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Machine Learning Approach To Automated Early Warning System For Medical Vital Signs Monitoring

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Abstract

Precise and timely detection of deteriorating vital signs is an important aspect of patient safety and clinical intervention. The current standard of monitoring systems lacks automated early warning systems, instead using manual observation to make judgments. This manual approach can lead to delays in detecting critical changes in a patient's condition. We present a novel approach to developing an automated early warning system for vital signs using a hybrid method that combines LSTM (Long Short Term Memory) and XGBoost (Extra Gradient Boost), both methods offer robust predictive modeling that is able to capture the complex and often non-linear relationships inherent in physiological data. This research believes that using a novel technique that combines LSTM and XGBoost advances predictive systems in healthcare-based technology as well as laying the groundwork for even further innovations in early warning systems. The early warning system will evaluate vital signs such as respiratory rate, SpO_2 levels, heart rate, body temperature, and pulse which can recognize and predict early signs of clinical deterioration, allowing early intervention and may save a patient's life. This research will use error metrics such as MAPE, MAE (Mean Absolute Error), MSE, RMSE, and MAD to compare the predicted actual values.

1. INTRODUCTION

The monitoring of vital signs is one of the most important parts of healthcare [1]. These signs, which are mainly composed of blood pressure (BP), temperature, heart rate (HR), oxygen saturation (SpO_2), and respiratory rate (Resp) reflect the patient's condition in real time. This often gives the first signs of abnormalities and a delayed detection might lead to the patient's deteriorating health. A way to detect abnormalities beforehand is an automated early warning system, which reduces the mortality rate caused by undetected abnormalities [2].

The underlying reasons for choosing the aforementioned vital signs vary for each sign. Blood pressure (BP) is selected because it is an indicator of oxygen delivery to the organs [3]. Temperature is chosen because it can sufficiently represent the human immune response [4] and show whether one's temperature is in an acceptable range. The human heart rate (HR) is also an important vital sign that could show what the cardiovascular system is currently experiencing [5]. Furthermore, the heart rate can also show early signs of cardiac arrest and sepsis [6]. Oxygen saturation (SpO_2) shows the overall percentage of oxygen found in haemoglobin (HB) [7]. This can show if the person has hypoxia, which should be treated quickly. Respiratory rate (Resp) is chosen as a monitored variable as it is the most sensitive indicator of deterioration [8]. Pulse shows the assessment of cardiac activity in one's body [5]. This includes heart rate, rhythm, amplitude, and regularity.

Out of all the vital signs, the two most important vital signs that could give information about an early deterioration are pulse and respiratory rate. When the pulse and respiratory rate experience abnormal and sudden changes, these are the first signs of deterioration [9]. This means that most early deterioration can be detected by these two signs. However, to further understand the deterioration, all vital signs must work together as one.

It is important to note that the importance of measuring vitals is not only a way of detecting immediate health concerns but also to prevent complications in the long run [10]. Thus, by constantly monitoring these parameters, doctors can be able to identify emerging trends and patterns that may indicate the development of chronic diseases or other severe ailments. To explain, continuous observance of blood pressure changes will help identify hypertension early enough hence allowing for timely intervention and management before more serious cardiovascular issues occur [11]. Similarly, a record of temperature over time may assist in diagnosing infections or inflammatory illnesses at an early stage thus helping in reducing complications associated with this condition.

Moreover, the introduction of an automatic early warning system aids not only in its discovery but also takes away some responsibilities from doctors, given the rising demand for healthcare services coupled with inadequate medical practitioners supply [12]. Early warning systems can provide a means to optimize resource allocation and prompt interventions. These systems make use of complex algorithmic tools.

Several papers [13], [14] have stated that the development of early warning systems has been critical in helping doctors, nurses and other medical professionals detect abnormalities before symptoms of said abnormalities occur. Despite the great importance of early warning systems, other studies mostly comprise literature reviews merely stating the importance of early warning systems, not the methods for developing them mathematically. Cliffton [15] has developed an early warning system by using Gaussian Process Regression, which is known to give accurate results within an acceptable confidence interval.

One drawback of the Gaussian Process Regression is that it is a complex machine-learning technique, where it has a time complexity of $O(n^3)$ [16]. Since a high time complexity is not desirable, this paper aims to use a novel approach by combining LSTM and XGBoost to obtain results with similar accuracy as Gaussian Process Regression while having a significantly lower time complexity. Both of these methods, LSTM and XGBoost, are chosen due to the LSTM's ability to capture temporal data and XGBoost's ability to handle skewed datasets [17] as most vital signs data have a certain skewness [18].

2. METHOD

There will be three methods that will be used in this research, the LSTM networks (Long Short-Term Memory), the XGBoost Tree, and the proposed LSTM-XGBoost Method. These methods will be discussed in sections 2.1 and 2.2, while the novel proposed method and how to compare the results of LSTM, XGBoost, and LSTM-XGBoost hybrid will be discussed in section 2.3.

2.1 Long Short-Term Memory

Long Short-Term Memory is a modification of the RNN (Recurrent Neural Network) method that solves the vanishing error problem [19]. There are three main gates of the LSTM network, the forget gate, the input gate, and the output gate. Refer to Figure 1 to take a look at an image of the LSTM network.

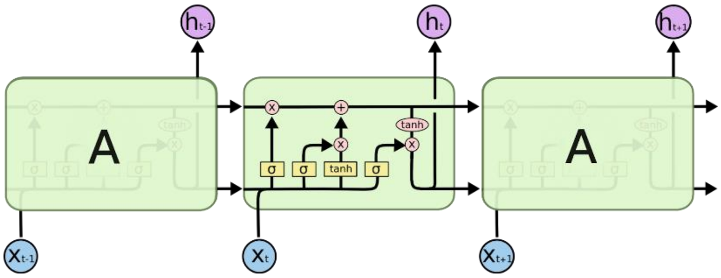

Figure 1. LSTM Network of Cells

Forget gates ft are gates that are used by neurons to figure out whether they want to "keep the information" or decide that the information is useless and throw it away [20]. These gates will output a value between 0 and 1 where the closer to 0 the output is, the more likely it will be thrown away. The closer it is to 1, the more likely the information will be saved. These gates have the equation as follows.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \quad (1)$$

Where W_f are the weights of the forget gate, h_{t-1} is the hidden layers of time at point $t-1$, x_t is the data at time t_1, and b_f is the bias term, and σ is the sigmoid function can be written as

$$\sigma = \frac{1}{exp(-l \times s)}; \quad s = \sum_{i=1}^{n} w_i x_i + \mathrm{b}; \quad l \in R^+ \tag{2}$$

The sigmoid function returns an output that has more than two possible values. The output is then modified by a continuous function with a range of 0 to 1. The modifying function maps a vast input domain into a smaller range of outputs.

Input gates are used to decide what information will be stored in the store cell. There are two steps in this process. The first step is using the input gate layer to decide which information to update. The equation of this step can be written as

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{3}$$

The next step is to find new candidate values by using the layers. These new candidates will be multiplied by the input gate to create and update the state. The equation for this step can be written as

$$\widetilde{C} = tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{4}$$

Now to update the old cell state, the forget gate will be multiplied by the cell state $t-1$ and it will be added with the new candidates multiplied by the input gate. Updating the cell state is a critical step of LSTM as with this step, the calculations will return optimal solutions. The new cell state has the equation as follows

$$C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C}_t \tag{5}$$

Lastly, the output gate outputs new information from the input gate and will determine which hidden layer will be sent to the next cell. The output cell (eq. 6) and the new hidden layers that will be sent to the next cell (eq. 7) have the formulas as follows respectively.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{6}$$

$$h_t = o_t \odot tanh(C_t) \tag{7}$$

2.1 XGBoost

XGBoost is a scalable machine-learning method for tree boosting [21]. Tree boosting has been shown to give state-of-the-art results on many standard classification benchmarks [22]. The scalability of XGBoostis the main factor behind its speed. An example of the XGBoost tree is shown in Figure 2.

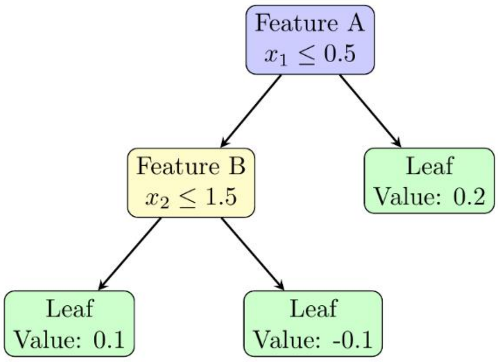

Figure 2. XGBoost Tree Example with Two Features and Three Leaves

The first step in gradient boosting starts with the objective function. Where the objective function that will be minimised is as follows.

$$\mathcal{L}(\phi) = \sum_{i=1}^{n} l(y_i, \widehat{y}_i) + \sum_{k=1}^{n} \Omega(f_k) \tag{8}$$

$$\text{Where } \Omega(f) = \gamma T + \frac{1}{2}\lambda||w||^2$$

It should be noted that l is the loss function that measures the difference between the predicted value $\widehat{y}_i$ and the actual value y_i. This difference may be the mean squared error in regression or the logistic loss in classification. Ω is the regularisation term for the regression tree functions with T defined as the number of leaves in the tree, w as the weight of the leaf, γ and λ are regularisation parameters.

After that, the model will be trained additively. Let $\widehat{y}_i^{(t)}$ be the prediction for x_i at iteration t, and f_t be the new tree added at iteration t to minimise the following objective function.

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} \left[l\left(y_i, \widehat{y}_i^{(t-1)}\right) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t) \tag{9}$$

$$\text{Where } g_i = \frac{\partial}{\partial \hat{y}^{(t)}} l\left(y_i, \widehat{y}_i^{(t-1)}\right); \quad h_i = \frac{\partial^2}{\partial^2 \hat{y}^{(t)}} l\left(y_i, \widehat{y}_i^{(t-1)}\right)$$

Equation (9) can be optimised using second-order approximation to approximate the objective function. Thus the objective function for the t-th iteration can be written as:

$$\widetilde{\mathcal{L}}^{(t)} = \sum_{i=1}^{n} \left[g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t) \tag{10}$$

Let there be I_j such that the definition of $I_j = \{\mathrm{i}|\mathrm{q}(x_i) = \mathrm{j}\}$ as the instance set of leaf j. Equation (10) can be written with expanding Ω as follows.

$$\tilde{\mathcal{L}}^{(t)} = \sum_{i=1}^{n}\left[g_i f_t(x_i) + \frac{1}{2}h_i f_t^2(x_i)\right] + \gamma T + \frac{1}{2}\lambda||w_j||^2$$
$$= \sum_{j=1}^{T}\left[\left(\sum_{i\in I_j} h_i\right)w_j + \frac{1}{2}\left(\sum_{i\in I_j} h_i + \lambda\right)w_j^2\right] + \gamma t \tag{11}$$

When each tree f_t is constructed to minimise the objective function. Under normal circumstances, it is impossible to enumerate the entirety of all possible tree structures. Thus a greedy algorithm is used to add branches to the tree after starting with a single leaf. By letting $I = I_L \cup I_R$ where I_L and I_R represent the instance sets of the left and right nodes respectively after the split in branches. The structure of the tree is determined by selecting splits based on their loss reduction, which serves to measure the improvement in the objective function. The formula for loss reduction after the split is as follows.

$$\mathcal{L}_{split} = \frac{1}{2}\left[\frac{\left(\sum_{i\in I_L} g_i\right)^2}{\sum_{i\in I_L} h_i + \lambda} + \frac{\left(\sum_{i\in I_R} g_i\right)^2}{\sum_{i\in I_R} h_i + \lambda} - \frac{\left(\sum_{i\in I} g_i\right)^2}{\sum_{i\in I} h_i + \lambda}\right] - \gamma \tag{12}$$

2.3 LSTM-XGBoost Hybrid

This research proposes an LSTM-XGBoost Hybrid that utilises both methods for a more accurate forecasting method. There are two steps in this hybrid method [23]. Firstly, the training dataset, which is 80% of the dataset, will be fed into the LSTM network with one epoch a 64 batch size. The fitted values will then be chosen as the first predicted values for the XGBoost tree. This will then trigger step two, which will feed the same 80% of the dataset to the XGBoost trees with 5 max depth, 0.1 learning rate, 10 estimators, and 10 rounds. This method will then use this model to predict and forecast the dataset. The flowchart of this method can be seen in Figure 4. The parameters chosen for this hybrid were chosen to make the predictions faster.

To analyze the results of these predictions further, some error metrics are going to be used. In this research, MAPE (Mean Average Percentage Error), MAE (Mean Average Error), MAD (Mean Absolute Deviation), MSE (Mean Square Error), and RMSE (Root Mean Square Error) [24]. These metrics have the equation as follows.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100\% \tag{13}$$

$$MAE = \frac{\sum_{t=1}^{n} F_t - A_t}{n} \tag{14}$$

$$MAD = \frac{1}{n}\sum_{t=1}^{n}|F_t - \overline{F}| \tag{15}$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(F_t - A_t)^2 \tag{16}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(F_t - A_t)^2} = \sqrt{MSE} \tag{17}$$

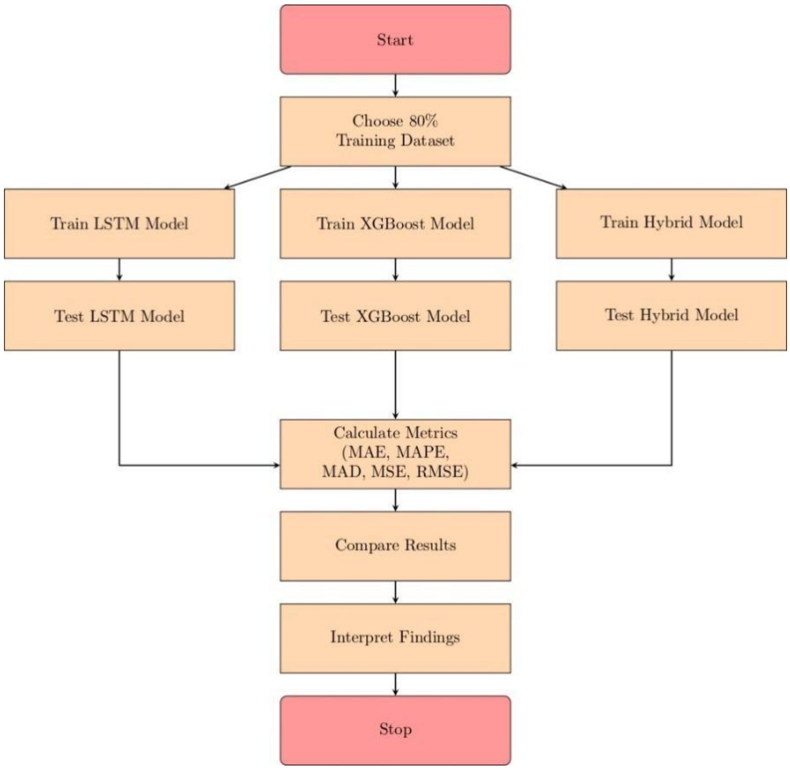

Figure 3. Proposed LSTM-XGBoost Hybrid and Error Metrics Comparison Flowchart

3. RESULTS AND DISCUSSION

The data used for this research is a patient's vital signs data set, including SpO2 or oxygen saturation, Heart Rate, Temperature, Respiration Rate, and Pulse. The shortened graph associated with the vital signs data used can be seen in Figure 2.

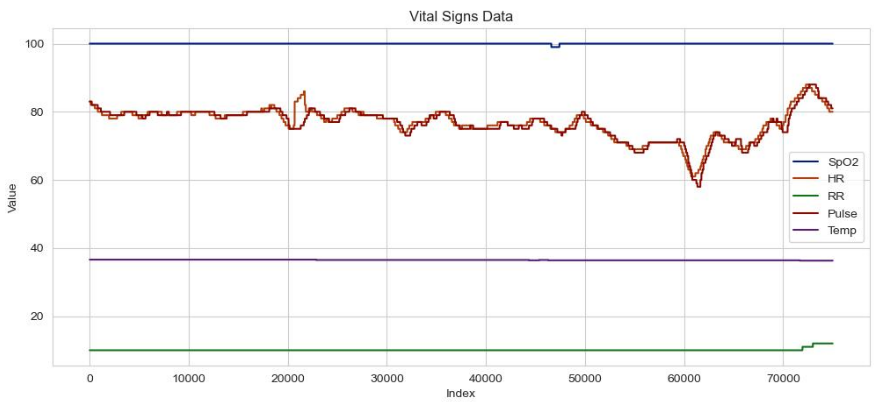

Figure 4. Vital Signs Dataset from Index 0 to 75000

The real data set is a recording of a patient for 125396 indexes, where each index corresponds to a millisecond. The values of each data at index i can be shown in Table 1.

Table 1. Vital Signs Dataset

Index	SpO_2	Heart Rate	Temperature	Respiration Rate	Pulse
1	100	83	36.6	10	83
2	100	83	36.6	10	83
3	100	83	36.6	10	83
⋮	⋮	⋮	⋮	⋮	⋮
125394	99	90	36.2	11	91
125395	99	90	36.2	11	91
125396	99	90	36.2	11	91

Data source*:* https://outbox.eait.uq.edu.au/uqdliu3/uqvitalsignsdataset/_cases.html#case03

By using 80% of the dataset as a training set and 20% of the dataset as testing, the LSTM networks with one epoch got the following results.

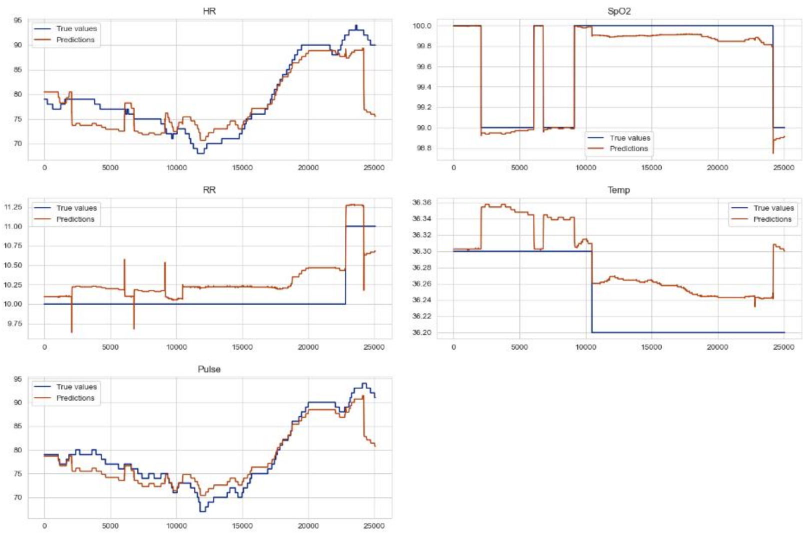

Figure 5. LSTM Initial Prediction

The next step is to input the predicted values with the least error into the XGBoost tree system. The following table shows the value with the least error, the original values, and the absolute error of the prediction. The result of this LSTM-XGBoost Hybrid model can be seen in the following Figure.

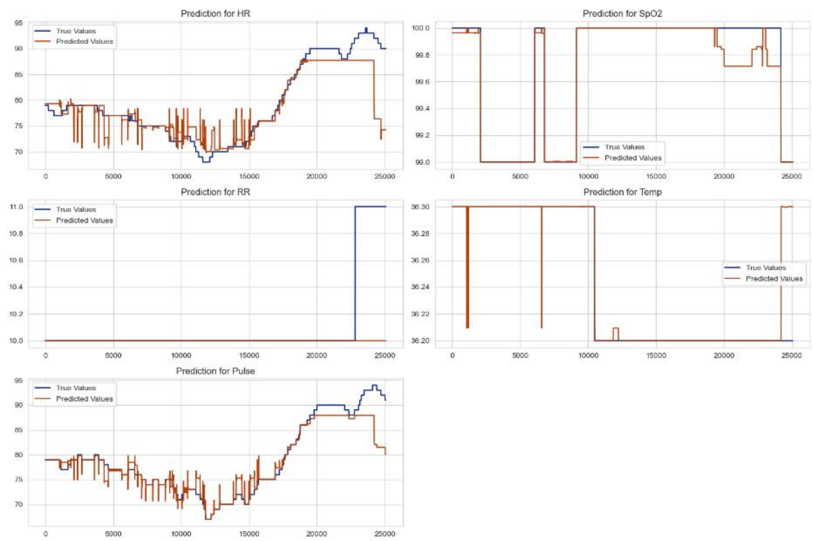

Figure 6. LSTM-XGBoost Hybrid Model Predictions

Whereas the predicted values of the vital signs data set with only a single XGBoost model can be seen in the following figure.

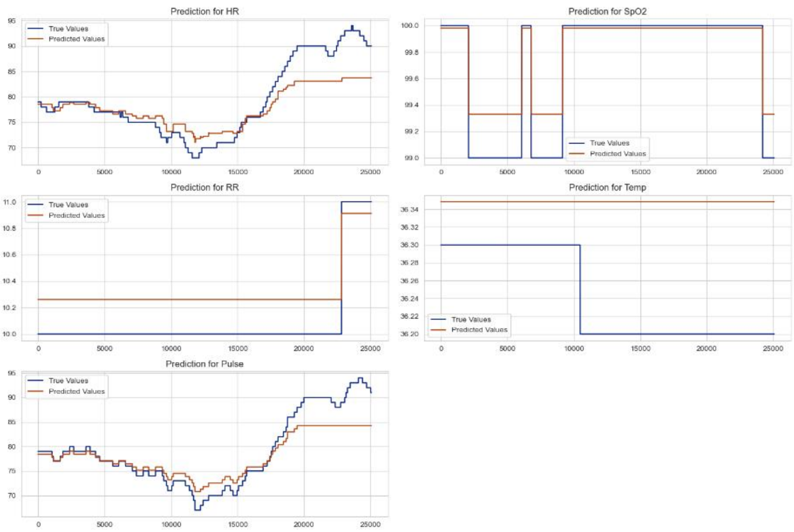

Figure 6. XGBoost Model Predictions

Tables 2-4 shows the metric results shown in Section 2.3 and in Equations (13), (14), (15), (16), and (17). The least values in the metrics will show the best model.

Table 2. LSTM Error Metric

Metric	SpO_2	Heart Rate	Temperature	Respiration Rate	Pulse	Average
MAPE	0.0768%	3.6463%	0.1267%	2.3259%	2.5780%	1.7507%
MAE	0.0766	2.9064	0.0459	0.2351	2.04901	1.0626
MAD	0.4104	6.0977	0.0486	0.1636	5.9087	2.5258
MSE	0.0092	15.6275	0.0026	0.0673	7.9849	4.7383
RMSE	0.096	3.9532	0.0509	0.2595	2.8258	1.4371

Table 3. XGBoost Error Metric

Metric	SpO_2	Heart Rate	Temperature	Respiration Rate	Pulse	Average
MAPE	0.1097%	3.4948%	0.2948%	2.4479%	2.8603%	1.8415%
MAE	0.1088	2.9206	0.1068	0.2455	2.3767	1.1517
MAD	0.4104	6.0977	0.0486	0.1636	5.9087	2.5258
MSE	0.0319	16.1126	0.0138	0.0627	11.3779	5.5198
RMSE	0.1786	4.0141	0.1176	0.2505	3.3731	1.5869

Table 4. LSTM-XGBoost Error Metric

Metric	SpO_2	Heart Rate	Temperature	Respiration Rate	Pulse	Average
MAPE	0.0484%	2.2481%	0.0106%	0.8173%	1.4552%	0.9159%
MAE	0.0484	1.8698	0.0038	0.0899	1.2404	0.6505
MAD	0.4104	6.0977	0.0486	0.1636	5.9087	2.5258
MSE	0.0122	12.1854	0.0003	0.0899	6.6192	3.7814
RMSE	0.1104	3.4908	0.0191	0.2998	2.5728	1.2986

It is shown that the usage of the LSTM-XGBoost Hybrid for this model with the same parameters will forecast data with the least error metrics. This means that the proposed LSTM-XGBoost model will predict better if a short time is needed.

4. CONCLUSION

In conclusion, combining popular machine learning methods such as LSTM and XGBoost yields positive results. The combined machine learning technique has fulfilled its purpose by achieving both more accurate results and faster processing speeds by using less iterations. If LSTM and XGBoost were to be used alone, more iterations are needed to obtain the same results as the hybrid model. The proposed technique effectively addresses the need for speed in vital signs monitoring. However, it should be noted that the accuracy of the proposed method will not be as accurate as high-iteration machine learning methods.

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