Healthcare Operations and Black Swan Event for COVID-19 Pandemic: A Predictive Analytics

Jinil Persis Devarajan, Arunmozhi Manimuthu, and V Raja Sreedharan

***Abstract*—COVID-19 pandemic has questioned the way healthcare operations take place globally as the healthcare professionals face an unprecedented task of controlling and treating the COVID-19 infected patients with a highly straining and draining facility due to the erratic admissions of infected patients. However, COVID-19 is considered as a white swan event. Yet, the impact of the COVID-19 pandemic on healthcare operations is highly uncertain and disruptive making it as a black swan event. Therefore, the study explores the impact of the COVID-19 outbreak on healthcare operations and develops machine learning-based forecasting models using time series data to foresee the progression of COVID-19 and further using predictive analytics to better manage healthcare operations. The prediction error of the proposed model is found to be 0.039 for new cases and 0.006 for active COVID-19 cases with respect to mean absolute percentage error. The proposed simulated model further could generate predictive analytics and yielded future recovery rate, resource management ratios, and average cycle time of a patient tested COVID-19 positive. Further, the study will help healthcare professionals to devise better resilience and decision-making for managing uncertainty and disruption in healthcare operations.**

***Index Terms*—COVID-19 (novel corona), data analytics, deep learning, extreme learning machine (ELM), long short-term memory (LSTM), multilayer perceptron, prediction, time series.**

I. Introduction

A NOVEL strain of coronavirus named as 2019-nCov by the World Health Organization (WHO) causes severe acute respiratory syndrome and has a virulent effect on the hosts. The contagion potential of COVID-19 and its human–human velocity of transmission is much more alarming compared to other pandemics faced by the world [1]–[3], [48]. Moreover, the effect of COVID-19 on well-developed healthcare systems is massive and the fragile healthcare systems in developing countries such India are facing an alarming situation struggling to combat COVID-19 each passing day [2], [4]. Despite the sealing measures with stringent movements nationwide enforced by Governmental bodies, the evolution of new COVID cases is peaking almost exhausting the available healthcare resources and it was anticipated by the healthcare professional globally making it as a white swan event [79]. However, the healthcare service providers battling to decrease the morbidity and mortality due to COVID-19, other essential healthcare services provided to the public catering to other plethora of non-COVID related diseases and ailments have still got a setback in priority. Further, pandemic's impact on the *Fast-moving consumer goods* industry that supplies essential commodities is facing supply chain disruptions and struggling to handle the chaotic situation created by this pandemic to meet the erratic demands of the consumers exhibiting altered behavior trends due to the corona outbreak [5]–[7], [81]. Other sectors including agriculture, automobile, transportation, retail, and e-commerce industries are facing downtrends in terms of growth and productivity [8]. Hence, in order to tackle the shortage of essential resources and facilities and mitigate the impact of this pandemic on all sectors, the government is strategizing several actionable plans. Such uncertainty and disruption were not anticipated by the leaders globally, making the COVID-19 impact as a black swan (BS) event. Therefore, the COVID-19 outbreak was initially perceived as a white swan event. However, many nations and organizations neither anticipated nor prepared for such disastrous impacts of the pandemic hence making it as a BS event, and healthcare centers or COVID care centers are no exception to this event, and they were hugely disrupted due to the COVID-19 pandemic.

Further, to address the uncertainty and disruption, researchers are attempting to unleash and harness the potential of using artificial intelligence (AI) to devise solutions to some of these problems [9]–[11]. Based on these findings, the study proposes the following research question: ***How to manage healthcare operations for BS events such as COVID-19 pandemic through prediction models.***

To achieve this, a segmented Poisson model is proposed to predict daily new cases so that turning points in corona outbreaks can be identified which would help the governments to devise strategies and enforce regulations [35]. Moreover, few studies developed a cloud-based AI framework to obtain corona-related analytics, where a robust Weibull model is employed to predict corona cases in real-time across different countries. However, the performance metrics of the fitted model are not much encouraging in terms of the deviation between actual and predicted values [13]. Further, to understand the trend in prevalence

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and incidence of the pandemic, autoregression-based prediction models are developed [14]. Later, simulation-based predictive analytics of the pandemic spread is attempted by few researchers [2], [15], [16]. However, in the presence of incomplete and limited raw data, machine learning models and deep learning models that are composed of multiple levels of abstraction could draw out the intricate relationship structures present in the data [75]–[77], [88] for better combating COVID-19 in the healthcare environment.

II. Related Works

A. Understanding the BS Events

According to Taleb [89] "Black swan (BS) is a highly improbable event with three principal features: it is unpredictable; highly disruptive; and after its occurrence, we propose a justification making it less random and more probable, than it was in the beginning." Further, Taleb goes on by explaining that the challenge is – "Lack of knowledge when it comes to rare events with serious consequences." Further, to understand BS clearly, we need to understand similar events such the White Swam (WS) and Grey Swam (GS).

A white swan is a highly assured event with three principal qualities: it is certain; its impact can easily be projected; and, after the event, we make a portrayal of the event which can be well recognized, and any mistakes in judgment are related to ambiguity in decision making [79]. Only difference between a WS and GS is that impact of a GS event can be predicted with propagating effect. Based on this assumption, Taleb says, the COVID-19 pandemic was a WS event. However, as COVID-19 spread across the world, it creates a huge ripple affecting our daily life and its huge, massive impact is highly unpredictable in nature affected with several uncertain events. For example, the healthcare professional has seen the impact of the SARS and MERS virus in the past and their impact. Still, combating COVID-19 was a daunting task in healthcare operations. Further, the countries initiated lockdown and healthcare centers faced a sudden influx of patients. Such a situation was one-of-a-kind situation and has never occurred globally. Also making it as a first-time experience to healthcare professionals and their inexperience to handle serious event/crisis constituted a BS. So, the COVID-19 outbreak initially considered as a WS event later turned out to be a BS event due to its devastating impact on healthcare operations around the world and highly disrupted the hospitals and healthcare centers leaving decision makers ambiguous and perplexed [77], [88]. Further, according to the *Black Swan Theory (BST)*, a BS event consists of five tenets [75]–[80]. They are as follows.

1) Under the rubric of the BST, the first tenet is that an entirely unexpected outlier with little or no reference model to work with.
2) Second, appear to be retrospectively expected and predictable. For example, the case of the financial crisis in 2008.
3) The aforesaid "retrospective predictability" is linked to the third tenet of BST; that BS often arise due to a human illusion of awareness. Here, we tend to assume that readily we can identify monocausal inputs forming a given result. However, the truth is yet to be explored.
4) Fourth tenet, is in terms of implications, for example, can be found in the case of Apparel Industries, which started producing face masks and minimized the cloth production and diversifying from the traditional practices which rarely goes along their expected trajectory in their field of application.
5) Fifth, humans are tricked into substantially similar but entirely different descriptions for events. Taleb [89] points out that the individuals muddling the two subtle terms "no indication of disease" and "indication of no disease," which are totally different scenarios projected in a similar way.

Based on the five tenets, it is obvious that the COVID-19 and its impact on healthcare operations is a BS event. Therefore, the present study has attempted to develop a prediction model to forecast daily new and active corona positive cases using time series analysis and simulation models to aid medical professionals in making a better decision for efficient resource utilization and provide better patient care for disruptive events.

B. COVID 19 Outbreak

In March 2020, the WHO confirmed that the COVID-19 as a global pandemic is threatening many countries worldwide. After the WHO's announcement, all the country heads ordered mandatory lockdowns for all citizens to curb the virus spread [48]. However, the spread of the COVID-19 virus is rapid and many are being affected. Due to this, there is a sudden rise in COIVD-19 positive cases in the hospitals. Furthermore, the healthcare professionals and frontline workers struggle as the present healthcare operations are more likely to be efficiency-driven with optimized resource utilization. The sudden surge in demand for healthcare facilities that are unpredicted and unforeseen by the healthcare professionals is the biggest challenge disrupting the conventional healthcare operations [52], [59]. The healthcare systems are overwhelmed with corona-positive cases every day, each with varied levels of infection, differently activated immune systems, comorbidities, and differently symptomatized COVID-related conditions which may lead to hard to predict demand for treatment facilities [22]. While predicting the demand for healthcare facilities is very hard, researchers are struggling to predict the COVID outbreak in nations quantitatively because of the huge variation in the progression rate, duration of spread, and significant turning points in the outbreak with respect to countries, terrains, people in terms of their immune systems and their behavioral aspects and governance [26]. Further, healthcare operation was highly disrupted, and its operations become tedious to the COVID-19, which is elaborated in the following section.

C. Healthcare Operations in Crisis

Nowadays the healthcare services are in high demand as the global population is affected by the novel coronavirus. In the past, virus from the similar family affected many people in Asian countries and created a lot of stress on healthcare operations [11]

Further, the aging population with other comorbid conditions requires advanced healthcare services making the healthcare operations more difficult to manage. Moreover, the healthcare organizations are pluralistic in nature, where multiplayers such as physicians, nurses, medical professionals, consultants, and staff members work together to provide essential services to the patients whose demand also increases [9], [19]. As, the demand for patient care increases, the operation becomes tedious and challenging too. Further, the allocation of resources such as bed, equipment, life support system, and medicine require detail planning by the hospital administration [20], [76]. Moreover, planning of such operations is crucial as it ensures the well-being of the patient. Also, the performance of the healthcare systems is challenged because of the disproportionate demand and supply leading to poor treatment or delay in in-patient services [12], [13]. Further, as the multiple players work together, decision making is highly influenced and may lead to bias in some cases, further deteriorating the performance. Hence, in the case of COVID-19 scenario, the main challenge is to match the supply and demand in the healthcare operations. The existing models are not able to respond to the dynamic demand of the COVID cases.

Based on the learning from the past pandemic, WHO supported all countries in relief measures toward the contagious disease and other pandemics [52]. Further, people living in overcrowded areas are more exposed and with poor sanitation and lack of other basic facilities could not isolate them. Also, several healthcare organizations are taking initiatives by sharing information through platforms and crowdfunding to provide testing kits and clinical supplies to the needy. Also, the specialized biocontainment unit used for other deadly diseases can be altered to treat COVID-19 patients [52]. So, based on these findings, the authors are motivated to examine the number of COVID-positive patients incoming to healthcare systems everyday and the number of COVID-positive patients remaining in the healthcare systems every day after recovery or mortality and develop accurate prediction models using machine learning approaches to support the healthcare professionals and ensure seamless healthcare operations for better patient wellbeing [90]. Since many minute micro-level heterogeneous factors related to COVID infection, symptoms, detection, treatment, and recovery are unknown yet, macro-level analyses and study of life-cycle-long factors affecting in-patient services are being studied [18]. Hence, foreseeing COVID cases help better preparedness in corona care centers. Moreover, it is important to predict the future course of COVID-19 in order to increase public awareness, improve preparedness, and develop resilient healthcare systems capable of handling the disruption and uncertainty in the decision making imposed by the COVID-19 pandemic.

D. *Time Series Analysis*

This article considers time-series-based prediction modeling, as the COVID outbreak is stimulated by events differently timed in different places, and once introduced at a place, it follows a unique growth pattern based on several unknown, uncertain, and complex factors [19]. Luo [18] has suggested to consider predictive monitoring of macro-level life-cycle-long parameters which require forward-looking signals depicting future scenarios. Hence, in this article, monitoring conditions of resources and patients and thereby managing healthcare operations and devising strategies and policies are based on two important signals such as predicted new and active cases. Prediction models to accurately forecast these signals are developed in this article.

Time series analysis of the data is traditionally used to analyze the trend in the evolution of variables over a period of time due to the occurrence of various unpredictable events in the environment and helps to predict the future data points [20]. Commonly used quantitative time series forecasting methods include regression methods, smoothing methods, autoregressive methods, and machine learning methods [21], [22]. A time series can be mathematically represented as $Y = \{y_1, y_2, y_3, \ldots, y_t\})$ which represents the chronological sequence of values of time series variable *Y* that evolved over a time period *t*. By observing the statistical properties of a time series over a time period, future values $\{y_{t+1}, y_{t+2}, y_{t+3}, \ldots\}$ can be forecasted which can be used effectively in planning, decision making, and policy making [23]. Theoretically, time series includes trend, seasonal, and random error components that affect its stochastic behavior [24]. Stochastic time series data can be modeled using regression methods by removing the trend and seasonality effects [25]. The random irregular patterns that introduce noise in the time series are tackled by smoothing methods [26], [27]. Due to uncertain and independent events occurring during the observation time period, time series variable exhibits noise patterns and smoothing methods attempt to segregate data signal and noise from every data point observed during the time period. The dependent structure of events occurring during the observed time period introduced stochastic behavior alongside deterministic behavior [28]. Such stationary time series can be addressed by using autoregressive models and machine learning models [29]–[31]. Due to the occurrence of extreme events in highly dynamic systems, time series exhibit sudden bursts and jumps making it nonlinear which could be effectively dealt with deep learning [23], [32].

E. *Univariate Time Series Models*

Literature addresses several time series process such as condition monitoring of machines/engines [33], [85] demand prediction [34], and price prediction [35]. Univariate time series analysis is extensively studied and statistical regression-based methods are widely employed assuming that the time series variable has a linear relationship with time [36]. Such nonstationary time series exhibiting trends can be modeled using regression. The mathematical representation of regression model of a univariate time series is represented as

$$y_t = \beta_0 + \beta_1 t + \varepsilon_t \tag{1}$$

where y_t is the time series variable at time *t*, β_0 and β_1 are regression coefficients, and ε_t is the error term. In order to obtain this model, it is essential to estimate the model parameters ($\beta_0,\ \beta_1$) with the historical data using the least squares estimation method [37], [38]. This process is often termed as fitting or learning. Assuming that the data during time period T is known, the values of $\widehat{\beta_0}$ and $\widehat{\beta_1}$ can be estimated by minimizing the lease square function which is represented as

$$L_{(\beta_0,\,\beta_1)} = \sum_{t\in T}\varepsilon_t^2 = \sum_{t\in T}(y_t-\beta_0-\beta_1 t)^2. \tag{2}$$

The values of $\widehat{\beta_0}$ and $\widehat{\beta_1}$ can be obtained by solving the following first-order partial differential equations

$$\frac{\partial L}{\partial\beta_0} = 0 \text{ and } \frac{\partial L}{\partial\beta_1} = 0. \tag{3}$$

1) Statistical Methods: It is a statistical univariate time series model that also assumes a linear relationship between time and the predicted variable and hence would not be able to tackle nonlinear properties of the time series variable. However, autoregressive integrated moving average models or ARIMA models or Box-Jenkins models can be developed to tackle nonhomogeneous behavior of time series exhibiting random statistical properties with respect to time [14], [14], [30], [39]–[42]. Such stationary time series assumes that 1) expected value of a time series variable $E(y_t)$ does not depend on time *t*. (2) The autocovariance function $\mathrm{cov}(y_t, y_{t+k}) = f(k)$ where *k* denotes the time lag. Hence, ARIMA model considers dependent relationship an observation and some lagged observations and uses differencing technique to make the time series stationary if required and then applies smoothing methods on lagged observations. ARIMA (*p, d, q*) model where *p* representing the number of lagged observations, *d* representing the degree of differencing, and *q* representing the order of moving average [43]. Autoregressive model with *p* lags and *q* number of moving averages can be represented as

$$\begin{aligned} y_t &= \mu + \psi_1\, y_{t-1} + \psi_2 y_{t-2} + \ldots + \psi_p y_{t-p} - \varepsilon_t \\ &\quad - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \ldots - \theta_q\varepsilon_{t-q} \end{aligned} \tag{4}$$

where $\psi_1 \ldots \psi_p$, $\theta_1 \ldots \theta_q$are model parameters, *p* and *q* are the hyperparameters, and y_{t-i} is a lagged observation sequence which is sequence lagged by *i* from the original sequence. Introducing backward shift operator, *B*, such that B^k $y_t = y_{t-k}$, the model can be represented as

$$\psi\,(B)\,\nabla^d\, y_t = \theta_0 + \theta\,(B)\,\varepsilon_t \tag{5}$$

where

$$\psi\ (B) = 1 - \sum_{i\,=\,1}^{p}\psi_i B_i \tag{6}$$

$$\theta\ (B) = 1 - \sum_{i\,=\,1}^{q}\theta_i B_i. \tag{7}$$

Here ∇^d represents the differencing operation where *d* is the hyperparameter that denotes the number of differencing operations that are needed to transform it to stationary time series.

2) Machine Learning Methods: Machine learning helps to develop data-driven decision-making tools for healthcare [77], [88], managing supply chain [78], [80], [89], agriculture [45]–[47], so on and so forth. Machine-learning-based forecasting models enable accurate predictions with high dimensional, instable, and nonlinear data [21],[86]. In this article, the dataset consisting of time series of new corona cases and active cases every day is characterized with stationarity and nonlinearity, and hence, machine learning techniques and deep learning techniques are explored [87]. Machine learning methods take the input samples that are transformed into suitable representations and split them into training and test data points and apply a learning mechanism to construct a prediction rule and develop a fitted model [48]. This model is further evaluated with the test data points and the performance of the model is investigated. Deep learning techniques further analyze the data in multiple levels of abstraction to capture representative patterns available in the data [17].

Extreme learning machine (ELM) is a fast learning machine with a higher level of generalization capability that is constructed with a single-hidden layer feed-forward neural network [33], [49]–[51]. The hidden layer is made up of a suitable number of hidden nodes which is an important hyperparameter of the learning method. The input layer of the ELM takes a proportion of data points as training input and assigns specific random input weights to each node which is then given to the hidden layer. Suppose there are *n* training samples and *i*th instance can be represented as $(y_i, t_i)|y_i \in \mathcal{R}^n, t_i \in \mathcal{R}^n$ where $y_i = [y_{i1}, y_{i2}, \ldots, y_{in}]^T$ and $t_i = [t_{i1}, t_{i2}, \ldots, t_{in}]^T$ having random input weight vector, $w_i = [w_{i1}, w_{i2}, \ldots, w_{in}]^T$. If a hidden layer has *m* nodes with activation function *g*(*t*), ELM model can be mathematically represented as

$$\sum_{i\,=\,1}^{m}\beta_i g_i\,(t_j) = \sum_{i\,=\,1}^{m}\beta_i g_i\,(w_i.t_j + b_i) = \hat{y}_j;\, \forall j = 1,\ldots,N \tag{8}$$

where $\beta_i = [\beta_{i1}, \beta_{i2}, \ldots, \beta_{in}]^T$ is the weight vector connecting nodes of the hidden layer to the output layer, b_i is the threshold of the *i*th hidden node. ELM generalizes the *n* training samples with *m* hidden nodes through the activation function iteratively, and if the predicted values $\hat{y}_i = [\hat{y}_{i1}, \hat{y}_{i2}, \ldots, \hat{y}_{in}]^T$ yield zero errors, then w_i, β_i, b_i exist for every sample by applying Moore–Penrose generalized inverse [23], [33], [35], [51]–[53] of the hidden layer to output layer such a way that

$$\sum_{i\,=\,1}^{m}\beta_i G\,(w_i.t_j + b_i) = y_j;\, \forall j = 1,\ldots,N. \tag{9}$$

The above equation attempts to equalize y_j *and* $\widehat{y_j}$ by applying $Y = L.\beta$. The output weights can be determined by Moore–Penrose generalized inverse of matrix *L* as $\beta = \grave{L}\ .Y$. Unlike artificial neural networks [54], [87], the weight vector is not updated iteratively and each sample goes through a single step wherein the output weight vector is determined using Moore–Penrose generalized inverse and hence converges fast and generalizes the input samples at high speed.

Feedforward multilayer perceptron (MLP) is a deep learning network where an artificial neural network is integrated with backpropagation algorithm for training the network to model nonlinear stationary time series [55]–[59]. It consists of an input layer with one or more lagged observations, one or more hidden layers, and an output layer. Consider *m* sets of lagged observations of $\{y_{t-1}, y_{t-2}, \ldots, y_{t-m}\}$ that are fed into the input layer, which are then presented to a hidden layer having *n* nodes. MLP model that yields the predicted values is mathematically represented as

$$\hat{y}_t = w_0 + \sum_{j=1}^{n} w_j f\Big(\sum_{i=1}^{m} \beta_{ij} y_{t-i} + \beta_{0j}\Big) + \varepsilon_t \qquad (10)$$

where $w_i = [w_{i1}, w_{i2}, \ldots, w_{in}]^T$ is the weight vector between the hidden layer and the output layer, β_{ij} is the weight vector between the input layer and hidden layer, and *f* is the nonlinear activation function. Here a sliding time window method is used to set up lags.

Long short-term memory (LSTM) is a variation of recurrent neural network used to predict nonlinear time series data which uses internal memory to remember both long-term and short-term values of the time series variable [60]–[64]. LSTM networks also consist of input layer, hidden layer, and output layer and are constructed with units having a memory cell and the units together form LSTM layer. Each unit consists of input, output, and forget gates which are used to remember values for a certain length of time.

Consider an input and output sequences, y_t, $\hat{y}_t$ where $t = \{12, \ldots T\}$ denotes the time period over which the input sequence y_t is observed. Each LSTM unit receives input y_t and computes $\hat{y}_t$ by considering the state of the previous hidden node, h_{t-1}. Consider weight vectors w_i, w_f, w_c, w_o, w_y and biases b_i, b_f, b_c, b_o, b_y for computing input value, forget value, current state value, output value, and predicted value, respectively, which are computed iteratively by backpropagation algorithm. The input gate computes i_t, which is to be stored in the current unit state and a candidate state for future, forget gate computes f_t which is to be forgotten from the previous cell state, and updates the current state by replacing the old state and the output gate computes o_t which is then used to compute the desired $\hat{y}_t$ by filtering the new state [65]. This process can be represented using the following equations:

$$\text{Input gate}: i_t = g1\left(w_i.\left[h_{t-1}, y_t\right] + b_i\right);$$
$$\widehat{c_t} = g2\left(w_c.\left[h_{t-1}, y_t\right] + b_c\right). \qquad (11)$$
$$\text{Forget gate}: f_t = g1\left(w_f.\left[h_{t-1}, y_t\right] + b_f\right);$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \hat{c}_t \qquad (12)$$
$$Output\ gate: o_t = g1\left(w_o.\left[h_{t-1}, y_t\right] + b_o\right);$$
$$h_t = o_t \odot g2\left(c_t\right); \hat{y}_t = g3\left(w_y h_t + b_y\right) \qquad (13)$$

where *g1, g2,* and *g3* are the activation functions and $\odot$ is the element-wise product of the vectors which is called as Hadamard product [62]. The memory in each unit allows it to consolidate the values over a period of time and observe the long-term properties. During training, the input sequence and the output sequence are compared to obtain loss function of ε_t which could be mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), or mean absolute percentage error (MAPE). This is used to update the weights and hence fed back to the LSTM units. The hyperparameters of the LSTM network are hidden layers, nodes in each hidden layer, momentum values, initial weights, epochs, optimization algorithms, activation functions, decay rate, learning rate, batch size, number of units in LSTM layer, dense layer and dropout layers, gradient normalization [62], [66].

F. *Multivariate Time Series Models*

Multivariate time forecasting are complex problems that often exist in real-world situations where more than one strongly temporally correlated variables that have nonlinear relationships often together affect the system dynamically and hence generalizing a prediction model which is a function of these variables is a difficult task [22], [67], [68]. Consider two-time series y_{1t} representing a number of new COVID cases per day and y_{2t} representing a number of active COVID cases per day.

1) Statistical Methods: Multivariate ARIMA(p,q) model (MARIMA) is another multivariate time series analysis method in which k-variate backward shift operator is defined that can be represented as

$$\left(I + \psi_1 B + \cdots + \psi_p B^p\right)\ y_t = \left(I + \theta_1 B + \cdots + \theta_p B^q\right)\ \varepsilon_t \qquad (14)$$

where *I* is the $(k \times k)$ identity matrix and the short form can be written as

$$\psi\left(B\right)\ y_t = \theta\left(B\right)\varepsilon_t$$
$$y_t = \psi^{-1}\left(B\right)\theta\left(B\right)\ \varepsilon_t = \phi\left(B\right)\varepsilon_t \qquad (15)$$

such that $\phi(l) \rightarrow 0\ \ for\ \ l \rightarrow \infty$ a decreasing function. Similarly,

$$\varepsilon_t = \theta^{-1}\left(B\right)\psi\left(B\right)\ y_t = \pi\left(B\right)\varepsilon_t \qquad (16)$$

vector autoregression (VAR) model is used in multivariate time series analysis extensively which is also an extended version of univariate autoregression models [69]. *p*-lag vector autoregressive model can be represented as

$$y_{1t} = a_1 + \pi_{11}^1 y_{1t-1} + \pi_{12}^1 y_{2t-1} + \pi_{11}^2 y_{1t-2} + \pi_{12}^2 y_{2t-2} + \cdots + \varepsilon_{1t} \qquad (17)$$

$$y_{2t} = a_2 + \pi_{21}^1 y_{1t-1} + \pi_{22}^1 y_{2t-1} + \pi_{21}^2 y_{1t-2} + \pi_{22}^2 y_{2t-2} + \cdots + \varepsilon_{2t} \qquad (18)$$

where *p* is the number of lagged observations and π represents the matrix that shows the dependence between lagged observations of both y_{1t} and y_{2t}.

2) Machine Learning Methods: Learning-based multivariate time series analysis is gaining importance nowadays because of the capability of these algorithms to understand the nonlinear dependencies between the multiple time series variables and accurately predicting them [75]. Deep learning architectures such as LSTM are extensively studied to develop prediction models for various real-world applications. Univariate LSTM is presented in the previous section which is found to be very accurate to make short-term predictions by observing long-term dependencies [66]. Here LSTM layer takes input from the previous LSTM layer or input layer which feeds the lagged observation sequences into each LSTM unit present in the layer. The training phase of the multivariate LSTM model can be performed in multiple steps or parallel together. In this article, bivariate time series of new and active corona cases are analyzed using LSTM in parallel simultaneously and the results are obtained.

G. Simulation of Healthcare Systems

Simulation analysis of the global supply chains due to the coronavirus outbreak is presented to assess the performance of supply chain, time to recover, critical disruption time, and propagation rate of disruptions [8]. These analyses have made better visualization of risk assessment leading to alternative supply chain designs and backup routes to improve supply chain resilience amidst pandemics. Based on simulation experiments, COVID recovery and fatality rates are identified with a 90% confidence level in the People's Republic of China using the Levenberg–Marquard algorithm [70], [72]. The relationship among vulnerable, unprotected, infected, and recovered COVID cases are also explained using simulation model using Markov chain Monte Carlo algorithm and protection, infection, cure and mortality rates, average incubation, average quarantined times are established [2]. Crisis management drills are carried out virtually and discrete event simulation is used to generate uncertain events and the key performance parameters are obtained [71]. Outpatient flow in hematology–oncology clinic is modeled using discrete event simulator to understand the dynamics of the healthcare and to reduce waiting times and various performance measures such as average time to prepare, time to analyze, throughput, complaints are assessed [72]. Thus, the authors in this article propose an integrated COVID management model consisting of prediction and simulation frameworks and establish critical performance parameters from the system such as patients' recovery, mortality, progression and growth rates, and resource management ratios.

III. Research Methods

To develop prediction models for forecasting the course of COVID in the future, experiments are conducted in the R platform using open source COVID datasets [18]–[20]. Therefore, the study focused on predicting the COVID patient admission in the healthcare environment based on information from the public health department. Moreover, the performance of the prediction models relies on the nature of the data and its characteristics, and hence it is very critical to select appropriate methods in modeling and analysis [21]–[23]. The prediction results are fed to the COVID healthcare management system and the healthcare operations carried out and the patients' flow are simulated to assess and monitor critical parameters.

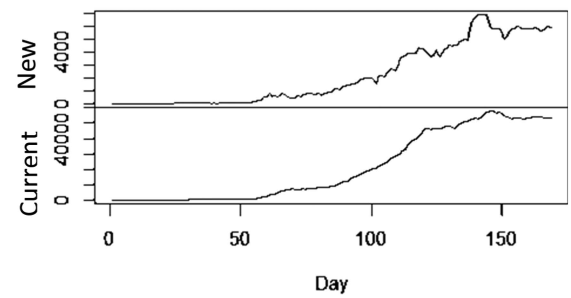

Fig. 1. Time series plot of new and active cases per day.

A. Dataset

Corona pandemic has hit many countries across the world. Novel coronavirus was first identified in late 2019 and the spread is rapidly virulent that by mid-2020 more than 6 million people were infected with COVID.[1] In the absence of a vaccine or other drugs to treat COVID positive cases, the government is regulating different policies to exercise social distancing through lockdown measures to curb the spread of this disease. However, there is a serious need for technology interventions to help manage, mitigate, and control this problem by developing various novel solutions through analytical modeling using public health data captured in various online repositories [83]–[84]. The daily progression of COVID in different countries is present on different websites. For experimental purposes, a daily burst of corona-positive cases in the southern part of India is obtained. India has the largest number of corona-positive cases identified so far in Asia as of May, 2020. Indian Council of Medical Research has approved reverse transcription polymerase chain reaction (RT-PCR) kits and more than 4 million people are tested for COVID as of now and the positive cases are admitted to specific healthcare systems for rigorous treatments.[2] The data including the number of new cases and active cases present every day, the number of samples collected, the proportion of positives and negatives across various states are presented in the repositories. The number of active cases that prevail every day with corona positive results and the number of new confirmed cases in a particular region for about 169 days from the first day of the COVID outbreak are taken into consideration in this study.[3] The time series plot of the evolution of new COVID cases and active cases in a particular region considered in this article is presented in Fig. 1. The time series plot helps to understand whether trend and seasonality exist in a dataset (refer Fig. 1).

The statistical analysis of the collected data is presented in Table I.

The COVID dataset used in this article consists of two-time series data viz, new cases and actives cases every day from the first day of the outbreak. The time series plot shows that the new cases fluctuate due to various events that happen in the region, however, active cases show an increasing trend over the considered time period (refer Fig. 1). The autocorrelation

[1] [Online]. Available: https://coronavirus.jhu.edu/map.html
[2] [Online]. Available: https://www.icmr.gov.in/
[3] [Online]. Available: https://stopcorona.tn.gov.in/

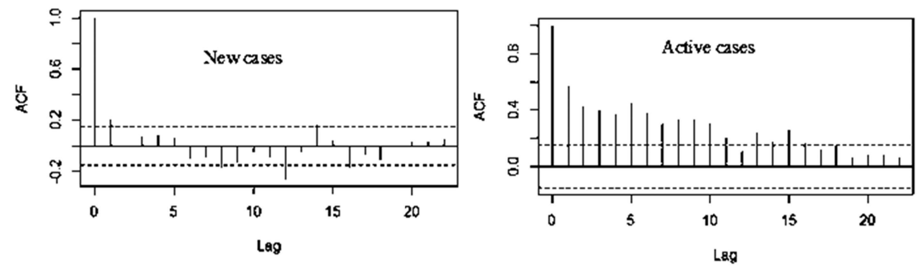

Fig. 2. ACF plots.

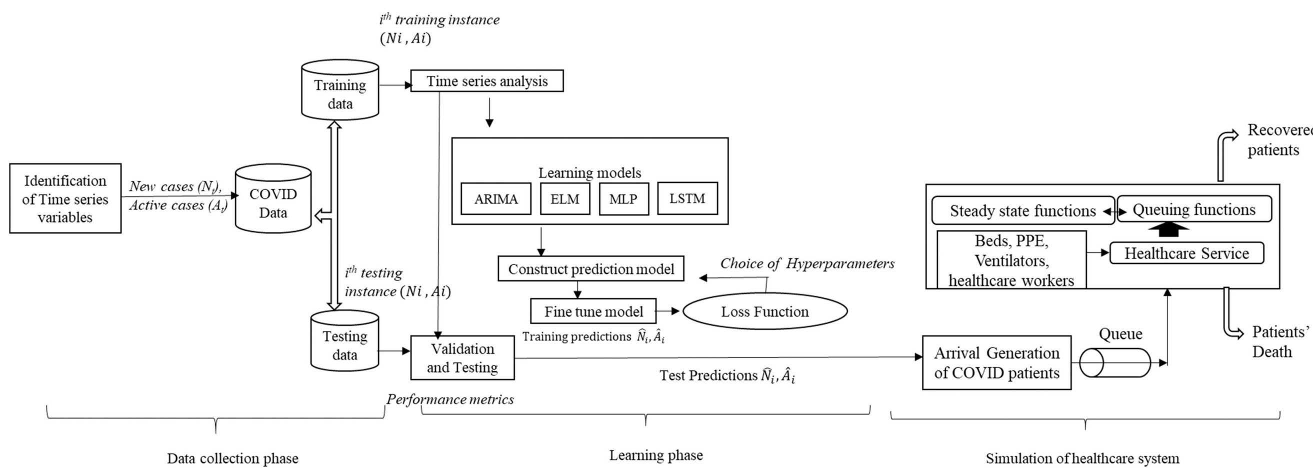

Fig. 3. Research framework.

TABLE I
STATISTICAL ANALYSIS OF TIME SERIES DATA

Time series	*Current*	*New*
Mean	21287.66	2209.83
Standard Error	1698.12	180.71
Median	9021	938
Mode	1	0
Standard Deviation	22075.57	2349.26
Sample Variance	487330625.3	5519025.91
Kurtosis	-1.48	-1.15
Skewness	0.51	0.65
Range	57967	6993
Minimum	1	0
Maximum	57968	6993

function (ACF) that yields the autocorrelation values of the time series at lagged intervals are presented in Fig. 2.

From Fig. 2, it can be observed that the time series of new and actives cases are found to have stationary patterns. It can also be observed from the time series plots that there are sudden bursts and jumps present in both series.

B. Model Development

In this article, univariate prediction models are developed for forecasting new and active COVID cases daily by considering them as two different series and multivariate prediction models considering both the series viz., new and active COVID cases together [82]. Though autocorrelation due to temporal heterogeneity occurs in the time series of both new and active corona-positive cases over the observation period, the degree of autocorrelation varies across the time. Hence, it is essential to investigate the problem as both univariate and bivariate to observe possible improvement in prediction accuracy. The best model will be selected and further used in the simulated healthcare management system for assessing and monitoring important parameters such as status of resources and patients' recovery which further leads to better planning of healthcare operations. The research framework is presented in Fig. 3. In this study, based on the characteristics of data drawn out in the previous section, the methods such as ARIMA, ELM, MLP, and LSTM are used to develop predicting models to forecast active and new cases of corona positives every day using time series analysis [14], [39]. In general, COVID prediction models can be developed by obtaining relevant time series. Here time series data of new cases and active cases of corona positives are considered. The dataset consists of daily new and active cases from the first day of the outbreak till August 22, 2020. The dataset is classified into training and test datasets using 70:30 ratio, which is set based on repeated simulation runs. The training phase constructs the prediction through the forecasting method selected. Also, univariate time series analysis is done to realize the course of new cases every day in terms of evolving and active cases remaining after possible recovery or mortality individually.

The dependency of these two-time series varies over the period and due to the variation in the spread rate and recovery rate. Hence, it is also important to perform multivariate time series analysis of these two variables together which could possibly help to understand the progression of the virus. During training, the prediction model is constructed based on the training instances iteratively. However, for ARIMA- and ELM-based prediction models, in order to address temporal heterogeneity in the time series, different time lags of the training instances are generated which are then fed into ARIMA and ELM models. Experiments on ARIMA-based univariate linear time series analysis has been carried out using "forecast" package in R[4]. Since the time series plot (refer Fig. 1) exhibit stationarity due to the spatial heterogeneity in the time series, autoregressive forecasting method such as ARIMA is used to develop a prediction model. "nnfor" package in R is used to carry out time series forecasting using machine learning models such as ELM and MLP with high performance and less training time.[5] Also due to the presence of nonlinearity in the time series, the deep learning LSTM model is also developed in this article using "keras" package[6] with "tensorflow" interface.[7] Also, bivariate prediction models are developed by considering the correlation between new and active corona positives together using VAR, MARIMA, and LSTM techniques. "vars,"[8] "marima"[9] packages in R are used to develop bivariate prediction models using VAR and MARIMA. Because of the computational complexity in the multilevel LSTM Google Colab platform in Python is used to develop a bivariate prediction model using LSTM [40]. The fitted models developed are iteratively fine-tuned to minimize the deviation of the predicted values from the actual values. The hyperparameters of the models are set at which the deviation is minimum or zero. The parameters of the models are identified based on repeated simulation runs. In the testing phase, the test dataset is used. The models forecast the future values in the test period and actual values are compared. From the deviation between the actual and predicted values, many important statistics can be obtained about the performance of the developed models. Consider n test datapoints of new and active cases on jth day, represented as N_j and A_j, respectively. If $\hat{N}_j$ and $\hat{A}_j$ are the predicted values obtained from a model, then MAPE can be expressed as

$$\mathrm{MAPE} = \frac{1}{n} \sum_{j=1}^{n} \left| \frac{\hat{N}_j - N_j}{N_j} \right|. \tag{19}$$

MAE can be expressed as

$$\mathrm{MAE} = \frac{1}{n} \sum_{j=1}^{n} \left| \hat{N}_j - N_j \right| . \tag{20}$$

MSE can be expressed as

$$\mathrm{MSE} = \frac{1}{n} \sum_{j=1}^{n} \left(\hat{N}_j - N_j \right)^2. \tag{21}$$

RMSE can be expressed as

$$\mathrm{RMSE} = \sqrt{\frac{1}{n} \sum\nolimits_{j=1}^{n} \left(\hat{N}_j - N_j \right)^2} . \tag{22}$$

Similarly, MAPE, MAE, MSE, and RMSE are determined for predicting actual cases using different prediction techniques.

The forecasted data having new and active COVID cases can be fed into a simulated model of the healthcare management system. The simulated model generates new and active COVID cases by capturing the evolution of these values in the dynamic system over a period of time. Based on the theory of eigenvalues and eigenvectors, steady-state solutions are obtained and stability of the system is further examined. The COVID management model is presented in Fig. 4.

IV. Results and Discussion

In this section, the application of various forecasting methods on COVID prediction and their evaluations are presented.

A. *Results of Univariate Time Series Models*

Univariate time series analysis using ARIMA, LSTM, ELM, and MLP on daily new and active corona cases in the southern part of India has been performed individually. The time-series data of new and active cases are obtained through an open source repository,[10] and 169 data points are obtained out of which 118 data points are used for training and 51 data points are used for testing and validation. The predicted values of new and active cases each day are obtained during the training and testing phase for various forecasting techniques are plotted along with the actual values in Figs. 5 and 6, respectively.

It can be observed from Figs. 5 and 6 that the new and active cases over the time period fluctuate due to various dependent or independent events that occur during the pandemic outbreak such as immigration/emigration of people, mass gathering that happened in the near past, lockdown imposition, so on, and so forth during the outbreak. From Fig. 5, it can be understood that ELM has yielded close results with the actual new cases that are experienced during the spread. Fig 6 reveals that ELM has yielded close results with the actual active cases that exist every day during the spread. The performance of the prediction models developed is determined with the test dataset. The prediction models are trained using the instances of the first 118 days of the outbreak. The new cases and active cases for the next 51 days are predicted by the models, and ELM and MLP based models have generalized well when compared to other models. ELM applies batch and incremental learning in single-layered artificial neural network architecture whereas MLP applies deep learning in multiple-layered artificial neural network architecture. The predicted results are compared with the actual values from the test dataset and the results are presented in Table II.

[4][Online]. Available: https://cran.r-project.org/web/packages/forecast/index.html

[5][Online]. Available: https://cran.r-project.org/web/packages/nnfor/

[6][Online]. Available: https://cran.r-project.org/web/packages/keras/index.html

[7][Online]. Available: https://cran.r-project.org/web/packages/tensorflow/index.html

[8][Online]. Available: https://cran.r-project.org/web/packages/vars/index.html

[9][Online]. Available: https://cran.r-project.org/web/packages/marima/

[10][Online]. Available: https://stopcorona.tn.gov.in/

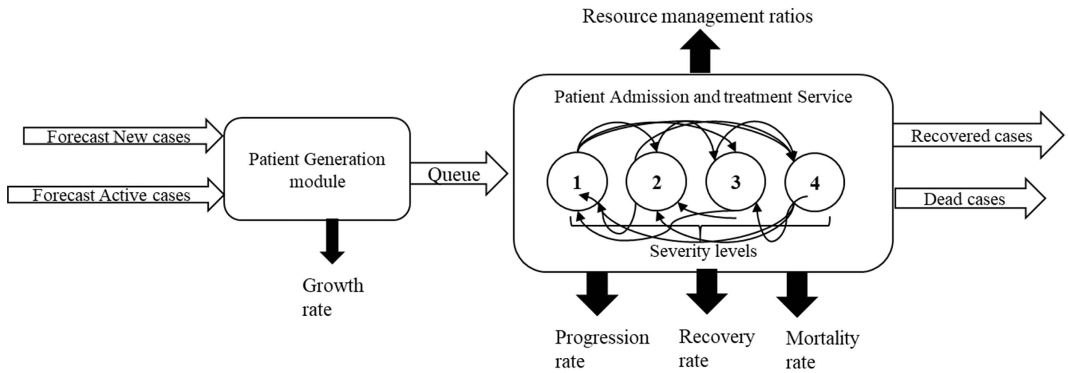

Fig. 4 COVID healthcare management system.

TABLE II
PERFORMANCE OF UNIVARIATE TIME SERIES MODELS

Time Series	**New COVID Cases**			**Current COVID cases**		
Metrics	MAE	RMSE	MAPE	MAE	RMSE	MAPE
ARIMA	3677.83	4292.98	0.67	35307.36	43541.21	0.66
LSTM	1623.54	1661.19	0.30	13722.04	14014.80	0.26
ELM	485.58	686.90	0.09	5137.19	7027.33	0.10
MLP	667.91	845.96	0.12	11145.41	13255.66	0.21

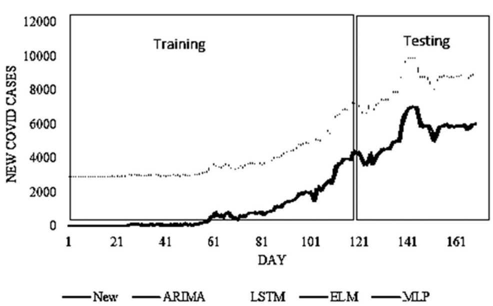

Fig. 5 Actual versus predicted values of new cases.

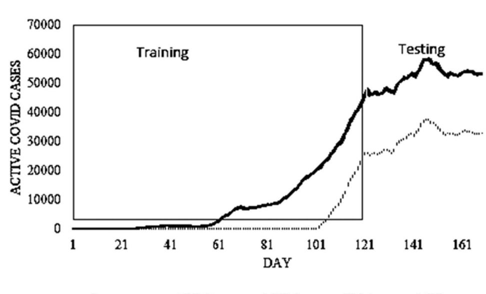

Fig. 6. Actual versus predicted values of active cases.

It can be observed from Table II that in case of predicting new/active cases ELM and MLP yield minimum error and hence show better performance measures when compared to LSTM and ARIMA. Hence it can be concluded that the time series of new and active cases have non-linear temporal relationships and therefore machine learning methods yield better results when compared to regression-based methods and recurrent learning.

B. Results of Multivariate Time Series Models

In this section, the performance metrics obtained by applying VAR, MARIMA and LSTM techniques for forecasting multivariate time series data (N_t, A_t) are presented in Table III.

It can be observed that multivariate time series of new and active cases every day increases the deviation between actual and predicted values thereby increasing the error in prediction (refer Table III). The performance measures of the techniques in predicting multivariate time series are more than that of the univariate time series (refer Tables II and III). Hence, it is better to develop univariate time series models. In this article, multivariate and univariate models are developed using regression and machine learning methods. The selection of suitable prediction models based on the behavior and characteristics of time series can be made based on the following framework and how the healthcare management system can be simulated driven by the prediction model is presented in Fig. 7.

Moreover, Janssen and van der Voort [91] buttressed the importance of the adaptive mechanism to predict the COVID-19 outbreak and the deployment model (refer Fig. 7) can serve as an adaptive mechanism to evaluate the growth rate, severity progression rate, recovery rate, resource management rate for the new cases, and create an agile environment for rapid response and improve the healthcare operation. These prediction models are no doubt helpful in planning and scheduling healthcare operations. According to healthcare professional's

TABLE III
PERFORMANCE OF MULTIVARIATE TIME SERIES MODELS

Time series	**New cases**			**Active cases**		
Metrics	MAE	RMSE	MAPE	MAE	RMSE	MAPE
VAR	1181.389	1302.509	0.24	53108.22	53248.54	10.12
MARIMA	5054.361	5164.84	0.93	2805.473	2957.382	0.57
LSTM	50853.46	50996.1	98.29	4996.721	5083.567	92.42

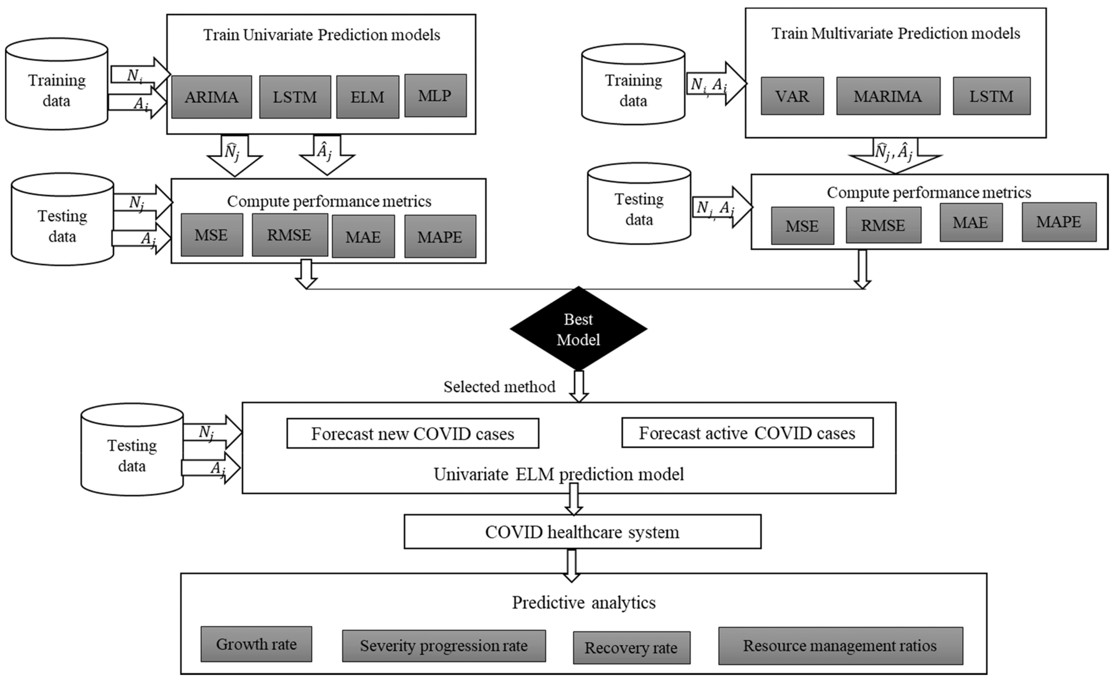

Fig. 7 Deployment framework.

resources such as ventilators, personal protective equipments (PPEs), and rapid test kits are priority for better patient care.

Also, better management of these resources helps the healthcare system to become resilient and efficient. From the simulation of the healthcare management system, for the evolution trend of new and active COVID cases, the study identified that key resource management ratios and system performance measures are presented in Fig. 8. Fig. 8 presents the predictive analytics depicting the system parameters in terms of growth rate of the COVID cases, mortality rate and recovery rate of COVID patients, and the disease progression among the patients during their patients' lifecycle are established. Fig. 8 also presents the key system performance measures such as the utilization of PPE, the disinfecting cycles of ventilators whenever allotted to infected patients per day, number of discarded units of PPE, RT-PCR kits after use with an infected patient. From the results of the simulation-based predictions of new cases, MAE, RMSE, and MAPE values are achieved to be 91.49, 134.73, and 0.13, respectively, and from the results of the simulation-based predictions of active cases, MAE, RMSE, and MAPE values are achieved to be 321.02, 389.04, and 0.01, respectively. Hence, it could be concluded that the data-driven simulation modeling of the COVID healthcare system has yielded high prediction accuracy.

C. Discussion of Findings

The following are the major findings from this article.

1) COVID-19 pandemic has led to many hard to predict problems amongst which new victims of corona positives each day and the active cases that remain each day after possible recovery or death are two significant predictions that can greatly aid the healthcare professionals and policy makers to combat against this pandemic effectively.
2) The time series plots of new cases and active cases everyday show the randomness in the progression of the COVID-19 pandemic which could be caused by innumerable random events occurring in the region under consideration and their combinations in total.
3) It is also found that the trend in the new cases and active cases shows temporal autocorrelation which is obvious during this corona pandemic due to the presence of a large number of independent events distorting the progression of the disease in an expected manner.

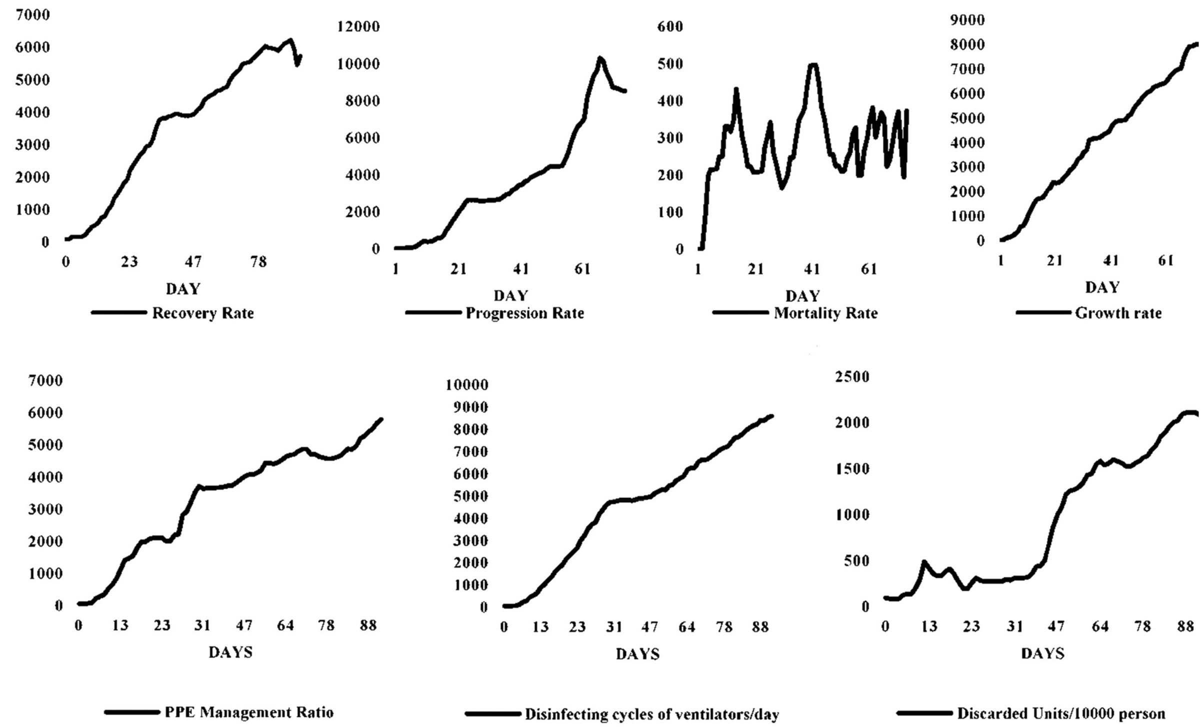

Fig. 8 Simulation analytics.

4) It can also be observed from the time series plots exhibit nonlinear progression of the disease marked by spikes and bursts.
5) ELM-based forecasting model proposed in this article was able to make accurate forecasts of new and active cases each day with MAPE values of 0.09 and 0.10, respectively. These projections of new and active cases of corona positives everyday will help all the frontline workers and management professionals during this crisis to better understand the demand of healthcare facilities and better manage their healthcare operations.
6) The healthcare management system for managing the COVID-19 crisis is further simulated using the forecasted time series data with high prediction accuracy and the performance of the system and key parameters capturing the dynamics of the system are established.

Also, the study has unique contributions for each tenet of BST. For the first tenet, the study provides a deployment framework (see Fig. 7) that can be adapted by the healthcare professionals for their daily prediction of COVID-19 cases and manage their resources accordingly. Answering to the second tenet, the present work acts as a reference model which can be used by a medical professional to predict the demand for resources. For, the third tenet, the deep-learning model using the ARIMA, LSTM, ELM, and MLP coupled with the simulation provides the results to understand the impact of the COVID-19 outbreaks. The deployment model can be modified into an application for easy evaluation of the demand prediction, maximizing its implication for the frontline workers for the fourth tenet. Finally, the proposed model is a simple and effective tool for predicting the COVID-19 outbreak, making it as an effective mechanism for decision making for the medical professionals in BS events.

V. Implications of the Study

A. Practical Implications

This article has significant implications for prevention and control, preparedness, and public policy related to the COVID-19 situation. Moreover, the prediction models proposed in the study can foresee ***"Hard to predict"*** kind of time series variables related to the tenets of the BS events. Further, the framework identifies the gap between the demand and supply for healthcare operations especially in terms of critical resources such as ventilators, PPE, and RT-PCR kits. Through addressing the disproportionate demand supply problem in the healthcare environment, patient well-being and seamless treatment can be achieved. Furthermore, a better understanding of propagation trends, data-driven simulation model for healthcare operations was developed. This would enable preparedness in terms of manpower, beds, intensive care beds, rapid test kits, PPEs, ventilators, medical supplies, drugs for facing the spikes, and burst of cases. Moreover, the present study identified the demand spike in resource requirement, which can enable the frontline workers to allocate the resources effectively and safeguard themselves from the threat of attracting the disease.

B. Theoretical Contributions

The work consists of several implications. First, the study highlights the need for the healthcare systems to be coupled with AI and predictive analytics to manage this COVID-19 outbreak prediction. Second, the present study evaluated the COVID dataset which features a sudden spike in demand and characterized by stationary and nonlinearity behaviors, which is first of its kind as a rare observation in the field of machine-learning-based prediction. Third, performance investigation of machine learning and deep learning models with rare and real-world data set for healthcare operations linking to the tenets of the BST. Further, very few studies have explored the BS theory and its link to the COVID-19 outbreak for smooth planning of healthcare operations leading to a unique contribution to the literature. Finally, based on the findings, the study has explored the BST and highlighted how a white swan event can eventually turn into a BS event and its impact on the healthcare operations is evaluated using the machine-learning-based models.

C. Limitations of the Study and Future Directions

The prediction model incorporating several causal factors including clinical, nonclinical, pathological, environmental, political, social, and economic factors would be highly reliable in well-known problems having highly reliable causal information [73]. Since such causal information is lacking at this stage of COVID spread, in this article, the authors have used time-series analysis to study the complex and uncertain behavior of COVID outbreak. Further, in order to tackle nonlinearity and uncertainty, machine learning algorithms are employed, and efficient prediction analytics has been performed to handle the life-cycle-long parameters in a COVID health care center. Nevertheless, in the future, such studies on developing causal models would help better preparedness and resiliency in the healthcare systems to tackle pandemics such as COVID.

Early prediction of active and new cases is the better scenario for managing COVID outbreak efficiently. However, the uncertain and highly unexpected events stimulated by patients' clinical conditions including comorbidities, progression, spread, and mutation of coronavirus itself, conditions in the healthcare system such as resource availability, governmental policies related to movement restrictions, social events, cooperation from public etc., contributes to prediction error. Also, these affect the convergence of the model and also necessitate continuous training of the model to predict accurately daily new and active cases for better preparedness using the insights obtained from predictive analytics. Also, prediction models for weekly/monthly forecasts can also be developed in the future.

On the grass-root level, every patient affected by COVID has to be treated differently though COVID care centers adopt standardized versions of protocol released by WHO from time to time. The progression and recovery of a patient are heavily affected by the patient's medical and nonmedical attributes based on which events happen in the life-cycle of a patient leading to recovery/progression. In the point of view of managing healthcare operations, the amount or time healthcare resources allotted to a particular patient accordingly vary based on the recovery/progression rate observed in patients currently present in a healthcare system. Thereby, a simulated model for depicting the predicted load on the healthcare system is developed in the study using the new and active cases predicted by the time-series analysis. The daily new cases and specifically the active cases present in a COVID care center in a day which is determined based on new and recovered cases of that day is also predicted in this study using machine-learning-based time-series analysis so as to handle heteroscedastic, dynamic, and unknown attributes present in the problems [74].

Another limitation of the study is that the proposed model did not link the patient-tracing concept, which could be the extension for the future study. Moreover, the study tried its best to address the tenets of the BST, however, it cannot be generalized as it requires more testing to generalize the findings. Further, the predictive analytics from this article can trigger efficient policy making and better decision making for patient care. Therefore, the deployment model can be further developed into a dashboard for visualization and effective decision making.

Although the present model is focusing on developing a healthcare management framework for COVID-19 related operations in Tamil Nadu state province of India, future researchers can develop a similar model to predict the herd immunity for different geographical locations.

VI. Conclusion

BST clearly shows that the highly uncertain and disruptive events can make the decision making and healthcare operations more mundane and ambiguous and the COVID-19 Pandemic is one such event. Even though many countries have anticipated the COVID-19 spread, none were able to foresee the disruption it can cause to our daily life making it a part of the BS event. Moreover, the crisis is quite hard to predict, therefore this article focused on predictive analytics for better handling the COVID-19 crisis using machine learning methods. The agenda behind the model is to support the front-line workers with better information to make a timely decision and to foresee the demand and supply pattern for different resources in the healthcare setting. COVID-19 pandemic has opened up to many hard to predict problems amongst which new victims of corona positives each day and the active cases that remain each day after possible recovery or death are two significant parameters that can greatly aid the healthcare professionals and drive the policy makers to combat against this pandemic effectively. Moreover, the time series plots of new cases and active cases every day show the randomness in the progression of the COVID-19 pandemic which could be caused by innumerable random events occurring in the region. Also, it was found that the trend in the new cases and active cases shows temporal autocorrelation which is very obvious during this corona pandemic due to the presence of a large number of independent events distorting the progression of the disease in an expected manner. Different prediction models developed using ARIMA, LSTM, ELM, and MLP have yielded accurate forecasts of new and active cases. However, ELM has outperformed other models during the testing phase and was found to be effective for predicting the demand and supply for the resources for patient care. Further, these prediction models are no doubt helpful in planning and scheduling healthcare operations. Efficient and resilient management of the COVID-19 healthcare system was further assessed using simulation modeling. According to the healthcare specialists, ventilators, PPEs, and rapid test kits known as RT-PCR kits are priority essentials for ensuring better patient treatment and seamless testing facility. From the simulation experiments, resource management ratios and disease-spread-related parameters are identified which further stimulates more preparedness in the system.

Many healthcare organizations are focused on delaying the virus spread by quarantining the infected individuals and maintaining the social distancing in public places. This will allow the researchers to have enough time to develop a new vaccine for the COVID-19 disease. Because the vaccine can lead to herd immunity making the people resistant to the COVID-19 infection. This, in turn, will end the COVID-19 pandemic officially over the time.

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