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Centralized CNN–GRU Model by Federated Learning for COVID-19 Prediction in India

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***Abstract*— In 2019, the corona virus was found in Wuhan, China. The corona virus has traveled several countries in the world from the beginning of 2020. The early estimation of COVID-19 cases is one of the efficient approaches to control the pandemic. Many researchers had proposed the deep learning model for the efficient estimation of COVID-19 cases for different provinces in the world. The research work had not focused on the discussion of robustness in the model. In this study, centralized federated-convolutional neural network–gated recurrent unit (Fed-CNN–GRU) model is proposed for the estimation of active cases per day in different provinces of India. In India, the uneven transmission of COVID-19 virus was seen in 36 provinces due to the different geographical areas and population densities. So, the methodology of this study had focused on the development of single deep learning algorithm, which is robust and reliable to estimate the active cases of COVID-19 in different provinces of India. The concept of transfer and federated learning is involved to enhance the estimation of active cases of COVID-19 by the CNN–GRU model. The study had considered the active cases per day dataset for 36 provinces in India from 12 March, 2020 to 17 January, 2022. Based on the study, it is proven that the centralized CNN–GRU model by federated learning had captured the transmission dynamics of COVID-19 in different provinces with an enhanced result.**

***Index Terms*— Convolutional neural network (CNN), COVID-19, deep learning, federated learning, gated recurrent unit (GRU), long short-term memory (LSTM), recurrent neural network (RNN), transfer learning.**

I. INTRODUCTION

AT THE end of December 2019, there was an outbreak of unknown pneumonia with dry cough, fever, and fatigue found in Huanan Seafood Wholesale Market in Wuhan, China [1]. On 30 January, 2020, the first case of COVID-19 was reported in India [2]. As Indian government spends about 3.5% of total gross domestic product (GDP) on health, which is half of the overall world GDP spent on health infrastructure by WHO members, the public health infrastructure of India was badly affected due to the inadequate numbers of hospital beds, ventilators, doctors, and other medical personnel [3]. This kind of pandemic brings the unsustainable situation for the government and medical health infrastructure. The disruption of logistics and supply had affected the availability of material, medicine, and equipment during the COVID-19 pandemic [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33]. The imposition of lockdown for a long period of time is not the efficient solution to eradicate the COVID-19 pandemic. To develop the sustainable solution for medical health infrastructure, one of the approaches to combat the pandemic was its early estimation. The early estimation of COVID-19 cases helps the government to predict the healthcare requirements and also to take the decision for imposing the different levels of lockdowns and restrictions in certain areas.

The time-series analysis deals with the analysis of change in variable with respect to time and helps to predict the future trend of the variable [7]. Many studies were carried out for the efficient estimation of COVID-19 by the mathematical models. Mahajan et al. [8] had proposed a compartmental susceptible (S)–symptomatic (I)–purely asymptomatic (P)–hospitalized (H)–exposed (E)–recovered (R)–deceased (D) (SIPHERD) model for the prediction of confirmed cases, active cases, death cases, and daily new cases of COVID-19 in India. The study had also focused on the impact of lockdown and number of tests per day in COVID-19 prediction of India. Samui et al. [9] had proposed compartmental susceptible (S)–asymptomatic (A)–reported infectious (I)–unreported infectious (U) (SAIU) for the prediction of daily new cases and cumulative confirmed cases in India. The study had also introduced the calculation of basic reproduction number. Sarkar et al. [10] had proposed the mathematical model to monitor the dynamics of six different compartments, which include susceptible, asymptomatic, recovered, infected, isolated infected, and quarantined susceptible for India and 17 states in India. The mathematical parameters in the model were optimized for different provinces separately to forecast the end of COVID-19 pandemic. It has been noted that different compartmental models have individual parameters for different factors, which controls the transmission dynamics of COVID-19. These static governing differential equations face the limitation to estimate the COVID-19 cases and become more complex due to the effect of external factors, which include mutations of coronavirus, population density and geographical location, and restrictions imposed by government.

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TABLE I
SUMMARY OF THE LITERATURE FOR COVID-19 PREDICTION BY DEEP LEARNING

Sr No.	Reference	Proposed Deep Learning Model	Case Study	Input: Time Series Variable	Main Contribution
1	Ma et al. [24]	LSTM Markov Model	US, Brazil, Britain & Russia	Cumulative Confirmed Cases	Based on the comparison with LSTM model, LSTM Markov model had done the prediction with 60% reduction in Root Mean Squared Error (RMSE).
2	Verma et al. [25]	LSTM, Stacked-LSTM, Bi-LSTM, ED-LSTM, CNN & CNN-LSTM Model	States in India which include Tamil Nadu, Kerala, Maharashtra & Karnataka	Daily Confirmed Cases	The study had carried out the forecasting of 7, 14, 21 days in different states. Based on the comparison of RMSE & Mean Absolute Percentage Error (MAPE) of models, Stacked-LSTM & CNN-LSTM model had outperformed other deep learning models.
3	Alassafi et al. [26]	RNN & LSTM Model	Saudi Arabia, Malaysia & Morocco	Daily Confirmed & Death Cases	LSTM & RNN had given the precision accuracy of 98.58% & 93.45% respectively.
4	ArunKumar et al. [27]	RNN-LSTM & RNN-GRU Model	Iran, Chile, Mexico, Russia, Brazil, UK, Peru, South Africa, India & USA	Cumulative Confirmed, Recovered & Death Cases	Both RNN-LSTM & RNN-GRU model had performed reasonably well for the forecasting of confirmed, fatalities & recovered cases in these countries for upcoming 60 days.
5	Ghany et al. [28]	LSTM Model	GCC countries which include Qatar, UAE, Saudi Arabia, Bahrain, Oman & Kuwait	Daily Confirmed & Death Cases	Based on the forecasting by LSTM model, the study had determined whether the Covid-19 transmission is controllable in different GCC countries.

The domestic and international travels also have an impact on the transmission of COVID-19 [11]. The availability of medical facilities and experience of central and state governments to handle the COVID-19 pandemic are also the major factors to be considered for combating the COVID-19 pandemic [12]. Liu [35] had proposed the regression model to predict the number of laboratory confirmed COVID-19 cases in China. The study had considered the distance from Wuhan as one of the control variables for prediction. It is difficult to develop the universal/centralized mathematical model, as the mathematical parameters vary based on social, cultural, and economic factors. So, the mathematical models are capable to deal with stationary time-series analysis, which introduce deterministic behavior. While, sudden changes in a dynamical system bring noisy and stochastic behavior in time-series data points, which can be addressed with deep learning models [13]. Deep learning is a part of artificial intelligence, which had brought breakthrough in different domains, which include visual recognition, speech, and natural language processing. The approach of deep learning helps to extract the pattern present in the data with the different stages of abstraction and gives accurate data-driven decisions [14], [15]. A convolutional neural network (CNN), recurrent neural network (RNN), long short-term memory (LSTM), and gated recurrent unit (GRU) are the most important deep learning algorithm, which are able to deal with large amount of data. CNN plays a key role in the extraction of features from the data, while RNN captures the trend present in the past information of the sequential data and helps to forecast the future information [16], [17], [18]. RNN has a major drawback, as it suffers from the problem of short-term memory when it works with the longer sequential data. The LSTM mechanism overcomes the issue of short-term memory in RNN. LSTM consists of gating mechanism with three gates, which include input gate, forget gate, and output gate. The input gate retains the required information in current cell state. The forget gate determines whether the information from the previous LSTM cell has to be removed. The output gate determines the output from the LSTM cell [19]. The gating mechanism helps to retain the information from the sequential data with a long-term dependency. GRU also overcomes the issue of short-term memory. GRU consists of two gates, which include update gate and reset gate. The update gate determines the relevancy of the information from the past sequence

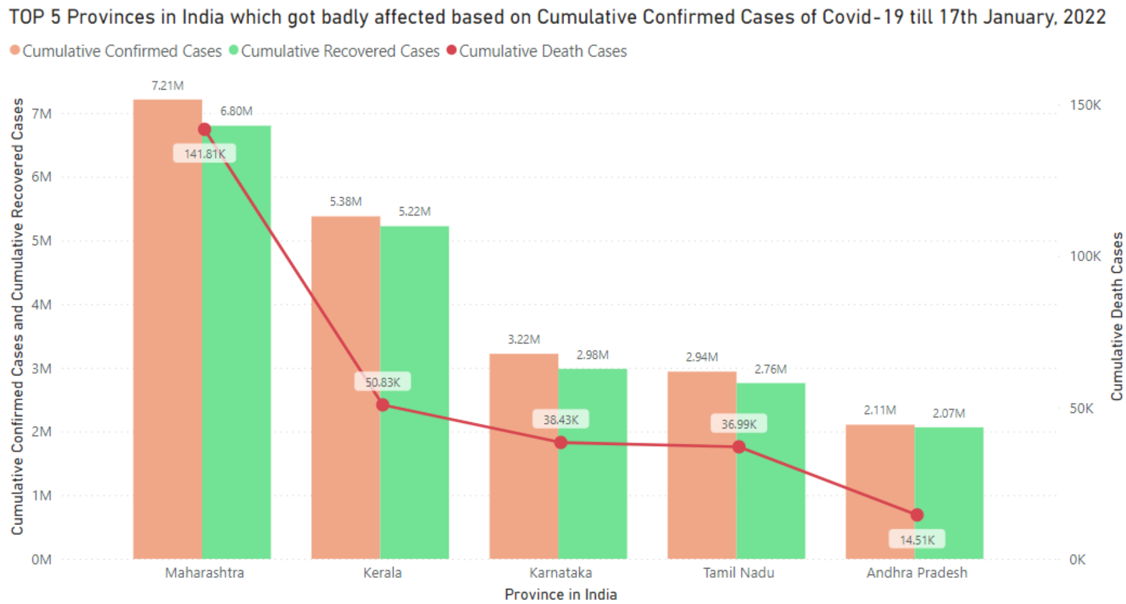

Fig. 1. Top-5 provinces in India that got badly affected based on cumulative confirmed cases of COVID-19 until 17 January, 2022.

required in future. The function of update gate is similar to the output gate of LSTM cell. The reset gate determines whether the information from the past sequence has to be removed. The reset gate works as the combination of input and forget gates of LSTM cell. GRU does not contain memory cell to store the current cell state, which is present in LSTM [20], [21]. So, the number of learnable parameters in GRU is less as compared with the LSTM with the same number of hidden units. CNN, RNN, LSTM, GRU, and their hybrid models are used for time-series analysis in different domains, which include finance, weather, and epidemic [22], [23], [25].

In Table I, different deep learning architectures are used for the efficient prediction of COVID-19 cases for different provinces in the world. It has been observed that the deep learning models are trained and tested on the same parent provinces. The study had not addressed the robustness in the model. The deep learning model also fails to give efficient early estimation of COVID-19 cases due to the changes in social, cultural, and economic factors. The transmission dynamics of COVID-19 vary in different provinces based on the population density and geographical area. So, the proposed deep learning model should be robust and accurate to capture the different transmission trends of COVID-19. Sometimes, the deep learning model fails to predict the COVID-19 cases accurately, as it was trained on the data, which has lack of dynamics. Sometimes, the deep learning model with fixed hyperparameters cannot predict the COVID-19 cases accurately for different provinces, because these provinces have different transmission trends of COVID-19. Pandianchery et al. [29] had proposed the pretrained LSTM model with the approach to train the model on the province with favorable dynamics in data and test for rest of the provinces in India. The study had focused on the principle of model adaptation to track the COVID-19 cases for different provinces in India. As the pandemic evolves, the new trend of COVID-19 will be noticed in different provinces. Then, this kind of approach faces the limitation to efficiently estimate the COVID-19 cases due to the lack of robustness in the deep learning model. Nowadays, studies are directed toward the different approaches of deep domain adaptation, which leverages the deep learning models by learning more transferable patterns and representations [30]. Federated learning is one of the approaches, which is inclined toward the principle of deep domain adaptation. Federated learning is a collaboratively decentralized technology, which preserves the privacy of data and only shares the updates of statistical models. It had played a significant role in different domains, which include healthcare, block chain, and cyber security. A federated learning approach helps to develop the centralized statistical model from decentralized training data. It focuses on training the statistical model on the remote data and summarizes the locally updated learnable parameters. These parameters are subjected to weighted average to improve the results of the shared statistical model [31], [32]. It helps to enhance the robustness and efficacy of the deep learning model, which overcomes the problem of domain shift.

In the literature, the study had not focused on the development of centralized deep learning model based on the principle of deep domain adaption, which is capable to track the different transmission dynamics of COVID-19. So, this is the first study, which focuses on the development of the centralized deep learning model by federated learning approach for the efficient estimation of COVID-19 cases in 36 different provinces of India. In federated learning approach, the summarization of locally updated learnable parameters after being trained on decentralized COVID-19 data of each provinces enhances the robustness in the deep learning model. This kind of approaches can be adopted during the evolution of pandemics and to efficiently estimate the COVID-19 cases

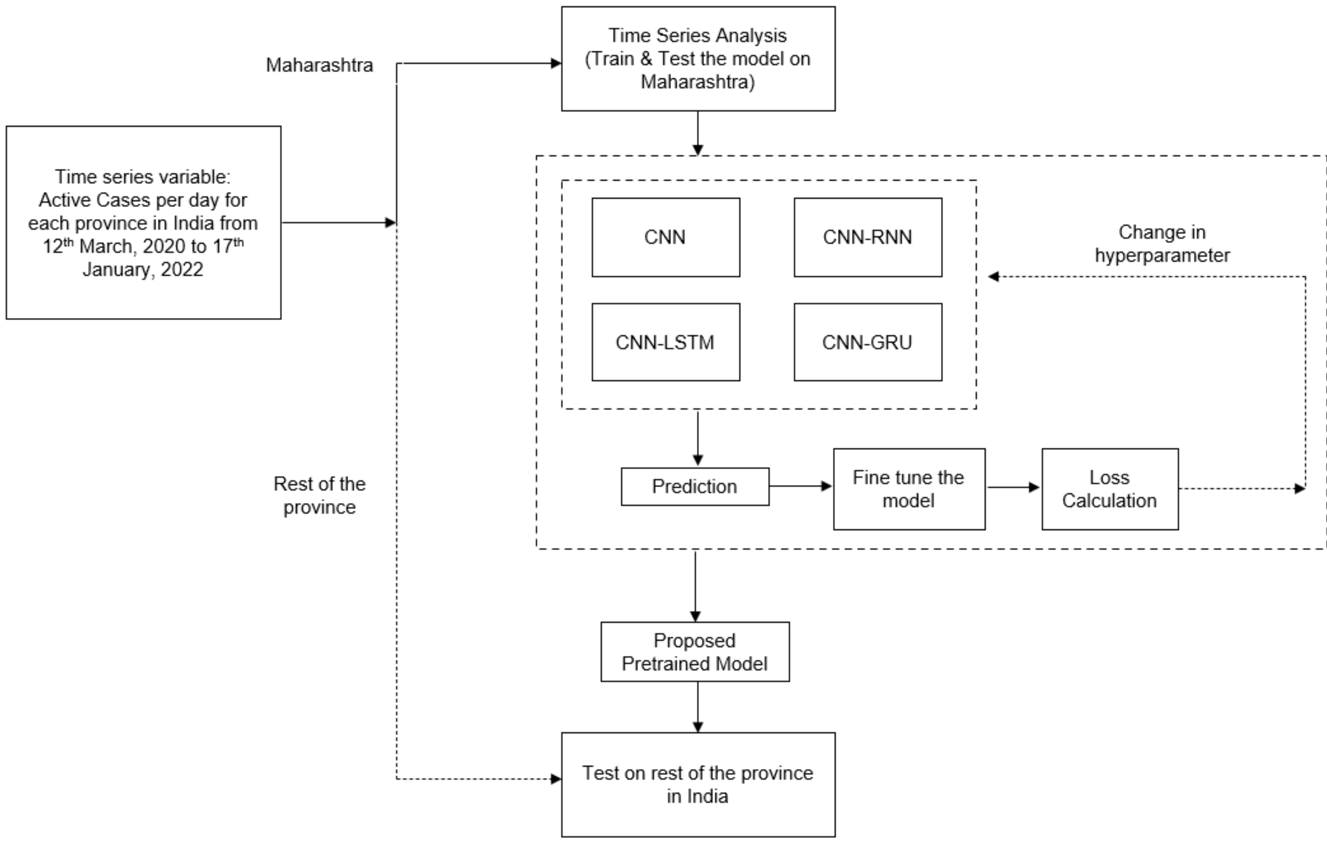

Fig. 2. Detailed framework to train the CNN-based model on province with favorable dynamics and test for rest of the provinces in India.

in future. The insights from the model helps the government, medical health infrastructure, and logistics to do the strategic planning during the pandemic [33], [34].

II. Methodology

A. Dataset Description

The dataset for states and union territories in India is extracted from Source: https://prsindia.org/covid-19/cases. The dataset consists of active cases per day, cumulative confirmed, cured/discharged, and deceased cases for each province in India. The dataset considered for the study is from the duration of 12 March, 2020 to 17 January, 2022. The dataset had captured the first, second, and surge in the third wave of pandemic in India. Based on data exploration, as shown in Fig. 1, Maharashtra is one of the states, which was badly affected by the COVID-19 pandemic. In Maharashtra, the cumulative confirmed cases and deceased cases had crossed 7.21 and 0.14 million, respectively. Apart from Maharashtra, states, which include Kerala, Karnataka, Tamil Nadu, and Andhra Pradesh, had reported large number of cumulative confirmed cases.

B. Proposed Work

In this study, CNN and CNN-based hybrid models are used for the prediction of active cases per day in different provinces of India. The CNN-based hybrid model includes CNN–RNN, CNN–LSTM, and CNN–GRU. In these hybrid models, the CNN layer captures the spatial features from the data based on sliding window approach and fed it into the RNN, LSTM, or GRU layer to capture the sequential information present in the data. To address the objective, the study had focused on the development of centralized model for COVID-19 prediction. Initially, the CNN-based model is developed and optimized on the dataset of single province, which have favorable dynamics. The study had considered the comparison of two approaches for the prediction of time-series data point as follows.

Approach-1: The architecture of the optimized CNN-based model (trained on province with favorable dynamics in data) is adopted to locally train and test for rest of the provinces in India.

Approach-2: In this approach, the study had considered the different stages for the development of centralized model for COVID-19 prediction in different provinces of India. The detailed comparison has been done at the different stages to showcase the enhancements in COVID-19 prediction. The different stages are as follows.

1) *Stage-1:* By transfer learning, the pretrained model (trained on province with favorable dynamics in data) is tested for rest of the provinces. From the research framework shown in Fig. 2, CNN, CNN–RNN, CNN–LSTM, and CNN–GRU are the deep learning algorithms, which are trained and tested on province with favorable dynamics. Based on the comparison of mean absolute error (MAE), the model, which gives least error, is considered

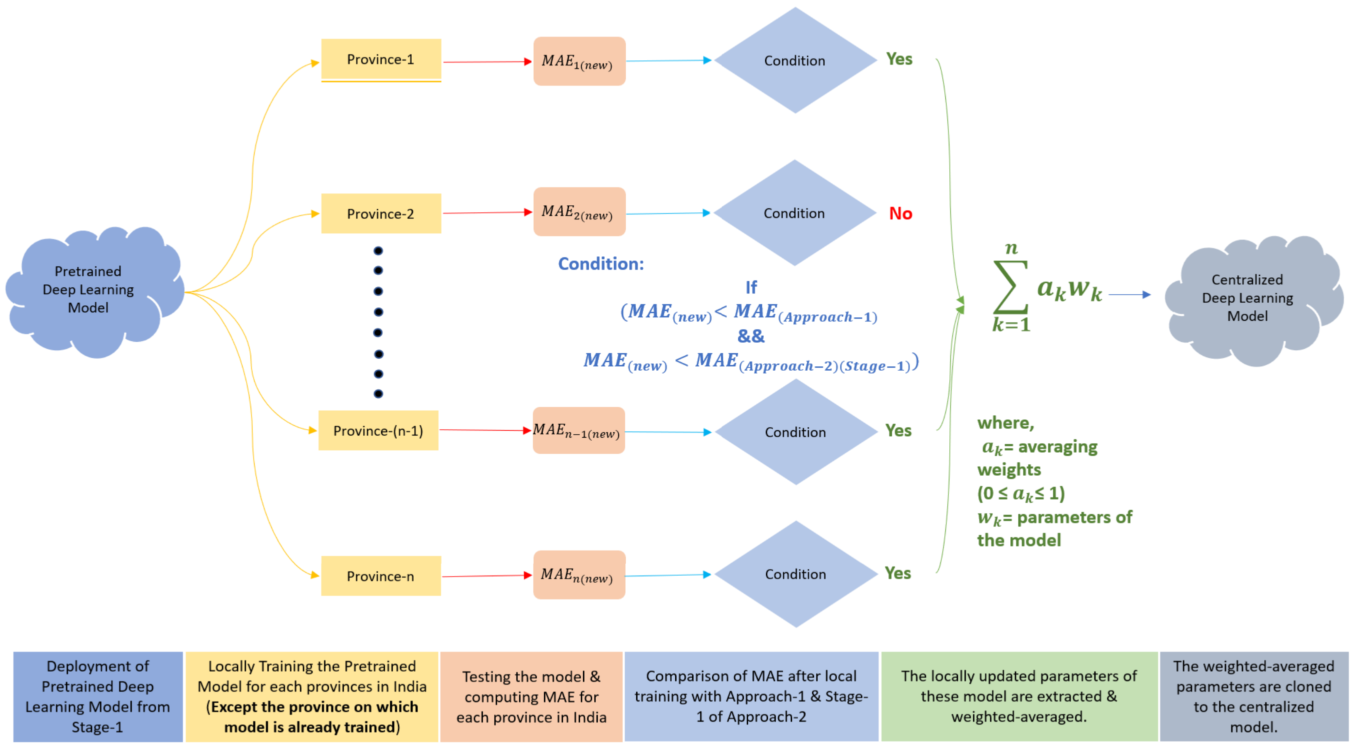

Fig. 3. Detailed framework for the development of the centralized deep learning model by federated learning approach.

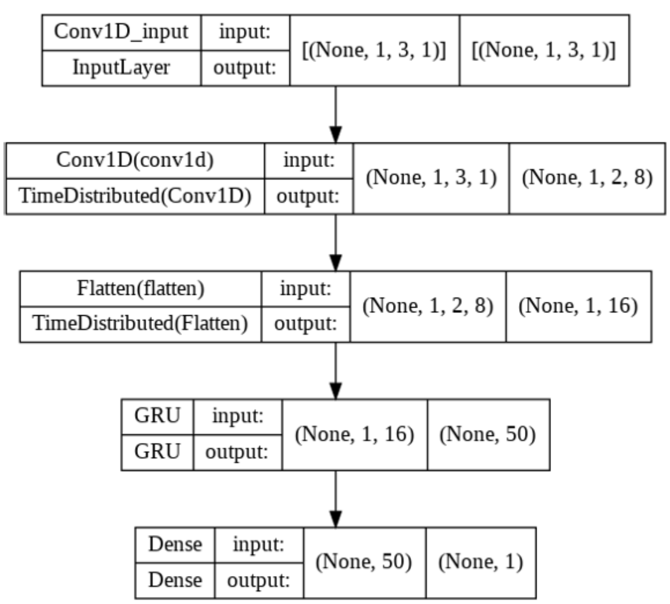

Fig. 4. Visualization of layer input and output in the CNN–GRU model.

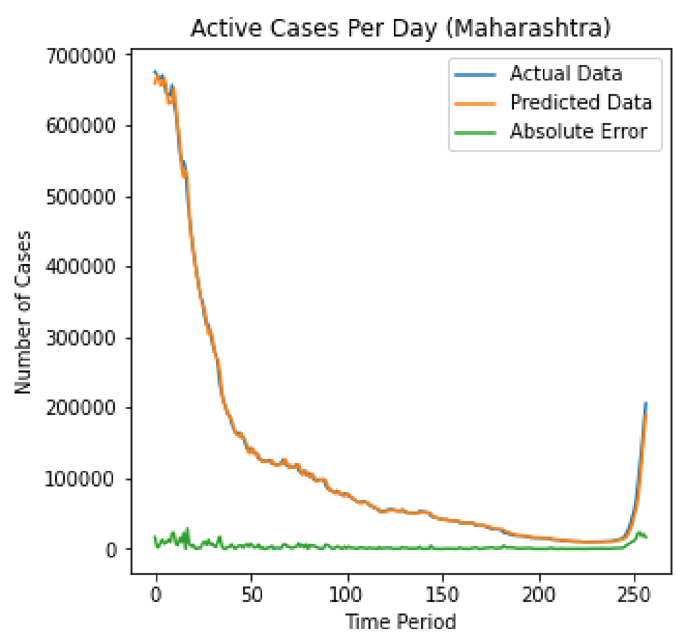

Fig. 5. Comparison between actual data of Maharashtra and predicted data by CNN–GRU.

for the further study. The pretrained model is tested to capture the different transmission trends of COVID-19 for rest of the provinces in India.

2) *Stage-2:* In this stage, the study had focused on the development of the centralized deep learning model and enhancement of prediction results by federated learning approach as compared with Stage-1 and Approach-1. The detailed framework for Stage-2 is shown in Fig. 3.

The pretrained deep learning model from Stage-1 is deployed for local training on the provinces of India. After locally training the model, the model is tested on the same parent province, and MAE is computed. The new MAE after local training is compared with MAE results from Stage-1 and Approach-1 for each of the provinces. Based on the comparison, the province,

TABLE II
COMPARISON BETWEEN DIFFERENT DEEP LEARNING ARCHITECTURES

Sr No	DL Model	Input Step Size	Filter Size	No of hidden units in Dense Layers	No of hidden units in RNN Layers	Kernel Size (CNN)	No of learnable parameters	MAE
1	CNN	3	8	150, 1	*	2	2,725	3703.13
2	CNN-RNN	3	16	1	50	2	4,249	3405.47
3	CNN-LSTM	3	16	1	150	2	1,09,999	3168.58
4	CNN-GRU	3	8	1	50	2	10,275	**3095.99**

TABLE III
COMPARISON BETWEEN APPROACH-1 AND APPROACH-2 BASED ON MAE

Sr No.	State	CNN-GRU		
		Approach-1	Approach-2	
			Stage-1	Stage-2
1	Andhra Pradesh	1999.93	858.21	**820.09**
2	Arunachal Pradesh	47.41	43.17	**41.75**
3	Assam	583.06	**405.59**	417.49
4	Bihar	535.82	444.73	**391.29**
5	Chhattisgarh	1658.91	496.71	**392.19**
6	Goa	471.72	171.59	**140.83**
7	Gujarat	879.31	517.32	**362.51**
8	Haryana	912.98	502.9	**321.78**
9	Himachal Pradesh	406.91	217.59	**187.94**
10	Jharkhand	590.19	303.85	**214.07**
11	Karnataka	4181.69	2555.66	**2199.26**
12	Kerala	9784.23	3617.26	**3428.51**
13	Madhya Pradesh	805.92	415.83	**313.98**
14	Maharashtra	3095.99	3095.99	**2986.88**
15	Manipur	300.44	148.31	**148.29**
16	Meghalaya	180.37	90.04	**85.09**
17	Mizoram	2920.86	230.84	**228.08**
18	Nagaland	69.04	36.81	**36.79**
19	Odisha	754.27	631.23	**612.42**
20	Punjab	316.91	359.93	**230.16**
21	Rajasthan	1326.61	783.45	**603.75**
22	Sikkim	58.89	47.85	**46.63**
23	Tamil Nadu	2299.59	1298.79	**949.18**
24	Telangana	282.17	**223.18**	248.37
25	Tripura	**82.29**	83.49	82.64
26	Uttar Pradesh	929.56	954.65	**844.38**
27	Uttarakhand	1098.73	374.29	**252.49**
28	West Bengal	1402.18	645.81	**531.62**
29	Andaman and Nicobar Islands	10.02	4.65	**4.22**
30	Chandigarh	212.54	38.83	**24.62**
31	Dadra and Nagar Haveli and Daman and Diu	10.66	**9.47**	**9.47**
32	Delhi	795.68	588.09	**430.03**
33	Jammu and Kashmir	202.42	213.69	**181.81**
34	Lakshadweep	246.52	16.76	**15.36**
35	Puducherry	379.54	93.21	**84.97**
36	Ladakh	20.46	**17.19**	17.49

which had shown the enhancement in prediction results, is selected. The locally updated parameters of the model from the selected provinces are extracted and weighted averaged. Then, the weighted-average parameters are cloned to the centralized deep learning model.

III. RESULTS AND DISCUSSION

In this study, CNN, CNN–RNN, CNN–LSTM, and CNN–GRU are used to train and test on the province with favorable dynamics in data. From Fig. 1, Maharashtra had reported large number of cumulative confirmed and deceased cases. Maharashtra was badly affected by COVID-19 pandemic due to the high population density. So, the CNN-based model is trained on the dataset of Maharashtra, which has favorable dynamics in data. The active cases dataset has been normalized between 0 and 1 by MinMax Scaler. To train and test the model, the train dataset is taken from the duration of 12 March, 2020 to 5 May, 2021, and the test dataset is taken from the duration of 6 May, 2021 to 17 January, 2022. The CNN-based model is trained with 419 days and tested for 257 days. These models are trained for 1000 epochs, and relu is used as an activation function. In model, rmsprop is

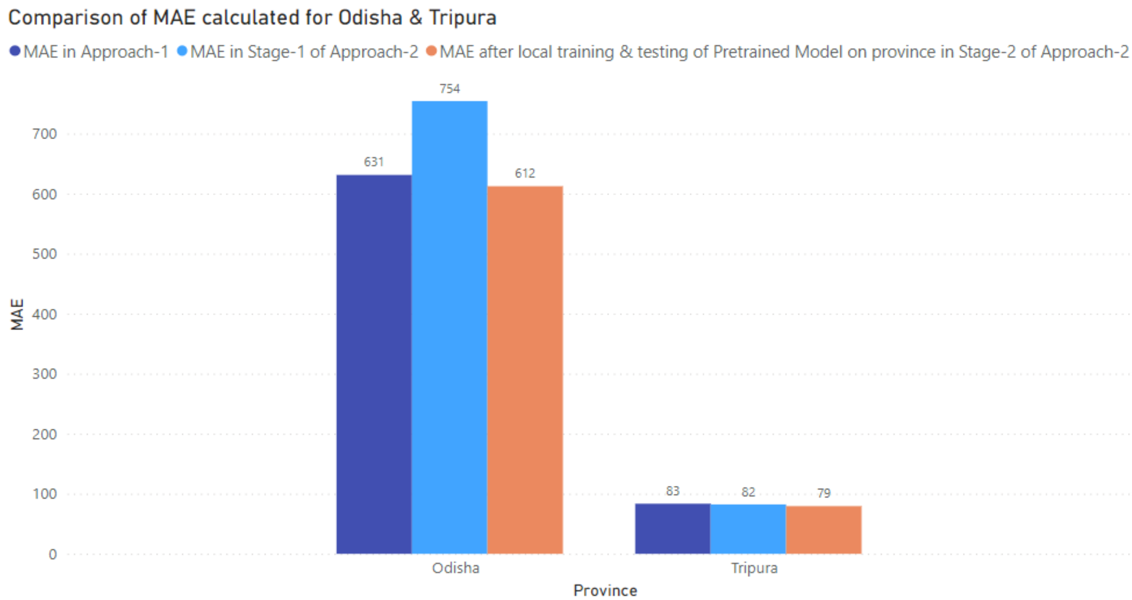

Fig. 6. Comparison of MAE calculated for Odisha and Tripura after local training and testing of pretrained model in Stage-2 of Approach-2.

used as an optimizer, and mean squared error is used as a loss function. The metrics used for the comparison between the different deep learning architectures are MAE. These models had done the prediction for one day ahead. The CNN-based models are optimized based on the filter size (8, 16, 32, and 64), input step size (3–10), and hidden units in dense and RNN layers. The hyperparameters and results of optimized CNN and CNN-based hybrid models are shown in Table II.

From Table II, the CNN–GRU model with an input step size as 3 tested on the dataset of Maharashtra has given the least MAE of 3095.99. The visualization of the layer input and output in CNN–GRU model is shown in Fig. 4. The comparison between actual and predicted data by the CNN–GRU model tested on the dataset of Maharashtra is shown in Fig. 5.

According to Approach-1, the architecture of the optimized CNN–GRU model (trained on the dataset of Maharashtra) is adopted to locally train and test for rest of the provinces. In Stage-1 of Approach-2, the pretrained model (trained on the dataset of Maharashtra) is tested on the test data of rest of the provinces in India by transfer learning. The MAE is calculated for the prediction of active cases for each province by Approach-1 and Stage-1 of Approach-2 shown in Table III.

In Stage-2 of Approach-2, the pretrained model from Stage-1 is deployed for each province in India except Maharashtra. The pretrained model is locally trained and tested for each province, and MAE is calculated. After local training of the model, MAE of each province in Stage-2 is compared with MAE in Approach-1 and Stage-1 of Approach-2. Based on the comparison, the provinces, which had shown the enhanced prediction results, are selected. The enhancement in the prediction result shows that the model had learned some new trends in the data. In the experiment, province, which include Odisha and Tripura, had shown the improvement in prediction results. The MAE calculated for the prediction of active cases in Odisha and Tripura is 612.42 and 79.47, which is comparatively low as compared with the MAE in Approach-1 and Stage-1 of Approach-2, as shown in Fig. 6. The improvement in prediction result of Tripura is not significant as compared with Odisha. The parameters of model locally trained on these provinces are extracted and weight averaged. The weights are assigned to the parameters based on the prediction results of the model on the dataset of Maharashtra. Based on varying the weights from 0 to 1, the weights assigned for parameters of the locally trained model of Odisha and Tripura are 1 and 0, respectively. This weight-averaged parameters of the model had given the least MAE equal to 2986.88 on the test data of Maharashtra. It was notated that the centralized Fed-CNN–GRU model in Stage-2 had outperformed the pretrained model in Stage-1 based on the prediction result of Maharashtra. Then, the weight-averaged parameters are cloned to the centralized Fed-CNN–GRU model. The MAE results of each province in Stage-2 are shown in Table III.

From Table III, it was noted that the MAE results of many provinces by Approach-1 are very high as compared with Stages-1 and -2 of Approach-2. In Approach-1, the CNN–GRU model with fixed hyperparameter is used for different provinces, which had failed to capture the distinct transmission dynamics, as shown in Figs. 7–10. For Mizoram in Fig. 9, the CNN–GRU model of Approach-1 is trained on the data, which has lack of dynamics. So, the model had failed to capture the transmission trend in the test data. During the first and second waves of pandemic, the provinces in India had shown uneven transmission trend of COVID-19 because of diversity in geographical location and population density. Hence, it is proven that the deep learning model with fixed hyperparameter is not robust and accurate to capture the different transmission dynamics of COVID-19. In Stage-1 of Approach-2, the prediction results have been improved

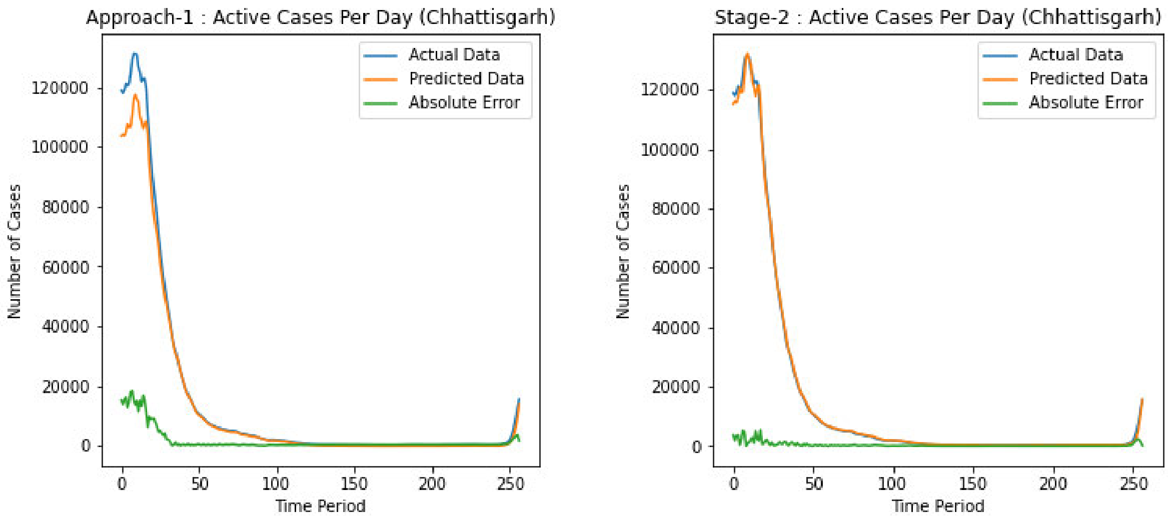

Fig. 7. Prediction of active cases per day by Approach-1 and Stage-2 of Approach-2 for Chhattisgarh.

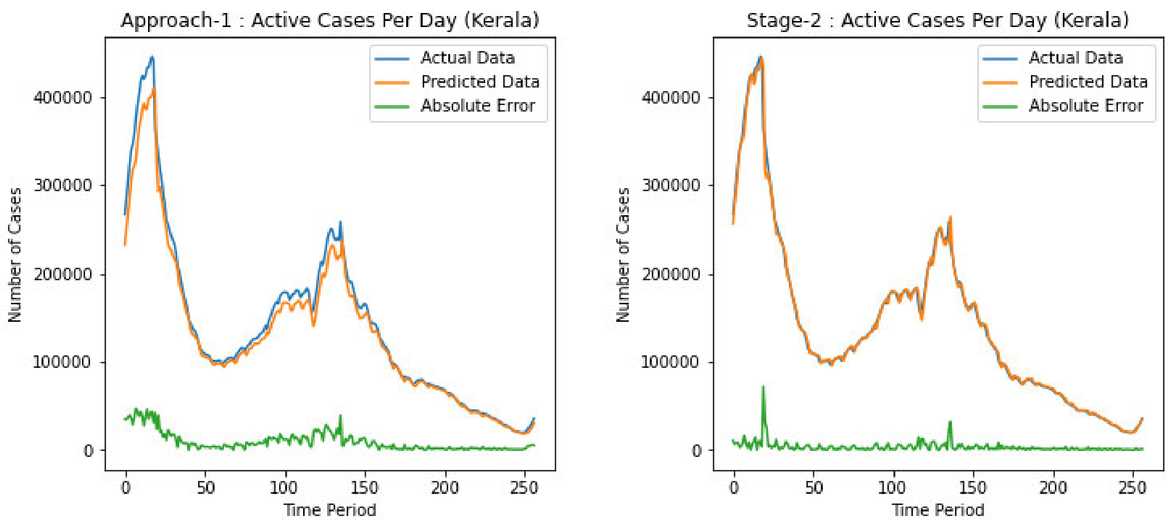

Fig. 8. Prediction of active cases per day by Approach-1 and Stage-2 of Approach-2 for Kerala.

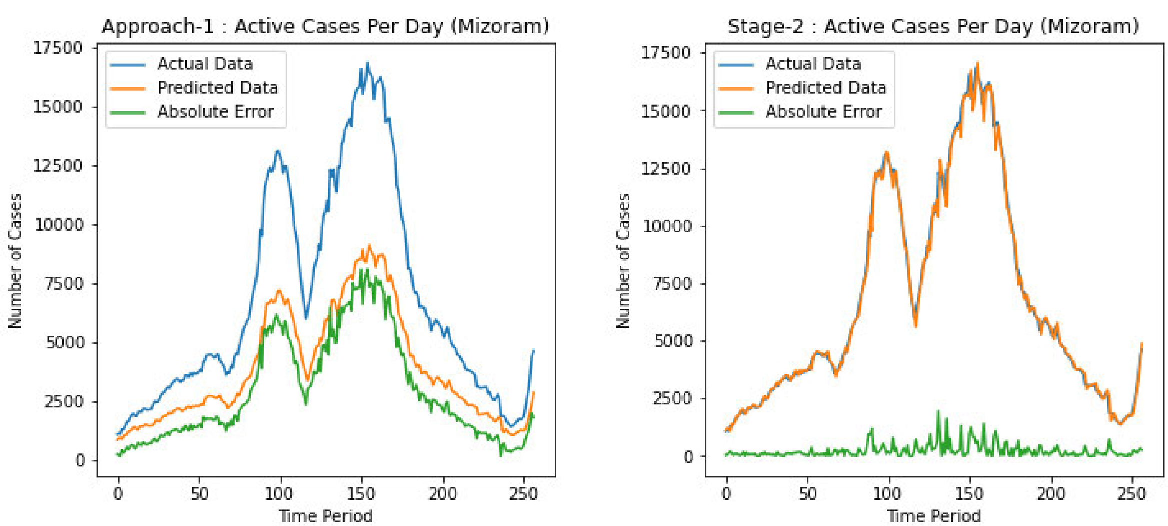

Fig. 9. Prediction of active cases per day by Approach-1 and Stage-2 of Approach-2 for Mizoram.

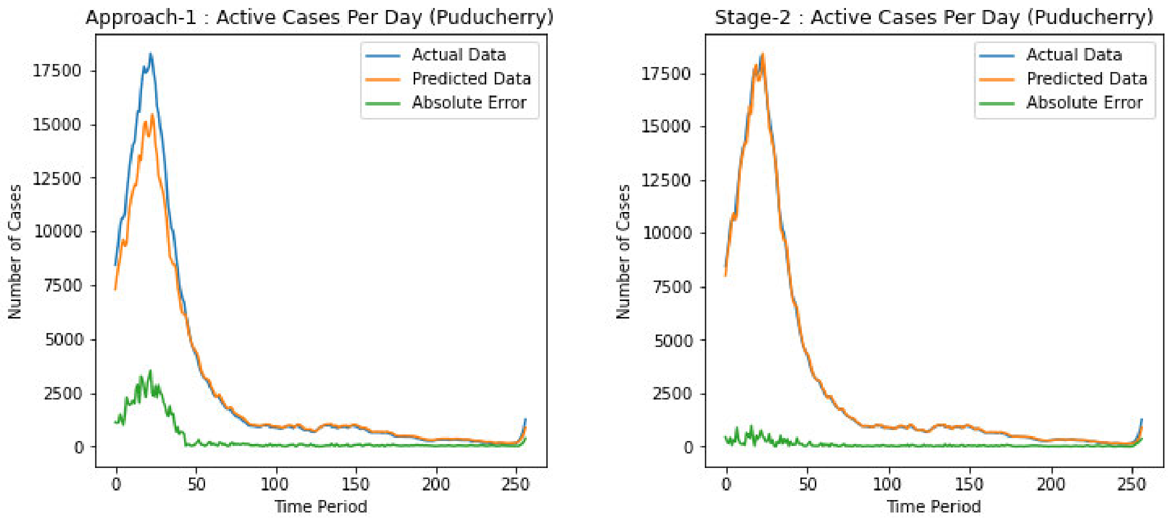

Fig. 10. Prediction of active cases per day by Approach-1 and Stage-2 of Approach-2 for Puducherry.

drastically as compared with Approach-1. The pretrained model in Stage-1 had captured the COVID-19 transmission for different provinces. The transfer learning in Stage-1 generally helps the provinces, which has lack of data. So, instead of development and optimization of deep learning model on data with less dynamics, the adaption of pretrained model in Stage-1 helps the government to predict the COVID-19 cases accurately. In the literature, Pandianchery et al. [29] had proposed the pretrained LSTM model by the approach of transfer learning for COVID-19 prediction in different provinces of India. From the experiments, it has been proven that the federated learning approach of Stage-2 had updated the parameters of the model, which had enhanced the prediction results as compared with the transfer learning approach in Stage-1 for majority of the provinces in India. The federated learning approach leverages the performance of deep learning models by the deployment of pretrained model on different provinces to learn the new trends/patterns present in the remote data. The proposed methodology in this study helps the government to track the transmission dynamic of COVID-19 accurately. In Lakshadweep, the first case was reported on 18 January, 2021 after the first wave of pandemic in other provinces of India. So, instead of the development of deep learning on less data, the pretrained model with the federated learning approach can be adapted to predict the COVID-19 cases. The centralized Fed-CNN–GRU model by federated learning can be deployed in real scenario to capture the different trends of COVID-19 in India.

IV. Limitations and Future Scope

As research advances toward the deep domain adaption, the centralized Fed-CNN–GRU model had successfully captured the transmission dynamics of COVID-19 in 36 different provinces of India. There are many external factors, which can change the transmission trend of COVID-19. The external factors, which mainly include human migrations, festivals, religious events, and mutation of corona virus, can trigger the transmission of COVID-19 among the population. The Fed-CNN–GRU model faces the limitation to accurately estimate the COVID-19 cases due to the effect of these external factors. So, it is required to retrain the model and to update the learnable parameters of the model by federated learning approach with respect to the changes in the transmission trend of COVID-19. The efficiency of medical health infrastructure also plays a key role to control the pandemic. The availability of hospital beds, ventilators, oxygen cylinders, COVID-19 testing facilities, and vaccination drive has a direct impact on the transmission trend of COVID-19. In the proposed Fed-CNN–GRU model, there is no involvement of availability of medical facilities, which fails the model to successfully capture the transmission dynamics of COVID-19. The proposed centralized Fed-CNN–GRU model is not a transmission model, so it cannot capture the transmission dynamic of COVID-19 efficiently. The future scope of this work will be based on the development of deep learning model considering multivariate time-series analysis. In multivariate time-series analysis, inclusion of variables corresponding to medical facilities helps the deep learning model for better prediction of COVID-19 in India.

V. Conclusion

The study had focused on the development of the centralized Fed-CNN–GRU model for the COVID-19 prediction in different provinces of India. The study had shown the enhancement in the results of prediction at the different stages of development in the model. In the initial phase of study, the CNN-based models are developed and optimized on the dataset of Maharashtra, which has favorable dynamics in data. Based on the comparison of MAE between different CNN-based models, the CNN–GRU model had outperformed on the test data of Maharashtra. In Approach-1, it is proven that the deep learning model with fixed hyper parameters had failed to capture the different transmission trends of COVID-19 cases in different provinces of India. In Stage-1 of Approach-2, the pretrained model (trained on the dataset of Maharashtra) is tested on the rest of the provinces in

India by transfer learning approach. Based on the comparison of MAE between Approach-1 and Stage-1 of Approach-2, the results of prediction are improved and also capable to capture the different transmission trends of COVID-19 in India. In Stage-2 of Approach-2, the Fed-CNN–GRU model had shown the enhanced prediction results by the adaption of federated learning approach. So, the study had shown that the centralized model developed by federated learning approach is robust and reliable to capture the different transmission trends of COVID-19 in India. The adaption of pretrained models by transfer and federated learning approach generally helps the province, which has lack of dynamics in data. The study had also shown that the prediction results are further enhanced by federated learning approach, as the centralized deep learning model is developed from the decentralized data, which has different patterns/trends. The proposed approach for COVID-19 estimation helps the government and medical health infrastructure to take the appropriate decision during the different phases of pandemic.

References

[1] Y. C. Wu, C. S. Chen, and Y. J. Chan, "The outbreak of COVID-19: An overview," *J. Chin. Med. Assoc.*, vol. 83, no. 3, p. 217, 2020.

[2] S. D. Chowdhury and A. M. Oommen, "Epidemiology of COVID-19," *J. Digestive Endoscopy*, vol. 11, no. 1, pp. 3–7, 2020.

[3] A. F. Siddiqui, M. Wiederkehr, L. Rozanova, and A. Flahault, "Situation of India in the COVID-19 pandemic: India's initial pandemic experience," *Int. J. Environ. Res. Public Health*, vol. 17, no. 23, p. 8994, Dec. 2020.

[4] K. Gkiotsalitis and O. Cats, "Public transport planning adaption under the COVID-19 pandemic crisis: Literature review of research needs and directions," *Transp. Rev.*, vol. 41, no. 3, pp. 374–392, May 2021.

[5] M. Kamargianni, C. Georgouli, L. P. Tronca, and M. Chaniotakis, "Changing transport planning objectives during the COVID-19 lockdowns: Actions taken and lessons learned for enhancing sustainable urban mobility planning," *Cities*, vol. 131, Dec. 2022, Art. no. 103873.

[6] V. Simić, I. Ivanović, V. Dorić, and A. E. Torkayesh, "Adapting urban transport planning to the COVID-19 pandemic: An integrated fermatean fuzzy model," *Sustain. Cities Soc.*, vol. 79, Apr. 2022, Art. no. 103669.

[7] M. Gerdes, "Decision trees and genetic algorithms for condition monitoring forecasting of aircraft air conditioning," *Expert Syst. Appl.*, vol. 40, no. 12, pp. 5021–5026, Sep. 2013.

[8] A. Mahajan, N. A. Sivadas, and R. Solanki, "An epidemic model SIPHERD and its application for prediction of the spread of COVID-19 infection in India," *Chaos, Solitons Fractals*, vol. 140, Nov. 2020, Art. no. 110156.

[9] P. Samui, J. Mondal, and S. Khajanchi, "A mathematical model for COVID-19 transmission dynamics with a case study of India," *Chaos, Solitons Fractals*, vol. 140, Nov. 2020, Art. no. 110173.

[10] K. Sarkar, S. Khajanchi, and J. J. Nieto, "Modeling and forecasting the COVID-19 pandemic in India," *Chaos, Solitons Fractals*, vol. 139, Oct. 2020, Art. no. 110049.

[11] C. K. Manzira, A. Charly, and B. Caulfield, "Assessing the impact of mobility on the incidence of COVID-19 in Dublin city," *Sustain. Cities Soc.*, vol. 80, May 2022, Art. no. 103770.

[12] J. Chen, X. Guo, H. Pan, and S. Zhong, "What determines city's resilience against epidemic outbreak: Evidence from China's COVID-19 experience," *Sustain. Cities Soc.*, vol. 70, Jul. 2021, Art. no. 102892.

[13] J. P. Devarajan, A. Manimuthu, and V. R. Sreedharan, "Healthcare operations and black swan event for COVID-19 pandemic: A predictive analytics," *IEEE Trans. Eng. Manag.*, early access, Jun. 2, 2022, doi: 10.1109/TEM.2021.3076603.

[14] J. D. Kelleher, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2019.

[15] V. S. Mohan, V. Sowmya, and K. P. Soman, "Deep neural networks as feature extractors for classification of vehicles in aerial imagery," in *Proc. 5th Int. Conf. Signal Process. Integr. Netw. (SPIN)*, Feb. 2018, pp. 105–110.

[16] J. C. B. Gamboa, "Deep learning for time-series analysis," 2017, *arXiv:1701.01887*.

[17] S. Albawi, T. A. Mohammed, and S. Al-Zawi, "Understanding of a convolutional neural network," in *Proc. Int. Conf. Eng. Technol. (ICET)*, Aug. 2017, pp. 1–6.

[18] N. Aloysius and M. Geetha, "A review on deep convolutional neural networks," in *Proc. IEEE Int. Conf. Commun. Signal Process. (ICCSP)*, Apr. 2017, pp. 588–592.

[19] G. Van Houdt, C. Mosquera, and G. Npoles, "A review on the long short-term memory model," *Artif. Intell. Rev.*, vol. 53, no. 8, pp. 5929–5955, 2020.

[20] G. Shen, Q. Tan, H. Zhang, P. Zeng, and J. Xu, "Deep learning with gated recurrent unit networks for financial sequence predictions," *Proc. Comput. Sci.*, vol. 131, pp. 895–903, Jan. 2018.

[21] R. Dey and F. M. Salem, "Gate-variants of gated recurrent unit (GRU) neural networks," in *Proc. IEEE 60th Int. Midwest Symp. Circuits Syst. (MWSCAS)*, Aug. 2017, pp. 1597–1600.

[22] S. Selvin, R. Vinayakumar, E. A. Gopalakrishnan, V. K. Menon, and K. P. Soman, "Stock price prediction using LSTM, RNN and CNN-sliding window model," in *Proc. Int. Conf. Adv. Comput., Commun. Informat. (ICACCI)*, Sep. 2017, pp. 1643–1647.

[23] S. Aswin, P. Geetha, and R. Vinayakumar, "Deep learning models for the prediction of rainfall," in *Proc. Int. Conf. Commun. Signal Process. (ICCSP)*, Apr. 2018, pp. 657–661.

[24] R. Ma, X. Zheng, P. Wang, H. Liu, and C. Zhang, "The prediction and analysis of COVID-19 epidemic trend by combining LSTM and Markov method," *Sci. Rep.*, vol. 11, no. 1, pp. 1–14, Aug. 2021.

[25] H. Verma, S. Mandal, and A. Gupta, "Temporal deep learning architecture for prediction of COVID-19 cases in India," *Expert Syst. Appl.*, vol. 195, Jun. 2022, Art. no. 116611.

[26] M. O. Alassafi, M. Jarrah, and R. Alotaibi, "Time series predicting of COVID-19 based on deep learning," *Neurocomputing*, vol. 468, pp. 335–344, Jan. 2022.

[27] K. E. A. Kumar, D. V. Kalaga, C. M. S. Kumar, M. Kawaji, and T. M. Brenza, "Forecasting of COVID-19 using deep layer recurrent neural networks (RNNs) with gated recurrent units (GRUs) and long short-term memory (LSTM) cells," *Chaos, Solitons Fractals*, vol. 146, May 2021, Art. no. 110861.

[28] K. K. A. Ghany, H. M. Zawbaa, and H. M. Sabri, "COVID-19 prediction using LSTM algorithm: GCC case study," *Informat. Med. Unlocked*, vol. 23, Jan. 2021, Art. no. 100566.

[29] M. S. Pandianchery, E. A. Gopalakrishnan, V. Sowmya, V. Ravi, and K. P. Soman, "Explainable AI framework for COVID-19 prediction in different provinces of India," 2022, *arXiv:2201.06997*.

[30] M. Wang and W. Deng, "Deep visual domain adaptation: A survey," *Neurocomputing*, vol. 312, pp. 135–153, Jul. 2018.

[31] T. Li, A. K. Sahu, A. Talwalkar, and V. Smith, "Federated learning: Challenges, methods, and future directions," *IEEE Signal Process. Mag.*, vol. 37, no. 3, pp. 50–60, May 2020.

[32] S. P. Ramu et al., "Federated learning enabled digital twins for smart cities: Concepts, recent advances, and future directions," *Sustain. Cities Soc.*, vol. 79, Apr. 2022, Art. no. 103663.

[33] H. Pan, Y. Kwak, and B. Deal, "Participatory development of planning support systems to improve empowerment and localization," *J. Urban Technol.*, vol. 29, no. 2, pp. 33–54, 2022.

[34] H. Pan, S. Geertman, B. Deal, J. Jiao, and B. Wang, "Planning support for smart cities in the post-COVID era," *J. Urban Technol.*, vol. 29, no. 2, pp. 1–5, Apr. 2022.

[35] L. Liu, "Emerging study on the transmission of the novel coronavirus (COVID-19) from urban perspective: Evidence from China," *Cities*, vol. 103, Aug. 2020, Art. no. 102759.