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Research Article

Integrated Fuzzy Cognitive Map and Chaotic Particle Swarm Optimization for Risk Assessment of Ischemic Stroke

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Abstract:

Stroke diagnosis is an incredibly difficult process since it involves the interaction of both controllable and uncontrollable factors. The diagnosis of stroke is significantly influenced by these factors, which include a variety of factors such as age, blood pressure, gender, obesity, diabetes, smoking, and heart disease, amongst others. It is vital to develop an intelligent system that enables treatment to be administered in a timely and effective manner. This study discusses the application of the soft computing approach, more specifically fuzzy cognitive mapping (FCM), for the goal of estimating the possibility of patients suffering from an ischemic stroke. The chaotic particle swarm optimization technique has been utilized for the purpose of training the FCM training system. The consideration the opinions that were provided by neurologists in order to ascertain the risk rate that was associated with each individual. In order to a cross-validation with tenfold overlap was utilized. The results obtained from this method were compared to those obtained by support vector machine (SVM) and K-nearest neighbour computations, which were performed on 110 real-world observations. The proposed method demonstrated an exceptional level of performance, as seen by its overall accuracy of 94.6 percent and its standard deviation of 3.1 percent.

1. Introduction

Main Main Fuzzy Cognitive Maps (FCMs) are a modelling approach first introduced by Kosko in [1]. A combination of neural networks and fuzzy logic is utilized in this approach. Systems that are characterized as neuro-fuzzy are known as FCMs. They were initially developed by Axelrod and Kosko [1,2] as an expansion of other types of cognitive maps. These systems are equipped with the capacity to integrate human knowledge and become more proficient in it through the process of learning. Fuzzy concept maps (FCMs), which are an integration of fuzzy set theory and cognitive mapping, offer a helpful framework for capturing the dynamics of connected concepts that are contained inside complex systems.

Diagrammatic representations of FCMs can be thought of as graphical models that consist of nodes and weighted edges. Each node in the diagram is a representation of a tangible concept that exists in the real world. These concepts include characteristics such as quality, performance, and properties. Within the context of a causal approach, the weighted edges illustrate the relationships that exist between these concepts. Fuzzy cognitive models (FCMs) are characterized by enhanced interpretability, numerical reasoning, and knowledge representation competency. These models inherit properties from both fuzzy logic and neural networks. Consequently, FCMs have many uses in many different domains within the field of numerical science. Among the applications that fall under this category are the following: decision-making, [3,4,5] expert systems development Á. Garzón Casado et al. [6], smart city initiatives [7], modelling gene regulatory networks (GRNs) [8], the development of intelligent machines [9] and the solving of difficult problems like the modelling of COVID-19-related issues [10].

The widespread recognition of fuzzy cognitive models (FCMs) as a potentially useful technique for modelling and simulating complex systems, which are characterized by flexibility, abstraction, and fuzzy reasoning, has led to the development of novel

concepts and learning algorithms for FCMs. This research has been going on for quite some time. The currently available learning algorithms for FCMs, on the other hand, are in need of enhancement, a more robust mathematical basis, and more validation on more complex systems. To make FCMs far more useful and practical, we need to fix their flaws like the abstract estimation of the initial weight matrix and find ways to refine expert knowledge even more. As a consequence of this, the design of learning algorithms continues to be an intriguing and significant research avenue in this context (figure 3).
Few algorithms have been created specifically for learning FCM, as stated in the literature [11,12]. Recent technological advancements have resulted in the implementation of these algorithms. The major purpose is to identify appropriate values for the weights of the FCM so that it may be guided to the steady state that is desired. In order to achieve this purpose, it is necessary to minimize a function that has been precisely defined. Experts' provision of the initial weight matrix approximation is crucial to the success of several well-established algorithms. As suggested by Koulouriotis et al. [13] an innovative method of FCM learning suggests the implementation of Evolution Strategies for computing appropriate weight matrices. This is just one example of the unique approach.
To maximize the structure and weights of FCMs, evolutionary strategies must be applied, which means evolutionary computation techniques must be used. Evolutionary algorithms belong to a class of optimization techniques that are inspired by natural selection and genetic processes. It is possible to optimize the architecture or structure of FCMs by applying evolutionary algorithms. Part of this procedure is figuring out how many concepts, relationships, and feedback loops the map contains. In FCMs, the optimization of the weights of the connections can be accomplished by the utilization of genetic algorithms, differential evolution, or other evolutionary methodologies. This optimization aims to identify the set of weights that minimizes the value of an objective function, which is commonly linked to the FCM's performance or accuracy in capturing system dynamics. When it comes to learning rule augmentation, evolutionary algorithms can be applied to modify or develop the learning rules used in FCMs. In order to do this, the rules governing how the FCM modifies its weights in response to provided data or expert information must be changed.
Particle Swarm Optimization (PSO) was used by Parsopoulos [14] to train the FCM algorithm. His approach utilizes historical facts and progresses toward a specific state of affairs. The search space in PSO is explored by a swarm of virtual particles. It is necessary to establish constraints in order to preserve the integrity of the FCM structure while it is being trained. If this is not done, there is a possibility that the FCM will be altered to such an extent that it will lose its intended meaning and will no longer accurately represent the physical system that it was designed to model. A memetic technique that mixes PSO with deterministic and stochastic local search strategies was utilized in the tests that carried out [15,16]. When compared to other methodologies, this hybrid strategy produced outcomes that were more favorable. For the purpose of diagnosing celiac disease (CD) in 89 individuals, the PSO technique was utilized in the research that was described in [17]. When compared to the Bayesian networks that are often utilized for this diagnostic task, the results indicated a greater level of accuracy and a faster convergence rate. Khan and Chong provide an alternative approach that utilizes a genetic algorithm [18]. The original concept vector is derived from the desired ultimate state through the process of backward engineering, which is carried out using this algorithm. In their study [19], introduced a genetic optimization technique designed especially for multi-objective decision-making applications. This method simultaneously considers the activation values of two or more nodes at the same time when constructing the weight matrix. An alternative method to solve this problem was provided by (Stach et al. [20,21] using a Real-Coded Genetic Technique (RCGA) parallel processing algorithm. There's a chance that this solution works better. This method is especially intended for training big models with several dozen nodes. At the apex of the efforts made to overcome these obstacles, an inventive algorithm was published in the literature [22]. This novel method combines ensemble Fuzzy Cognitive Maps (FCMs) with a multi-objective evolutionary algorithm to reconstruct gene regulation networks (MOEA).
This paper proposes a novel learning method for fuzzy cognitive maps (FCM) using a swarm intelligence algorithm. More precisely, the system's proper weight matrices are found by applying the Chaotic Particle Swarm Optimization (CPSO) technique [22]. A clearly defined objective function is minimized in order to achieve this.

2. Fuzzy cognitive maps overview

In Kosko's work [1], FCMs were introduced as directed graphs with signed edges, with the goal of modeling causal reasoning and computational inference processing. Symbolic representation is utilized by FCMs to describe and model systems. They use concepts to illustrate different system behaviors and properties with this representation.

The simulation of the system dynamics is achieved by means of the interaction among these concepts. Both qualitative and quantitative data can be represented in a variety of ways utilizing FCMs. When building an FCM, it is necessary to have human experience and information about the system incorporated into the design. For this reason, FCMs are utilized as a method for integrating the acquired knowledge regarding the causal linkages that exist between the various aspects, traits, and components that make up the system. An FCM is made out of nodes, which are concepts.

$$C_i,\ i = 1,..., N \tag{1}$$

An FCM is a fuzzy digraph with signed edges, organized into Nn concept nodes. These concept nodes are represented by a vector C, which contains their respective state values.

$$C = [C1 ,C2 ,...,CNn] \tag{2}$$

Ci is a member of the set [0, 1], where i is a number between 1 and Nn, where Nn is the value of the state of theith concept node. The weight matrix W, which is Nn × Nn in size, is used to specify the causal linkages that exist between every pair of relationship nodes.

$$W=\begin{bmatrix} w_{11} & w_{12} & \dots & w_{1N_n} \\ w_{21} & w_{22} & \dots & w_{2N_n} \\ \vdots & \vdots & & \vdots \\ w_{N_n 1} & w_{N_n 2} & \dots & w_{N_n N_n} \end{bmatrix} \tag{3}$$

Here, the relationship strength among concept nodes i and j is represented by the symbol wij, which belongs to the set [-1, 1], where i, j = 1, 2,,Nn. One of the most fundamental illustrations is shown in Figure 1, which has five concept nodes. The weight matrix that corresponds to this image is shown in Figure 1. The value of w12 equals 0.4, for example, shows that there is a positive excitatory connection between node 1 and node 2 with a strength of 0.4. In this case, the value of w13equals zero, which indicates that there is no connection between nodes 1 and 3. In a similar manner, the value of w44 = 0.9 indicates a positive feedback loop for node 4, which suggests that it has a self-reinforcing affect for the node.

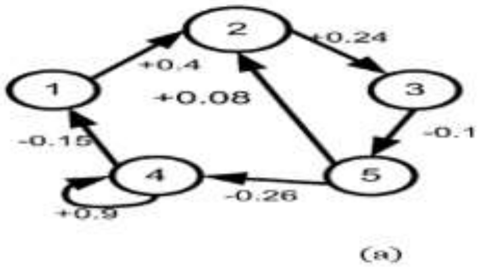

***Figure 1**. FCM fundamentals illustrations and weight matrix.*

It is possible to determine if the link between the two notions is direct or inverse by examining the sign of wij. The direction of causation specifies whether concept Ci influences concept Cjor whether concept Cjinfluences concept Ci. As a result, there are three distinct categories of weights:

$$\begin{cases} W_{ij}>0, & \text{represents positive causality,} \\ W_{ij}<0, & \text{represents negative causality,} \\ W_{ij}=0, & \text{represents no relation.} \end{cases}$$

There is a connection between the weight matrix and the state values of connecting concept nodes at thetth iteration, which has an impact on the value at the (t + 1)th iteration, which indicates the time point t. consequence of this is that the dynamics of FCMs can be described by the equation that is presented below:

$$C_i^{t+1}=g\left(C_i^t+\sum_{j=1}^{N_n} w_{ji}\, C_j^t\right) \tag{4}$$

At the tth iteration, the state value of node i is represented by the notation, which is written as C_i^t. g (·) is a transfer function that allows the expression level to be contained within the range of [0, 1] in this particular context. The sigmoid transfer function is widely considered to be superior to other transfer functions, according to comparison research. However, there are several transfer functions that can be employed. The sigmoid transfer function that is utilized is as follows, as a result:

$$g(x)=1/(1+e^{-\beta x}) \tag{5}$$

In this context, the parameter β is utilized to ascertain the degree of steepness of the function in relation to zero, and the choice of this value is contingent upon the specific nature of the situation at hand.In most cases, a value of β that is relatively small is suitable for highly nonlinear systems. In this particular case, the value of β is established to be 5, which is a value that is frequently employed in a variety of FCM learning systems.

The weight matrices that are generated by automated learning methods have a tendency to be significantly denser than the weight matrices that are actually used. To put it another way, when compared to the genuine weight matrices, the learnt weight matrices have a considerably higher number of individuals that are not zero. Taking into account not only the variance between the data that is accessible and the data that is generated, but also the structure of the weight matrix that is learned, is of utmost significance when it comes to the process of learning. The objective function of an evolutionary algorithm in FCM often entails determining whether or not a certain solution is optimal or fit for the problem at hand. In this context, the fitness or optimality of a solution correlates to a specific weight matrix. Quantifying the degree to which the

FCM, which is represented by its weight matrix, corresponds to the behavior that is either observed or desired by the system is the objective function's primary goal. More precisely, the objective function often comprises measuring the difference or error between the replies generated by the FCM and the response sequences that are actually gathered from the system. The objective of evolutionary algorithms, such as genetic algorithms, is to optimize this objective function by iteratively modifying the parameters of the FCM, which are the weights in the weight matrix. To improve the FCM's ability to capture the dynamics of the system, this is done in order to improve its performance. It is common practice to minimize the difference between the simulated responses of the FCM and the actual responses of the system when formulating the objective function. The formulation of the objective function is dependent on the particular learning goals and characteristics of the system that is being investigated.

3. Chaotic particle swarm optimization (cpso)

In order to improve the swarm's capabilities in terms of exploration and exploitation, the CPSO algorithm, which is a unique form of the standard PSO algorithm, incorporates concepts from chaos theory. The addition of controlled chaotic behavior into the equations used to update the velocity of particles in CPSO results in the particles exhibiting behaviors' that are more diverse and unexpected within the search space. This feature facilitates improved global convergence and the ability to escape local optima. The infusion of chaos into CPSO strikes a balance between exploration and exploitation, enabling the algorithm to adeptly navigate intricate and multi-modal optimization landscapes. CPSO has exhibited promising outcomes in addressing demanding optimization problems, particularly those characterized by high dimensionality or nonlinearity. The original PSO velocity and position updating equations of particles are given as

$$v_i^{(k+1)} = wV_i^k + c_1 * rand_1 * (P_{besti} - P_i^k) + c_2 * rand_2 * (G_{best} - P_i^k) \quad (6)$$

$$P_i^{(k+1)} = P_i^k + v_i^{(k+1)} \quad (7)$$

The term "chaos" characterizes the seemingly unpredictable behaviour of a nonlinear, bounded, and non-converging dynamical system with only a few independent variables. Chaotic sequences, demonstrating easily and rapidly generated patterns, can be efficiently stored. Among the various maps illustrating chaotic behaviour, logistic maps find widespread use. The following equations can describe the chaotic sequences and random variables produced by employing logistic maps.

$$rand_1(k) = \lambda * rand_1(k-1) * [1 - rand_1(k-1)] \quad (8)$$

$$rand_2(k) = \lambda * rand_2(k-1) * [1 - rand_2(k-1)] \quad (9)$$

When considering the logistic map, the chaotic sequence is determined by the equation:

$$c_r(k) = \lambda * c_r(k-1) * [1 - c_r(k-1)] \quad (10)$$

$rand_1(0), rand_2(0)$ and $c_r(0) \notin \{0, 0.25, 0.5, 0.75, 1\}$

When $\lambda = 4$, the logistic map displays argotic behaviour within the interval (0, 1). However, with a given value of k, the distribution of the logistic map deviates from uniformity. Specifically, values within the intervals [0, 0.1] and [0.9, 1] occur more frequently than across the rest of the range [0, 1]. In the context of CPSO, the velocity equation undergoes modification as follows:

$$V_i^{(k+1)} = w * V_i^k + C_1 * C_r * (P_{best} - P_i^k) + C_2 * (1 - C_r) * (G_{best} - P_i^k) \quad (11)$$

wmax The initial inertia weight value is equal to 0.9.
wmin The inertia weight's final value is 0.4.
itermax Maximum amount of allowable iterations
Cr Deterministic displaying chaotic dynamics
λ The driving parameter, which ranges from 0 to 4, governs the behavior of the chaotic sequence.
C_r x_i^k ith chaotic variable for kth iteration, which has been distributed in range [0, 1]

Optimization algorithms incorporating chaos produce diverse outcomes owing to their extreme sensitivity to initial conditions. Chaotic optimization algorithms demonstrate proficiency in locating global optima due to their distinctive motion patterns. Their capacity to escape local optima enhances global optimization performance, effectively addressing the original PSO algorithm's tendency to become trapped in local extremes and exhibit slow convergence in later stages. Figure 2 depicts the flow chart of the CPSO algorithm. The FCM concepts' values and the weights W_{ji}^K are updated utilizing (11) and (12). The algorithm has two distinct termination conditions that determine its completion. The initial condition focuses on minimizing the specified objective function:

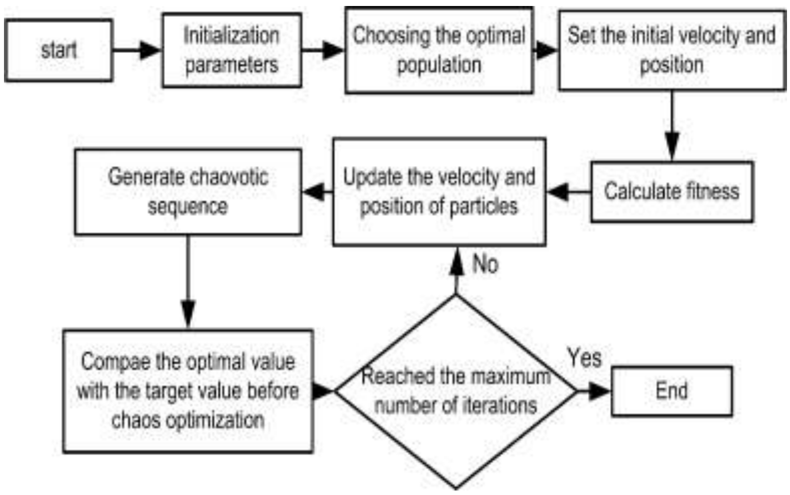

Figure 2. *Flow chart of CPSO*

$$F_1 = \sqrt{\left\|\mathrm{DOC}_j^{(K)} - T_j^2\right\|} \qquad (12)$$

The ultimate value of the decision output concept (DOC) is denoted by the symbol $\mathrm{T_j}$, and the value of DOC is considered to be within the interval of $\left[\mathrm{T_j^{max}} \cdot \mathrm{T_j^{min}}\right]$. The second termination condition is derived from the sequential changes of two values of DOCj, which are considered according to the following equation:

$$F_2 = \left|\mathrm{DOC}_j^{(K+1)} - \mathrm{DOC}_j^{(K)}\right| < € \qquad (13)$$

Here, € represents the tolerance level aimed at minimizing changes in the DOC values. The tolerance value is considered as 0.5%. The algorithm concludes when the specified termination conditions are satisfied.

4. Defining a stroke and introducing the risk factors involved in establishing a FCM model

Stroke is a neurological illness that happens to people of all ages all over the world and has a significant influence on their lives. It has an incidence rate that ranges from 0.2 to 2 instances per thousand persons, making it the third most widespread cause of morbidity in the United States of America, after cardiovascular disease and cancer. Both the mortality rate and the incidence of stroke-related morbidity were reported to be 4.4 percent in Iran in 2003 [24]. The incidence of morbidity that was associated with stroke was reported to be eight percent. Stroke can be broken down into two primary categories: (i) hemorrhagic strokes and (ii) ischemic strokes. The latter form of stroke is the more common, accounting for between 85 and 90 percent of all strokes. Ischemic strokes are more likely to develop when the blood supply to a particular region of the brain is either greatly reduced or completely cut off, which results in a diminished supply of oxygen and nutrients to that particular region. The loss of function and eventual death of brain cells is the consequence of this interruption, which can last anywhere from a few minutes to several hours [25,26]. As a consequence of this, this condition is regarded as a medical emergency, highlighting the crucial requirement for immediate treatment in order to reduce damage and prevent neurological dysfunction in the future. As a result of the critical nature of every second in the management of stroke, the importance of rapid diagnosis and action is brought into sharper focus. As shown in Figure 4, the risk factors for ischemic stroke consist of twelve different factors, split into two categories: those that can be controlled and those that cannot be controlled. Each of these factors plays an important part in the diagnosis of the disease. After doing a physical examination and analyzing the findings of specific tests, neurologists incorporate these risk factors into the process of diagnosing strokes. In accordance with the information presented in Table 1, the values that are associated with these factors are conveyed through four, three, or two fuzzy values that

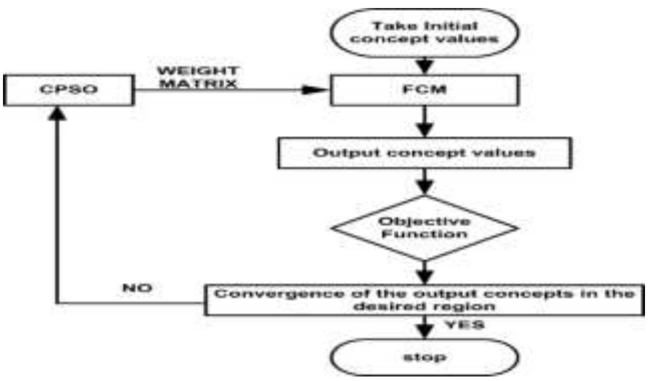

Figure 3. *Flowchart of the proposed learning algorithm*

represent high, and very high, low, medium linguistic variables individually. Based on the HDL cholesterol notion, for example, this study utilizes three linguistic variables: low, which is less than 35, medium, which is less than 60, and high, which is greater than 61. The aforementioned ideas were gathered from patients who were referred to Iran's Amiralmomenin Hospital. These concepts were identified by three neurologists: Dr. Mohammadzad, Dr. Hagigat, and Dr. Asgarpour. Furthermore, the FCM model that is described in this study is founded on the observations made by these neurologists, who were responsible for determining both the input and output concepts.An illustration of the membership functions that indicate the risk rate for a stroke can be found in Figure 5.

5. Application of Fuzzy Cognitive Maps (FCM) for Assessing the Risk of Stroke.

The neurologists were tasked with articulating the impact of each concept on others and establishing was done after the neurologists had identified the concepts of input and output. For the purpose of defining the relationships between concepts by means of linguistic variables such as high, low, and medium, these rules are a useful tool for professionals. Within the range of [0, 1], a value is assigned to each of the linguistic variables. As an illustration, the following is an outline of the relationship between blood pressure (C2) and the output concept (C13), which is based on the assessments of neurologists: One of the neurologist's states that when the blood pressure is medium, the risk rate that corresponds to it is also considered to be medium. Based on the assertions of Neurologist Two, the linked risk rate is judged to be high when the blood pressure is medium. A statement made by Neurologist Three: A danger rate that is considered to be very high is the outcome of having a blood pressure that is medium. By utilizing the SUM approach, it was possible to combine the three linguistic variables, which are medium, high, and extremely high. Subsequently, the value from C2 to C13 was determined to be 0.54, as shown in Figure 6. This was accomplished by applying the centre of gravity method in the process of defuzzification. All of the initial weights for the Fuzzy Cognitive Map (FCM) were obtained in a similar manner, utilizing processes that were analogous to those described in Table 2. The weights that were derived for the proposed FCM model are displayed in Figure 7, which illustrates the relationship between the concepts and the weights that were derived for the model. With regard to the estimation of the risk of suffering an ischemic stroke, this correlation is demonstrated.

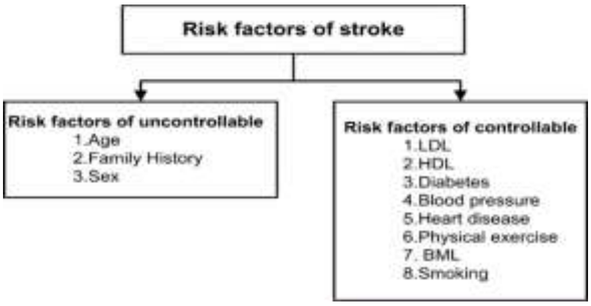

Figure 4. *Risk factors of ischemic stroke*

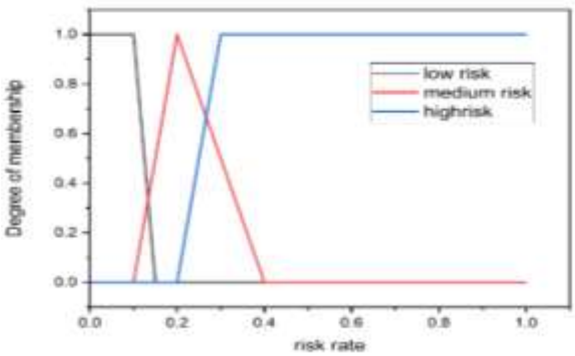

Figure 5*. Membership functions of output concept (C_{13})*

6. Results and Discussion

Neurologists recognized twelve features or concepts as inputs for addressing this issue; the output concept for decision-making was designated as C13.Within the fuzzy set, this output concept is characterized as a variable that encompasses low, medium, and high categories among its categories. These classifications are defined as follows, according to the neurologists' points of view: According to the risk rate of an ischemic stroke during the following five years, the range of values is as follows: $0.32 \leq high < 1, 0 \leq low \leq 0.15$, and $0.16 \leq medium \leq 0.31$. The values of concepts are changed in an iterative manner until a final state is reached during the process of developing the FCM model for stroke prevention. The starting values of these concepts are critical because they represent the fundamental characteristics of the FCM, which are necessary for its implementation and have a major impact on the occurrence of strokes. Two samples of test data, one pertaining to a male and the other to a female, are shown below in order to provide further clarification on this topic. Example 1: When it comes to this particular situation, the information reported in Table 3 belong to a male patient who has a history of stroke. Neurologists predicted that there was a moderate risk of the patient experiencing another stroke. From the beginning, the values are normalized inside the interval of [0, 1] by utilizing the equation that is presented as given equation 14:

***Table 1**: Diagnostic criteria for ischemic stroke using the FCM model*

Concepts	Number of fuzzy values	Type of values
C_1: Age	3	old >66, young <45, middle age 46-65.
C_2: blood pressure	4	high 151-170, very high>171, low<130, medium 131-150,
C3: LDL cholesterol	4	high 161-190, very high >191, low<130, medium 131-160
C4: HDL cholesterol	3	high >61, low<35, medium 36-60
C5: diabetes	3	high>126, low<70, medium 71-125,
C6: heart disease	2	absent, present
C7: family history	2	yes, no
C8: smoking	2	yes, no
C9: BMI	3	high >26, low<19, medium 20-25
C10: exercise	2	yes, no
C11: sex	2	male, female.
C12: stroke history	2	yes, no
C13: risk of stroke	3	high, low, medium.

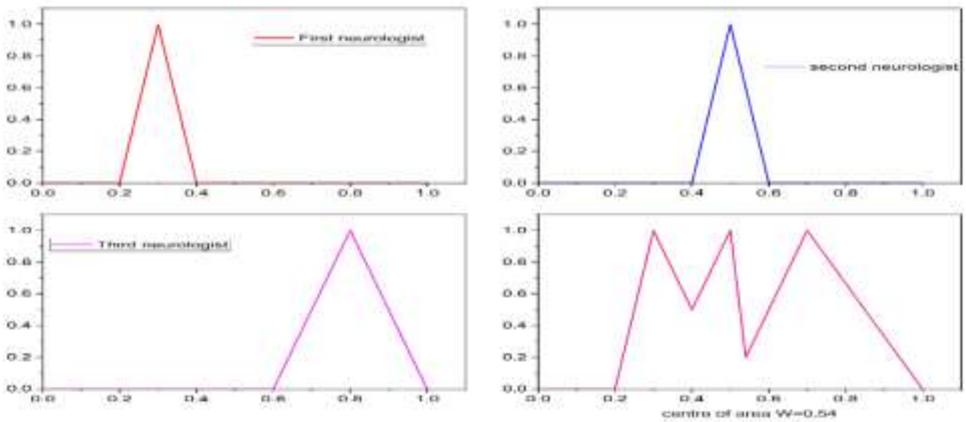

***Figure 6.** Three linguistic factors are aggregated via the SUM method.*

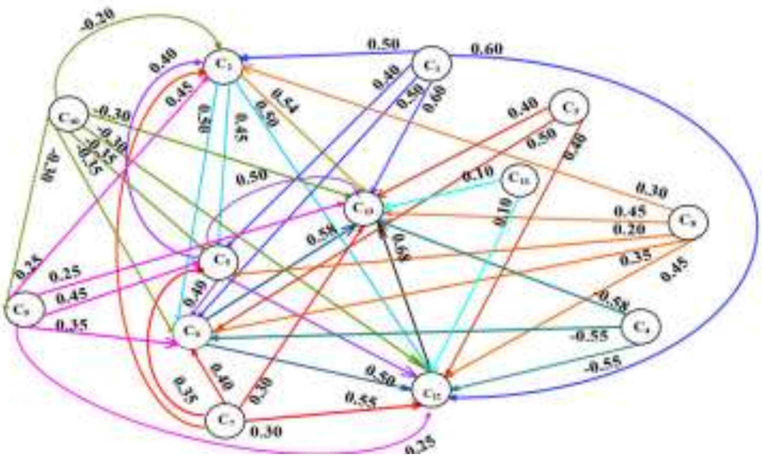

***Figure 7.** Initial values of weights allocated to the proposed FCM model for estimating the risk of Ischemic Stroke*

Table 2. *Initial weights that were suggested by psychologists*

concepts	**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	0.550	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	0.4	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

$$x_{normalized} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (14)$$

The following is a determination of the initial input values after the aforementioned values have been normalized: The value of CInitial is equal to [0.68 0.5 0.28 0 0 1 0.4 0 1 1 0].Up to the point that the FCM reaches equilibrium, these initial values, in addition to the weight matrices that are given in Table 2, are updated in an iterative manner in accordance with one equation. Table 4 shows that, following seven iteration steps, the concept values have not changed, suggesting that a balanced state has been reached. As a consequence, the output idea value becomes stable at 0.6798 after seven iterations have been completed. After performing the calculation outlined in (15), the risk rate comes out to be 36 percent, which the neurologists classify as high risk. The CPSO algorithm is utilized in order to establish the initial weights of the FCM, which roughly corresponds to the response of the system to actual data. The schematic of concept values illustrates the identified point of convergence, which is also referred to as the balance point, as illustrated in Figure 8.

$$\mathrm{Risk}(x) = \begin{cases} 0, & x \leq 0 \cdot 5 \\ \frac{x - 0 \cdot 5}{0 \cdot 5} \times 100\%, & 0 \cdot 5 < x \leq 1 \end{cases} \quad (15)$$

7. Applying the cpso algorithm to fcm for the assessment of stroke risk rate.

The goal of this study is to create an FCM learning method based on CPSO. The fundamental goal is to find the values that indicate the cause-effect linkages between concepts; in essence, the weights of the FCM that result in the behavior that is intended for the system. The establishment of these weights is of great relevance and makes a significant contribution to the consolidation of
FCMs as a reliable methodology. Values of the output concept that are within the limits established by the experts characterize the system's intended behavior. Essentially, these limits are dependent on the particular problem that is being addressed at the moment. The purpose of utilizing this algorithm is to improve the modeling of system behavior and to raise the efficiency of FCM. The ultimate goal is to produce satisfactory outcomes through the training of FCM. The learning procedure shares some similarities with the training of neural networks.
Let us Consider C1……CN be the concepts of FCM and Cout1,…Coutm, be the output concepts.
The user has the intention of limiting the values of these output concepts to a certain extent within defined boundaries.

$$A_{\mathrm{out}\,i}^{min} \leq A_{\mathrm{out}\,i} \leq A_{\mathrm{out}\,i}^{max}, \quad i = 1, \dots, m, \quad (16)$$

the experts have predetermined, which are essential for the system that is being represented to function correctly. In light of this, the primary objective is to identify a size matrix.

$$W = [W_{ij}], \quad i,j = 1, \dots, N \quad (17)$$

After a total of 25 iterations, the stroke risk rate reaches a value of 0.6273 as a consequence of the application of the training method in the first case. This represents a risk rate of 25 percent, which, according to the neurologists' opinion, falls within the range of 0.16 to 0.31, and is, therefore, considered to be of medium risk. The sequence diagram of idea values and it illustrates the process that was followed until convergence by using the CPSO method. Second illustration: As shown in

Table 5, the neurologists predicted that the patient would have a low risk of experiencing another stroke based on the information provided by the female patient.
Following the normalizing of the values mentioned above in accordance with the formula (14), the first concept values that are obtained are as follows: [0.53 0.2 0.19 0.5 0.13 1 1 1 0.26 0 0 0 0]. Following the completion of the FCM simulation, the initial values are provided as follows: CFCM = [0.51014 0.54601 0.53014 0.51014 0.54195 0.57495 0.51114 0.53114 0.52386 0.53014 0.51014 0.57043 0.58674]. After seven iterations, the output idea value reaches a stable point of 0.59674, which indicates a risk rate of 18 percent. In order to ensure that decisions are made based on reliable information, the CPSO algorithm is utilized to approximate the system's response to a real value. Table 6 provides a full description of the weight matrix that is modified by the CPSO method.Table 7 provides the Proposed CPSO-FCM system evaluation results in the iteration. Consequently, following the implementation of the CPSO algorithm, the final concept values, which were obtained after 25 iterations, are as follows:

Table 5. *Ischemic stroke risk was calculated for a female without stroke history.*

Age	64
Blood sugar	85
Heart disease	1
Blood pressure	120
LDL	100
HDL	45
Family history	1
Smoking	1
Physical exercise	0
BMI	26.8
Sex	0
Stroke history	0

[0.5141 0.5370 0.5141 0.5141 0.5344 0.5428 0.5141 0.5141 0.5104 0.5141 0.5141 0.5522 0.5621] is the formula for creating the final value of CFinal.As a result, the DOC value reaches 0.5621, which indicates a recurrent stroke risk of 12 percent. This risk is classed as low risk within the neurologist's opinion range of $0 \leq$ low≤ 0.15. Proposed CPSO-FCM system evaluation results in the iteration. Table 8 and 9 shows the system evaluation results with the KNN classifier in ten iterations. The proposed system underwent evaluation using the 10-fold cross-validation method, employing 110 real datasets within the age range of 28–95 years. The approach involved using nine datasets for training and one dataset for testing in each iteration. Accuracy and recognition rates for the test dataset were computed in every implementation. Following ten iterations, the algorithm's overall accuracy, derived from the mean of accuracies, was determined to be (94.6± 3.1) %.

8. Conclusion

The timely identification and treatment of stroke is of the utmost importance. Not only does early diagnosis increase the likelihood of the patient recovering and surviving the stroke, but it also protects the patient from the severe repercussions that would otherwise be associated with the stroke. The purpose of this research was to present an efficient method that makes use of a soft computing technique, more precisely fuzzy cognitive mapping in conjunction with the CPSO evolutionary algorithm. This methodology, which attempts to create a forecast regarding the risk rate of ischemic stroke over the following five years, takes into consideration the core risk variables that are associated with the condition. In order to significantly enhance the functionality of the FCM, the implementation of the CPSO algorithm was of critical importance. A higher level of accuracy in disease diagnosis was achieved by the utilization of this technology, which combined the knowledge and experience of specialists with the fuzzy logic system. The objective of this study is not the implementation of a new system but rather to leverage an existing system and expand its application to a novel domain. This aims to derive new insights and knowledge in the realm of stroke disease. A comparison was made between the results that were obtained from the performance of the system and the average of the findings that were provided by the neurologists.

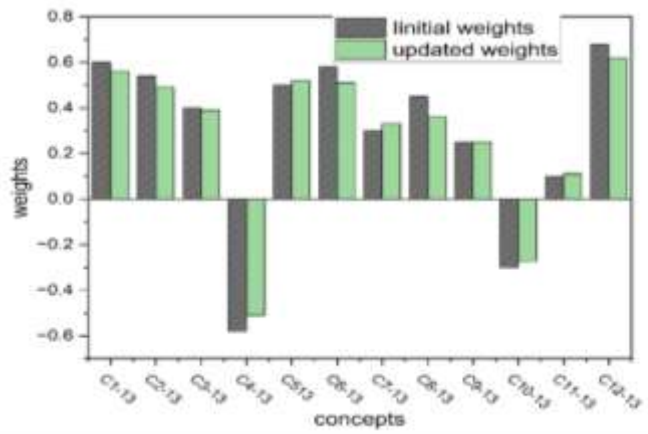

Figure 8. All concepts wights related to concept 13.

Table 4. *The values of FCM concepts at each of the seven iteration steps.*

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}
0.67	0.51	0.38	0.28	0.27	0	0	0.98	0.39	0	1	1	0
0.54532	0.5820	0.5352	0.4321	0.5774	0.3265	0.52	0.5623	0.5320	0.52	0.5798	0.6235	0.632
0.5235	0.5932	0.5345	0.4912	0.5846	0.5623	0.5321	0.5235	0.5332	0.5312	0.5542	0.6496	0.6723
0.53718	0.6021	0.5346	0.5123	0.5963	0.6170	0.5421	0.53718	0.5421	0.5346	0.5425	0.6482	0.6778
0.5318	0.6032	0.5612	0.5412	0.5975	0.6185	0.5468	0.5372	0.5421	0.5348	0.5310	0.6472	0.6798
0.5318	0.6032	0.5612	0.5412	0.5975	0.6185	0.5468	0.5372	0.5421	0.5348	0.5310	0.6472	0.6798
0.5318	0.6032	0.5612	0.5412	0.5975	0.6185	0.5468	0.5372	0.5421	0.5348	0.5310	0.6472	0.6798

Table 6. *Updated weight matrix with CPSO algorithm for the first example*

concepts	**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	0.42	0	0	0.34	0.48	0	0	0	0	0	0.55	0.56
C_2	0	0	0	0	0.41	0.46	0	0	0	0	0	0.55	0.49
C_3	0	0	0	0	0	0.43	0	0	0	0	0	0.42	0.39
C_4	0	0	0	0	0	-0.42	0	0	0	0	0	-0.51	-0.51
C_5	0	0.38	0	0	0	0.39	0	0	0	0	0	0.45	0.52
C_6	0	0	0	0	0	0	0	0	0	0	0	0.46	0.51
C_7	0	0.42	0	0	0.32	0.36	0	0	0	0	0	0.24	0.33
C_8	0	0.25	0	0	0.18	0.36	0	0	0	0	0	0.36	0.36
C_9	0	0.28	0	0	0.39	0.31	0	0	0	0	0	0.21	0.25
C_{10}	0	-0.19	0	0	-0.31	-0.31	0	0	-0.28	0	0	-0.26	-0.27
C_{11}	0	0	0	0	0	0	0	0	0	0	0	0.08	0.11
C_{12}	0	0	0	0	0	0	0	0	0	0	0	0	0.62
C_{13}	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 7. *Proposed CPSO-FCM system evaluation results in the iteration*

Folds	Accuracy	Low-rate recognition	Medium rate recognition	High-rate recognition
1	92%	1	0.78	1
2	80%	0.68	1	0.77
3	90%	1	0.82	1
4	99%	1	1	1
5	92%	0	0.78	1
6	100%	1	1	1
7	100%	1	1	1
8	99%	1	1	1
9	93%	1	0.86	1
10	92%	0	1	1

Table 8. *System evaluation results with the SVM classifier in ten iterations*

Folds	Accuracy	Low-rate recognition	Medium rate recognition	High-rate recognition
1	80%	1	0.61	1
2	81%	0.67	1	0.74
3	83%	1	0.81	0.82
4	90%	1	1	0.84
5	82%	0	0.76	0.88
6	93%	1	0.80	1
7	92%	1	1	0.86
8	93%	0.56	1	1
9	93%	1	0.86	1
10	82%	0	1	0.89

Table 9. *After 10 iterations, the system's performance was assessed using the KNN classifier.*

Folds	Accuracy	Low-rate recognition	Medium rate recognition	High-rate recognition
1	71%	1	0.61	1
2	73%	0.67	1	0.74
3	80%	1	0.81	0.82
4	82%	1	1	0.84
5	90%	0	0.76	0.88
6	83%	1	0.80	1
7	80%	1	1	0.86
8	82%	0.56	1	1
9	82%	1	0.86	1
10	82%	0	1	0.89

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
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