Deep Learning for Multivariate ICU Beds Forecasting During Global Healthcare Crisis: COVID-19 Case Study

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Abstract— **The coronavirus disease 2019 (COVID-19) placed significant and unprecedented challenges on the Tunisian public healthcare system. Healthcare facilities were overwhelmed by a surge in demand, resulting in crisis-level shortages of essential healthcare resources, including qualified personnel, respiratory support equipment, and Intensive Care Unit (ICU) beds. This resource scarcity created a critical imbalance between demand and healthcare system capacity, severely compromising the ability to provide adequate and timely patient care during the COVID-19 crisis. Accurate prediction of future case numbers and medical equipment needs is crucial to assist healthcare facilities in optimizing resource allocation during the COVID-19 epidemic surges. This paper presents a Long Short-Term Memory (LSTM) recurrent neural network model to forecast the required number of intensive care unit (ICU) beds. Various error quantification metrics measure the LSTM model's performance, such as the R2, MAE, MSE, and RMSE. Despite the proposed LSTM model demonstrating good predictive performance, we observe a deviation of approximately ±3 beds between the predicted values and the actual number of occupied beds, which can be significant in Tunisian public hospitals during the COVID-19 outbreak.**

Keywords—Public health care system, hospital resource forecasting, coronavirus disease 2019 (COVID-19), Deep Learning (DL), Long Short-Term Memory model (LSTM).

I. Introduction

The global COVID-19 pandemic revealed critical vulnerabilities in allocating and managing healthcare resources. The healthcare system was confronted with overwhelming patient loads, requiring timely intervention and adequate treatment to combat a new viral disease that spreads rapidly like the SARS-CoV-2 virus. Healthcare managers face the critical task of making informed decisions about the most effective use of the limited healthcare resources, including equipment and staff, as they struggle to maintain high-quality care and control associated costs. However, this last outbreak of SARS-CoV-2 exposed significant inadequacies in public healthcare facilities, highlighting their insufficient resources and inadequate preparedness to handle the surge in patients. The evaluation of the government actions and response strategies to the emerging pandemic has shown that the fight against COVID-19 has been severely impeded by the fragility and weaknesses of the national healthcare system [1]. This pandemic severely impacts the healthcare system, significantly disrupting public service delivery, particularly in the early stages [2]. One of the most critical issues was the severe staffing shortages, as the virus's rapid spread led to high infection and mortality rates among healthcare workers. The outbreak also exposed significant deficiencies in medical staff training and a lack of preparedness [3]. Furthermore, the healthcare system faced financial difficulties in recruiting additional qualified personnel to manage the increased patient load, further exacerbating the crisis. There was a critical shortage of essential medical supplies, including personal protective equipment, antiviral medications, and testing kits. The limited testing capacity forced hospitals to rely on Rapid COVID-19 tests despite their inferior accuracy, causing delays in diagnosing and isolating infected patients.

The most significant shortcomings that emerged in the Tunisian public healthcare system were the severe shortage of hospital beds, particularly ventilators and ICU beds. Typically, Intensive Care Units (ICUs) are not designed to handle such a high volume of patients requiring advanced respiratory and organ support. To address this issue, new healthcare facilities called COVID-19 units were established to provide specialized services for contaminated patients during the COVID-19 pandemic [4]. However, despite these efforts, the COVID-19 units quickly reached full capacity and could not admit additional patients. This forced medical staff to triage patients, often prioritizing those with the best chance of survival and leaving others without the necessary treatment, leading to avoidable deaths [5]. In response to this intense pressure, Tunisian public hospitals reorganized their limited resources by suspending many essential healthcare services, canceling planned treatments, and delaying all elective surgical activities across various departments until the pandemic subsided. Consequently, regular patients could not attend follow-up and acute care visits, avoiding risking exposure to contagious [2]. The reallocation of human and material resources was primarily aimed at managing the overwhelming influx of COVID-19 patients requiring intensive care. Additionally, it was intended to break the contamination cycle and protect noninfected patients from the risk of catching the virus.

Indeed, this strategic decision is a double-edged sword, yielding both advantageous and detrimental impacts. On the positive side, it represents a crucial strategy to avert service blockages and shortages of beds or personnel, while minimizing the number of new infections. This is crucial for avoiding scenarios where services are overwhelmed and maintaining the availability of critical resources. On the negative side, the total mobilization of hospital resources exclusively for COVID-19-affected patients, whose numbers are highly variable and subject to numerous factors, presents significant challenges. Under-sizing results in the unavailability of necessary care and insufficient critical resources, leading to bottlenecks in the COVID-19 care processes, slowing down operations, inability to meet patient needs, resulting in extended wait times, and adverse effects on patient wellness [6]. This strain can result in an increased risk of burnout and breakdowns. In fact, during the peak of the coronavirus pandemic, we observed overworked healthcare professionals and overused respiratory equipment within public hospitals. This led to critical situations where many patients had to share the same respiratory equipment and even hospital beds. Oversizing and reserving more hospital resources than necessary during the pandemic leads to underutilizing these limited resources, resulting in idle assets and wasted potential. This underutilization directly translates into increased costs, as these resources remain unused when they could be reallocated to treat and serve daily care consultations or perform urgent surgeries. The financial and operational inefficiencies caused by this resource misallocation can further strain an already overburdened public healthcare system, reducing its ability to handle the surge demands adequately. Consequently, effective resource management necessitates a balanced approach to avoid oversizing and undersizing. This involves flexible and dynamic resource allocation based on accurate demand forecasting and continuous monitoring to ensure the optimal utilization of these critical hospital resources.

The present study aims to determine how effectively the Deep approach can predict the demand for Intensive Care Unit (ICU) Beds at Sahloul University Hospital Center (UHC) in Tunisia, during the COVID-19 pandemic. UHC Sahloul is a critical healthcare facility that was pivotal in managing and treating infected patients with COVID-19. In this research, we employ the Long Short-Term Memory (LSTM) to evaluate its efficacy in optimizing the management of critical hospital resources, specifically ICU beds. The focus on ICU beds is driven by the substantial challenges posed to Intensive Care Units (ICUs) during the COVID-19 outbreak. The SARS-CoV-2 virus, responsible for COVID-19 disease, often leads to severe viral pneumonia and acute respiratory distress syndrome (ARDS), necessitating intensive respiratory and multi-organ support. This motivates us to develop a predictive model to estimate the number of ICU beds needed in the short and medium-term horizons based on various factors such as the virus's reproductive rate, the positive rate, and other relevant variables.

This paper is structured as follows. Section 2 reviews related work addressing the prediction of hospital resources during global pandemics, particularly on forecasting ICU beds using the LSTM RNN deep learning approach. Section 3 details the material and methods, including a description of the datasets, data preprocessing, the case study application, and a thorough explanation of the proposed LSTM model. Additionally, it covers the model's implementation and parameter settings. The section concludes with the presentation of relevant evaluation metrics used to evaluate the accuracy of the proposed model. The study continues in section 4, wherein we summarize and discuss the main findings and results. Section 5 concludes the paper with final remarks and discusses potential directions for future research.

II. Related Work

Deep Learning (DL) algorithms have gained significant attention in recent years due to their capacity to model complex temporal patterns and predict nonlinear time-dependent system dynamics [7]. During the recent SARS-CoV-2 pandemic, the Long-Short-Term Memory (LSTM) model emerged widely in various health research and medical decision-making areas. These models were extensively used to forecast the spread of the COVID-19 disease, analyze disease trends, and simulate the dynamic behavior of the pandemic [8]. In addition to predicting future waves of infections, LSTM models have also been employed to forecast daily case numbers [9-10-11], recovered cases, mortality rates [12], and other critical indicators. Estimating such indicators is crucial for decision-makers and government authorities to counter the spread, implement necessary interventions, manage hospital capacity, and optimize resource allocation for more effective patient care. Indeed, some studies have addressed important topics such as the estimation of hospital admissions and the need for resources like qualified personnel, ventilators, and ICU beds for better capacity planning during the COVID-19 outbreak, which is also the main focus of this study.

Stasinos et al. [13] assessed the effectiveness of advanced forecasting approaches, including ARIMA, SARIMAX, ARTXP, and multivariate regression, for predicting short-to-medium-term ICU bed demand during the SARS-CoV-2 pandemic. The study utilized time series data from six key variables, including confirmed cases, hospitalizations, ICU bed occupancy, intubated patients, recovered patients, and deaths. Mahmoudian et al. [14] used an LSTM model to forecast the Hospital Bed Capacity, based on factors like the number of hospitalized patients and their length of stay. Tello et al. [15] introduced a machine-learning (ML) approach using the K-Support Vector Machine (K-SVM) model to forecast weekly inpatient bed demand. Their prediction model is based on variables such as type of inpatient admission, observation, and recovery following overnight surgical procedures, to optimize resource allocation in the emergency department and Post-Anesthesia Care Unit (PACU). Martinez et al. [16] compared the Holt-Winters and Bayesian VAR models to forecast COVID-19-related hospitalizations across six facilities. Their findings, based on MAPE values, suggest that while both models offer reliable short-term forecasts, their accuracy significantly declines for long forecasting horizons. Zhang et al. [17] developed a Temporal Convolutional Network (TCN) model to forecast the demand for hospital and ICU beds, ventilators, as well as the projected number of COVID-19 cases and deaths. This Machine-Learning method uses data on resource consumption, pandemic dynamics, population mobility, weather conditions, and public policy to train TNC models for predicting the weekly average of each of the five COVID-related targets. [18] proposed an ensemble approach integrating artificial neural networks, autoregressive neural networks, and ICD compartment models to forecast ICU demand during the COVID-19 pandemic at the regional level. Borges et al. [19] integrated Prophet and LSTM models to improve the accuracy of daily ICU admissions forecasting during the outbreak, considering the daily number of infected cases, vaccination coverage, social distancing metrics, and many other factors to explain the variation in COVID-19 hospital ICU demand. [20] developed a multilayer LSTM model to predict medical equipment demand and outbreak spread during the COVID-19 outbreak in Turkey, demonstrating its effectiveness in predicting future case numbers and equipment needs. [21] introduced a Bi-LSTM approach to estimate the number of COVID-19 cases, along with the anticipated needs for regular wards, and ICU/semi-ICU ward capacity. [22] utilized a fully connected Deep Neural Network (DNN), LSTM, and Transformer model (TM) to predict daily new infected cases and identify factors influencing transmission, such as vaccination rates, hospital admissions, intensive care unit (ICU) patients, and other relevant variables. The LSTM model achieved the highest predictive accuracy, with an error of less than 2%, outperforming other approaches.

TABLE I. PERFORMANCE COMPARISON OF FORECASTING MODELS FOR ICU BED DEMAND FORECASTING.

Study	Model	MAE	RMSE	MAPE
[17]	TCN	-	-	15.75
[14]	SARIMA	-	9.5	-
	LR	-	8.6	-
	LSTM	-	9.1	-
[13]	K-SVR	4.87	5.77	1.42
	K-SVR (3)	6.33	6.99	1.67
	ARIMA	14.15	17.44	4.47
[19]	ARIMA	38.50	46.64	17.52
	Multivariate regression	38.79	49.67	18.14
[22]	SIR model	-	-	5.69
[23]	Exponential smoothing ETS	-	6	11
[24]	Linear Regression	9.26	11.53	2.90
	LSTM	12.85	15.92	4.00
	MLP	11.09	13.20	3.40
	Random Forest	14.57	17.91	4.70
	Moving Average	14.06	16.80	4.30
	Holt-Winters	8.62	10.25	2.60
[25]	ARIMA	-	-	35
[18]	ARIMAX	-	-	11.41
	ICD	-	102.92	36.77
[26]	Multiplicative Holt-Winters	10.06	12.37	22.36
	SARIMA	8.60	10.46	16.98
[27]	ARIMA	12.4	18.5	14.3
	STL + Regression	14.2	20.3	16.8
	Random Forest	10.8	17.1	12.7

Forecasting ICU demand during the COVID-19 outbreak is challenging due to the rapidly evolving epidemiological dynamics, which can generate significant bias in predictions. ARIMA-based models and SEIR depend on the availability of extensive historical time series data to reliably estimate model parameters [13]. Regression models often ignore exogenous factors, such as the stringency of government interventions, that substantially influence infection dynamics and thus hospitals' demand. The LSTM architecture is widely recognized for its predictive accuracy and independence from predefined assumptions about infection dynamics, thereby reducing the risk of model bias or misspecification [28]. Its data-driven flexibility allows it to capture and learn complex patterns specific to pandemics, consistently outperforming traditional models in predicting COVID-19.

III. MATERIALS AND METHODS

A. Data

Data on daily ICU hospitalizations of COVID-19 cases were gathered from the COVID-19 unit, Intensive Care Unit (ICU), Emergency Department (ED), and seventeen other regular medical inpatient units that were involved in managing the COVID-19 patients during the pandemic at the University Hospital Center (UHC) Sahloul in Tunisia, in the time window between 25 September 2020 to 12 December 2021. The remaining data is publicly available through international databases [29], including the incidence rate, severity rate, reproduction rate, and positivity rate of the coronavirus disease, as shown in Table II, representing a sample of one week of the used dataset. The dataset was split into 90% for training and 10% for testing (see Table III).

TABLE II. A ONE-WEEK DATA SET OF THE EXPLAINED VARIABLE (ICU BEDS) AND THE EXPLANATORY VARIABLES USED IN THE LSTM MODEL.

Dates	ICU beds	Incidence rate	Rigor rate	Reproduction rate	Positivity rate
2021/07/05	30	28,57	74,07	1	0,4479
2021/07/06	27	64,18	74,07	1	0,3732
2021/07/07	14	79,50	74,07	1	0,4294
2021/07/08	28	67,29	74,07	1	0,3721
2021/07/09	20	68,84	74,07	1	0,3758
2021/07/10	30	75,15	74,07	1	0,4444
2021/07/11	30	53,35	74,07	1	0,3590

TABLE III. OUTPUT OF THE SPLITTING PROCEDURE

Data	Train	Test
In days	399 days	44 days
Date	25/09/2020-28/10/2021	29/10/2021-12/12/2021
Percentage %	90 %	10 %

- **Incidence rate** is the most useful rate for monitoring the dynamics of the COVID-19 pandemic.

$$\frac{\textit{Number of new cases detected over 7 days}}{\textit{target population}} * 100{,}000 \quad (1)$$

- **Rigor rate** is a composite metric derived from 9 response indicators, such as school closures, travel bans, and workplace shutdowns.

- **Reproduction rate** is the average number of subsequent infections one infected individual generates.

- **Positivity rate** is the average number of secondary infections generated by an infected individual in a population where a portion of individuals have acquired immunity to the disease.

We normalized the dataset before using the LSTM model, as the sigmoid and tanh activations are sensitive to the magnitude of input values. This ensures all input features are on a similar scale, improving training efficiency without being biased by different feature scales. To preprocess the data for training, we employ a time-series forecasting approach using past observations to predict the number of COVID-19 cases hospitalized in the ICU beds. So, we look back at 14 days (n_{past} = 14) to predict the next day's value (n_{future} =1), which can be mathematically represented as flow:

$$x[i] = \begin{bmatrix} x_{i-n_{past}} \\ x_{i-n_{past}}+1 \\ \cdot \\ \cdot \\ \cdot \\ x_{i-1} \end{bmatrix} \text{for i} = n_{past}, n_{past}+1, \ldots, n_{samples}-1 \quad (2)$$

$$y[i] = x_{i-n_{future}} - 1 \text{ for i} = n_{past}, n_{past}+1, \ldots, n_{samples}-1 \quad (3)$$

The training dataset train X has the shape of (398, 14, 5), indicating that it includes 398 samples, each comprising 14 past observations across 5 features. Meanwhile, the prediction dataset train Y has a shape of (398,1), representing the corresponding future value for each sample. The next section will outline the implementation details of the LSTM model and the evaluation metrics chosen to assess its performance.

B. *Proposed LSTM model architecture*

Long-Short-Term Memory (LSTM) is a machine learning algorithm based on Recurrent Neural Networks (RNNs). The LSTM model is versatile and not limited to specific applications, it has demonstrated success across many tasks requiring long-range memory, including time series forecasting, image and video captioning, text recognition, natural language processing, sentiment analysis, and many other domains. A wide variety of problems are suited to using the LSTM model due to its ability to address the exploding and vanishing gradients problems, which hinder learning long-range dependencies in sequential data [30]. Recurrent Neural Networks (Fig.1) are highly effective for settling sequential data due to their ability to transform continuous input sequences to corresponding output sequences while capturing temporal dynamics [31]. However, classical RRNs face the vanishing gradient problem during back-propagation, which limits the influence of input, making RNN performance unsatisfactory for long-term dependence problems [32]. The LSTM architecture replaces hidden layers in traditional DNNs with memory blocks, which regulate the propagation of inputs and outputs through gating mechanisms. Each block contains memory cells and three multiplicative units as described in Fig. 2:

Input gates control input activations into memory cells.

- Output gates control output activation into the network.
- The forget gate allows for adaptive forgetting or resetting of memory.
- Cell state serves as the LSTM's internal memory, transferring and preserving relevant information across time steps.

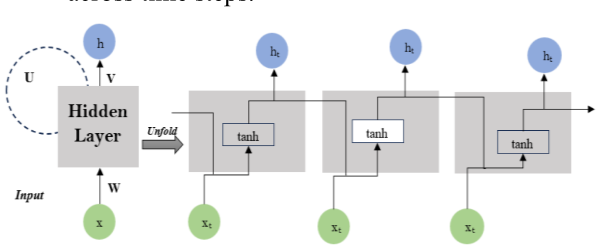

Fig. 1. Architechture of traditional RNN

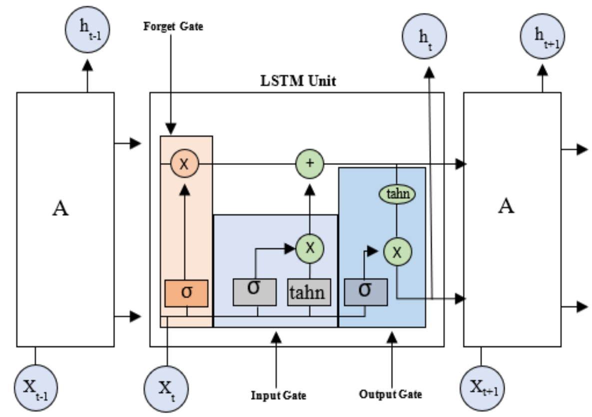

Fig. 2. The proposed LSTM RNN architecture

TABLE IV. LSTM LAYERS ARCHITECTURE

Layer	Output shape	Parameters
Lstm_2 (LSTM)	(None, 14, 64)	17,920
Lstm_3 (LSTM)	(None, 32)	12,416
Dropout_1 (Dropout)	(None, 32)	0
Dense_1 (Dropout)	(None, 1)	33

Tables IV and V summarize the architecture and settings of the LSTM model employed in this work. The optimal hyperparameters of the LSTM model were determined through a manual tuning process. The proposed model consists of an input layer, followed by an LSTM layer with 64 units, outputting sequences of shape (None, 14, 64) and containing 17,920 parameters. A subsequent LSTM layer with 32 units is applied, reducing the output shape to (None, 32) with 12,416 parameters. Regularization is incorporated throughout the model using a dropout layer of an output shape of (None,32), while a dense layer reduces the output to a shape of (None, 1) with 33 trainable parameters. The model employs the ReLU activation function, with MSE as the loss function. Optimization is performed using the Adam optimizer, configured with a learning rate of 0.001 and an epsilon value of $1e^{-07}$. Two configurations were employed, consisting of 100 and 1000 training epochs, respectively, to evaluate the impact of training duration on our model's performance.

TABLE V. PARAMETERS OF THE PROPOSED LSTM MODEL

Parameters	Value
Activation function	ReLU
Optimizer	Adam
Loss function	Mean Squared Error (MSE)
Learning rate	0.001
Epsilon	1e-07
Epochs	100-&1000
Dropout	0.2

C. *LSTM model assessment metric*

We used various metrics to assess the accuracy of the LSTM model's predictions, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). The mathematical formulation of MAE, MSE, and RMSE is given in the equations as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |\text{ Predicted Value} - \text{Actual Value }| \quad (4)$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n} \frac{|\text{ Actual Value} - \text{Predicted Value }|}{\text{Actual Value}} \quad (5)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \frac{|\text{ Actual Value} - \text{Predicted Value }|}{\text{Actual Value}}} \quad (6)$$

IV. Results and Discussion

This section began by analyzing the loss function, using Mean Squared Error (MSE) to assess the LSTM models' accuracy by quantifying the average squared deviations between actual and predicted values. The number of epochs significantly impacts the effectiveness of the proposed LSTM model, as demonstrated in Figs. 3 and 4. The training loss exhibited a notable reduction from 0.0691 at 100 epochs to 0.0170 at 1000 epochs, while the test loss decreased from 0.0731 to 0.0277 over the same intervals. With more training epochs, these results underscore the model's improved ability to learn and fit the training data more effectively. Moreover, the consistent decrease in test loss indicates that our LSTM model fits the training data well and demonstrates enhanced generalization ability.

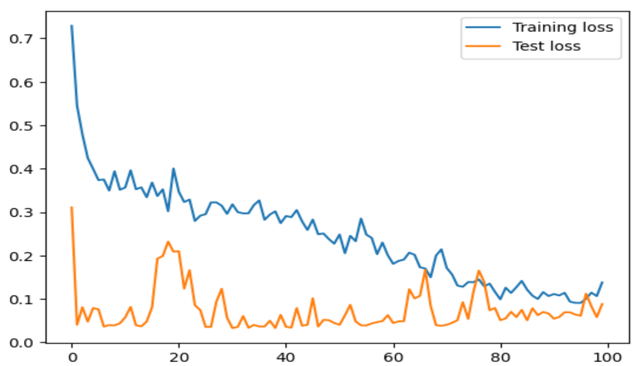

Fig. 3. The evolution of training and test loss across 100 epochs

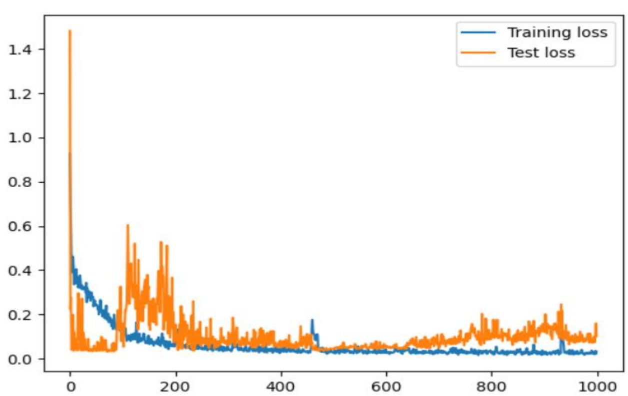

Fig. 4. The evolution of training and test loss across 1000 epochs.

Although MSE is a widely used metric for regression tasks, it may not fully capture the model's overall performance. Therefore, to provide a more rigorous evaluation, additional metrics were applied to objectively evaluate the predictive precision of the proposed LSTM model, as presented in the table as fellow:

TABLE VI. LSTM MODEL PERFORMANCE METRICS

R2	MAE	RMSE
0.93	2.7	3.59

The R^2 value of 0.93 indicates that our proposed LSTM model explains 93% of the variance in the ICU bed values, indicating a strong performance. This result suggests that the model effectively captures the underlying data patterns, providing accurate predictions that closely align with observed data. The error quantification measure, MAE, yields a value of 2.7, indicating a mean deviation of approximately ±3 ICU beds between predicted and actual values. To further evaluate the effectiveness of our LSTM model, we benchmarked its performance against baselines forecasting models (Table 1). Our model consistently outperformed traditional approaches, achieved significantly lower forecasting error values than K-SVR (MAE = 4.87, RMSE = 5.77) [13] and ARIMA (MAE 12.4, RMSE 18.5) [28]. it also demonstrated superior accuracy relative to the LSTM model reported in [14] (MAE = 12.85, RMSE = 15.92). These results underscore the model's enhanced reliability and forecasting precision. In addition to predictive accuracy, the model achieved a test-time execution of 0.0574 seconds, reinforcing its practicality for rapid decision support in critical care settings during epidemic conditions.

While the deviation may appear relatively small, it could impact critical decisions and directly affect patient life, where ICU beds are a crucial resource and often unavailable during the COVID-19 pandemic. Even minor discrepancies of 3 beds can lead to overestimation or underestimation of capacity. This is further evidenced by the normalized RMSE of 29.92%, indicating that the LSTM model's predictions differ, on average, from the observed number of occupied ICU beds by nearly 30%. This difference between the prediction values and the observed ICU bed usage can significantly affect public hospital resource allocation. Especially during a global crisis like the COVID-19 pandemic, even a few beds can represent a substantial difference in patient care.

V. Conclusion

In this study, we introduce a Long Short-Term Memory (LSTM) model to predict the necessary beds in the Intensive Care Units (ICU beds) during the global pandemic of COVID-19. The R^2 value reflects the performance of the proposed LSTM model in capturing underlying data patterns. However, the MAE and RMSE values highlight moments where the model's prediction deviates from the actual values, emphasizing the need for further refinement. Overall, while the LSTM model demonstrates strong predictive performance on the training set, the variation observed in test loss suggests some challenges with generalization, particularly in the later epochs. This serves as a promising starting point, where in future works, we will explore more advanced architecture beyond vanilla LSTM, such as Bidirectional LSTM. Additionally, we will consider combining the LSTM model with other machine learning approaches, such as CNN-LSTM, to achieve optimal predictive performance. Furthermore, the challenges in modeling may arise from the reliability of our data and the complexity of identifying influential variables. To address these issues, we will prioritize enhancing data preparation and consider incorporating additional variables and factors to better explain the variations in ICU bed usage.

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