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HOSPITAL SERVICES QUALITY PREDICTION USING A NEW DEEP FUZZY LEARNING MODEL

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ABSTRACT

Hospital services play a crucial role in people's lives, and continuous improvement in these services is essential. The prediction is paramount to determine the quality and suitability of the hospital's services. Yet the complexity of predicting increases, especially when dealing with intangible services such as hospital services. Many traditional prediction methods suffer from a gradual decline in accuracy and a simultaneous increase in the error rate especially in time series data. This paper introduces a new model, called Deep Fuzzy Learning Prediction (DFLP), for accurately predicting hospital service quality. The model combines fuzzy logic and deep learning neural network techniques and utilizes a set of quality parameters. DFLP's nodes represent different memberships among fuzzy sets, and the model adapts its internal fuzzy membership functions based on input data and time. Each node within the DFLP model box represents a different membership among the fuzzy sets. The membership scenarios vary when adding or removing a group of hospitals from the prediction process. This is due to changes in the fuzzy membership centers, resulting in membership changes. The DFLP model offers an effective way to predict and adapt to the dynamic nature of hospital services across time series. The model is tested on data from more than 4500 hospitals in the United States collected by the Centers for Medicare and Medicaid Services (CMS). The results show a significant convergence between the model's prediction and the actual services provided by hospitals. The results were compared with Long Short-Term Memory (LSTM) networks and Bidirectional LSTM (Bi-LSTM) networks and showed the superiority of the proposed model over traditional prediction networks. The proposed model achieved an accuracy of 96.68%, while LSTM and Bi-LSTM obtained 92.30% and 94.45%, respectively.

KEYWORDS

Prediction; deep learning; Fuzzy theory; Gaussian distribution; Hospital service quality.

1. INTRODUCTION

In recent years, intelligent computing systems have witnessed remarkable advancements, driving transformative progress and groundbreaking innovations in the healthcare sector. (Abdel-Aty et al., 2020). One of the most critical functions of management is the service quality prediction system (Al-Khafaji and Al-Shamery, 2025), but several institutions face many problems in service prediction. The difficulty lies in finding clear parameters for measuring the institution's services (Petropoulos et al., 2022). Without predicting the services and continuing in the competitive market, it leads to the failure of the entire institution (Aldahiri, Alrashed and Hussain, 2021). Various reasons drive institutions to undergo the prediction process, these reasons include service improvement, decision-making about future services, budget allocation, communication with the audience, and identifying strengths and weaknesses in their services (Parker et al., 2019) (Yazdani, Shahriari and Haghani, 2025).

Researchers addressed the process of predicting services from different aspects. Some of them went on to predict banking services (Narteh, 2018), aviation services (Perçin, 2018), Internet services (Yin et al., 2020), and many other services that touch people's lives. Despite significant efforts, several barriers and challenges still hinder the widespread use of reliable applications for large-scale service prediction (Yahyaoui, El-Qurna and Almulla, 2020). In the healthcare sector, the significance of healthcare services and their impact on human life, quality improvement, and quality assurance have drawn increased attention from experts, researchers, and health service organizations (Al-khafaji and Al-Shamery, 2024) (AlOmari, 2021). Quality improvement has become essential, and the demand for quality management and control is on the rise (Salih Al-Shamery, 2020) (Ferreira et al., 2023).

The purpose of this paper is to use hospital data to predict the quality of services. To achieve this goal, the paper proposes a model that combines two powerful techniques: fuzzy logic and deep neural networks. This fusion is designed to address the challenges presented by problems that lack clear classifications, particularly in the realm of hospital service prediction.

The research is motivated by three reasons. Firstly, fuzzy logic is excellent at handling uncertain and imprecise data. In the real world, clear boundaries between categories are often hard to define, and fuzzy logic can help to deal with such situations. Secondly, deep learning neural networks are exceptional at detecting complex and hidden patterns within data. This is particularly valuable in fields where traditional methods might struggle to uncover intricate relationships. In hospital service assessment, there can be subtle interdependencies among various service attributes that contribute to the overall assessment. Lastly, the combination of fuzzy logic and deep learning allows the model to make well-informed decisions that take into account both uncertain data and underlying patterns. This combination is vital for making accurate predictions in domains like hospital services, where outcomes depend on various factors that are often intertwined.

The proposed hybrid model is a groundbreaking innovation that integrates fuzzy logic and deep learning. It presents several significant contributions that make it a versatile and adaptable solution to prediction hospital services. The model introduces an adaptive learning mechanism that continuously refines its performance, allowing it to adapt to changing data and requirements. This adaptability ensures that the model's accuracy improves over time. Furthermore, the model's flexible structure can accommodate varying sets of features and categories, making it suitable for different prediction scenarios without significant modifications. The model's defuzzification layer transforms fuzzy outputs into crisp, interpretable results, improving practical decision-making. The model includes a preprocessing stage that prepares raw data for subsequent stages, enhancing the efficiency and accuracy of the overall prediction process. The model's evaluation and adaptive learning stages involve collaboration with domain experts, ensuring that the model aligns its prediction more closely with real-world assessments. Lastly, the model's hybrid approach and adaptive learning can potentially be applied to other domains facing similar challenges of uncertainty and pattern detection, making it a valuable innovation beyond hospital service prediction.

2. RELATED WORK

Numerous researchers have dedicated their efforts to predicting various aspects of hospital service quality (Abdel-Basset et al., 2019). Hospital services were classified as intangible, meaning they cannot be physically touched or tried, and their exact outcomes cannot be predicted. Purchasing a tangible commodity is relatively easier than acquiring a service (Hill, 1999). Consequently, the prediction of hospital services involves considerable uncertainty, which further increases with the volume of data provided by hospitals. Dealing with ambiguity presents significant data understanding, classification, and decision-making challenges.

To address the uncertainties, present in the raw data, fuzzy learning is highly recommended to solve many scientific problems (Deng et al., 2016). The proposed model is Deep Fuzzy Learning Prediction (DFLP), which combines two techniques: fuzzy logic and deep learning neural networks. The DFLP leverages the predictive power of neural networks and fuzzy logic's ability to handle data uncertainties. By integrating these two approaches, DFLP aims to provide a robust and effective method for predicting hospital service quality. The related studies mentioned in this section have explored the prediction of healthcare services from various perspectives.

Li, et al. presented a decision-making approach for predicting hospital service quality by combining fuzzy rough set theory with Bayesian copula networks within neighborhood operators. The Copula Bayesian network model is used to graphically illustrate the interrelationships between various factors, while Copula helps obtain the joint probability distribution. Fuzzy rough set theory with neighborhood operators is employed to handle subjective evidence from decision-makers. The method's efficiency and practicality are demonstrated through a real hospital service quality analysis (Li et al., 2023). However, the approach mainly relies on subjective evidence and specific probabilistic assumptions, which may limit its generalizability and robustness when applied to diverse healthcare datasets.

Altuntas et al. proposed an evaluation model to address the following questions: What are the potential impact levels of service quality dimensions on the quality of service practically? What should be prioritization among the service quality dimensions and Which dimensions of service quality should be improved primarily? A real-life case study in a public hospital is carried out to reveal how the proposed model works. The results that have been obtained from the case study show that the proposed model can be conducted easily in practice. It is also found that there is a remarkably high service gap in the public hospital, in which the case study has been conducted, regarding the general physical conditions and food services. However, the model largely concentrates on qualitative assessments, lacking integration with advanced predictive analytics that could enhance its decision-making capacity. (Altuntas, Dereli and Erdoğan, 2022).

The goal of Mrabet et al. is to prove how patient happiness in the healthcare industry relates to various health service quality aspects. The purpose of the study is to identify the most important aspects of service quality that can be used to predict how patients perceive the quality of private healthcare services. In Tlemcen City, Algeria, a field study was conducted on a sample of 208 patients. After using structural equation modeling to analyze the data, it was shown that reliability, tangibility, assurance, and accountability were more relevant in influencing patient satisfaction than empathy. This shows that patients are more likely to have a favorable opinion of the medical service if they believe that it is credible, trustworthy, and of a high caliber (Mrabet, Benachenhou and Khalil, 2022).

A meta-analysis and systematic review applied the SERVQUAL method to evaluate healthcare service quality across selected Asian countries, focusing on the five core dimensions: tangibility, reliability, responsiveness, assurance, and empathy. Out of 96 initially identified studies, 15 met the inclusion criteria, involving a total of 5903 participants. The results revealed consistent and significant gaps between patients' expectations and perceptions in all five dimensions, with the largest gaps found in reliability and tangibility, and the smallest in empathy and responsiveness. This confirmed SERVQUAL as a widely used tool for assessing healthcare service quality; however, its reliance on expectation–perception gaps limits its predictive and adaptive capacity in rapidly evolving healthcare environments (Jonkisz, Karniej and Krasowska, 2022).

Heidari et al. presented a study in 2024. The study focused on evaluating and predicting the level of services provided by the intensive care unit (ICU) in hospitals, specifically for humans suffering from serious diseases. This paper proposes a framework that employs work-motivational factors (WMFs) and ergonomics to evaluate the performance of various ICUsused, uses statistical methods to predict the level of services the data envelopment analysis (DEA) and uses principal component analysis (PCA) to verify the validity of the results. Through analyzing the model, the model concluded that the accuracy of work decreases as the working time of employees working in the intensive care unit increases (Heidari et al., 2024).

Previous studies have predominantly focused on the patient's perspective, primarily through the "SERVQUAL" methodology, to predict service quality. While understanding patient expectations is crucial for quality improvement, it's essential to recognize that patients might not fully notice the technical intricacies that significantly influence their health outcomes. A comprehensive assessment of all hospital sectors is imperative, especially focusing on the technical (non-clinical) procedures. This broader analysis should encompass crucial factors such as monitoring mortality rates, hospital readmissions, healthcare safety protocols, and the utilization of technical tools like radiology and MRI. These technical aspects play a pivotal role in enhancing the overall quality of healthcare services. By encompassing a more holistic view of hospital operations, we can gain a more comprehensive understanding of healthcare quality and uncover possibilities for enhancement that extend beyond solely considering patient expectations.

3. THEORETICAL BACKGROUND

This section is concerned with the theoretical background information of hospital quality and the techniques used in this research are explained.

3.1. Hospital quality

The effectiveness of any prediction model depends significantly on the quality of the data input and the efficiency of the model itself. prediction of hospital services requires a comprehensive understanding of all the different care sectors within a hospital. Hospitals consist of multiple sectors and various procedures, some of which may not be directly observable but are crucial for the prediction process. In addition to the necessity of analyzing the behavior of hospitals over time to predict the future of service quality (Endeshaw, 2021). Technical quality refers to services that are not directly perceived by patients and may require specialized knowledge, making it hard for patients to assess (Mahmoudi et al., 2020). On the other hand, functional quality can be assessed from the patient's viewpoint since they are the recipients of healthcare services. prediction of functional quality from patients' perspectives is not only important for the prediction of service quality but also essential for the survival of the institution in a competitive market (Lee et al., 2000). Additionally, there is a pressing need to measure the quality of services because discrepancies between recommended and actual procedures exist, leading to medical errors that can impact patient health (Kohn, Corrigan and Donaldson, 2000).The Centers for Medicare & Medicaid Services (CMS) have classified quality into seven main categories: mortality, safety of care, readmission, patient experience, effectiveness of care, timeliness of care, and efficient use of medical imaging (Bilimoria and Barnard, 2016) . Each category represents a different aspect of healthcare, and by assessing hospitals through these categories, their performance can be evaluated from multiple perspectives. These categories encompass both functional and technical services, providing a comprehensive view of the hospital's overall quality. For instance, patient experience and timeliness of care evaluate functional services, while mortality, safety of care, readmission, timeliness of care, and efficient use of medical imaging assess technical services. Continuously predicting hospitals and analyzing their behavior gives us a broad and insightful outlook to predict the future of these hospitals' services.

3.2. Fuzzy theory and deep learning

Fuzzy logic is a method used to handle problems that lack clear classifications (Bai, Zhuang and Wang, 2007).Professor Zadeh introduced the concept of fuzzy logic (Zadeh, 1965).Fuzzy sets form the foundation of fuzzy logic and consist of elements with varying degrees of membership, which are determined by membership functions (MF), Fig. 1 illustrates different types of membership functions.

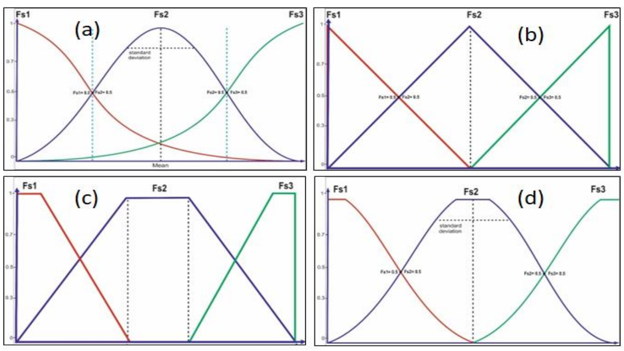

Fig.1 (a) Gaussian, (b) Triangular, (c) Trapezoidal, (d) Bell-Shaped.

In a fuzzy set. Eq.1 represents the degree of membership represented as a value between 0 and 1 (Ross, 2005). This degree of membership indicates the extent to which an element belongs to the fuzzy set. By using fuzzy logic, the model can deal with uncertain and imprecise data, which is especially valuable when assessing complex and ambiguous problems, such as those encountered in the prediction of hospital service quality (Aydın and Chouseinoglou, 2013), (Yucel et al., 2012), and (Singh, Prasher and Kaur, 2018) .

$$Z = \{ [x.\mu_Z (x)|\ x \in X]\} \quad (1)$$

Where μ_Z (x) has a value between (0, 1), represents the membership degree of element x.

Deep learning neural networks are powerful in processing data and detecting hidden patterns for use in decision-making (Suparta and Alhasa, 2016) (Scorzato, 2024) (Al-Taie and Baiee, 2025), It consists of input layer, a group of hidden layers, and output layer, each layer consists of set neurons with parallel processing (LeCun, Bengio and Hinton, 2015) (Li et al., 2022) (Yassin, Valizadeh and Abdulaal, 2025) (Shneen, Salih and Jiaad, 2025), Fig. 2 shows the basic structure of prediction neural networks.

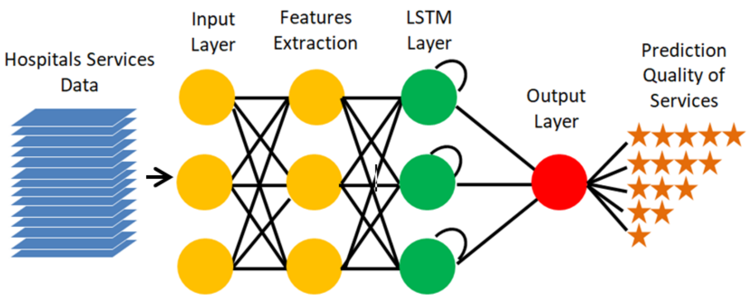

Fig.2 The basic structure of prediction neural networks.

In the input layer, historical hospital service quality data are fed into the neural network. The feature extraction layers are responsible for processing this data and detecting intricate patterns that might not be immediately apparent. The LSTM layer is the basic unit of the prediction model (Zhao et al., 2020)(Khan et al., 2021) (DiPietro and Hager, 2020) (Yang, Yu and Zhou, 2020), as shown in Fig. 3.

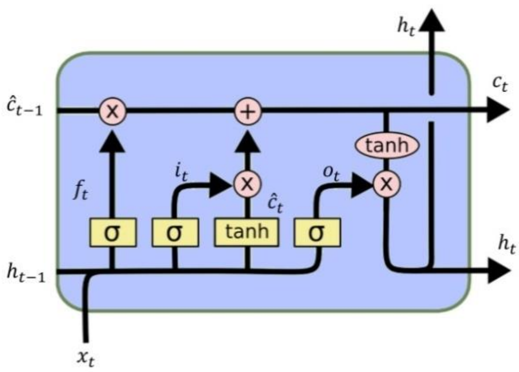

Fig.3 The basic unit of the prediction model (LSTM).

The LSTM node consists of three gates:

- Forget Gate (ft) – This gate decides what part of the previous memory (c_{t-1}) should be kept or discarded. It looks at the current input (x_t) and the previous output (h_{t-1}) and produces values between 0 and 1. A value close to 0 means "forget this," and close to 1 means "keep this."
- Input Gate (it) – This gate determines how much new information from the current input should be added to the memory. It works together with a candidate memory (ĉ_t) that proposes new information to store.
- Output Gate (ot) – This gate decides what part of the memory should be sent as the output (h_t) for this time step. The memory goes through a tanh function to scale values before multiplying by the output gate.

The final layer, the output layer, produces the results or predictions based on the processed data and patterns discovered in the hidden layers. Deep neural networks are capable of learning through training on large datasets, allowing them to excel in various tasks, including image recognition, natural language processing, and decision-making.

4. RESEARCH METHODOLOGY

The proposed model comprises three main stages: the preprocessing stage, the DFLP stage, and the evaluation and adaptive learning stage. Fig. 4 provides an overview of the key stages of the proposed model.

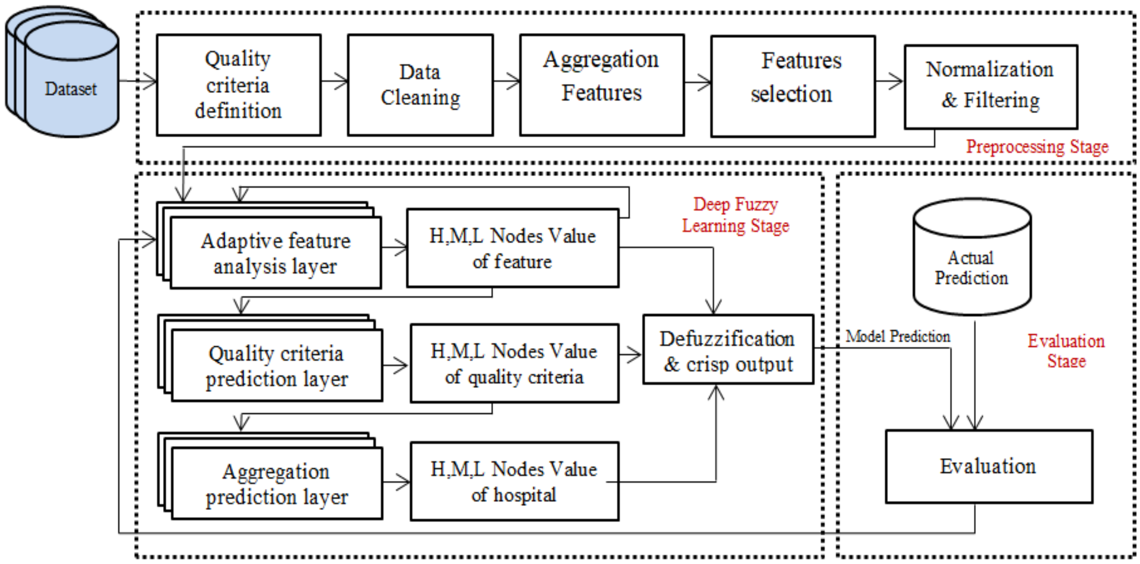

Fig.4 The main stage of the DFLP model.

The initial stage is preprocessing, the raw data obtained from hospitals is preprocessed to prepare it for prediction. It includes several techniques such as data cleaning, aggregation features, feature selection, transformation, and normalization to ensure the data is in a suitable format for the subsequent stages. The second stage is deep learning fuzzy prediction, which is the core stage of the model. It includes several techniques such as fuzzy logic and deep learning neural networks. The third stage is the evaluation model, the model's performance is evaluated based on the actual results and predictions obtained from the model. It includes several measures such as accuracy (ACC), root mean square error (RMSE).

4.1. Dataset of hospital services

Here, data is a set of features that represents the basis of any model, data collection and analysis have become an essential motivation for decision-making, it gained wide ground after becoming easier to assemble and inexpensive in storage. Add to that, data must be collected correctly, trustworthy, and unbiased because it will lead to mistaken decisions. The data used in this study consisted of a set of features for more than 4,500 hospitals in the United States collected by CMS from 2013 to 2025. The dataset is online on the website "https://data.medicare.gov". This dataset involves many features of healthcare institutions' services such as cleanliness, quietness, communication with the patient, post-operative care, death rate, safety of medical care, techniques used, care in the emergency department, and many others. Overall, the proposed model aims to provide a robust and effective method for the prediction of services of hospitals based on the data time series.

4.2. Pre-processing stage

4.2.1. Quality criteria

When the data is too large to be processed, it is easier and more accurate to divide the data into categories and it represents the quality criteria. The data was divided into seven criteria: mortality, patient experience, safety of care, readmission, effectiveness of care, timeliness of care, and efficient use of medical imaging.

4.2.2. Features selection for each quality criteria

The database contains many features; it is important to select the best features that achieve quality categories. The selection is done based on correlation attribute evaluation is one of the filter methods as in Eq.2 with threshold < 0.9. The number of features in this step has become 55 features, divided as follows: (10 features for patient experience), (7 features for mortality), (9 features for readmission), (6 features for timeliness of care), (6 features for effectiveness of care), (11 features for safety of care), (6 features for efficient use of medical imaging).

$$cor(x,y) = \frac{\sum(X_i-\bar{X})(Y_i- \bar{Y})}{\sqrt{\sum(X-\bar{X})^{2}}\sqrt{\sum(Y-\bar{Y})^{2}}} \tag{2}$$

Where X is the feature, Y is the target class, $\bar{Y}$ is the average of the target class, and $\bar{X}$ is the average of the feature.

4.2.3. Normalization and filtering hospital

One of the most important data pre-processing operations is normalization. This importance is gained because the features have different scales, so normalization works to adjust the scale of the data and make the data within a specific scale between 0 and 1, as in Eq.3. Eq.4 is utilized for normalization and determines the orientation of features, where a high score indicates the best performance and a low score represents poorer performance. Eq.4 the scale so that lower values indicate worse outcomes and higher values indicate better ones. For example, for deaths, higher original values become lower after applying this equation.

Let f ∈ F, where F is the features, v ∈ V where V is the hospital

$$\hat{v} = \frac{v - max_f}{max_f - min_f} \tag{3}$$

$$\hat{v} = 1 - \frac{v - max_f}{max_f - min_f} \tag{4}$$

Flittering hospitals refers to excluding hospitals from the prediction if they fail to report at least three measures in each quality criterion. This approach provides stronger motivation for hospitals to report a comprehensive set of features, as it ensures they remain eligible for assessment and prediction of services.

4.3. Deep fuzzy learning prediction (DFLP) stage

The DFLP model is made up of six layers: input, adaptive feature analysis layer, quality criteria prediction layer, aggregation prediction layer, defuzzification, and output. By combining fuzzy logic and deep learning, the DFLP model aims to take advantage of the strengths of both methodologies and achieve improved accuracy and performance in its applications. Fig. 5 depicts the layers of the DFLP model.

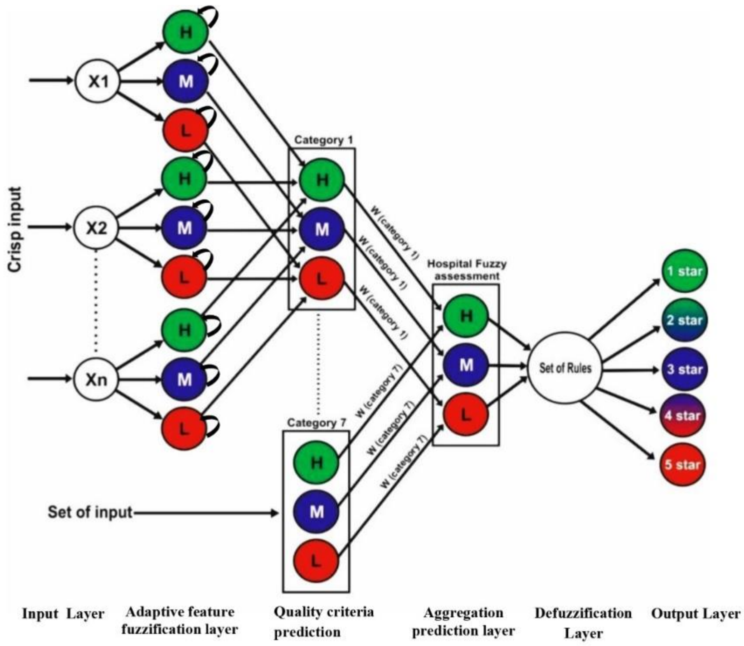

Fig.5 Deep fuzzy learning prediction (DFLP)

4.3.1. Adaptive feature analysis layer

This layer analyzes each feature value based on the Fuzzification technique is a process to convert a real value feature into a fuzzy value. In nature, data take a Gaussian distribution, and the Gaussian membership function is most common in the fuzzy logic literature. DFLP model used the Gaussian membership function with three fuzzy sets High (H), Medium (M), and Low (L), look at Fig. 6. The degree of membership of each measure is calculated by Eq.5.

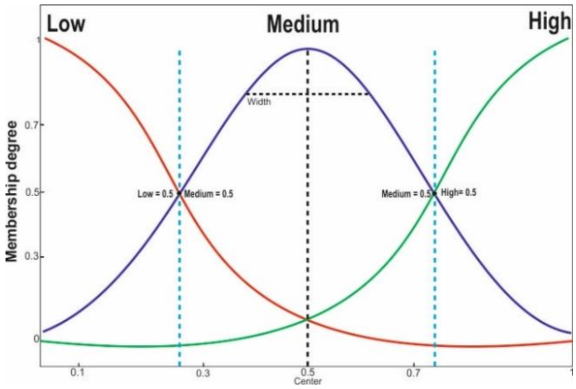

Fig.6 Gaussian membership function

Let a ∈ A, where A= {Low, Medium, High}

$$\mu_{a \in A}(v \in V(f \in F)) = e^{\left(-\frac{(C_a - v)^2}{2S_a{}^2}\right)} \quad (5)$$

Where C is the mean of feature f, S is Standard deviation of feature f.

Indeed, the feature values of the hospital do not decompose into three fuzzy sets (H, M, L). The membership of a feature can be decomposed into the following fuzzy sets: "H only" (high membership), "between H and M" (membership between high and medium), "M only" (medium membership), "between M and L" (membership between medium and low), and "L only" (low membership). Algorithm 1 illustrates the initial phase of adaptive deep learning, which serves as the first step in the overall process.

This process is repeated for all previous historical data from hospitals because this gives us a clear vision of the hospital's behavior in the future. By monitoring the membership of each node and using LSTM within each node as shown in Eqs. 6,7, 8, 9, and 10, the results of future prediction show us the quality of services. In this layer, the prediction begins and grows deeper in the DFLP model.

Let z ∈ Z, where Z= {Node (L) , Node(M), Node (H)}

$$z_t = \sigma(W_z.[z_{t-1}, x_t] + b] \quad (6)$$

$$\sigma(y) = \frac{1}{1+e^{-y}} \quad (7)$$

$$\mathrm{i_t = \sigma(w_i.[h_{t-1}, x_t] + b_i)} \quad (8)$$

$$\mathrm{o_t = \sigma(w_o.[h_{t-1}, x_t] + b_o)} \quad (9)$$

$$\mathrm{h_t = o_t * tanh(C_t)} \quad (10)$$

Where z_t is the value of node in time t, x_t is sequence of value form, $z_{t-1}$is the output of previously output, W_z is the weight of the node, b is represents the bias, σ is the sigmoid activation function.

To calculate the number of nodes in this layer is linearly proportional to the number of inputs, Eq.11 shows this:

$$n_1 = \varepsilon . |x| \tag{11}$$

Where n_1 represents the number of nodes in this layer, ε represents the number of nodes (L, M, and H) corresponding with the cardinality of input feature |x|.

Algorithm 1. Adaptive fuzzy learning (Fuzzification layer)

Input :Two dimensional array DS (F, V)
Let F be the set of features, and V be the set of hospitals.
Define C(F) as an array to store the means of each feature.
Define S(F) as an array to store the standard deviations of each feature.
Begin
  for each f in F
    Cf = Mean(f)
    Sf = Standard_deviation(f)
    for each v in V
      $\mu M\ (v(f)) = e^{(-\frac{(C_f - v)^2}{2S_f^2})}$ *// Calculate the membership of each value of the feature for node M*
      If v(f) > Cf then
        $\mu H\ (v(f)) = e^{(-\frac{(C_f - v)^2}{2S_f^2})}$ *// Calculate the membership of each value of the feature for node H*
        $\mu L(v(f)) = 0$
      else
        $\mu L\ (v(f)) = e^{(-\frac{(C_f - v)^2}{2S_f^2})}$ *// Calculate the membership of each value of the feature for node L*
        $\mu H(v(f)) = 0$
      End if
    End for
  End for
  Return μH, μM, μL for each v in V and f in F
End

4.3.2. Quality criteria prediction layer

In this layer, the membership features are integrated to generate quality criteria prediction, constituting the second step in adaptive deep learning, as show in Fig. 7. This step is carried out in parallel for all quality criteria. The category membership is computed by consolidating the feature memberships that are relevant to particular quality criteria, and this calculation is performed using Eq.12.

Let k ∈ K where K is quality criteria.

$$\mu_{a \in A}(\mathrm{k} \in K) = \frac{\sum \mu_{a\ (\forall f \in k)}}{|(\ \forall f \in k)|} \tag{12}$$

Some hospitals may not report all features either due to the absence of these features or the limited sample size available for those features. As a result, these features are neglected in the prediction process. The model's prediction is based on the features that are available in each category. To ensure adaptability, the model is designed to be flexible and can handle a dynamic number of inputs. This means that the model can accommodate varying sets of features without compromising its performance, allowing for a more versatile and robust prediction process.

To calculate the number of nodes in this layer is linearly proportional to the number of quality criteria, Eq.13 shows this:

$$n_2 = \varepsilon.\,|K| \qquad (13)$$

Where n_2 represents the number of nodes in this layer, ε represents the number of nodes (L, M, and H) corresponding with the cardinality of input feature |K|.

4.3.3. Aggregation prediction layer

In this layer, the membership values of the seven quality criteria are aggregated to generate a fuzzy prediction for the hospital, as show in Fig. 8. Each node connection with the nodes corresponds to such as the input of mortality node H is the output of all node H from the previous layer for the feature that relates to mortality quality criteria. This step is the third stage in adaptive deep learning and is accomplished using Eq.14. The aggregation process combines the category memberships to create an overall prediction of the hospital's performance, incorporating information from all categories to form a comprehensive evaluation.

$$\mu_{a\,\epsilon\,A}(v\ \in V) = \sum \mu_a(k\ \epsilon\ K)\ w(k) \qquad (14)$$

Where W is weight of the category.

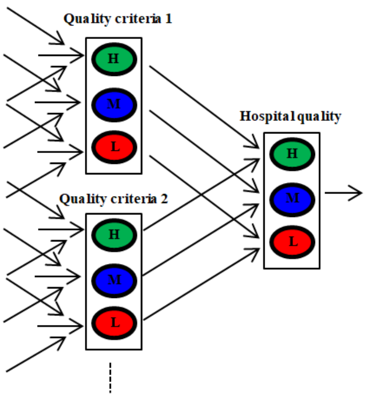

Fig. 8 The quality criteria nodes corresponds to three nodes of hospital quality

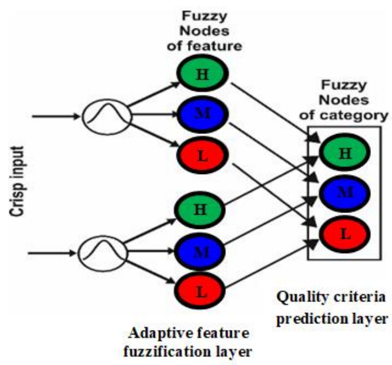

Fig. 7 The feature corresponds to three nodes of quality criteria

To calculate the number of nodes in this layer, Eq.15 shows this:

$$n_3 = \varepsilon \qquad (15)$$

Where n_3 represents the number of nodes in this layer, ε represents the number of nodes (L, M, and H).

The significance of each quality criterion can vary in the prediction process. Some quality criteria are more important than others. These include patient experience, mortality, safety of care, and readmission. Other categories, such as effectiveness of care, timeliness of care, and efficient use of medical imaging, are less significant. To account for these differences in importance, CMS (Centers for Medicare & Medicaid Services) has assigned weights to each category. These weights are determined by specialists and experts in the field, and they are used to highlight the impact of certain categories over others during the assessment process. You can refer to Table 1 for more information on these weights.

Table 1 Weight of the quality criterion

No	Rules	Prediction
1	If ($\mu_H(v) > 0.8$)	5 Star
2	If ($\mu_H(v) >= 0.7$) & ($\mu_M(v) > \mu_L(v)$)	5 Star
3	If ($\mu_H(v) >= 0.7$) & ($\mu_L(v) > \mu_M(v)$)	4 Star
4	If ($\mu_H(v) >= 0.5$) & ($\mu_M(v) >= \mu_L(v)$)	4 Star
5	If ($\mu_H(v) >= 0.5$) & ($\mu_L(v) > \mu_M(v)$)	3 Star
6	If ($\mu_M(v) > 0.8$)	3 Star
7	If ($\mu_M(v) >= 0.7$) & ($\mu_H(v) > \mu_L(v)$)	4 Star
8	If ($\mu_M(v) >= 0.7$) & ($\mu_L(v) > \mu_H(v)$)	3 Star
9	If ($\mu_M(v) >= 0.5$) & ($\mu_H(v) > = \mu_L(v)$)	4 Star
10	If ($\mu_H(v) >= 0.5$) & ($\mu_L(v) > \mu_H(v)$)	3 Star
11	If ($\mu_L(v) > 0.8$)	2 Star
12	If ($\mu_L(v) >= 0.7$) & ($\mu_H(v) > \mu_M(v)$)	2 Star
13	If ($\mu_L(v) >= 0.7$) & ($\mu_M(v) > \mu_H(v)$)	1 Star
14	If ($\mu_L(v) >= 0.5$) & ($\mu_H(v) >= \mu_M(v)$)	2 Star
15	If ($\mu_L(v) >= 0.5$) & ($\mu_M(v) > \mu_H(v)$)	1 Star

4.3.4. Defuzzification layer

Defuzzification is the process of transforming a fuzzy set into a crisp set, making the output more interpretable and usable. After computing the hospital membership, each hospital will have varying degrees of membership in the fuzzy sets (L, M, and H).

In the prediction model, five output classes represent the star ratings: 1 star, 2 stars, 3 stars, 4 stars, and 5 stars. To achieve this, the three nodes (L, M, and H) need to be converted into five crisp sets using the rules base, knowledge base, and fuzzy operators. These rules were established during the training phase to achieve the highest accuracy compared to the actual results. as depicted in Table 2. The specific rules in the knowledge base can be configured based on the desired system outputs, enabling the model to provide appropriate star ratings for each hospital based on their fuzzy memberships. Fig. 9 provides an overview of the proposed model structure.

The number of node in this layer is $n_3 = 1$ that use the rule to transforming a fuzzy set into a crisp set, finally to calculate the number of nodes for all DFLP model as expression below :

$$N_{DFLP} = 2|m| + n_1 + n_2 + n_3 + \mathrm{c} \tag{16}$$

Where N_{DFLP} is number of nodes of DFLP, m is number of input multiplied by two because input layer and Gaussian distribution analysis of features layer, and c is represent number of prediction classes.

Table 2 The rules to convert fuzzy sets into crisp sets (defuzzification).

No	Rules	Prediction
1	If ($\mu_H(v) > 0.8$)	5 Star
2	If ($\mu_H(v) >= 0.7$) & ($\mu_M(v) > \mu_L(v)$)	5 Star
3	If ($\mu_H(v) >= 0.7$) & ($\mu_L(v) > \mu_M(v)$)	4 Star
4	If ($\mu_H(v) >= 0.5$) & ($\mu_M(v) >= \mu_L(v)$)	4 Star
5	If ($\mu_H(v) >= 0.5$) & ($\mu_L(v) > \mu_M(v)$)	3 Star
6	If ($\mu_M(v) > 0.8$)	3 Star
7	If ($\mu_M(v) >= 0.7$) & ($\mu_H(v) > \mu_L(v)$)	4 Star
8	If ($\mu_M(v) >= 0.7$) & ($\mu_L(v) > \mu_H(v)$)	3 Star
9	If ($\mu_M(v) >= 0.5$) & ($\mu_H(v) >= \mu_L(v)$)	4 Star
10	If ($\mu_H(v) >= 0.5$) & ($\mu_L(v) > \mu_H(v)$)	3 Star
11	If ($\mu_L(v) > 0.8$)	2 Star
12	If ($\mu_L(v) >= 0.7$) & ($\mu_H(v) > \mu_M(v)$)	2 Star
13	If ($\mu_L(v) >= 0.7$) & ($\mu_M(v) > \mu_H(v)$)	1 Star
14	If ($\mu_L(v) >= 0.5$) & ($\mu_H(v) >= \mu_M(v)$)	2 Star
15	If ($\mu_L(v) >= 0.5$) & ($\mu_M(v) > \mu_H(v)$)	1 Star

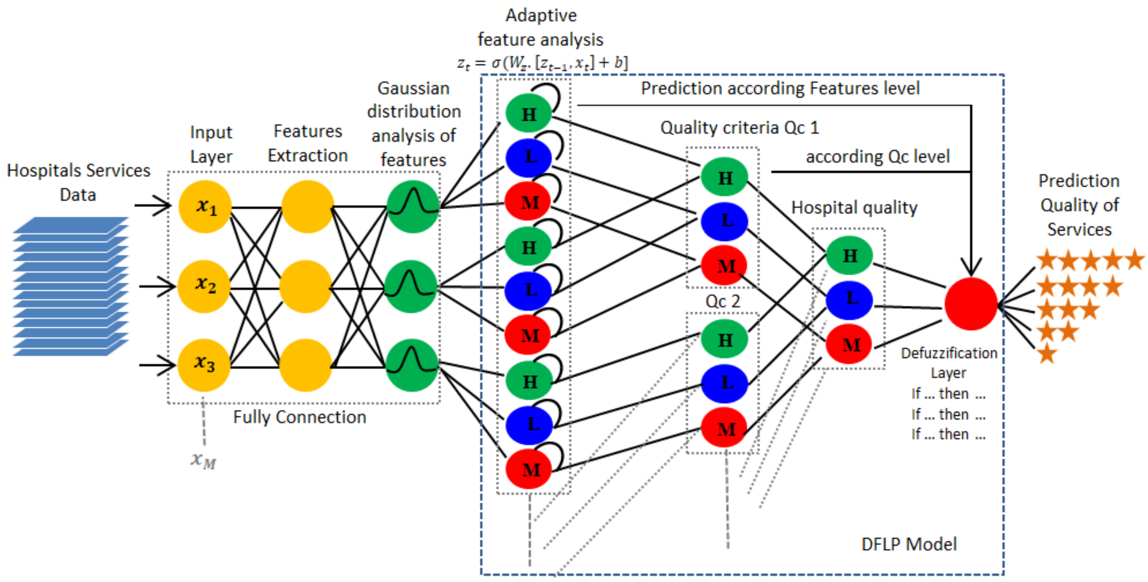

Fig. 9 The proposed model structure overview

4.4. Evaluation and adaptive learning stage

In this stage, the outputs are thoroughly evaluated to achieve highly accurate results by minimizing the error rate between the model outputs and expert assessments. The DFLP model employs an adaptive learning approach to continually improve its results. This improvement is accomplished through two steps in the learning process. The first step is the structural aspect, which involves several degrees of freedom, such as determining the number of fuzzy sets, the type of membership functions, the aggregation method, and the fuzzy operator used. These choices impact the model's ability to capture and represent complex patterns in the data. The second step is the parametric aspect, which encompasses essential parameters that describe the shapes and distribution of the membership functions and the set of rules employed to make the final decision. These parameters play a crucial role in fine-tuning the model's performance and ensuring its adaptability to different datasets and evaluation scenarios. By combining both the structural and parametric aspects, the DFLP model can continuously evolve and adjust its membership functions and rule base to enhance its accuracy and effectiveness in making assessments, this model uses accuracy (Acc) as in Eq.14, Error Rate (Err) as in Eq.15, Precision (Pre) as in equation 16, Recall (Rec) as in Eq.17, F1-measure (F1) as in equation 18, to ensure the prediction is more closely with expert evaluations.

$$Acc = \frac{TP+TN}{TP+FN+FP+TN} \tag{17}$$

$$Err = \frac{FP+FN}{TP+FN+FP+TN} \tag{18}$$

$$Pre = \frac{TP}{TP+FP} \tag{19}$$

$$Rec = \frac{TP}{TP+FN} \tag{20}$$

$$F1 = \frac{2*Pre*Rec}{Pre+Rec} \tag{21}$$

Where TP is true positive, TN is true negative, FP is false positive, FN is false negative.

5. RESULTS AND DISCUSSION

The DFLP model was implemented on the data sourced from the open data published by CMS. The data were used from 2013 to 2023 for each year used more than one dataset, therefore, more than 20 historical data were considered, representing the level of hospital services in each year. Before the preprocessing process, each dataset contained more than 200 features representing the quality of services, which were reduced to 55 features using aggregation methods and feature selection.

The first stage of the prediction process begins by entering all data from 2013 to 2023 into the model, and each data set is analyzed individually. The adaptive feature fuzzification layer begins by analyzing the membership of each feature among the three nodes (L, M, and).

Each feature will correspond to three nodes (L, M, and H), the membership of the feature is determined between these nodes, so it will be either L, LM, M, MH, or H, depending on the pre-training data for the nodes obtained through analyzing the quality area in each feature based on Gaussian distribution, as well as on the current feature score to determine the membership percentage for each node.

The outcomes reveal a clear correlation between higher-quality services and hospital prediction levels. Additionally, if a hospital has a single poor service, it will have membership in the low fuzzy set (L Node), Table 3 shows the membership of hospitals among nodes for feature

MORT_30_AMI that represents The death rate for heart attack patients and the feature MORT_30_CABG that represent The death rate for CABG surgery patients between to the year 2022 and 2025.

Table 3 Fuzzification for some features in the hospital dataset

Year : 2022				Year : 2023			Year : 2024			Year : 2025		
Feature (MORT_30_AMI)				Feature (MORT_30_AMI)			Feature (MORT_30_AMI)			Feature (MORT_30_AMI)		
Hospital- Id	L	M	H	L	M	H	L	M	H	L	M	H
10005	0	0.12	0.88	0	0.07	0.93	0	0.04	0.96	0	0.06	0.94
50280	0	0.96	0.04	0	0.98	0.02	0	0.89	0.11	0	0.8	0.2
50390	0.32	0.68	0	0.2	0.8	0	0.3	0.7	0	0.31	0.69	0
170146	1	0	0	1	0	0	0.9	0.1	0	1	0	0
Feature (MORT_30_CABG)				Feature (MORT_30_CABG)			Feature (MORT_30_CABG)			Feature (MORT_30_CABG)		
Hospital- Id	L	M	H	L	M	H	L	M	H	L	M	H
10005	-	-	-	0.2	0.8	0	0.1	0.9	0	0.11	0.89	0
50280	0	0.6	0.4	0	0.5	0.5	0	0.6	0.4	0	0.65	0.35
50390	1	0	0	0.4	0.6	0	0.7	0.3	0	0.6	0.4	0
170146	1	0	0	1	0	0	0.9	0.1	0	0.96	0.04	0

The table above shows the difference in membership between the three nodes (L, M, and H) between 2022 and 2025 for each hospital. Repeating this process on all previous data collected over the years and based on the LSTM layer gives us a clear view of the behavior of hospitals and the development of their services. The more previous data, the more accurate the prediction of the quality of future services.

After the first layer, the data flows to the quality criteria prediction layer, during which the results of the memberships that were analyzed in the first layer are collected for each node. This stage represents the prediction of the quality of services at the criteria level as depicted in Table 4. As data continues to flow towards the aggregation prediction layer, all memberships from the criteria layer are collected to give us a comprehensive picture of the services forecast for the whole hospital.

Table 4 Criteria prediction layer for some instances in the hospital dataset in mortality criteria.

Year :2022				Year :2023			Year :2024			Year :2025		
Mortality Category				Mortality Category			Mortality Category			Mortality Category		
Hospital- Id	L	M	H	L	M	H	L	M	H	L	M	H
10005	0	0.06	0.94	0	0.05	0.95	0	0.03	0.97	0	0.06	0.94
50280	0.13	0.68	0.19	0.1	0.62	0.28	0.1	0.44	0.46	0.1	0.39	0.51
50390	0.758	0.224	0.018	0.658	0.324	0.018	0.418	0.424	0.158	0.3	0.542	0.158
170146	1	0	0	0.9	0.1	0	0.9	0.1	0	0.98	0.02	0

As a consequence, the DFLP model is deemed accurate to reflect the reality of hospital services and their quality. The final decision of the prediction hospital's quality of service level will be based on its membership degrees among the three fuzzy sets (L, M, and H). This information can be observed in Fig.10, which illustrate the distribution and classification of hospitals according to their fuzzy memberships, ultimately aiding in decision-making and prediction of hospital services.

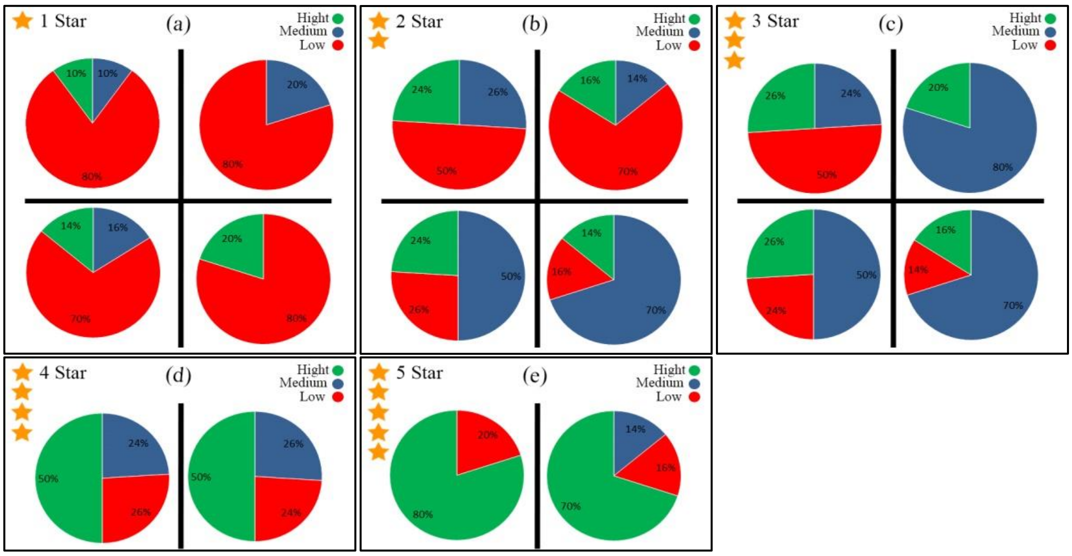

Fig. 10 Membership of decision (a) 1 star, (b) 2 stars, (c) 3 stars, (d) 4 stars, (e) 5 stars.

The results from the DFLP model demonstrate that over half of the hospitals fall within the prediction range of class 3 stars to 4 stars. The ACC of the model is reported to be 96.68% when compared to human expert prediction, Fig. 11 shows the confusion matrix of the prediction model.

Fig.11 Confusion matrix of prediction model

Table 6 present confusion matrix measure for each prediction class, indicating a relatively small discrepancy between the model's prediction and expert judgments.

Table 5 Acc, Err, Pre, Rec, and F1 for each prediction class.

prediction	Acc	Err	Pre	Rec	F1
1 star	97.1	2.9	98.57	97.1	97.83
2 star	96.2	3.8	96.2	96.2	96.2
3 star	96.2	3.8	94.03	96.2	95.10
4 star	96.6	3.4	96.31	96.6	96.45
5 star	97.3	2.7	98.68	97.3	97.98
Total	96.68	3.32	96.76	96.68	96.71

The table above shows that the Acc rate is 96.68 %, and the F1 rate is 96.71%. Although there is a difference between the two measurements, the Acc depends in its calculation on the number of correct predictions divided by all predictions. In contrast, the F1 rate depends on precision and recall. Therefore, the F1 measure gives a more comprehensive view of the model's performance.

Fig.12 provides the frequency distribution of hospitals among the different prediction classes compared to real prediction, proposed model, LSTM, and Bi-LSTM, which likely gives an overview of the distribution of hospitals according to their star ratings. This information can be valuable for understanding the overall quality of hospital services and identifying areas where improvement may be needed.

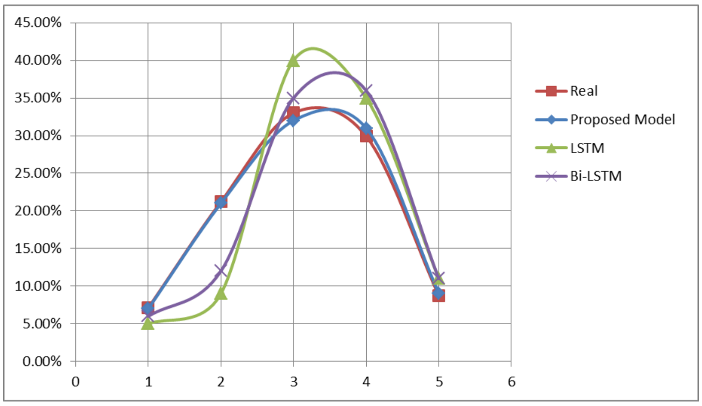

Fig.12 Frequency of hospitals among the classes comparison with real prediction, proposed model, LSTM, and Bi-LSTM

The proposed DFLP model clearly outperforms traditional time series forecasting methods, achieving an impressive accuracy of 96.68%. Its superiority lies in the fuzzy representation of feature values, which captures uncertainty and variability while preventing error accumulation, and in its hierarchical architecture, where fuzzy projections are processed through dynamic topology Bi-LSTM layers to extract both intrinsic feature patterns and temporal dependencies. The DFLP highlights the benefit of integrating fuzzy logic with deep temporal modeling. Despite being limited to US hospital data, reliant on CMS weighting schemes, and relatively complex computationally, the model offers tangible practical value: it empowers hospital administrators to make proactive decisions, optimizes resource allocation, and provides policymakers with data-driven insights to enhance healthcare quality. In essence, the DFLP model not only delivers superior predictive performance but also bridges the gap between analytical precision and practical applicability in hospital management.

6. CONCLUSION

In this paper, we presented the Deep Learning Prediction (DFLP) model, designed to predict hospital services and rank hospitals based on time data series. The DFLP model combines deep learning neural networks and fuzzy logic to achieve this. Deep learning neural networks are known for their ability to predict and identify hidden patterns, while fuzzy logic is powerful at handling uncertain and imprecise information. The DFLP model is made up of six layers, each node within the black box represents a fuzzy set (L, M, and H). This processing occurs in parallel, and the learning process is adaptive. This means the model fine-tunes its parameters to achieve the highest possible accuracy in predicting hospital services and ranking hospitals. The adaptability of the model enables it to handle varying inputs and adjust its behavior according to the available data, this helps in reducing the gradual error across time series.

DFLP can effectively manage partial inputs, considering that not all hospitals report all features, either due to their absence or limited sample sizes. The hierarchical structure of the model provides flexibility in prediction enabling it to predict the service of hospitals based on single or multiple features, single or multiple quality criteria, or through a comprehensive prediction of service quality encompassing various aspects. Overall, the DFLP model is robust compared to traditional deep learning models and showed the accuracy of Prediction at 96.68% compared to realistic predictions, LSTM, and Bi-LSTM, making it a valuable tool in hospital ranking and performance evaluation for hospitals.

For future work, the model could be tested on international hospital datasets to assess its generalizability, explore alternative fuzzy membership functions to enhance flexibility, and be developed into an online decision-support tool for hospital administrators and policymakers.

In the end, it becomes evident that combining the uncertain fuzzy method with deep learning yields significant explanatory power for analyzing hidden patterns because the decision-making process gradually progresses from uncertainty to an inevitable decision.

DECLARATION

Conflict of interest The authors have no conflicts of interest to declare. All co-authors have seen and agree with the manuscript's contents and there is no financial interest to report. We certify that the manuscript is original work and is not under review at any other publication.

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