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Mohammed K. Al-Khafaji

Eman S. Al-Shamery

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Keywords

Prediction; Hospital service quality; Collaborative filtering; Bi-LSTM network; Kalman filter

RESEARCH PAPER

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Mohammed K. Al-Khafaji*, Eman S. Al-Shamery

Software Dept., Information Technology College, University of Babylon, Hilla, Iraq

Abstract

Health is one of the most important aspects of human well-being, and access to high-quality healthcare is essential for a good quality of life. Providing top-level health services at all times is crucial. However, the research in healthcare poses significant challenges due to the diversity and variations of medical practices across different hospitals. This paper aims to tackle the challenge of data missing and scattering during data collection. Then, the quality of services (QoS) offered by healthcare facilities will be analyzed and predicted from the patient's perspective. The model begins preprocessing data by data cleaning, handling missing values, and scattering data using clustering, similarity techniques, and collaborative filtering methods. Then, it focuses on predicting QoS using a structured structure for bidirectional long short-term memory (Bi-LSTM) networks. Finally, the model employs a Kalman filter method to optimize prediction by reducing the squared error between the model prediction and the actual prediction. In this study, two types of databases were used. The first data was from Iraqi hospitals in various geographical areas: Al-Hillah General Teaching Hospital in Babylon (H1), Al-Kafeel Hospital in Karbala (H2), Al-Yarmouk Hospital in Baghdad (H3), and Diwaniyah Women's and Children's Hospital in Diwaniyah (H4). The data was collected through questionnaires in both manual and electronic form. The second data was obtained from United States hospitals; it was collected by the Centers for Medicare and Medicaid Services (CMS). The model achieved an accuracy of 98.4 %, precision of 98 %, recall of 97.7 %, and F1-measure of 97.6 % with the U.S. hospital databases, outperforming many models such as deep learning techniques (LSTM and Bi-LSTM), regression, and random forest.

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1. Introduction

Healthcare is a fundamental and urgent requirement; it is essential for survival, development, growth, productivity, and well-being in life. It derives its legitimacy from satisfying one of the basic human needs [1]. Healthcare services are those measures undertaken by the government to benefit members of society, including health, education, government subsidies, support policies for some consumer goods medical, social insurance, cultural services, housing services, and the environment [2].

There is no doubt that the spread of diseases and the low level of healthcare reflect badly on all development efforts and hinder economic and social progress in society [3,4]. It is impossible to plan healthcare ignoring the constant interaction between health and the social environment [5]. Quality of Service (QoS) is a relative measure that compares expected quality with perceived quality. Perceived quality includes two types: technical quality and functional quality. Technical quality means what is provided to the customer, and it is related to the basic need that is seeking to be satisfied. Functional quality is the quality degree of how the service is

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* Corresponding author.
E-mail addresses: Mohammedkodayera.sw@student.uobabylon.edu.iq (M.K. Al-Khafaji), emanalshamery@itnet.uobabylon.edu.iq (E.S. Al-Shamery).

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estimated, which can be called the quality of the output, which is usually evaluated after obtaining the service. In return, artistic quality is considered the quality of work that is usually evaluated during service provision [6].

Predicting the QoS from the patient's viewpoint is crucial because the patient is the main recipient of the service [7]. The study focused on predicting QoS in four different Iraqi hospitals located in various geographical areas: Al-Hillah General Teaching Hospital in Babylon (H1), Al-Kafeel Hospital in Karbala (H2), Al-Yarmouk Hospital in Baghdad (H3), and Diwaniyah Women's And Children's Hospital in Diwaniyah (H4). It examined various aspects of QoS that align with the actual services provided by hospitals in Iraq. The study used both electronic and paper questionnaires to assess QoS over time and predict future quality. Additionally, to demonstrate the model's generalization, the study also analyzed the QoS for 4500 U.S. hospitals using data from the Centers for Medicare and Medicaid Services (CMS). The prediction of the level of services from the patient's viewpoint has many incentives, such as creating an interactive environment between hospitals and service recipients and following up on reactions to the service procedures that the patient receives. On the other hand, this is reflected in hospitals to provide the best services, create a competitive environment between hospitals, improve their service procedures, and redistribute their resources to provide the best service. Therefore, predicting the level of services benefits the service recipient in the end [8].

Machine learning methods can make final predictions about QoS [9,10], but their basic structure is not compatible with dynamic changes and real-time prediction [11]. On the other hand, all machine learning methods predict at most one quality of service. This study aims to develop a prediction deep learning model that multi-dimension services at the same time and meets dynamic changes input over time.

Another major benefit of the deep learning methods, compared with the traditional machine learning method [12], the deep learning method can deal with time series input [13]. That means these methods are qualified to predict future values according to previous observations [14−17]. This paper proposes a new framework, the Bidirectional Long Short-Term Memory (Bi−LSTM) Prediction model, to achieve a prediction of hospital services from a patient's viewpoint. The traditional methods (neural networks, SVM, etc.) cannot deal with sequential data, the Bi-LSTM techniques have the benefit of predicting the sequence of future value according to previous observations. The Bi-LSTM, especially, merges the notion of time series by analyzing its learning in two directions (from the past to the future, then from the future to the past) [18]. In general, the proposed methodology consists of three main tasks: the collecting and preprocessing of data, then the prediction using the proposed model, and finally, the optimization of the results and correcting the prediction error using a Kalman filter.

The paper starts with a general introduction. It then discusses related works, reviews the Bi-LSTM network and Kalman filter method, presents the proposed methodology, and shares results, experimental findings, and conclusions.

2. Related work

Many researchers investigated the QoS provided by hospitals. They addressed the QoS from several aspects due to the importance of these services, and they are in direct contact with people's lives [19]. Predicting the QoS is an administrative process aimed at developing hospital management and how the patient receives the service. The prediction of the QoS is an explanation of the impression of the patient about services and how the patient receives them [20].

Álvarez-Chaves et al. presented a study on the management of emergency departments and what it requires to properly develop the quality of services and ensure high-quality service provision at all times. To achieve this goal, it is necessary to predict the number of patients who will arrive at the emergency department. The sample was collected daily in Spanish hospitals by counting the number of cases entering and leaving the emergency departments. The study used two types of algorithms: time series (autoregressive, Holt-Winters, seasonal autoregressive integrated moving average [21], and Prophet [22]) and feature matrix (linear regression [23], ElasticNet [24], eXtreme Gradient Boosting [25], and generalized linear models [26]), for prediction with the best results. The study concluded that using ensembles of prediction algorithms gives better results [27].

Paramartha et al. presented a study to measure patient loyalty and analyze the factors that affect patient loyalty; one of the most important of these factors is the quality of services. The study presented the effect of factors such as tangibility, responsiveness, assurance, empathy, and reliability on patient loyalty and discovered their individual and collective effects. The data were collected through 72 questionnaires distributed to patients; they were analyzed by multiple linear regression analysis conducted with SPSS, and the results showed that there was a relationship between these factors and patient loyalty, individually or collectively [28]. Additionally, Guspianto et al. presented a study to measure patient loyalty to the hospital and studied the factors influencing patient loyalty using a four-point Likert scale and analyzed using the Partial Least Squares-Structural Equation Model. The results showed that patient loyalty is strongly linked to the quality of services provided by hospitals [29].

Due to the proliferation of services and their varying quality, Yan et al. presented the "MFDK" model to predict the quality of services that the user receives. The model consists of three stages: scattering processing, a model using deep neural networks (CNN-BiLSTM), and prediction correction using the Kalman filter in real-time. The model was tested on the WS-DREAM dataset, and the model showed superiority compared to traditional models [18].

Hospitals provide complex services that must be quick and timely to create a comfortable environment for the patient. Wulandari et al. presented a study to predict patient loyalty to the hospital and the effect of service quality on patient loyalty. The dataset was collected from the patient's answers according to the Likert scale; linear regression was used to predict the desired goal, where the variables (x) and the goal (y) are looked at, whether positively or negatively, and the value of (y) is predicted on this basis. The results showed that 97.5 % of patient loyalty depends on the quality of services and 2.5 % depends on other factors [3].

Many researchers have examined patient satisfaction in high-level and low-level hospitals. Alibrandi et al. presented a model based on game theory under the title of quick fictitious play algorithm to measure the level of patient satisfaction as part of the game and the services provided as another part of the game. Data were studied in the years 2008–2013 and 2018 to test the results of predicting the level of patient satisfaction with the service provided, with an error rate of 5 %. The results showed that the patient tends to go directly to high-level hospitals; the researchers recommended the necessity of adopting a hierarchical health model that starts from the lowest to the highest [30].

Based on previous research and other studies, it is evident that there are no established standards for evaluating QoS. Additionally, the sample size studied is small and limited to a local geographical area. It is essential to establish fixed standards for measuring the level of patient satisfaction with the service. These standards should consider QoS and address the fundamental needs required to ensure patient comfort and satisfaction. In addition to the small sample size and the absence of appropriate standard criteria to assess the quality of services, these studies failed to address the preprocessing methods and how to handle bias and inaccuracies in questionnaires, lacking clear solutions in this regard. Furthermore, they did not discuss the practical applicability of the systems or the feasibility of implementing the models in real-world situations. This paper offers a comprehensive solution to many of the shortcomings identified in previous research.

3. Deep learning and Kalman filter

This section outlines the techniques and literature used in this paper to achieve the goal of predicting the QoS provided by hospitals from the user's perspective. The paper employed a developed model of Bi-LSTM networks to predict QoS based on time series data. Additionally, a Kalman filter was used to optimize the results and update the weights of the neural network [31]. The paper will explain the rationale for using these methods and how they were employed.

3.1. Bi-LSTM

Bi-LSTM is a kind of Recurrent Neural Network (RNN) that analyzes sequential data in two directions (forward and backward) [32]. It merges LSTM's strengths with bidirectional processing to capture both past and future aspects of time series input.

To understand the Bi-LSTM, it is essential to first comprehend that of LSTM [33]. LSTM architecture learns long-term dependencies between time series and sequences of data occurrences [34]. Instead of the feedforward networks [35], which cannot process the notion of time series data, or RNNs that are inhibited by the problem of vanishing gradient, the LSTM models are stronger alternatives to traditional learning. LSTM architectures handle the issue of inefficient updating of weight through the training process (vanishing gradient) by achieving long-range dependency [36].

Bi-LSTM networks use memory to preserve the behavior of sequence input data [37], which allows them the ability to predict the future [38]. These networks rely on forward feeds and backward feeds (see Fig. 1) . The feed-forward data passes from the first layer to the last layer with a set of hidden layers within the network, and the network updates the memory based on previous observations. On the contrary, in backward processing, where data passes from the last layer to the first layer, memory occurs

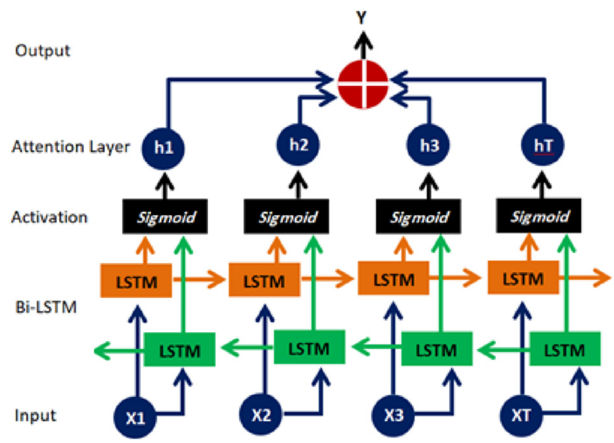

Fig. 1. Descriptive diagram of the functioning of Bi-LSTM.

based on future observations. The combination of the forward state and the backward state gives strength to forecasting the future, as future observations as well as previous observations are taken advantage of, which gives highly accurate forecasting accuracy [39].

3.2. Kalman filter

It is an algorithm developed by the scientist Kalman in 1960 [40]. The Kalman filter is used to correct the dynamic model prediction over time [41]. It uses statistical measures based on the Gaussian distribution to reduce the square error between the actual predictions and the model predictions to a minimum error [42], as in Fig. 2. The Kalman filter includes the equation of time update and the equation of state update [43], assuming there is a linear model with current state and observation, as equations below:

$$X_t = Ax_{t-1} + Bu_{t-1} + W_{t-1} \tag{1}$$

$$z_t = Hx_t + V_t \tag{2}$$

Where X_t ,Z_t the states of the model and the observation at time t, respectively, u_{t-1} is the control

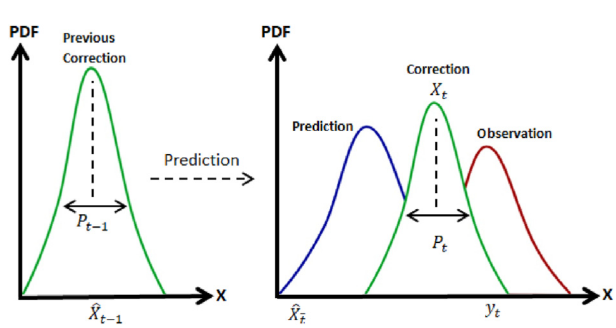

Fig. 2. Kalman filter scheme.

variable at time t − 1, A and B are the transfer matrix state and the transfer matrix input state, respectively, W_{t-1}, V_t are Gaussian-distributed noise, and H is the transformation matrix. The Kalman filter time update equations are:

$$\hat{X}_{\bar{t}} = A\hat{X}_{t-1} + BU_{t-1} \tag{3}$$

$$P_{\bar{t}} = AP_{t-1}A^T + Q \tag{4}$$

Where $\hat{X}_{\bar{t}}, \hat{X}_{t-1}$ are prior and posterior state estimate at time t and t-1, respectively, $P_{\bar{t}}, P_{t-1}$ are the prior and posterior estimates covariance at time t and t-1, respectively, and Q is the state noise covariance. The Kalman filter state update equations are:

$$K_t = \frac{P_{\bar{t}}H^T}{HP_{\bar{t}}H^T + R} \tag{5}$$

$$\hat{X}_t = \hat{X}_{\bar{t}} + K_t(Z_t - H\hat{X}_{\bar{t}}) \tag{6}$$

$$P_t = (I - K_tH)P_{\bar{t}} \tag{7}$$

Where K_t is the gain matrix, and R is the observation noise covariance.

4. The proposed methodology

This section outlines the proposed methodology, which includes data pre-processing, QoS prediction, and optimization. Fig. 3 illustrates the proposed model, and each step will be explained in the following sections.

4.1. Data description and collection

In this paper, we prepared two types of data:

Dataset-1: This dataset contains local data from Iraq, collected through a questionnaire consisting set of questions related to service quality. Each question offered ten answer options that represented the quality of various services. The questions addressed the following aspects:

- M1. General cleanliness (in patient rooms and bathrooms).
- M2. Nurse-patient communication.
- M3. Doctor-patient communication
- M4. Staff communication with patients, including explaining medications and providing prompt assistance.
- M5. Communication about medications and instructions for use after discharge from the hospital.

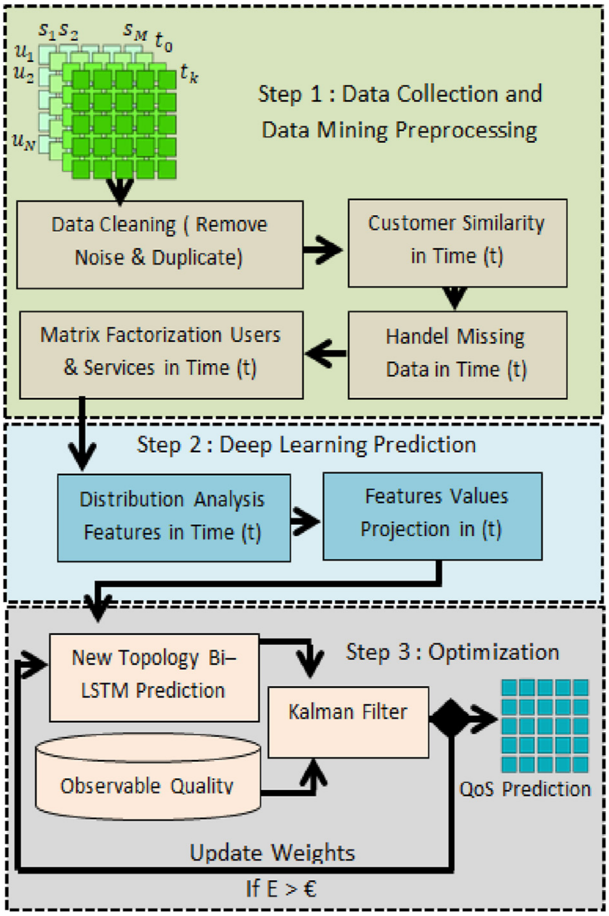

Fig. 3. Framework of proposed model.

- M6. Explanation of healthcare procedures and post-discharge guidelines for patients.
- M7. Noise levels in the hospital vicinity surrounding the patients.
- M8. Cost of treatment, in terms of price and availability of medicines.
- M9. Whether patients would recommend others to go to the hospital.

These questions covered criteria such as care timing, empathy, care impact, tangibility, and reliability.

Four hospitals in central Iraq were selected for the study, and samples were collected over various periods. More than 100 questionnaires were gathered from each hospital, reflecting patients' perspectives on the services provided. In total, over 400 questionnaires were collected from time point 1 (t1) to time point 10 (t10) during the years 2023–2024. This resulted in a total sample size of over 4000 responses from both men and women of varying ages. After reviewing the collected data, the total number of valid questionnaires was reduced to 3500 by excluding those that contained biases or had multiple responses to individual questions.

Dataset-2: It is from United States hospitals, updated regularly, and represents quality standards similar to those used in the first data set. This data is available on the website “https://data.medicare.gov.”.

4.2. Data mining preprocessing

Before diving into the prediction process, the data was found to contain numerous irregularities and required cleaning. Questionnaires with multiple answers, as well as duplicate and biased responses, were excluded. Moreover, the data needs to address the sparsity of data. Let's assume there is a set of users (patients) $U = \{u_1, u_2, u_3, \ldots., u_N\}$, a set of services $S = \{s_1, s_2, s_3, \ldots., s_m\}$, and different times $T = \{t_1, t_2, t_3, \ldots., t_K\}$. Therefore, the data is in the form of a cube (R) that represents three dimensions: user, service, and time. To reach any value (V) represented by three dimensions $v_{n,m,k} \in R$. As shown in Fig. 4,

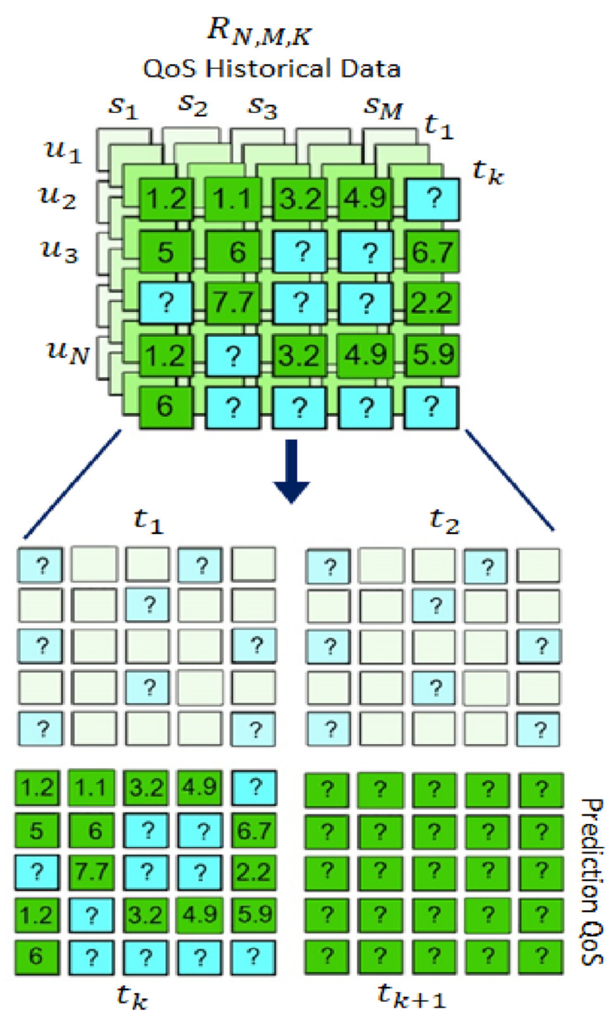

Fig. 4. Three dimensions historical data (user, service, and time).

the main objective of the model can be summarized as predicting the QoS at t_{K+1}. However, the data is missing and sparse because patients don't use all services, which creates irregular historical data and directly impacts the accuracy of the prediction.

Hospitals offer a wide range of services to patients, which vary based on each patient's specific needs. As a result, each patient receives some services while missing out on others, making it difficult to assess their overall experience. This leads to data sparsity. To address this issue, similarity user methods and collaborative filtering techniques were employed [44].

In similarity user methods, extracting missing information involves clustering the patients into closer groups and then measuring the distance between objects. This can be used to predict missing values or social behavior. This paper used the concept of similarity between users to fill in missing data. It employed Euclidean distance measures, as shown in Equation (8).

$$d(X,Y) = \sqrt{\sum_{i=1}^{n} (y_i - x_i)^2} \tag{8}$$

Each user is represented as a vector of the evaluated services. After identifying similar users, missing information for the user (u_x) is filled in by the user (u_y) is filled in with the minimum Euclidean value from the user. Then the process of processing the missing data continues with the Matrix Factorization (MF) technique is a popular method for collaborative filtering. MF involves breaking down the users-services matrix into two lower-rank matrices. The first matrix represents the users' characteristics, while the second matrix represents the services' characteristics. The original matrix is then reconstructed by multiplying these two matrices together. This resulting matrix does not contain missing values, as its values are predicted by breaking down the original matrix into two lower-rank matrices and reassembling them.

4.3. Distribution and projection of the feature values in time

After the first stage, the historical data was converted from sparsity and irregular data to regular data. The data was separated by time, starting from t_1 to t_K and then prediction t_{K+1}.The first layer in deep learning is to analyze feature $\{f_1, f_2, f_3, \ldots, f_M\}$ in each time $\{t_1,\ t_2,\ t_3,\ \ldots\ldots,\ t_K\}$, based on the Gaussian distribution. This step is crucial, each feature will be divided into three quality regions depending on the distribution of the feature at a certain time, the regions are the lower of the curve (L), the middle of the curve (M), and the top of the curve (H). As in Equation (9), each user's assessed value of a specific service was projected to these regions depending on the degree of assessed value and the Gaussian distribution of the feature.

$$M_{u,f} = e^{\left(-\frac{(f-\bar{f}\,)^2}{2\sigma^2}\right)} \tag{9}$$

Where $\bar{f}$ is mean of f, σ is standard deviation of f.

This layer has many advantages. Each feature (f) will be analyzed separately at each time (t). Therefore, the user's assessed value to any (f) at each time (t) will be into a competitive state for the same time (t), this produces more accurate and more reliable results.

4.4. Developed Bi–LSTM prediction model

The second layer of deep learning in this paper is adding a deep learning network Bi-LSTM networks, to predict the QoS according to the user's viewpoint. This paper presents a developed model through development in the structure of the Bi-LSTM, by adding three nodes (L, M, and H) representing the quality regions according to the analysis done in the previous layer for each feature as shown in Fig. 5. Each feature is represented by three nodes to predict its quality of service (QoS). This approach differs significantly from the traditional Bi-LSTM network, which uses a single node for each feature. By utilizing multiple nodes, the model achieves higher prediction accuracy, as it can capture more precise details. Additionally, this structural change

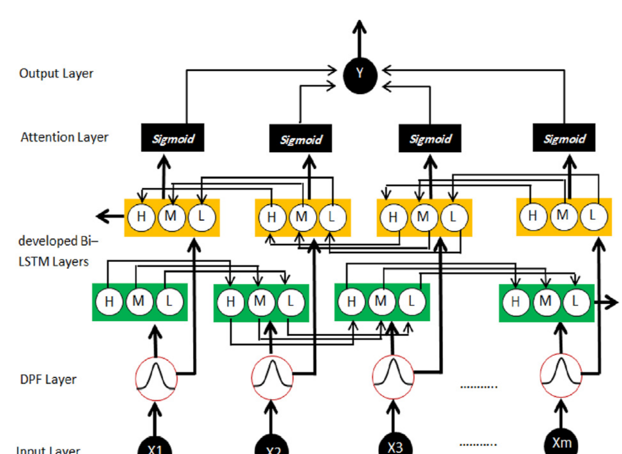

Fig. 5. Developed Bi–LSTM prediction model.

is directly proportional to the QoS, which can be categorized as high, medium, or low as the nodes (H, M, L).

Bi-LSTM networks deal with data time series in two directions, the forward and the backward. Data passes in the forward direction from t_1 time t_k to time, while in the backward direction, data passes reverse from t_k time t_1 to time. Based on this configuration of the network, a feature vector is created according to the data time series, as in Equation (10).

$$\overrightarrow{V_f} = \{x_{t1}, x_{t2}, x_{t3}, \ldots\ldots, x_{tk}\} \tag{10}$$

Where x is the value of feature f in time t.

Each value of the vector (x) is decomposed into three nodes (L, M, and H) depending on the value of the feature in time t and the distribution of the feature at the same time t. Analyzing each value into three values with different affiliations determines the quality of service achieved by the particular hospital in the time t. Referring to Fig. 5 for more details, note that each node is linked to the corresponding nodes of the same rank. In the forward direction, for example, the node (L) in time (t) is connected with the node (L) in time (t+1), as in Equation (11), while in the backward direction, the node (L) in time (t+1) is connected with the node (L) in time (t), as in Equation (12), this applies to all other nodes (L, M, and H).

Let $z \in Z$, where $Z =$ *{Node (L), Node(M), Node (H)}*

$$\overrightarrow{z_{f_t}} = \sigma\left(W_z.[h_{t-1}, x_t] + b_f\right) \tag{11}$$

$$\overleftarrow{z_{f_t}} = \sigma\left(W_z.[h_{t+1}, x_t] + b_f\right) \tag{12}$$

Where z_{f_t} is the value of node for feature f in time t, x_t is sequence of feature value form $\overrightarrow{V}_f$, h_{t-1} is the output of the $z_{f_{t-1}}$, h_{t+1} is the output of the $z_{f_{t+1}}$, W_z is the weight of the node, b_f is represents the bias of feature f, and σ is the sigmoid activation function, whose equations is:

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{13}$$

Fig. 6 show the inter calculation process of the input sequence feature in $\overrightarrow{\mathrm{V}}_{\mathrm{f}}$ and memory unit is as follows:

$$i_t = \sigma(w_i.[h_{t-1}, x_t] + b_i) \tag{14}$$

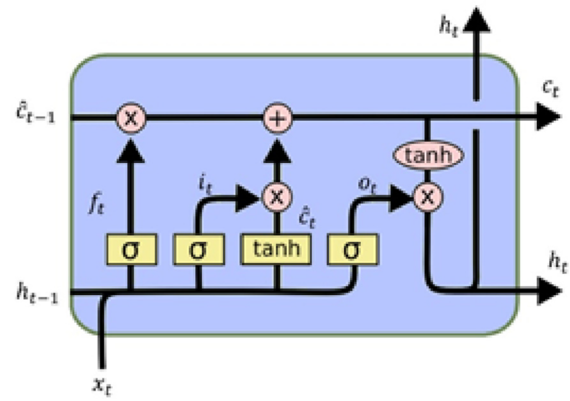

Fig. 6. LSTM basic unit.

$$\hat{c}_t = \tanh(w_c + \cdot [h_{t-1}, x_t] + b_c) \tag{15}$$

$$c_t = f_t * c_{t-1} + i_t * \hat{c}_t \tag{16}$$

Where $\hat{c}_t$ is variable calculation through the activation function tanh, i_t is variable calculation through the activation function sigmoid, c_t is the value of the memory state with sequence feature, w_i, w_c are weight matrices, and b_i, b_c are bias matrices.

The output information for LSTM untie, whose expression is:

$$o_t = \sigma(w_o.[h_{t-1}, x_t] + b_o) \tag{17}$$

$$h_t = o_t * \tanh(C_t) \tag{18}$$

Where o_t is the output of LSTM unite and calculation for each node (L, M, and H), C_t is short-term memory, and h_t is final output of LSTM.

After this layer, the model has three values of h_t for each node (L, M, and H), the data is forwarded to the attention layer to obtain the final output that represents the prediction value as in the equation below.

$$\overrightarrow{y_k} = h_{t(L)} * \min(f_t) + h_{t(M)} * \bar{f} + h_{t(H)} * \max(f_t) \tag{19}$$

The Bi-LSTM is forward layer and Backward layer, as show in expiration:

$$y_{k+1} = \left[\overrightarrow{h_k}, \overleftarrow{h_k}\right] \tag{20}$$

In summary, Algorithm 1 is show deep learning prediction model stage:

Algorithm 1, deep learning prediction model stage

```
Input: regular time series data
Output: Prediction Value quality of Service
Let T is time, U is users, f is feature
For each t ∈ T
   For each f ∈ F
      f_mean = Mean(f_t),
      f_max = Max(f_t),
      f_min = Min(f_t),
      f_σ = Std(f_t),
      Store f_mean, f_max, f_min, f_σ
   End For
End For
For each f ∈ F
   Create V_f(→) = {f_t1, f_t2, f_t3, ……., f_tk}
M_t = 0, L_t = 0, H_t = 0
   For v ∈ V_f(→)
      M_t = e^(-(v - f_t,mean)^2 / (2 f_t,σ^2))
      If v < f_t,mean
         L_t = 1 - M_t, H_t = 0
      Else
         H_t = 1 - M_t, L_t = 0
      End If
      Calculation Bi-LSTM as in Equations (11) to 18)
End for
y_k(→) = M_t * f_mean + L_t *, f_min + H_t * f_max
End for
y_{k+1} = [h_k(→), h_k(←)]
```

4.5. Optimization and Kalman filter

The third stage of the proposed model includes optimization the model results with the actual results using the Root Mean Square Error (RMSE) and adjusting the network weights using the Kalman filter. The square of the error between the model's predictions and the real services it provides by hospitals is calculated as in Equation (21). If RMSE is very large, the weights are adjusted using a Kalman filter. In this way, the gradual error that occurs over time is treated by adjusting the network weights at each time t.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} y_i - \overline{y_i}}{n}} \tag{21}$$

This step utilizes the Kalman power to estimate the squared error ratio, leveraging its ability to determine noise and the deviation of prediction from observed prediction over a time series. Additionally, In addition, it benefits from the flexibility of neural networks in updating their weights. The approach involves analyzing the error with the Kalman filter and subsequently updating the weights in the neural network. The square error rate is determined by considering the outputs of the neural network as the outputs of the Kalman filter, then determining the error rate for updating the weights as shown in the equations below. This method improves prediction stability and accuracy, especially with noisy and diverse data.

$$\overline{x_{\bar{t}}} = y_{\bar{t}} = A_{t-1} y_{t-1} \tag{22}$$

$$P_{\bar{t}} = P_{t-1} {A_{t-1}}^2 + Q \tag{23}$$

Where $\overline{x_{\bar{t}}}$ is prediction of Kalman filter and is represented by $y_{\bar{t}}$ is the prediction of deep neural network at time t-1, and $A_{t-1 = \frac{y_{\bar{t}}}{y_{\overline{t-1}}}}$.

The gain matrix shows the level of difference between network predictions and actual services, and this measure is used to adjust the network weights. As in the expressions below:

$$K_t = \frac{P_{\bar{t}}}{P_{\bar{t}} + R} \tag{24}$$

$$Ky_t = y_{\bar{t}} + K_t \left(Actual_{t-1} - y_{\bar{t}} \right) \tag{25}$$

$$w_t = w_{t-1} + \Delta w_t \tag{26}$$

$$\Delta w_t = \alpha \frac{\partial K y_t}{\partial w_t} \tag{27}$$

Where w_t is the weight at time t, w_{t-1} is the weight at time t-1, Δw_t is a weight change between t and t-1, and α is the learning rate.

Algorithm 2, summarized optimization and Kalman filter:

Algorithm 2, optimization and Kalman filter

```
Input Prediction Model (y)
Output: Update Weight Of deep neural network
Let T is time
For each t ∈ T
  Calculations Ky_t by RMSE as Equation 21
  While RMSE > € Do
     Calculations Ky_t by Equation (22–25)
     Δw_t = α ∂Ky_t/∂w_t
     w_t = w_{t-1} + Δw_t
  End While
End For
```

5. Results and discussion

The model was implemented on a Windows 10 computer with Core i7 specifications using Visual Studio 2022 and the C# programming language. The data collection took over ten months, during which data was collected at different intervals from time 1 to time 10. Various methods, including paper or electronic, were used to collect the data from Iraqi hospitals, and an electronic page was created to facilitate this process. This page can be accessed through a mobile phone or any internet-connected device. The total sample dataset was more than 3500 patients' viewpoints. For the sample to be consistent, the study ensured that half consisted of males and females of different ages, as shown in Fig. 7. The sample collection methods included manual (paper-based) and electronic (website and mobile phone) approaches.

The sample collection process presents numerous challenges, particularly due to the significant differences in standards between Iraqi and American hospitals. To address this issue, scales were specifically designed to align with the realities of Iraqi hospitals. To enhance the potential for applying this model in other countries, it is essential to study the existing services in those countries and establish standards that reflect their unique contexts.

After collecting data, there was a lot of scattered data because some service users didn't answer all the questions. To solve this, the study used a clustering and similarity technique and collaborative filtering to fill in the missing data and make predictions. This process is crucial for filling in missing data, and its success depends on accurate predictions of missing data at each time. Higher prediction accuracy leads to better model performance in later stages. It's clear from Table 1 that the percentage of missing data is significantly reduced after processing using clustering and similarity between service users. The factorization matrix breaks down the features into two lower-order matrices to uncover the underlying features and fill in all missing data.

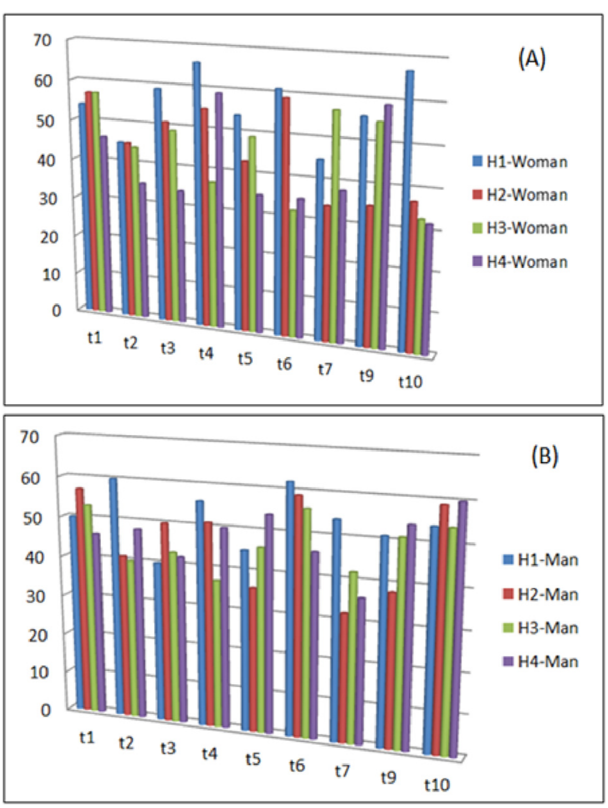

Fig. 7. The total sample dataset according time and hospital (H1, H2, H3, and H4): A: Woman, B: Man.

After ensuring data consistency and completeness, the quality services prediction phase for time t+1 begins with two important layers:

The first layer involves analyzing each feature at each time point to determine its quality areas (L, M, and H). This is done by determining the mean of each feature and then assigning each value among the three quality areas. Table 2 shows the mean of

Table 1. The percentage of missing data before and after the pre-processing stage.

Time	Missing data (%)	After similar technique (%)	After factorization matrix (%)	Prediction accuracy of missing values (%)
T1	54	31	0	90.1
T2	43	30	0	92.2
T3	23	18	0	97.1
T4	29	20	0	97.1
T5	32	21	0	93.2
T6	56	39	0	90.5
T7	43	29	0	93.2
T8	34	24	0	94.3
T9	21	11	0	98.3
T10	38	21	0	93.5

Table 2. The mean of each feature according to time.

Mean	T1	T2	T3	T4	T5
M1	4.897	5.162	4.849	5.178	5.095
M2	5.014	5.217	4.906	5.102	5.045
M3	4.988	4.95	4.86	4.92	4.98
M4	4.840	5.009	5.193	4.921	4.978
M5	5.200	4.995	5.081	5.081	5.073
M6	4.880	5.073	5.047	5.007	5.167
M7	4.811	5.248	4.992	5.045	4.964
M8	4.720	4.906	5.224	4.976	4.859
M9	5.181	5.143	4.988	5.128	5.152

Mean	**T6**	**T7**	**T8**	**T9**	**T10**
M1	5.109	5.133	5.226	4.978	4.474
M2	5.260	4.921	5.136	5.205	4.603
M3	5.109	5.050	5.291	5.176	4.477
M4	4.875	5.136	4.782	5.052	4.515
M5	5.088	5.093	4.780	5.026	4.422
M6	5.002	5.062	4.952	5.064	4.668
M7	4.711	5.114	4.995	5.064	4.202
M8	4.828	4.964	5.152	5.193	4.436
M9	4.873	4.720	4.988	5.093	4.389

each feature (M1, M2, M3, …., and M9) in time (T1, T2, T3, ….., and T10).

After identifying the mean of each feature, each value is then assigned a quality percentage based on the three quality areas, which are represented as nodes in the Bi-LSTM layers. This step is crucial as it determines the service quality value for each hospital and its ranking compared to other hospitals. It also provides accurate predictions by taking into account any service failures over time. Table 3 shows some projections of the values or each hospital for each feature at each time point.

Each node (L, M, and H) value is calculated using the Bi-LSTM gate at each time step. Analyzing the region quality as nodes and combining these values leads to highly accurate predictions. Tables 4 and 5 show the predictive accuracy of the proposed model compared to other techniques.

In the prediction process, it is evident that there are disparities in the quality of services offered by hospitals in Iraq and the United States. The level of service in US hospitals ranged from 85 to 90 percent, while in Iraqi hospitals, it ranged from 30 to 55 percent. Fig. 8 illustrates the service level prediction for the proposed model and other techniques.

Table 3. Projections of the hospital's value according to measure and time.

Id	M1-T1			M2-T1			M3-T1		
	L	M	H	L	M	H	L	M	H
H1	0.12	0.88	0	0.43	0.57	0	0.22	0.78	0
H2	0	0.79	0.21	0.2	0.8	0	0.3	0.7	0
H3	0.32	0.68	0	0.29	0.71	0	0.6	0.4	0
H4	1	0	0	0.61	0.39	0	0.8	0.2	0
Id	**M1-T2**			**M2-T2**			**M3-T3**		
	L	M	H	L	M	H	L	M	H
H1	0.1	0.9	0	0.41	0.51	0	0.43	0.57	0
H2	0	0.75	0.25	0	0.9	0.1	0	0.78	0.22
H3	0.22	0.88	0	0.4	0.6	0	0.	0.81	0.19
H4	1	0	0	0.54	0.46	0	0.7	0.3	0

Table 4. Prediction value of Proposed Model (PM) comparison with Observable Prediction (OP), Bi-LSTM (BL), LSTM (LS), Regression (Rg), Random Forest (RF) for United State hospitals.

Time	PM	OP	BL	LS	Rg	RF
T1	85.3	86	82	76	70	81.4
T2	87	88	81	76	69.1	88.3
T3	84	86	80	77	74	83
T4	89	87	81	74	76	85
T5	90	90.1	81	75.6	72	86
T6	86	84	81	76	71	83
T7	92	90	85	81	80	81
T8	91	92	84	79	70	87
T9	88	85	81	75	70	84
T10	91	90	84	80	69	89
Tk+1	88	91	85	81	70	85

Table 5. Prediction value of Proposed Model (PM) comparison with Observable Prediction (OP), Bi-LSTM (BL), LSTM (LS), Regression (Rg), Random Forest (RF) for Iraqi hospitals.

Time	PM	OP	BL	LS	Rg	RF
T1	52.9	54	49	40.1	34.1	50
T2	48	50	46.9	37.1	30.2	52
T3	49.1	48	45.1	37.2	32.1	42
T4	40.4	41	38.1	31.5	25.3	37
T5	30.6	32	29.1	20.1	12.4	29
T6	32.8	35	30.1	20.2	15.4	32
T7	38.7	39	35.1	30.1	25.1	40
T8	39.2	40	31.2	22.4	24.4	38
T9	43.7	44	40.1	34.1	25.3	41
T10	41.3	41	36.7	29.1	23.1	38
Tk+1	42.5	43	38.1	32.2	26.1	40

To evaluate the accuracy of the predictions made by the proposed model concerning the quality of services provided by hospitals in Iraq and the United States, Table 6 presents various metrics are Accuracy (Acc), Precision (Pre), Recall (Rec), and F1-measure (F1) were calculated each time to assess the quality of the predictions.

It is worth noting that the accuracy of the proposed model's prediction of the quality of services for Iraqi hospitals is 95.8 %. In comparison, the accuracy of the prediction for American hospitals is 98.4 %. This is due to differences in sample size and missing data during sample collection.

In an experiment on the data to determine the importance of each step of the proposed model, Table 7 shows the overall accuracy of the model and

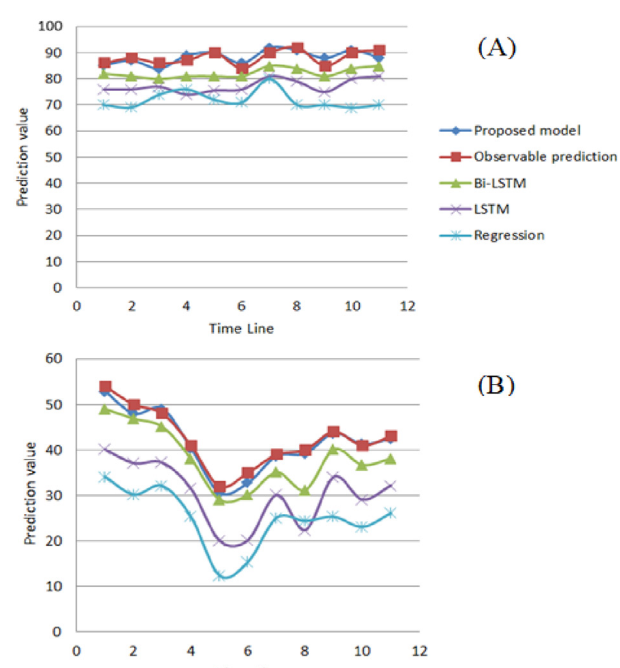

Fig. 8. The level of service in: A: United State hospitals, B: Iraqi hospitals.

Table 6. Evaluation metrics for the proposed model prediction.

Time	United State hospitals				Iraqi hospitals			
	Acc (%)	Pre (%)	Rec (%)	F1 (%)	Acc (%)	Pre (%)	Rec (%)	F1 (%)
T1	99	98	99	98	97	98	96	97
T2	99	99	96	97	96	95	96	95
T3	99	99	97	98	95	97	95	96
T4	97	98	96	97	96	94	98	96
T5	99	98	99	98	94	94	99	96
T6	98	99	96	97	97	99	96	97
T7	98	98	98	98	95	94	97	95
T8	98	96	99	97	99	97	98	97
T9	98	97	99	98	94	93	96	94
T10	99	97	99	98	96	97	94	95
Tk+1	98	99	97	98	95	94	95	94
Avg	98.4	98	97.7	97.6	95.8	95.6	96.4	95.6

Table 7. Accuracy of both databases after removing each step of the proposed model.

Data set	Iraqi Hospitals	United State Hospitals
Final accuracy (%)	95.8	98.4
Accuracy without Preprocessing (%)	80.4	81.7
Accuracy without optimization (Kalman Filter) (%)	88.3	89.1

the accuracy after removing each step of the proposed model.

6. Generalization of the model in the real world

The model's applicability in the real world is quite feasible and has already been demonstrated through the sample used in this research. However, several challenges need to be addressed to generalize the model across various hospital environments worldwide:

- Before implementing the model, it is essential to establish standards for evaluating service quality, aligning with systems adopted by the state while fostering a competitive environment among hospitals.
- A questionnaire should be designed to engage users interactively, capturing their responses and expressions to better understand the essence of the services provided by hospitals.
- The sample should be collected over different periods and times, ensuring that respondents represent various age groups. This diversity is vital for obtaining a consistent sample that reflects service quality at different times and among patients of varying ages.
- Preprocessing the collected data is crucial, as it enhances data accuracy by eliminating biased or inaccurate responses. Additionally, it is important to consider the patient's conditions and health status during this process.

7. Conclusion

Countries around the world are striving to enhance healthcare quality, which requires continuous evaluation of healthcare institutions. This study utilized innovative methods and techniques to predict the quality of medical services from the patient's perspective. One of the primary challenges encountered before starting the prediction process was dealing with issues related to missing and scattered data. Patients have different views on the services they receive, and given that hospitals provide a wide range of services, it is difficult to evaluate all aspects of the care offered.

The prediction process is summarized in three steps: the preprocessing, during which data missing and scattering were addressed using clustering, similarity techniques, and collaborative filtering. Then the prediction step employs a developed Bi-LSTM model. Lastly, the optimization of the results using the Kalman filter.

The model was tested in four hospitals in Iraq and also in hospitals in the United States. It demonstrated a high capability to predict service quality, achieving an accuracy rate of 98.4 %. Furthermore, it showed significant superiority over existing models in the field of service quality prediction.

In future work, the model can be expanded to include a broader range of Iraqi hospitals and more comprehensive criteria. This will necessitate the establishment of facilities for data collection and the creation of a competitive environment among hospitals, which will ultimately benefit patients significantly.

Ethics information

We certify that we have read the Journal's "Publication Ethics" shown on the link: https://kijoms.uokerbala.edu.iq/home/publication_ethics.html. We confirm that we follow these "Publication Ethics" strictly. All coauthors have seen and agree with the manuscript's contents. We certify that the manuscript is original work and is not under review at any other publication.

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Conflicts of interest

The authors have no conflicts of interest to declare.

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