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# Hybrid deep recurrent neural networks for COVID-19 detection and diagnosis

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***Abstract***---Corona virus Disease (COVID-19) is an acute pandemic which has put the lives of millions of people worldwide at risk during recent times. There is a high demand to develop effective tools and methods to diagnose the COVID infection in people at an early stage to prevent the spread of the disease to a larger community. This paper aims to provide a systematic method for COVID diagnosis using machine learning and deep learning algorithms. The proposed method Hybrid Deep Recurrent Neural Network (HDRNN) is a fusion of Convolution Neural Networks (CNN) and Long Short-Term Memory-Recurrent Neural Networks (LSTM-RNN) to detect COVID infection efficiently from X-ray samples. CNN is employed in the proposed method primarily to extract the essential features from the X-ray images and LSTM is suitable to classify the COVID affected patients with more fidelity. The dataset used in this work consists of an aggregate of 3470 images including COVID affected and Pneumonia affected samples. The experimental results carried out on the collected dataset with the proposed HDRNN method demonstrated an accuracy of 99.4%, F1 Score 98.7%, Sensitivity of 99.3% and Specificity of 99.2 %. The results obtained from the HDRNN method were compared with

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the results generated by applying conventional RNN method for the same dataset. The comparative analysis validated that the proposed HDRNN method outperformed in detecting the COVID affected patients with more exactness.

***Keywords*---**COVID-19 diagnosis, Machine learning, Deep learning architectures, CNN, RNN.

## Introduction

The applications of machine learning (ML) and deep learning (DL) algorithms in Covid-19 diagnosis have come into diagnosis, due to the lack of knowledge about detection, diagnosis and prognostication in the earlier days. There arises the need for a giant technology that can handle the huge data that is generated every day and process the data in order to track the tremendous spread of the disease. Thereby the applications of artificial intelligence came into existence. ML has the ability to think and act like humans and DL incorporates the same, along with handling billions of data with no compromise in performance and accuracy. ML algorithms include three types of learning - Supervised learning, Unsupervised learning and Reinforcement learning. As far as recent research is considered, supervised learning algorithms work well for Covid-19 diagnosis. Supervised learning algorithms use dataset that has labelled input and output, on the vice versa, unsupervised learning algorithms work on unlabeled input and output and clusters are formed based on the similarities and other properties. Reinforcement learning neither uses labelled data nor unlabeled data; instead, the learning system is allowed to attempt a variety of methods to attain a particular outcome.

The rest of the paper is organized as follows: the available modalities section explains the different parameters, benchmark datasets that aids in early detection and diagnosis. The feasible ML and DL algorithms are explained in the next section. Materials and Methods section comprises the dataset description and the specifications of the proposed method. Results and Discussion section presents the results obtained by applying the proposed Hybrid Deep Recurrent Neural Network. Furthermore, the results from the proposed method are compared against the results obtained using conventional Recurrent Neural Networks.

## Available Modalities

The following section explains the different modalities and supporting parameters that are helpful in early detection and diagnosis of corona virus using machine learning and deep learning algorithms. The most identified symptoms for corona virus are fever, cold, cough, throat infection, headache and body pain. Based on this, certain parameters are identified by the Ministry of Health, Israel and framed as a dataset, with the following features - Age, Gender, Fever, Shortness of breath, Cough, sore throat, headache, shortness of breath and the possibility of being in contact with the confirmed individual [1]. Another set of clinical parameters are identified in Veneto, to predict the mortality rate in ICU due to Covid-19. The research mainly aims at categorizing the patients of high risk and low risk. The variables are identified based on the primary set of symptoms like lack of oxygen, arterial partial pressure of oxygen and a certain score or index is calculated for the same, for example organ failure assessment score, so based on the index score, the severity rate varies [2]. It is identified that senior citizens and people with medical problems like cardiovascular disease, lung disease, diabetes is apparently prone to severe illness. As coronavirus directly impacts the lungs, CT scans and X-ray images are highly helpful and more accurate in detection and diagnosis. Apart from the above-mentioned clinical parameters, there are many benchmark datasets containing CT scan and X-ray samples, available in public forums like Kaggle and government websites like WHO.

**Machine Learning Algorithms**

The following section summarizes the various ML algorithms like Logistic Regression (LR), Naive Bayes (NB), Support Vector Machine (SVM), Decision Tree (DT), Random Forest, k-nearest neighbors (KNN), Gradient Boost (DT), that helps in early detection and diagnosis of Covid-19 [3] [4] [5]. Naive Bayes classifier is a simple probabilistic classifier that works based on Bayes theorem. The classifier assumes that the effect of a particular feature in a class is independent of other features. This hypothesis simplifies computation, and hence the classifier is called naive. Such an assumption is called class conditional independence. Decision tree is a class of supervised learning algorithms that makes predictions by creating decision rules for a given dataset. These algorithms offer solutions for both classification and regression problems, by splitting the dataset into smaller subsets. Attribute selection measures like information gain and Gini index are used to measure the importance of an attribute in a dataset. Based on these measures, the attributes are sorted out from root to leaf in the form of trees. Random forest is a type of decision tree learning that creates multiple decision trees and the output is calculated based on voting mechanism. Since the outcome is calculated from the results of multiple decision trees, this type of learning is said to be ensemble learning. KNN is considered to be a lazy learning and non-parametric supervised learning algorithm that can be used for both classification and regression.

**Deep Learning Algorithms**

The following section outlines the various DL architectures like Artificial Neural Networks (ANN), Convolution Neural Network (CNN) that aids in early detection and diagnosis of Covid-19. ANN is one of the broad disciplines of Artificial Intelligence that aims to mimic human brain behavior, in order to make the machines understand and make decisions like a human. The study of neural networks has been motivated in part by the observation that biological learning systems are built of very complex webs of interconnected neurons. The structure of ANN comprises densely interconnected units, each of which accepts single real valued inputs and produces single valued outputs. Similar to the human brain that has neurons interconnected to each other, ANN also has neurons that are interconnected to one another in several layers of the networks. ANN consists of an input layer, hidden layer and an output layer, depending on the type of application; modifications are made to the basic neural network architecture. ANN is also called perceptron or single layer perceptron, when the neural network can learn only linear functions. In order to make the network learn non -linear functions, the number of hidden layers is increased; hence the network becomes a multi-layer perceptron (MLP). Similarly, more such modifications are made in the basic neural network architecture for advanced sets of applications. Fig 1., interprets the different types of ANN frameworks.

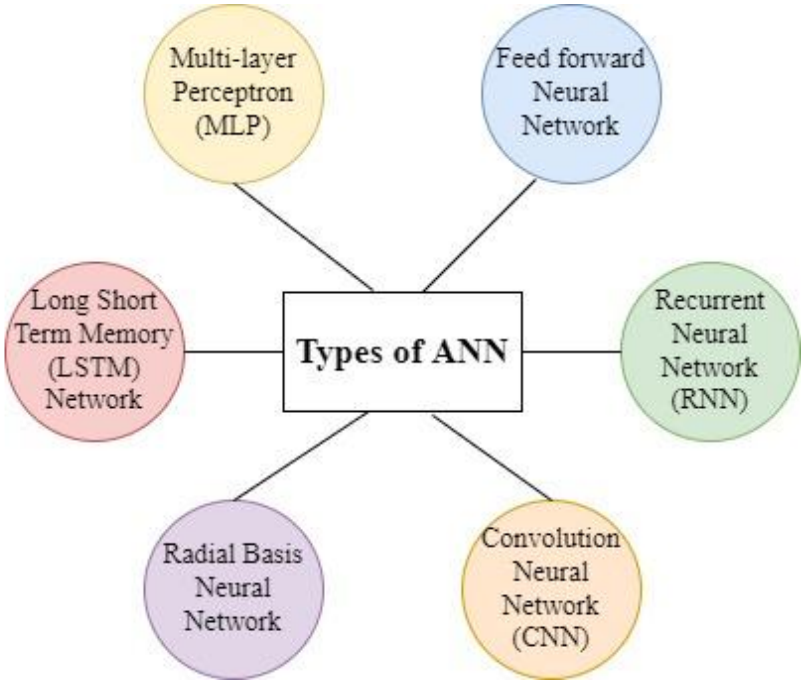



Fig. 1. Types of ANN Frameworks

ANN was used to predict Covid - 19 based on certain perspectives that include clinical symptoms, pulmonary symptoms and sociodemographic factors. In order to avoid unnecessary visits to medical centers and to make the patients take up self-tests, ANN based predictive system was modelled. With the help of increased hidden layers and sigmoid activation function, the system was able to predict the possible non-linear patterns among the various factors and the importance for each of the above-mentioned factors were calculated, which will be more helpful in finding the likelihood in the Covid-19 diagnosis [6].

MLP and LR were used to diagnose Covid-19 in Iran. The data was collected in terms of clinical symptoms and sociodemographic factors from 6 different patient groups in dissimilar provinces of Iran. A set of statistical tests such as Chi square test, Analysis of Variance (ANOVA) and Kruskal Wallis Test and machine learning models such as neutral network and logistic regression were considered. Statistical techniques were used to identify the characteristics and symptoms in each region. As a result, diseases such as pulmonary disorders, diabetes, coronary heart diseases and hypertension were identified as the most common underlying diseases. Machine learning models were used to classify Covid positive andnegative patients. The two-layer feed forward neural network was created with an input layer, hidden layer, output layer along with sigmoid and SoftMax activation functions. Both of the models were evaluated with the parameters like accuracy, sensitivity and specificity. It was observed that the accuracy of the MLP model was higher than the LR model as well as both the models was really helpful in corona diagnosis. [7].

Among the different frameworks, Convolution Neural Networks (CNN) and Recurrent Neural Networks (RNN) are widely used in Covid-19 detection and diagnosis. As traditional MLP's suffer from the dimensionality issues in case of high-resolution images, CNN came into existence. CNN performs a special type of mathematical operation called convolution, in its hidden layers, that extracts high level features. CNN takes images as input, assigns learnable weights and biases, extracts the different levels of features and finally performs classification. The structure of CNN consists of input layers, multiple hidden layers and an output layer. The hidden layers of a CNN typically consist of a series of convolutional layers that perform simple convolution operations. The hidden layers of a CNN include convolutional layers, pooling layers, fully connected layers and normalization layers. In this manner, CNN performs two operations; feature learning and classification - lines, curves, edges present in the images are identified in the feature learning phase, followed by classification where a fully connected layer assigns a probability for the object on the image being what the algorithm predicts it is.

Parameters from different CNN architectures are combined into a fusion framework, in order to screen the infected individuals based on Chest X-ray images (CXR). As RT-PCR reports may fail in certain cases, imagery modalities like Chest X-ray images, CT scans can be efficient in Covid-19 detection and diagnosis. Parameters from the pre-trained models ResNet, VGC and Inception were fused into a cloned architecture in order to extract the features required for the final prediction. The performance of all the three models were evaluated and observed that ResNet50V2 outperforms the other two CNN architectures [8]. Similarly, CT images were also used in diagnosing Covid-19 using the combination of CNN architectures. Such type of fusion learning is called transfer learning or ensemble learning. When a model is built using the combination of different architectures, such learning is said to be ensemble learning. The architectures like DenseNet, Channel boosted CNN, ResNet, AlexNet, VGG16 were combined to form the ensemble classifier, in which certain pre-trained features from the above architectures were extracted along with the high-level features from CT images. Such a fusion learning framework helps in reducing the time taken to train the deep learning model and to minimize the generalization error [9].

Similarly, RNN is a type of neural network that saves the current input of a particular layer, where the output from the previous step is fed as input to the current step. Hence RNN can be utilized in processing electronic health records. In case of medical data, RNN can be used to predict the future events based on the medical history. In case of Covid-19 diagnosis, RNN was used to predict the risk of developing critical outcomes for COVID-19 patients using historical electronic health record data of the patients [10].Similar to CNN, RNN can also process chest CT scan images to identify the presence of Covid-19. The different types of RNN - Long Short-Term Memory Networks (LSTM), Gated Recurrent Units (GRU) were combined to form an ensemble model, through which the important features were extracted. The parameters for the proposed model were tuned using Improved Bat algorithm and classification was performed using Multi-class SVM [11].

The salient features identified in the literature survey are as follows - When compared to RT PCR tests, CT scan images are found to be more accurate. Out of the different modalities available, image-based modalities play a huge role in disease diagnosis and hence CT scan and X-ray images can be utilized for screening patients, early detection and diagnosis. Instead of relying on the laboratory tests, machine learning and deep learning techniques offer quicker results and are found to be accurate when compared with laboratory results. Deep learning frameworks provide more efficient results when compared to traditional ML algorithms like linear regression, SVM, decision trees. ML techniques are found to be accurate for making predictions, to take the research to the next higher level to prediction, early detection and diagnosis comes into existence, where ANN, CNN, RNN works best when compared to traditional ML algorithms. As ANN lacks in capturing the non-linear features, it is recommended to proceed with CNN and RNN. Hence the proposed model is modelled as a hybrid framework that includes the functionalities of CNN and RNN.

## Materials and Methods

This section describes how the raw X-ray images can be used in the process of detection of COVID-19 using the approach of Hybrid Deep Recurrent Neural Networks (HDRNN). The first stage in the proposed method includes the pre-processing step which involves passing the X-ray images in raw form. The pre-processing stage includes three important techniques such as data normalization, data shuffling and resizing of the data. This data after performing pre-processing will be split into data for training and testing purposes. The data in the training set will be trained using the proposed hybrid deep recurrent neural network which is a combination of Convolutional Neural networks and Recurrent Neural Networks. Accuracy and Loss for Training and validation stages were calculated separately. Accuracy and loss during training phase was computer after every epoch. Similarly, accuracy and loss during the validation stage was calculated using the five-fold cross validation technique. Various performance metrics including accuracy, F1 score, Sensitivity and Specificity were used to determine the performance of the proposed HDRNN method.

## Dataset Description

The dataset collected from various sources consists of different sets of images in two classes of cases including Pneumonia affected patients and COVID affected patients. Data with two classes of images were collected to facilitate the comparative analysis of COVID-19 infection from patients with Pneumonia. X-ray Images for Pneumonia cases were collected from Kaggle repository. X-ray images of people affected by COVID-19 were collected from various online sources such as Radiopaedia[13] and GitHub[12]. The collected X-ray images were resized into 224x224 resolution and used for the further analysis. The detailed split up of the collected images for the training and testing phases are tabulated in Table 1.

Table1
Dataset description

| Cases | Training Phase | Testing Phase |
| --- | --- | --- |
| COVID affected images | 1310 | 425 |
| Pneumonia affected images | 1310 | 425 |
| Total Images | 2620 | 850 |

**Proposed Method**

This section covers a brief description of the architecture and working of the proposed Hybrid Deep Recurrent Neural Network (HDRNN).

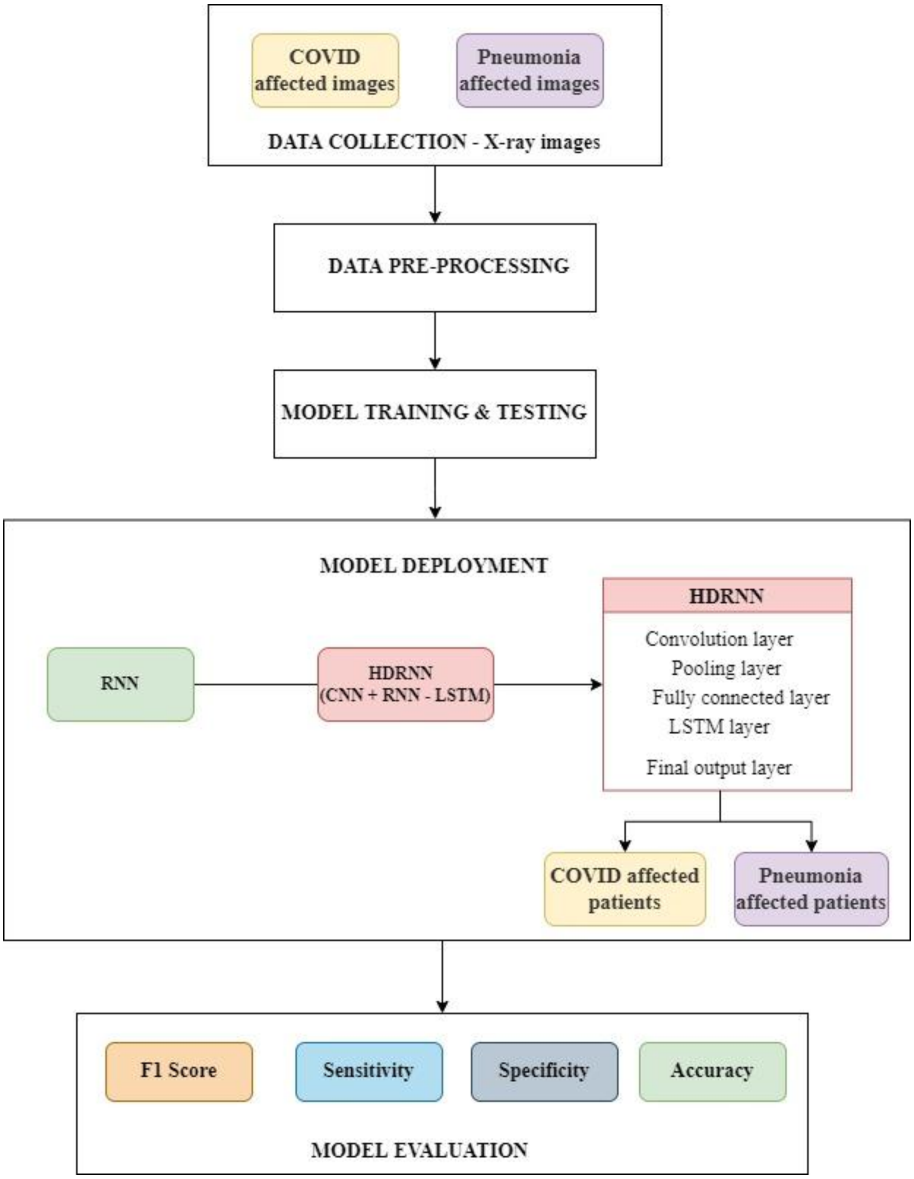



Fig. 2. Proposed HDRNN Architecture

The proposed HDRNN is a combination of Convolutional Neural Network architecture and LSTM framework in Recurrent Neural Network which is used primarily to detect the COVID infection in patients automatically. The major purpose to combine these two deep architectures is to employ CNN for the extraction of aggregated features from X-ray images and RNN to be used for the classification purposes. The proposed architecture on the whole consists of 18 layers in total which are summarized in the Table 2

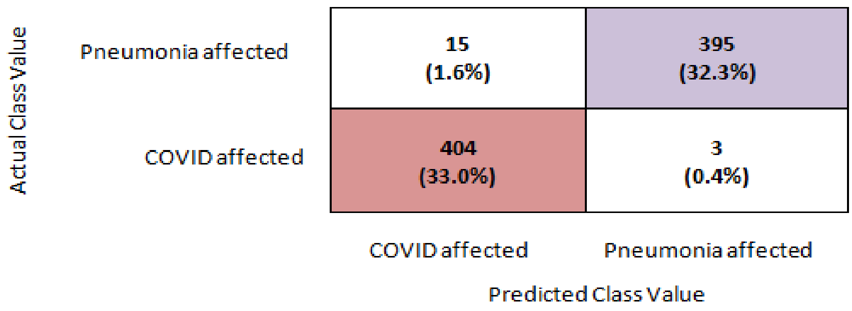
Table 2
HDRNN Architecture Layers

| Layer in the HDRNN architecture | Number of Layers |
|---|---|
| Convolutional Layers | 11 |
| Pooling Layers | 4 |
| Fully connected Layers | 1 |
| Long-Short Term Memory Layer | 1 |
| Final Output Layer | 1 |

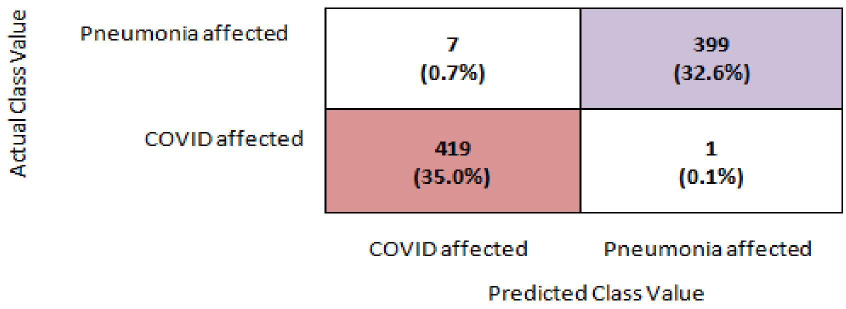
Each block of convolution is built with the mixture of 2D CNNs along with 1 pooling layer and a dropout layer. The dropout rate fixed in the dropout layer is up to 20%. The number of kernels in the convolution layer is 3x3 and the activation function used primarily in this layer is the Rectified Linear Unit. This layer is built in such a way to facilitate the feature extraction process. The pooling function used in the max pooling layer includes the max pooling function with a maximum size of the kernels to be 2x2. This max pooling function is employed mainly to reduce the size in terms of the dimensions in the image. The convolved feature map is finally transferred to the RNN layer which consists of the LSTM setup to extricate the time information with respect to the data. The output layer consists of the SoftMax activation function and the final shape after the convolution process is (none, 5, 5 512). When the reshaping technique is deployed to the obtained output, the size of the image transferred as input to the RNN layer becomes (25,512). The data passed on to the LSTM layer are analyzed with respect to the time-based features and then transformed into the Fully connected layer which classifies the images into two groups such as Covid affected patients and Pneumonia affected patients.

**Results and Discussion**

The results obtained for the chosen dataset by employing Recurrent Neural Network (RNN) architecture and the proposed Hybrid Recurrent Neural Network (HDRNN) is briefly discussed in this section.




(a) Confusion matrix of RNN architecture




(b) Confusion matrix of proposed HDRNN architecture

Fig. 3. Confusion Matrix Comparison for RNN Vs HDRNN

Fig. 3. Represents the comparison between the confusion matrices obtained during the testing phase for the RNN and the proposed HDRNN methods. Out of the 850 images chosen for the testing phase, the RNN architecture misclassified up to 18 images with 3 misclassifications for COVID affected patients. Comparatively only 8 images were misclassified by the proposed HDRNN architecture with only one misclassification for COVID affected patients. This is more evident to claim that the proposed architecture performs better than the conventional RNN architecture in classifying COVID affected patients effectively with minimum number in the case of False positive/negative values and more in number for True positive/negative values.

Table 3
Performance Metrics for RNN architecture

| Class Label/ Metrics | COVID affected | Pneumonia affected |
|---|---|---|
| F1 Score | 97.3 | 97.4 |
| Specificity | 98.1 | 99.5 |

| | | |
|---|---|---|
| Sensitivity | 98.8 | 96.1 |
| Accuracy | 98.3 | 98.2 |

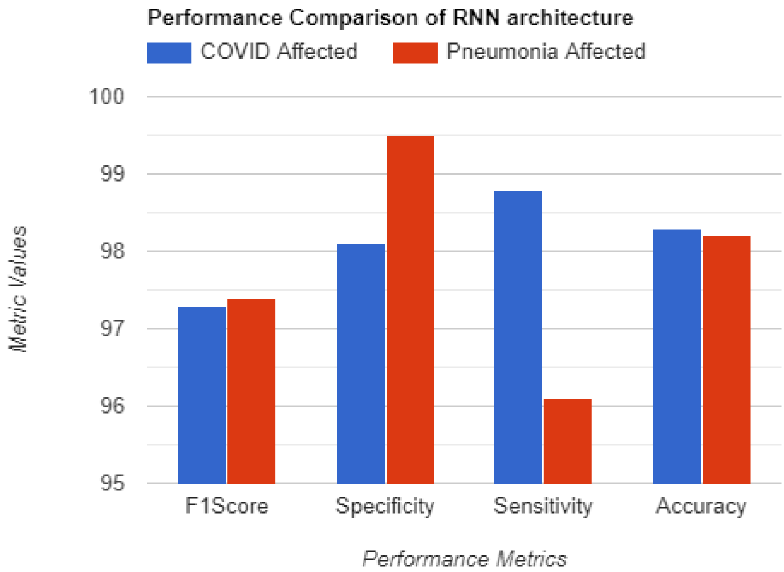



Fig. 4. Performance comparison of RNN Architecture

Table 3 summarizes the performance metrics values obtained from RNN architecture for the chosen dataset. The graphical representation of the results obtained from the RNN architecture is presented in Figure 4. The Performance metric values generated from conventional RNN architecture for detecting COVID affected patients are 97.3% F1 Score, 98.1% Specificity values, 98.8 Sensitivity values and 98.3 Accuracy. Similarly, in order to detect the Pneumonia affected patients RNN architecture showed the performance values as 97.4 F1 Score, 99.5 Specificity values, 96.1 Sensitivity values and 98.2 Accuracy values.

Table 4
Performance Metrics for HDRNN architecture

| Class Label/ Metrics | COVID affected | Pneumonia affected |
|---|---|---|
| F1 Score | 98.7 | 98.8 |
| Specificity | 99.2 | 99.5 |
| Sensitivity | 99.3 | 98.1 |
| Accuracy | 99.4 | 99.4 |

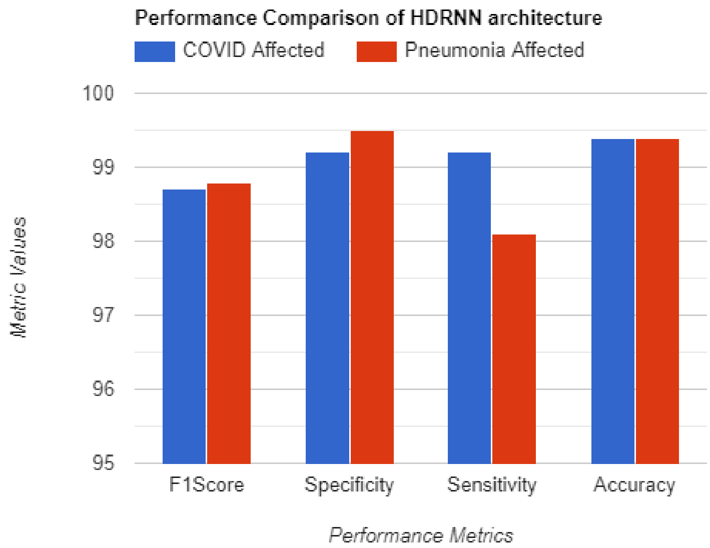



Fig. 5. Performance Comparison of HDRNN Architecture

Table 4 shows the performance demonstrated by the proposed HDRNN architecture in the classification of COVID affected patients and Pneumonia affected patients. As per the results obtained, HDRNN architecture shows 98.7% F1 Score, 99.2% Specificity values, 99.3% Sensitivity values and Accuracy of 99.4% in detecting the COVID affected patients. Similar to that, the performance metric values obtained for the Pneumonia affected patients are as 98.8% F1 Score, 99.5% Specificity, 98.1% Sensitivity and 99.4 Accuracy. On analyzing the results obtained from the proposed method, Hybrid Deep Recurrent Neural Networks which is a combination of convolutional Neural Networks and Long Short-Term Memory Networks in Recurrent Neural Networks, it is evident that it outperforms the RNN architecture as the true negatives predicted are high and false negatives predicted are low. The comparative study on the results obtained from the existing and proposed methods shows that the HDRNN architecture demonstrated remarkable performance for the detection of COVID-19 by extracting the features from X-ray images.

## Conclusion

COVID-19 pandemic has created a sensitive health emergency across the globe and has become a great threat to human lives. Hence, it is essentially vital to recognize the COVID positive cases with more precision. In this regard, Hybrid Deep Recurrent Neural Network is introduced to diagnose COVID infection in patients using raw X-ray images. The proposed method is a combination of CNN and LSTM-RNN, in which CNN is used in order to perform the extraction of appropriate features from the input data and the LSTM part of RNN is used to perform the classification tasks. Once the features are extracted, it is combined with the LSTM network to obtain the timing information and thus eventually classify between COVID affected and Pneumonia affected patients. The proposed HDRNN shows a higher performance with accuracy up to 99.4%. Conventional

RNN method is also applied to the same dataset and generated results are compared with the results obtained from HDRNN method. The performance comparison revealed that the proposed method outperformed the conventional method by producing better results. This proposed method can serve effectively to medically diagnose COVID infection in patients to a greater extent. There are two limitations identified with the respect to the proposed system. One is the size of the samples taken for the training and testing phases. When the sample size is increased with more images, then the model training and testing will be even more efficient. Second, when X-ray images with other disease symptoms than COVID, then the classification process is less reliable. The future work can be extended with an intent to overcome these limitations encountered.

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