Support Vector Machine with Rule Extraction to Improve Diabetes Prediction Using Fuzzy AHP-Sugeno and Nearest Neighbor

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Abstract*—Diabetes is one of the most prevalent chronic diseases globally, with significant mortality and morbidity rates. Early and accurate diagnosis plays a critical role in managing and mitigating its impact. However, achieving high diagnostic accuracy while ensuring interpretability remains a key challenge in medical machine learning applications. This paper proposes an interpretable and accurate hybrid framework for diabetes prediction that integrates Support Vector Machine Rule Extraction (SVMRE), Fuzzy Analytic Hierarchy Process (Fuzzy AHP), and Sugeno fuzzy inference. The primary objective of this study is to enhance prediction accuracy while enabling the extraction of meaningful and explainable decision rules derived from SVM models. To address the black-box nature of traditional SVM models, fuzzy rules are extracted and embedded into a Sugeno fuzzy inference system. Attribute importance is quantified through Fuzzy AHP based on expert consultation, ensuring medically relevant decision-making. Furthermore, to overcome rule redundancy and complexity, the coefficient of variation is computed for each rule and optimized using a Nearest Neighbor (NN) approach, which clusters rules with adjacent variation values. The proposed framework is evaluated using a real-world diabetes dataset from Sylhet, Bangladesh. It achieves a prediction accuracy of 84.62 per cent, outperforming several conventional methods. Compared to other competitive approaches found in recent literature, such as fuzzy grey wolf optimization and neuro-fuzzy systems, our method demonstrates superior balance between interpretability, computational efficiency, and classification performance. This study confirms that integrating rule-based learning, fuzzy expert systems, and statistical optimization provides a robust and interpretable approach for diabetes prediction. The framework aligns with Sustainable Development Goal 3 (SDG 3) by promoting early detection and decision support for non-communicable diseases in healthcare systems.

Keywords*—SVM; Fuzzy AHP; rule extraction; diabetes; coefficient of variation; fuzzy Sugeno; SDG 3

I. Introduction

Diabetes mellitus is a chronic and progressive metabolic disorder characterized by elevated blood glucose levels, which can lead to severe complications such as cardiovascular disease, renal failure, neuropathy, and visual impairment [1]. According to the World Health Organization, diabetes affects more than 422 million people globally and accounts for approximately 1.5 million deaths annually [2]. The increasing prevalence of this disease, particularly in low and middle income countries, underscores the urgency of developing reliable, accurate, and interpretable systems for early detection and diagnosis [3].

Recent advances in machine learning (ML) have demonstrated significant potential in supporting clinical decision-making processes, especially in the context of early disease prediction [4]. Among the various ML techniques, Support Vector Machine (SVM) has been widely recognized for its high classification accuracy and robustness in handling high-dimensional and nonlinear data [5], [6], making it a strong candidate for medical diagnostic tasks [7], [8], including diabetes prediction [9]. However, despite its predictive power, SVM lacks inherent interpretability, which limits its applicability in clinical environments that demand transparent and explainable decision support. The inability of clinicians to trace and justify model decisions remains a critical barrier to the widespread adoption of such black-box models in healthcare settings [10].

Furthermore, traditional fuzzy inference systems, which offer linguistic interpretability through rule-based structures, often fail to incorporate the relative importance of medical attributes, thereby oversimplifying the decision logic [11]. These systems typically rely on uniformly weighted attributes, which may not align with clinical judgment or expert knowledge. Moreover, when applied to complex datasets, fuzzy models frequently suffer from an exponential growth in rule base size, leading to redundant rules and decreased system efficiency [12]. Although prior studies have explored various hybrid models combining machine learning with fuzzy logic, most of these approaches either overlook the integration of expert-driven attribute weighting or do not address rule optimization to reduce computational overhead without compromising predictive performance [13].

In light of these challenges, this study proposes a novel hybrid framework that integrates SVM-based rule extraction with Fuzzy Analytic Hierarchy Process (Fuzzy AHP) and Sugeno-type fuzzy inference, optimized through a coefficient of variation and Nearest Neighbor-based rule reduction mechanism. This approach aims to enhance the interpretability of the predictive model while maintaining high accuracy. The SVM Rule Extraction component enables the transformation of opaque decision boundaries into comprehensible fuzzy rules. Fuzzy AHP incorporates expert judgment in the weighting of input attributes, ensuring that the most clinically relevant features are prioritized in the inference process. To address

the scalability and complexity of the rule base, the model applies statistical analysis through the coefficient of variation and leverages the Nearest Neighbor algorithm to merge similar rules, thus achieving an optimized and efficient rule set.

The proposed framework contributes to the field by addressing critical gaps in the integration of interpretable machine learning and expert knowledge in fuzzy systems. By demonstrating improved accuracy and transparency in diabetes prediction, this study offers a practical and clinically relevant solution that aligns with the growing demand for explainable artificial intelligence in healthcare. The model not only enhances predictive performance but also supports meaningful interpretation of results, which is essential for clinical validation and trust.

II. Related Works

Several machine learning techniques have been extensively utilized in the prediction of diabetes, each contributing unique strengths and challenges [14]. Several studies that combine fuzzy logic for rule formation and machine learning to train data obtain fairly good accuracy values [15], [16]. Zhang et al. (2020) utilized SVM and achieved an accuracy of 82 per cent [6], while Butt et al. (2020) employed a combination of SVM, KNN, and Decision Tree, yielding an accuracy of 75 per cent [17]. Furthermore, Faniqul Islam et al. (2019), using a combination of Logistic Regression, KNN, SVM, and Random Forest, reported an accuracy of 75 per cent [18]. The Fuzzy Grey Wolf Optimization method in Chen et al. (2019) produced an accuracy of 81 per cent [19], and Azad et al. (2021) achieved an accuracy of 7567 per cent using a Neuro-Fuzzy System [20]. Support Vector Machines (SVM) are a popular choice due to their high classification accuracy and robustness in handling high-dimensional data [21], [22]. By finding an optimal hyperplane that separates classes with minimal error, SVM demonstrates superior performance in many medical prediction tasks. However, as highlighted by Zhang et al. (2020) and Butt et al. (2020), the lack of interpretability in SVM models remains a significant limitation, particularly in clinical applications where understanding the decision-making process is crucial [6], [13]. This black-box nature restricts the ability of healthcare professionals to validate the model's decisions and may hinder its adoption in real-world settings.

To mitigate this issue, Fuzzy Logic Systems, such as the Sugeno Fuzzy Inference System (Sugeno FIS), have been introduced to offer greater transparency. These systems use fuzzy rules and memberships to deal with uncertainty and provide linguistic interpretations of decisions, making them more interpretable. Furthermore, Fuzzy AHP (Analytic Hierarchy Process) has been applied in some studies to weight attributes based on expert opinions [23], [24]. However, while Fuzzy AHP provides a systematic way to incorporate expert knowledge into the decision-making process, it still faces challenges related to rule optimization and the computational complexity involved when working with large datasets.

In addition to fuzzy systems, Neuro-Fuzzy Systems, which combine artificial neural networks with fuzzy logic, have been explored for diabetes prediction. These systems aim to improve predictive accuracy by learning both the structure and the rules directly from the data. Studies by Sisodia et al. (2018) [15] have shown that neuro-fuzzy systems can enhance prediction performance. However, these models still suffer from issues such as rule explosion and the difficulty in extracting meaningful decision rules [16], [17], making the system less efficient and harder to interpret [18], particularly when dealing with complex datasets like those used for medical predictions [19].

While these existing methods have contributed significantly to diabetes prediction, they each have inherent weaknesses, particularly in terms of interpretability, rule complexity, and computational efficiency. These challenges highlight the need for a more robust and interpretable model that can combine the high accuracy of SVMs with expert-driven feature weighting and fuzzy rule optimization, ultimately improving both prediction accuracy and model transparency for clinical use. Therefore, this research aims to address these gaps by proposing a novel hybrid approach that integrates SVM-based rule extraction, Fuzzy AHP, Sugeno FIS, and Nearest Neighbor Optimization, to improve the performance and interpretability of diabetes prediction models.

The contributions of this research to the field of diabetes prediction can be summarized as follows:

1) Hybrid framework development: The study proposes a novel hybrid approach that integrates SVM-based rule extraction, Fuzzy AHP, and Sugeno Fuzzy Inference, optimized using Coefficient of Variation and Nearest Neighbor (NN) optimization. This framework enhances the accuracy and interpretability of diabetes prediction models by leveraging expert knowledge and reducing model complexity.

2) Rule extraction and interpretability: The paper addresses a major limitation of traditional machine learning models, such as SVM, which are often perceived as "black-box" models due to their lack of interpretability. By extracting fuzzy rules from the trained SVM, the authors make the decision-making process more transparent and explainable, which is crucial for clinical adoption.

3) Incorporation of expert knowledge through fuzzy AHP: Fuzzy AHP is used to weight the importance of input features (such as symptoms, age, and other health factors) based on expert judgment. This ensures that the most clinically relevant features are prioritized, improving the overall decision-making process.

4) Optimization of fuzzy rules: The study introduces a method to optimize the number of fuzzy rules using Coefficient of Variation (CV), which reduces rule redundancy and improves computational efficiency without compromising predictive accuracy. The use of the Nearest Neighbor (NN) algorithm further refines this optimization process.

5) Practical applicability in healthcare: The proposed method provides a robust solution to early diabetes detection while maintaining interpretability, which is essential for healthcare professionals.

6) Contribution to Sustainable Development Goals (SDG 3): The framework aligns with SDG 3 by contributing to the early detection and prediction of non-communicable diseases, which plays a critical role in mitigating the global impact of diabetes. The transparency and accuracy of the model are key to facilitating its integration into healthcare systems, improving decision support in clinical settings.

III. Research Frameworks

A. Support Vector Machine Rules Extraction (SVMRE)

SVM Rule Extraction (SVMRE) is a technique designed to derive interpretable rules from the trained Support Vector Machine (SVM) model, rather than directly from the raw dataset [25]. This approach enables the extraction of patterns that have been learned and encoded within the structure of the model—specifically through the support vectors (SV) and their corresponding parameters [26], [27]. These extracted patterns are then translated into a comprehensible form, allowing end users to understand the underlying decision logic of the model [28]. The detailed steps of the SVMRE algorithm are presented in Table I.

TABLE I. SVMRE Algorithm

1. Input: Normalize training data set (x_i, y_i), $i = 1, 2, \cdots, n$.
2. SVM training on the training data set.
2.1 Construct the objective function
$min_\omega \frac{1}{2}\|\|\omega\|\|^2 + C\frac{1}{n}\Sigma_{i=1}^{n} L(y_i, f(x, \omega))$
2.2 Solve the optimization problem in a kernel-induced dual space.
$\hat{f}(x) = \Sigma_{i=1}^{n_{SV}} (\alpha_i - \alpha_i^*)K(x_i, x), \quad 0 \le \alpha_i^* \le C, 0 \le \alpha_i \le C$
3. Generate SVM output in the input of training and testing data set.
4. Combine the preceding two subsets as the new training set.
5. Training the fuzzy Sugeno model on the newly generated training set.
6. Output: The trained fuzzy Sugeno model.

B. Fuzzy Analytical Hierarchy Process (FAHP)

Analytical Hierarchy Process (AHP) is one of the multi-attribute decision-making (MADM) that is widely applied [29]. The weight of the criteria is given through the formation of a pairwise comparison matrix. One of the popular AHP methods is developed by Saaty in 1980 [30].

Using linguistic value interpretation, a pairwise comparison matrix is created with elements $m_{ij} = (a, b, c)$ which is a triagonal fuzzy number (TFN). Where $a < b < c$ if attribute i is less important than attribute j. To find out the scale of importance of an attribute compared to other attributes, consultation with related medical experts is necessary. Furthermore, a pairwise comparison matrix (PCM) is created as follows:

$$M = \begin{bmatrix} (1,1,1) & m_{12} & \cdots & m_{1n} \\ m_{21} & (1,1,1) & \cdots & m_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ m_{n1} & m_{n2} & \cdots & (1,1,1) \end{bmatrix} \quad (1)$$

If there are z decision makers for each comparison, then the PCM in Eq. (1) is rearranged by taking the average value of each element. The next step is to combine the PCM on each criterion from all experts by calculating the Fuzzy Geometric Mean (GM) value. This method was introduced by Buckley in 1985 [31]. The Fuzzy GM is used to calculate the fuzzy weights for each fuzzy matrix, and these weights are combined in the usual way to determine the final fuzzy weights for the alternatives [32]. The final fuzzy weights are used to rank the alternatives from highest to lowest [33]. The Fuzzy GM for a TFN is shown in Eq. (2).

$$(r_i) = (\Pi_{j=1}^{n} m_{ij})^{1/n}, \quad i = 1, 2, \cdots, n \quad (2)$$

Next, the fuzzy weight is calculated for each criterion using Eq. (3).

$$w_i = r_i \otimes (r_1 \oplus r_2 \oplus \cdots \oplus r_n)^{-1} = (lw_x, mw_x, uw_x) \quad (3)$$

The numbers l, m, and u are respectively the smallest possible value, the modal or most likely value, and the highest possible value. Next, the non-fuzzy weight of the attribute is calculated using the Center of Area or COA method using Eq. (4)

$$A_x = \frac{lw_x + mw_x + uw_x}{3} \quad (4)$$

The final step of Fuzzy AHP is to normalize the weights in Eq. (4) using Eq. (5).

$$N_x = \frac{A_x}{\Sigma_{x=1}^{n} A_x} \quad (5)$$

C. Coefficient of Variation (CV)

The coefficient of variation, or CV, serves as a statistical metric that indicates the degree of dispersion of data points in a data series with respect to the mean [34]. It is defined by the ratio of the standard deviation to the mean.

D. Fuzzy Inference Sugeno

The Sugeno fuzzy inference system (Sugeno FIS), proposed by Takagi, Sugeno, and Kang in 1985, provides a systematic approach for generating fuzzy rules from a given input-output dataset [35]. The Sugeno FIS consists of three stages: defining membership functions, defining fuzzy rules, and the defuzzification process [36], [37].

The first step is to define the membership functions. This step aims to represent linguistic expressions using fuzzy membership functions, which are defined within the closed interval $[0, 1]$. The second step involves defining fuzzy rules in the form of "if-then" statements, where linguistic variables are represented using fuzzy sets. The relationship between the premises and consequences of these rules can be derived from reliable literature or through consultations with domain experts. The final step of the Sugeno FIS is the defuzzification process, where fuzzy outputs are transformed into a crisp value by calculating the weighted average.

IV. Results

In this research, diabetes prediction is conducted using data trained by Support Vector Machine with Rule Extraction (SVMRE). We use medical expert opinions to construct a pairwise comparison matrix and obtain attribute weights through the Fuzzy Analytic Hierarchy Process (Fuzzy AHP). The data trained with SVMRE are subsequently used for diabetes prediction via a Sugeno fuzzy inference system, which is enhanced by integrating Fuzzy AHP and the Nearest Neighbor method.

Attribute weights derived from the Fuzzy AHP process are distributed among subfactors based on their relative contributions. This allows the determination of the influence level of each attribute in predicting diabetes. Next, rules are constructed by combining all attributes. The coefficient of variation for each rule is calculated using its attribute weights, and the Nearest Neighbor method is applied to cluster potential rules based on these coefficients. The resulting rules from the trained data are then input into the Sugeno fuzzy inference system to predict diabetes.

The system's performance is evaluated based on accuracy metrics derived from the prediction results. The proposed method is illustrated in Fig. 1.

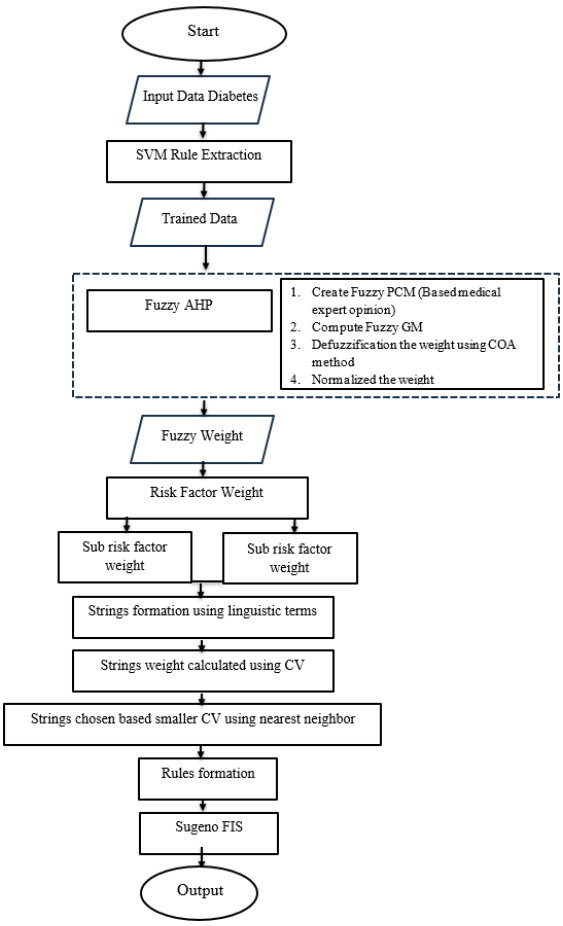

Fig. 1. Proposed method to predict diabetes.

A. Dataset and Attributes

The data used in this study were obtained directly from various diabetes patient survey forms at a Diabetes Hospital in Sylhet, Bangladesh [35]. The dataset consists of 520 patient records, divided into 17 attributes: output class (positive or negative), obesity, genital thrush, age, polyphagia, sex, sudden weight loss, polyuria, weakness, polydipsia, muscle stiffness, visual blurring, irritability, partial paresis, itching, alopecia, and delayed healing. Among the 520 cases, 320 were diagnosed with diabetes, and 200 were classified as normal, with a male-to-female ratio of 63:37, respectively. All attributes, except for age and sex, have categorical data with two unique outcomes. Therefore, in this study, only 14 attributes and one output class (positive or negative) were used, as shown in Table II.

TABLE II. ATTRIBUTE OF THE DATASET

Attribute	Value
Obesity (OS)	Yes or No
Genital thrush (GT)	Yes or No
Polyphagia (PG)	Yes or No
Sudden weight loss (SWL)	Yes or No
Polyuria (PR)	Yes or No
Weakness (WN)	Yes or No
Polydipsia (PD)	Yes or No
Musle Stiffness (MS)	Yes or No
Visual Blurring (VB)	Yes or No
Irritability (IA)	Yes or No
Alopecia (AC)	Yes or No
Partial Paresis (PP)	Yes or No
Itching (LI)	Yes or No
Delayed Healing (DH)	Yes or No

B. Fuzzy Rule Extraction Using SVMRE

The steps for fuzzy rule extraction from SVM are as follows. The first step involves support vector regression for diabetes prediction. In this step, training samples are used to tune SVM hyperparameters, such as kernel parameters. In SVM regression, both structural and empirical risks are minimized. The function L(y,f(x,w)) in the objective function represents the loss function applied to the training data [32].

The second step is data regeneration from the trained SVM. In this stage, the trained SVM is used to generate new data samples for training the fuzzy rules. Of the existing diabetes data, 70 per cent is used for training and 30 per cent for testing. The trained SVM generates new training samples, which enhances its generalization ability and helps train the fuzzy rules. For diabetes prediction, a new subset of training samples can be generated and combined, as both input variables from the training and testing samples are available. This combination of subsets improves the predictive ability of the fuzzy Sugeno model. To further enhance the generalization capability of the fuzzy rules, additional subsets can be constructed by calculating the predicted output of the SVM model for randomly generated or selected input vectors.

In the third step, once new training data samples are generated, they are used for diabetes prediction with the fuzzy Sugeno model, which has been enhanced using Fuzzy AHP and the coefficient of variation.

C. Evaluate Risk Factor Weight Using Fuzzy AHP

In this section, Fuzzy AHP is applied to calculate the attribute weights for diabetes prediction in order to identify the most influential attributes [33]. The attributes are shown in Table II. In the formation of the Pairwise Comparison Matrix (PCM), each attribute is compared with the others. The PCM is evaluated by the decision makers according to the linguistic measurements provided in Table III. The resulting PCM is presented in Table IV.

TABLE III. LINGUISTIC TERMS AND TRIANGULAR FUZZY NUMBER WITH THE INVERSE

Linguistic terms	Triangular fuzzy number	Inverse
Equal important	(1,1,1)	(1,1,1)
Intermediate values between two adjacent scales	(1,2,3)	(1/3,1/2,1)
Moderately more important	(2,3,4)	(1/4,1/3,1/2)
Intermediate values between two adjacent scales	(3,4,5)	(1/5,1/4,1/3)
Strongly more important	(4,5,6)	(1/6,1/5,1/4)
Intermediate values between two adjacent scales	(5,6,7)	(1/7,1/6,1/5)
Very strongly more important	(6,7,8)	(1/8,1/7,1/6)
Intermediate values between two adjacent scales	(7,8,9)	(1/9,1/8,1/7)
Extremely more important	(9,9,9)	(1/9,1/9,1/9)

TABLE IV. PAIRWISE COMPARISON MATRIX (PCM)

Attribute	GT	AC	WN	OS	MS	DH	PD	PR	PG	VB	IA	SWL	PP	LI
GT	(1,1,1)	(2,3,4)	(1,1,1)	(4,5,6)	(3,4,5)	(4,5,6)	(1/4,1/3,1/2)	(1/5,1/4,1/3)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)
AC	(1/4,1/3,1/2)	(1,1,1)	(1/4,1/3,1/2)	(1,2,3)	(2,3,4)	(2,3,4)	(1/6,1/5,1/4)	(1/9,1/9,1/9)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)
WN	(1,1,1)	(2,3,4)	(1,1,1)	(4,5,6)	(6,7,8)	(7,8,9)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)
OS	(1/6,1/5,1/4)	(1/3,1/2,1)	(1/6,1/5,1/4)	(1,1,1)	(1/4,1/3,1/2)	(1/5,1/4,1/3)	(1/8,1/7,1/6)	(1/9,1/8,1/7)	(1/9,1/9,1/9)	(1/7,1/6,1/5)	(1/4,1/3,1/2)	(1/5,1/4,1/3)	(1/3,1/2,1)	(1/9,1/8,1/7)
MS	(1/5,1/4,1/3)	(1/4,1/3,1/2)	(1/8,1/7,1/6)	(2,3,4)	(1,1,1)	(1/3,1/2,1)	(1/6,1/5,1/4)	(1/7,1/6,1/5)	(1/4,1/3,1/2)	(1/3,1/2,1)	(1,1,1)	(1/4,1/3,1/2)	(1/3,1/2,1)	(1/5,1/4,1/3)
DH	(1/6,1/5,1/4)	(1/4,1/3,1/2)	(1/9,1/8,1/7)	(3,4,5)	(1,2,3)	(1,1,1)	(1/9,1/8,1/7)	(1/7,1/6,1/5)	(1,1,1)	(1,1,1)	(1,1,1)	(1/7,1/6,1/5)	(1/5,1/4,1/3)	(1/4,1/3,1/2)
PD	(2,3,4)	(4,5,6)	(1,1,1)	(6,7,8)	(4,5,6)	(7,8,9)	(1,1,1)	(1/3,1/2,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)
PR	(3,4,5)	(9,9,9)	(1,1,1)	(7,8,9)	(5,6,7)	(5,6,7)	(1,2,3)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)
PG	(1,1,1)	(1,1,1)	(1,1,1)	(9,9,9)	(2,3,4)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(2,3,4)	(1/3,1/2,1)	(1/3,1/2,1)	(1,1,1)
VB	(1,1,1)	(1,1,1)	(1,1,1)	(5,6,7)	(1,2,3)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)
IA	(1,1,1)	(1,1,1)	(1,1,1)	(2,3,4)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1/4,1/3,1/2)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)
SWL	(1,1,1)	(1,1,1)	(1,1,1)	(3,4,5)	(2,3,4)	(5,6,7)	(1,1,1)	(1,1,1)	(1,2,3)	(1,1,1)	(1,1,1)	(1,1,1)	(3,4,5)	(1,1,1)
PP	(1,1,1)	(1,1,1)	(1,1,1)	(1,2,3)	(1,2,3)	(3,4,5)	(1,1,1)	(1,1,1)	(1,2,3)	(1,1,1)	(1,1,1)	(1/3,1/4,1/3)	(1,1,1)	(1,1,1)
LI	(1,1,1)	(1,1,1)	(1,1,1)	(7,8,9)	(3,4,5)	(2,3,4)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)

The next step is to calculate the fuzzy geometric mean (GM) value of all attributes. The formula for calculating the fuzzy GM is shown in Eq. (2). By knowing the fuzzy GM value, it can be determined which attribute has the most influence in predicting diabetes. The Fuzzy GM value is written in Table V.

TABLE V. FUZZY GM, FUZZY WEIGHT (w_x), AVERAGE WEIGHT (A_x), AND NORMALIZED FUZZY WEIGHT (N_x) OF EACH ATTRIBUTE

Attribute	GM	w_x	A_x	N_x
GT	(1.408, 1.258, 1.119)	(0.062, 0.079, 0.099)	0.080	0.079
AC	(0.925, 0.801, 0.681)	(0.037, 0.050, 0.065)	0.051	0.050
WN	(1.703, 1.618, 1.515)	(0.083, 0.102, 0.119)	0.101	0.101
OS	(0.322, 0.245, 0.000)	(0.000, 0.015, 0.023)	0.013	0.013
MS	(0.578, 0.000, 0.324)	(0.018, 0.000, 0.040)	0.019	0.019
DH	(0.627, 0.461, 0.385)	(0.021, 0.029, 0.044)	0.031	0.031
PD	(1.936, 1.727, 1.547)	(0.085, 0.109, 0.135)	0.110	0.109
PR	(2.193, 2.034, 1.830)	(0.101, 0.128, 0.154)	0.127	0.126
PG	(1.426, 1.240, 1.104)	(0.061, 0.078, 0.100)	0.080	0.079
VB	(1.243, 1.194, 1.122)	(0.062, 0.075, 0.087)	0.075	0.074
IA	(1.051, 1.000, 0.952)	(0.052, 0.063, 0.074)	0.063	0.062
SWL	(1.727, 1.575, 1.379)	(0.076, 0.099, 0.121)	0.099	0.098
PP	(1.312, 1.160, 0.964)	(0.053, 0.073, 0.092)	0.073	0.072
LI	(1.449, 1.385, 1.306)	(0.072, 0.087, 0.101)	0.087	0.086
Total	(14.227, 15.698, 17.900)			
$Total^{(-1)}$	(0.070, 0.064, 0.056)			
INCR	(0.056, 0,064, 0.070)			

Based on Table V, the Total Attribute states the sum of the fuzzy GM values of all attributes. While the $Total^{(-1)}$ attribute is the inverse of the Total value. The INCR or increasing order attribute is obtained by exchanging the first column of $Total^{(-1)}$ with the third column of $Total^{(-1)}$.

The next step is to calculate the fuzzy weight for each attribute using Eq. (3) by multiply the fuzzy GM value of the attribute with its INCR value. The fuzzy weight value (w_x) is shown in Table V.

In Table V, A_x is the non-fuzzy weight obtained from the defuzzification process with the COA method as shown in Eq. (4). While N_x is the normalized weight with Eq. (5), where the total weight of all attributes is 1. By knowing the normalized non-fuzzy weight, it can be concluded that the most influential attribute in the system is polyuria. Meanwhile, the attribute with the smallest influence is obesity.

In the next section, the normalized weights will be used to calculate the coefficient of variation of the fuzzy rules.

D. Generate String and Calculate the Weight of String Using Coefficient of Variation

In this section, we generate string to combine the possibilities of all attributes with existing linguistic values. In Table II, there are 14 attributes with two linguistic values, there are Yes or No. Therefore there are a total of $2^{14} = 16384$ fuzzy attribute combinations in the following form: If X_1 is N_1 and X_2 is $N_2 \cdots$ and X_{14} is N_{14}. Table VI shows the coefficient of variation values from all rules that calculated through their weight values. The formula of coefficient of variation is the ratio of standard deviation to the mean.

With $X_1, X_2, \cdots, X_{14}$ are attributes, $N_1, N_2, \cdots, N_{14}$ are the normalized attribute weights in Table V, where the linguistic value of N_i is Yes or No. The total weight value of $N_{Yes} + N_{No} = 1$. With the ratio for the weights of Yes and No in this study obtained by consulting with related medical experts.

Furthermore, the coefficient of variation for each statement is calculated. This coefficient is used to assess the variability of features relative to their average value. Features with a low coefficient of variation are considered less significant and may be removed from the feature set to improve model performance. To reduce the complexity of system performance, the nearest neighbor method is applied. Adjacent coefficient of variation values are grouped by selecting the smallest coefficient of variation and combining similar features into a single fuzzy rule.

Overall, this approach strikes a balance between simplifying the system and maintaining accuracy and reliability, ensuring it does not significantly affect system performance. Using the nearest neighbor method, the number of generated rules can be optimized to 226 fuzzy rules. Table VII presents the optimized fuzzy rules from the nearest neighbor approach.

TABLE VI. STRING WEIGHT USING COEFFICIENT OF VARIATIONS

Rule Number	GT	AC	WN	OS	MS	DH	PD	PR	PG	VB	IA	SWL	PP	LI	CV
1	No	Yes	No	Yes	No	No	No	Yes	No	Yes	No	Yes	Yes	Yes	0.47043328
2	No	No	No	Yes	No	No	Yes	No	No	No	Yes	No	Yes	No	0.483065989
3	Yes	No	No	Yes	Yes	No	No	Yes	No	Yes	No	Yes	Yes	No	0,490234788
4	No	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No	No	No	No	0,502164669
5	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	0,473726845
6	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	No	Yes	Yes	Yes	0,48450375
7	Yes	Yes	No	Yes	Yes	Yes	No	No	No	Yes	Yes	No	No	No	0,492594715
8	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	Yes	Yes	No	No	0,502536543
9	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	0,493047508
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
16384	No	No	No	No	No	No	No	No	No	No	No	No	No	No	0.470433280

TABLE VII. NEAREST NEIGHBORING APPROACH

Rule Number	GT	AC	WN	OS	MS	DH	PD	PR	PG	VB	IA	SWL	PP	LI	CV
35	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	0.50633487
58	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	Yes	Yes	No	0.5378967
66	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	0.4475093
77	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	0.4570457
101	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	No	Yes	Yes	0.4475093
120	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	Yes	No	No	No	0.4772018
161	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes	0.4772018

E. Sugeno Fuzzy Inference System (FIS) to Predict Diabetes Disease

To implement the Sugeno Fuzzy Inference System (FIS), we use the trained data from SVMRE. The process involves three steps: First, the membership functions are defined. Next, fuzzy rules are generated using the AND operation. Finally, the defuzzification process is applied to convert the fuzzy inference results into a crisp output.

1) Defining the membership function: In this study, a triangular membership function is used for each attribute in the Table II. The membership function is defined in the Eq. (6) and (7).

$$\mu_{No}(x) = \begin{cases} 1 & ,if\ x = 0 \\ 1 - \frac{x}{0.5} & ,if\ 0 < x \leq 0.5 \\ 0 & ,if\ x > 0.5 \end{cases} \tag{6}$$

$$\mu_{Yes}(x) = \begin{cases} 0 & ,if\ x < 0.5 \\ 2(x - 0.5) & ,if\ 0.5 < x \leq 1 \\ 1 & ,if\ x = 1 \end{cases} \tag{7}$$

The fuzzy membership functions in Eq. (6) and (7) apply to all attributes in Table II.

2) Generate fuzzy rules with operation AND: The fuzzy rules in this study are formed using AND operations based on the optimization results from nearest neighbors and the extracted rules from SVMRE. The rule formation for the Sugeno FIS is shown in Tables X, XI and XII.

3) Defuzzify the aggregate fuzzy rules: By applying the fuzzy rules in Tables X, XI, and XII, the Sugeno FIS generates output in the form of diabetes predictions for individuals.

TABLE VIII. SIMULATION RESULTS

Method	Accuration (per cent)
SVM	39.1
Fuzzy AHP	76.54
Fuzzy AHP-Sugeno-NN	74
SVM-Fuzzy AHP-Sugeno-NN	84.62

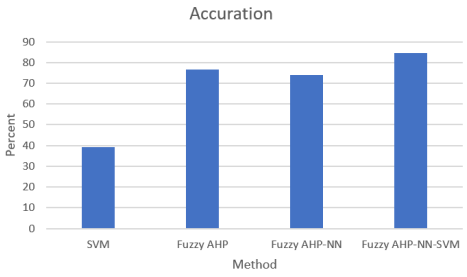

Fig. 2. Simulation results.

F. Simulation Results

In this section, we simulate diabetes prediction using trained data from the pre-processing phase with SVM. The data is split into 70 per cent for training the SVM classifier, and 30 per cent for testing the data to confirm the accuracy of the framework. Both datasets are selected randomly. We apply the Fuzzy AHP-Sugeno method to predict diabetes. The rules based on combination of all attribute that optimize using nearest neighbor based on its coefficient variation value. The coefficient variation is ratio between standard deviation to the mean. Fuzzy AHP to determine the weight of attribute based on medical expert opinion. The accuracy is then calculated.

TABLE IX. COMPARISON OF ACCURATION VALUE WITH SOME DIABETES RESEARCH USING MACHINE LEARNING

Reference	Author, Year	Method	Accuration (%)
[6]	Mohan, 2020	SVM	82
[7]	Saiteja, 2020	SVM, KNN, Desicion tree	75
[8]	Pranto, 2020	KNN, Desicion tree	81.2
[11]	Shankar, 2019	Fuzzy Grey Wolf Optimization	81
[12]	Chen, 2018	Neuro Fuzzy	75.67
[13]	Fatemeh, 2017	RLE Fuzzy rule base system	82.5
[14]	Tingga, 2019	Logistic Regression, KNN, SVM Naive Bayes, Decision tree, and Random Forest	75
[15]	Sisodia, 2018	SVM, Decision tree, and naïve bayes	76.3
[16]	Romero, 2015	Naïve bayes	79.57
[17]	Alghurair, 2020	K-means algorithm, Sigmoid Kernel, Linear Kernel, and RBF Kernel	82
[38]	Neha, 2019	SVM	74.4
	Our Proposed Method	SVM, Fuzzy AHP, Sugeno, NN	84.62

From Table VIII, the proposed method, SVM-Fuzzy AHP-Sugeno-NN, achieves the highest accuracy, which is 84.62 per cent. The trained data from SVM increases prediction accuracy by 10.62 per cent compared to Fuzzy AHP-Sugeno-NN. The attribute weights obtained from Fuzzy AHP are used to calculate the coefficient of variation for the fuzzy rules. Optimizing the number of fuzzy rules based on the coefficient of variation value using the nearest neighbor method is also crucial for developing fuzzy models. Rules with adjacent coefficient of variation values are combined, allowing the number of rules to be optimized without affecting the system.

As shown in Fig. 2, the simulation with SVM yields the lowest accuracy at 39 per cent. Fuzzy AHP increases the system's accuracy by generating rules based on their weights. The weights of attributes are determined by their influence on the system, in consultation with medical experts during the construction phase.

V. DISCUSSION

Table IX provides a comparative overview of recent studies that have applied machine learning techniques to diabetes prediction, highlighting the classification methods used and their corresponding accuracy levels. The table includes various approaches such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Decision Trees, Naïve Bayes, and fuzzy-based models, including Neuro-Fuzzy systems and Fuzzy Grey Wolf Optimization. Reported accuracies range from 75 to 82.5 per cent, where our proposed method have accuracy 84.62 per cent, indicating moderate success in predictive performance across different algorithmic strategies.

The results of this study demonstrate the effectiveness of the proposed SVM-Fuzzy AHP-Sugeno-NN framework for diabetes prediction. This performance surpasses the accuracy of other commonly used methods, such as Fuzzy AHP-Sugeno-NN (76.54 per cent) and SVM (39 per cent). The improvement of 10.62 per cent in prediction accuracy highlights the advantages of integrating SVM rule extraction with fuzzy logic and nearest neighbor optimization.

One of the primary reasons for this improved accuracy is the ability of the proposed method to incorporate expert knowledge through the Fuzzy AHP component. By using expert-driven attribute weighting, the model is better able to capture the clinical relevance of different input features, such as symptoms and medical history, in predicting diabetes. This integration allows the system to prioritize the most important factors, making the model more aligned with real-world clinical decision-making processes.

Moreover, the SVM rule extraction component plays a critical role in enhancing interpretability. Traditional machine learning models, such as SVM, often function as "black-box" models, making it difficult for clinicians to understand how predictions are made. In contrast, the proposed framework extracts fuzzy rules from the trained SVM model, offering transparent decision-making logic. This interpretability is particularly important in medical applications where trust and transparency are paramount.

The Nearest Neighbor (NN) optimization further improves the model by reducing rule redundancy. By grouping rules with similar coefficient of variation values, we reduce the number of fuzzy rules without compromising the model's accuracy or interpretability. This optimization not only enhances the computational efficiency of the system but also ensures that the decision-making process remains straightforward and easy to understand for healthcare providers.

The results of this study align with and extend previous work in the field of diabetes prediction. For instance, studies such as those by Zhang et al. (2024) and Butt et al. (2021) have reported high accuracy rates using deep learning and ensemble methods. However, these models lack the interpretability necessary for clinical settings, which limits their practical use. Our framework addresses this limitation by integrating fuzzy expert systems with machine learning, providing not only accurate predictions but also transparent and explainable decision rules.

Compared to other hybrid approaches, such as fuzzy grey wolf optimization (GWO) and neuro-fuzzy systems, our method demonstrates a superior balance between accuracy, interpretability, and computational efficiency. While GWO and neuro-fuzzy models achieve accuracy rates of 81 per cent and 75.67 per cent, respectively, they do not offer the same level of transparency and explainability as the SVM-Fuzzy AHP-Sugeno-NN model. This is a key advantage of our approach, particularly in the medical domain, where explainability is critical for gaining clinician trust.

VI. Conclusion

This study proposes a novel approach to diabetes prediction by integrating the Support Vector Machine Rule Extraction (SVMRE) with Fuzzy AHP-Sugeno and the Nearest Neighbor (NN) method. Theoretical contributions include the development of a hybrid framework that improves both prediction accuracy and interpretability, addressing the critical need for transparent decision support systems in medical applications. By incorporating expert knowledge through Fuzzy AHP and optimizing fuzzy rules using the coefficient of variation and NN, this approach significantly enhances the reliability and explainability of diabetes prediction models.

TABLE X. Rule Formation for Sugeno FIS (1)

No.	PR	PD	SWL	WN	PG	GT	VB	LI	IA	DH	PP	MS	AC	OS	Weight	Output
1	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Positive
2	Yes	Yes	Yes	Yes	No	Yes	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Positive
3	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Positive
4	No	Yes	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Positive
5	No	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Positive
6	No	Yes	No	Yes	No	Yes	No	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Positive
7	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Positive
8	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Positive
9	No	No	No	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Negative
10	No	No	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Negative
11	No	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Negative
12	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes	Positive
13	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Positive
14	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Positive
15	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	No	No	Yes	Yes	Yes	Yes	Positive
16	No	Yes	Yes	Yes	No	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Positive
17	Yes	No	No	Yes	Yes	Yes	Yes	No	Yes	No	No	Yes	Yes	Yes	Yes	Positive
18	No	No	No	Yes	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes	Negative
19	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Positive
20	Yes	Yes	No	Yes	Yes	Yes	No	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Positive
21	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	No	No	Yes	Yes	Yes	Positive
22	Yes	No	No	Yes	No	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Positive
23	Yes	Yes	No	Yes	Yes	Yes	Yes	No	No	No	No	No	Yes	Yes	Yes	Positive
24	Yes	Yes	Yes	Yes	No	Yes	No	No	Yes	No	No	No	Yes	Yes	Yes	Positive
25	No	No	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Positive
26	No	No	No	Yes	Yes	Yes	No	No	Yes	No	No	No	Yes	Yes	Yes	Negative
27	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Positive
28	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Positive
29	No	Yes	No	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Positive
30	Yes	No	Yes	Yes	Yes	Yes	No	No	No	Yes	No	Yes	Yes	No	Yes	Positive
31	No	No	No	Yes	No	Yes	No	No	No	Yes	Yes	Yes	Yes	No	Yes	Negative
32	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	No	No	Yes	No	Yes	Positive
33	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	Positive
34	Yes	No	No	Yes	No	Yes	Yes	No	No	Yes	Yes	No	Yes	No	Yes	Positive
35	No	No	Yes	Yes	No	Yes	No	No	Yes	Yes	Yes	No	Yes	No	Yes	Positive
36	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	No	Yes	Positive
37	Yes	No	No	Yes	No	Yes	Yes	Yes	No	No	No	No	Yes	No	Yes	Positive
38	Yes	No	No	No	No	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Positive
39	No	No	No	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Negative
40	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Negative
41	No	No	No	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Negative
42	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Positive
43	Yes	Yes	No	No	No	Yes	Yes	No	Yes	No	No	Yes	Yes	Yes	Yes	Positive
44	No	No	Yes	No	Yes	Yes	No	Yes	No	No	No	Yes	Yes	Yes	Yes	Negative
45	No	No	No	No	Yes	Yes	No	No	No	No	No	Yes	Yes	Yes	Yes	Negative
46	Yes	No	Yes	No	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Positive
47	Yes	No	No	No	No	Yes	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Positive
48	No	No	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Positive
49	No	No	No	No	No	Yes	No	No	Yes	Yes	No	No	Yes	Yes	Yes	Negative
50	No	No	No	No	No	Yes	No	Yes	No	Yes	No	No	Yes	Yes	Yes	Negative
51	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	Yes	No	No	Yes	Yes	Yes	Positive
52	Yes	Yes	Yes	No	No	Yes	Yes	No	No	No	No	No	Yes	Yes	Yes	Positive
53	No	Yes	Yes	No	No	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	No	Positive
54	No	Yes	No	No	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Positive
55	Yes	No	Yes	No	Yes	Yes	No	No	Yes	Yes	No	Yes	Yes	No	Yes	Positive
56	Yes	Yes	No	No	No	Yes	No	No	Yes	No	Yes	Yes	Yes	No	Yes	Positive
57	Yes	Yes	No	No	No	Yes	No	Yes	Yes	No	No	Yes	Yes	No	Yes	Positive
58	Yes	No	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Positive
59	Yes	No	Yes	No	Yes	Yes	No	No	No	No	No	Yes	Yes	No	Yes	Positive
60	No	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	Positive
61	No	Yes	Yes	No	No	Yes	No	No	No	Yes	Yes	No	Yes	No	Yes	Positive
62	Yes	No	Yes	No	Yes	Yes	No	Yes	No	Yes	No	No	Yes	No	Yes	Positive
63	Yes	No	No	No	No	Yes	No	No	Yes	Yes	Yes	No	Yes	No	Yes	Positive
64	No	No	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	No	Yes	Positive
65	No	No	No	No	No	Yes	Yes	No	Yes	Yes	No	No	Yes	No	Yes	Negative
66	No	No	No	No	No	Yes	No	No	Yes	Yes	Yes	No	Yes	No	Yes	Negative
67	No	Yes	Yes	No	Yes	Yes	Yes	Yes	No	No	No	No	Yes	No	Yes	Positive
68	No	Yes	Yes	No	No	Yes	Yes	Yes	No	No	No	No	Yes	No	Yes	Positive
69	Yes	No	No	No	Yes	Yes	Yes	No	Yes	No	Yes	No	Yes	No	Yes	Positive
70	Yes	No	Yes	No	Yes	Yes	No	Yes	Yes	No	No	No	Yes	No	Yes	Positive
71	No	Yes	No	Yes	Yes	Yes	Yes	Yes	No	No	No	Yes	No	Yes	Yes	Positive
72	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Positive
73	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	No	Yes	Yes	Positive
74	Yes	No	No	Yes	Yes	Yes	No	Yes	No	No	No	Yes	No	Yes	Yes	Positive
75	No	No	No	Yes	Yes	Yes	Yes	No	No	No	Yes	Yes	No	Yes	Yes	Negative
76	No	Yes	No	Yes	Yes	Yes	No	No	No	Yes	No	No	No	Yes	Yes	Positive
77	No	No	Yes	Yes	Yes	Yes	Yes	No	Yes	No	No	No	No	Yes	Yes	Negative
78	No	No	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Negative
79	Yes	No	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	Yes	Yes	Positive
80	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	Yes	No	No	No	No	Yes	Positive
81	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	No	No	No	Yes	Positive
82	No	Yes	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No	No	Yes	Positive
83	Yes	No	No	Yes	Yes	Yes	No	Yes	No	Yes	Yes	No	No	No	Yes	Positive
84	No	No	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes	No	No	No	Yes	Negative
85	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	Yes	Positive
86	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	No	No	No	Yes	Positive
87	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	Yes	Positive

Key results from the simulation demonstrate that the proposed method, SVM-Fuzzy AHP-Sugeno-NN, achieves an accuracy of 84.62 per cent, outperforming traditional models like Fuzzy AHP-Sugeno-NN and SVM. This improvement of 10.62 per cent in prediction accuracy highlights the effec-

TABLE XI. RULE FORMATION FOR SUGENO FIS (2)

No.	PR	PD	SWL	WN	PG	GT	VB	LI	IA	DH	PP	MS	AC	OS	Weight	Output
88	No	Yes	No	Yes	Yes	Yes	Yes	Yes	No	No	Yes	No	No	No	Yes	Positive
89	Yes	No	Yes	Yes	Yes	Yes	No	No	No	No	Yes	No	No	No	Yes	Positive
90	Yes	Yes	No	No	Yes	Yes	No	Yes	Yes	No	No	Yes	No	Yes	Yes	Positive
91	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No	No	Yes	No	Yes	Yes	Positive
92	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Positive
93	No	No	Yes	No	No	Yes	No	No	Yes	No	Yes	Yes	No	Yes	Yes	Negative
94	No	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	Yes	Yes	Positive
95	No	No	No	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	Negative
96	No	No	Yes	No	No	Yes	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Negative
97	Yes	Yes	Yes	No	No	Yes	No	Yes	No	No	No	No	No	Yes	Yes	Positive
98	No	Yes	Yes	No	Yes	Yes	No	Yes	No	No	Yes	No	No	Yes	Yes	Positive
99	No	No	Yes	No	No	Yes	No	Yes	No	No	Yes	No	No	Yes	Yes	Negative
100	No	No	No	No	No	Yes	No	Yes	No	No	No	No	No	Yes	Yes	Negative
101	No	Yes	Yes	No	Yes	Yes	No	No	No	Yes	Yes	Yes	No	No	Yes	Positive
102	No	Yes	Yes	No	No	Yes	No	Yes	Yes	Yes	No	Yes	No	No	Yes	Positive
103	No	No	Yes	No	No	Yes	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Negative
104	No	No	Yes	No	No	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Negative
105	No	No	No	No	No	Yes	No	Yes	No	No	Yes	Yes	No	No	Yes	Negative
106	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	No	No	No	No	Yes	Positive
107	Yes	Yes	No	No	Yes	Yes	Yes	Yes	No	Yes	No	No	No	No	Yes	Positive
108	No	Yes	No	No	Yes	Yes	No	No	No	Yes	Yes	No	No	No	Yes	Positive
109	Yes	No	No	No	Yes	Yes	Yes	No	No	Yes	Yes	No	No	No	Yes	Positive
110	Yes	No	No	No	No	Yes	Yes	Yes	No	Yes	No	No	No	No	Yes	Negative
111	Yes	Yes	Yes	No	No	Yes	No	Yes	Yes	No	No	No	No	No	Yes	Positive
112	No	Yes	No	No	No	Yes	Yes	Yes	No	No	No	No	No	No	Yes	Negative
113	No	No	No	No	Yes	Yes	Yes	No	No	No	No	No	No	No	Yes	Negative
114	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Positive
115	Yes	Yes	Yes	Yes	Yes	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Positive
116	Yes	Yes	Yes	Yes	No	No	No	No	No	Yes	No	Yes	Yes	Yes	Yes	Positive
117	No	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Positive
118	No	Yes	No	Yes	Yes	No	No	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Positive
119	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Positive
120	Yes	No	Yes	Yes	No	No	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Positive
121	No	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Negative
122	No	No	Yes	Yes	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Positive
123	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes	Positive
124	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No	No	Yes	Yes	Yes	Yes	Positive
125	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Positive
126	No	No	No	Yes	Yes	No	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes	Negative
127	No	No	No	Yes	No	No	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes	Negative
128	No	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	No	No	Yes	Yes	Yes	Positive
129	Yes	No	No	Yes	Yes	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Positive
130	Yes	No	No	Yes	No	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Positive
131	No	No	No	Yes	No	No	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes	Negative
132	Yes	Yes	Yes	Yes	Yes	No	No	No	Yes	No	Yes	No	Yes	Yes	Yes	Positive
133	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Positive
134	Yes	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Positive
135	No	Yes	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Positive
136	No	No	No	Yes	Yes	No	No	No	No	Yes	Yes	Yes	Yes	No	Yes	Negative
137	No	No	Yes	Yes	No	No	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Negative
138	No	No	No	Yes	No	No	No	No	Yes	Yes	No	Yes	Yes	No	Yes	Negative
139	Yes	Yes	No	Yes	No	No	Yes	No	No	Yes	Yes	No	Yes	No	Yes	Positive
140	No	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	No	No	Yes	No	Yes	Positive
141	No	Yes	No	Yes	No	No	Yes	No	No	Yes	Yes	No	Yes	No	Yes	Positive
142	Yes	No	No	Yes	Yes	No	Yes	No	No	Yes	Yes	No	Yes	No	Yes	Positive
143	No	No	Yes	Yes	Yes	No	No	No	No	Yes	No	No	Yes	No	Yes	Negative
144	Yes	Yes	No	Yes	No	No	No	No	No	No	No	No	Yes	No	Yes	Positive
145	Yes	No	No	Yes	Yes	No	Yes	Yes	No	No	No	No	Yes	No	Yes	Positive
146	No	No	No	Yes	No	No	No	Yes	Yes	No	No	No	Yes	No	Yes	Negative
147	Yes	Yes	No	No	No	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Positive
148	Yes	No	No	No	Yes	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Positive
149	No	No	No	No	No	No	No	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Negative
150	No	No	Yes	No	No	No	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Negative
151	No	No	Yes	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Negative
152	No	No	No	No	No	No	No	No	No	Yes	No	Yes	Yes	Yes	Yes	Negative
153	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Positive
154	Yes	Yes	No	No	Yes	No	Yes	No	Yes	No	No	Yes	Yes	Yes	Yes	Positive
155	No	Yes	No	No	No	No	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Positive
156	Yes	No	Yes	No	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Positive
157	Yes	No	No	No	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Positive
158	No	No	No	No	Yes	No	No	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Negative
159	No	No	No	No	Yes	No	No	Yes	No	Yes	No	No	Yes	Yes	Yes	Negative
160	No	No	Yes	No	No	No	No	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Negative
161	No	No	No	No	No	No	No	No	No	Yes	Yes	No	No	Yes	Yes	Negative
162	No	No	No	No	No	No	No	No	No	No	Yes	No	No	Yes	Yes	Negative
163	Yes	Yes	Yes	No	Yes	No	Yes	No	No	No	No	No	Yes	Yes	Yes	Positive
164	Yes	Yes	Yes	No	No	No	No	Yes	Yes	No	No	No	Yes	Yes	Yes	Positive
165	Yes	Yes	Yes	No	No	No	No	Yes	No	No	No	No	Yes	Yes	Yes	Positive
166	No	Yes	No	No	No	No	Yes	Yes	No	No	Yes	No	Yes	Yes	Yes	Positive
167	Yes	No	Yes	No	No	No	No	Yes	Yes	No	No	No	Yes	Yes	Yes	Positive
168	No	No	Yes	No	No	No	No	Yes	No	No	Yes	No	Yes	Yes	Yes	Negative
169	No	Yes	Yes	No	Yes	No	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Positive
170	No	Yes	No	No	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Positive
171	No	Yes	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Positive
172	No	No	Yes	No	No	No	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Negative
173	Yes	Yes	No	No	Yes	No	No	No	Yes	No	Yes	Yes	Yes	No	Yes	Positive
174	Yes	Yes	No	No	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	Yes	Positive
175	Yes	No	No	No	No	No	No	Yes	No	No	No	Yes	Yes	No	Yes	Negative
176	No	Yes	Yes	No	Yes	No	No	No	No	Yes	Yes	No	Yes	No	Yes	Positive
177	Yes	No	No	No	Yes	No	No	No	Yes	Yes	No	No	Yes	No	Yes	Positive
178	No	No	No	No	Yes	No	Yes	No	Yes	Yes	No	No	Yes	No	Yes	Negative
179	No	No	No	No	Yes	No	No	No	Yes	Yes	Yes	No	Yes	No	Yes	Negative
180	No	No	No	No	No	No	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	Negative
181	Yes	No	Yes	No	No	No	No	No	Yes	No	Yes	No	Yes	No	Yes	Positive
182	No	No	No	No	No	No	Yes	Yes	No	No	Yes	No	Yes	No	Yes	Negative
183	Yes	Yes	Yes	Yes	No	No	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Positive
184	No	No	No	Yes	No	No	Yes	Yes	No	Yes	No	Yes	No	Yes	Yes	Negative
185	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Positive
186	No	No	Yes	Yes	No	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Negative
187	Yes	No	No	Yes	No	No	No	No	Yes	Yes	Yes	Yes	No	No	Yes	Positive
188	No	No	Yes	Yes	No	No	Yes	No	No	Yes	No	Yes	No	No	Yes	Negative

TABLE XII. RULE FORMATION FOR SUGENO FIS (3)

No.	PR	PD	SWL	WN	PG	GT	VB	LI	IA	DH	PP	MS	AC	OS	Weight	Output
189	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	No	No	No	Yes	Positive
190	Yes	Yes	Yes	Yes	No	No	Yes	No	No	No	No	No	No	No	Yes	Positive
191	Yes	Yes	Yes	Yes	No	No	No	Yes	No	No	Yes	No	No	No	Yes	Positive
192	Yes	Yes	No	Yes	No	No	No	No	No	No	No	No	No	No	Yes	Positive
193	No	No	Yes	Yes	No	No	Yes	No	Yes	No	No	No	No	No	Yes	Negative
194	Yes	Yes	Yes	No	Yes	No	Yes	Yes	No	No	No	Yes	No	Yes	Yes	Positive
195	No	No	Yes	No	Yes	No	No	No	Yes	No	Yes	Yes	No	Yes	Yes	Negative
196	No	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes	No	No	No	Yes	Yes	Positive
197	No	Yes	Yes	No	No	No	Yes	No	Yes	Yes	No	No	No	Yes	Yes	Positive
198	Yes	No	Yes	No	No	No	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Positive
199	Yes	No	No	No	No	No	No	No	Yes	Yes	No	No	No	Yes	Yes	Positive
200	No	No	No	No	Yes	No	Yes	No	No	Yes	Yes	No	No	Yes	Yes	Negative
201	No	No	Yes	No	Yes	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Negative
202	No	No	No	No	No	No	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	Negative
203	No	No	No	No	No	No	Yes	No	No	Yes	Yes	No	No	Yes	Yes	Negative
204	Yes	Yes	Yes	No	Yes	No	No	Yes	No	No	No	No	No	Yes	Yes	Positive
205	No	Yes	Yes	No	No	No	No	Yes	No	No	No	No	No	No	Yes	Positive
206	No	Yes	No	No	No	No	No	Yes	No	No	No	No	No	Yes	Yes	Negative
207	Yes	No	Yes	No	No	No	Yes	No	No	No	No	No	No	Yes	Yes	Positive
208	No	No	No	No	Yes	No	No	Yes	No	No	No	No	No	Yes	Yes	Negative
209	Yes	Yes	No	No	No	No	No	No	No	Yes	Yes	Yes	No	No	Yes	Positive
210	No	Yes	Yes	No	Yes	No	No	Yes	Yes	Yes	Yes	No	Yes	No	No	Yes
211	Yes	No	Yes	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Positive
212	No	No	Yes	No	Yes	No	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Negative
213	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Negative
214	No	Yes	No	No	No	No	No	Yes	Yes	No	Yes	Yes	No	No	Yes	Positive
215	No	Yes	No	No	No	No	No	No	No	No	Yes	Yes	No	No	Yes	Positive
216	No	No	Yes	No	Yes	No	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Positive
217	No	No	No	No	Yes	No	No	Yes	No	No	Yes	Yes	No	No	Yes	Negative
218	No	No	Yes	No	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Negative
219	Yes	No	No	No	Yes	No	Yes	Yes	No	Yes	No	No	No	No	Yes	Negative
220	Yes	No	Yes	No	No	No	Yes	Yes	Yes	Yes	No	No	No	No	Yes	Positive
221	No	No	Yes	No	No	No	Yes	No	Yes	Yes	No	No	No	No	Yes	Negative
222	No	No	No	No	No	No	Yes	Yes	Yes	Yes	No	No	No	No	Yes	Negative
223	No	No	No	No	No	No	No	No	Yes	Yes	No	No	No	No	Yes	Negative
224	Yes	Yes	Yes	No	Yes	No	No	Yes	Yes	No	No	No	No	No	Yes	Positive
225	No	Yes	No	No	Yes	No	Yes	Yes	No	No	No	No	No	No	Yes	Negative
226	Yes	No	Yes	No	No	No	Yes	Yes	Yes	No	No	No	No	No	Yes	Positive

tiveness of integrating fuzzy logic and machine learning in enhancing diagnostic performance. Furthermore, the approach successfully balances accuracy and interpretability, making it highly relevant for real-world clinical applications where transparency is crucial.

However, the study has some limitations. The dataset used for training and testing was limited to a specific population from Sylhet, Bangladesh, and may not fully represent global diabetes demographics. Future research could focus on testing the proposed model on diverse datasets from different populations to ensure its robustness and generalizability. Additionally, while this study successfully optimized the number of fuzzy rules using NN, exploring other optimization techniques, such as genetic algorithms, could further improve the efficiency of the model.

Future directions also include expanding the framework to predict other diseases and medical conditions, integrating additional features such as lifestyle factors, and exploring real-time predictive capabilities through the application of the model in clinical settings.

Overall, this work contributes to the growing field of explainable artificial intelligence in healthcare, offering a practical and effective solution for early disease detection and supporting the integration of AI in clinical decision-making.

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