Application of Fuzzy Decision Intelligent Recommendation System in Personalized Health Management of Hospitals

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Abstract: *Medical care relies heavily on the Intelligent Health Recommendation System (HRS). Effective healthcare networks are therefore essential to the process of making medical decisions. The key goal is to maintain the efficacy of information security and ethical considerations while ensuring appropriateness. Healthcare recommendation systems must produce results such as diagnosis suggestions, healthcare insurance, and information related to health issues. This article highlights the hospital authority's capacity to provide a personalized recommendation system and offers a Fuzzy Intelligent Recommendations System (FIRS). The input patient data is analyzed using a Modified Fuzzy Rule-based Neural Network (MFRNN) to predict potential illnesses. In the intelligent healthcare system, the data privacy is maintained using Multi-Criteria-based Decision Making (MCDM) and Fuzzy assisted Analytical Hierarchy Process (Fuzzy-AHP and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)). The suggested fuzzy intelligent system outperformed previous methods using larger datasets, which only managed a 97.75% prediction accuracy. Furthermore, when contrasted with conventional models, the MFRNN showed much lower error rates and better reliability in risk assessment. The security risk study's findings show that the proposed fuzzy model has the potential to deliver the best risk assessment performance compared to other models.*

Keywords: *Intelligent system, healthcare recommendation system, decision support system, fuzzy neural network, multi-criteria decision making.*

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1. Introduction

In many domains (such as e-commerce and decision support systems), recommender systems have recently shown themselves extremely helpful for online users in managing information overload [5]. Nonetheless, research on recommender system architecture and evaluation in practical scenarios is currently ongoing. To assist doctors in predicting a therapy key, we have researched and developed a recommender system to transfer this technology into the medical field. The population of cities and metropolises worldwide are increasing, and more people are migrating or traveling. The issue of healthcare requires particular attention to create better policies and administration. Additionally, the massive influx of new illnesses is too great to manage, and patients' conditions are improving daily using conventional methods [16]. The medical industry has been under much strain lately because of the constant rise in patients with chronic illnesses and the need for ongoing medical care. Several therapeutic applications have been developed to alleviate the strain on long-term hospital patients [14, 18]. Because it focuses on improving lifestyle development, intelligent health has recently garnered much attention and positive vision in science and technology.

Digital technology-enabled healthcare generally refers to a service plan that uses electronic devices like laptops, tablets, or smartphones to provide healthcare to individuals at anytime, anywhere [1]. Mobile health-related information services may be essential for patient care, population health and self-care, medical decision-making regarding patient collaboration, and patient information [2, 11]. There have been a lot of recent developments in information technology, and gadgets are now evaluated according to the individual characteristics of their users. Fuzzy and neural networks can indeed govern and process the gathered data. Numerous sensors gather health data from people; these gadgets could be anything the person provides, such as a smart clock [6]. This concept can be based on the suggested health system. One of the most essential philosophical pillars upheld by fuzzy logic today is the application of fuzzy sets in the health care industry and the numerous facets of health [27].

Today's healthcare monitoring and recommendation systems are rapidly growing, collecting large amounts of data and health-related information systems for improved patient management [22]. Traditional algorithms deal with clear facts but cannot handle ambiguous and inaccurate information regarding diabetes diagnoses. As a result, the traditional ontology is combined with fuzzy logic. Several systems have recently proposed fuzzy logic to improve diabetes diagnosis [13]. However, there is a wider range of foods available, which is linked to a higher risk of developing diabetes, and both the number of people with diabetes and the risk variables are rising quickly. Because most risk factors are highly hazy and unpredictable, type-1 fuzzy logic-based systems cannot extract exact membership values; as a result, the systems produce subpar results. Consequently, it is thought that type-2 fuzzy logic using a fuzzy ontology is useful for identifying specific physiological data regarding a patient's body and suggesting diabetes treatments.

Akhtar *et al.* [3] thoroughly investigated traditional and fuzzy decision-making methods to address medical and health issues. Gul [12] discovered hybrid approaches and Analytical Hierarchy Process (AHP) methodologies were the healthcare industry's most widely used decision-making methods. The primary purpose of these methods was to evaluate the caliber of services provided by the medical sector and healthcare. Shaygan and Testik [25], fuzzy techniques were used to choose projects that addressed the root causes of poor performance. They proved that the best approach for decision-making was the FAHP, which incorporates project management quality and enables the acquisition of more precise, objective, and scientific outcomes. The writers also recognized the benefits of fuzzy AHP. Bellahcene *et al.* [4], the authors addressed selecting information systems projects. They suggested that the best instruments for their assessment and selection were a Weighted Additive Fuzzy Programming Goals (WAFGP) method and an integrated AHP.

1) **Research Problem**

Patients and healthcare professionals may be overwhelmed by the growing amount and complexity of health information, resulting in less-than-ideal decision-making, especially for individualized health management. Integrating diverse data sources while protecting patient privacy and security is a common problem for legacy healthcare systems. As a result, intelligent recommendation systems that are both efficient and secure enough to give fast and accurate health advice are critically needed.

Personalized health management is increasingly gaining importance in modern healthcare due to its potential to improve patient outcomes through tailored medical interventions. Despite advancements in Healthcare Recommendation Systems (HRS), significant challenges remain in achieving accurate and reliable predictions while maintaining patient data privacy. Existing systems often lack robustness in handling complex, multi-dimensional healthcare data, leading to suboptimal decision-making. Moreover, integrating fuzzy logic with neural networks for health prediction remains underexplored, particularly in addressing uncertainties inherent in medical data. This study aims to bridge these gaps by proposing the Fuzzy Intelligent Recommendation System (FIRS), which incorporates a Modified Fuzzy Rule-based Neural Network (MFRNN) for enhanced prediction accuracy. Furthermore, the model ensures data privacy using a Multi-Criteria Decision-Making (MCDM) approach combined with Fuzzy-assisted Analytical Hierarchy Process (Fuzzy-AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The proposed framework seeks to improve prediction reliability and safeguard patient information by addressing these critical challenges.

2) **Research Problem**

With healthcare data's increasing volume and complexity, developing accurate and reliable prediction systems has become a critical challenge. Traditional healthcare recommendation systems often struggle to efficiently process multi-dimensional, heterogeneous data, resulting in limited prediction accuracy and inconsistent decision-making. Additionally, ensuring data privacy remains a significant concern, especially when dealing with sensitive patient information.

3) **Research Motivation and Novelty**

The healthcare industry is undergoing digital transformation, leading to more sophisticated decision-making systems that use data-driven approaches. Developing a FIRS that efficiently combines many medical data inputs while protecting user privacy is the driving force behind this research. The research innovation improves prediction accuracy and reduces healthcare costs by integrating fuzzy concepts and neural network MFRNN. Strong security management in the healthcare system is guaranteed by incorporating MCDM techniques. In addition, the research offers a new understanding of how fuzzy logic can simplify processing complicated health data, leading to individualized therapy recommendations. The results show that, compared to traditional models, the predictive accuracy and risk assessment are significantly enhanced, which is a huge leap forward for health informatics.

The contribution of this study is as follows:

- The patient's risk level is computed using the fuzzy rules and predicted using a fuzzy neural network. This proposed intelligent recommender system provides suggestions based on the risk predicted by

the modified fuzzy rule-based Neural network to the patients. The standard FNN is modified with the logic operator NN instead of a dense layer of FNN.
- Train, validate, and export the deep learning model to a hospital or medical information and documentation system. Based on the results of MFRNN, the risk is predicted and recommended to the physician through intelligent decision-making.
- To add privacy to the healthcare data, the IDM system is evaluated using Fuzzy assisted AHP and TOPSIS.
- The experimental study assesses fuzzy outcomes' accuracy, reliability, and error rate compared to existing models.

The structure of the paper is organized as follows: section 2 provides a comprehensive literature survey, highlighting existing approaches and identifying research gaps. Section 3 presents the proposed methodology, including integrating fuzzy neural networks and multi-criteria decision-making techniques. Section 4 covers the experimental analysis, including a comparative study to evaluate the effectiveness of the proposed system. Finally, section 5 concludes the research, summarizing key findings and future directions.

2. Literature Review

Ponnusamy *et al*. [20] offer a suggested intelligent HRS utilizing the Restricted Boltzmann Machine (RBM)-Coevolutionary Neural Network (CNN) deep learning system. TensorFlow and Python were used to develop our suggested solution. Utilizing the health care dataset, we compare the performance of the proposed strategy to alternative approaches utilizing different error quantities. Additionally, the proposed method's accuracy, precision, recall, and F-measure were contrasted with the existing approaches. Mani *et al*. [15] aim to create a new predictive model for health data storage that will satisfy patient demands and provide quick storage choices, even when data comes in from wearable technology. The author synthesized a training validation from limited data samples of experts with connections among storage variables to develop the Machine Learning (ML) classifier. The outcomes support the ML methodology's validity.

Gavurova *et al*. [9] aimed to create a sophisticated fuzzy decision-making model for assessing and choosing healthcare initiatives to close the regional development gap. We developed the following logical hypothesis for this study based on the description given above: the project chosen for funding should be seen favorably if it can accomplish its objectives and raise the degree of development in its area. A sophisticated fuzzy model was built to consider the area's degree of development. Sharma and Samant [24] developed a healthcare recommendation to improve multilevel decision-making regarding various illnesses' severity and health risk. A fuzzy inference algorithm determines the degree of danger for patients. The patients receive recommendations from this suggested intelligent recommender system, depending on the danger the fuzzy inference system predicts. Ochoa *et al*. [19] describe creating a novel recommendation system that uses multi-criteria decision operators and projected outcomes derived from continuous-valued logic. By reducing the number of parameters that can be trained, this method is more secure from adversarial attacks and more transparent than traditional deep learning approaches. This is because the model's results mimic logical processes of decision-making based on the hierarchy of relevant physiological parameters.

To evaluate the effectiveness of technological integration, Quasim *et al*. [21] suggest the Smart Healthcare Administration Evaluation using Fuzzy Decision Making (SHME-FDM) approach. Thus, this study uses a fuzzy AHP-TOPSIS to assess the confidentiality of predictions about healthcare. The study assesses fuzzy outcomes' accuracy, dependability, and error rate. The security risk analysis shows that the fuzzy model may be the optimum risk evaluation model.

Sahoo *et al*. [23] address information quality, reliability, authenticity, and privacy issues to guarantee the timely availability of vital information. This research presents a smart HRS that utilizes the RBM, a Convolutional Neural Network (CNN) approach to shed light on the potential of big data analytics in building a powerful health recommender engine. The suggested deep learning technique (RBM-CNN) exhibits fewer errors than alternative methods.

Hassan and Elagamy [13] introduce an ML-based HRS system that reliably uses patient symptoms to forecast diseases and offers individualized medical advice. Using a large symptom-disease dataset using Support Vector Classifier (SVC) and Random Forest (RF) models, the system achieves remarkable disease prediction accuracy of 97.75%. These findings outperform those of related studies, like one that used fuzzy logic and hybrid CNN approaches and obtained 99% accuracy, but depended on smaller datasets with less diversity. The study shows how ML may create scalable and effective healthcare systems, spanning the gap between precise forecasting and practical treatment plans. Chen and Chu [7] focus on two distinct long-term care facilities as their empirical subjects, with institution A views the Internet of Things (IoT) as the most important aspect. According to the investigation, three major elements are thought to impact various long-term care facilities: electronic medical records, telemedicine, and global positioning systems. Table 1 summarizes the research gap identified from existing works.

The research that was evaluated shed light on how healthcare recommendation systems have progressed through the application of data mining, fuzzy decision-making, and ML. These developments have strengthened personalization, data security, and risk evaluation. These advancements have not eliminated the problems of data scalability, tailored patient insights, and real-time processing. By integrating data from multiple disciplines, improving prediction accuracy, and strengthening privacy protections, the proposed FIRS hopes to fill these shortcomings. Previous studies in intelligent healthcare decision-making often faced limitations in handling uncertain and imprecise medical data and challenges with model interpretability and scalability. Traditional approaches, such as purely rule-based systems or standalone neural networks, struggled to balance accuracy with explainability, leading to models that either lacked robustness in complex healthcare scenarios or were perceived as black boxes by medical professionals. Additionally, these methods often failed to adapt effectively to diverse patient profiles and dynamic healthcare environments. To address these gaps, our study proposes a hybrid fuzzy-logic-based neural network model that combines the interpretability of fuzzy logic with the learning capabilities of neural networks. This integration enhances decision accuracy and provides transparent and adaptable decision-making processes, making it well-suited for real-time healthcare applications. By effectively managing uncertainty and offering personalized predictions, our approach fills the existing research gap and contributes to developing more reliable and scalable healthcare decision support systems.

Table 1. Research gap analysis of existing models.

Study	Contribution	Results achieved	Limitations
Ponnusamy *et al*. [20]	Data mining methods and RBM-CNN deep learning for healthcare datasets.	Enhanced healthcare personalization.	Limited integration of unstructured, multidisciplinary data.
Mani *et al*. [15]	Predictive model for health data storage from wearable technology.	Efficient health data storage.	Inadequate real-time data processing and scalability considerations.
Gavurova *et al*. [9]	Fuzzy decision-making model for regional healthcare initiative assessment.	Improved project assessment.	Generalized focus, not tailored for individual patient data.
Sharma *et al*. [24]	Fuzzy inference algorithm for risk assessment in healthcare recommendations.	Better risk evaluation.	Focused on generalized recommendations, lacks personalized insights.
Ochoa *et al*. [19]	Multi-criteria decision operators with continuous-valued logic.	Transparent and secure model.	Limited application in dynamic healthcare environments.
Quasim *et al*. [21]	SHME-FDM approach for healthcare data confidentiality using fuzzy AHP-TOPSIS	Reliable security risk evaluation.	Limited practical validation in real-world healthcare systems.
Sahoo *et al*. [23]	Intelligent HRS using RBM-CNN for personalized tele-health.	Reduced error rates.	Lack of real-time data processing and scalability.
Hassan and Elagamy [13]	ML-based HRS using SVC and RF models for disease prediction.	High disease prediction accuracy.	Limited dataset diversity; high dependency on symptom-disease dataset.
Chen and Chu [7]	Analysis of key factors in long-term care facilities.	Identified critical factors like IoT, EMR, and telemedicine for health management.	Limited generalizability beyond the studied institutions.

3. Proposed Methodologies

The proposed HRS analyzes the patient's medical events based on their health data gathered from the sensors and delivers the RS using fuzzy rule-based modified FNN. The user interface is created using this neural network model, as shown in Figure 1. A physician checks the patient's health status recommendation by sending the request to the proposed MRFNN and returning the recommendation response about the health care. The patient's health data are stored in the centralized cloud repository for further storage and access. The MDM uses fuzzy AHP and TOPSIS to ensure health data privacy. The developed model is experimented with, and the results are visualized using the evaluation metrics.

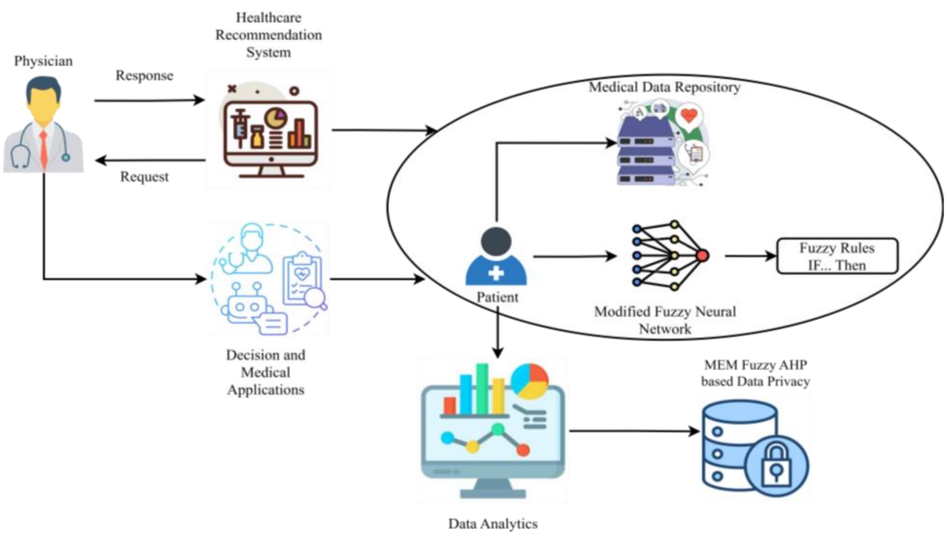


Figure 1. Overview of the proposed intelligent fuzzy health recommendation system.

3.1. Data Synthesis

This intelligent system monitors patients with different illnesses, and RS responds according to their health status. The synthesis data consists of data from different Heart, Kidney, and Liver disease samples from the UCI repository [https://archive.ics.uci.edu]. The patient health data attributes used for this study of three diseases are shown in Table 2. The parameters used to measure the healthy status of heart disease, liver disease, and kidney disease are shown in Table 3.

Table 2. Patient data attributes from the dataset.

Attributes	Heart disease	Kidney disease	Liver disease
Age	Chest Pain (CP)	Blood Pressure (BP)	Total Bilirubin (TB)
Sex	Cholesteroal (Ch)	Anemia (An)	Direct Bilirubin (DB)
Bp	Resing Bp (RBp)	Albumin	Alkaline Phosphotase (AP)
Anemia	Resing ECG (RECG)	sugar	Almaline_Aminotransferase (Al-Amino)
Albumin	Maximum Heart Rate (MHR)	RBC (Red blood cells)	Aspartate_ Aminotransferase (As-Amino)
Sugar	Slope of exercise at peak (Slope)	White_Blood_Cells (WBC)	Total proteins (Tpro)
RBC	Major_Vessels number (Ca) (0-3)	Albumin	RBC count
WBC	Plain location of chest (PChest)	Appetite (App)	Ratio_Albumin (A/G)
RBC count	Resting Hr (RHr)	Coronary Artery Disease (CAD)	Globulin_Ratio (GR)

Table 3. Healthy measurement of considered diseases.

Parameters	Range	[Min, Max]	Disease_risk
Liver data			
As-Amino	0 to 35 IU/I	[10,40] units	-
Al-Amino	O to 45 IU/I	[7, 56] units	
Kidney data			
Gender	Male	[120,60]	-
	Female	[110,50]	
Potassium (mmol/L)	3.6 to 5.2	-	Normal
	5.3 to 5.5		High
	Above 6		Very high
Heart data			
BP (mmHg)	90/60	-	High
	120/80		Normal
	140/190		Very high
Cholesterol (mg/dL)	100 – 129	-	Fit
	130-159		Border
	160-189		High
	Above 190		Very high

3.2. Modified-Fuzzy Neural Network

The intelligent fuzzy decision-based HRS uses the prediction model for recommendation and intelligent monitoring. The modified FNN is incorporated with the logic operator NN rather than the normal dense layer Rectified Linear Unit (ReLU). The outcome of this MFNN has become the input to the fuzzy interface based on fuzzy rules for the recommendation system.

Fuzzy neural networks are learning machines that use neural network approximation techniques to investigate fuzzy systems. The neural network addresses the issues once many observed examples are considered. The black box receives these observations and uses them for training. It is challenging to extract the intelligible rules from the structure of the neural network. Linguistically defined language rules were used by the fuzzy system. The fuzzy logic system is altered despite insufficient or contradictory data. Since no official process exists, tuning has been done using a heuristic technique. In Figure 2, the FNN structure is displayed. The input, fuzzification layer, fuzzy rules layer, and defuzzification layer are its four layers. This study proposes a hybrid approach to integrate fuzzy logic with neural networks to improve decision-making accuracy in real-time control systems. The schematic begins with the fuzzification of inputs, where crisp numerical data (such as temperature, pressure, or speed) are mapped to fuzzy sets using predefined membership functions. These fuzzy inputs are fed into a neural network model, typically a Multi-Layer Perceptron (MLP), which processes the fuzzy data through multiple hidden layers. The neural network adjusts the fuzzy inference rules by learning from past data and optimizing the weights and biases through backpropagation. After processing, the output from the neural network undergoes defuzzification, converting the fuzzy output back into crisp values for system control or decision-making. The integration ensures that linguistic rules and quantitative data contribute to the model, enhancing performance in uncertain and non-linear scenarios, such as automated manufacturing system control.

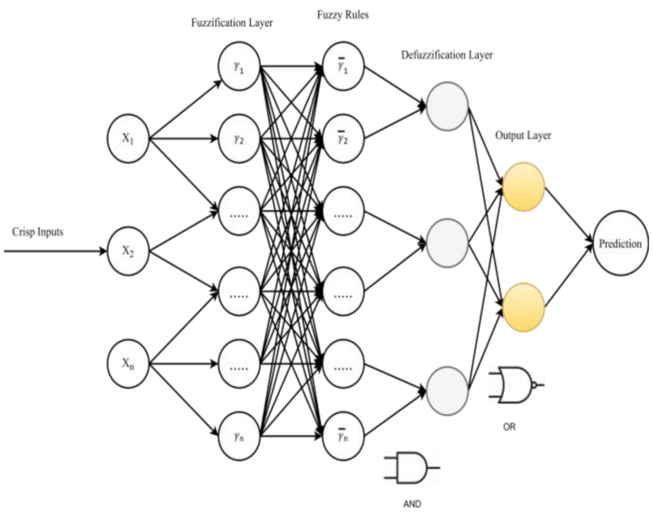


Figure 2. Modified FNN.

The input neuron from the i^{th} to the j^{th} neuron is denoted as I_i^j, the output neuron from the i^{th} to the j^{th} neuron is denoted as O_i^j. Each layer function is declared as follows:

1. Input layer: the input layer of the FNN takes the crisp input of patient health data from the synthesized dataset. This layer does not process anything.

$$O_i^{(1st\ layer)} = I_i^{(1st\ layer)} \tag{1}$$

2. Fuzzification layer: it is the second layer that processes the input with a membership function as denoted in Equations (2) and (3):

$$I_{ij}^{(2)} = (O_i^{(1)} - \gamma_{ij})^2/\sigma_{ij}^2 \quad (2)$$

$$O_{ij}^{(2)} = \exp\left(I_{ij}^{(2)}\right) + f((O_i^{(1)}) \quad (3)$$

Where f is an activation function. Inference layer, fuzzy rules:

$$I_i^{(3)} = F_{net}(a).F_{terminal}(a) \quad (4)$$

$$O_i^{(3)} = I_i^{(3)} \otimes U(p) \quad (5)$$

3. Defuzzification layer: the output is computed based on the weighted function:

$$I^{(4)} = \sum_{i=1}^{N} W_i\, O_i^{(3)} \quad (6)$$

$$O^4 = \frac{I^{(4)}}{\sum_{i=1}^{N} O_i^{(3)}} \quad (7)$$

The general FNN uses the ReLU function in the dense layer. This study implements a Logical operator-based NN [8] rather than the dense layer, which uses the logical operations of weights and bias as shown in Table 4. The considered loss function is Mean Squared Error (MSE) as in Equation (8):

$$MSE = \sum_{i=1}^{n} (Y_i - Y'_i)^2 \quad (8)$$

Table 4. Logical operations performed with MFNN.

Weight between the ith and jth neuron (W_{ij})	Bias of ith neuron (B_i)	Logical operation
1	-1	AND
1	0	OR
0	1	$NOT(X)$
-1	1	$NOT\ (Y)$
-1	1	$NOT(X)\ and\ NOT(Y)$

3.3. Fuzzy Rules

The fuzzy neural network uses this inference system to generate fuzzy rules, as discussed in Table 5, to generate the fuzzy decisions for healthcare. Finally, the defuzzification process converts the fuzzy values into crisp values.

Table 5. Fuzzy rules for intelligent decision making.

Rule no.	Condition (IF)	Result (THEN)	Explanation
1	If (Temp=High) AND (PulseRate=Low)	Cholesterol=High	High temperature and low pulse rate indicate a possible health issue leading to high cholesterol levels.
2	If (Temp=High) AND (Bp=VeryHigh)	Cholesterol=VeryHigh	High temperature combined with very high blood pressure signals a severe health condition, resulting in very high cholesterol.
3	If (Temp=Normal) AND (Bp=VeryHigh)	Cholesterol=VeryHigh	Normal body temperature with very high blood pressure indicates a significant health risk, leading to very high cholesterol.
4	If (Temp=Normal) AND (PulseRate=Medium)	Cholesterol=Fit	Normal body temperature and medium pulse rate suggest a healthy cardiovascular system, resulting in normal cholesterol levels.
5	If (Temp=High) AND (PulseRate=Low)	Potassium=High	High temperature and low pulse rate indicate a possible electrolyte imbalance, especially in liver-related conditions, leading to high potassium levels.

3.4. MDM-Fuzzy-AHP

The ongoing misuse of the records containing the priceless medical data has embarrassed the healthcare organizations. A solid, dependable information security strategy in healthcare web apps can raise the revenue and reputation of healthcare businesses. An MCDM approach could be a turning point in accomplishing this goal. Providing sufficient knowledge protection for each web application is a decision-based process. In some activities, multi-criteria decision-making mechanisms are essential and crucial. Although its Multi-Criteria Decision Methodology (MDM) includes a variety of approaches, fuzzy MDM is among the most successful methods available today.

MCDM is responsible for resolving difficult challenges [10] with the involvement of decision makers. This model was used in several studies to assess the vulnerability to natural hazards. The unstructured problem is broken down into different parts using this method, which entails the following five steps:

- *Step* 1: Establish the goals and split the elements.
- *Step* 2: Establishing decision criteria and solution alternatives.
- *Step* 3: A pairwise comparison matrix is created using the influences of each factor. When the component is more significant, this value falls between 1 and 9; when it is less significant, it falls between 1/2 and 1/9.
- *Step* 4: Use the Eigenvalue technique to calculate relative weight.
- *Step* 5: Calculate the Consistency Ratio (CR) using Equation (9):

$$C = \frac{\lambda_{max} - n}{n - 1} \quad (9)$$

Where n is the total number of health care factors and λ is the maximum eigenvalue determined from the comparison matrix.

$$CR = \frac{C}{RI} \quad (10)$$

Where the number of components is correlated with the random consistency index, or *RI*. It is consistent even when the *R* value is below 0.1.

4. MDM-TOPSIS: developed to address decision-making issues with inconsistent criteria, it relies on Euclidean distance to carry out the actions [26]. Based on how close the model is to finding the ideal answer and how close it is to finding the opposing

solution, this model ranks the alternatives. The goal is to find the distance between the evaluation object and the ideal solution, then rank the solutions based on that distance. The ideal answer is the one that is maximally distant from the alternative solution while simultaneously being the nearest to it.

- *Step* 1: Forming the first Decision Matrix (M). There are *m* alternatives and *n* criteria in each cycle. Every choice is shown as a vectorization, with X_{ij} Standing for the ith choice of the j^{th} criterion. In light of this, the *M* is created as in Equation (11).

$$M = \begin{pmatrix} X_{11} & X_{12} & \dots & X_{1n} \\ X_{21} & X_{22} & \dots & X_{2n} \\ \dots & \dots & \dots & \dots \\ X_{m1} & X_{m2} & \dots & X_{mn} \end{pmatrix} \quad (11)$$

- *Step* 2: As in Equations (12) and (13), normalize M to offset the impact of different scales.

$$n_{ij} = \frac{X_{ij} - X_i'}{X_i'' - X'} \quad (12)$$

$$n_{ij} = \frac{X_{ij} - X_i''}{X_i' - X_i''} \quad (13)$$

Where, X_{ij}, X_i", X_i' are decision matrix elements, X_i" and X_i' are the max and min values of the considered criterion, respectively.

$$X_i'' = \max(X_1, \dots X_m) \quad (14)$$

$$X_i' = \min(X_1, \dots X_m \quad (15)$$

- *Step* 3: by a weighted matrix based on the normal value matrix multiplied by the criterion derived by AHP.
- *Step* 4: Identifying ideal and non-ideal solutions divides the criteria into positive and negative groups. The positive criteria include soil, rainfall, and slope that raise the chance of flooding. On the other hand, elements that fall under the negative criteria, like altitude, reduce the danger.
- *Step* 5: Use Equations (16) and (17) to calculate the separation between the ideal and non-ideal solutions.

$$D_i'' = \sqrt{\sum_{i=1}^{n} (V_{ij} - V_j'')^2} \quad (16)$$

$$D_i' = \sqrt{\sum_{i=1}^{n} (V_{ij} - V_j')^2} \quad (17)$$

The distances of the ideal and non-ideal solutions are denoted by D_i" and D_i', respectively. Pixel *I*'s value according to the *j* criteria is denoted by V_{ij}. The criteria's positive and negative values are denoted by V_j" and V_j' is, respectively.

- Step 6: Pixel ranking TOPSIS calculates each pixel's score, and Equation (18) is used to get the similarity index. The greater the health risk, the closer the number is to 1.

$$C_i *= \frac{D_i'}{D_i' + D_i''} \quad (18)$$

The TOPSIS algorithm compares alternatives according to the data weight value [17]. The fuzzy TOPSIS model, which uses the fuzzy function, is more compatible than the non-Fuzzy TOPSIS technique discussed in the steps. The MDM-TOPSIS for IDM is carried out as above.

Once the consistency ratio using MDM-AHP as per Table 6, when healthcare management is implemented, MDM-TOPSIS assists in handling the resulting insecure data. The triangular fuzzy scale transforms the fuzzy values into crisp equivalents during defuzzification.

Table 6. Linguistic factors and triangular fuzzy number using the MDM-AHP-TOPSIS method.

Linguistic factors	Crisp values	Triangular fuzzy scale
Normal/Fit	1	(0,1,3)
Border	3	(1,3,5)
High	5	(3,5,7)
Very high	7	(5,7,9)

Lastly, the evaluation method based on fuzzy AHP-TOPSIS suggested by the sensitivity analysis uses fuzzy decision making. Sensitivity analysis attempts to ascertain the outcome of modifications to the actions or parameters in this process of safe information management. It shows how sensitive a certain transition is. This sensitivity study can be performed to ascertain how a change may impact operations by quantifying the potential impacts of various change types on the overall process, workflow, or activity. This study makes making decisions or developing recommendations for policymakers easier based on enhancements to the analysis model in certain variables.

Metrics Used

Factors including true positive, false positive, true negative, and false negative are used to gauge the model's performance. The following formulas are used to calculate the model's accuracy, recall, precision, and F1-score based on these variables. ROC and error measures are also used to analyse the system's performance.

$$Accuracy = \frac{(Tp + Tn)}{(Tp + Tn + Fp + Fn)} \quad (19)$$

$$Recall = \frac{Tp}{(Tp + Fn)} \quad (20)$$

$$Precision = \frac{Tp}{(Tp + Fp)} \quad (21)$$

$$F1 - Score = \frac{2 * Recall * Precision}{(Recall + Precision)} \quad (22)$$

5. Results and Discussions

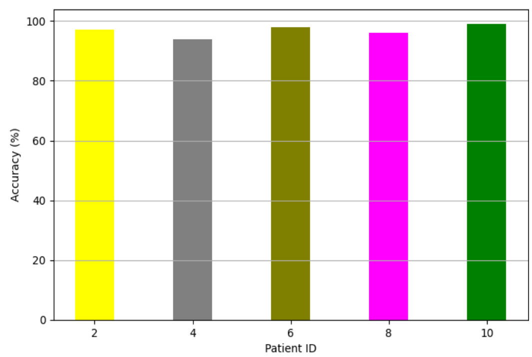
This section uses the evaluation findings of the smart healthcare management system and fuzzy neural network to calculate the prediction efficiency of health data. A straightforward, simple-to-implement fuzzy logic system for decision-making supported the proposed approach. Fuzzy judgments and sensor data create the proposed system's structure. In the second step, fuzzy logic was used to ascertain the patient's status after the input data had been acquired and set up. The fuzzy logical system used concluded and assessed its dependability and accuracy. Table 7 discusses the performance metrics used in this research.

Table 7. Parameters used in this research.

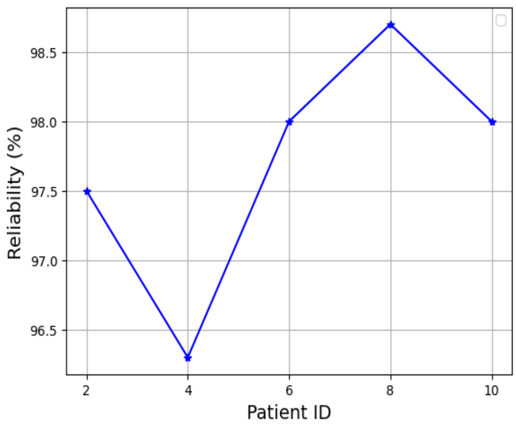
Parameter	Description
Linguistic factors	Normal/Fit, Border, High, and Very High
Benchmark models	RBM-CNN based health recommendation system [20], Random forest [15], Continuous Value Multi Criteria Operators (CVMCO) [19], and Fuzzy AHP-TOPSIS [21]
Metrics considered	Accuracy, reliability, precision, recall, F1-Score, and error rate.
Decision metrics	Fp, Tn, Tp, Fn.

5.1. Performance Analysis of Proposed MFNN-based Fuzzy Intelligent Decision System (FIDS)

The accuracy and reliability of FIDS are analyzed, and the results are shown in Figure 3. For analysis, 10 patients are selected and their risk prediction based on the recommendation for patient ID is evaluated in terms of accuracy in Figure 3-a) and reliability in Figure 3-b). The accuracy of the proposed model-based recommendation system fluctuated between 95.6% and 98.1% for accuracy and 97.5% and 98.7% reliability for a random number of 10 patients.



a) Accuracy assessment.



b) Reliability assessment.

Figure 3. FIDS of health risk prediction.

The error rate performance of the proposed system is shown in Figure 4. The fuzzy decision mismatch or wrong decisions are considered errors. The sensor data with the fuzzy decisions are considered errors for real-time monitoring. The reduced error rate of 0.241% is secured for the patient ID with 2.

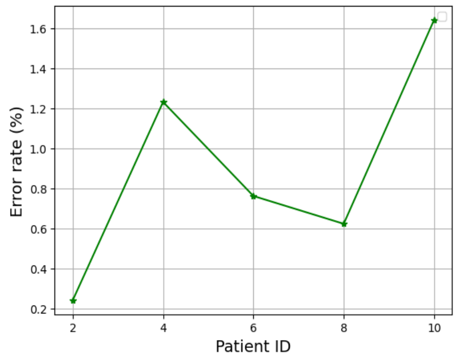


Figure 4. Error rate comparison for proposed FIDS.

The five alternatives and their respective criteria for choosing the weight are listed in Table 7 to analyze the FIDS based on the multi-criterion factors. The sensitivity of the proposed model results depends on the weights, and there were five alternatives for five criteria or factors, which are considered the information factors from the experts.

Table 8. Sensitivity analysis of MDM Fuzzy-AHP.

Alternatives	Criteria 1	Criteria 2	Criteria 3	Criteria 4	Criteria 5	Weight
A1	0.0341	0.0283	0.0452	0.0283	0.0129	0.0432
A2	0.0218	0.0211	0.0482	0.0281	0.0151	0.0441
A3	0.0228	0.0281	0.0521	0.0381	0.0281	0.0421
A4	0.0312	0.0223	0.0482	0.0452	0.0323	0.0512
A5	0.0221	0.0302	0.0527	0.0372	0.0281	0.0628

Based on these weights found in Table 8, the proposed MFNN has been applied to FIDS, and the accuracy for the training and test sets is shown in Figure 5 based on several instances. It has been noted that for 100 instances, the accuracy has fluctuated, and the obtained accuracy for the training set is 0.978, and for the testing set is 0.953. Similarly, the training and testing loss value analysis is shown in Figure 6. The reduced obtained loss value for the training set is 0.11, and the testing set is 0.21.

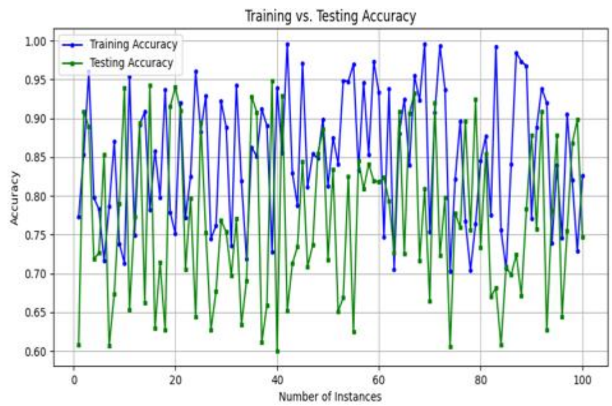


Figure 5. Performance of the proposed model, training and testing accuracy.

Figure 6. Performance of the proposed model training and testing loss.

5.2. Comparative Analysis

The performance of the proposed model is compared with the RBM-CNN based health recommendation system [20], Random forest [15], Continuous Value Multi Criteria Operators (CVMCO) [19], and Fuzzy AHP-TOPSIS [21]. According to a percentage split, 20% of the data was used for testing and 80% for training. The obtained accuracy of the proposed and considered approaches is illustrated in Figure 7, which shows 0.978, 0.953, 0.942, 0.962, and 0.968 for proposed MFNN, RBM-CNN, CVMCO, and FuzzyAHP-TOPSIS, respectively. The obtained precision of the proposed and considered approaches is 0.975, 0.952, 0.934, 0.953, and 0.953 for proposed MFNN, RBM-CNN, CVMCO, and FuzzyAHP-TOPSIS, respectively. The obtained recall of the proposed and considered approaches are 0.971, 0.951, 0.923, 0.925, and 0.912 for proposed MFNN, RBM-CNN, CVMCO, and FuzzyAHP-TOPSIS, respectively. The F1-scores of the proposed and considered approaches are 0.946, 0.892, 0.847, 0.912, and 0.934 for proposed MFNN, RBM-CNN, CVMCO, and FuzzyAHP-TOPSIS, respectively. Comparatively, the proposed model secured improved performance over the considered approaches.

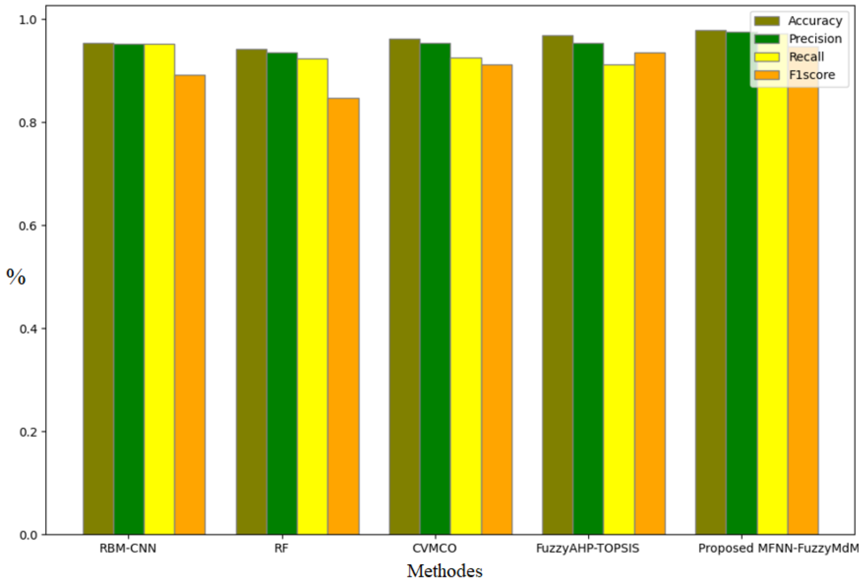


Figure 7. Performance comparison.

The proposed fuzzy intelligent system identified the disease risk level and recommended the physician for further medical assistance. A total of 300 patients are considered for this analysis. As denoted in Table 9, based on the fuzzy results, if stated as 1, the patient's health is at high risk. If the fuzzy denotes the value 0.5, then it denotes the medium risk recommended, and the value of 0 denotes no risk and recommends doing normal fitness exercises.

Table 9. Prediction and recommended results.

Patient ID	**Diseases**	**Prediction**	**Recommendation by proposed fuzzy-based IDS**
P15	Heart	High risk	Visit the doctor immediately.
P27	Heart	Risk	Need for a doctor's visit.
P30	Liver	High	Consult a doctor and take immediate medication.
P65	Kidney	Medium	Suggested to take a proper diet with medicine as per the doctor's consultation.
P97	Heart	Normal	Suggested to do normal exercise.

Table 10. Time complexity analysis.

Model	**Training complexity**	**Inference complexity**
Proposed MFRNN	0(k·n·m)	0(n·m+p)
RBM-CNN [20]	0(k^2+n)	0(n·m)
Random Forest [15]	0(T·n log n)	0(T·d)
CVMCO [19]	0(n)	0(1)
Fuzzy AHP-TOPSIS [21]	0(n·m)	0(n·m)

Table 10 discusses training (time) and inference (prediction) complexities for the proposed model in comparison with the existing references RBM-CNN based health recommendation system [20], Random forest [15], CVMCO [19], and Fuzzy AHP-TOPSIS [21]. The number of epochs k for analyzing n no. of input patient IDs, m no. of neurons in the neural network, 0(n·m) analysis in the forward pass with the p no. of fuzzy rules in comparison with the existing tree counts T, and depth of trees d.

The performance of the proposed method outperforms traditional approaches due to its hybrid integration of fuzzy logic and neural networks, which enhances decision-making accuracy and robustness. The fuzzy logic component is particularly beneficial in handling uncertainty and imprecision in the input data, while the neural network learns complex patterns from large datasets and improves generalization to new, unseen data. This combination ensures a more reliable and adaptable system than methods relying solely on fuzzy logic or neural networks. Furthermore, the hybrid approach significantly reduces computational complexity while maintaining high interpretability, as fuzzy rules provide transparent decision-making processes. The outperformance is particularly evident in noisy or incomplete data scenarios, where traditional models struggle, but the hybrid system remains resilient. Experimental verification shows a noticeable improvement in decision speed and accuracy, especially compared to baseline models such as decision trees or simple neural networks. This combination of enhanced learning capabilities, adaptability to various data distributions, and improved interpretability accounts for the superior performance of the proposed method.

5. Conclusions

An analysis of such a system of governance was conducted because of innovative alternatives like direct healthcare. A clever Healthcare Management assessment utilizing the Fuzzy Decision-Making System (FDMS) is suggested to assess technical integration performance. Therefore, using the FAHP in conjunction with the fuzzy TOPSIS of the intelligent health care system, the report investigated the security of personal health data privacy. The evaluation's findings recommended using this model in real time while creating an application or smart health management system. The modified fuzzy neural network intended for predicting health status was assessed in this study, and the best performance was discovered. The proposed fuzzy-logic-based neural network model has significant potential for real-world implementation in hospitals and medical healthcare centers. Its ability to handle uncertain, noisy, and incomplete data, which is common in healthcare, makes it well-suited for real-time decision support. The hybrid model can provide personalized treatment recommendations based on individual patient data, enhancing the precision of diagnostics and improving patient outcomes. Moreover, the interpretability of fuzzy logic allows healthcare professionals to understand and trust the system's predictions, facilitating better decision-making. The model's scalability enables it to handle large volumes of data, and its integration with existing hospital systems like Electronic Health Records (EHR) ensures seamless functionality in clinical environments. Predicting health risks early supports proactive interventions, reducing complications, and hospital readmissions. This combination of accuracy, adaptability, and transparency makes the model a promising tool for enhancing healthcare services, improving patient care, and streamlining medical workflows in real-world settings. This study intended to enhance this assessment in the future by adding more data and security criteria using Blockchain and advanced ML methods. The experimental analysis of the proposed MFNN with fuzzy MDM on three types of disease datasets shows the effective and efficient performance in predicting patients' health risks and recommending suggestions to physicians for real-time medicine. Online applications in the medical domain require a practical and effective information security strategy. The medical environment is becoming increasingly digital, embracing computers and the internet in every way. The completed study project evaluated the various data protection elements that affect the information security of web applications in the medical field. The proposed model secured an accuracy of 97.8% with a reduced error rate of 0.11. Potential researchers and doctors can benefit from the research consequence endeavor by developing online apps that are safe from the outset. Comparatively speaking, a modern solution with effective MDM technology requires less evaluation. Additionally, our research revealed incredibly thorough results with a low error rate.

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