Journal of Simulation and Analysis of Novel Technologies in Mechanical Engineering
17 (4) (2025) 0047~0058
DOI 10.71939/jsme.2025.1223884

Research article

Assessment of stroke risk using soft computing

Mahsa Khodadadi

Department of Electrical Engineering, Bon.C., Islamic Azad University, Bonab, Iran

dr.mah.kh@iau.ac.ir, Mahsa.khodadadi@gmail.com

(Manuscript Received --- 08 Nov. 2025; Revised --- 26 Dec. 2025; Accepted --- 29 Dec. 2025)

Abstract

Stroke risk assessment is complex in biomedical engineering due to the interaction of multiple clinical and lifestyle-related risk factors, which may not be consistently or comprehensively evaluated in routine clinical practice. To address this challenge, this study proposes a non-learning soft computing framework based on fuzzy cognitive mapping for stroke risk assessment. The proposed model integrates expert knowledge from three neurologists to construct the fuzzy cognitive map and assigns individual risk levels into low, moderate, and high categories. Model performance was evaluated using 10-fold cross-validation on a dataset of 110 individuals and benchmarked against the fuzzy c-means clustering algorithm and logistic regression. Experimental results demonstrate that the proposed FCM-based system outperforms the comparative methods, achieving an overall classification accuracy of 90.7%. These findings indicate that the proposed approach provides an interpretable and effective decision-support tool for stroke risk assessment.

Keywords: Assessment, Biomedical engineering, Fuzzy cognitive maps, Ischemic, Risk, Stroke.

1- Introduction

Health remains a universal concern, especially as the prevalence of serious illnesses continues to pose growing risks to humanity. Ensuring prompt and precise disease detection is essential for safeguarding individuals from both current and emerging health threats. Advances in soft computing techniques and biomedical engineering have played a vital role in enhancing the management, diagnosis, treatment, and overall care within healthcare systems. [1]. The diagnosis of diseases is a very complex and ambiguous task in medical science, with the theoretical data analysis methods not being very effective in obtaining appropriate medical information; however, computer-assisted techniques have emerged as a highly effective means of supporting the identification of various medical conditions. A variety of artificial intelligence techniques have been employed for data representation and interpretation. Among these, fuzzy cognitive mapping stands out as a comparatively less familiar yet valuable soft computing approach [2]; however, it serves as a powerful technique for representing causal relationships and inferences, capable of articulating the explicit conceptual framework of a system. This is achieved through the integration of key features from both fuzzy logic and neural networks. The approach introduces

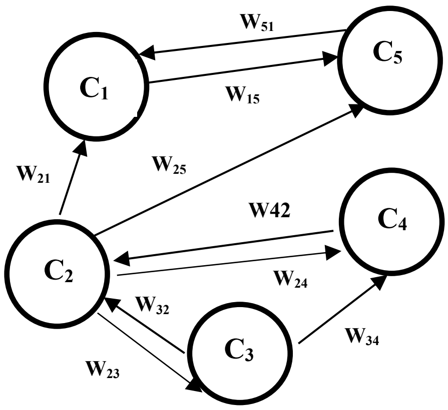

Fig.1 A sample FCM with 5 concept and 9 edge

a conceptual model that is not restricted to precise numerical values or measurements, making it particularly suitable for capturing concepts that lack structure. The behavior of complex systems can be represented through various concepts within a Fuzzy Cognitive Map (FCM), where each node corresponds to a specific characteristic or defined state of the system [3, 4]. The widespread adoption of FCM is attributed to its ease of construction, analytical flexibility, and applicability in system design. Its strengths include compatibility with diverse domains, the ability to accommodate uncertain knowledge, relatively simple modeling, efficiency in terms of time, and support for high-level decision-making [5, 6]. FCM has found applications across a wide range of scientific and industrial domains. These include decision-support systems, political and military sciences, electrical engineering, information systems, business management, supervision and production processes, systems analysis, computer science, and medicine, among others [7, 8]. Moreover, FCM is regarded as a contemporary and highly effective approach for disease diagnosis. Its applicability extends to areas such as diagnostic forecasting, classification, and decision-making [9]. In recent years, a growing body of research has applied fuzzy cognitive mapping across diverse medical fields. Notable examples include its use in stroke ischemic diagnosis [8], Parkinson's disease prediction [10], musculoskeletal rheumatic disease diagnosis [7], classification of plantar changes [11], differential diagnosis modeling of febrile diseases [12], and early diagnosis of Covid-19 [13]. Stroke ranks as the third leading cause of mortality worldwide and represents one of the primary contributors to neurological disorders, posing a major global health concern. As a medical emergency, rapid detection and precise diagnosis are vital to minimizing irreversible harm and improving patient outcomes. Nonetheless, stroke can sometimes remain undetected during the initial evaluation, underscoring the importance of accurate diagnosis in forecasting patient prognosis and guiding effective treatment [8]. A variety of artificial intelligence (AI) approaches have been explored to enhance the accuracy of treatment prediction and prognosis stroke onset [14]. Recent research highlights fuzzy cognitive maps as a promising classification technique within the medical domain [3]. Therefore, using fuzzy cognitive maps to classify stroke patients could be an interesting research topic because, according to the free-throw theory, it is not certain that a particular classifier is the best for all data, and these experimental results determine the effectiveness of the classifiers. This research did not focus on developing a new system; instead, it utilized an existing framework and expanded its application to the stroke domain to generate new insights. This study is the first to investigate the interpretability and stability of a non-learning fuzzy cognitive mapping system used for stroke risk assessment. In this model, the causal relationships between risk factors are defined by the knowledge and experiences of three neurologists, and the weights are fixed. Also, the mutual influence of risk factors and their interactions is clearly shown to physicians. The approach offers a comprehensive tool to support physicians in making timely and accurate stroke diagnoses. In practice, the patient's stroke risk is calculated from real clinical data, and the resulting values are compared with the average assessments of several neurologists. The accuracy of the proposed approach is evaluated and compared against the fuzzy c-means algorithm and logistic regression. Findings suggest that the presented method, along with the simulation of several neurologists' opinions, has better performance than that of a physician. The paper is organized as follows: Section 2 introduces the fuzzy cognitive map. Section 3 provides an overview of stroke, highlighting both modifiable and non-modifiable risk factors associated with ischemic stroke. Section 4 details an enhanced FCM-based model for stroke assessment, which applies three patient profiles to determine the 5-year ischemic stroke risk and evaluates the system's performance. Section 5 concludes the work.

2- Fuzzy cognitive maps

Fuzzy cognitive maps are a soft computing technique designed to emulate human-like reasoning and decision-making. Introduced by Kosko in 1986, they are represented as directed graphs incorporating a feedback loop [1]. FCMs are employed to model systems characterized by interdependencies and computational complexity. They are composed of a set of nodes, or concepts, with N denoting the total number of concepts. Each node represents a fundamental component of the system and is assigned a value within the interval [0, 1]. In an FCM, concepts are interconnected through weighted edges that express their causal relationships [15]. Figure 1 illustrates a simple example containing five nodes and nine weighted connections. The weight assigned to the link between two concepts, C_j and C_i, lies within the range [-1, 1], and the value of this weight depends on the strength of the cause-and-effect relationship between C_j and C_i. The relationship between these concepts is either positive or negative, as described by W_{ji}. Therefore, three weights can exist, with $W_{ji}>0$ representing a positive relationship, $W_{ji}<0$ indicating a negative relationship, and $W_{ji}=0$ indicating that there is no relationship between these concepts. By specifying the value of the concept and the weights, the FCM converges to the stability condition the stability condition. During each iteration, the value of a concept P_i is influenced by the concepts connected to it and is updated based on the (1):

$$P_i^{(k+1)} = \text{f}(P_i^{(k)} + \sum_{\substack{j=1 \\ j\neq i}}^{n} P_j^{(k)} * W_{ji}) \quad (1)$$

Where, f denotes the sigmoid threshold function, and here $\lambda \geq 0$ is the parameter that determines that all values are calculated and the process continues until the FCM converges to a stationary state after a few iterations. The slope of the function is defined as follows [8]:

$$\text{f} = \frac{1}{1+e^{-\lambda x}} \quad (2)$$

3-Define stroke and introduce risk factors for FCM model design

Stroke is a serious neurological disorder that affects individuals of all ages across the

Table 1: FCM model concepts for the of assessment stroke risk

C_N	Concepts	Type of values
C_1	Age	Three fuzzy values (Young, Middle age, Old)
C_2	Blood Pressure	Four fuzzy values (Low, Medium, High, Very high)
C_3	LDL Cholesterol	Four fuzzy values (Low, Medium, High, Very high)
C_4	HDL Cholesterol	Three fuzzy values (Low, Medium, High)
C_5	Diabetes	Three fuzzy values (Low, Medium, High);
C_6	Heart Disease	Two discrete values (Yes , No)
C_7	Family History	Two fuzzy values (Yes , No)
C_8	Smoking	Two fuzzy values (Yes , No)
C_9	BMI	Three fuzzy values (Low, Medium, High)
C_{10}	Exercise	Two fuzzy values (Yes , No)
C_{11}	Sex	Two fuzzy values (Female , Male)
C_{12}	C_{12}: Stroke History	Two fuzzy vales (Yes , No)
C_{13}	Risk of Stroke	Three fuzzy values (Low, Medium, High)

globe. In the United States, it ranks as the third leading cause of death, following coronary heart disease and cancer, with an incidence ranging from 0.2 to 2 per thousand people. In Iran, the post-stroke morbidity rate was reported at 8% in 2003, while the mortality rate stood at 4.4%. Strokes are generally divided into two main types: hemorrhagic and ischemic. Ischemic stroke, the more prevalent form, accounts for approximately 85% of all cases. It arises when blood flow to a region of the brain is obstructed or markedly reduced, depriving the affected area of essential oxygen and nutrients. This interruption, which can persist from minutes to several hours, leads to cellular dysfunction and eventual cell death. Consequently, ischemic stroke is considered a medical emergency, and rapid intervention is crucial to minimize brain damage and subsequent neurological impairments, making every second critical for timely diagnosis and treatment [16]. The risk factors and symptoms of ischemic stroke encompass twelve characteristics, which are categorized as modifiable or non-modifiable and play a key role in disease assessment. These factors are represented using two, three, or four fuzzy values, corresponding to linguistic variables such as low, medium, high, and very high, as summarized in Table 1. The input data for these factors were collected from 110 real cases at Imam Reza Hospital in Tabriz city and evaluated by three neurologists: Dr. Mohammadzadeh, Dr. Hagigat, and Dr. Asgarpour. The fuzzy cognitive map model proposed in this study is grounded in the neurologist's assessments, which guided the selection of both input and output concepts. Figures 2 and 3 illustrate the membership functions for family history (C_7) and BMI (C_9), respectively.

4-Steps to build FCM for assessing ischemic stroke risk rate

Once the neurologists determined the input and output concepts, they were asked to evaluate the influence of each concept on the others and to define the interrelationships using linguistic variables expressed through fuzzy "if-then" rules. Each linguistic variable is represented within the interval [0, 1]. In this approach, the relationship between two concepts is defined by a neurologist using fuzzy linguistic variables, which represent the strength and direction of causality. For instance, a specialist can describe the cause-and-effect connection between concepts C_i and C_j through fuzzy rules as follows:

If the value of the concept C_i is A, then the value of the concept C_j is B, where the

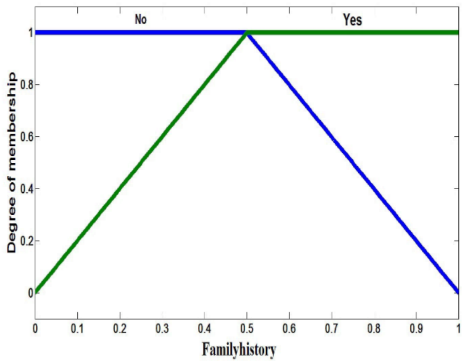

Fig. 2 Membership function for the family history input concept

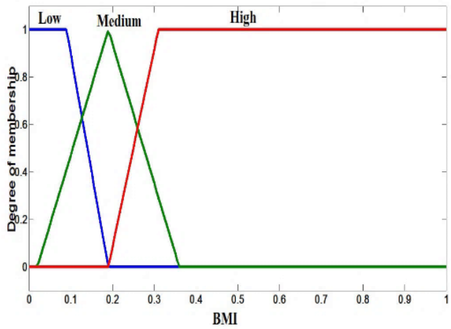

Fig. 3 Membership function for the BMI input concept

linguistic weight W_{ij} is assigned as Z. Here, A, B, and Z are all fuzzy linguistic variables that capture the degree of influence between the concepts [1]. Neurologists often have differing opinions regarding the influence of one concept on another. To derive the final linguistic weights, the three sets of linguistic variables provided by each specialist were aggregated. The overall weight was then converted into a numerical value using the centroid defuzzification method. This approach allows neurologists to qualitatively express the strength of causal relationships without relying on precise numerical values. Each connection is evaluated through fuzzy inference, and the resulting fuzzy weights are defuzzified using the centroid method to generate the initial FCM weight matrix [1, 3]. The following example demonstrates the process of deriving numerical weights from the assessments of neurologists. Three specialists evaluated the relationship between concepts C_3 (LDL) and C_{13} (stroke risk rate) using fuzzy rules as follows:

First neurologist: If the LDL (C_3) is low, then the stroke risk rate (C_{13}) is low.

Second neurologist: If the LDL (C_3) is medium, then the stroke risk rate (C_{13}) is medium.

Third neurologist: If the LDL (C_3) is medium, then the stroke risk rate (C_{13}) is high. These three linguistic assessments low, medium, and high were aggregated using the SUM method to generate the final linguistic weights. The weight from C_3 to C_{13} was then quantified as 0.38 through centroid defuzzification, as illustrated in Fig. 4. Applying the same procedure to the other relationships, all non-zero matrices obtain weights, as shown in Table 2 and Fig. 5, which are respectively the initial weight matrix and FCM model for the prediction of the risk of stroke with numerical values of the initial weights. Therefore, it can be said that the steps of building FCM for determining ischemic stroke risk rate are as follows:

Step 1: Identify the concepts/risk factors for ischemic stroke (shown in Table 1) and determine the relationship between them by neurologists.

Step 2: The estimated severity of the relationship between factors (if any) by the neurologists is assumed to be the original weight matrix (given in Table 2).

Step 3: Normalize the initial values of the concept according to the Equation in [8].

Step 4: Take the initial concept values and the weights matrix.

Step 5: Updating new concept values according to (1).

Step 6: Consider the new value as an initial value in the next iteration.

Step 7: Repeat the steps until reaching equilibrium and meeting the following condition:

$$P_i^K - P_i^{K-1} \leq 0 \cdot 001 \quad (3)$$

Table 2: Initial weight values proposed by neurologists for assessing the risk of stroke

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
C_1	0	0.55	0	0	0.35	0.4	0	0	0	0	0	0.60	0.60
C_2	0	0	0	0	0.46	0.45	0	0	0	0	0	0.52	0.54
C_3	0	0	0	0	0	0.44	0	0	0	0	0	0.40	0.40
C_4	0	0	0	0	0	-0.55	0	0	0	0	0	-0.54	-0.58
C_5	0	0.40	0	0	0	0.45	0	0	0	0	0	0.50	0.50
C_6	0	0	0	0	0	0	0	0	0	0	0	0.55	0.58
C_7	0	0.45	0	0	0.35	0.40	0	0	0	0	0	0.30	0.30
C_8	0	0.30	0	0	0.20	0.35	0	0	0	0	0	0.45	0.45
C_9	0	0.25	0	0	0.45	0.35	0	0	0	0	0	0.25	0.25
C_{10}	0	-0.20	0	0	-0.35	-0.35	0	0	-0.30	0	0	-0.30	-0.30
C_{11}	0	0	0	0	0	0	0	0	0	0	0	0.10	0.10
C_{12}	0	0	0	0	0	0	0	0	0	0	0	0	0.68
C_{13}	0	0	0	0	0	0	0	0	0	0	0	0	0

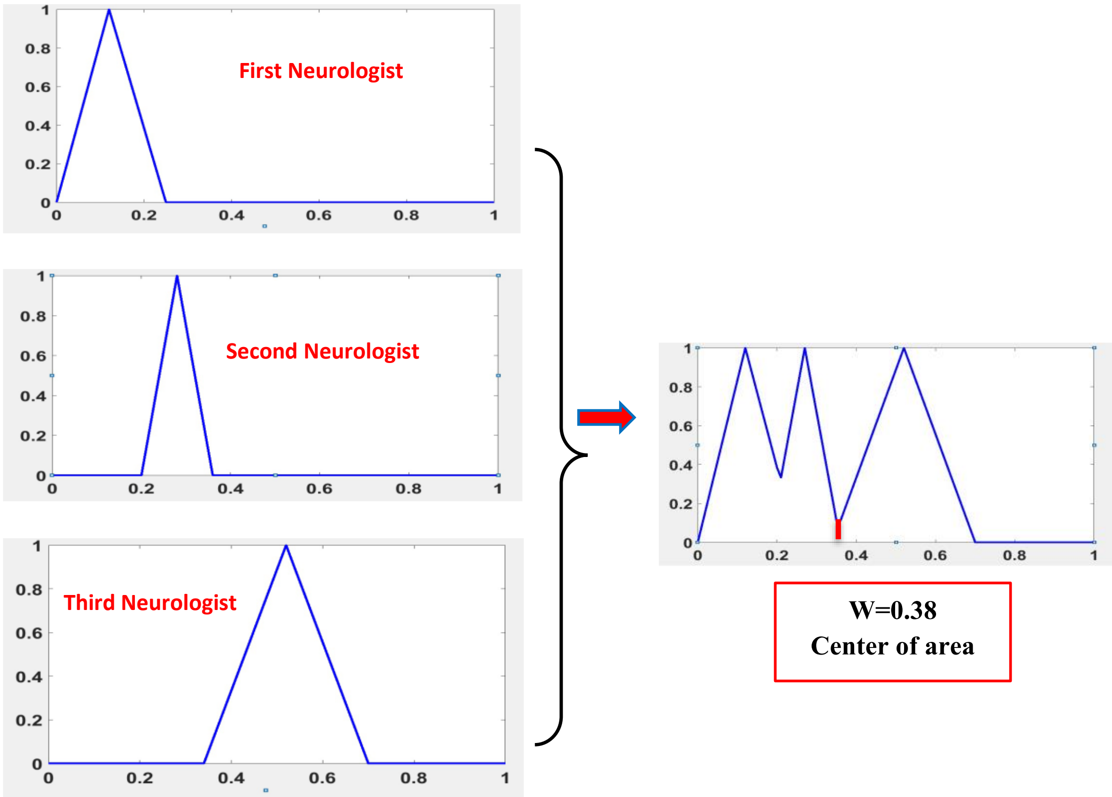

Fig. 4 Aggregation of three linguistic variables using the SUM method

Step 8: Stopping the procedure by obtaining the final concept values (P_{Final}).

4-1- Simulation and evaluation results

In this study, twelve characteristics are employed as input variables, while C_{13} represents the output variable, determined by neurologists, to indicate the probability of ischemic stroke occurrence within five years. The decision outcome is modelled as a fuzzy set variable with three categories,

Table 3: Values of fuzzy cognitive map concepts at 7 iteration steps for the first example

P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9
0.7	0.55	0.44	0.25	0.54	0	1	0	0.83
0.54711	0.58715	0.52967	0.51687	0.53639	0.5	0.63577	0.56573	0.55579
0.53686	0.60243	0.53569	0.53483	0.53614	0.5337	0.61466	0.59239	0.53745
0.53617	0.60398	0.5361	0.53604	0.53613	0.53596	0.61349	0.59381	0.53621
0.53613	0.60411	0.53612	0.53612	0.53613	0.53611	0.61343	0.5939	0.53613
0.53613	0.60412	0.53613	0.53613	0.53613	0.53612	0.61342	0.59391	0.53613
0.53613	0.60412	0.53613	0.53613	0.53613	0.53613	0.61342	0.59391	0.52453

P_{10}	P_{11}	P_{12}	P_{13}
0	1	1	0.1
0.5	0.56709	0.68327	0.67212
0.5337	0.5382	0.65162	0.67947
0.53596	0.53626	0.64898	0.67791
0.53611	0.53613	0.64879	0.67768
0.53612	0.53613	0.64877	0.67765
0.53613	0.53613	0.64877	0.67765

low, medium, and high, defined according to neurologists' assessments as follows: 0≤low≤0.14, 0.15≤medium≤0.30, and 0.31≤high≤1. To clarify this framework, three examples of experimental data are presented. A 75-year-old male patient was evaluated with the following clinical profile: blood pressure of 190, LDL cholesterol of 160, HDL cholesterol of 35, blood sugar level of 180, no history of heart disease, positive family history, non-smoker status, BMI of 35.5, absence of regular physical activity, and a previous stroke. Based on these indicators, neurologists assessed the individual's stroke risk as high. Before analysis, all variables were normalized to the [0,1] range using the equation in [8].

The resulting normalized input values are as follows: P_{Intial} = [0.7 0.55 0.44 0.25 0.54 0 1 0 0.83 0 1 1 0.1 The initial input value, together with the weight matrix provided in Table 2, was iteratively updated using (1) until the FCM stabilized. As presented in Table 3, the system reached equilibrium after seven iterations, at which point the concept values no longer changed. The final output concept obtained at iteration seven was 0.67765. Applying the equation in [8], this corresponds to a calculated risk rate of 35%, which neurologists classify as high risk, consistent with the interval 0.31≤high≤1. Figure 6 illustrates the convergence process through the sequence diagram of concept values.

Second example: A 74-year-old male patient with no prior history of stroke was assessed. His clinical parameters included: blood pressure of 160, LDL cholesterol of 140, HDL cholesterol of 37, blood sugar of 95, absence of heart disease, positive family history, non-smoker status, BMI of 24, and lack of regular physical exercise. Based on these indicators, neurologists estimated his probability of experiencing a stroke as medium. After normalization of the above values, yielding the following initial conceptual values: P_{Intial}= [0.68 0.4 0.36 0.3 0.15 0 1 0 0.26 0 1 0 0.1]. The normalized input values, after simulation with the FCM model, are obtained as follows: P_{FCM}= [0.52354 0.56572 0.52354 0.52354 0.56098 0.57631 0.52354 0.52354 0.51615 0.52354 0.52354 0.59458 0.61386]. As illustrated, the output concept stabilized

Table 4: The proposed fuzzy cognitive map system evaluation results in 10 iterations

	Accuracy	Recognition rate low	Recognition rate medium	Recognition rate high
Fold 1	81%	1	0.6	1
Fold 2	81%	1	1	0.6
Fold 3	100%	1	1	1
Fold 4	81%	0.5	0.66	1
Fold 5	91%	0	0.75	1
Fold 6	91%	1	0.66	1
Fold 7	100%	1	1	1
Fold 8	100%	1	0	1
Fold 9	91%	1	0.75	1
Fold 10	91%	1	0.66	1

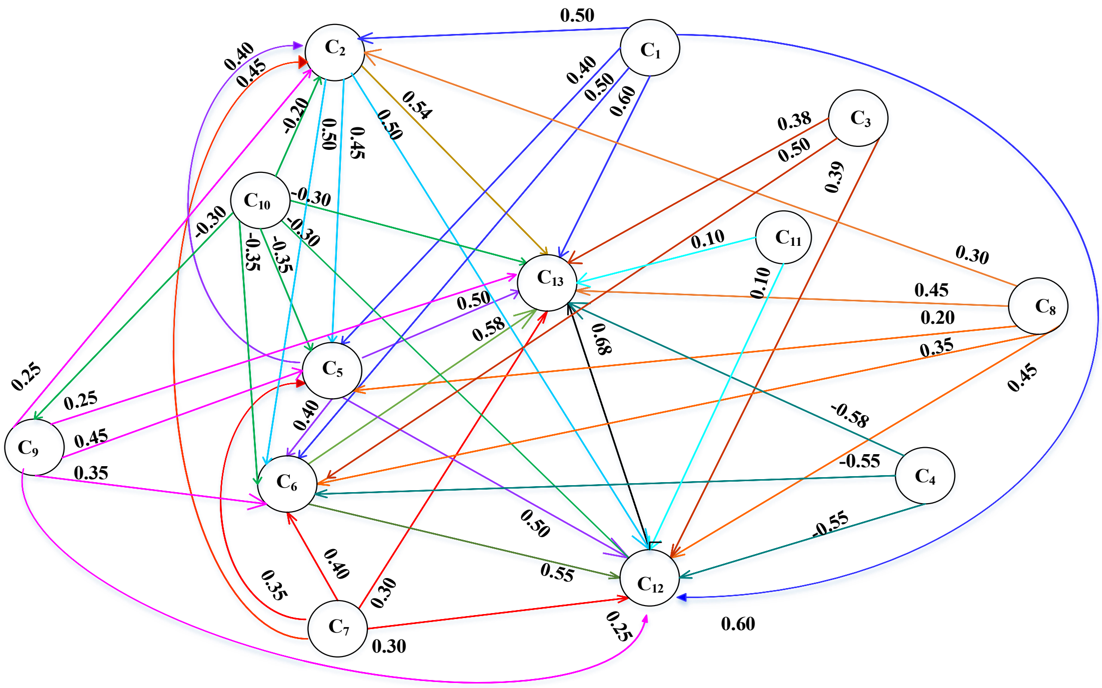

Fig. 5 Proposed FCM model with the assigned initial values of weights for the assessment of ischemic stroke

after six iterations, converging to a value of 0.61386. This corresponds to a calculated risk rate of 22%, which neurologists classify as medium risk, consistent with the interval 0.15 ≤ medium ≤ 0.30.

Third example: a 60-year-old female patient with no prior stroke history was assessed. Her clinical profile included: blood pressure of 130, LDL cholesterol of 145, HDL cholesterol of 42, blood sugar level of 100, no heart disease, no family history, smoker status, BMI of 27, and lack of regular physical activity. Based on these parameters, neurologists predicted a low probability of stroke. After normalization of the above values, the following initial concept values were obtained: $P_{Intial} =$

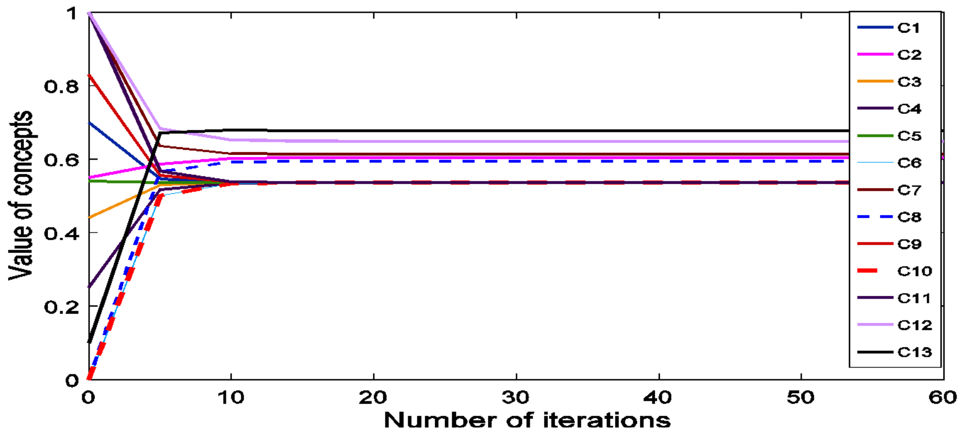

Fig. 6 Subsequent values of concepts till convergence for the first example

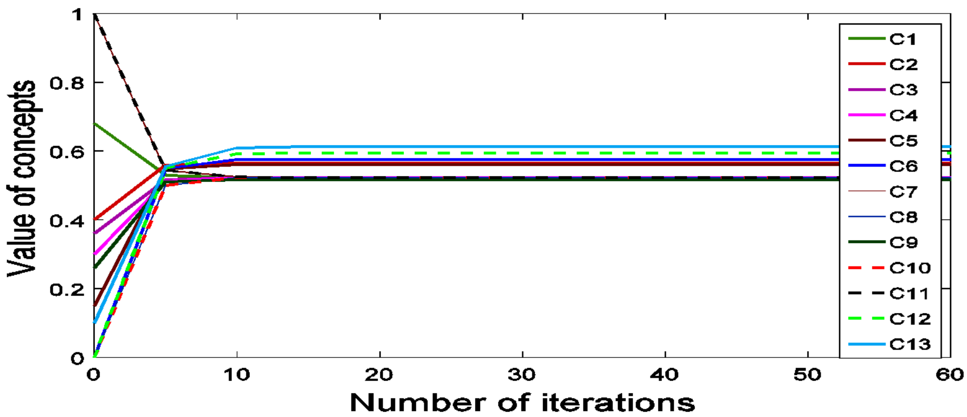

Fig. 7 Subsequent values of concepts till convergence for the third example

[0.47 0.25 0.38 0.3 0.17 0 0 1 0.41 0 0 0 0.1]. The normalized input values, following simulation with the FCM model, are presented as follows: P_{FCM} = [0.51151 0.53162 0.51151 0.51151 0.52931 0.53653 0.51151 0.51151 0.50798 0.51151 0.51151 0.54508 0.55403]. As observed, the output concept stabilized after five iterations, converging to a value of 0.55403. This corresponds to a calculated risk rate of 10%, which neurologists classify as low risk, consistent with the interval 0≤low≤0.14. Figure 7 presents the sequence diagram of concept values, illustrating the convergence achieved. To assess the performance of the proposed system, 110 real patient datasets, ranging in age from 28 to 95 years, were employed. Although this sample size allows for statistical analyses and evaluation of model performance, the limited nature of the data to a specific clinical setting may limit the generalizability of the results to other healthcare centers or different populations. To increase the statistical robustness of the

Table 5: The system evaluation results with the fuzzy c-means clustering algorithm in 10 iterations

	Accuracy	Recognition rate low	Recognition rate medium	Recognition rate high
Fold 1	81%	1	0.6	1
Fold 2	72%	0.5	1	0.8
Fold 3	81%	1	0.75	1
Fold 4	81%	0.5	0.66	1
Fold 5	81%	0	0.6	1
Fold 6	81%	1	0.66	0.87
Fold 7	91%	1	1	0.88
Fold 8	81%	1	0	0.88
Fold 9	81%	1	0.75	0.83
Fold 10	91%	1	0.66	1

results, 10-fold cross-validation was used. However, it is obvious that increasing the data set and including data from multiple healthcare centers in future studies can help improve the statistical power and generalizability of the results. In a 10-fold validation cross method, nine subsets were used for training, while the remaining subset served as the test set. For each iteration, the accuracy and recognition rate were calculated based on the test dataset. Table 4 presents the results of the algorithm applied to the 11 test datasets. After 10 iterations, the overall accuracy, calculated as the average across all datasets, was 90.7%. Additionally, for better comparison, the data used in this article were clustered using the fuzzy c- means. This algorithm is one of the most important and useful clustering algorithms. Indeed, clustering is an unsupervised learning method; it is often called classification. In the fuzzy c-means clustering techniques, the samples are split into c clusters. The number of c is predetermined. The fuzzy c-means algorithm is widely used in the medical field for disease diagnosis because of its effectiveness in recognizing systems [17, 18]. Therefore, this can be considered a potential competitor of FCMs. In this study, the weighting parameter is 2, the number of clusters is 3, the tolerance level is 0.00001, and the number of iterations is 100. Table 5 shows the accuracy and recognition rate in each iteration of the fuzzy c-means clustering algorithm. For ensuring greater accuracy of the proposed system results, in addition to fuzzy c-means, logistic regression is also used. Logistic regression is a supervised learning method used in the medical field. In the logistic regression model, the decision threshold is considered to be 0.5 [19]. The results of the accuracy and recognition rate in each iteration of the logistic regression are depicted in Table 6. The results of the evaluation of the proposed system showed that this model provides more stable performance when dealing with ambiguous and correlated data compared to the logistic regression method. While logistic regression faces limitations due to the assumption of linear relationships and relative independence of variables, fuzzy cognitive mapping can represent a more complex structure of causal relationships and, as a result, improve decision-making accuracy. This difference was especially evident in data with a higher level of uncertainty. Therefore, it can be said that the proposed model, which utilizes prior knowledge and addresses overlapping class uncertainty, performs better than both the unsupervised method and the linear

Table 6: The system evaluation results with the logistic regression algorithm in 10 iterations

	Accuracy	Recognition rate low	Recognition rate medium	Recognition rate high
Fold 1	91%	1	0.75	1
Fold 2	81%	0	1	0.85
Fold 3	91%	1	0.85	1
Fold 4	91%	0.65	1	1
Fold 5	81%	0	1	0.65
Fold 6	81%	1	0.75	0
Fold 7	91%	1	1	0.85
Fold 8	81%	1	0	0.85
Fold 9	81%	1	0.85	0.65
Fold 10	91%	0.75	1	1

supervised method. This indicates the ability of the proposed model in assessing stroke risk.

5- Conclusion

Early detection and treatment of stroke are crucial, as timely diagnosis not only enhances the patient's chances of recovery and survival but also mitigates the severe consequences associated with the condition. This study introduces an effective approach using a soft computing technique known as fuzzy cognitive modeling to predict the risk of ischemic stroke over the next five years based on key risk factors. By integrating expert knowledge with a fuzzy logic framework, this method improves the accuracy of disease prediction. To validate its performance, the system's results were compared with the average opinions of the mentioned neurologists. The total accuracy of this method for 110 real data sets is 90.7% compared with the fuzzy c-means algorithm and logistic regression. The findings indicate that FCM modeling closely aligns with expert clinical judgment. Overall, the results of this study indicate that the proposed system based on fuzzy cognitive mapping can be used as an effective decision support tool in stroke assessment and provides a good balance between accuracy, flexibility, and interpretability compared to the compared methods.

References

[1] Khodadadi, M., Shayanfar, H., Maghooli, K., & Hooshang Mazinan, A. (2019). Prediction of stroke probability occurrence based on fuzzy cognitive map. *Automatika: časopis za automatiku, mjerenje, elektroniku, računarstvo i komunikacije*, *60 (4),* 378-385.

[2] Apostolopoulos, I. D., & Groumpos, P. P. (2023). Fuzzy cognitive maps: Their role in explainable artificial intelligence. *Applied Sciences*, *13*(6), 3412.

[3] Amirkhani, A., Papageorgiou, E. I., Mohseni, A., & Mosavi, M. R. (2017). A review of fuzzy cognitive maps in medicine: Taxonomy, methods, and applications. *Computer methods and programs in biomedicine*, *142*, 129-145.

[4] Subramanian, J., Karmegam, A., Papageorgiou, E., Papandrianos, N., & Vasukie, A. (2015). An integrated breast cancer risk assessment and management model based on fuzzy cognitive maps. *Computer methods and programs in biomedicine*, *118(3)*, 280-297.

[5] Bautista, J. A. R., Chaparro-Cárdenas, S. L., Hernández-Zavala, A., Gallegos-Torres, R. M., Zequera, M., Tovar-Barrera, Y., ... & Huerta-Ruelas, J. A. (2022). Fuzzy cognitive map to classify plantar foot alterations. *IEEE Latin America Transactions*, *20(7),* 1092-2000.

[6] Orang, O., de Lima e Silva, P. C., & Guimarães, F. G. (2023). Time series forecasting using fuzzy cognitive maps: a survey. *Artificial Intelligence Review*, *56*(8), 7733-7794.

[7] Akinnuwesi, B. A., Adegbite, B. A., Adelowo, F., Ima-Edomwonyi, U., Fashoto, G., & Amumeji, O. T. (2020). Decision support system for diagnosing rheumatic-musculoskeletal disease using fuzzy cognitive map technique. *Informatics in medicine unlocked*, *18*, 100279.

[8] Khodadadi, M., Shayanfar, H., Maghooli, K., & Hooshang Mazinan, A. (2019). Fuzzy cognitive map based approach for determining the risk of ischemic stroke. *IET systems biology*, *13*(6), 297-304.

[9] Bakhtavar, E., Valipour, M., Yousefi, S., Sadiq, R., & Hewage, K. (2021). Fuzzy cognitive maps in systems risk analysis: a comprehensive review. *Complex & Intelligent Systems*, *7*(2), 621-637.

[10] Shukla, D. K., & Sharma, M. Fuzzy Cognitive Maps based Mathematical Model for Prediction of "Parkinson Disease".

[11] Bautista, J. A. R., Chaparro-Cárdenas, S. L., Hernández-Zavala, A., Gallegos-Torres, R. M., Zequera, M., Tovar-Barrera, Y., ... & Huerta-Ruelas, J. A. (2022). Fuzzy cognitive map to classify plantar foot alterations. *IEEE Latin America Transactions*, *20*(7), 1092-2000.

[12] Obot, O., John, A., Udo, I., Attai, K., Johnson, E., Udoh, S., ... & Uzoka, F. M. (2023). Modelling differential diagnosis of febrile diseases with fuzzy cognitive map. *Tropical Medicine and Infectious Disease*, *8*(7), 352.

[13] Akilashri, P., & Nithya, G. (2024). An Integrated Framework for Early Differential Diagnosis of COVID-19 using Improved Fuzzy Cognitive Map Approaches. *Indian Journal of Science and Technology*, *17*(23), 2390-2400.

[14] Ruksakulpiwat, S., Phianhasin, L., Benjasirisan, C., & Schiltz, N. K. (2023). Using neural networks algorithm in ischemic stroke diagnosis: a systematic review, *Journal of Multidisciplinary Healthcare*, 16, 2593-2602.

[15] Hoyos, W., Aguilar, J., & Toro, M. (2023). PRV-FCM: An extension of fuzzy cognitive maps for prescriptive modeling. *Expert Systems with Applications*, *231*, 120729.

[16] M. Khodadadi, L. Khodadadi, "A fuzzy expert system for predicting the risk of ischemic stroke based on modifiable risk factors," Int. J. Smart Electr. Eng., in press.

[17] Khang, T. D., Vuong, N. D., Tran, M. K., & Fowler, M. (2020). Fuzzy C-means clustering algorithm with multiple fuzzification coefficients. *Algorithms*, *13*(7), 158.

[18] Salman, Z., & Alomary, A. (2024). Performance of the K-means and fuzzy C-means algorithms in big data analytics. *International Journal of Information Technology, 16(1),* 465-470.

[19] Khanday, A. M. U. D., Rabani, S. T., Khan, Q. R., Rouf, N., & Mohi Ud Din, M. (2020). Machine learning based approaches for detecting COVID-19 using clinical text data. *International Journal of Information Technology, 12(3*), 731-739.