Prediction of COVID-19 cases using the weather integrated deep learning approach for India

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Running Title: Role of climate on COVID-19 transmission and Prediction

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Abstract:

Advanced and accurate forecasting of COVID-19 cases plays a crucial role in planning and supplying resources effectively. Artificial Intelligence (AI) techniques have proved its capability in time series forecasting of the non-linear problems. In the present study the relationship between weather factor and COVID-19 cases was assessed and also developed a forecasting model using long short term memory (LSTM), a deep learning model. The study found that the specific humidity has a strong positive correlation, whereas there is a negative correlation with maximum temperature and positive correlation with minimum temperature was observed in various geographic locations of India. The weather data and COVID-19 confirmed cases data (1st April-30th June 2020) was used to optimize univariate and multivariate LSTM time series forecast models. The optimized models were utilized to forecast the COVID-19 cases for the period 1st July 2020 to 31st July 2020 with 1 to 14 days of lead time. The results showed that the univariate LSTM model was reasonably good for the short term (1day lead) forecast of COVID-19 cases (relative error < 20%). Moreover, the multivariate LSTM model improved the medium range forecast skill (1-7days) after including the weather factors. The study observed that, the specific humidity played a crucial role in improving the forecast skill majorly in the West and northwest region of India. Similarly, the temperature played a significant role in model enhancement in the Southern and Eastern regions of India.

Keywords: SARS-CoV-2, COVID-19, Specific Humidity, Temperature, Prediction, LSTM, India.

Introduction:

Severe acute respiratory syndrome coronavirus 2 (SARS CoV-2) that causes the coronavirus disease 2019 (COVID-2019) was first emerged in Wuhan, China in early December 2019 (Li et al., 2020; Shen et al., 2020). Since then the disease has quickly spread around the world and established local transmission in many countries including the Americas, Europe, Africa and Asia. This rapid spread of the COVID-19 cases may be due to a lack of proper information about disease etiology and transmission patterns during the early stage of the epidemic (Zhong et al., 2020). On January 7, 2020, this novel strain of SARS CoV-2 was isolated and confirmed the circulation in the populace and causes COVID-19. On January 30, 2020, WHO (World Health Organisation) declared the COVID-19 outbreak as a public health emergency of international concern (WHO 2020a) and confirmed as a global pandemic on March 11, 2020 (Cucinotta and Vanelli 2020). The pandemics disrupt human life, public health care systems and economies are unprecedented, and impacts will continue till the vaccine is developed. During the first wave of the pandemic many countries has been locked down and non-essential services were shut down and adopted social distancing and face mask-wearing made compulsory. As of October 22, 2020, more than 40 million COVID-19 cases and 1.1 million deaths reported globally (WHO 2020b).

SARS-CoV-2 belongs to the genus *Betacoronavirus* which includes the SARS CoV-1, Middle East Respiratory Syndrome (MERS) and two other human coronaviruses (HCoV-OC43 and HCoV-HKU1) (Kissler et al., 2020). The SARS-CoV-2 spread faster than the two of its ancestor viruses SARS-CoV-1 and MERS may be due to high transmission rates produced by asymptomatic carriers (Vellingiri et al., 2020; Bai et al., 2020). HCoV-OC43 and HCoV-HKU1 are the most common causes of the common cold and respiratory illness outbreaks during wintertime in temperature regions (Su et al., 2016; Killerby et al., 2020;

Neher et al., 2020). Similarly, the SARS-COV 2 is closely related to bat derived viruses bat-SL-CoVZC45 and bat-SL-CoVZXC21 and distinct from SARS-CoV-1 (-79% similarity) and MERS-CoV (-50% similarity) (Lai et al., 2020; Jiang et al., 2020; Liu et al., 2020). SARS-CoV-2 is deadly because the case fatality rates are much higher than influenza (de Wit et al., 2016; Fauci et al., 2020). During the initial period of outbreak the case fatality rate (CFR) was 15%, subsequently, with more data emerged, the CFR decreased to between 4·3% and 11·0%, and later to 3·4% (Chen N et al., 2020; Wang D et al., 2020;WHO 2020b) and currently the CFR is 2.75% (calculated based on COVID-19 cases and deaths reported worldwide as of October 22, 2020) (WHO 2020b).

Along with other countries the COVID-19 cases are also reported in India. The first case of COVID-19 was identified on January 30, 2020 in Kerala state, India, and it was imported from China (Rawat 2020). The number of corona cases is gradually increasing across the nation hence, to flatten the curve, India suspended visas for all international travelers from March 13, 2020 onwards. Followed by a travel ban, the Government of India announced a nationwide lockdown (from March 25 to May 31, 2020) to minimize human activity across the country (Ministry of Health & Family Welfare, GOI). The unlock processes started from June 1, 2020, except for containment zones. Similarly, COVID-19 testing capability has been increased rapidly to identify and isolate the infected populace for minimizing the spread. The all India positivity rate (percentage of confirmed among the total tests) is between 8-9%, whereas some of the states located in south India have more positivity rates including Maharashtra (20%), Andhra Pradesh (12.3%), Karnataka (12%), Goa (10.4), and Tamil Nadu (8.6%) (ICMR). Indian Council of Medical Research (ICMR) conducted the COVID-19 tests among the severe acute respiratory illness (SARI) patients during an early phase of the pandemic in India, and found that 1.8% (104 out of 5911) of SARI patients tested positive for

COVID-19 from 52 districts located in 20 states/Union Territories. The positivity rate was zero during the period February 15 to March 14, 2020 and increased up to 2.6% during the period March15 to April 02, 2020. The seroepidemiological survey conducted between May 11 to June 4, 2020 in 700 villages/wards, from the 70 districts of the 21 states of India shows that 0.73% (6.4 million) of the adults exposed to the coronavirus (ICMR COVID study group Abraham et al., 2020; Gupta et al., 2020; Murhekar et al., 2020). As of October 22, 2020, 7.76 million of COVID-19 cases and 1.17 million deaths were reported in India (mygov).

Environmental factors can affect the epidemiological transmission of many infectious diseases. Several studies have revealed that climate and weather conditions could influence the spatial and temporal distribution of infectious diseases (Shuman 2010; Dhara et al., 2013). The *coronaviridae* family viruses SARS CoV-1 and MERs CoV are also shown seasonal variations and prefers in low temperature and humidity (Casanova et al., 2010). Similarly, at the early stage of the COVID-19 pandemic, researchers have reported that, the temperature had positive association and humidity had negative association with the cases in many regions of the World (Liu, et al.,2020; Briz-Redónet al., 2020; Chen B et al., 2020, Oliveiros et al., 2020,Sahin 2020; Bashir et al., 2020; Ma et al., 2020; Wang J et al., 2020). However, a negative linear relationship between temperature and daily cumulative cases of COVID-19 are also observed (Prata et al., 2020). Many studies have suggested that the COVID-19 spread is more in the cold and temperate climate than the warm and tropical climate, consistent with the behaviour of a seasonal flu respiratory virus (Bloom-Feshbach et al., 2013).

The machine learning and deep learning techniques are the branches of Artificial Intelligence (AI) and provides powerful predictive capabilities and superiority over conventional statistical modelling (Singal et al., 2013; Miguel-Hurtado et al., 2016; Beam and Kohane, 2018). Despite the high predictive power these algorithms are not widely exposed in public health data analysis. Here, we aim to apply deep learning algorithm on integrated data sets (epidemiology and climate data) and deployed the multivariate long short-term memory (LSTM) modelling framework used to forecast COVID-19 trends in India. Similarly, the LSTM has been used successfully to forecast for dengue and influenza (Nadda et al., 2020; Leonenko et al., 2017). Moreover, previous studies have used relative humidity and absolute humidity to understand its role in COVID-19 transmission. But, studies on the influenza virus shows that specific humidity is an important factors for disease transmission. Hence the present study used the specific humidity along with other climatic factors to understand COVID-19 transmission and forecast in India.

2.Methods:

2.1:Data:

All 28 states and 08 Union Territories of India covering latitude (8°N-38°N) and longitude (68°E-98°E) were considered for the study. Daily counts of laboratory-confirmed COVID-19 cases of all the states of India were collected from the Ministry of Health and Family Welfare (MoHFW), Government of India from April 1 to July 31, 2020. Similarly, the daily meteorological parameters of a specified period consist of temperature (minimum, maximum and mean) and specific humidity (SH) extracted from NCEP/NCAR reanalysis data (Kalnay et al.,1996) (https://psl.noaa.gov/).

2.2:Correlation Analysis:

To understand the weather impact on COVID-19 cases, the lag (0-14) correlation coefficients are computed between daily meteorological parameters and daily COVID-19 cases for different states in India during the period April 1 to July 31, 2020. The popular statistical formula Pearson Correlation Coefficient (r) is utilized to measure the strength and linear relationship between daily COVID-19 cases (X) and surface meteorological parameters (Y), and the values are ranging between -1.0 to 1.0. The correlation coefficient values are computed as

$$r(X,Y)=\frac{\sum_{i=1}^{N}(X_i-\overline{X})(Y-\overline{Y})}{\sqrt{\sum_{i=1}^{N}(X-\overline{X})^2\sum_{i=1}^{N}(Y-\overline{Y})^2}}$$

2.3:Long-Short Term Memory (LSTM) Model:

A Long Short-Term Memory (LSTM) network is a kind of Recurrent Neural Network (RNN) that attempts to model time or sequence dependencies (Hochreiter and Schmidhuber, 1997**;** Sagheer and Mostafa 2019; Shastri et al., 2020; Arora et al., 2020). LSTM falls under the category of deep learning and it is performed by feeding back the output of a neural network layer at time t to the input of the same network layer at time $t + 1$. The proposed work was carried out using the Keras implementation of an LSTM network (Fig.1). The computations were carried out on a five-node system each with an eight-core Intel i7-9700 CPU working at 3 GHz and 32 GB memory each with Keras.

The block diagram of a basic multi-input LSTM network and the memory transformation between each cell of LSTM was presented in Fig.1a and Fig.1b. The LSTM cell consists of three gates: input gate (i_t), forget gate (f_t), and output gate (o_t) with different functionality (Fig.1c). The forget gate is responsible for forgetting information that is not required anymore, while the input gate is used for adding new useful information. The output gate updates the hidden states at every time step. Each gate is a feed-forward neural network with many hidden units as shown in Fig.1d. The mathematical representation of LSTM is given below in Eqs. (1)-(5) (Hochreiter and Schmidhuber, 1997).

$i_t = \sigma\left(w_i x_t + u_i h_{t-1} + b_i\right)$----------------------------(1)

$f_t = \sigma\left(w_f x_t + u_f h_{t-1} + b_f\right)$----------------------------(2)

$o_t = \sigma\left(w_o x_t + u_o h_{t-1} + b_o\right)$-----------------------------(3)

$h_t = o_t \times \tanh\left(i_t \times \tanh\left(w_g x_t + u_g h_{t-1} + b_g\right) + f_t \times s_{t-1}\right)$------------------ (4)

Where σ, i, f, o, and g represent the sigmoid function, input gate, forget gate, output gate, and un-gated input transformation respectively. The weights (w_i, w_f, w_o, w_g and u_i, u_f, u_o, u_g) are represented in a matrix format, bias (b_i, b_f, b_o, b_g) are represented in vectors, and S_{t-1} represents the cell state of the previous time step.

The present study utilized both univariate and multivariate LSTM models for forecasting the daily cases of a given state. The univariate model (Control Experiment (CTL)) utilizes the confirmed daily COVID-19 cases time-series data to forecast the future (next day) COVID-19 cases of the selected state in India. To understand the weather impact on coronavirus transmission, four experiments were conducted with the multivariate LSTM model (Table1). The time-series data (April 1 to July 31, 2020) was divided into two parts and the first three months (April-June) data utilized for training and the last one month (July) data was utilized for testing purposes. The LSTM model was optimized with a minimum error by manually considering different hyper-parameters, such as the number of units in the hidden layer, the number of hidden layers, etc. The univariate and multivariate LSTM models were optimized with different weather parameters separately and utilized for forecasting purposes. The forecasts are generated with univariate (CTL) and multivariate (CTL_SH, CTL_Tmax, CTL_Tmin, CTL_Tmean) LSTM models and evaluated with observed data (Table1). Further, we have also generated the forecasts with a different combination of the weather parameters and evaluated with the observed data of highly affected states for COVID-19 in India.

Experiments	**Input data (Time series data)**	**Output data**
CTL	COVID-19 cases	Forecasted COVID-19 cases
CTL_SH	COVID-19 cases & specific humidity	Forecasted COVID-19 cases
CTL_Tmax	COVID-19 cases & maximum temperature	Forecasted COVID-19 cases
CTL_Tmin	COVID-19 cases & minimum temperature	Forecasted COVID-19 cases
CTL_Tmean	COVID-19 cases & mean temperature	Forecasted COVID-19 cases

**CTl: Control experiment, SH: Specific Humidity, Tmax: Maximum Temperature, Tmin: Minimum Temperature, Tmean: Mean Temperature.*

Table1: Description of the LSTM models utilized for the experimental forecast.

2.4:Model evaluation:

2.4.1:Relative Error (RE): The relative error is the ratio between the absolute error and the absolute value of the observation.

$$\Re = \frac{100 * |X_m - X_o|}{|X_o|}$$

Where X_m is the model forecasted and X_o is the observed COVID-19 cases in a single day.

3. Results:

3.1 Spatio-Temporal variability of COVID-19 cases and climate in India:

Figure-2 illustrates the spatial distribution of COVID-19 cases by month wise shown for different states of India, from which a geographical heterogeneity of cases was observed. Before the onset of the Southwest monsoon (i.e. April and May), there were only 182,143 cumulative cases observed in India, and the majority of the cases were reported from the Western (Maharashtra, Gujarat, Rajasthan), Northern (Madhya Pradesh, Uttar Pradesh, Delhi) and Southern states of India (Tamil Nadu) (Fig.2). After the onset of monsoon, there was a rapid growth in cases (cumulative cases during June and July >14 lakhs) and by the end of July, more than 16 Lakh cases were reported in India (Fig.2). However, the maximum number of cases were reported from the Southern states (Maharashtra, Andhra Pradesh, Tamil Nadu, and Karnataka), and moderate cases from the states located in Central, East, and Western parts of India. Similarly, the low number of COVID-19 cases are reported from the states located in North and Northeast region of India.

Figure-3 depicts the spatio-temporal variation of 2m-specific humidity (SH), 2m-maximum temperature (Tmax), 2m-minimum temperature (Tmin), and 2m-mean temperature (Tmean) during April, May, June, and July of current year over India. It was observed that the monthly average SH values were very low (<0.01 kg/kg) over Central India (CI), Northwest India (NWI), and North India (NI); moderate (0.01-0.02 kg/kg) SH values over the states located in East and West coast of India; and high (>0.02 kg/kg) over Kerala and Tamil Nadu during the early stage (April and May) of the pandemic. Whereas the SH was slowly increased from South to North during the monsoon season (June and July) and the high values were observed in July over the Central and East India region. The spatial maps of maximum temperature show that most of the regions in Central and Northwest India record more than 40°C during the pre-monsoon season and it is reduced to <30°C during the monsoon progress over the South and Northeast India. Similarly, the minimum temperature ranges between 20 and 30°C during the premonsoon period and reduced to 20°C and 24°C during the onset of monsoon was observed.

3.2: Association between weather and COVID-19

To understand the weather effect on COVID-19 cases, the lag (0-14 days) correlation coefficients (CC) computed between daily COVID-19 cases and surface meteorological parameters (SH, Tmax, Tmin, Tmean) for the period April 01 to July 31, 2020. Similarly, the study considered 14 days lag correlations due to the symptoms of COVID-19 that will appear after the incubation period which is typically ranging between 1 to 14 days. The correlation coefficient values for lag1, lag7, and lag14 over different states of India shown in figure-4. The correlation maps describe that the specific humidity has a strong positive association with COVID-19 cases for most of the states in India. Maximum correlation (>0.75) values found in Central and North-West India, and moderate correlation (0.5-0.75) values were found in the East coast and some parts of North India (Fig.4). It was observed that the lag7 correlations are slightly better than the lag1 in majority of the states. The mean temperature and maximum temperature have a strong negative association with COVID-19 cases over South India and a positive association with foothills of the Himalaya region. Similarly, minimum temperature also has a strong positive association over the North, Northwest, and Northeast India but a weak negative association was found over the South India region (Fig.4).

3.3: Univariate LSTM model:

The present study utilized the three months (April 01 to June 30, 2020) data for training and one-month data (July 01 to July 31, 2020) for testing the model. The proposed univariate LSTM model was trained and optimized with time-series data of confirmed COVID-19 cases and fit the model for forecasting COVID-19 cases. The model performance is evaluated with the robust statistical technique of relative error for each forecasted day. The results show that the average relative error (31 days) for univariate LSTM (CTL) is reasonably good (<20%) with lag1 (short-term forecast, i.e. 24-hour forecast) for most of the states in India. It is also noted that the univariate LSTM model outperformed compared to the multivariate LSTM model for the states of Andhra Pradesh, Karnataka, Delhi, Bihar, Odisha, and Uttar Pradesh (Fig.5). The univariate LSTM captured trend very well for both estimated and observed cases in these states (Fig.6). However the major disadvantage of the univariate model is that the forecast skill is decreased with long-term lead data.

Andhra Pradesh and Karnataka are COVID-19 affected states in India, the cases were very low during the pre-monsoon season, whereas the virus transmission was so rapid in monsoon season and more than one lakh cases reported in July from these states. The LSTM model was optimized with the confirmed case data (CTL) and performed well (relative error <15% for Lag1) in capturing the exponential growth of the pandemic, whereas the multivariate model optimized with the weather data underestimated the confirmed cases in these states. The LSTM model shown its capability not only in increasing trend but also in capturing the decreasing trend in Delhi (relative error=15%). Similarly, the multivariate LSTM model optimized with minimum temperature has shown slight improvement than univariate LSTM in lead 2, 3 and 4 days lead forecasts in Delhi (Fig.5c). It is also observed that the exponential growth of cases in Uttar Pradesh and Bihar states and the univariate model well captured the observed values and weather integrated multivariate LSTM model underestimate observed cases (Fig.5d,f).

3.4: Multivariate LSTM model:

The states (Maharashtra, Madhya Pradesh, Gujarat, Rajasthan, Haryana, and Punjab) located in West, Northwest India, shown excellent forecasting skill for the multivariate LSTM model (CTL_SH; model optimized with the specific humidity and COVID-19 cases) compared to the univariate LSTM model. It was also observed that the correlation coefficient between specific humidity and COVID-19 cases were significant in these regions. Moreover the study shows that the forecasting skill of the model was improved with the lagged specific humidity (lag1-lag7) over these regions and it is a significant sign for medium-range forecasting (Fig & &8).

Among all the states, the state of Maharashtra reported the highest number of COVID-19 cases In India. The multivariate LSTM model (CTL_SH) with specific humidity shown better performance (relative error <8%) with lag7 data (Fig.7a). Similarly, the forecasting plot (with one-week advance data) shows that the model with other weather variables (CTL, CTL_Tmax, CTL_Tmin, and CTL_Tmean) were overestimating the daily cases whereas the specific humidity (CTL_SH) followed the observed trend and close to the observed data (Fig.8a). Similarly, the forecast skill was adequate with the specific humidity for the states of Gujarat (lag1), Madhya Pradesh (lag3), Rajasthan (lag3), Haryana (lag1) and Punjab (lag5) (Fig.8b-f).

In the case of high humid regions (Kerala, Tamil Nadu, and West Bengal) the forecast skill is improved with the multivariate LSTM model which is optimized with the temperature data (Fig.9). The forecast skill was outperformed with lead1 (relative error <10%) for Tamil Nadu and West Bengal states and the skill is improved with the maximum and mean temperature. However in Kerala, the forecast skill was slightly low (relative error between 20% and 30%) with all variables and a slight improvement observed in the model which was optimized with the minimum temperature. The forecast plot clearly shows that the temperature based LSTM models close to the observations compare to the humidity based model in these humid states (Fig.9).

4. Discussion:

The COVID-19 cases started during the winter season (the first case reported on January 30, 2020) and the maximum number of cases were reported over Maharashtra and Kerala before the national wide lockdown (March 25, 2020) implemented in India. The virus transmission was so rapid after the onset of monsoon and the maximum number of positive cases were reported from Maharashtra, Karnataka, Andhra Pradesh, Tamil Nadu, Uttar Pradesh, Kerala, Delhi and West Bengal. Based on the earlier studies, the RNN based LSTM models have been shown an adequate skill in short-range (one day lead) forecasting of COVID-19 cases (Shastri et al., 2020; Arora et al., 2020). Hence, the present study developed weather integrated multivariate LSTM models to improve prediction skills in short to long-range forecasting of daily cases of COVID-19 over different states in India. The output of our proposed model can help planners and health authorities to implement appropriate control measures. The state-wise predictions will help the public health authorities to balance the disease load which medical facilities can take, and this would also help to resume the economic activities otherwise it may create livelihood challenge for the people.

During the early stage of the pandemic, Wu et al. (2020) reported that the humidity and temperature has an effect on COVID-19 cases. The initial understanding is that the daily new cases have shown reduction with an increase in temperature (1°C increase associated with a 3.08% reduction) and humidity (1% increase associated with a 0.85% reduction). Lin et al., 2020 also studied the temperature and humidity effect on COVID-19 transmission in the Asian countries and observed that the high relative humidity with low-temperature increases the COVID-19 transmission, and high humidity with high temperature reduce the COVID-19 Transmission. Similarly, to understand the impact of weather on the survival of coronavirus, Dbouk and Drikakis, 2020 conducted a study with heat and mass transfer correlations and found that the reduction in coronavirus viability under low humidity and high-temperature condition. They also found that the high relative humidity increases the airborne virus viability in any environmental temperature conditions.

COVID-19 transmission rates are mainly depending on the evaporation rate of the contaminated saliva droplets which is released from the infected person to the surrounding environment (Dbouk and Drikakis, 2020). The evaporation rate mainly depends on humidity, temperature, and wind speed. The contaminated droplets are more resistant to evaporation when the relative humidity is close to the saturation point, which will allow the contaminated droplet cloud to move longer distances from the source (Dbouk and Drikakis, 2020). A recent study revealed that the droplets (released from the infected person while speaking) size larger than 50 μm fall to the ground very fast, whereas the droplet less than this size slowly reduce their radii based on the evaporation rate of the surrounding environment and remain airborne for a longer duration (Roland R. Netz and William A. Eaton 2020). Hence, the higher (lower) relative humidity increase (decrease) the airborne virus viability during the calm wind conditions and possible pathway for acceleration in a COVID-19 disease outbreak.

To understand the COVID-19 disease transmission over different states in India, we have analyzed the potential evaporation data during pre-monsoon and monsoon season and presented the spatio-temporal values in Fig.10. At the early stage of the pandemic (pre-monsoon season) the maximum number of cases were reported from Maharashtra, Gujarat, Rajasthan, Delhi, and Uttar Pradesh (Central, north, west, and north-west India) but the disease transmission was very low (monthly cumulative cases <20,000) during the pre-monsoon season. The potential evaporation rates (>500W/m^2) were very high in central, north, west, and north-west India regions during the pre-monsoon season due to the high maximum temperatures (> 40°C) and low specific humidity (<0.01kg/kg) for these regions (Fig.3 and Fig.9). The virus viability and travel distance may be low due to the high maximum temperatures and low specific humidity. The national wide lockdown and the unfavourable weather conditions during the pre-monsoon season reduced the disease transmission over central, west, and north-west states in India. The potential evaporation rates were slowly reduced in June (after monsoon onset) and reported very low values (<200 W/m^2) during July in the south, east, and north-east India regions. These low evaporation rates due to low temperatures and high specific humidity increased the virus viability in the atmosphere (aggravation of airborne transmission) maybe the possible reason for the significant increase of COVID-19 cases in south India (Fig.10).

Conclusions:

Our results suggested that the skill of the univariate LSTM model which is optimized with confirmed COVID-19 time series data was outperformed for highly affected states like Andhra Pradesh, Karnataka, Uttar Pradesh, Deli, Bihar, and Odisha. It was also noticed that the skill of the univariate model is good in short-range forecasting (lag1) and the skill is decreasing with increasing lead period. The major findings of the study explained that the medium range (1-7 days lead) forecasting skill has shown adequate skill in some of the states in India when the LSTM models are integrated with time-series weather data including specific humidity and temperature. The results show that the developed multivariate LSTM models optimized with specific humidity (CTL_SH) shown adequate skills in the medium-range forecast of daily COVID cases over the states located in the west and northwest India region. It was also observed that the developed multivariate LSTM models with temperature time series data performed very well over the states located in high humid regions including Kerala, Tamil Nadu, and West Bengal. The present study demonstrated the forecasting skill of the LSTM model is improved at medium and long-range scales due to the integration of weather data in India. The forecasting skill may improve further by incorporating high-resolution weather data, increasing the length of training data and optimization methods in LSTM models. Further these models helps the public health authorities for outbreak preparedness, better management of logistics and policy decisions.

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Competing financial interests:

The authors declare no competing financial interests exist.

Ethical Statement:

The authors declare that an ethical statement is not applicable because the case information has been gathered.

Data Availability Statement:

The data used in this study are available from the corresponding author upon request.

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Figure Legends

Figure-1: Keras implementation of multi-parameter LSTM (a) The basic LSTM structure (b) Unrolled representation of LSTM (c) Architecture of an LSTM cell (d) Internal structure of a cell gate.

Figure-2: Spatial maps of monthly cumulated COVID-19 cases over different states in India during pre-monsoon (April and May) and monsoon season (June and July) of the year 2020.

Figure-3: Spatial-temporal variation of surface meteorological parameters (2m-specific humidity, 2m-mean temperature, 2m-maximum temperature, and 2m-minimum temperature) during the pre-monsoon and monsoon season over India.

Figure-4: Correlation between confirmed COVID-19 cases and meteorological parameters (2m-specific humidity, 2m-mean temperature, 2m-maximum temperature, and 2m-minimum temperature) during the period 01st April 2020 to 31st July 2020.

Figure-5: Skill (Average relative error) of univariate (CTL) and multivariate (CTL_SH, CTL_Tmax, CTL_Tmin, CTL_Tmean) LSTM models during the test period (1st July 2020 to 31st July 2020) for the states of Andhra Pradesh, Karnataka, Delhi, Bihar, Odisha, and Uttar Pradesh. Where L1 to L14 represents the 1to 14 days of lag data utilized for forecasting of the next day COVID-19 cases.

Figure-6: Time series data of COVID-19 cases forecasted by univariate (CTL) and multivariate (CTL_SH, CTL_Tmax, CTL_Tmin, CTL_Tmean) LSTM models during the test period (1st July 2020 to 31st July 2020) for the states of Andhra Pradesh, Karnataka, Delhi, Bihar, Odisha, and Uttar Pradesh.

Figure-7: Skill (Average relative error) of univariate (CTL) and multivariate (CTL_SH, CTL_Tmax, CTL_Tmin, CTL_Tmean) LSTM models during the test period (1st July 2020 to 31st July 2020) for the states of Maharashtra, Gujarat, Madhya Pradesh, Rajasthan, Haryana, and Punjab. Where L1 to L14 represents the 1to 14 days of lag data utilized for forecasting of the next day COVID-19 cases.

Figure-8: Time series data of COVID-19 cases forecasted by univariate (CTL) and multivariate (CTL_SH, CTL_Tmax, CTL_Tmin, and CTL_Tmean) LSTM models during the test period (1st July 2020 to 31st July 2020) for the states of Maharashtra, Gujarat, Madhya Pradesh, Rajasthan, Haryana, and Punjab.

Figure-9: Skill (Average relative error) of univariate (CTL) and multivariate (CTL_SH, CTL_Tmax, CTL_Tmin, CTL_Tmean) LSTM models during the test period (1st July 2020 to 31st July 2020) for the states of Tamil Nadu, West Bengal, and Kerala. Where L1 to L14 represents the 1to 14 days of lag data utilized for forecasting of the next day COVID-19 cases.

Figure-10: Spatial-temporal variation of potential evaporation rate (W/m^2)during pre-monsoon and monsoon season over India for the year 2020.