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Covid-19 Severity Prediction And Classification Using Lstm Based Autoencoder

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ABSTRACT

COVID-19 (Coronavirus) is a pandemic situation and it affects the social and economics of the country. Hence, there is a need for robust prediction model that can ensure better prediction outcomes. Early diagnosis and finding the severity of diseases are the major concerns of the medical experts. An automated model is essential for predicting the severity of the COVID-19 and the diagnosis will assists the experts. Deep learning (DL) models are efficient mechanism that can able to process the massive data which is in different formats like clinical symptoms. This work presents the DL model to analyze the medical data consists of 65,000 patients records and 26 features. Here, the optimal features are selected by the optimizer called Enhanced sky driver optimization (ESDO). With the selected features, the DL model Long short Term memory (LSTM) based AutoEncoder (AE) is used to screen the severity of COVID-19 patients. The performance of the proposed LSTM based AE is compared with other DL models and achieved better accuracy of. Further, this model predicted the severity cases as mild, moderate and severe. The medical experts can use these outcomes for finalizing the type of medical treatment that has to be given to the affected patients on time.

Keywords*:* Coronavirus, Severity, Optimal Features, Deep Learning, Enhanced Sky Driver Optimization

1. INTRODUCTION

COVID-19 was initially identified in December 2019 in Wuhan city, China. Suddenly, this COVID-19 begins to spread in various countries [1]. The countries like United States (US), Germany, Italy, the United Kingdom (UK) and Spain are highly affected due to this disease. The propagation of this disease is faster when the human beings are in nearby environment. It is a respiratory disorder and it is occur due to SARS -CoV-2 (severe acute respiratory syndrome coronavirus-2). The most common symptoms are fever and cough; further other symptoms like sore throat, chest discomfort and mucus development may occur [2].

This COVID-19 may lead to pneumonia and it has 5.9% of death risk. Based on the report of the author Jiang et al. [3] showed that the mortality rate was about 4.5% over the world and the mortality rate of the people in the age of 70 to 79 years was 8%. Then, the people above the age of 80 years was 14.7%. It was also proved that the people above the 50

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age with chronic disorder are at the high risk and hence the precautions must be taken [4]. Approximately, 1.6 to 3.6% of people are affected due to the contact with the affected patients. Hence, COVID-19 can affect more number of people since the preventive measures are not developed [5].

The basic diagnostic model is RT-PCR (reverse transcription-polymerase chain reaction) and it is the laboratory process that depends on the RNA (ribonucleic acid) and DNA (deoxyribonucleic acid). It is used for determining the volume of particular RNA with the help of fluorescence [6]. These tests are carried on the medical analysis samples of thick mucus in the nasal. These samples are obtained by providing swab into the nose for collecting secretions. Though, RT-PCR can find the SARS-COV-2, in certain cases it generates the false results. People who undergone clinical symptoms and same CT (Computed Tomography) images are identified as the negative case. When there are more samples, results may be delayed and affect the people with complex problems [7-8].

To provide an accurate detection and effective measure, there is a need of model which improves the survival rate of the affected person is essential. Recently, various approaches have been developed to outperform the laboratory analysis [9-13]. Analyzing the chest infections assisted the radiologists in diagnosing the COVID-19 early. The imaging modalities like X rays and CT are used for identifying the presence of disease. Recently, the machine learning (ML) and deep learning (DL) models have attained huge interest because of the availability of massive data. These models assist to find the relation from the data without setting them priority [14-15]. Some of the ML and DL models utilized for the prediction of COVID-19 are SVM (Support vector machine), LR (Logistic regression), NB (naïve bayes), CNN (convolutional neural network), RNN (recurrent Neural Networks), LSTM (Long Short Term Memory) and GRU (gated recurrent unit) [16-17]. The major contributions of this work are:

- To present an automated deep learning (DL) model for the severity prediction (mild, moderate and severe) of COVID-19.
- To present the feature selection model using Enhanced sky driver optimization (ESDO) for selecting the optimal features.
- To reduce the system complexity and enhance the accuracy the DL model Long short Term memory (LSTM) based AutoEncoder (AE).

The rest of the section is presented as: Section 2 is about the recent literature works based on the COVID-19 prediction; Section 3 presents the proposed COVID-19 prediction with mathematical calculations. Section 4 discuss about the results and the entire work is concluded in section 5.

2. Related works

Some of the recent research works based on the DL and ML models used for the COVID-19 prediction are listed in this section.

Podder et al. [18] presented a various ML models for predicting COVID-19 using the data collected from the hospital Israelita Albert Einstein. The feature selection model univariate was used for selecting best 25 features with the respective scores. From the experimentation, it was proved that the serum glucose has high impact in the prediction of the disease. Further, the models XGBoost and LR achieved better accuracies of 92.67% and 92.58%. Iwendi et al. [19] presented various ML models for analyzing the effect of COVID-

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19 on Brazil and Mexico. This work considered only the demographic data, symptom reports and clinical risk for predicting recovery and mortality rate of the patients. The model of Mexico achieved better accuracy of 93% and the model of Brazil achieved better accuracy of 69%.

ArunKumar et al. [20] demonstrated 60 days forecast report of the COVID-19 using the DL models like RNN with GRU and LSTM. This work considered the dataset of John Hopkins and emphasized the necessity of different factors like age, population density, healthcare facility and preventive measures. Ketu and Mishra [21] presented CNN with LSTM model for forecasting the COVID-19 over India. This model utilized convolutional layer for extracting the essential features and LSTM was used for identifying the long and short terms dependencies. This work used Arogya Setu App and ministry of healthcare app for the experimentation and achieved better MAPE and R^2 values of 32.7 and 1 respectively.

Sayed et al. [22] presented various ML models for predicting the severity risk of the COVID-19 patients on the basis of the X-ray images. Here, the pre-trained DL model CheXNet and hand-crafted features techniques were used for selecting the most useful features and evaluated on the six ML classifiers. Among all ML models, XGBoost achieved better accuracy and precision of 97% and 98% on X-ray dataset. Kao and Perng [23] presented a DL model for the early prediction of COVID-19 in the US. This work utilized the data of first confirmed cases of fourteen days before and output was generated for after the testing day in the US. The CNN based LSTM was used for finding the confirmed cases and this model achieved better MSE and PSNR values of 1.664 and 55.69 dB.

Pandey et al. [24] presented a Susceptible, Exposed, Infectious, Recovered (SEIR) and regression models for the COVID-19 prediction. The prediction was on the basis of the data obtained from the John Hopkins on the period of 30 January to 30 march, 2020. This work achieved a better RMSLE values of 1.52 and 1.75 for SEIR and regression models. Aljameel et al. [25] developed the ML models like LR, RF and XGBoost for the predicting the severity of the COVID-19. This work collected the data samples from the Hospital King Fahad University. Then, the 10-fold cross validation was used to split data and the SMOTE was used for balancing the data. Experimentation was carried out for 20 clinical features and identified the survival and death rate of the affected patients.

3. Proposed methodology

The existing research works utilized the data from the text data and CT images for the COVID-19 prediction. This work considers the symptoms which is in the text format. The major aim of this work is for detecting the cases of COVID-19 cases and for predicting the severity using the analysis of the symptoms. For achieving the better results of the DL model, the feature selection model must be more relevant. Hence, this work presents an efficient optimization based DL model for the severity prediction of the COVID-19. Figure 1 illustrates the workflow of the COVID-19 prediction model.

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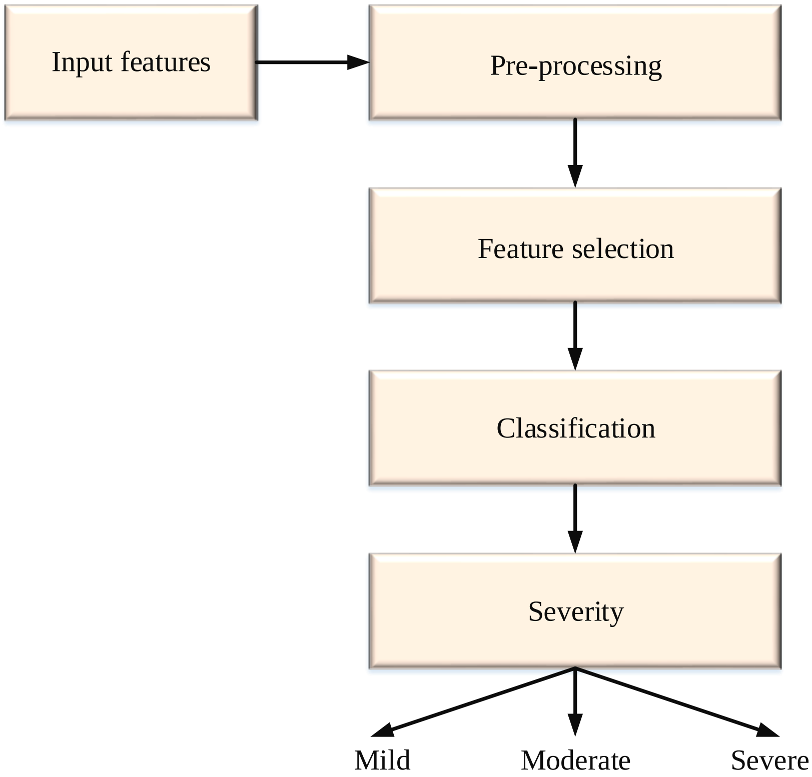

Figure 1: Workflow of the COVID-19 prediction model

3.1 Dataset acquisition

This work considered the dataset of 26 different features which includes symptoms of disease and other personal details. These information are helpful to find whether the people have COVID-19 or not according to pre-defined symptoms. Based on the report of WHO, the symptoms are classified. The data has six parameters that has major impact on whether the person is affected by COVID-19 or not. Those parameters are country, age, symptoms, other symptoms, severity and contact.

3.2 Data pre-processing

Initially, the parameters are ranked for confirming the impact contributing the prediction. Every label in the parameter is generated by the categorical variables. The features are represented in binary format 1 for presence and 0 for absence. There are 26 features are present in the dataset, among them irrelevant parameters are eliminated which doesn't have high impact on the prediction. Table 1 presents the features which are selected for the feature selection process.

Table 1: Features of the dataset

Features	**Type**
Tiredness	Symptom
Sore throat	Symptom
Fever	Symptom
Pain	Symptom
Dry cough	Symptom
Diarrhea	Symptom

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Nasal blocking	Symptom
Breathing complex	Symptom
Running nose	Symptom
Age (0 to 9)	personal
Age (10 to 19)	personal
Age (20 to 24)	personal
Age (25 to 59)	personal
Age (>60)	personal
Transgender	personal
Male	personal
Female	personal
Mild	Severity
Moderate	Severity
Severe	Severity
Non-contact	Non-symptoms
contact	Non-symptoms

3.2 Feature selection

The features obtained from the pre-processing is provided into the feature selection stage for producing the optimal features set. In this work, the metaheuristic algorithm enhanced sky driver optimization (ESDO) [26] is utilized. The characteristics of ESDO is inspired by various evolutionary algorithms. The exploration behavior simulate the path that ski drivers take down-hill. The fitness function on the basis of the feature values are given as:

$$Fitness = \frac{1}{N}\frac{S(match(S_j(k), V_l(k))}{G} \qquad (1)$$

where N is the total vectors in the obtained COVID-19 data, S is the score, G id the total features, $S_j(k)$ is the k^{th} position in the j^{th} vector and $V_l(k)$ is the k^{th} position in the l^{th} vector.

The mathematical formulation of ESDO is given in the following section:

Agent's position $(Y_j \in \Re^m)$: This phase is utilized for computing the fitness function (FF) at the location and m is the search space's dimension.

Prior best position P_j :For every search agent, the fitness value is computed by FF and the value of fitness and current position are compared. Then, the best position is recorded.

Average global solution A_j :In this stage, like grey wolf optimizer (GWO), the search agents goes to the global point and it indicates the average of three best solutions. It is given as:

$$A_j = \frac{Y_\alpha + Y_\beta + Y_\gamma}{3} \qquad (2)$$

where Y_α, Y_β, and Y_γ are the three best solutions.

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Agent's velocity V_j : The positions of the agents are updated by integrating the velocity and it is given as:

$$Y_j^{t+1} = Y_j^t + V_j^t \qquad (3)$$

where

$$V_j^{t+1} = \begin{cases} g \sin\,(rand1)(Q_j^t - Y_j^t) + \sin\,(rand1)(A_j^t - (Y_j^t) & when \;\; rand1 \le 0.5 \\ g \sin\,(rand1)(Q_j^t - Y_j^t) + \cos\,(rand1)(A_j^t - (Y_j^t) & when \;\; rand2 > 0.5 \end{cases} \qquad (4)$$

where V_j is the velocity of Y_j, $rand1$ and $rand2$ are the random numbers and it is the range of 0 to1. Q_j is the j^{th} agent's best solution, A_j is the average global solution and g is the variable used for balancing the exploration and exploitation ability. It is computed as:

$$g^{t+1} = \beta g^t \qquad (5)$$

where t is the present iteration and β is the term used for reducing the value of g.

However, the traditional SDO has the issues like unbalanced exploration and slow convergence. To overcome this issue, this work introduces an ESDO used for balancing the exploration and exploitation of SDO. It is found from Equation (4) that the choosing randomly local and global search with the switch probability will affect the SDO to fall into local optimum. Further, $rand1$ and $rand2$ in Equation (4) doesn't have the capacity to adjust local and global search. Hence, the guiding variable is used in this equation to adjust local and global search. It is expressed as:

$$V_j^{t+1} = \begin{cases} g_t \times g \sin\,(rand1)(Q_j^t - Y_j^t) + \sin\,(rand1)(A_j^t - (Y_j^t) & when \;\; rand1 \le 0.5 \\ 1 - g_t \times g \sin\,(rand1)(Q_j^t - Y_j^t) + \cos\,(rand1)(A_j^t - (Y_j^t) & when \;\; rand2 > 0.5 \end{cases} \qquad (6)$$

where g_t is the guiding variable and it is computed by:

$$g_t = 1 - \frac{t}{\max\_iter} \qquad (7)$$

where $\max\_iter$ is the maximum iteration.

In the feature selection stage, the solution in space is the initial features set, the solutions are randomly initialized. The optimal features of the ESDO ensures the exploration capacity for finding the global optimal value. Hence, it is proved that this optimization is not trapped by local optima. Algorithm 1 defines the pseudocode of the optimal feature selection by ESDO.

Algorithm 1: Pseudocode of the optimal feature selection
Initialize the positions of agents Y_j and the velocity V_j
Evaluate the fitness function using Equation (1)
  while $t \le \max\_iter$
    for all search agents **do**
      Compute the value of fitness

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Arrange the search agents on the basis of value of fitness
Compute average global solution and previous best position
Produce the new solution by updation of position of the agents using the Equation (3)
The agent's velocities are adjusted using the Equation (6)
end for
end while
Return the optimal value

Among the 26 features, 22 features are given to the features selection stage. In this the ESDO provides 11 features as the optimal which is shown in Table 2. The features are ranked on the basis of the frequency criterion and these features are used for predicting the positive cases. When compared to the Table 1, the personal information of the patients are eliminated; that is 11 features.

Table 2: Features obtained by ESDO

Features	Rank
Tiredness	2
Sore throat	8
Fever	7
Pain	4
Dry cough	3
Diarrhea	5
Nasal blocking	1
Running nose	9
Moderate	17
Severe	18
Contact	21

3.3 Classification

The next process is the training of the produced optimal features set with the DL model LSTM based AE for predicting the status of the COVID-19 patients. Here, the data is split into positive and negative cases; when the LSTM based AE model achieved better accuracy the severity is predicted. To process this, the input data is prepared for performing the multi-classification. In this case, the severity based features are considered as the three attributes (mild, moderate and severe).

LSTM: The network LSTM has four neural network layer and the initial layer is called as λ sigmoid layer (forget gate). It provides the values of 0 (no data pass) and 1 (all data pass) in the prior cell state C_{t-1}. Figure 2 shows the structure of LSTM which has input gate, forget gate and output gate.

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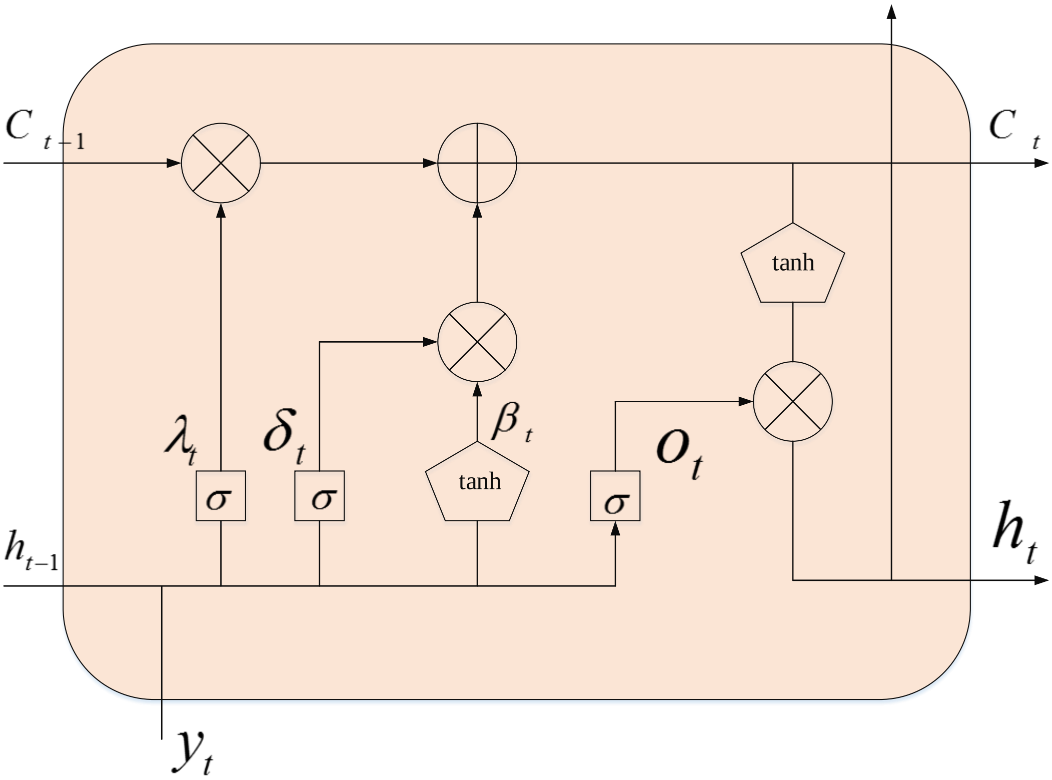

Figure 2: Structure of LSTM

The initial layer is expressed as:

$$\lambda_t = \sigma(W_\lambda[h_{t-1}, y_t] + b_\lambda \quad (8)$$

where σ is the sigmoid function, W_λ is the weighting layer, b_λ is the bias, y_t and h_t are the input and output at the time t.

The next layer δ is the input gate layer and it is represented as:

$$\delta_t = \sigma(W_\delta[h_{t-1}, y_t] + b_\delta \quad (9)$$

where W_δ is the weighting layer and b_δ is the bias. The tanh (hyperbolic tangent term) layer β is updated as:

$$\beta_t = \tanh(W_\beta[h_{t-1}, y_t] + b_\beta \quad (10)$$

The prior state C_{t-1} to the present state C_t is represented as:

$$o_t = \sigma(W_o[h_{t-1}, y_t] + b_o \quad (11)$$

W_o is the weighting layer and b_o is the bias. Finally, the C_t is updated by tanh function and it is given as:

$$h_t = \sigma_t \tanh(C_t) \quad (12)$$

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AE: It is the DL model that used back propagation for producing the output vector. It is used for compressing the input data into low dimensional space and again reconstructs the data. It utilizes a nonlinear activation and multiple layers for learning the nonlinear relation between the data. Figure 3 shows the structure of AE which has input layer, hidden and output layer.

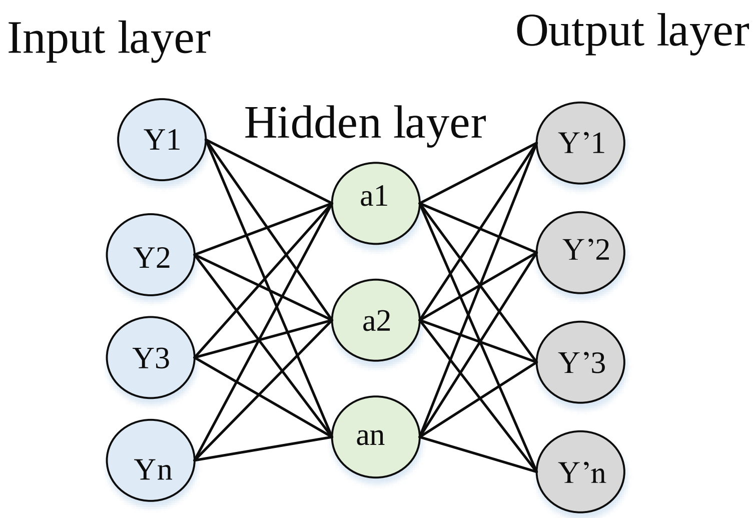

Figure 3: Structure of AE

The AE is the unsupervised learning model and it has two stages like encoder and decoder. The major aim of the encoder stage is to minimize the dimensionality of the input data Y based on the following expression:

$$Z = \sigma(WY + b) \quad (13)$$

where Z is the latent term, σ, W and b are the activation function, weight and bias factor.

Similarly, the decoding stage is trained on the basis of the following expression for obtaining the output data.

$$Z' = \sigma'(W'Y + b') \quad (14)$$

The major aim of the AE is to create the output vector same as the original data by minimizing the reconstruction error. This error is achieved by SSE (sum of squared error) and it is computed by:

$$Z' = \sigma'(W'Y + b') \quad (15)$$

The decoder is used for regenerating the initial data on the basis of the output of the encoder.

LSTM based AE: In the existing works, the LSTM is used for the COVID-19 prediction. Training the LSTM can minimize the loss and it can ensure better performance. Further, AD has the benefit of it tries to learn the proper parameters for the reconstructing the input at the output layer. In this work, LSTM based AE is used for learning the network's representation in semi-supervised manner. As shown in Figure 4, this network has multi encoder and decoder and every stage has multi-LSTM units. The input data Y_t is encoded using the encoder block for generating the constant feature vector X_t. Here, the timestamp is set as 1

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for the blocks of LSTM. The encoder blocks minimize the dimensions and it is reduced to 128, 64, 32 and 16 after the four layers of encoder. The last encoded vector obtain is X_t and it indicates the compressed data.

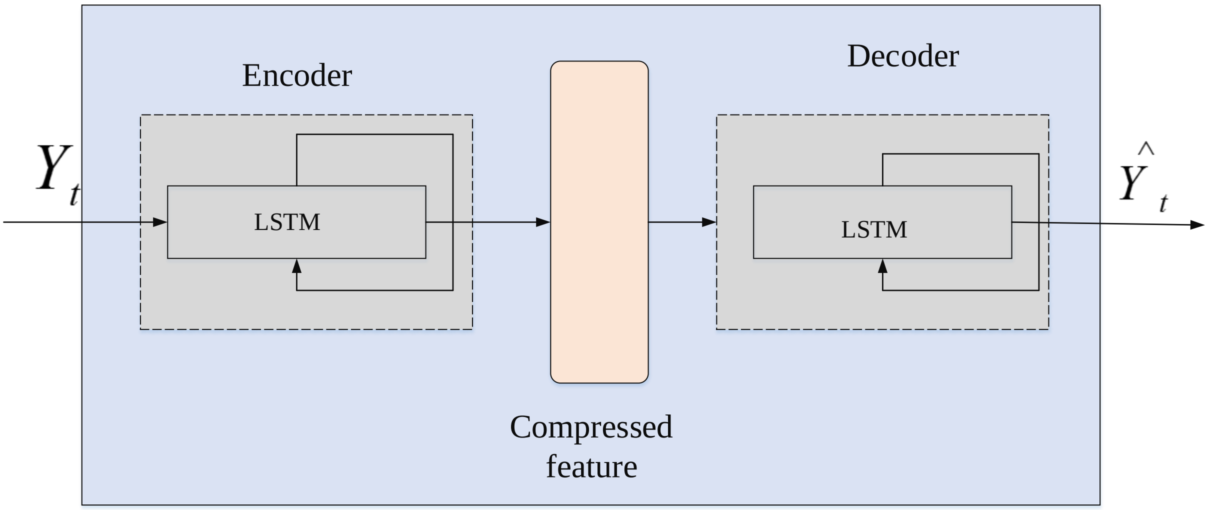

Figure 4: Structure of LSTM based AE

The encoded data is provided into the decoder to generate the output feature vector. Let $\hat{Y}_t$ is the decoder's input feature vector and in this decoders the layers are rearranged. The $\hat{Y}_t$ is then provided through the number of LSTM layers for generating the $\hat{X}_t$. The dimensions 16, 32, 64 and 128 are increased after the four layers of decoder. At last, the last layer of the decoder is given to the FC (fully connected) layer for generating the output $\hat{X}_t$.

After finding the positive cases, the features are provided to the further stage for the severity prediction. The prognosis is evaluated on the basis of multi-classification and it is carried out LSTM based AE.

4. Results analysis

The hardware architecture utilized in this work is an Intel I7-8700k CPU with 32 GB RAM. Further, Python is used as basic programming language and Python packages like NumPy, OpenCV, Pandas and tensorFlow are also utilized. Table 1 presents the hyperparameters of LSTM based AE.

Table 1: Hyperparameters of LSTM based AE

Hyperparameters	**Values**
Activation function	Tanh
Optimizer	SGD
Epoch size	300
Loss function	SSE
Learning rate	0.001
Number of hidden layers	1

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Number of hidden layers nodes	512

4.1 Performance measures

The performance measures like accuracy, precision, recall, confusion matrix, ROC (region of characteristics) curve and P-R (precision-recall) curve are computed in this work. The expression's used for computing these performances are listed below:

Accuracy: The accuracy of classification is the ratio of the accurate prediction over the entire data samples. It is expressed as:

$$A = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \qquad (18)$$

Recall: It is the total of true positives to the overall samples with respect to the positive classes. It is defined as:

$$R = \frac{T_p}{T_p + F_n} \qquad (19)$$

Precision: It is the ratio of accurate prediction that belongs to the entire positive class and it is expressed as:

$$P = \frac{T_p}{T_p + F_p} \qquad (21)$$

where T_p is true positive (correct amount of data), F_p is false positive (case that is diseased and predicted as positive), T_n is true negative (case that is diseased and predicted as negative) and F_n is false negative (the case is positive and predicted as negative).

The major aim of this work is to classify the condition of the patients into positive and negative cases of COVID-19 and prediction of severity using the LSTM based AE. Here, the text data of the patients has 65,000 records. The following section shows the comparison of the performances like accuracy, precision and recall. To show the efficiency of the classifier, the methods like LSTM, autoencoder, RNN, capsule network are compared with the proposed LSTM based AE.

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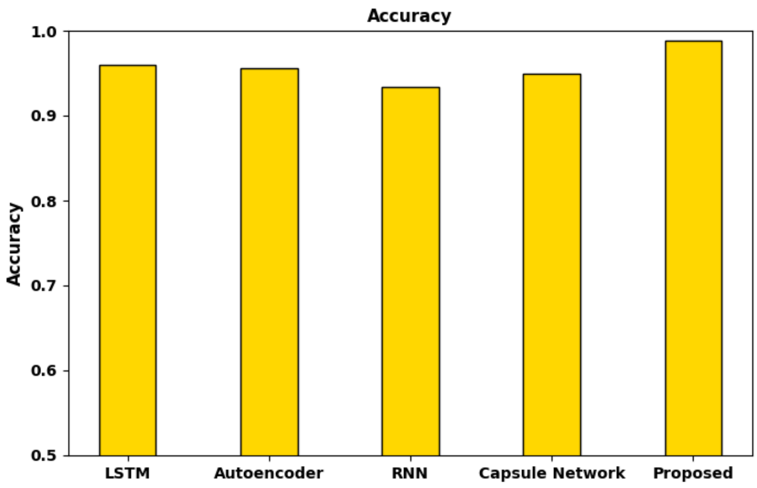

Figure 5: Comparison of accuracy performance

Figure 5 represents the accuracy performance of the methods like LSTM, autoencoder, RNN, capsule network are compared with the proposed LSTM based AE. When comparing all the performance of the classifiers, the proposed model achieved better accuracy of 99.02% on the COVID-19 dataset. Further, this proposed model exploited X ray image of small size as an input.

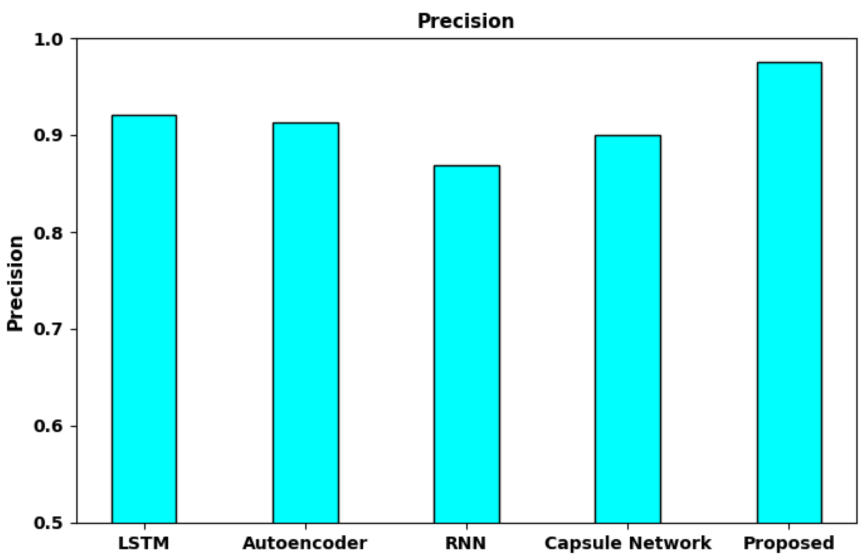

Figure 6: Comparison of precision performance

Figure 6 represents the accuracy performance of the methods like LSTM, autoencoder, RNN, capsule network are compared with the proposed LSTM based AE. Here, the precision value of the proposed LSTM based AE is 12.5%, 11.3%, 23.5%, and 10.7% better than the LSTM, autoencoder, RNN and capsule network. From the experimental results it is observed that the proposed model outperformed the other models due to the integrated nature of the LSTM and

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AE. The proposed model integrated the advantages of LSTM and AE; thereby achieved better results.

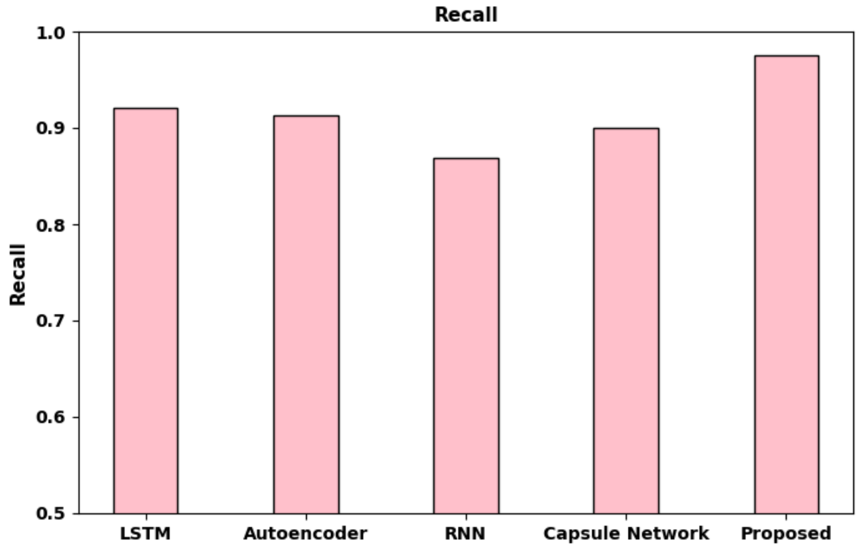

Figure 7: Comparison of Recall performance

Figure 7 represents the recall performance of the methods like LSTM, autoencoder, RNN, capsule network are compared with the proposed LSTM based AE. Here, the precision value of the proposed LSTM based AE is 13.15%, 12.3%, 31.5%, and 11.73% better than the LSTM, autoencoder, RNN and capsule network. The proposed model achieved better results due to the better feature selection by ESDO. By selecting the proper optimal features, the proposed model takes less time to complete the process and achieved better recall value.

The following confusion matrix shows the performance of severity prediction like mild, moderate and sever. Hence, the same dataset is considered to be more adaptable to predict the severity of COVID-19 patients. However, the dataset is binary and it is labelled to encode the features into 1-mild, 2-moderate and 3-severe. The values of the features of the positive cases are obtained from the data and provided into LSTM based AE to perform multi-class classification.

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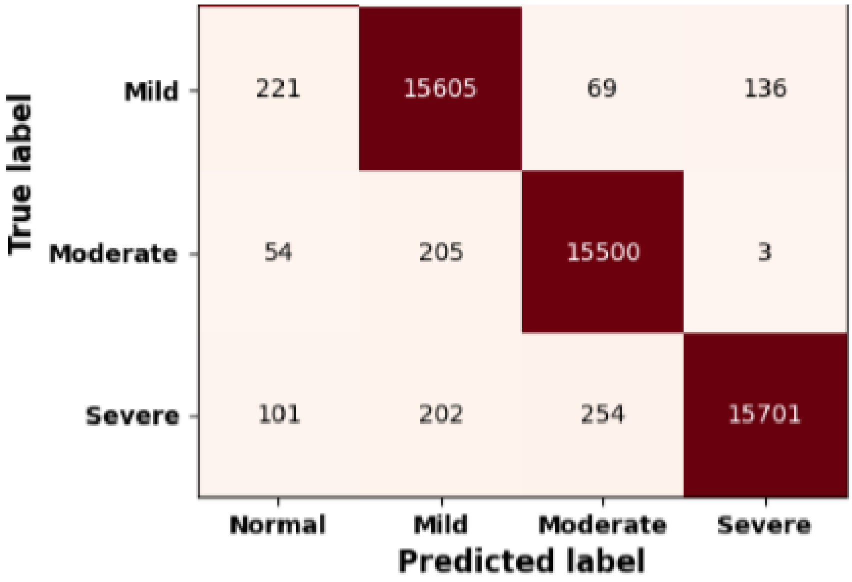

Figure 8: Confusion matrix of the proposed LSTM based AE

Figure 8 presents the confusion matrix of the proposed LSTM based AE which shows the severity of the COVID-19. The predicted label is shown in x axis and the true label is shown in y axis. Here, 15,605 samples are classified as mild, 15,500 samples are classified as moderate and 15,701 samples are classified as severe cases.

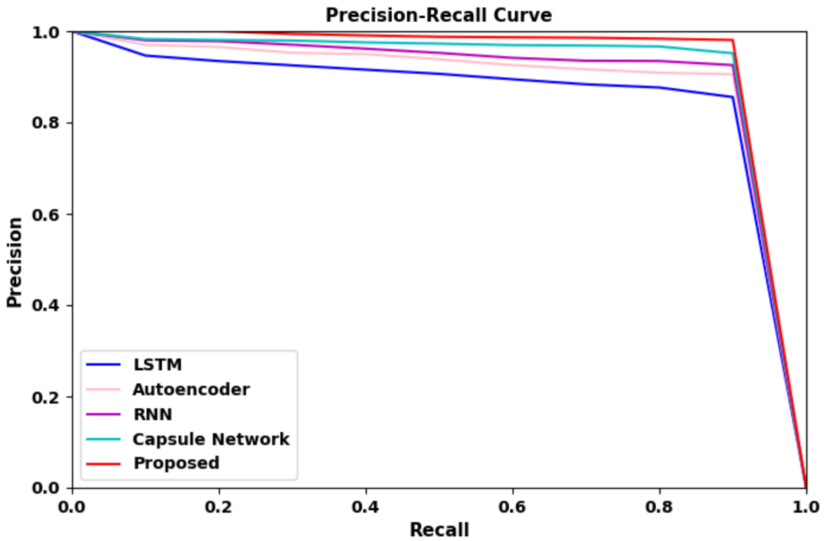

Figure 9: P-R curve comparison of the various models

Figure 9 represents P-R curve comparison of the various models LSTM, autoencoder, RNN, capsule network are compared with the proposed LSTM based AE. Here, recall refers to the sensitivity and precision refers to the specificity. In this work, this curve is used for balancing the positive and negative samples of the data. This curve provides more information than the ROC curve when the balancing problem is checked for the binary classification. From the Figure, it is observed that the proposed LSTM based AE achieved better P-R value of 0.99.

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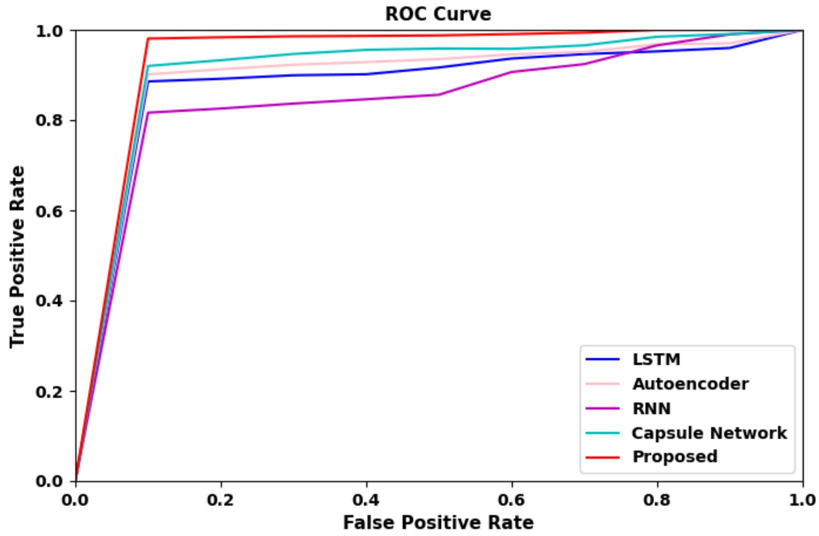

Figure 10: ROC curve comparison of the various models

Figure 10 represents ROC curve comparison of the various models LSTM, autoencoder, RNN, capsule network are compared with the proposed LSTM based AE. This curve is used for evaluating the performance of the binary classification. Further, area under curve (AUC) evaluation shows the performance of ROC in which value of 1 shows the better prediction performance. From the graph it is observed that the AUC value of LSTM, autoencoder, RNN, capsule network and the proposed model are 0.95, 0.96, 0.97, 0.98 and 0.99 respectively.

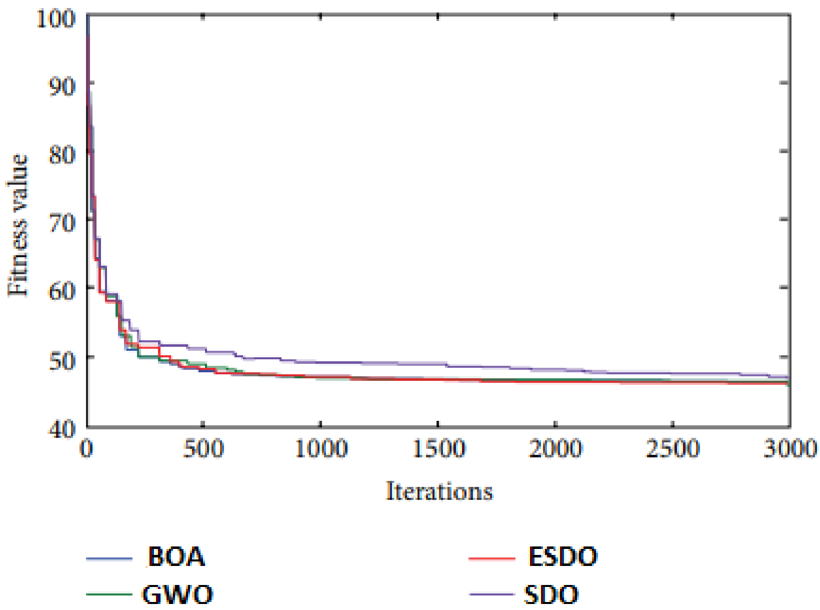

Figure 11: Comparison of convergence

Figure 11 represents the comparison of convergence of the various optimization like BOA (butterfly optimization algorithm) [27], GWO [28], SDO and the proposed optimization ESDO. The performance is carried out for varying the iteration of 0 to 3000. The proposed

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optimization ESDO converges after the 500th iterations and the value of fitness is 50. Hence, it is proved that the proposed optimization ESDO overcomes the slow convergence and trapped into local optima. Hence, this proposed optimization is well suitable for the feature selection which is the major novelty of this work.

5. CONCLUSION

Presently, COVID-19 is one of the major threat to the world and the statistical report by WHO show that there are more than 1.7 million death cases. The speedy recover model to detect the positive cases using the clinical data is a challenging process. Hence, this research work aims to develop an optimization based DL model for screening COVID-19 patients. The data has medical and personal details of the people from different countries. Using this medical data, the COVID-19 was predicted successfully and also achieved better results in the severity prediction. Initially, the pre-processing stage was created and the data was applied on the feature selection on the basis of the ESDO. This optimized developed an optimal features need for the classification. The classifier LSTM based AE was used for classifying the severity like mild, moderate and severe. This proposed model achieved better classification accuracy and precision of 99.02% and 98.23% respectively on the COVID-19 data. In the future, the analysis will be carried for the highly affected areas of COVID-19 in India. Further, the performance of this proposed methodology will be carried out on the large datasets.

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