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Indeterminacy Handling of Adaptive Neuro-fuzzy Inference System Using Neutrosophic Set Theory: A Case Study for the Classification of Diabetes Mellitus

Rajan Prasad*
Artificial Intelligence Research Center, Department of Computer Science and Engineering, Babu Banarasi Das University, Lucknow, India
E-mail: rajan18781@gmail.com
ORCID iD: https://orcid.org/0000-0002-5238-9690
*Corresponding author

Praveen Kumar Shukla
Artificial Intelligence Research Center, Department of Computer Science and Engineering, Babu Banarasi Das University, Lucknow, India
E-mail: drpraveenkumarshukla@gmail.com
ORCID iD: https://orcid.org/0000-0002-9227-8856

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Abstract: Early diabetes diagnosis allows patients to begin treatment on time, reducing or eliminating the risk of serious consequences. In this paper, we propose the Neutrosophic-Adaptive Neuro-Fuzzy Inference System (N-ANFIS) for the classification of diabetes. It is an extension of the generic ANFIS model. Neutrosophic logic is capable of handling the uncertain and imprecise information of the traditional fuzzy set. The suggested method begins with the conversion of crisp values to neutrosophic sets using a trapezoidal and triangular neutrosophic membership function. These values are fed into an inferential system, which compares the most impacted value to a diagnosis. The result demonstrates that the suggested model has successfully dealt with vague information. For practical implementation, a single-value neutrosophic number has been used; it is a special case of the neutrosophic set. To highlight the promising potential of the suggested technique, an experimental investigation of the well-known Pima Indian diabetes dataset is presented. The results of our trials show that the proposed technique attained a high degree of accuracy and produced a generic model capable of effectively classifying previously unknown data. It can also surpass some of the most advanced classification algorithms based on machine learning and fuzzy systems.

Index Terms: N-ANFIS, SVNS, SVNN, Neutrosophic Set, Diabetes, Indeterminacy, ANFIS, Hybrid System, Machine Learning, Neutrosophic Classifier.

1. Introduction

Diabetes mellitus (DM) is an autoimmune disease in which the body fails to produce enough insulin or uses insulin improperly, leading to abnormally high blood glucose levels [1]. In 2021, 537 million individuals were diagnosed with diabetes. This figure is expected to exceed 783 million by 2045. Furthermore, according to the international diabetes federation (IDF), diabetes killed 6.7 million people in 2021, and it will become the seventh largest cause of mortality by 2030[2]. Diabetes patients are increasing year by year, putting a strain on the healthcare system, despite the fact that more than half of them is unaware of their condition. It could take a decade or more to detect them. Renal failure, nerve damage, eyesight loss, and high blood pressure are all serious health consequences. In addition, if therapy is delayed, a stroke may occur. Diabetes is now an incurable illness, and its treatment efficacy is mostly based on proper diagnosis and appropriate treatment. Diabetes, on the other hand, can cause major injury to the body and make treatments difficult. Researchers have tried a variety of technologies and algorithms to detect diabetes in recent years and Machine learning is one of them. Machine learning has shown to be a useful tool in a multitude of industries, including healthcare, during

the fourth industrial revolution [3-6]. Artificial intelligence (AI)[7], information retrieval[8], Artificial neural networks (ANN)[9-11], and many other ML disciplines are regarded as important in the healthcare industry, particularly in the diabetes diagnosis[12]. While the majority of these technologies can accurately predict illnesses, their designs and reasoning processes are not always interpretable, making them difficult to understand and hence classed as black boxes [13]. As a result, it is critical to use human-interpretable and intelligible technology. Another problem of these technologies is that they are incapable of dealing with data ambiguity [14].

To resolve these concerns, fuzzy logic [15,16] is used. It is seen as a generalization of Boolean logic, with values ranging from 0 to 1, denoted by the degree of membership. Fuzzy logic is related to the human cognitive processes. As a result, it may be used to deal with data ambiguity. Fuzzy logic has shown to be a beneficial tool for classification issues since it allows for overlapping class definitions and has great skills for dealing with ambiguity and vagueness [17-20]. Furthermore, using a fuzzy rule-based approach with IF-THEN rules increases interpretability and adds to our understanding of the classifier construction [21]. An intuitionistic fuzzy set (IFS) [22] is an extension of fuzzy set; it is based on membership function and non-membership degree for a specific fuzzy element. The hesitancy level will decrease as the membership value of an element increases as more information about the fuzzy element is gathered. The IFS set becomes a fuzzy set when a hesitant value becomes zero [23]. The disadvantage of IFS is that, it is unable to handle indeterminacy. To overcome this issue, Smarandache proposed the Neutrosophic Set (NS) [24], which is made up truth, indeterminacy, and falsity-membership degrees. Every NS feature has a degree of truth (T), as well as a degree of falsehood (F) and indeterminacy (I). This concept originated from others such as the crisp set, intuitionistic fuzzy set, fuzzy set, and interval-valued fuzzy set [25, 26].

Although the fuzzy set and intuitionistic fuzzy set are widely used to describe the fuzzy characteristics of object classes by membership degree, they are incapable of dealing with indeterminant information. Smarandache (1998) suggested neutrosophic set, a generalization of fuzzy and intunistic fuzzy sets. Afterword, Wang et al. (2010) introduced the Single-valued Neutrosophic set, which is defined by truth, falsity, and indeterminacy membership functions independently. It is a subclass of NS that is frequently used in real-world applications.

The SVNS can be defined as follows:

Assume X is a universe of discourse. An SVNS Y in X is denoted as $Y = \{\langle x, P_Y(x), I_Y(x), N_Y(x)|x \in X\rangle\}$, $P_Y(x), I_Y(x), N_Y(x) \in [0,1]$ Where $P_X(r), I_X(r),$ and $N_X(r)$the truth, indeterminacy and falsity membership are functions, respectively, for any $x \in X$ and $0 \leq P_Y(x) + I_Y(x) + N_Y(x) \leq 3$.

A single valued neutrosophic number (SVNN) can be obtained from the neutrosophic membership function. For the simplicity a SVNN is represented as $Y = \langle P_Y, I_Y, N_Y\rangle$. Suppose that $Y_1 = \langle P_{x1}, I_{x1}, N_{x1}\rangle$ and $Y_2 = \langle P_{x2}, I_{x2}, N_{x2}\rangle$ are two SVNNs. They contain the relations such as Equality, inclusion, Complement, Union and Intersection.

In this case, Y is a variable, and w, x, y, and z are scalar parameters describing the shape of the correspondence membership functions. We may extract the truth, indeterminacy, and falsity values of the input parameter using the membership functions$\langle T_\alpha, I_\alpha, F_\alpha\rangle$, $\langle T_\beta, I_\beta, F_\beta\rangle$, $\langle T_\gamma, I_\gamma, F_\gamma\rangle$, $\langle T_\delta, I_\delta, F_\delta\rangle$, $\langle T_\xi, I_\xi, F_\xi\rangle$, $\langle T_\eta, I_\eta, F_\eta\rangle$, $\langle T_\theta, I_\theta, F_\theta\rangle$, $\langle T_\vartheta, I_\vartheta, F_\vartheta\rangle$, and class level $\langle T_\mu, I_\mu, F_\mu\rangle$.

Jang et al. (1993) proposed the Adaptive Neuro-fuzzy Inference System (ANFIS), which is a more interpretable modeling tool. Fuzzy rules are generated in ANFIS using the Sugeno model. If the pair(x, y) is used as the input and the two pairs (A_1, B_1) and (A_2, B_2) represent the fuzzy sets of two linguistic variables, then the following TSK-rules can be defined as:

$$Rule1: if\ x\ is\ A_1\ and\ y\ is\ B_1, then\ f_1 = m_1A_1 + n_1B_1 + k_1$$

$$Rule2: if\ x\ is\ A_2\ and\ y\ is\ B_2, then\ f_2 = m_2A_2 + n_2B_2 + k_2$$

In this case, f_1 and f_2 are the outputs within the fuzzy region defined by the two fuzzy rules, and x, y, whereas k_i(i=1,2) are design parameters selected during the training phase.

Fig.1 depicts the generic structure of an ANFIS model, which incorporates five-layer feed-forward neural networks and outputs one liner. The functions of each layer are described as follows: Layer 1 is referred to as the fuzzification layer. It employs membership functions to generate fuzzy clusters of input data. The parameters used to establish the form of the membership function are referred to as the antecedent parameter set. Equation (1) computes the membership degree of each antecedent.

$$O_{1i} = \mu_{Ai}(x), i = 1,2 \quad , \ O_{1i} = \mu_{B_{i-2}}(y), i = 3,4 \tag{1}$$

Layer 2 is known as the rule layer. Membership values obtained in the fuzzification layer are used to produce firing strengths (w_i) for the rules. Equation (2) is used to calculate (w_i) values.

$$O_i^2 = w_i = \mu_{A_i}(x).\mu_{B_i}(y) \ \ i = 1,2. \tag{2}$$

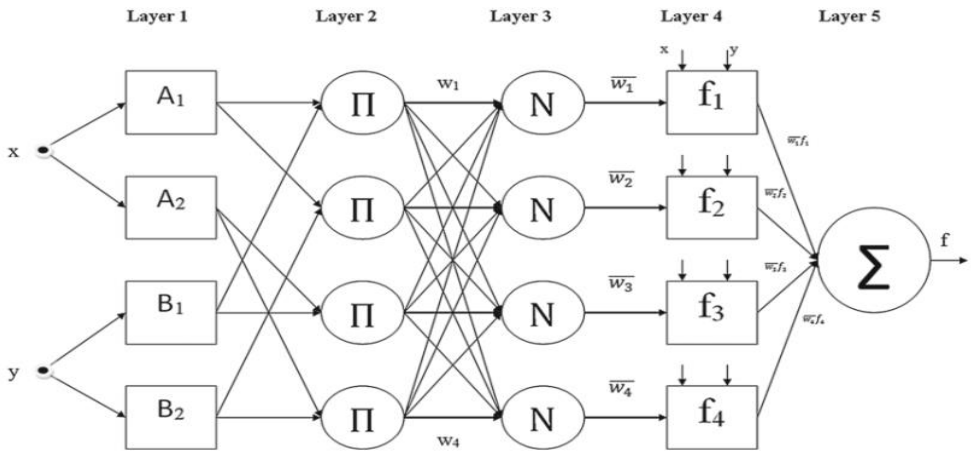


Fig.1. Structure of ANFIS

Layer 3 is known as the normalizing layer. For each rule, it computes normalized firing strengths. As indicated in Equation (3), the normalized value is the ratio of the ith rule's firing strength to the sum of the firing strengths.

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1+w_2+w_3+w_4} \qquad i \in \langle 1,2,3,4 \rangle \tag{3}$$

Layer 4 is referred to as the defuzzification layer. In each node of this layer, weighted values of rules are determined, as shown in equation (4). This value is computed using a first-order polynomial.

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \tag{4}$$

The normalization layer's output is $\bar{w}_i$ and the parameter set $\langle p_i, q_i, r_i \rangle$ are referred to as the consequence parameters. Each rule's number of consequence parameters is one greater than the number of input parameters.

Layer 5 is referred to as the summation layer. By adding the outputs of each rule in the defuzzification layer, the final outcome of ANFIS is achieved.

$$O_i^5 = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{5}$$

The primary goal is to detect diabetes in its initial stages, allowing patients to receive prompt medical attention and avoid the devastating consequences of this terrible disease. To predict diabetes, the proposed model does not require sophisticated data. It predicts diabetes rather than based on simple dataset properties.

This article incorporates our input.

- We suggest a unique strategy for dealing with indeterminacy in real-world data, claiming more accurate dataset categorization.
- The proposed approach combines the benefits of neutrosophic logic and ANFIS, the neutrosophic logic used to discern the neutrality of the dataset and a sophisticated fuzzy inference system used to categorize the neutrality of the dataset.
- The adaptive neuro-fuzzy inference system's modular structure is utilized to categorize the truth, indeterminacy, and falsity membership values.
- The proposed model presents a trade-off between interpretability and accuracy.
- The combination of Neutrosophy logic with a neuro-fuzzy system may be beneficial in developing a trustworthy and explainable system with great accuracy.

The following is the article structure: Section 2 presented the literature survey; Section 3 presented the description of the suggested model. Section 4, demonstrated the modeling of crisp dataset into neutrosophic environment and identification of the diabetes using proposed model using Pima Indian diabetes dataset, Section 5 showed the experimental results and depth analysis, and Section 6 presented the conclusion and future research goals.

2. Literature Survey

This section investigates the many methods and procedures that may be used to anticipate the beginning of diabetes. M. H. Ahmed et.al [27] proposed a method of an effective diabetes analysis. The suggested model was built

using K-means clustering and support vector machine (SVM). The commotion expulsion approach is being used to ensure that hidden instances and missing features are evacuated from the Pima Indians Diabetes data set. M. R. Daliri [28], proposed, a binary PSO technique, numerous medical illnesses have been explored using various data sets such as the PIMA Indian Diabetes Database and the Wisconsin breast cancer data set. The system's efficacy is then assessed in terms of accuracy, information gain, and F1 score value. K. Dwivedi [29] provided an intelligent approach for enhancing the accuracy of diabetes diagnosis utilizing an adaptive neuro-fuzzy inference system (ANFIS) and principal component analysis (PCA). To be more explicit, the PCA technique is utilized to minimize the number of characteristics in the diabetes data set. The ANFIS classification technique is crucial for detecting diabetes early. In another study done by Polat, Kemal, and Salih Güneş [30], The goal of this project is to increase diabetic illness detection accuracy by integrating PCA with ANFIS. The suggested system is divided into two parts. In the first stage, a diabetic illness dataset with eight characteristics is reduced to four using principal component analysis. Diabetes illness is diagnosed in the second stage using an adaptive neuro-fuzzy inference system.

M. Anouncia et al. [31], proposed diabetes diagnostic models in which they collect hospital data and symptoms associated with a specific disease. The accuracy of the knowledge base has a significant impact on the performance of the prediction system. To solve this issue, a rudimentary set-based prediction system was created and implemented. The proposed method uses 19 people's symptoms as input to determine the type of diabetes they have. Rough set-based prediction models have been shown to outperform current rule-based prediction models. Alasaady, Maher Talal, and colleagues[32] suggested a method for detecting diabetes based on the Pima Indians diabetes dataset utilizing the adaptive neuro-fuzzy inference system (ANFIS) (PIDD). The suggested technique has three stages: pre-processing, classification, and assessment. The pre-processing stage includes normalization, imputation, and anomaly identification. The data was normalized, missing values were replaced, and the local outlier factor (LOF) approach was used for pre-processing. ANFIS classifiers were trained in the classification stage using the neural network's hybrid learning method. Finally, the assessment algorithms employ the sensitivity, specificity, and accuracy metrics from the previous step. S. Muthukaruppan and M. J. Er [33] describe a particle swarm optimization (PSO)-based fuzzy expert system for coronary artery disease detection (CAD). The system was created using the Cleveland and Hungarian Heart Disease databases. Because the datasets contain a large number of input qualities, a decision tree (DT) was employed to identify the attributes that contribute to the diagnosis. The DT output was turned into crisp if-then rules before being processed into a fuzzy rule basis. PSO was used to fine-tune the fuzzy membership functions (MFs). The created fuzzy expert system has a classification accuracy of 93.27% after using the improved MFs.

Ganji, Mostafa Fathi, and Mohammad Saniee Abadeh[34], introduced the approaches for improving prognosis, diagnosis, and therapy planning. The goal of this research is to employ an Ant Colony-based classification system called FCS-ANTMINER to extract a set of fuzzy rules for diabetic condition diagnosis. We will examine several current methodologies and offer a novel and efficient methodology that yields significant results for the categorization of diabetic diseases. FCS-ANTMINER contains novel features that distinguish it from previous approaches that use Ant Colony Optimization (ACO) for classification tasks. The classification accuracy obtained is 84.24%, indicating that FCS-ANTMINER beats various well-known and current approaches in classification accuracy for diabetic illness diagnosis.

Bhuvaneswari and Manikandan [35], suggested a novel diabetic diagnosis approach that integrates a recently established a temporal fuzzy ant miner tree (TFAMT) classifier for effective detection in the type-II diabetes research. This study also mentions a new time weighted genetic method for improving recognition accuracy by pre-processing picture and text data. In addition, intelligent fuzzy rules are produced using TFAMT's weighted temporal capability, and the fuzzy rule extractor is used to reduce the number of functions in the resulting regulations. The proposed TFAMT - TWGA paradigm achieves 83.7% accuracy when evaluated using the UCI registry and the DR Dataset. El-Sappagh et al [36] propose a fuzzy ontology-based case-based justification paradigm for the treatment of diabetes. It presents a fuzzy semantic retrieval technique as well as a fuzzy case-based OWL2 ontology for managing various types of functionalities. The fuzzy ontology has 60 potential diabetes occurrences. The resultant application will provide answers to complex diabetes-related issues including the abstract interpretation of medical concepts and the management of unclear vocabulary. The associated fuzzy case-base ontology has 63 definitions, 54 (fuzzy) entity characteristics, 138 (fuzzy) data type characteristics, 105 fuzzy data types, and 2640 instances. The accuracy of proposed model is 97.67%.

Recently, several machine learning approaches have recently been mapped into the Neutrosophic Sets (NSs) environment to enhance the efficiency of existing learning algorithms and deal with inadequate input in the real world [37]. As a result, the essential conceptions and concepts of Neutrosophic are outlined, as well as certain achievements and expansions on the NSs. Thus, to influence the indeterminacy, ambiguity, or inconsistency that frequently defines real-world circumstances [38]. Information asymmetry, such as ambivalence, contradiction, inconsistency, and imperfection, is common in real-world learning issues. If we can model the learning problem as it exists in reality, using the defects in the data, we may be able to shorten the data science process. However, the NS is difficult to implement in real-world situations because it is a philosophical concept.

To address this issue, Wang, Haibin and colleagues [39] formalized the concept by developed a single-valued neutrosophic set (SVNS). A subset of the generalized neutrosophic set is an SVNS. The goal of SVNS is to create a framework for modeling erroneous information. In contrast to traditional machine learning approaches, single-valued neutrosophic learning algorithms address difficult learning issues with limited input [40].

To deal with ambiguity, imprecision, incompleteness, and inconsistent data, SVNS can be employed efficiently in real-world scientific and technical domains. Broumi and Smarandache [41] used a single-valued neutrosophic set to examine the essential properties of similarity and distance in a neutrosophic environment.

3. Proposed Model

In this section, we present the suggested model's architectural design as well as the operation of each layer. Aside from that, we compare our suggested solution to generic ANFIS layer by layer.

The proposed model is depicted in fig.2 the data layer is used to preprocess input variables, after which the neutrosophic layer is used for transforming the crisp values to neutrosophic values. The role of the ANFIS layer is the classification of three different membership functions individually, and the classification layer uses a threshold value to compare the indeterminant state of the ANFIS model. Table 1 shows the proposed model descriptions and comparisons with generic ANFIS. Section 4 presents the detailed description along with the case study of the suggested model.

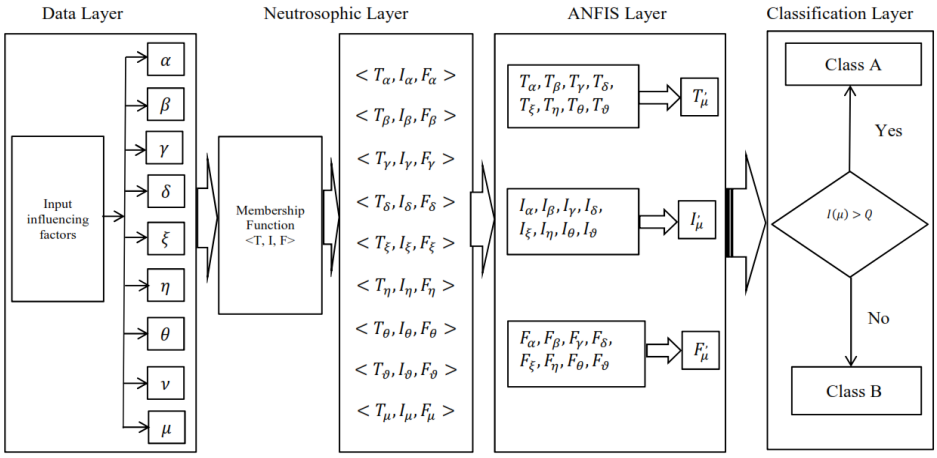


Fig.2. SVNS-ANFIS Model for classification of Diabetes Mellitus

Table 1. Proposed Model Description and Comparison with ANFIS

Layer	Generic ANFIS	Neutrosophic-ANFIS
Layer-1	The original dataset is reduced to a single set of fuzzy membership values.	The applied raw dataset is transformed into three membership function values: truth, indeterminacy, and falsehood. < T, I, F >, Each membership value is assigned to one of three ANFIS.
Layer-2	Estimate the firing strength.	Membership values should be converted to neutrosophic expressions.
Layer-3	It computes firing strengths that have been normalized.	Each ANFIS evaluates the firing strength of truth, indeterminacy, and falsity membership values independently and computes normalised firing strengths before defuzzification.
Layer-4	This is known as the defuzzification layer. The weighted values of rules are determined in each node of this layer.	Calculate final belongingness membership and forecast indeterminacy.
Layer-5	It is known as the summation layer. The final ANFIS result is created by combining the defuzzification layer's outputs.	---

4. Experimental Setup

In this section, we investigate the characteristics of an experimental dataset, then describe the statistics and correlation matrix, and finally choose attributes that are used as inputs to the suggested model.

4.1. Dataset Description

The dataset used in this study is freely available for open research on the UCI machine learning repository. This dataset contains a number of variables that we used to forecast whether or not the patient would develop diabetes. The women in the dataset are all over the age of 21. The dataset included 768 test cases, which contains 268 diabetics and 500 non-diabetic cases. The dataset has nine features: plasma glucose concentration, pregnancy number, serum insulin, and diastolic blood pressure, body mass index, triceps skin fold thickness, age, diabetes pedigree function and outcome. The remaining eight properties, on the other hand, are feature variables that are unrelated. The target class variable only

has two options: Diabetic and Non-Diabetic. Table 1 contains more specifics about each dataset attribute.

4.2. Classification of Diabetes Mellitus Using N-ANFIS

The main objective of this section is to classify the indeterminacy of the ANFIS using Neutrosophic sets the function of each layer's is describe as follows:

A. Data Layer

The main objective of the data layer is that preprocessing of the dataset and selection of highly correlated parameters for the Neutrosophication process. The parameters, as well as their descriptions and value ranges, are shown in Table 2.

Table 2. Features of PID Dataset

#.	Parameters	Descriptions	Min-Max
1	Pregnancies	Number of times the person gets pregnant	0-17
2	Blood Glucose	Represents Concentration of glucose in blood	1-199
3	Blood Pressure	Represents diastolic blood pressure	0-122
4	Skin Thickness	Represents triceps skinfold thickness	0-99
5	Serum insulin	Represent 2 h serum insulin	0-846
6	Body mass index	It derives from weight and height of person	0-67.1
7	Diabetes pedigree function	Represent the history of the patient	0.0078-2.42
8	Age	Age of the person in years	21-81
9	Class level		yes/no

B. Neutrosophic Layer

Due to taking measurements glitches in mechanisms, there is generally incompleteness, uncertainty, and imprecision in the measured data. The class level attribute implies uncertainty, imprecision, and incompleteness as well. As a result, the parameters obtained from the data layer that influences the class level need for Neutrophication. We used trapezoidal Equation (6) and triangular Equation (7) neutrosophic membership functions to perform Neutrosophication.

$$f(a;w,x,y,z)=\begin{cases}0, & a\ll w\\ \frac{a-w}{b-a}, & w\ll a\ll x\\ 1, & x\ll a\ll y\\ \frac{z-a}{z-y}, & y\ll a\ll z\\ 0, & a\gg z\end{cases} \tag{6}$$

$$f(a;w,x,y)=\begin{cases}0, & a\ll w\\ \frac{a-w}{x-w}, & w\ll a\ll x\\ \frac{y-b}{y-x}, & x\ll a\ll y\\ 0, & a\gg y\end{cases} \tag{7}$$

Table 3 summarizes the conversion of crisp parameters to neutrosophic values, with each parameter represented by one of three values: truth, indeterminate, or falsity. The membership function (α), represent the number of pregnancies, similarly β, γ , δ ,ξ ,η ,θ and ϑ are represented as Blood Glucose, Blood Pressure, Skin Thickness, Serum insulin, Body mass index, Diabetes pedigree function and Age. Whereas, membership function (μ) represent the class level attribute. Fig. 3 depicted 24 membership functions that are used as input variable into three different ANFIS.

C. ANFIS Layer

This layer constitutes with three ANFISs, the first ANFIS takes the input of the truth membership values $\langle T_\alpha, T_\beta, T_\gamma, T_\delta, T_\xi, T_\eta, T_\theta, T_\vartheta\rangle$, second ANFIS takes the indeterminacy membership $\langle I_\alpha, I_\beta, I_\gamma, I_\delta, I_\xi, I_\eta, I_\theta, I_\vartheta\rangle$, and

the third ANFIS takes the falsity membership values $\langle F_\alpha, F_\beta, F_\gamma, F_\delta, F_\xi, F_\eta, F_\theta, F_\vartheta \rangle$ derived from the preceding layer. The outcome of the first ANFIS is obtained with the help of equation (8), similarly equation (9) and (10), indicates the outcomes of the second and third ANFIS.

Table 3. Statistical description sample dataset

Parameter	Minimum	Maximum	Average	Std.dev.
Pregnancies	0.0000	14.0000	3.3613	3.1373
Blood Glucose	71.0000	197.0000	123.4873	29.4439
Blood Pressure	0.0000	100.0000	67.8739	19.6246
Skin Thickness	0.0000	52.0000	21.1008	16.4081
Serum insulin	0.0000	846.0000	99.781513	141.8440
Body mass index	0.0000	52.9000	31.7361	8.3700
Diabetes pedigree function	0.0780	2.2880	0.5035	0.3552
Age	21.0000	65.0000	32.5800	10.5985
Class	0.0000	1.0000	0.4285	0.4969

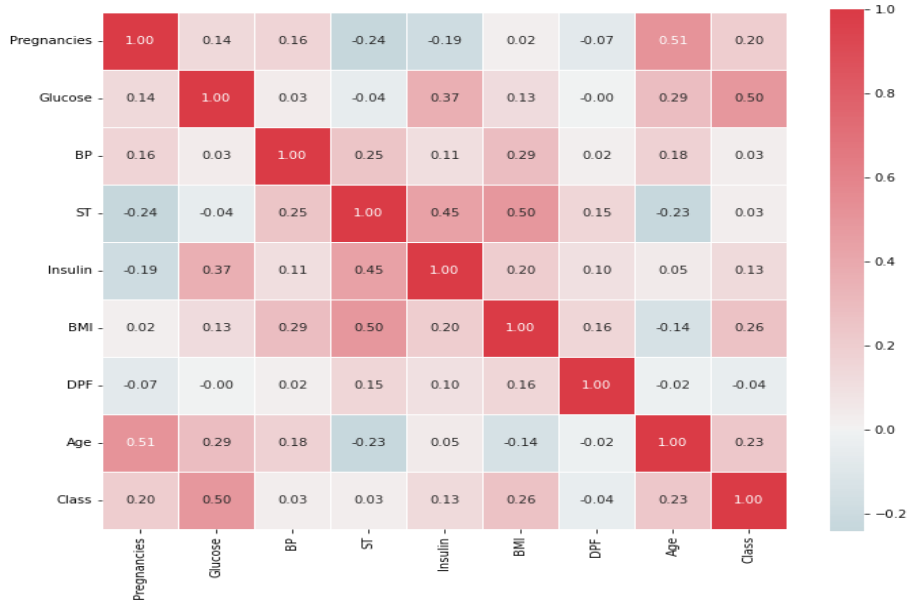


Fig.3. Correlation matrix of the sample dataset

$$f_T(T_\alpha, T_\beta, T_\gamma, T_\delta, T_\xi, T_\eta, T_\theta, T_\vartheta) = T'_\mu \tag{8}$$

$$f_I(I_\alpha, I_\beta, I_\gamma, I_\delta, I_\xi, I_\eta, I_\theta, I_\vartheta) = I'_\mu \tag{9}$$

$$f_F(F_\alpha, F_\beta, F_\gamma, F_\delta, F_\xi, F_\eta, F_\theta, F_\vartheta) = F'_\mu \tag{10}$$

D. Classification Layer

The classification layer is used to compute the final indeterminacy score using Equation (11) and the final belongingness membership degree μ was calculated from the NS triplet as $\mu = T'_\mu + I'_\mu - F'_\mu$.

$$I(x) = \frac{(2+(T_r - I_r - F_r))}{3} \tag{11}$$

Where $I(x) \in [0,1]$

5. Result Analysis and Discussion

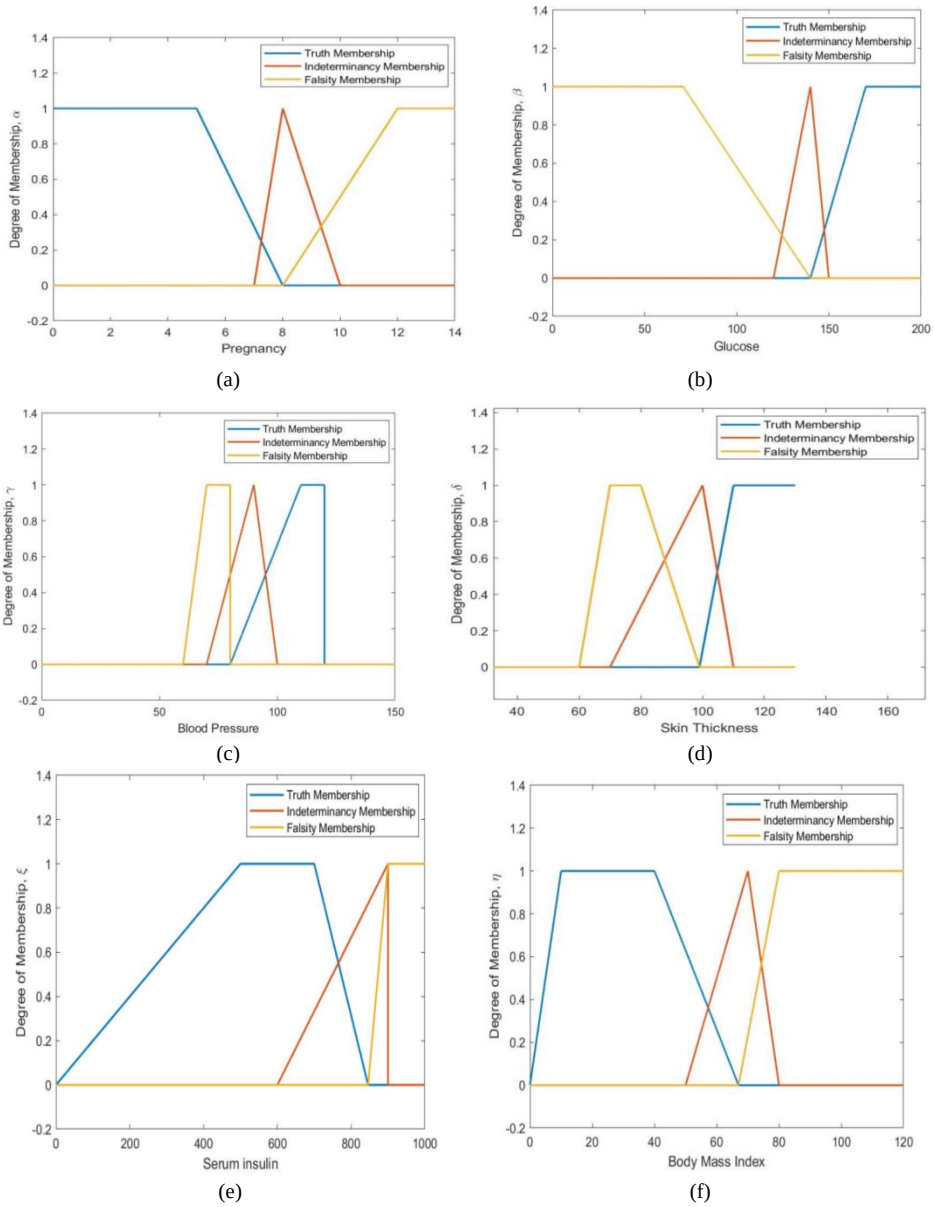
Before exploring into the suggested model in depth, it is necessary to understand the sample dataset's division and experimental context. The suggested model was written in Python 3.8 and contains all required libraries. The dataset was split into two parts: training and testing. 70% of the dataset was utilized for training and 30% for testing, and the dataset was normalized between 0 and 1 using the min-max approach. Table 2 displays the dataset's parameters, full explanations, and minimum and maximum values. The statistical description sample dataset utilized for the experiment

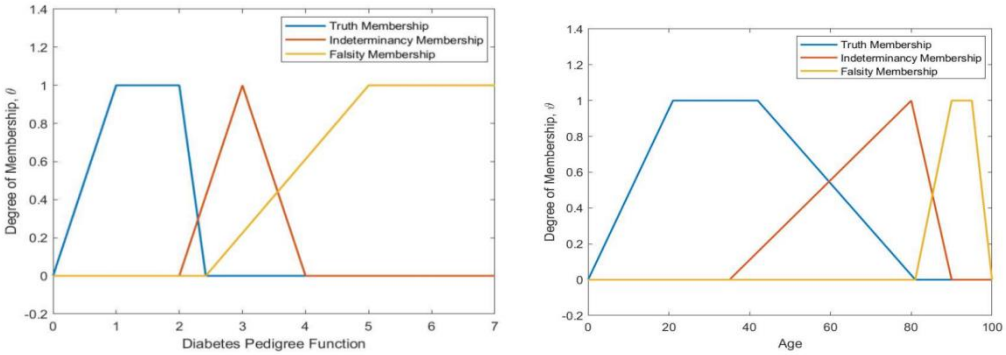
is described in Table 3. The parameters' range is represented by the minimum, maximum, average, and standard deviation values.

As shown in table 4, we represent the strongly correlated parameters in dark red as truth membership values, light red as indeterminacy membership values, and very light red as falsity membership values using the correlation matrix given in fig.3. We employed two membership functions for the neutrosophication process: trapezoidal and triangular membership functions (Eq.6) and (Eq.7). Fig. 4 depicts the results of trapezoidal and triangular membership.

Table 4. MFs parameters of influencing factors

Attribute Symbol	Truth	Indeterminate	Falsity
α	Trapmf [0 0 5 8]	Trimf [7 8 10]	Trapmf [8 12 14 14]
β	Trapmf,[140 170 200 200]	Trimf,[120 140 150]	Trapmf,[0 0 71 140]
γ	Trapmf,[80 110 120 120]	Trimf,[70 90 100]	Trapmf,[60 70 80 80]
δ	Trapmf,[99 110 130 130]	Trimf,[70 100 110]	Trapmf,[60 70 80 99]
ξ	Trapmf,[0 500 700 846]	Trimf,[600 900 900]	Trapmf,[846 900 1000 1000]
η	Trapmf,[0 10 40 67]	Trimf,[50 70 80]	Trapmf,[67 80 120 120]
θ	Trapmf,[0 1 2 2.42]	Trimf,[2 3 4]	Trapmf,[2.42 5 7 7]
ϑ	Trapmf,[0 21 42 81]	Trimf,[35 80 90]	Trapmf,[81 90 95 100]
μ	Trapmf,[0-1]		





(g) (h)

Fig.4. Shows the neutrosophic membership function of eight parameters

The experimental outcomes of trapezoidal and triangular membership function in terms of single value neutrosophic number (SVNN) are shown on table 5. It is clear that values of α β, γ , δ ,ξ ,η ,θ and ϑ are represents the three values. These values presented in the form of ⟨ T, I, F⟩, whereas the μ represent the target class. The target class have two different class indicates as 0 for non-diabetic and 1 for diabetic. Therefore, the new neutrosophic dataset presented in table 5 have been used as input of the third layer of the suggested model.

Table 5. Results of memberships values during the neutrosophication phase

$t.no$	α	β	γ	δ	ξ	η	θ	ϑ	μ
1	(0.6,0.2,0)	(0.148,0.46,0.03)	(0.72,0.45,0)	(0.35,0.20,0)	(0,0.88,0.538)	(0.336,0.37,0.30)	(0.627,0.167,0.183)	(0.5,0.32,0.21	1
2	(0.88,0.33,0.45)	(0.85,0.44,0.32)	(0.6,0.5,0.4	(0.29,0.3,0.2)	(0,0,0)	(0.26,0.6,0.8)	(0.35,0.45,0.78)	(0.31,0.45,0.89)	0
3	(0.80,0.60,0.34)	(0.18,0.76,0.40)	(0.6,0.4,0.8)	(0,0,0)	(0,0,0)	(0.23,0.3,0.5)	(0.67,0.20,0.69)	(0.32,0.68,0.79)	1
4	(0.10,0.50,0.45)	(0.89,0.02,0.39)	(0.6,0.6,0.4)	(0.23,0.3,0.8)	(0.9,0.4,0.7)	(0.28,0.17,0.56)	(0.16,0.70,0.65)	(0.21,0.54,0.68)	0
5	(0,0.40,0.67)	(0.13,0.45,0.21)	(0.4,0,0.7)	(0.3,0.5,0.8)	(0.16,0.8,0.4)	(0.43,0.1,0.70)	(0.2,0.88,0.47)	(0.33,0.61,0.72)	1
6	(0.50,0.34,0.5)	(0.11,0.3,0.6)	(0.7,0.4,0.3)	(0,0,0)	(0,0,0)	(0.25,0.6,0.4)	(0.2,0.34,0.54)	(0.30,0.65,0.73)	0
7	(0.30,0.50,0.40)	(0.78,0.4,0.8)	(0.5,0.3,0.8)	(0.3,0.2,0.7)	(0.8,0.5,0.3)	(0.31,0.4,0.7)	(0.24,0.31,0.58)	(0.26,0.44,0.58)	1
8	(0.10,0.40,0.30)	(0.11,0.43,0.78)	(0,0,0)	(0,0,0)	(0,0,0)	(0.35,0.3,0.45)	(0.13,0.70,0.65)	(0.29,0.54,0.71)	0
9	(0.2,0.43,0.11)	(0.19,0.56,0.78)	(0.7,0.3,0.9)	(0.4,0.5,0.8)	(0.5,0.4,0.3)	(0.30,0.5,0.9)	(0.15,0.70,0.65)	(0.53,0.33,0.48)	1
10	(0.80,0.33,0.70)	(0.12,0.9,0.67)	(0.9,0.6,0.9)	(0,0,0)	(0,0,0)	(0,0,0)	(0.2,0.35,0.57)	(0.54,0.52,0.66)	1
11	(0.4,0.22,0.33)	(0.11,0.70,0.3)	(0.9,0.2,0.6)	(0,0,0)	(0,0,0)	(0.37,0.6,0.8)	(0.19,0.70,0.65)	(0.30,0.61,0.39)	0
12	(0.10,0.31,0.11)	(0.16,0.70,0.21)	(0.7,0.4,0.8)	(0,0,0)	(0,0,0)	(0.38,0.45,0.67)	(0.5,0.37,0.81)	(0.34,0.67,0.75)	1
13	(0.10,80,0.43)	(0.13,0.8,0.3)	(0.8,0.3,0.2)	(0,0,0)	(0,0,0)	(0.27,0.41,0.56)	(0.96,0.70,0.65)	(0.57,0.80,0.90)	0
14	(0.10,0.33,0.45)	(0.18,0.59,0.76)	(0.6,0.3,0.7)	(0.2,0.3,0.8)	(0.8,0.4,0.6)	(0.30,0.23,0.87)	(0.39,0.48,0.78)	(0.59,0.56,0.87)	1
15	(0.5,0.4,0.7)	(0.16,0.6,0.33)	(0.7,0.2,0.6)	(0.19,0.4,0.7)	(0.1,0.7,0.5)	(0.25,0.8,0.6)	(0.58,0.7,0.8)	(0.51,0.44,0.65)	1
16	(0.7,0.33,0.45)	(1,0.45,0.89)	(0,0,0)	(0,0,0)	(0,0,0)	(0.30,0.76,0.60)	(0.48,0.4,0.6)	(0.31,0.58,0.71)	1
17	(0.0,0.0,0.0)	(0.11,0.70,0.3)	(0.8,0.4,0.6)	(0.4,0.7,0.8)	(0.2,0.3,0.1)	(0.45,0.8,0.30)	(0.55,0.32,0.76)	(0.32,0.60,0.89)	1
18	(0.7,0.20,0.54)	(0.10,0.65,0.43)	(0.7,0.4,0.9)	(0,0,0)	(0,0,0)	(0.29,0.6,0.81)	(0.25,0.45,0.87)	(0.32,0.51,0.72)	1
19	(0.1,0.06,0.08)	(0.10,0.8,0.6)	(0.3,0.6,0.5)	(0.3,0.8,0.2)	(0.8,0.3,0.4)	(0.43,0.30,0.24)	(0.18,0.70,0.65)	(0.33,0.62,0.70)	0
20	(0.1,0.66,0.067)	(0.11,0.54,0.32)	(0.7,0.8,0.8)	(0.3,0.2,0.7)	(0.9,0.6,0.5)	(0.34,0.6,0.7)	(0.52,0.9,0.57)	(0.32,0.35,0.80)	1
21	(0.30,0.07,0.06)	(0.12,0.30,0.70)	(0.8,0.6,0.8)	(0.4,0.1,0.3)	(0.2,0.3,0.5)	(0.39,0.3,0.56)	(0.70,0.44,0.87)	(0.27,0.67,0.88)	0
22	(0.8,0.4,0.7)	(0.99,0.60,0.80)	(0.8,0.4,0.7)	(0,0,0)	(0,0,0)	(0.35,0.4,0.8)	(0.38,0.46,0.78)	(0.50,0.74,0.60)	0
23	(0.7,0.2,0.1)	(0.19,0.50,0.80)	(0.9,0.4,0.8)	(0,0,0)	(0,0,0)	(0.39,0.8,0.4)	(0.4,0.1,0.3)	(0.41,0.73,0.53)	1
24	(0.9,0.65,0.30)	(0.11,0.0,0.98)	(0.8,0.6,0.5)	(0.3,0.5,0.9)	(0,0,0)	(0.29,0.50,0.69)	(0.2,0.3,0.6)	(0.29,0.44,0.77)	1
25	(0.11,0.51,0.30)	(0.14,0.4,0.6)	(0.9,0.4,0.7)	(0.3,0.3,0.8)	(0.1,0.4,0.6)	(0.36,0.6,0.9)	(0.25,0.3,0.8)	(0.51,0.35,0.98)	1
26	(0.10,0.34,0.32)	(0.12,0.3,0.8)	(0.7,0.6,0.5)	(0.2,0.6,0.9)	(0.1,0.11,0.5)	(0.31,0.33,0.67)	(0.20,0.3,0.4)	(0.41,0.41,0.28)	1
27	(0.7,0.6,0.3)	(0.14,0.50,0.40)	(0.7,0.6,0.8)	(0,0,0)	(0,0,0)	(0.39,0.4,0.79)	(0.25,0.3,0.7)	(0.43,0.74,0.58)	1
28	(0.1,0.4,0.8)	(0.97,0.54,0.67)	(0.6,0.6,0.8)	(0.1,0.5,0.2)	(0.1,0.4,0.5)	(0.23,0.2,0.6)	(0.48,0.2,0.8)	(0.22,0.48,0.56)	0
29	(0.13,0.21,0.40)	(0.14,0.3,0.7)	(0.8,0.2,0.7)	(0.1,0.9,0.3)	(0.1,0.1,0.9)	(0.22,0.29,0.89)	(0.24,0.53,0.9)	(0.57,0.50,0.89)	0
30	(0.5,0.32,0.42)	(0.11,0.22,0.60)	(0.9,0.2,0.5)	(0,0,0)	(0,0,0)	(0.34,0.50,0.9)	(0.33,0.45,0.79)	(0.38,0.68,0.58)	0
31	(0.5,0.32,0.43)	(0.10,0.5,0.70)	(0.7,0.6,0.5)	(0.2,0.6,0.4)	(0,0,0)	(0.36,0.40,0.70)	(0.54,0.76,0.45)	(0.60,0.33,0.67)	0
32	(0.3,0.8,0.32)	(0.15,0.12,0.40)	(0.7,0.6,0.8)	(0.3,0.6,0.2)	(0.2,0.4,0.5)	(0.31,0.60,0.8)	(0.88,0.4,0.54)	(0.28,0.59,0.89)	1
33	(0.3,0.30,0.8)	(0.88,0.4,0.54)	(0.5,0.8,0.7)	(0.1,0.1,0.0)	(0.5,0.4,0.6)	(0.24,0.8,0.9)	(0.26,0.74,0.56)	(0.22,0.87,0.40)	0
34	(0.6,0.4,0.7)	(0.92,0.50,0.80)	(0.9,0.4,0.2)	(0,0,0)	(0,0,0)	(0.19,0.9,0.45)	(0.18,0.8,0.67)	(0.28,0.56,0.85)	0
35	(0.10,0.3,0.23)	(0.12,0.20,0.7)	(0.7,0.8,0.4)	(0.3,0.1,0.6)	(0,0,0)	(0.27,0.6,0.87)	(0.51,0.21,0.60)	(0.45,0.71,0.60)	0
36	(0.4,0.7,0.54)	(0.10,0.3,0.89)	(0.6,0.7,0.9)	(0.3,0.3,0.4)	(0.1,0.9,0.82)	(0.24,0.56,0.97)	(0.96,0.6,0.50)	(0.33,0.68,0.30)	0
37	(0.11,0.51,0.90)	(0.13,0.8,0.56)	(0.7,0.8,0.4)	(0,0,0)	(0,0,0)	(0.33,0.2,0.76)	(0.42,0.2,0.7)	(0.35,0.53,0.43)	0
38	(0.9,0.3,0.45)	(0.10,0.20,0.50)	(0.7,0.8,0.5)	(0.3,0.7,0.8)	(0,0,0)	(0.32,0.92,0.87)	(0.65,0.20,0.69)	(0.46,0.54,0.52)	1

39	(0.2,0.32,70)	(0.90,0.6,0.3)	(0.6,0.4,0.8)	(0.4,0.2,0.7)	(0,0,0)	(0.38,0.2,0.65)	(0.50,0.4,0.64)	(0.27,0.70,0.76)	1
40	(0.4,0.9,0.45)	(0.11,0.17,0.87)	(0.7,0.5,0.4)	(0.4,0.7,0.3)	(0.2,0.6,0.7)	(0.37,0.8,0.79)	(0.13,0.70,0.65)	(0.56,0.60,0.35)	1
41	(0.3,0.7,0.9)	(0.18,0.40,0.67)	(0.6,0.8,0.9)	(0.2,0.5,0.6)	(0.7,0.3,0.6)	(0.34,0.66,0.89)	(0.27,0.54,0.74)	(0.26,0.57,0.59)	0
42	(0.7,0.6,0.3)	(0.13,0.38,0.78)	(0.8,0.2,0.7)	(0,0,0)	(0,0,0)	(0.40.28,0.78)	(0.69,0.63,0.9)	(0.37,0.40,0.61)	0
43	(0.7,0.6,0.3)	(0.10,0.6,0.9)	(0.9,0.2,0.5)	(0.1,0.8,0.2)	(0,0,0)	(0.22,0.7,0.54)	(0.23,0.5,0.23)	(0.48,0.57,0.87)	0
44	(0.9,0.5,0.3)	(0.17,0.11,56)	(0,9,0.7,0.8)	(0.2,0.4,0.8)	(0.2,0.4,0.9)	(0.45,0.4,0.87)	(0.72,0.39,0.65)	(0.54,0.56,0.76)	1
45	(0.7,0.5,0.4)	(0.15,0.9,0.4)	(0.6,0.5,0.7)	(0,0,0)	(0,0,0)	(0.27,0.4,0.60)	(0.29,0.40,0.79)	(0.40,0.69,0.87)	0
46	(0,0,0)	(0.18,0.4,0.78)	(0.6,0.3,0.8)	(0.3,0.9,0.1)	(0,0,0)	(0.42,0.78,0.67)	(0.18,0.70,0.65)	(0.25,0.59,0.48)	1
47	(0.1,0.5,0.7)	(0.14,0.6,0.3)	(0.5,0.6,0.8)	(0,0,0)	(0,0,0)	(0.29,0.7,0.77)	(0.54,0.4,0.78)	(0.29,0.76,0.98)	0
48	(0.2,0.4,0.8)	(0.71,0.4,0.11)	(0.7,0.8,0.4)	(0.2,0.7,0.8)	(0,0,0)	(0.28,0.22,0.56)	(0.58,0.4,0.54)	(0.22,0.52,0.67)	0
49	(0.7,0.5,0.3)	(0.10,0.3,0.7)	(0.6,0.8,0.5)	(0.3,0.2,0.1)	(0,0,0)	(0.39,0.66,0.54)	(0.34,0.44,0.75)	(0.31,0.68,0.76)	1
50	(0.7,0.6,0.6)	(0.10,0.5,0.70)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0.30,0.45,0.78)	(0.24,0.51,0.65)	0
51	(0.1,0.5,0.7)	(0.10,0.30,0.60)	(0.8,0.2,0.7)	(0.2,0.1,0.6)	(0.8,0.3,0.2)	(0.19,0.4,0.69)	(0.49,0.2,0.8)	(0.22,0.59,0.62)	0
52	(0.1,0.6,0.7)	(0.10,0.19,0.80)	0.5,0.8,0.7)	(0.1.0.5,0.8)	(0.3,0.6,0.5)	(0.24,0.2,0.55)	(0.52,0.2,0.7)	(0.26,0.84,0.47)	0
53	(0.5,0.6,0.6)	(0.88,0.50,0.67)	(0.6,0.8,0.6)	(0.2,0.1,0.7)	(0.2,0.3,0.5)	(0.24,0.4,0.88)	(0.34,0.40,0.70)	(0.30,0.78,0.87)	0
54	(0.8,0.4,0.7)	(0.17,0.64,0.71)	(0.9,0.2,0.5)	(0.3,0.4,0.6)	(0.3,0.5,0.7)	(0.33,0.7,0.54)	(0.46,0.2,0.7)	(0.58,0.34,0.98)	1
55	(0.1,0.4,0.7)	(0.15,0.4,0.8)	(0.6,0.7,0.8)	(0.4,0.2,0.4)	(0.3,0.4,0.2)	(0.34,0.6,0.9)	(0.78,0.5,0.6)	(0.42,0.46,0.67)	0
56	(0.1,0.3,0.9)	(0.73,0.53,0.90)	(0.5,0.7,0.8)	(0.1,0.4,0.7)	(0,0,0)	(0.23,0.5,0.7)	(0.24,0.2,0.17)	(0.21,0.24,0.60)	0
56	(0.1,0.5,0.8)	(0.18,0.7,0.30)	(0.6,0.8,0.9)	(0.3,0.9,0.6)	(0.3,0.5,0.4)	(0.37,0.7,0.9)	(0.34,0.4,0.7)	(0.41,0.84,0.65)	1
57	(0,0,0)	(1.0,0.4,0.7)	(0.8,0.6,0.7)	(0.6,0.4,0.3)	(0.1,0.1,0.8)	(0.46,0.8,0.5)	(0.96,0.2,0.6)	(0.31,0.78,0.64)	0
58	(0,0,0)	(0.14,60,0.42)	(0.8,0.8,0.9)	(0,0,0)	(0,0,0)	(0.40,0.5,0.8)	(0.17,0.70,0.65)	(0.44,0.54,0.40)	0
59	(0,0,0)	(1.0,0.5,0.2)	(0.6,0.3,0.7)	(0.4,0.1,0.2)	(0.1,0.4,0.2)	(0.41,0.5,0.9)	(0.17,0.40,0.7)	(0.22,0.39,0.54)	0
60	(0.2,0.6,0.7)	(0.84,0.3,0.7)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0.30,0.49,0.73)	(0.21,0.52,0.76)	0
61	(0.8,0.7,0.3)	(0.13,0.30,0.67)	(0.72,0.65,0.34)	(0,0,0)	(0,0,0)	(0.30,0.49,0.75)	(0.27,0.76,0.47)	(0.39,0.61,0.71)	1
62	(0.5,0.6,0.7)	(0.44,0.67,0.56)	(0.62,0.76,0.43)	(0,0,0)	(0,0,0)	(0.25,0.8,0.45)	(0.58,0.7,0.6)	(0.36,0.68,0.78)	0
63	(0.2,0.8,0.6)	(0.14,0.51,0.85)	(0.58,0.67,0.45)	(0.34,0.49,0.75)	(0.12,0.8,0.45)	(0.25,0.5,0.55)	(0.69,0.90,0.52)	(0.24,0.54,0.50)	0
64	(0.7,0.8,0.4)	(0.11,0.74,0.67)	(0.66,0.75,0.53)	(0,0,0)	(0,0,0)	(0.32,0.40,0.65)	(0.25,0.8,0.75)	(0.42,0.45,0.67)	1
65	(0.5,0.6,0.7)	(0.99,0.87,0.87)	(0.74,0.59,0.73)	(0.27,0.89,0.70)	(0,0,0)	(0.29,0.13,0.84)	(0.20,0.3,0.84)	(0.32,0.64,0.86)	0
66	(0,0,0)	(0.10,0.9,0.51)	(0.88,0.34,0.33)	(0.24,0.39,0.28)	(0,0,0)	(0.32,0.73,0.74)	(0.85,0.5,0.69)	(0.38,0.63,0.87)	1
67	(0.2,0.4,0.7)	(0.10,0.91,0.76)	(0.92,0.78,0.23)	(0,0,0)	(0,0,0)	(0.42,0.5,0.76)	(0.84,0.5,0.76)	(0.54,0.65,0.30)	0
68	(0.1,0.4,0.8)	(0.95,0.67,0.98)	(0.66,0.56,0.83)	(0.13,0.54,0.79)	(0.38,0.56,0.58)	(0.19,0.55,0.56)	(0.33,0.40,0.65)	(0.25,0.76,0.54)	0
69	(0.4,0.3,0.7)	(0.14,0.56,0.60)	(0.85,0.75,0.43)	(0.27,0.23,0.78)	(0.10,0.45,0.76)	(0.28,0.45,0.06)	(0.18,0.90,0.45)	(0.21,0.54,0.43)	0
70	(0.2,0.5,0.8)	(0.10,0.5,0.43)	(0.66,0.03,0.40)	(0.20,0.02,0.48)	(0.9,0.8,0.5)	(0.32,0.9,0.34)	(0.86,0.7,0.78)	(0.28,0.03,0.54)	1
71	(0.5,0.6,0.7)	(0.13,0.4,0.76)	(0.64,0.08,0.50)	(0.35,0.05,0.43)	(0.14,0.45,0.34)	(0.28,0.6,0.77)	(0.41,0.14,0.57)	(0.26,0.04,0.36)	0
72	(0.13,0.6,0.8)	(0.12,0.4,0.6)	(0.9,0.02,0.80)	(0,0,0)	(0,0,0)	(0.43,0.4,0.42)	(0.58,0.38,0.89)	(0.42,0.02,0.34)	1
73	(0.4,0.2,0.7)	(0.12,0.3,0.9)	(0.86,0.05,0.7)	(0.20,0.01,0.43)	(0.27,0.67.0.89)	(0.35,0.1,0.40)	(0.23,0.51,0.45)	(0.23,0.01,0.33)	0
74	(0.1,0.1,0.7)	(0.7,0.1,0.3)	(0.75,0.03,0.60)	(0.30,0.04,0.5)	(0,0,0)	(0.32,0.4,0.58)	(0.39,0.6,0.56)	(0.22,0.04,0.37)	0
75	(0.1,0.1,0.9)	(0,0,0)	(0.48,0.04,0.80)	(0.20,0.03,0.42)	(0,0,0)	(0.24,0.7,0.98)	(0.14,0.4,0.54)	(0.22,0.06,0.74)	0
76	(0.7,0.6,0.9)	(0.62,0.7,0.4)	(0.78,0.02,0.30)	(0,0,0)	(0,0,0)	(0.32,0.6,0.59)	(0.39,0.1,0.87)	(0.41,0.02,0.65)	0
77	(0.5,0.6,0.7)	(0.95,0.01,0.7)	(0.72,0.03,0.60)	(0.33,0.01,0.34)	(0,0,0)	(0.37,0.7,0.76)	(0.37,0.32,0.89)	(0.27,0.04,0.34)	0
78	(0,0,0)	(0.13,0.1,0.76)	(0,0,0)	(0,0,0)	(0,0,0)	(0.43,0.2,0.72)	(0.27,0.5,0.57)	(0.26,0.03,0.45)	1
79	(0.2,0.7,0.6)	(0.11,0.2,0.32)	(0.66,0.04,0.70)	(0.22,0.01,0.41)	(0,0,0)	(0.25,0.4,0.45)	(0.30,0.7,0.54)	(0.24,0.03,0.36)	0
80	(0.3,0.7,0.6)	(0.11,0.3,0.3)	(0.44,0.01,0.40)	(0.13,0.02,0.67)	(0,0,0)	(0.22,0.4,0.70)	(0.14,0.4,0.90)	(0.22,0.05,0.64)	0
81	(0.2,0.7,0.6)	(0.74,0.0,0.33)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0.10,0.2,0.32)	(0.22,0.04,0.58)	0
82	(0.7,0.6,0.9)	(0.83,0.4,0.78)	(0.78,0.06,0.40)	(0.26,0.03,0.19)	(0.71,0.45,0.67)	(0.29,0.3,0.43)	(0.76,0.7,0.59)	(0.36,0.06,0.65)	0
83	(0,0,0)	(0.10,0.1,0.5)	(0.65,0.04,0.30)	(0.28,0.06,0.87)	(0,0,0)	(0.24,0.6,0.30)	(0.23,0.7,0.43)	(0.22,0.01,0.33)	0
84	(0.5,0.6,0.7)	(0.13,0.07,0.34)	(0.10,0.08,0.59)	(0,0,0)	(0,0,0)	(0.48,0.8,0.87)	(0.22,0.7,0.46)	(0.37,0.05,0.54)	1
85	(0.2,0.7,0.6)	(0.11,0.0,0.78)	(0.74,0.02,0.70)	(0.29,0.01,0.46)	(0.12,0.5,0.87)	(0.32,0.4,0.47)	(0.69,0.8,0.69)	(0.27,0.02,0.36)	0
86	(0.13,0.6,0.8)	(0.10,0.06,0.89)	(0.72,0.01,0.20)	(0.54,0.05,0.57)	(0,0,0)	(0.36,0.6,0.69)	(0.17,0.8,0.42)	(0.45,0.04,0.49)	0
87	(0.2,0.7,0.6)	(0.10,0.0,0.67)	(0.68,0.03,0.60)	(0.25,0.02,0.34)	(0.71,0.67,0.39)	(0.38,0.5,0.54)	(0.32,0.4,0.62)	(0.26,0.07,0.67)	0
88	(0.15,0.6,0.8)	(0.13,0.06,0.50)	(0.70,0.05,0.35)	(0.32,0.03,0.46)	(0.11,0.46,0.19)	(0.37,0.1,0.50)	(0.15,0.3,0.85)	(0.43,0.08,0.38)	1
89	(0.1,0.1,0.9)	(0.10,0.07,0.39)	(0.68,0.58,0.37)	(0.19,0.02,0.44)	(0,0,0)	(0.26,0.5,0.98)	(0.16,0.5,0.84)	(0.24,0.04,0.45)	0
90	(0.1,0.1,0.8)	(0.8,0.04,0.18)	(0.55,0.38,0.39)	(0,0,0)	(0,0,0)	(0.19,0.1,0.65)	(0.25,0.8,0.75)	(0.21,0.02,0.30)	0

The truth, indeterminacy, and falsity membership values of 90 test instances are then utilized to train the ANFIS for truth, indeterminacy, and falsity, accordingly. In the initial parameters of the multiple ANFISs, the membership functions of input data are two trapezoid MFs, the membership function of output data is linear, and thus the output data will be generated using if-then rules. Furthermore, the proposed model uses a hybrid optimization technique and 120 epochs.

The learning method of the neuro-fuzzy network as defined as:

$$T'_{\mu} = \{x(n), d_T(n)\}_{N=1}^{N} \tag{12}$$

$$I'_{\mu} = \{x(n), d_I(n)\}_{N=1}^{N} \tag{13}$$

$$F'_{\mu} = \{x(n), d_F(n)\}_{N=1}^{N} \tag{14}$$

Where d_T , d_I, d_F denotes the truth, Indeterminancy and falsity SVNN of all membership functions.

Eq.(12), Eq.(13) and Eq.(14) denote the training data sample of truth, indeterminancy, and falsity respectivily used to train the individual ANFIS in supervised manner.

The error signal produced at the output of neuron j is defined as:

if $y_{T_j}(n)$ denote the output of jth neuron influences by stimulus $x_T(n)$ then

$$e_{T_j}(n) = d_{T_j}(n) - y_{T_j}(n) \tag{15}$$

Where $d_{T_j}(n)$ is the jth element of the desired-response vector $d_T(n)$

Similarily, the we can define error of the Indeterminancy and falsity SVNN as shows Eq.(16) and Eq.(17)

$$e_{I_j}(n) = d_{I_j}(n) - y_{I_j}(n) \tag{16}$$

$$e_{F_j}(n) = d_{F_j}(n) - y_{F_j}(n) \tag{17}$$

The instantanesous error energy of neuron j^{th} is defind in Eq.(18), Eq.(19) and Eq.(20) for the Truth, Indeterminancy and falsity as:

$$\mathfrak{e}_{T_j}(n) = \frac{1}{2} e_{T_j}^2(n) \tag{18}$$

$$\mathfrak{e}_{I_j}(n) = \frac{1}{2} e_{I_j}^2(n) \tag{19}$$

$$\mathfrak{e}_{F_j}(n) = \frac{1}{2} e_{F_j}^2(n) \tag{20}$$

and Eq.(21) define the total instantaneous error energy of the whole network by adding all error –energy at the output layer.

$$\mathfrak{e}_{n_{total}}(n) = \frac{1}{2}\sum_{j\in C} e_{T_j}^2(n) \quad + \frac{1}{2}\sum_{j\in C} e_{I_j}^2(n) + \frac{1}{2}\sum_{j\in C} e_{F_j}^2(n) \tag{21}$$

Finally, the we calculate the average energy of the whole training sample data as defined in Eq.(22)

$$\mathfrak{e}_{n_{avg}}(n) = \frac{1}{3N}\sum_{n=1}^{N}\sum_{j\in C} e_j^2(n) \tag{22}$$

Therefore, the synaptic weights of the ANFIS is adjusted by using the Eq.(21) and Eq.(22) and the error losses of the suggested model is shown in fig.5.

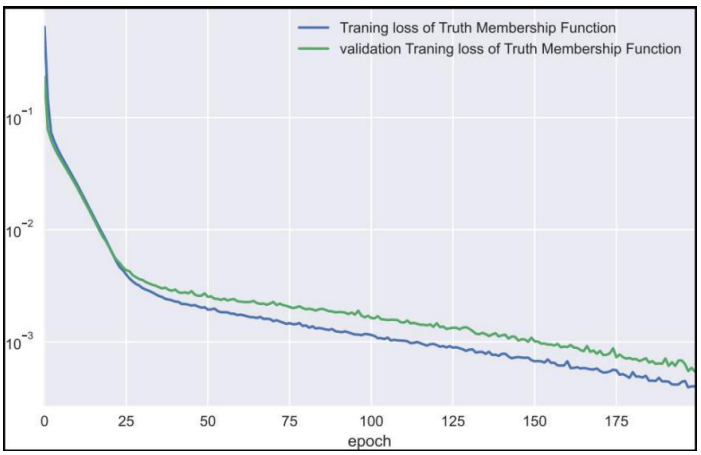


Fig.5. Training losses of truth membership function T_μ

Thus, the three ANFISs generate the training outputs T'_μ, I'_μ and F'_μ, and the SVNNs' score values correspond to the 90 training examples generated by the scoring function Eq. (11). The 30 testing scenarios are utilized in the suggested model testing to obtain indeterminacy. Table 6 shows the output values T'_μ, $I'_\mu$and F'_μ as well as the score value T(μ) for each test instance. To anticipate the sickness, the appropriate threshold Q is given as 0.65 based on the actual test report status. Fig. 5 shows that the suggested SVNN-ANFIS technique has a prediction accuracy of 99.20% during training

and 97.62% during testing using the following assessment criteria:

If I(μ) >0.60, then the Patient is Diabetic
If I(μ) <= 0.60, then the Patient is Non-Diabetic

Table 6. Shows the observed values of the suggested model throughout the testing phase

Test Case	T'_μ	I'_μ	F'_μ	μ	Predicted class	Actual Class
1	0.98	0	0.021	0.99	1	1
2	0.45	0.6	0.05	0.6	0	0
3	0.67	0.2	0.07	0.8	1	1
4	0.35	0.02	0.73	0.53	0	0
5	0.13	0.05	0.07	0.67	1	1
6	0.38	0.45	0.98	0.32	0	0
7	0.56	0.03	0.08	0.82	1	1
8	0.79	0.32	0.75	0.57	0	0
9	0.77	0.63	0.35	0.6	1	1
10	0.4	0.2	0.08	0.71	1	1
11	0.98	0.78	0.94	0.42	0	0
12	0.37	0.02	0.04	0.77	1	1
13	0.65	0.87	0.03	0.58	0	0
14	0.27	0.36	0.075	0.61	1	1
15	0.46	0.61	0.02	0.61	1	1
16	0.65	0.2	0.05	0.8	1	1
17	0.55	0.01	0.08	0.82	1	1
18	0.45	0.2	0.05	0.73	1	1
19	0.5	0.4	0.71	0.46	0	0
20	0.72	0.48	0.03	0.74	1	1
21	0.77	0.01	0.25	0.84	0	1
22	0.66	0.04	0.87	0.58	0	0
23	0.95	0.1	0.07	0.93	1	1
24	0.5	0.4	0.05	0.68	1	1
25	0.4	0.3	0.05	0.68	1	1
26	0.43	0.62	0	0.6	1	1
27	0.35	0.4	0.05	0.63	1	1
28	0.25	0.01	0.5	0.58	0	0
29	0.15	0.2	0.95	0.33	0	0
30	0.23	0.2	0.75	0.43	0	0

To study the impact of lacking indeterminacy and falsity information on prediction results, we predict the disease in the fourth phase of the SVNN-ANFIS techniques using only truth membership values. Fig. 5 shows the training and validation losses of the truth membership values. The optimal threshold value for T(μ) is 0.09, and the prediction accuracy in this circumstance is 95.20% during training and 90.47% during validation. Fig. 6 shows that the prediction accuracy curve of the SVNN-ANFIS technique varies in parabolic shape with the threshold level of I(μ) , whereas the prediction accuracy curve fluctuates generally smoothly with the change of the threshold value of T(μ) . This demonstrates that the SVNN-ANFIS approach is sensitive to the I(μ).

The prediction performance of the proposed SVNN-ANFIS approach is then compared to findings acquired from other existing benchmark methods used to predict diabetes mellitus, such as the ANN, Bayes classifier, kNN, and DT algorithms.

To evaluate the performance of suggested model we used confusion matrices, receiver operating characteristic curves (ROC), and probably approximately correct (PAC) are used. A confusion matrix is constructed of four matrices, namely true positive. True negative, false positive the confusion matrix can be used to compute the true positive rate. The larger the Area under the ROC Curve (AUC) value, the better the prediction performance.

With an AUC in the [0.85, 0.95] range, the classification results were outstanding. AUC greater >= 0.9.5 indicates exceptional performance.

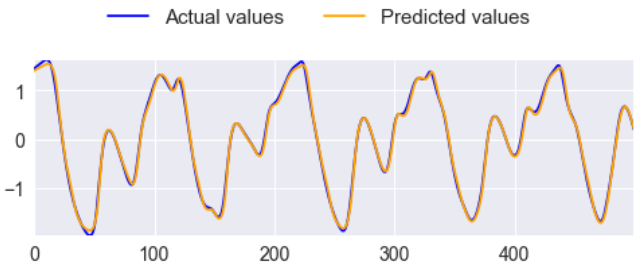


Fig.6. Prediction Accuracy of indeterminacy membership function $I_{\mu}^{'}$

Table 7 shows the suggested model's confusion matrices as well as the benchmark methodologies. The recommended model appears to have committed to achieving the lowest possible false positives and false negatives values during training and testing. In particular, throughout the testing procedure, the number of false positives and false negatives in the four existing benchmark techniques reached 5. All of the techniques in table 7 may have a higher True Positive Ratio (TPR) during training and testing, indicating that they have better predictive abilities for genuine diabetes positive cases. Except for ANN, these techniques are more beneficial to diabetics than to non-diabetics. This could be due to a mismatch in the training data between genuine diabetic cases and actual non-diabetic instances.

Table 7 shows the training and testing performance of the proposed model, as well as the findings of four existing benchmark methodologies. The PACs of the ANN, SVM, KNN, ANFIS, and recommended model were 93.56%, 87.23%, 86.50%, 97.25%, and 98.43% during testing. The AUCs of the comparative methods and the recommended approach in this case are 0.96, 0.97, 0.95, 0.97, and 0.99, respectively. For the 30 testing samples, the suggested approach achieves a maximum PAC of 98.43 and an AUC value of 0.99. The recommended system generates the best results during training and testing due to the neutrosophic expression of raw data in indeterminate and vague situations.

Fig. 6 depicts the forecast accuracy of indeterminant values. Except for a few locations, the curves of actual values and anticipated values strongly coincide. According to research publications, this line illustrates the accurate prediction of indeterminant values.

Table 7. Shows benchmark confusion matrices

Method	Actual Status	Predicted status			
		Training		Testing	
		Diabetic	Non-Diabetic	Diabetic	Non-Diabetic
ANN	Diabetic	37	12	15	5
	Non-Diabetic	5	70	4	30
SVM	Diabetic	40	3	16	5
	Non-Diabetic	4	67	3	22
KNN	Diabetic	28	11	13	3
	Non-Diabetic	2	84	3	27
ANFIS	Diabetic	32	14	14	2
	Non-Diabetic	13	73	2	76
SVNS-ANFIS	Diabetic	45	2	17	2
	Non-Diabetic	0	85	0	32

Table 8. Compares the outcomes of several strategies

Method	ANN	SVM	KNN	ANFIS	SVNS-ANFIS
Training					
ACC	0.96	0.97	0.95	0.97	**0.99**
PAC	93.56%	87.23%	86.50%	97.25%	**98.43%**
TPR	92.43%	88.78%	78.38%	93.33%	**97.32%**
TNR	95.12%	82.48%	91.43%	96.87%	**100%**
Testing					
ACC	0.94	0.82	0.85	0.96	**0.97**
PAC	92.55%	88.31%	85.87%	97.60%	**93.63%**
TPR	93.54%	80.39%	73.50%	93.40%	**100**
TNR	92.14%	92.54%	92.33%	94.21%	**97.48%**

6. Conclusions

In this research, we developed and investigated a method of using neutrosophic set theory with ANFIS to handle the indeterminacy of the ANFIS. In this technique, we employed a basic crisp dataset as an input layer, and then a neutrosophication layer converted the crisp data into a single-valued neutrosophic set (Truth, Indeterminant and falsehood). As a result, these values were used as inputs to the three separate ANFIS modules, which were used to classify the relationship using single-valued neutrosophic values. In the last layer, we compare the indeterminant value to a predetermined threshold value to obtain the predicted results. Our case study on dealing with the uncertainty of diabetes mellitus diagnosis demonstrates how to turn crisp data (the Pima Indian Diabetes Dataset) into a neutrosophic domain and execute the computation to deal with the uncertainty of diabetes mellitus diagnosis. Section 5 demonstrates the effectiveness of the proposed model by comparing ACC, PAC, TPR, TNR values to other current techniques. The outcomes show that the proposed model achieves greater accuracy than another and adequately deals with uncertain data. For the future studies, the proposed model will be used to diagnose more diseases and optimization techniques are applied to improve the system performance.

The disadvantage of the proposed model is that it is more difficult to implement than the other machine learning models. On the other hands, the system required high computing power because of it also generates a large quantity of data, similar to a regular machine or standard fuzzy system, because a single feature has three membership values: truth, indeterminacy, and falsity.

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Authors' Profiles

Rajan Prasad received the Bachelor of Technology in Computer Science & Engineering and Master of Technology in Software Engineering degrees from the Babu Banarasi das University, Lucknow India. He is Research Scholar in Department of Computer Science and Engineering, Babu, Banarasi Das University, Lucknow India. His research interest includes Fuzzy Systems, Machine learning and soft computing.

Dr. P. K. Shukla is currently working as a Head of Department in Computer Science and Engineering, Babu Banarasi Das University, Lucknow India. He has guided several PhD Scholars and published more than 30 research articles in reputed journals. His research interests are Fuzzy System, Machine Learning and interdisciplinary areas. He is also the editor of International Conference on Computer Vision and Robotics published in Springer Book Series, 'Algorithms for Intelligent Systems'.

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