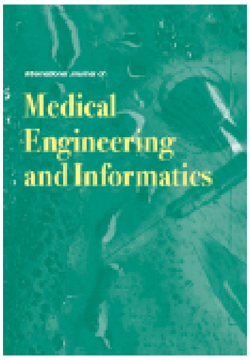

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Outbreak trends of fatality rate into coronavirus disease-2019 using deep learning

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Outbreak trends of fatality rate into coronavirus disease-2019 using deep learning

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Abstract: The World Health Organization (WHO) has declared the novel coronavirus as global pandemic on 11 March 2020. It was known to originate from Wuhan, China and its spread is unstoppable due to no proper medication and vaccine. The developed forecasting models predict the number of cases and its fatality rate for coronavirus disease 2019 (COVID-19), which is highly impulsive. This paper provides intrinsic algorithms namely – linear regression and long short-term memory (LSTM) using deep learning for time series-based prediction. It also uses the ReLU activation function and Adam optimiser. This paper also reports a comparative study on existing models for COVID-19 cases from different continents in the world. It also provides an extensive model that shows a brief prediction about the number of cases and time for recovered, active and deaths rate till January 2021.

Keywords: pandemic analysis; coronavirus disease-2019; COVID-19; linear regression; time series forecasting; long short-term memory; LSTM; deep learning.

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1 Introduction

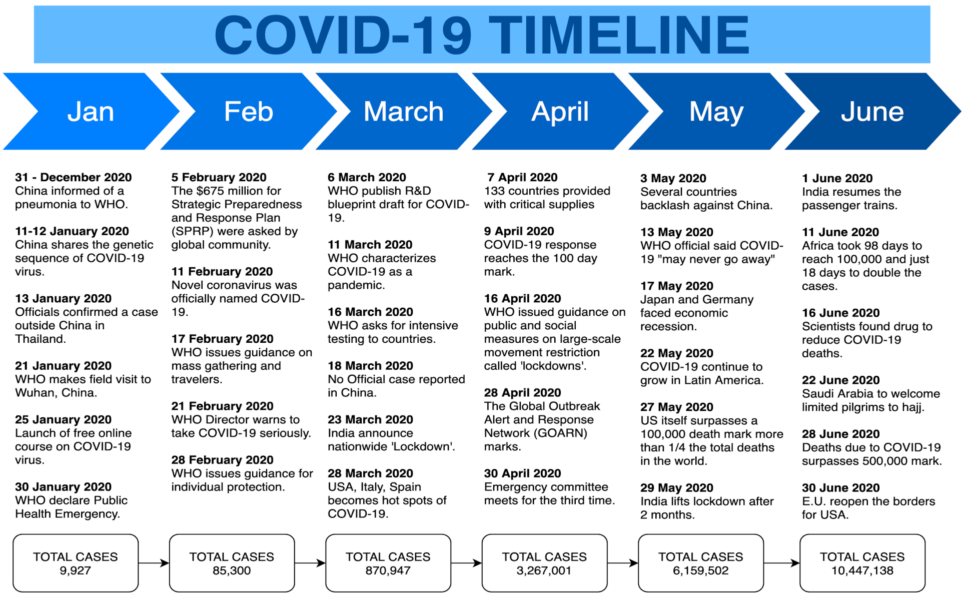
Coronaviruses are a family of viruses that can cause severe illness. It is also a type of coronavirus recently spreading in the world. Studies have shown that spread of viral pandemic depends on various factors like climates, humidity, temperature, airflow, etc. All the study here is based on the previous data recorded from 22 January 2020. Factors that determine transmission risk include whether a virus is still replication-competent, immunity of the person against the virus and conditions in which the virus can survive.

After the outbreak of COVID-19, worldwide communities have been working to make better plans to fight the COVID-19 virus. This paper can provide a rough estimate on the number of COVID-19 cases after a certain interval. Thus, helping them make even better plans and arrangements for the future. COVID-19 cases are growing in a total number of cases at an extremely high rate of doubling each month in the world till September 2020 then showed a slowdown in the new cases. Some countries like the USA, Brazil, India and Russia are reporting even higher rates of growing patients because of the dense population in cities (Ribeiro et al., 2020).

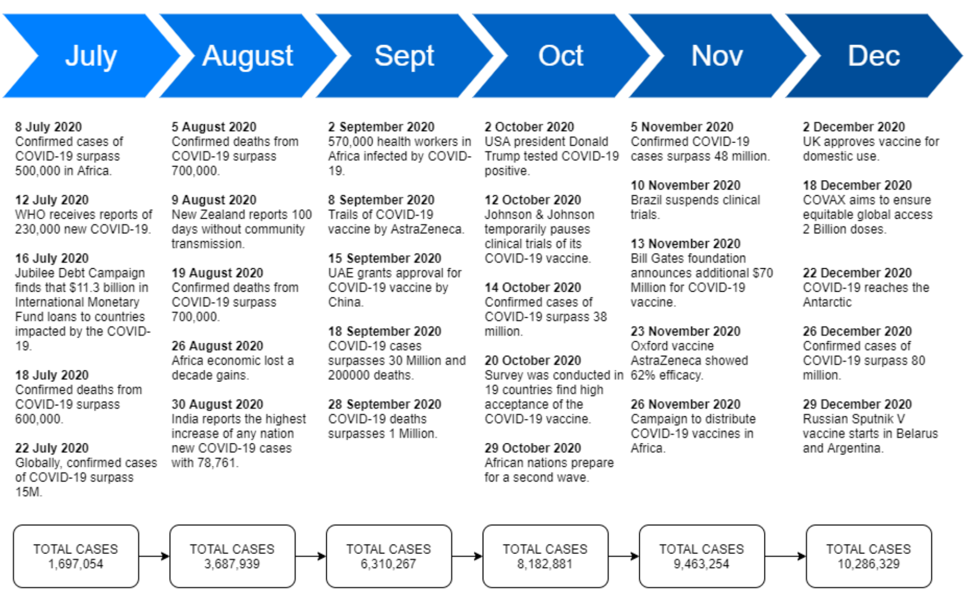
India reports the first case of COVID-19 on 30 January in Kerala when a student returned home from Wuhan University, China. India starts its airlift operation from Wuhan from 1 February to 27 February. Cases were limited and growing slowly but increased their pace of growth after religious activity and kept on growing. After this, large number of events has occurred in India. Prime Minister of India, first announced a 'Janta curfew' on 21 March 2020 and then declared a complete lockdown of 21 days on 23 March. Lockdown extended and remained for 2 months, so the process of unlocking starts with limited freedom of moments. The Government of India announced a package of $2 billion for 'India COVID-19 Emergency Response and Health System' on 7 April.

India has a large population of migrant labour urging the government to start transportation service, so on 1 June 'Shramik Express' was started (Tiwari et al., 2020; Sengupta, 2020).

Figure 1 (a) Timeline for evolution of COVID-19 cases at global perspective till June 2020 (b) Timeline for evolution of COVID-19 cases at global perspective July 2020 onward (see online version for colours)



(a)



(b)

In the meantime, COVID-19 patient cases were increasing. Patients were increasing to double in just 5–7 days. India has already witnessed the death of more than 20,000 patients. In the current situation, India stands third on the world total number of cases after USA and Brazil with 3.4 M cases in USA, 1.8 M cases in Brazil and 0.8 M cases in India (Ribeiro et al., 2020).

It is clear from Figure 1, large number of events has happened since the pandemic outbreak. In January, COVID-19 gained recognition by WHO and our countries. In February, some countries faced an outbreak and preventive measures were taken in other countries. In March, Virus spread to most of the world and India imposed lockdown. In April and May, some countries launched relief packages for improving medical and economic facilities but cases kept on increasing. In June, despite the increase, countries start economic activities. In July, countries started to lift lockdowns. In August, COVID-19 cases showed no decline in the number of cases. In September and October, companies start the trails for vaccine. In November and December, countries still counting the cases and waiting for vaccine (Timeline of the COVID-19 Pandemic in India, 2020).

The main contributions for this paper can be point out as follow:

- a predictive model based on linear regression and long short-term memory (LSTM) algorithm has been demonstrated for COVID-19 pandemic
- proposed a stacked LSTM model on confirmed cases and fatality rate till January 2021
- prediction is performed for regular intervals of one month.

2 Related work

History has shown that few pandemics can be deadly for the human race like Spanish Flu (de Jong et al., 1997), which killed millions of people and lasted for a couple of years. COVID-19 is showing no sign to end early (Chatterjee et al., 2021). Old research is important to shape the new researcher to make decisions on controlling the situation. In Shah et al. (2020), a Laplacian decomposition is used in Pine Witt Disease; and Benvenuto et al. (2020) discussed the clinicians to better understand the transmission of the outbreak.

In Dehesh et al. (2020), first attempted to predict the growth but not able to predict it accurately. In Zhang et al. (2020), discusses the method which is used to find the growth rate on the diamond princes' cruise. In George and Huerta (2018), the authors discussed real-time data that is used to calculate the model. This model has also proven to give reliable accuracy in COVID-19 due to which such cases depend on other social factors.

The work conducted by Bandyopadhyay and Dutta (2020) and Tomar and Gupta (2020) on machine learning and deep-learning model is used on COVID-19. Such work also reported machine learning models and one deep learning model demonstrated in Table 1.

The work done in Ceylan (2020) used ARIMA model to estimate COVID-19 patients using the in Italy, Spain and France. In Maier and Brockmann (2020), the authors discussed case numbers in Hubei compared to models are used. In Grasselli et al. (2020), the authors presented with COVID-19 outbreak in Lombardy, Italy. And Hamzah et al.

(2020) discuss the COVID-19 outbreak worldwide. The investigation done in Pandey et al. (2020) presented with the COVID-19 outbreak and preventive measures in India.

Table 1 Existing work in COVID-19 data prediction using machine and deep learning models

Reference	*Methodology*	*Result*	*Comparison*	*Conclusion*	*Comment*
Bandyopadhyay and Dutta (2020)	Neural network models: LSTM, GRU	Confirmed case accuracy = 87%	Author remain silent on actual number of cases	LSTM-GRU based RNN model provides a better result	Model performance metric accuracy, RMSE
Huang et al. (2020)	GRU, LSTM, MLP, CNN	Multiple algorithms applied on different cities are calculated	3,331.925 cases based on six neuron layers of LSTM	predicted according to the previous five days	Main focus was China
Tomar and Gupta (2020)	LSTM	Error within – 6.44 to 8 percentage.	7,308 cases as of 9 April	Estimated cases for next 30 days.	Main focus was India
Pandey et al. (2020)	Machine learning and deep learning models	Graphical representation for prediction	6,135 cases as of 13 April based on regression model	Proposed Bayesian optimisation, shallow LSTM	Early research data less than 90 days
Chandra et al. (2021)	LSTM	Declining number of cases	Daily new cases data for multiple cities	Estimate number of cases for 2 months	Main focus was India
Shastri et al. (2021)	Deep LSTM	97.9% accuracy for death cases	Daily death cases	Predictions for around 50 days	Main focus was India

Other notable contribution is Tiwari et al. (2020), the authors estimate that the mortality rate India is predicted to be around 2.39% where globally 3.4% is estimated by WHO as on 3 March 2020 (Liu et al., 2020).

3 Research methodology

This paper follows three techniques for time-series prediction on COVID-19 dataset: linear regression, moving average and stacked LSTM. In the later part of this section, it has been discussed with model for evaluation metrics, growth rate and fatality rate (Ardabili et al., 2020). This paper also focuses on a deep learning model due to its wide variety of architecture available implemented using LSTM for prediction based on time series data. LSTM is used widely for time series prediction, speech recognition, rhythm learning, music composition, grammar learning, handwriting recognition, human action recognition, etc. (Bouhamed, 2020).

Dataset is gathered from John Hopkins University (https://coronavirus.jhu.edu/). This data is updating daily and data is available from 22 January 2020 to 31 January 2021 at the time of writing this paper. The data is in time-series format with more than the necessary details used in the paper. It was clear from first glance that growth is slow in the beginning but within days spread is exponential (Shah et al., 2020).

Data is divided into two parts:

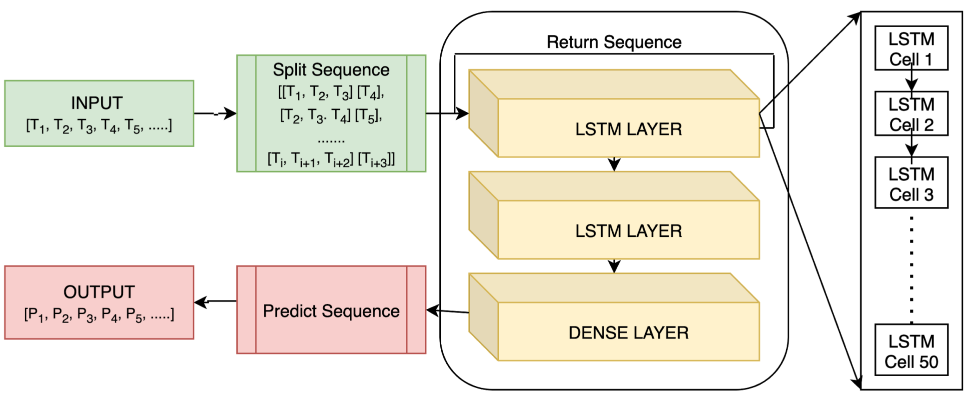
1 training data: 22 January 2020 to 31 December 2020

2 testing data: 1 January 2020 to 31 January 2020.

3.1 Stacked LSTM

Stacked LSTM is deep neural network architecture useful for predicting univariate time-series data. Deeper the architecture, more accurately the result is. Single hidden LSTM layer model followed by a standard feedforward output layer is a classic LSTM model. Here, it has been used with an advanced technique called stacked LSTM which is an extension to this model and contains multiple hidden layers on top of each other providing multiple memory cells. Most of the neural network architecture like CNNs and GANs have no memory. But RNNs can recall past training data. To help increase the performance, it uses LSTM (type of RNNs), where the outcome of the previous part is fed into the next part of the network after a bunch of mathematical operation.

Figure 2 Stacked LSTM model (see online version for colours)



LSTM is a type of sequential model used in predictive modelling. This has made a simple architecture to make the model simpler to understand and know its results by its native implementation (Vadyala et al., 2021). As an extension and future work of this paper, a complex model can be used to get even better results used in this paper. The primary reason to use LSTM is because of its architecture and uses of two layers of LSTM in which each layer of LSTM contains 50 cells along with a rectified linear unit (ReLU) activation function in which sequence is returned again for the first LSTM because of its fast convergence property. Adams optimisation algorithm with a mean squared error is used while compiling the model. This executes the modified stack LSTM model for 200 epochs and predicted the next 200 values as shown in algorithm below (Gampala et al., 2020).

Algorithm Mod_Stacked-LSTM

```
Input: array of size n: univariate time-series data of confirmed cases/fatality rate.
Output: array of size 200: predicted cases for next 200 days
number_of_steps = k
X,y = split_sequence(Input); X size is n*k and y size is n.
model = Sequential()
Add LSTM layer
Add another LSTM layer
Add Dense layer
Compiler the model
Fit(X, y, epoch)
Predict Values
```

While the number of COVID-19 cases is rapidly increasing in some countries of the world, some countries have controlled the spread of cases. Some countries have followed a strict lockdown while some focus on intensive testing to control the cases. One of the main reasons for rapid growth at the global level is the international travel of students and tourists. At the time of writing this paper, the growth rate of COVID-19 is around 500,000 per day and world is waiting for vaccine to arrive in market.

3.2 Linear regression and weighted moving average

State-of-art model which can help in verifying whether the growth of confirmed cases is linear or not linear regression. It is very clear from the exploratory data analysis that in the initial phase growth in the number of patients was exponential but in the later trends growth rate was on the lower side than the initial flood of cases. Linear regression is a linear model, there are a variety of modifications but this paper used a simpler approach that is minimising the squared loss called ordinary least squares linear regression.

Equation is generally of type: $y = mx + c$ (1)

This model is not much used for time series prediction because of the alternative methods given next because they also contain the information from previous days. Another one of the simplest models to predict time series data is moving averages. The moving average value can directly make predictions. This model looks simple but is extremely powerful in results for time series prediction. This works in a walk-forward manner, the model can be updated and predictions can be made for the next day.

$$MA(k) = \frac{\sum_{i=0}^{k} (D_i \cdot W_i)}{k} \tag{2}$$

$MA(k)$ moving average value with window size = k

k number of periods in the moving average

D_i value

W_i weight factor.

Growth rate is simply defined as percentage change in confirmed cases over the days.

$$Growth\ rate = \frac{N_1 - N_0}{N_0} \tag{3}$$

N_0 no. of cases of previous day

N_1 no. of cases of current day.

It is clear from the above formula that the lesser the growth rate the better the situation for controlling the pandemic situation (Shastri et al., 2020). The model predicts the time series data from June to next seven months considering the data of previous month. This paper implemented the data available till 31 December 2020. So, model evaluation metrics used is the Euclidean distance for 1 January 2021 to 31 January 2021 for this measure. It is clear from the formula that the lesser the distance better the model.

$$dist(p, q) = \sqrt{\sum_{i=0}^{k} (p_i - q_i)} \tag{4}$$

p first sequence

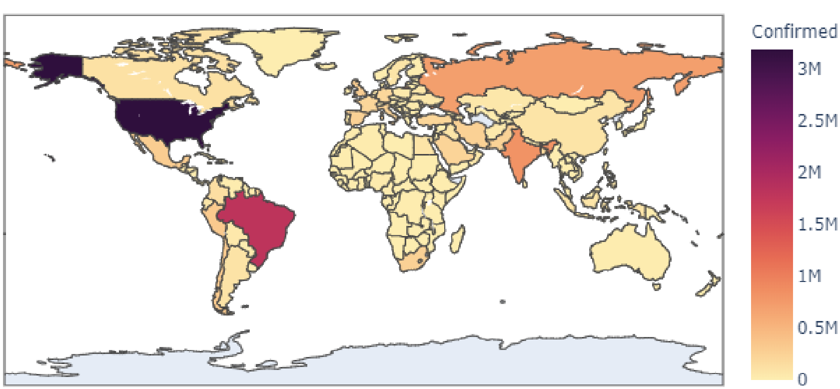
q second sequence.

Major benefit of choosing Euclidean distance is that it is aligned with the points of one sequence to another sequence and aligned sequences in test data and predicted data based upon the day.

4 Results and analysis

With the objective of predictive study, this paper implemented with three techniques namely – linear regression, moving average, and stacked LSTM. The former two techniques are related to machine learning while stacked LSTM is complex deep learning recurrent neural networks (RNN) which is more powerful in prediction of time-series data (Sun et al., 2021). This machine learning and deep learning approaches are implemented using *Keras* and *scikit-learn* using python for prediction of number of cases and fatality rate.

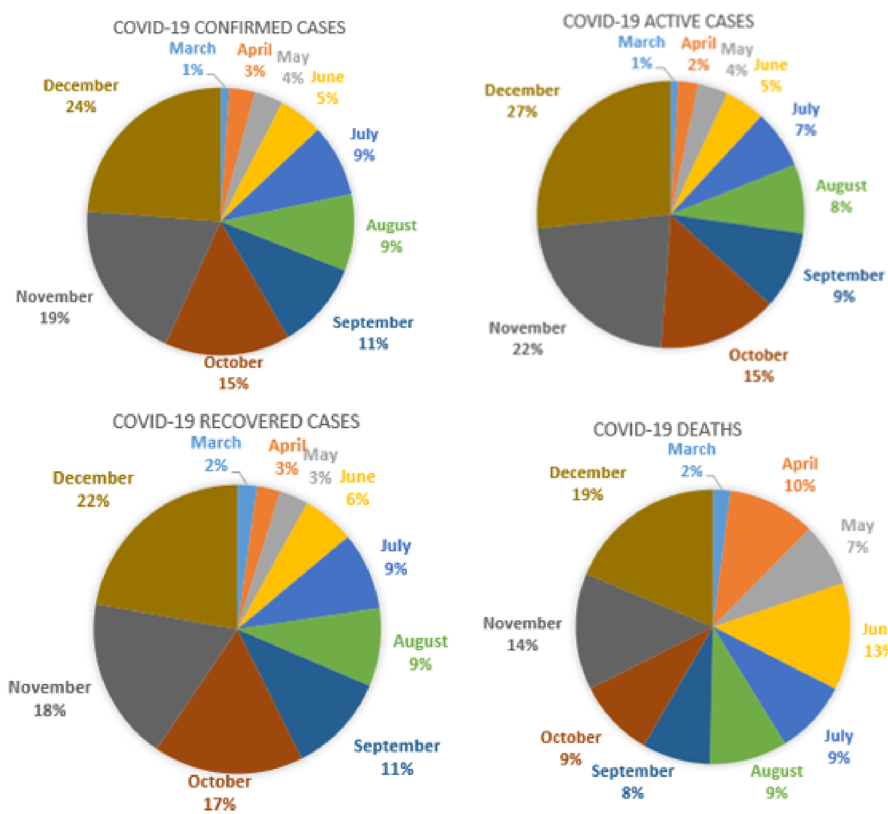
Figure 3 Confirmed cases of COVID-19 on world-map (see online version for colours)



World is witnessing a record jump in the number of cases with every new day. The recovery rate is also increasing because of the combined effort in collaboration with the states and countries. Every life matters and prediction of the fatality rate is as important as a prediction of the number of cases. Reason for improvement in recovery rate is due to the fact that medical institutions around the world are working to provide better medicine and facilities to patients (Bai et al., 2020).

Fatality rate is around 5% as of now and expected to go down because this is the usual trend in the last 2 months and expected to remain to slow down because medicine to fight the virus are also improving over time by the scientists and the fatality rate is directly dependent on medical facilities in the country. Our study is all based on the data available at the global level. Some articles and news claim that low testing and delayed reports of the COVID-19 positives in some countries are also reasons for this varying fatality rate. In severe cases, it accelerates the effects of the existing disease which can cause death due to pneumonia, severe acute respiratory syndrome (SARS), kidney failure and then it becomes too late to take COVID-19 test.

Figure 4 COVID-19 worldwide cases (see online version for colours)



It is clear from Figure 4 around March when the prominent number of cases started to report. Out of the total number of cases 41% of cases were reported in June only and 51% of cases were recovered in June. Despite the 41% of cases in June also total number deaths in June are 27%, 0.1% less than May and 10.2% less than April where April had only 22.9% of patients. Hence, such conditions are getting better but the number of cases is still growing at a high rate.

Figure 5 shows the total number of cases on y-axis and dates on the y-axis. Number of cases and growth rate in January 2020 and were very low but it was around mid-March 2020 when cases flooded around the world and then till May 2020 the number of cases increased at a linear rate.

Figure 5 Number of confirmed cases vs. time (see online version for colours)

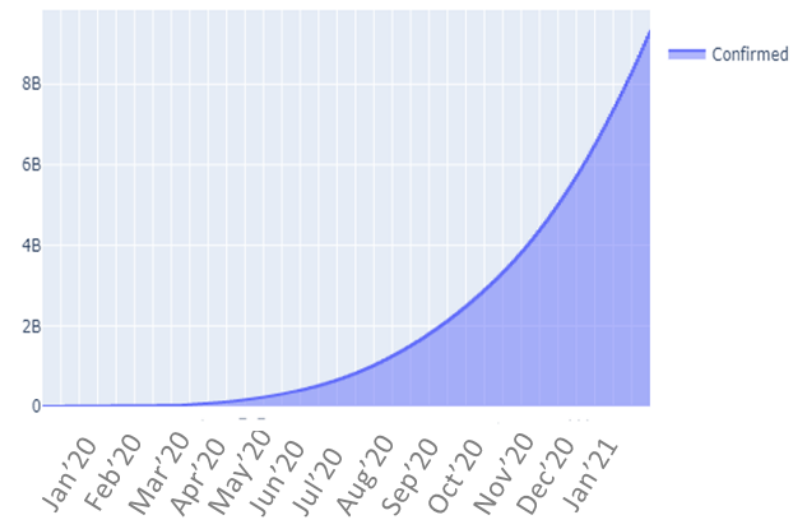
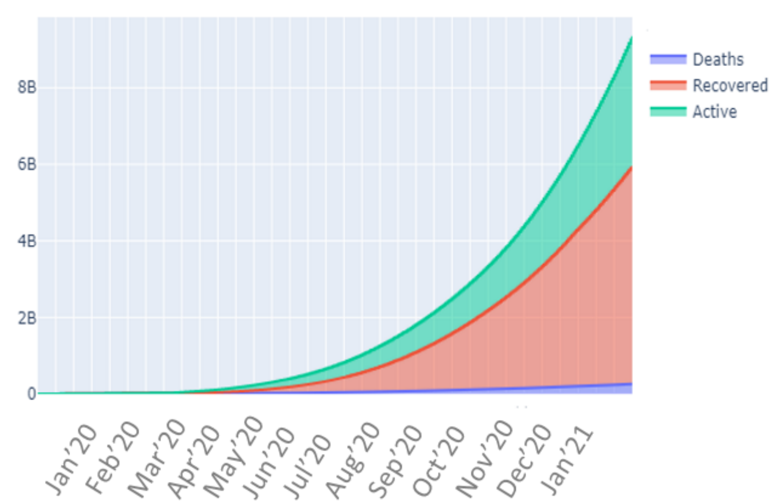


Figure 6 Number of cases vs. time for recovered, active and deaths (see online version for colours)



After June 2020, when most of the countries lifted lockdown, more stepper growth can be observed. This is the time when viruses outbreak new hotspots like Brazil and India. It can also be observed that in the start of outbreak active cases grew at much faster rate than recovered cases due to lack of medical service but later recovery rate also grew as the number of cases because of constant effort by researchers around the world till January 2021.

The fatality rate 'deaths per confirmed 100 cases' in the month of May reached 7 and have been decreasing since then. Same can be seen in the 'deaths per 100 recovered cases' that is also decreasing. In the start, the February fatality rate was less but still greater when compared to total recovered cases. In other words, fewer patients were getting recovered than the patients dying due to COVID-19 but now a large number of patients are recovering. In the month of April and May 2020 fatality rate touched a critical mark of 7 and above but patients were recovering at an even better rate than before. The condition was improving since then fatality rate is going down and patients are also recovering but the spread is growing continuously (Mathappan et al., 2020). The death rate is very low in January 2021 as depicted in Figure 6.

5 Discussion

The COVID-19 threat is alarming. It has affected normal human life, increased poverty and unemployment. Most economies in the world were already going through the tough phase before COVID-19 (Ryan et al., 2020). If the condition is not controlled this can initialise a worldwide economic recession which can last for years. From the COVID-19 timeline given above the spread of pandemic is serious. Every major country has confirmed that COVID-19 virus has spread in their nation. Prominent of them are the USA, Brazil, India and Russia with more than 0.5 M cases already registered in the country and still show no sign of slowing. The growth rate of these countries is also very high compared to other countries.

Table 2 Predictive analysis of different techniques in the world

	Linear regression		*Moving average*		*Stacked LSTM*	
Euclidean distance	201,6087.32		435,869.74		*44,327.00*	
Predictions	*TC*	*FR*	*TC*	*FR*	*TC*	*FR*
1 August 2020	782,538	3.96	39,519,557	6.01	*20,743,210*	*6.72*
1 September 2020	2,475,804	5.08	67,340,136	6.02	*38,764,596*	*7.01*
1 October 2020	4,114,449	6.72	101,320,475	6.02	*70,996,072*	*7.10*
1 November 2020	5,807,716	7.29	1,145,650,586	6.02	*132,676,296*	*7.13*
1 December 2020	7,446,361	8.37	199,795,838	6.03	*242,992,128*	*7.14*
1 January 2021	9,139,627	9.50	270,432,714	6.03	*454,099,584*	*7.14*

Note: TC – total cases; FC – fatality rate.

Table 2 shows that the Euclidean distance is minimum in the case of stacked LSTM. Linear regression models are effective in predicting data with linear growth rate but not working in case of COVID-19. Moving averages are for predicting long-term prediction whereas short-term predictions are not reliable. According to stacked-LSTM model world will reach 20 M cases by August, 38 M cases by September, 70 M by October, 132 M by November, 242 M by December, 450 M cases by the end of 2020 and 480 M cases by

January 2021. On applying the LSTM model for cases in India only, it will reach 1.8 M by August, 5.7 M by September, 17 M by October, 52 M by November, 157 M by December and 180 M by January 2021.

6 Conclusions

The entire world is facing a serious pandemic outbreak of coronavirus disease 2019 (COVID-19). This paper helps the human society and proposed a global specific model to derive the facts associated to such virus for mortality rate. It also presented a prediction-based multi-model using machine learning and deep learning methodologies that proposed to perform the best out of all the existing models. Such predictions can help the government to make the necessary arrangements to take safety measures. In this paper, the prediction for this pandemic spread has been made on data till January 2021 using John Hopkins dataset. According to stacked-LSTM model, the COVID-19 cases in the world will reach up to 450 M cases by the start of January 2021. On applying the LSTM model for cases in India only, it will be around 157 M by December 2020. It is expected to receive medication/vaccination for this COVID-19 very soon so that prevention can be made well in time. In the real scenario, medication controlled the further growth of spread. The proposed model in this paper can further be extended to an even more complex deep learning model based on gated recurrent unit (GRU) and convolutional neural networks (CNN).

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