Early Prediction of Covid-19 Disease with Machine Ana Deep Learning Approaches

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January 5, 2021

EARLY PREDICTION OF COVID-19 DISEASE WITH MACHINE ANA DEEP LEARNING APPROACHES

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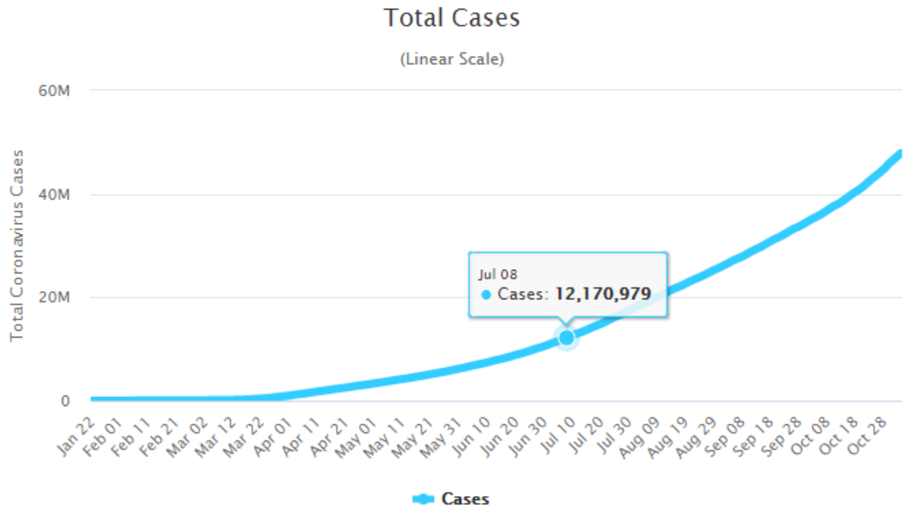
ABSTRACT

The coronavirus which causes COVID-19 disease has become a pandemic and has exposed all over the world and the cases are increasing daily .So that by using predictive algorithms we can predicate the diseases easily. Here, we perform clinical predictive models that estimate, using deep learning and laboratory data, which patients are likely to receive a

COVID-19 diseases. Some patients with coronavirus disease 2019 (COVID-19) show abnormal changes in laboratory myocardial injury markers, suggesting that patients with myocardial injury have a higher mortality rate than those without myocardial injury. This reviews possible mechanism of myocardial injury in patients with COVID-19. Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) affects the patients with COVID-19 in aspects of direct infection of myocardial injury, specific binding to functional receptors on cardiomyocytes, and immune-mediated myocardial injury. During hospitalization, the monitoring of laboratory myocardial injury markers in patients of COVID-19 should be strengthened. So it takes time to interpret the laboratory findings thus the limitations in terms of both treatment and findings are emerged. Due to such limitations, the need fir clinical decision making system with predictive algorithms has arisen.

INTRODUCTION

The coronavirus pandemic, which is COVID-19 pandemic, is an ongoing pandemic of coronavirus disease 2019 caused by the transmission of severe acute respiratory syndrome coronavirus , which was first identified in December 2019 in Wuhan, China. The outbreak was declared a Public Health Emergency of International Concern in January 2020, and a pandemic in March 2020. As of 20th September 2020, more than 41.3 million cases have been confirmed, with more than 1.13 million deaths attributed to COVID-19 and with recovered rate is 28.1 million Currently in India 7.71 million active case. COVID-19 affects different people in different ways and most of infected people will develop mild to moderate illness and recover without hospitalization. Some common symptoms are fever, dry cough, tiredness and some common symptoms are Loss of taste or smell, Nasal congestion, Conjunctivitis (also known as red eyes), Sore throat, Headache, Muscle or joint pain, Different types of skin rash, Nausea or vomiting, Diarrhea, Chills or dizziness. It also include some symptoms like Shortness of breath, Loss of appetite, Confusion, Persistent pain or pressure in the chest, High temperature (above 38 °C). Irritability, Reduced consciousness (sometimes associated with seizures), Anxiety, Depression, Sleep disorders, More severe and rare neurological complications such as strokes, brain inflammation, delirium and nerve damage. Most of people like 80% recover from the disease without going hospital treatment. And about 20% of those who get COVID-19 become seriously ill and require oxygen so will be admitted to hospital and another 5% becoming critically ill and needing intensive care. Some of Complications leading to death may include respiratory failure, acute respiratory distress syndrome (ARDS), sepsis and septic shock, thromboembolism, and multiorgan failure, including injury of the heart, liver or kidneys. In some situations, children can develop a severe inflammatory syndrome a few weeks after infection. People aged 60 and above 60, and those with underlying medical problems like high blood pressure, heart and lung problems, diabetes, obesity or cancer, are at higher risk of developing serious illness. However, anyone can get sick with COVID-19 and become seriously ill or die at any age since there is no proper symptoms. We should protect ourself like we should Stay safe by taking some simple precautions, such as physical distancing, wearing a mask, keeping rooms well ventilated, avoiding crowds, cleaning your hands by using soap and sanitizer, and coughing into a bent elbow or tissue and also we should avoid going outside the home unnecessary. Anyone with symptom should be tested. In some situations raid test is done and In most situations, a molecular test is used to detect COVID-19 and confirm COVID-19. Polymerase chain reaction (PCR) is the most commonly used molecular test. Since there is no vaccines at many potential vaccines for COVID-19 are being studied. Many potential vaccines for COVID-19 are being studied and several large clinical trials are done. If a vaccine is proven safe and effective, it must be approved by national regulators, manufactured, and distributed. WHO is working with partners around the world to help coordinate key steps in this process. Some of the laboratory finding have studied of COVID-19 outbreak. Since there is no vaccine still some of the symptoms for some of people may lead to death.



By using, artificial intelligence can predict and used in health care system to provide clinical decision, machine learning classifiers are effective to interpret themed-ical findings and Deep learning algorithms used to predict clinical findings for cancers, virus diseases, and biomedical studies this techniques are efficient and they can used to predict COVID-19 infection. So by using deep learning algorithm we can detect COVID-19 .In this we are using six different deep learning algorithm.

RELATED WORK

Health based systems are very critical, hence it is important to predict them accurately. Several health care systems use computer aided clinical predictive models like risk of heart failure [29] , mortality in pneumonia [30,31] , mortality risk in critical care [32-34] . These systems aide medical experts to comprehend and assess clinical findings better. In this paper, we are using recent advances of predictive models provide clinical model for COVID-19. Similar studies about clinical prediction for COVID-19 are limited in the literature. Authors in [26] , used machine learning techniques to predict the clinical severity of coronavirus. Data was obtained from Wenzhou Central Hospital and Cangnan People's Hospital in Wenzhou, China and cannot be accessible since the data is private. Eleven clinical features were considered and Logistic regression, k-nearest neighbourhood (KNN), 2 different decision trees, random forests and support vector machines (SVM) –classifiers were applied. The performance of the classifiers were evaluated with only accuracy values. Best accuracy was obtained with SVM classifier with 80%. In the another study[27] , authors applied machine learning classifiers to predict COVID-19 diagnosis. Clinical data was obtained from Hospital Israelita Albert Einstein at Sao Paulo Brazil. 18 clinical findings were considered in the study and classifiers were evaluated with AUC, sensitivity, specificity, F1- score, Brier score, positive predictive value, and negative predictive value. Only five different classifiers were applied including, SVM, random forests, neural networks, logistic regression, and gradient boosted trees. The best AUC scores were obtained with both SVM, and random forest classifiers with 0.847. In the study [28] of, clinical predictive model for COVID-19 was proposed. In the study, data was collected from Hospital Israelita Albert Einstein at Sao Paulo, Brazil like in this study and [27] Authors applied various machine learning applications including RF, NN (Neural Network), LR, SVM, XFB (Gradient Boosting) and determined the performance of classifiers by calculating sensitivity, specificity, and AUC scores.

3. METHODS AND DATA

3.1 Data description

Dataset contains the laboratory results of the patients seen at the Hospital Israelita Albert Einstein at Sao Paulo Brazil and can be accessed through [28]. Samples were collected from patients to detect SARS-CoV2 in the early months of 2020. Dataset contains 111 laboratory results from 5644 various patients. In that, positive patients rate was around 10% of which around 6.5% required hospitalization and 2.5% required critical care. Gender information has not been kept in the dataset. According to the study of [26 – 28], 18 laboratory results have a important role on COVID-19 disease. Thus, we removed remaining laboratory features to balance the dataset and to perform COVID-19 detection. Then we performed balancing. after balancing, dataset contains 18 laboratory results from 600 patients, since few of the 18 laboratory results are not known to some patients, the number of patients decreased from 5644 to 600. In the balanced dataset, we have 520 no findings and 80 COVID-19 patients. Table 1 shows the laboratory results.

Table 1
18 Laboratory findings of the patients in the dataset.

Laboratory Findings	Hematocrit, hemoglobin, platelets, red blood cells, lymphocytes, leukocytes, basophils, eosinophils, monocytes, serum glucose, neutrophils, urea, C reactive protein, creatinine, potassium, sodium, alanine transaminase, aspartate transaminase

Laboratory findings of the patients in the dataset.

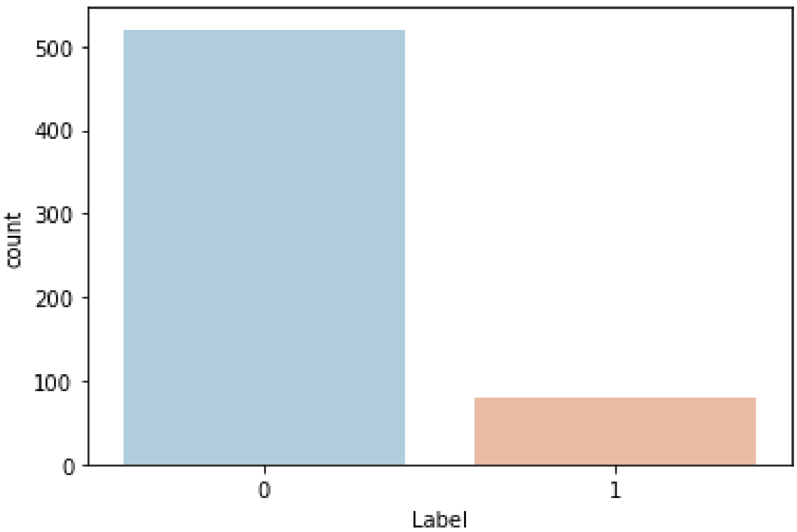
3.2. Deep learning application models

AI algorithms predict the outcomes based on historical data. Machine learning (ML) and deep learning (DL) algorithms can be considered as a subsets of the AI. It is an area that is based on learning and improving on its own by analyzing computer algorithms.

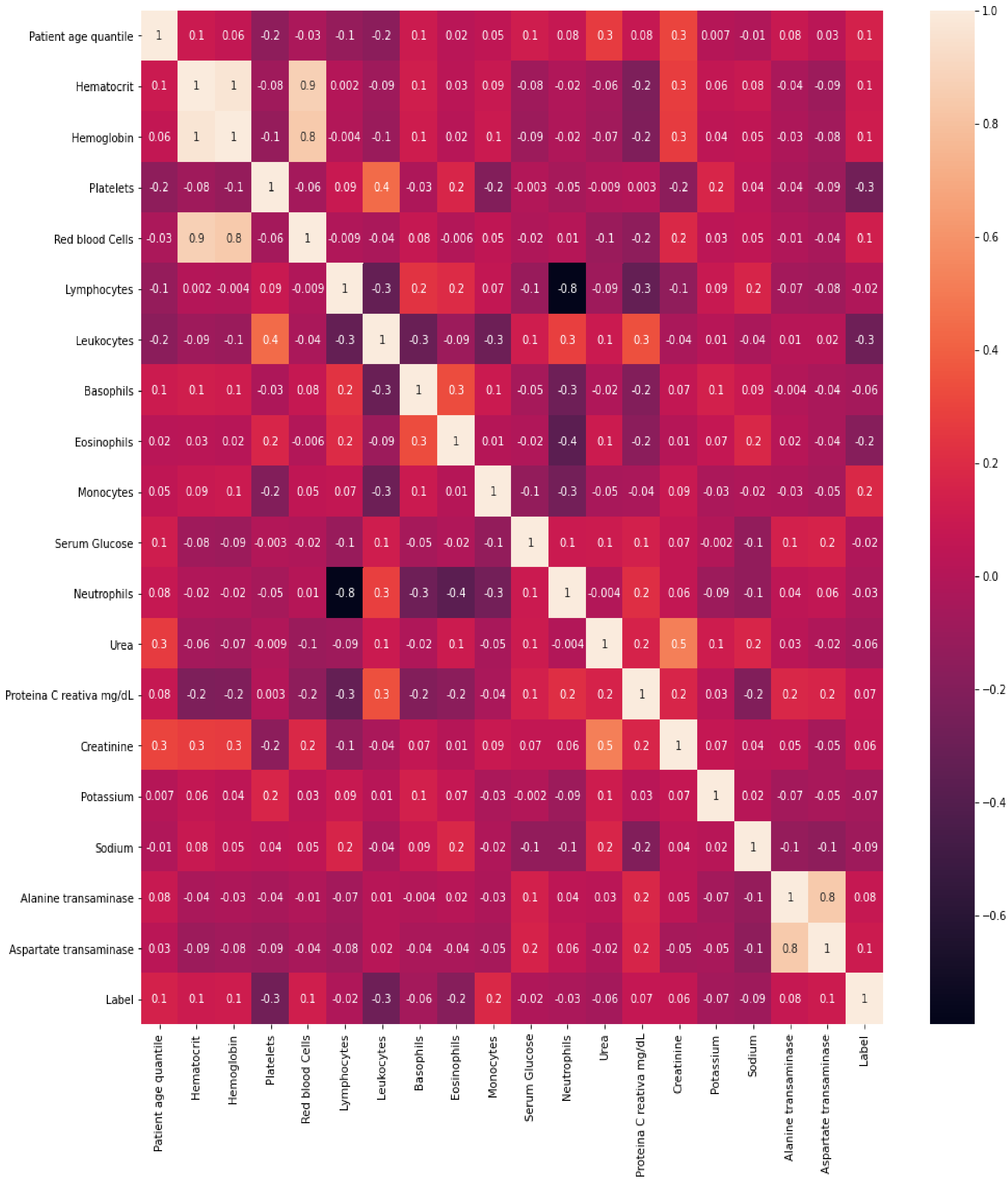
Here, we develop and calculate predictive models to determine the COVID-19 infection with laboratory results. For the study, we trained six different model types: Artificial Neural Network (ANN), Convolutional Neural Networks (CNN), Long-Short Term Memory (LSTM), Recurrent Neural Net- works (RNN), CNN, LSTM, and CNN, RNN. ANN is an information pro cessing technique, that is inspired by the nervous system of human brain. It is composed of neurons, activation functions, input, output, and hidden layers. CNN is one of the types of neural networks and is used in image classification problems. It includes convolutional layers, pooling layers, fully connected layers, and a classification layer. Convolution layers do feature extraction. CNN obtains features by itself. In the pooling layer, the dimension of the inputs is reduced. RNN is feed forward neural network which contains an internal memory. Output of RNN depends on the previous computation, while input function remains the same. RNN uses its internal memory to process the inputs. LSTM is the modified version of the RNN. In the LSTM, it is easier to remember the past data in the memory. The vanishing gradient problem of RNN is resolved in the LSTM networks. We developed two hybrid models including CNN,LSTM, and CNN,RNN.We followed a trial and error approach to set the parameters for each DL models. Table 2 emphasizes the parameters of each classifier. To get the performance of each of the developed predictive models, we calculated their performance in terms of accuracy, f1-score, precision, recall, and area under roc curve (AUC).

Table 2
Parameters of each DL classifier.

Parameters	ANN	CNN	LSTM	RNN	CNNLSTM	CNNRNN
Number of units	32,16,8	512,256	–	–	512,256	512,256
Number of layers	1,2,3	1,2	1	1	1,2	1,2
Activation function	ReLU	ReLU	ReLU	ReLU	ReLU	ReLU
Learning rate	1e-3	1e-3	1e-3	1e-3	1e-3	1e-3
Loss function	Binary crossentropy	Binary crossentropy	Binary crossentropy	Binary crossentropy	Binary crossentropy	Binary crossentropy
Number of epoch	250	250	250	250	250	250
Optimizer	SGD	SGD	SGD	SGD	SGD	SGD
Decay	1e-5	1e-5	1e-5	1e-5	1e-5	1e-5
Momentum	0.3	0.3	0.3	0.3	0.3	0.3
Number of fully connected units	–	2048,1024	2048,1024	2048,1024	2048,1024	2048,1024
Number of fully connected layers	–	1,2	1,2	1,2	1,2	1,2
Number of LSTM units	–	–	512	–	512	512
Number of RNN units	–	–	–	512	–	512
Dropout	–	–	–	0.25	0.15	0.15



overall patient count of the disease



Correlation between features in Laboratory findings of the patients in the dataset.

3.3 *Machine Learning and Ensemble Techniques based Predictive Models*

Artificial Neural Network:

ANN is built to simulate human brain. Thee network layers consists of units, which has inputs and outputs. ANN learns from input provided and gives the output based on the prediction. ANN usd back propagation to reduce errors. The practical applications for ANNs are far and wide, encompassing finance, personal communication, industry, education and so on.

Convolution Neural Network:

CNN is also known as ConvNet, is a type of neural network that specializes in data processing that has grid-like structure, like images. Each neurons has it's own receptive field and each neuron is connected to other neurons in a way they cover the whole visual field. Each neuron process in it's receptive field as well. The layers are made in suc a way that they first check for simple patterns like line, curve. Later they check for more complex patterns like face, objects.

Recurrent Neural Network:

Recurrent neural network (RNN) is a class of artificial neural network(ANN) where connections between units form a directed graph along a sequence. This allows it to exhibit dynamic temporal behavior for a time sequence. Unlike feed forward neural networks, RNNs can use their internal state as memory to process sequences of inputs**.**

LTSM:

LTSM is a type of artificial recurring neural network used in deep learning. LTSM has feedback connections. It can process sequence of data like video and speech along with single data points such as images. LTSM unit is composed of a cell, an input gate, output gate and forget gate. LSTM networks are well-suited to classifying, processing and making predictions based on time series data, since there can be lags of unknown duration between important events in a time series. The advantage of an LSTM cell compared to a common recurrent unit is its cell memory unit.

CNNLTSM:

CNN fails to easily model structures like images. Hence we use CNN with LTSM is specifically designed for special inputs.

CNN-RNN:

CNN techniques, although working well, fail to explicitly exploit the label dependencies in an image. Recurrent neural networks (RNNs) are used to address this problem. Combined with CNNs, the CNN-RNN framework learns a joint image-label embedding to characterize the semantic label dependency as well as the image-label relevance, and it can be trained end-to-end from scratch to integrate both information in a unified framework. Experimental results on public benchmark datasets demonstrate that the proposed architecture achieves better performance than the state-of-the-art multi-label classification model

APPLICATION RESULTS

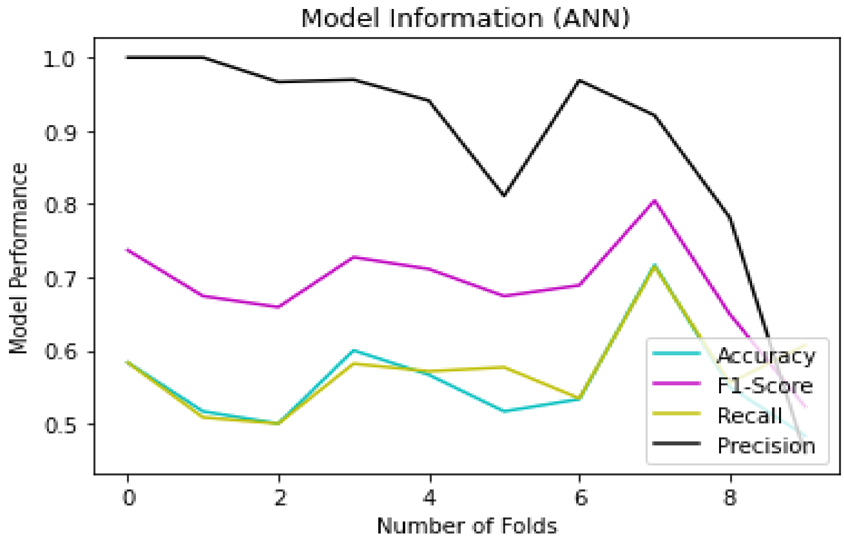
For COVID-19 predictions, we considered 18 laboratory findings from 600 patients. We used six different type of models to learn and predict the findings. Later, predictions were performed and the performance of the deep learning applications models were evaluated. Table 2 shows the results of all deep learning application models. In terms of predictive performance, we observed that the overall best identified models by AUC score were 62.50 by LSTM for predicting COVID-19 disease. Nevertheless, the best clinical prediction results achieved a respectable accuracy of 59.33%, f1-score of 71.48%, and recall of 65.99%, respectively with LSTM. From the results we can see that LTSM is the good model for prediction.

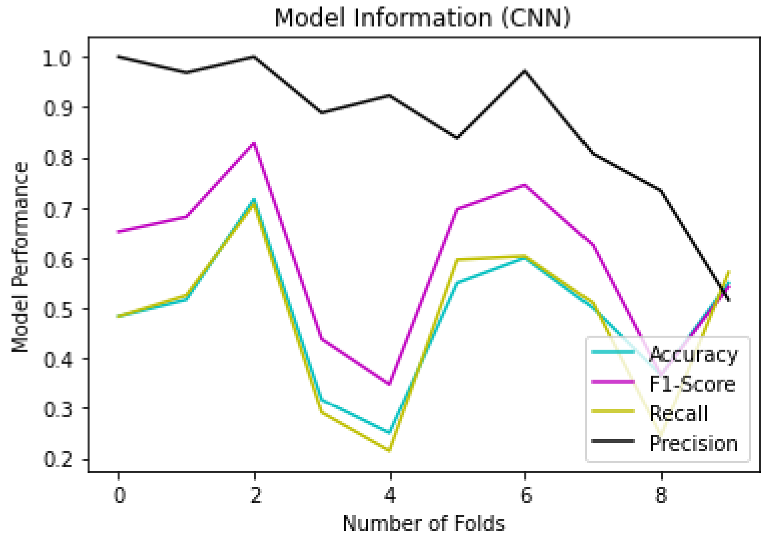
The F1-score, precision, and recall of all the models were observed above 48.00%. Precision can be defined as the ratio of correctly predicted positive observations to the total predicted positive observations. In information retrieval studies, a perfect precision should be 1. In this research, the best precision score was obtained with CNNLSTM with 0.8790. Recall is the ratio of correctly predicted positive observations to the all observations. Like precision, a recall score must reach to the 1 for the perfect classification process. The best recall value was obtained from LSTM deep learning application model with 0.6599. F1 score is the weighted average of precision and recall values. This evaluation criterion takes both false positives and false negatives. Basically getting a goof F1 score indicates less false positives and low false negatives. The perfect F1 score is, when the value is 1. We have best F1 value with LSTM 0.7148. AUC is the value used to determine which of the used models predicts the classes best. We prefer to have positive AUC for critical medical predictions as they are sensitive. AUC score of 0.5 means that there is no discrimination, a score between 0.6 and 0.8 is considered acceptable, a score between n 0.8 and 0.9 is considered excellent. In this study, recall is important evaluation criteria since it is computed by taking the ratio of correctly identified COVID-19 patients to the total number of COVID-19 diseased patients. By measuring the accuracy of the models, the researcher can prove that the research is generalizable, reliable, and valid [41].

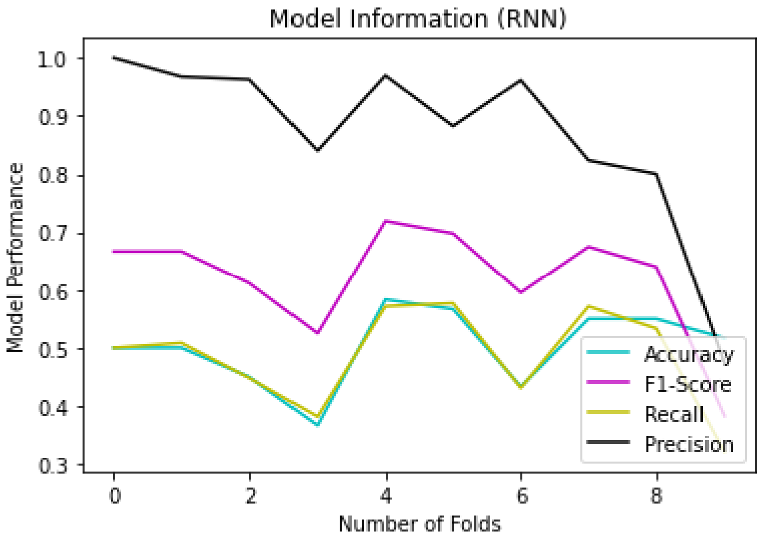
Table-3

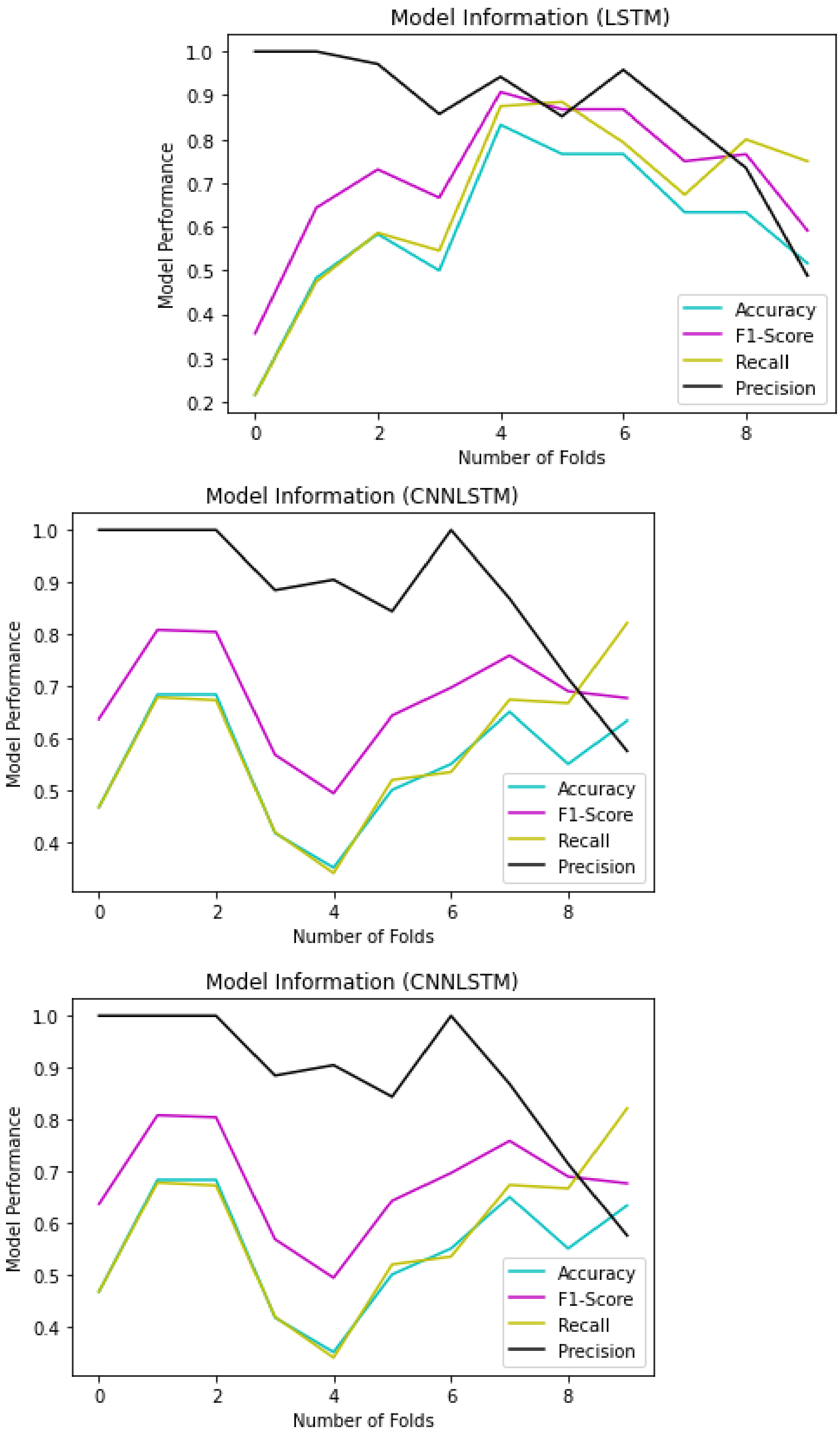
	Accuracy result	Recall result	Precision result	F1 result	ROC
ANN	0.5566666666666666	0.5733444625379167	0.881886300880109	0.6848545621945364	0.4788461538461538
CNN	0.485	0.474652763858742	0.8646689850520495	0.5922818766769595	0.4442307692307693
RNN	0.5016666666666667	0.48441452274590785	0.8681506893149757	0.6179789195238915	0.516826923076923
LSTM	0.5933333333333333	0.6599092600505726	0.8650284122792428	0.7148455213441114	0.5639423076923077
CNNRNN					0.5100961538461538
CNNLSTM	0.5483333333333335	0.5789792247634362	0.8790834056294582	0.6774208690503594	0.5177884615384615

Evaluation results of all deep learning application models with 10 fold cross-validation approach.


Model Information (ANN)
Model Performance
Number of Folds
Accuracy
F1-Score
Recall
Precision


Model Information (CNN)
Model Performance
Number of Folds
Accuracy
F1-Score
Recall
Precision


Model Information (RNN)
Model Performance
Number of Folds
Accuracy
F1-Score
Recall
Precision



F. 2. Evaluation results of all deep learning models with 10 fold cross-validation approach.

Conclusion

This paper measure the performance of 6 predictive models built on ANN,CNN,RNN,LSTM,CNNRNN and CNNLTM methods.These models are used to predict COVID-19 using various parameters provided in COVID-19 dataset.600 data samples are collected. In the first stage of the study, the data were standardized and then used as inputs for the deep learning models then classification was carried out and the performances of the models were measured with precision, recall, accuracy, AUC, and F1-scores. To validate the models, we applied 10 fold cross-validation approaches. In 10 fold cross-validation strategy, best meaningful results observed from LSTM deep learning model with accuracy of 59.33%, recall of 65.99%. All deep learning models developed in the study showed an accuracy of over 84%. Similar inferences can be made for precision and recall values.

In conclusion, we found evidence to suggest that deep learning application models can be applied to predict COVID-19 infection with laboratory findings. Our experimental results indicate that may be useful to help prioritize scarce healthcare resources by assigning personalized risk scores using laboratory and blood analysis data. In addition to these, our findings on the importance of laboratory measurements towards predicting COVID-19 infection for patients increase our understanding of the outcomes of COVID- 19 disease. Based on our study's results, we conclude that health- care systems should explore the use of predictive models that as- sess individual COVID-19 risk in order to improve healthcare re source prioritization and inform patient care.

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