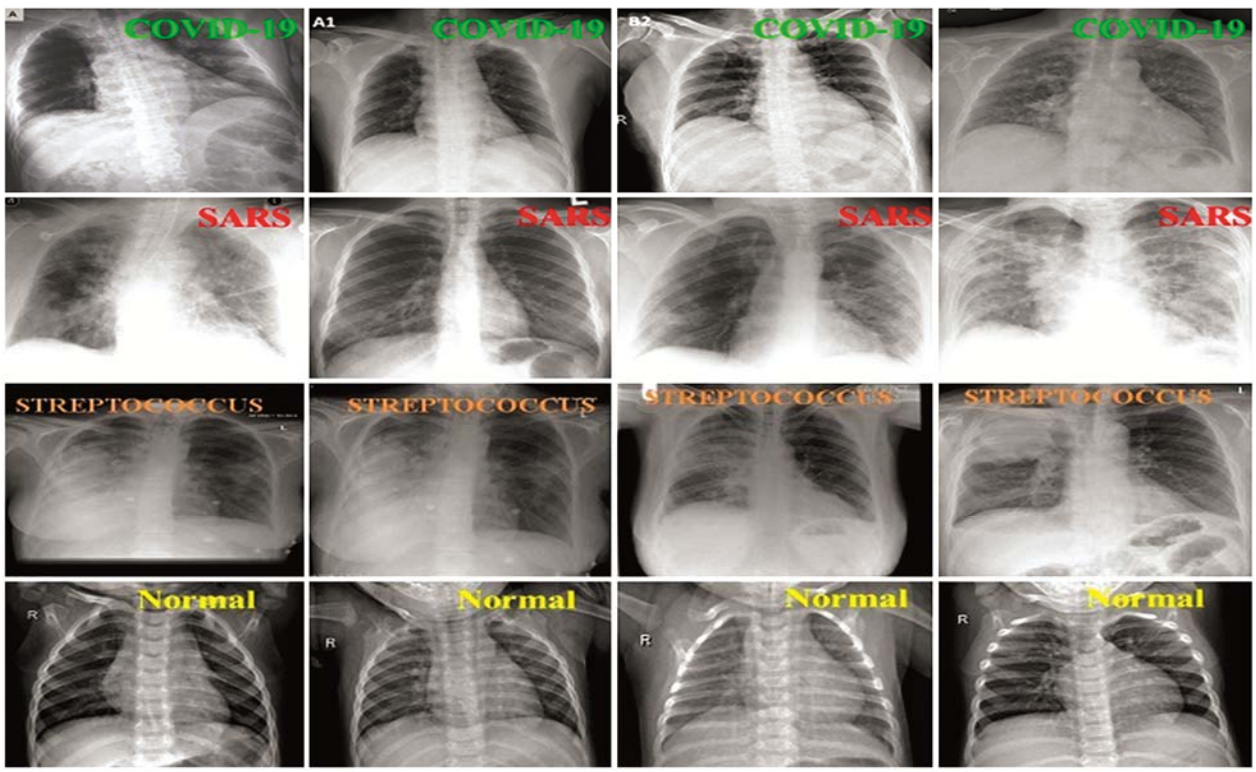

Fig. 3 — Some of the dataset image samples belonging to four categories namely, COVID-19, SARS, Streptococcus and normal patient

Experimental Results and Discussion

Covid-chest X-Ray dataset

In this section, the description of the dataset to carry out this experiment is given. Then the results of the proposed method have been evaluated after dividing the dataset into two parts: 75% training part and 25% test part using the train test split method given in Scikit-learn library in python. For training and testing of approach, we used COVID-chest X-Ray public dataset available on the github repository.[17] The network was trained and tested on Intel Core i5 8th Generation, 2.6 GHz processor with 16 GB of RAM along with 2GB 940MX NVIDIA GPU under Ubuntu 16.04 LTS operating system.

To test our proposed approach, we used COVID-chest X-Ray dataset which was created in the month of March, 2020 after corona pandemic happened at the highest level in the world. It contains six different types of diseases infected X-ray images. The samples of dataset of disease information are given in the (Fig. 3). Dataset contains X-ray and CT scan images. In which 90% of images are X-Ray images and the remaining 10% are CT scan images. The images of the dataset belong to ARDS (Acute Respiratory Distress Syndrome), Chlamydophila, COVID-19, *E.Coli*, Phneumocystis, and SARS (Severe Acute Respiratory Syndrome) categories moreover some X-ray images has no findings (having no categories and no relation with any diseases). This dataset contains the information of 136 patients along with the date when the disease was first detected and locations of the patients such as Italy, Spain, Washington, and Toronto, etc.

The dataset also contains the multiple images of the same patient at a certain interval of days to keep track of the progress of the patient's disease. The X-ray information has been captured from different views containing Posteroanterior (PA) view, Anteroposterior (AP) Supine view, Lumbar (L) view, and AP view. The size (Height and Width) of all the X-ray and CT scan images are different. The dataset is small in size and keeps on increasing every day as the number of patients is increasing in the world day by day. When we used this dataset for the experimentation, it had 374 X-Ray images from all types of disease categories. Some of the dataset samples have shown in Fig. 3.

Data Augmentation

Data Augmentation is an important step in the training phase of the deep neural network because it becomes essential when the amount of the training data is less and its goal is to increase the amount of training set to avoid over-fitting. To make the process of augmentation, we used the data magnification tool which is known as ImageDataGenerator provided by Keras Deep Learning framework. Using this tool, we have set different values to the parameters like rotation_range = 40, width_shift_range = 0.2, height_shift_range = 0.2, shear_range = 0.2, zoom_range = 0.2, horizontal_flip = True, fill_mode = 'nearest' to get augmented data. In this process, we enlarged the amount of the data to better train our network and reduced the over-fitting problem.

Disease Types Recognition using 2D-CNN

A 2D-CNN has been trained to recognize types of diseases such as COVID-19, SARS, Streptococcus diseases, and normal X-ray images. To recognize the types of disease, we trained the network with categorical-cross-entropy loss function with a learning rate of 10^{-3} and the value of decay is decreasing as the number of epoch is increasing. The architecture of the 2D-CNN is given in Fig. 2. The training and accuracy of the network are shown in Fig. 4.

It can be seen from the training curve of the network given in Fig. 4 (a) that, after 57 epochs there is no further change in the validation network, thus it has been considered as the best network. An accuracy of 95.73% has been recorded in the recognition of diseases as shown in Fig. 4(b). The Confusion matrix and recognition performance of each disease types have also been represented in Fig. 5(a) and 5(b) respectively.

It is clear from the confusion matrix given in Fig. 5(a) that our proposed system generated no error in recognizing the COVID-19 disease and recognized it by 100%. However, it gives some error during recognition of SARS and Streptococcus disease. The recognition accuracy of SARS disease is 91.0% while it is being misclassifying by 4.5% as a Streptococcus and 4.5 % as normal X-ray images. In addition to that, the Streptococcus disease has been recognized 91.3% correctly and it is being misclassifying by 8.7% as a normal patient.

It can be noticed from Fig. 5 (b) that individual class accuracies vary from 90.9 % to 100 % and COVID-19 disease has 100% recognition accuracy. Apart from the accuracy matrix, the performance of the network in terms of other matrices like precision, recall and f1-score, are also given in Table 1.

Discussion

In this paper, a Deep Neural Network-based approach is used to recognition four types of X-Ray images belonging from three disease types such as COVID-19, SARS, Streptococcus, and last normal patient images. We have used a small dataset named COVID-chest x-ray dataset for the experimentation.

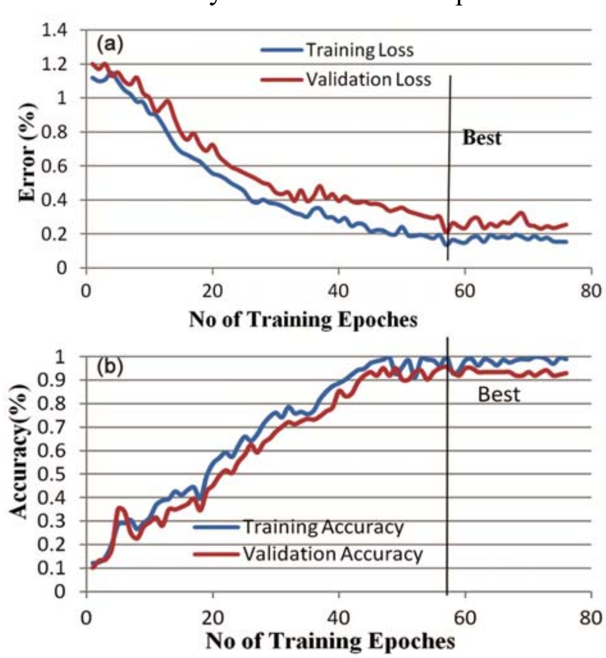

Fig. 4 — 2D-CNN for types of disease recognition (a) Training curve (b) Accuracy curve

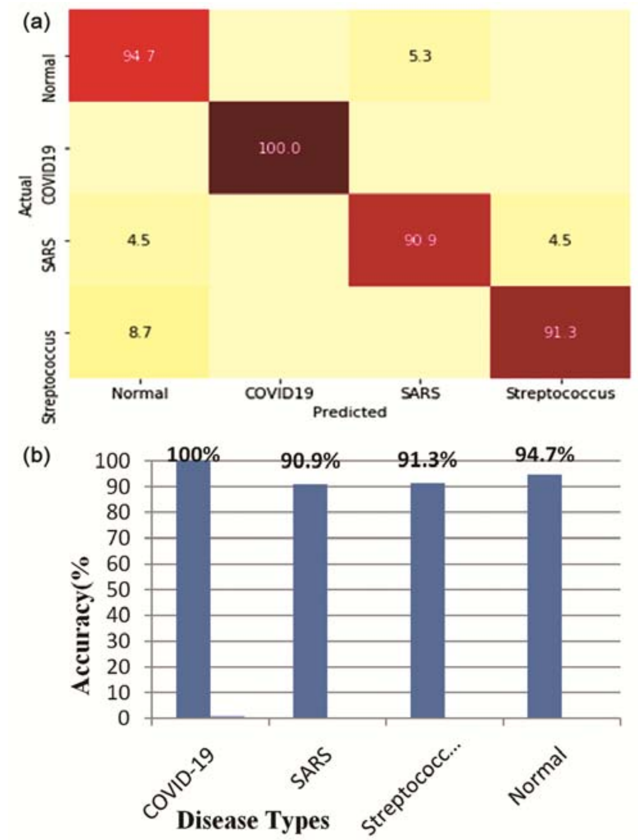

Fig. 5 — (a) Confusion matrix of 2D–CNN for types of disease recognition (b) Recognition performance of each individual disease

Table 1 — Precision, Recall and F1-score of 2D-CNN Network for Diseases Recognition

	Class	Precision	Recall	F1 score
2D- Convolutional Neural Network (2DCNN)	Covid-19	1.00	1.00	1.00
	Normal	0.85	.95	.89
	SARS	0.95	.91	.93
	Streptococcus	0.94	.91	.92
Average		0.94	0.94	0.93

We have also performed the data augmentation for creating a large database before applying the proposed method. After augmentation, we have randomly divided the dataset into two parts using the train test-split method. In the proposed method, disease types are classified into three categories such as COVID-19, SARS infected, Streptococcus infected. In recognition of these types of diseases, 2D-Convolution Neural Network is used by tuning its hyper-parameter. It is illustrated in Fig. 5 (b) that 2D-CNN recognized COVID-19 disease with an accuracy of 100%, however, the network has also classified the Streptococcus and SARS diseases with an accuracy of 91.3% and 90.9% respectively. It is described in Table 1 that the values of precision, recall, and F1-score are higher by using 2D-CNN.

Complexity Analysis of the System

The proposed deep learning approach to recognize COVID-19, SARS, Streptococcus diseases and normal patient is working in three stages. In the first stage, preprocessing and resizing of the input X-ray chest data is performed. Then, a data augmentation technique such as ImageDataGenerator is applied to generate the synthetic data using scaling, rotation and shear transformation on the input data and finally in the third stage, a supervised deep 2D-CNN has been trained to classify the diseases. Therefore, the complexity of our proposed system also exists in these mentioned stages. In the first stage, we resized our input data to the smaller size compared to the actual input size, because when dealing with large sized input images, we requires a much deeper network for features minimization and increases the computational complexity of the system. Hence, the existing system reduces the complexity occurred at the first stage to an adequate amount. In the subsequent stage, synthetic data has been generated using data augmentation technique to increase the amount of training data because a smaller amount of data may leads to the problem of network over fitting. Again our proposed system reduces the complexity by enhancing the input data. Similarly, this newly resized generated data reduces the training error during network training and results to better learning by the network and decreases the complexity at the third stage also. On the other hand, the computational complexity of our proposed system for features learning is 132.82 milliseconds, on the Intel 2.5 GHz Core-i5-7200U processor, which is relatively very low. Similarly the space complexity system is 166.25 K per input images on the same configuration system.

Comparison with State-of-Art Methods

The proposed approach is compared with state-of-art results on the COVID-chest X-Ray dataset. The comparative results have been shown in Table 2. It is stated from the Table 1 that our proposed approach is achieving better results among the methods given. A deep convolution neural network named Dark Covid Net[19] is proposed with nineteen convolutional layers and five maxpooling layers based on a real-time object detection system (YOLO) to detect COVID-19. Another method contains two approaches

Table 2 — Comparison with state-of-art method on covid-chest-X Ray dataset

Methods	Accuracy	Precision	Recall	F1-Score
Dark-Covid-Net[19]	87.02	89.96	85.35	87.37
Flat Efficient-Net[20]	93.34	93.93	93.96	93.94
H-Efficient-Net[20]	93.51	93.93	93.55	93.73
Proposed Method	95.73	94.00	94.25	93.50

named flat and hierarchical Efficient-Net[20] proposed for COVID-19 detection. Among the mentioned state-of-art methods our proposed approach gives superior results given in Table 2.

Conclusions

This paper presents a Deep Learning based approach for the recognition of COVID-19, SARS, and Streptococcus diseases from X-ray images. The proposed approach facilitates to recognize these diseases in real-time. The results of the proposed deep learning approach show the capabilities of deep learning techniques in medical image processing. In our proposed deep learning-based approach first, we increased the size of the dataset using data augmentation tool then a 2D-CNN is trained for the recognition of different types of diseases from X-Ray images using hyper tuning the parameters of the deep network. Using the proposed approach, an overall accuracy of 95.73% is achieved for all four classes. The value of Precision, Recall, and F1-score of the network are 0.94, 0.95, and 0.93 have been recorded respectively. From the experimental results, it is proved that our proposed deep learning-based approach is producing better results in terms of accuracy. The achieved results also show the superiority of deep convolution neural networks in medical image processing. This work also proposes the advantage of X-ray images to recognize different types of diseases. The future scope of this paper is to use deep learning methods for the recognition of different types of diseases using CT scan images.

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