IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received December 9, 2021, accepted January 8, 2022, date of publication January 11, 2022, date of current version January 24, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3142097

Prediction of Diabetes Empowered With Fused Machine Learning

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ABSTRACT In the medical field, it is essential to predict diseases early to prevent them. Diabetes is one of the most dangerous diseases all over the world. In modern lifestyles, sugar and fat are typically present in our dietary habits, which have increased the risk of diabetes. To predict the disease, it is extremely important to understand its symptoms. Currently, machine-learning (ML) algorithms are valuable for disease detection. This article presents a model using a fused machine learning approach for diabetes prediction. The conceptual framework consists of two types of models: Support Vector Machine (SVM) and Artificial Neural Network (ANN) models. These models analyze the dataset to determine whether a diabetes diagnosis is positive or negative. The dataset used in this research is divided into training data and testing data with a ratio of 70:30 respectively. The output of these models becomes the input membership function for the fuzzy model, whereas the fuzzy logic finally determines whether a diabetes diagnosis is positive or negative. A cloud storage system stores the fused models for future use. Based on the patient's real-time medical record, the fused model predicts whether the patient is diabetic or not. The proposed fused ML model has a prediction accuracy of 94.87, which is higher than the previously published methods.

INDEX TERMS Diabetic prediction, fuzzy system, fused machine learning model, diabetic symptoms, disease prediction.

I. INTRODUCTION

Diabetes is one of the world's largest ongoing chronic metabolic disorders. There are two types of diabetes, Type-1, and Type-2. When the immune system damages pancreatic Beta cells (β-cells), Type-1 diabetes transpires inside the body, which leads to the release a tiny amount of insulin or no insulin. Type-2 diabetes is an autoimmune disease in which cells of the body fail to interact with insulin, or the pancreatic cells do not produce enough insulin to regulate blood glucose levels. An insufficient amount of insulin causes the blood glucose levels to rise and the metabolism of carbohydrates, fats, and proteins to weaken, resulting in Type-1 diabetes. Diabetes symptoms include (i) Polyuria (ii) Polydipsia (iii) Weakness (iv) Polyphagia (v) Obesity (vi) Sudden-Weight-Loss (vii) Genital-Thrush (viii) Visual Blurring (ix) Itching (x) Irritability (xi) Delayed-Healing (xii) Partial-Paresis (xiii) Muscle-Stiffness (xiv) Alopecia, etc. [1]. Diabetes is a metabolic disease and which causes millions of deaths around the world yearly due to various health complications. An increase of 70% death ratio from diabetes has been observed between 2000 to 2019 in all over the world [2]. An intelligent ML-based diagnostic system is required to detect these types of fatal diseases. An ML-based expert decision system can successfully diagnose diabetes patients at an early stage. Researchers used various different types of datasets for the prediction of diabetes. ML based framework need an appropriate dataset having necessary features for training, and validation. The selection of appropriate and concerned features from the

The associate editor coordinating the review of this manuscript and approving it for publication was Baozhen Yao.

dataset increases the abilities of the ML model to predict accurately. The dataset used in the proposed system comes from the (University of California Irvine) UCI Machine Learning repository [3], compiled by the hospital of Sylhet, Bangladesh.

Diabetic Mellitus (DM) occurs due to malabsorption of food which alteres glucose level in the body. Preventive measures against malnutrition or obesity that are sometimes primary causes of diabetes include healthy diet and change of lifestyle. Furthermore, these measures help to control the blood pressure, and lower the risk of health complications. Medical checkup makes it easier to diagnose the disease of diabetes. Some laboratory tests are also conducted to detect the disease. Type-2 DM patients need life-saving insulin for as long as they stay alive. Thus, if left unaddressed, this unhealthy condition drains individuals, families, and national resources. Early detection and symptomatic treatment are essential to ensure the healthy life and well-being of pre-diabetic patients. An intelligent medical diagnosis system based on symptoms, signs, laboratory tests, and observations will be helpful in disease detection and prevention. Artificial Intelligence (AI) has also been applied to medical diagnosis systems in several interesting ways for disease detection. This research proposes a framework for early detection of diabetic patients using machine learning fusion.

II. LITERATURE REVIEW

Recent literature has produced a significant amount of research to recognize diabetic patients based on symptoms by applying machine-learning techniques. Based on supervised learning, hybrid learning, or ensemble learning, Pradhan *et al.* [4] applied various algorithms for diagnosing diabetes mellitus to gain higher accuracy rate, but the ensemble approach performs better than the other two approaches. In an ensemble approach, Kumari *et al.* [5] improved classification accuracy by applying a soft voting classifier to the Pima-Diabetes dataset and Breast-Cancer dataset. According to the results, soft voting classifier achieved 79.08 % accuracy compared to the other machine-learning algorithms.

Sarwar *et al.* [6] used machine-learning algorithms for the detection of diabetes at an early stage by using Pima Diabetes dataset. Their accuracy rates achieved from KNN and SVM were 77%, which is higher than the other four algorithms. A limitation of this paper is the size of the dataset and the missing values. Dey *et al.* [7] used supervised machine learning algorithms: SVM, KNN, Naive Bayes, and ANN with Min-Max scaling (MMS) on the Pima dataset. The accuracy of the model ANN with MMS is 82.35 %, which is higher than the other four algorithms. In [8], the researchers used machine-learning algorithms including Naive Bayes, Random Forest, and Simple CART and used the Weka tool to predict diabetes. The SVM classifier performs better and achieved a 79.13% accuracy, which is higher than the other three algorithms. Saru *et al.* [9] predicted diabetes using a model based on Logistic Regression, SVM, Decision Tree, and KNN. They also compared their accuracy rates without and with Bootstrapping. The accuracy rate of the decision tree with bootstrapping is 94.4%, which is higher than the other two algorithms.

By using machine learning algorithms such as Decision Tree, ANN, Naive Bayes, and SVM, Sonar and Jaya Malini [10] constructed a model to predict diabetic patients. The accuracy rate of the decision tree is 85%, which is higher than the other two algorithms. Wei *et al.* [11], in their paper, designed a model using ML algorithms such as the Naive Bayes, Deep Neural Network (DNN), Logistic Regression, and Decision Trees. The accuracy rate of DNN is 77.86%, which is higher than the other four algorithms. Faruque *et al.* [12] proposed a model that uses four ML algorithms – Support Vector Machine (SVM), C4.5 Decision Tree, K-Nearest Neighbor (KNN), and Naive Bayes to predict diabetes. The accuracy rate of the C4.5 Decision Tree is 73.5%, which is higher than the other three algorithms. Jain *et al.* [13] predicted diabetes, uses various ML algorithms like Neural Network (NN), Fisher Linear Discriminant Analysis (FLDA), Random Forest, Chi-square Automatic Interaction Detection (CHAID), and SVM. The accuracy rate of NN is 87.88%, which is higher than the other four algorithms.

ML algorithms are currently useful for the detection of diseases but the previous research models are less accurate because they usually focused on pre-processing techniques, data balancing, and various types of supervised and semi-supervised learning models. Therefore, it is required to find new technique with decision level fusion which would be able to integrate the accuracy of multiple machine learning algorithms with high disease detection accuracy. For this purpose, a fused ML model is proposed which uses two supervised machine-learning approaches including ANN and SVM [14]–[16] followed by fuzzy logic for decision level fusion.

III. MATERIALS AND METHODS

This article proposes a Fused Model for Diabetes Prediction (FMDP). The proposed FMDP model consists of two main phases. The first phase consist of Training Layer while the second phase consists of Testing Layer. The Training Layer is divided into different stages, including data acquisition, preprocessing, classification, performance evaluation, and machine-learning fusion. The dataset used in this research is taken from the UCI Machine Learning Repository [3]. In the Data Acquisition stage, a dataset that has enough features can be used to predict diabetes. Data is cleaned, normalized, and divided in to training and test dataset during the preprocessing stage. Preprocessed data can be used to train Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs) for the prediction. We can select several Machine-learning algorithms for the classification to achieve the required accuracy. However, in the proposed model, we used only two widely used ML algorithms (SVMs and ANNs) [14], [16], [19]. These algorithms are selected in this

research after some initial experiments where we have found these techniques more effective for this problem. We used various accuracy measures, including: accuracy, specificity, sensitivity, precision, and F1 score in the Performance Evaluation stage. If the proposed model does not meet the learning requirements, it will be retrained. When learning requirements are meet, the ANN and SVM outputs are used as inputs in machine-learning fusion. In the Machine-Learning Fusion stage, fuzzy rules are applied to the actual output of SVM and ANN results for final prediction. The fused trained model is then stored in the cloud.

The second phase of the proposed framework is reflected by the testing layer. The testing layer acquires dataset from medical database, and loads preprocessed training model from the cloud. A fused model is used to predict whether a diabetes diagnosis is positive or negative. Prediction accuracy is calculated by comparing the required output with the actual output.

The ANN model is trained with the preprocessed training dataset. We have divided the preprocessed data into training and test data with 70:30 ratio on the basis of class base split. For training the data we have used Bayesian regularization function with 5% is used for testing and 5% for validation, and the remaining 90% is used for training.

There are 16 hidden layers between input and output neurons. Where ω1, ω2, ω3… ω16 & ⍱1, ⍱2, ⍱3 … ⍱16 represents the input layer neurons and hidden layer neurons respectively. Output is represented as ''out ϖ''. A bias can be represented as ɦ1 and ɦ2. This produces an out ϑ and out ϱ based on the following equations 1 and 2.

$$\text{out}\vartheta = \frac{1}{1+\text{e}^{-(\text{ɦ}1\sum_{r=1}^{m}(\text{u}_{r,\vartheta}*\omega))}} \tag{1}$$

where, $\vartheta = 1,\ 2, \ldots,\ \text{n}$

$$\text{out}\varrho = \frac{1}{1+\text{e}^{-(\text{ɦ}2\sum_{\vartheta=1}^{n}(\text{ƥ}_{\vartheta,\varrho}*\ \text{out}\vartheta))}} \tag{2}$$

where, $\varrho = 1, 2, \ldots, \text{r}$

Using the squared error function, each output neuron's error can be calculated and summed to find the total error (E).

$$E = \frac{1}{2}\sum\nolimits_{\varrho}\left(\tau_{\varrho} - out_{\varrho}\right)^2 \tag{3}$$

Weights can be changed according to error using the formula in Equation.4

$$\Delta\omega\propto-\frac{\partial\text{E}}{\partial\omega} \tag{4}$$

Equation 5 updates the weight between a hidden layer and an output layer.

$$\Delta\text{ƥ}_{\vartheta,\varrho} = -\varepsilon\frac{\partial E}{\partial ⍱_{\vartheta,\varrho}} \tag{5}$$

As $⍱_{\vartheta,\varrho}$ cannot be calculated directly, so use the Equation. 6 formulae.

$$\Delta\text{ƥ}_{\vartheta,\varrho} = -\varepsilon\frac{\partial E}{\partial out_{\varrho}} \times \frac{\partial out_{\varrho}}{\partial net_{\varrho}} \times \frac{\partial net_{\varrho}}{\partial\text{ƥ}_{\vartheta,\varrho}} \tag{6}$$

where τ_{ϱ} represents the actual weight of ϱ as described in Equation. 7.

$$\Delta\text{ƥ}_{\vartheta,\varrho} = \varepsilon\left(\tau_{\varrho} - \text{out}_{\varrho}\right) \times \text{out}_{\varrho}\ \left(1 - \text{out}_{\varrho}\right)(\text{out}\vartheta) \tag{7}$$

Equations 8 and 9 describe how the weights b/w hidden-layer neurons and input-layer neurons are updated.

$$\Delta\tilde{\text{ʊ}}_{\text{i},\vartheta} \propto -\left[\sum\nolimits_{\varrho}\frac{\partial\text{E}}{\partial\text{out}_{\varrho}} \times \frac{\partial\text{out}_{\varrho}}{\partial\text{net}_{\varrho}} \times \frac{\partial\text{net}_{\varrho}}{\partial\text{out}_{\vartheta}}\right] \times[\frac{\partial\text{out}_{\vartheta}}{\partial\text{net}_{\vartheta}} \times \frac{\partial\text{net}_{\vartheta}}{\partial\tilde{\text{ʊ}}_{\text{i},\vartheta}}] \tag{8}$$

$$\Delta\tilde{\text{ʊ}}_{\text{i},\vartheta} = \xi\left[\sum\nolimits_{\varrho}(\tau_{\varrho} - out_{\varrho}) \times out_{\varrho}\,(1 - out_{\varrho}) \times \text{ƥ}_{\text{i},\vartheta}\right] \times out_{\varrho}\left(1 - out_{\varrho}\right) \times \omega_{\bar{\text{i}}} \tag{9}$$

The weights updating formula between hidden and output layer neurons is described in Equation.10.

$$\Delta\tilde{\text{ʊ}}_{\text{i},\vartheta}(\text{t}+1) = \tilde{\text{ʊ}}_{\text{i},\vartheta}(,\text{t}) + \lambda\ \Delta\tilde{\text{ʊ}}_{\text{i},\vartheta} \tag{10}$$

Once the training model has been successfully trained, it should be saved and validated with 30% of the remaining datasets. When results are saved, the output of the validation data is compared with the actual output and it is found that the prediction is 92.31%.

SVM generates a hyperplane that categorizes data based on classes. SVM categorizes diabetes symptoms into Positive and Negative [15], [17], [18]. Separating classes in a hyperplane begins by drawing a line. The line equation can be expressed in Equation.11.

$$\dot{\text{x}}_2 = \boldsymbol{a}\dot{\text{x}}_1 + \text{ƀ} \tag{11}$$

where $\boldsymbol{a}$ indicates the slope and b represents an intersecting point. Hence, it is written as follows:

$$\boldsymbol{a}\dot{\text{x}}_1 - \dot{\text{x}}_2 + \text{ƀ} = 0 \tag{12}$$

If $\dddot{\text{x}} = (\dot{\text{x}}_1, \dot{\text{x}}_2)^{\text{T}}$ & $\dddot{\omega} = (\boldsymbol{a}, -1)$, then Using the above expression, we can formulate an Equation. 13.

$$\dddot{\omega}.\dddot{\text{x}} + \text{ƀ} = 0 \tag{13}$$

Hyperplane equation can be used to analyze a three-dimensional vector. In Equation. 14, the vector of $\dddot{\text{x}} = (\dot{\text{x}}_1, \dot{\text{x}}_2)$ is represented by $\dddot{\omega}$.

$$\dddot{\omega} = \frac{\dot{\text{x}}_1}{\dot{\text{x}}} + \frac{\dot{\text{x}}_2}{\dot{\text{x}}} \tag{14}$$

In Equation.15, it is shown how n-dimensional vectors can be written.

$$\dddot{\omega}.\dddot{\text{x}} = \sum\nolimits_{i=1}^{\text{n}}\dot{\omega}_i\dot{\text{x}}_i \tag{15}$$

where, $i = 1, 2, \ldots, \text{n}$

Equation.15 enables to check whether the data has been classified correctly.

$$Đ_i = \acute{y}_i\left(\dddot{\omega}.\dddot{\text{x}} + \text{ƀ}\right)$$

Functional margins of datasets are referred to as $\dot{d}$ and are expressed as

$$\dot{d} = \min_{i=1\ldots m} \text{Đ}_i$$

The Geometric-Margin $\dot{d}$ of dataset provides the hyperplane that will be the optimal-hyperplane with the Lagrangian function

$$\text{Ɣ}\left(\dot{\omega}, \mathfrak{b}, \mathfrak{B}\right) = \frac{1}{2}\dot{\omega}\cdot\dot{\omega} - \sum_{i=1}^{m} \mathfrak{B}_i \left[\ddot{y}\left(\dot{\omega}.\dot{x} + \mathfrak{b}\right) - 1\right] \tag{16}$$

$$\nabla_{\dot{\omega}}\text{Ɣ}\left(\dot{\omega},\ \mathfrak{b}, \mathfrak{B}\right) = \dot{\omega} - \sum_{i=1}^{m} \mathfrak{B}_i y_i \dot{x}_i = 0 \tag{17}$$

$$\nabla_b \text{Ɣ}\left(\dot{\omega},\ \mathfrak{b}, \mathfrak{B}\right) = -\sum_{i=1}^{m} \mathfrak{B}_i y_i = 0 \tag{18}$$

After simplification, it can be written as

$$\dot{\omega} = \sum_{i=1}^{m} \mathfrak{B}_i y_i \dot{x}_i \quad \& \quad \sum_{i=1}^{m} \mathfrak{B}_i y_i = 0 \tag{19}$$

The Lagrangian function Ɣ is substituted.

$$\dot{\omega}\left(\mathfrak{B}, \mathfrak{b}\right) = \sum_{i=1}^{m} \mathfrak{B}_i - \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m} \mathfrak{B}_i \mathfrak{B}_j y_i y_j \dot{x}_i \dot{x}_j$$

Equation.20 can therefore also be used to define the above Equation.

$$\max_{\mathfrak{B}} \sum_{i=1}^{m} \mathfrak{B}_i - \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m} \mathfrak{B}_i \mathfrak{B}_j y_i y_j \dot{x}_i \dot{x}_j \tag{20}$$

where $i = 1, 2, 3, \ldots, m$

To avoid containment inequalities, apply the KKT (Karush-Kuhn-Tucker) condition to the Lagrangian multiplier procedure.

$$\mathfrak{B}_i \left[y_i \left(\dot{\omega}_i \cdot \dot{x}^* + \mathfrak{b}\right) - 1\right] = 0 \tag{21}$$

where $\dot{x}^*$ represents an optimum point, and the value for $\eth$ is positive; while for other points, it is nearly zero. Accordingly, the equation can be written as Equation.22.

$$\left[y_i \left(\dot{\omega}_i \cdot \dot{x}^* + \mathfrak{b}\right) - 1\right] = 0 \tag{22}$$

The points nearest the hyperplane are also known as support vectors. Based on Equation 23,

$$\dot{\omega} - \sum_{i=1}^{m} \mathfrak{B}_i y_i \dot{x}_i = 0 \tag{23}$$

In other words, it can be written as

$$\dot{\omega} = \sum_{i=1}^{m} \mathfrak{B}_i y_i \dot{x}_i \tag{24}$$

Equation. 24 gets the value of b when we compute it.

$$y_i\left[\left(\dot{\omega}_i \cdot \dot{x}^* + \mathfrak{b}\right) - 1\right] = 0 \tag{25}$$

Both sides of the equation are multiplied by y_i

$$y_i^2\left[\left(\dot{\omega}_i \cdot \dot{x}^* + \mathfrak{b}\right) - 1\right] = 0 \tag{26}$$

It is known that $y_i{}^2$ equals 1.

$$\mathfrak{b} = y_i - \left[\dot{\omega}_i \cdot \dot{x}^*\right] \tag{27}$$

$$\mathfrak{b} = \left\{\frac{1}{\text{Ś}}\sum_{i=1}^{\text{Ś}} \left(y_i - \left[\dot{\omega}.\ \dot{x}\right]\right)\right. \tag{28}$$

Equation.27 determines no. of support vectors Ś, and predictions that are made based on the hyperplane.

In Equation.28, the hypothesis function is described where $\dot{\omega}_i$ represent the optimum weight.

$$H\left(\dot{\omega}_i\right) = \begin{cases} +\mathbb{1} & if\ \left(\dot{\omega}_i.\dot{x} + \mathfrak{b}\right) \geq \mathbb{0} \\ -\mathbb{1} & if\ \left(\dot{\omega}_i.\dot{x} + \mathfrak{b}\right) < \mathbb{0} \end{cases} \tag{29}$$

When points are above to the hyperplane, i.e. $+\mathbb{1}$, represents diabetes positive, and points are below to the hyperplane, i.e. $-\ \mathbb{1}$, represents diabetes negative. We used the same dataset with SVM as well as with ANN. The data is trained by using and optimizing all of the available parameters of SVM in Matlab R2020a. The five-fold cross-validation process splits data into five levels and validates them accordingly.

Fuzzy logic uses membership functions. The fuzzy system uses SVM and ANN outputs as input variables. Membership functions define the set of rules that apply to both inputs and outputs. ANN and SVM used fuzzy logic to determine whether a patient's symptoms match a diabetes diagnosis or not. A mathematically fuzzy basis decision could be described as follows:

$$\zeta_{\text{ANN}} \cap \zeta_{\text{SVM}}\left(\text{ANN},\ \text{SVM}\right) = \min\left[\zeta_{\text{ANN}}\left(\text{ANN}\right),\ \ \zeta_{\text{SVM}}\left(\text{SVM}\right)\right] \tag{30}$$

The membership function of ANN is defined as ζ_{ANN} and that of SVM as ζ_{SVM}. According to the results, the outcome parameters for ANN and SVM are either 0 or 1.Two possible outcomes of each model produce four rules sets, which are given below.

- If the ANN model result is Positive (0) and SVM model result is Positive (0), then diabetes is Positive (0).
- If the ANN model result is Positive (0) and SVM model result is Negative (1), then diabetes is Positive (0).
- If the ANN model result is Negative (1) and SVM model result is Positive (0), then diabetes is Negative (1).
- If ANN model result is Negative (1) and SVM model result is Negative (1), then diabetes is Negative (1).

The individual prediction of ANN and SVM in terms of positive or negative is sent to the module of fuzzy logic, which consists of four rules (discussed above) reflected in fuzzy membership function in Table 1, where $\ddot{\mathfrak{Z}}$ reflects SVM membership function and $\mathfrak{Y}$ reflects ANN membership function. The fuzzy logic incorporates the decision level fusion for final prediction that whether the patient is diabetic or not. An algorithm for fuzzy inference can be expressed by $\bar{\text{R}}\,\ddot{\text{u}}^{\text{e}}$ which can be described as

$$\bar{\text{R}}\,\ddot{\text{u}}^{\text{e}} = \ddot{\mathfrak{Z}}^{\text{e}} \times \mathfrak{Y}^{\text{e}} \tag{31}$$

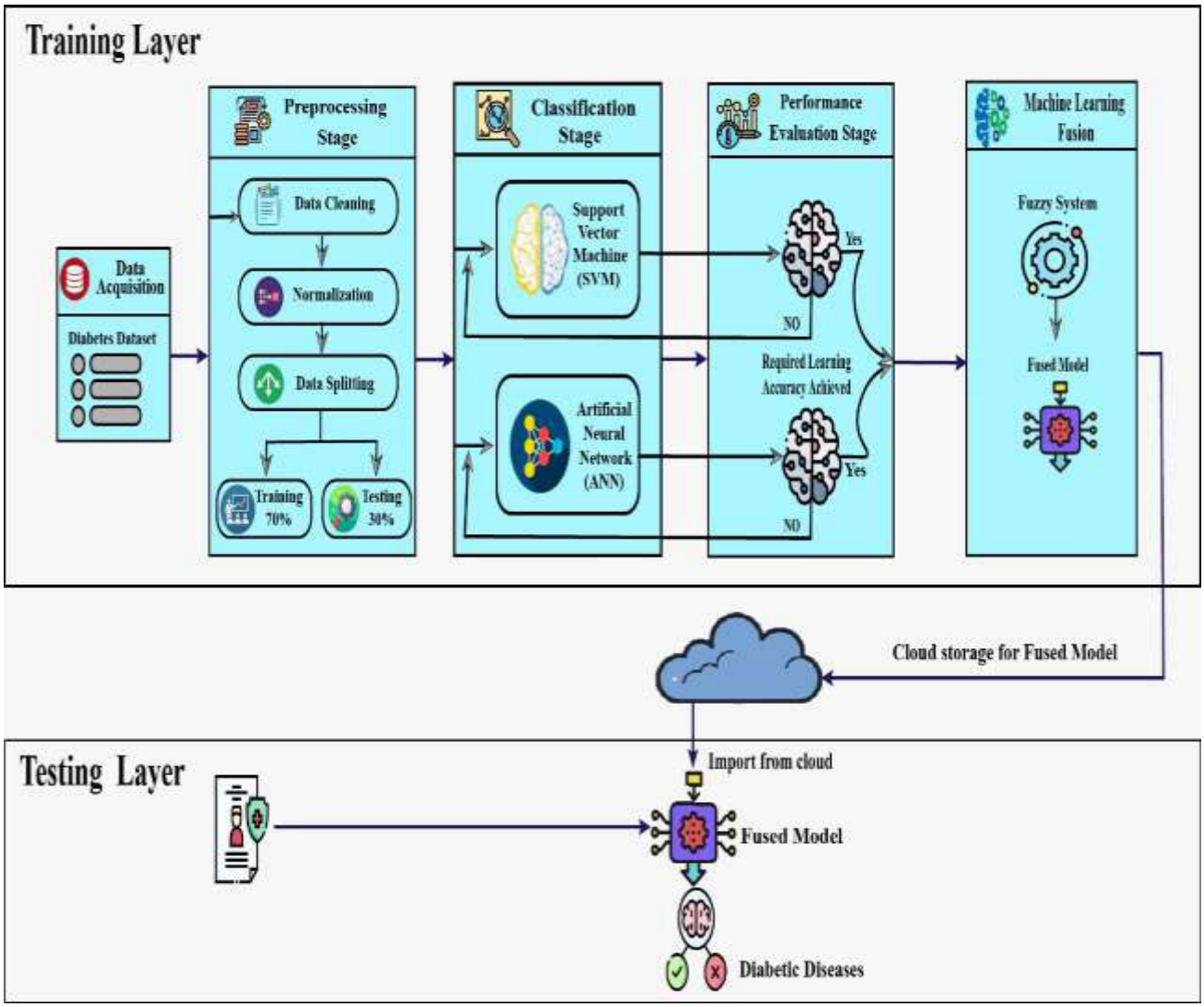


FIGURE 1. Proposed fused model for diabetes prediction (FMDP).

$$\zeta_{\text{ANN}\cap\text{SVM}} = \zeta_{SVM}\left(\breve{\mathfrak{Z}}\right) \cap \zeta_{ANN}\left(\mathfrak{H}\right) \tag{32}$$

Fuzzy relation $\mathcal{Q}_4$ is defined using the rules.

$$\mathcal{Q}_4 = \bigcup_{\dot{\mathfrak{e}}=1}^{4} \bar{\mathrm{R}}_{\cdot\,\cdot\,\cdot}^{\mathrm{e}}\,\mathrm{u}_{\cdot\,\cdot\,\cdot} \tag{33}$$

$$\zeta_{\ddot{\mathrm{R}}}(Decision) = \max_{1<\dot{\mathrm{x}}<4}\left[\prod_{\mathfrak{g}=1}^{4}\left(\zeta_{ANN_{\mathfrak{H}}}\zeta_{SVM_{\breve{\mathfrak{Z}}}}\right)\right] \tag{34}$$

A de-fuzzier can be applied using various types of methods like the center-of-area method (COA), the weighted average method; the mean of maxima method (MOM), and maximum-membership principle but the proposed model applies the centroid method de-fuzzier. The interface engine produces fuzzy output that is transformed using similar functionalities as the fuzzier to generate frangible output. Crisp points are discussed in Equation 35.

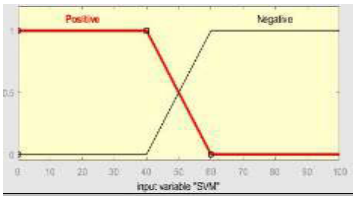
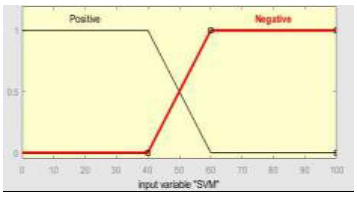
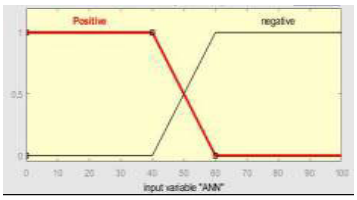
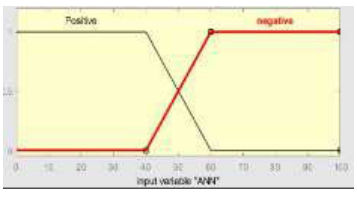
$$\mathcal{F} = \frac{\int_{\ddot{\mathrm{R}}} \zeta_{\ddot{\mathrm{R}}}\left(\dot{\ddot{\mathrm{R}}}\right) \mathrm{d}\ddot{\mathrm{R}}}{\int \zeta_{\ddot{\mathrm{R}}}\left(\dot{\ddot{\mathrm{R}}}\right) \mathrm{d}\ddot{\mathrm{R}}} \tag{35}$$

The graph in figure 2 describes that the x and y axes correspond to SVM and ANN, while z indicates the FMDP system. The FMDP System rule surface of diabetes can be seen in comparison to ANN and SVM results. The resultant FMDP System predicts no diabetes if both solutions predict no diabetes; And if both models predicts diabetes as yes then FMDP also predicts diabetes as yes.

Figure 3 shows that if ANN diagnoses yes (0) diabetes and SVM diagnoses no (1) diabetes, then the fused model also diagnoses yes (0) diabetes.

Figure 4 shows that if ANN diagnoses no (1) diabetes and SVM diagnose no (1) diabetes, then the fused model also diagnoses no (1) diabetes.

TABLE 1. Fuzzy membership functions of FMDP system.

$\mathrm{SVM}_{(\zeta_{\mathrm{SVM}(\ddot{\mathfrak{z}})})}$	$\zeta_{(\mathrm{Positive})}(\ddot{\mathfrak{z}}) = \left\{\max\left(\min\left(1, \frac{60-\ddot{\mathfrak{z}}}{20}\right), 0\right)\right\}$	
$\mathrm{SVM}_{(\zeta_{\mathrm{SVM}(\ddot{\mathfrak{z}})})}$	$\zeta_{(\mathrm{Negative})}(\ddot{\mathfrak{z}}) = \left\{\max\left(\min\left(\frac{\ddot{\mathfrak{z}}-40}{20}, 1\right), 0\right)\right\}$	
$\mathrm{ANN}_{(\zeta_{\mathrm{ANN}(\mathfrak{h})})}$	$\zeta_{(\mathrm{Positive})}(\mathfrak{h}) = \left\{\max\left(\min\left(1, \frac{60-\mathfrak{h}}{20}\right), 0\right)\right\}$	
$\mathrm{ANN}_{(\zeta_{\mathrm{ANN}(\mathfrak{h})})}$	$\zeta_{(\mathrm{Negative})}(\mathfrak{h}) = \left\{\max\left(\min\left(\frac{\mathfrak{h}-40}{20}, 1\right), 0\right)\right\}$	

In the proposed framework, the validation layer relates to the real-time diagnosis and classification of a diabetic. The proposed fused ML model can use real-time patient data as input and improve the disease detection system.

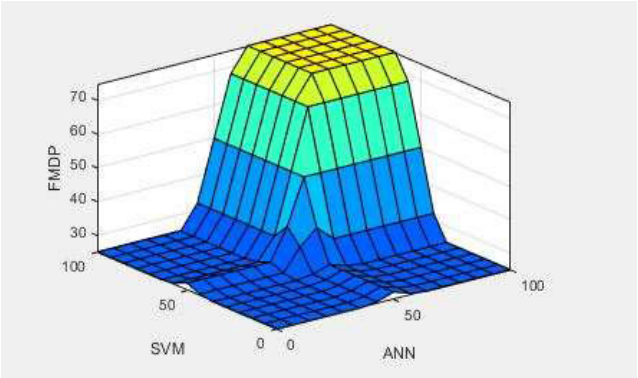


FIGURE 2. Proposed FMDP system rule surface.

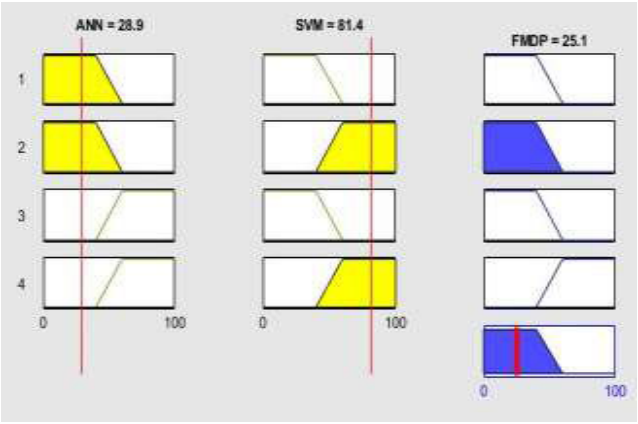


FIGURE 3. Proposed FMDP system result with diabetes (yes).

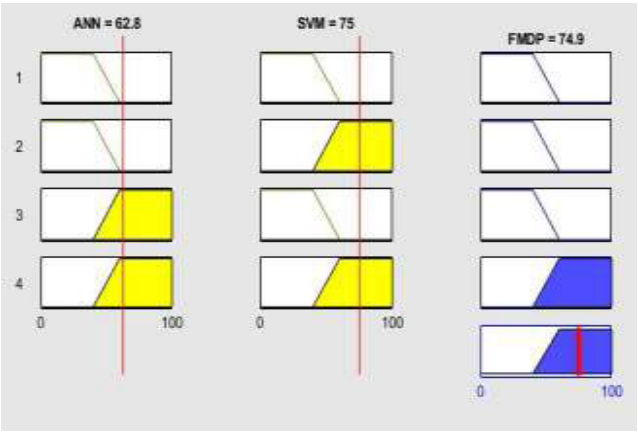


FIGURE 4. Proposed FMDP system result with diabetes (no).

IV. RESULTS AND DISCUSSION

To implement the proposed framework, we used a dataset [3] where the total number of instances is 520, and has 17 attributes based on diabetic symptoms. Sixteen features are independent, and one is the target feature (dependent). The target feature is labeled as the class, which has two values either 0 or 1. The class 0 represents that the person has diabetic symptoms (Positive) and class 1 represents that the person has no diabetic symptoms (Negative). The first feature of the dataset is Age in which 93 persons have age between 20 years to 35 years, 138 persons have age between 36 years to 45 years, 149 persons have age between 46 years to 55 years, 89 persons have age between 56 years to 65 years, and 51 persons are above 65 years. The second feature is Sex in which 382 are males and 192 are females. Male is reflected by "0" and Female is reflected by "1". The third feature is

TABLE 2. (Training) confusion-matrix for ANNs.

Input Values	Total= 364	Output Results: Positive $\dot{O}\dot{R}_0$	Output Results: Negative $\dot{O}\dot{R}_1$
	Positive ($\dot{E}\dot{R}_0$= 246)	236	10
	Negative ($\dot{E}\dot{R}_1$ = 118)	11	107

TABLE 3. (Testing) confusion-matrix for ANNs.

Input Values	Total= 156	Output Results: Positive $\dot{O}\dot{R}_0$	Output Results: Negative $\dot{O}\dot{R}_1$
	Positive ($\dot{E}\dot{R}_0$= 69)	61	8
	Negative ($\dot{E}\dot{R}_1$ = 87)	4	83

the Polyuria symptom, which has 258 values as ''yes'' and reflected by ''0'' and 262 values as ''no'', reflected by ''1''. The fourth feature is the Polydipsia symptom, which has 233 ''yes'' as ''0'' and 287 ''no'' as ''1''. The fifth feature is the Sudden weight loss symptom which has 217 ''yes'' as ''0'' and 303 ''no'' set to as ''1''. The sixth feature is the Weakness symptom, which has 305 ''yes'' set to ''0'' and 215 ''no'' set to ''1''. The seventh feature is the Polyphagia symptom, which has 237 ''yes'' set to ''0'' and 283 ''no'' set to ''1''. The eighth feature is the Genital Thrush symptom which has 116 ''yes'' set to ''0'' and 404 ''no'' set to ''1'' values. The ninth feature is the Visual Blurring symptom which has 233 values as ''yes'' and set to ''0'' and 287 as ''no'' set to ''1''. The tenth feature is the Itching symptom which has 253 as ''yes'' set to ''0'' and 267 has ''no'' set to ''1'' values. The eleventh feature is the Irritability symptom, which has 126 values as ''yes'' and set to ''0'' and 394 values as ''no'' set to ''1''. The twelfth feature is the Delayed healing symptom which has 239 ''yes'' values and set to ''0'' and 281 values as ''no'' set to ''1''. The thirteenth feature is the Partial paresis symptom which has 224 values as ''yes'' set to ''0'' and 296 values as ''no'' set to ''1'' v. The fourteenth feature is the Muscle stiffness symptom which has 195 values as ''yes'' set to ''0'' and 325 values ''no'' set to ''1''. The fifteenth feature is the Alopecia symptom, which has 179 values as ''yes'' set to ''0'' and 341 ''no'' set to ''1''. The sixteenth feature is the Obesity symptom, which has 88 ''yes'' set to ''0'' and 432 ''no'' set to ''1'' values.

In this article, MATLAB R2020a is used for simulation purposes. ANN and SVM are used for prediction, whereas fuzzy logic is used in decision-making. The dataset is divided into training and testing datasets with the ratio of 70:30. There are 364 instances, which are used in training of ANN and its confusion matrix is shown in Table 2.

Table. 2 describes the 246 positive cases, of which 236 cases were predicted accurately, whereas 10 cases were predicted incorrectly. However, there are 118 negative cases, of which 107 cases are predicted accurately, whereas 11 cases are predicted incorrectly.

There are 156 instances in testing data. The confusion matrix of ANN testing is shown in Table 3.

Table. 3 describes the 69 cases with positive diabetes, of which 61 cases predicted accurately, whereas 8 cases are predicted incorrectly. However, there are 87 cases of Negative diabetes, of which 83 cases are predicted accurately, whereas 4 cases are predicted incorrectly.

TABLE 4. (Training) confusion-matrix for SVMs.

Input Values	Total= 364	Output Results: Positive $\dot{O}\dot{R}_0$	Output Results: Negative $\dot{O}\dot{R}_1$
	Positive ($\dot{E}\dot{R}_0$ = 246)	227	19
	Negative ($\dot{E}\dot{R}_1$= 118)	13	105

TABLE 5. (Testing) confusion-matrix for SVMs.

Input Values	Total= 156	Output Results: Positive $\dot{O}\dot{R}_0$	Output Results: Negative $\dot{O}\dot{R}_1$
	Positive ($\dot{E}\dot{R}_0$ = 69)	59	10
	Negative ($\dot{E}\dot{R}_1$= 87)	7	80

TABLE 6. (Testing) confusion-matrix for FMDP.

Input Values	Total= 156	Output Results: Positive $\dot{O}\dot{R}_0$	Output Results: Negative $\dot{O}\dot{R}_1$
	Positive ($\dot{E}\dot{R}_0$= 69)	64	**5**
	Negative ($\dot{E}\dot{R}_1$ = 87)	3	84

We have used five-fold cross-validation for SVM. The confusion matrix of SVM training is shown in Table 4.

Table. 4 describes the 246 cases of positive diabetes, of which 227 cases were predicted accurately, whereas 19 cases were predicted incorrectly. However, there are 118 cases of negative diabetes, of which 105 cases are predicted accurately, whereas 13 cases are predicted incorrectly. There are 156 instances, which are used in testing of SVM and its confusion matrix is shown in Table 5.

Table. 5 describes the 69 cases of positive diabetes, of which 59 cases were predicted accurately, whereas 10 cases were predicted incorrectly. However, there are 87 cases of negative diabetes, of which 80 cases predicted accurately, whereas 7 cases were predicted incorrectly.

TABLE 7. Results of ANN, SVM, and proposed FMDP.

	SVMs Training	SVMs Testing	ANNs Training	ANNs Testing	FMDP Testing
Ǎccuracy	0.9121	0.8910	0.9423	0.9231	0.9487
Miss Rate	0.0879	0.109	0.0577	0.0769	0.0513
Ṡensitivity	0.9458	0.8939	0.9555	0.9385	0.9552
Ṡpecificity	0.8468	0.8889	0.9145	0.9121	0.9438
'Positive 'Prediction Vlaue	0.9228	0.8551	0.9593	0.8841	0.9275
Ṅegative'Prediction Vlaue	0.8898	0.9195	0.9068	0.9540	0.9655
Ḟalse 'Positive Rate	0.1532	0.1111	0.0855	0.0879	0.0562
Ḟalse Ṅegative Rate	0.0542	0.1061	0.0445	0.0615	0.0448
Ḟ1 Ṡcore	0.9342	0.8741	0.9574	0.9104	0.9412

TABLE 8. Comparison of FMDP with state-of-the-art techniques.

Authors/Papers	Approach	Accuracy (%)	Miss Rate (%)
S. Kumari et al [5]	Ensemble soft voting classifier	79.08 %	20.92%
M. A. Sarwar et al [6]	KNN & SVM	77%	23%
S. K. Dey et al [7]	ANN with Min-Max scaling	82.35 %	17.65%
A. Mir et al [8]	SVM	79.13%	20.87%
S. Saru et al [9]	Decision Tree after bootstrapping	94.4%	5.6%
P. Sonar et al [10]	Decision Tree	85%	15%
S. Wei et al [11]	Deep Neural Network	77.86%	22.14%
M. F. Faruque et al [12]	Decision Tree	73.5%	26.5%
B. Jain et al [13]	Neural Network	87.88%	12.12%
Proposed Model	Fused ML Decision	94.87%	5.13%

Table. 6 reflects the confusion matrix of testing with proposed fused model. It reflects the 69 cases of positive diabetes, from which 64 were predicted accurately, whereas 5 were predicted incorrectly. On the other hand, there are total 87 cases of negative diabetes, of which 84 cases predicted accurately, and 3 cases were predicted incorrectly.

In the formulas given below, $\ddot{O}\dot{R}_0$, $\ddot{O}\dot{R}_1$, $\acute{E}\dot{R}_0$, and $\acute{E}\dot{R}_1$ reflect the predicted positive output, predicted negative output, expected positive results and expected negative results respectively.

$$\text{Ǎccuracy} = \frac{(\ddot{O}\dot{R}_0/\acute{E}\dot{R}_0 + \ddot{O}\dot{R}_1/\acute{E}\dot{R}_1)}{(\acute{E}\dot{R}_0 + \acute{E}\dot{R}_1)} \tag{36}$$

$$\text{M}'\text{iss Rate} = \frac{(\ddot{O}\dot{R}_1/\acute{E}\dot{R}_0 + \ddot{O}\dot{R}_0/\acute{E}\dot{R}_1)}{(\acute{E}\dot{R}_0 + \acute{E}\dot{R}_1)} \tag{37}$$

$$\text{'Positive 'Prediction Vlaue} = \frac{(\ddot{O}\dot{R}_1/\acute{E}\dot{R}_1)}{(\ddot{O}\dot{R}_1/\acute{E}\dot{R}_1 + \ddot{O}\dot{R}_0/\acute{E}\dot{R}_1)} \tag{38}$$

$$\text{Negative 'Prediction Vlaue} = \frac{(\ddot{O}\dot{R}_0/\acute{E}\dot{R}_0)}{(\ddot{O}\dot{R}_0/\acute{E}\dot{R}_0 + \ddot{O}\dot{R}_1/\acute{E}\dot{R}_0)} \tag{39}$$

$$\dot{\text{S}}\text{pecificity} = \frac{(\ddot{O}\dot{R}_0/\acute{E}\dot{R}_0)}{(\ddot{O}\dot{R}_1/\acute{E}\dot{R}_1 + \ddot{O}\dot{R}_0/\acute{E}\dot{R}_1)} \tag{40}$$

$$\text{Sensitivity} = \frac{(\ddot{O}\dot{R}_1/\acute{E}\dot{R}_1)}{(\ddot{O}\dot{R}_1/\acute{E}\dot{R}_0 + \ddot{O}\dot{R}_1/\acute{E}\dot{R}_1)} \tag{41}$$

$$\dot{\text{F}}\text{alse Discovery Rate} = \frac{(\ddot{O}\dot{R}_1/\acute{E}\dot{R}_0)}{(\ddot{O}\dot{R}_1/\acute{E}\dot{R}_0 + \ddot{O}\dot{R}_0/\acute{E}\dot{R}_0)} \tag{42}$$

$$\dot{\text{F}}\text{alse 'Positive Rate} = 1 - \dot{\text{S}}\text{pecificity} \tag{43}$$

$$\dot{\text{F}}\text{alse Ṅegative Rate} = 1 - \dot{\text{S}}\text{ensitivity} \tag{44}$$

$$\dot{\text{F}}1\dot{\text{S}}\text{core} = 2 * \frac{\text{'Positive 'Prediction Vlaue} * \dot{\text{S}}\text{ensitivity}}{\text{'Positive 'Prediction Vlau} + \dot{\text{S}}\text{ensitivity}} \tag{45}$$

The performance of both models (ANN and SVM) along with the proposed fused model is evaluated by using various accuracy measures as discussed above and reflected in Table.7. It can be seen that the proposed fused model performed better on testing data as compared to both of the used models (ANN, SVM).

The proposed fused model is also compared to previous published models and techniques in Table.8. It can be observed that the proposed fused technique outperformed al l of the other published techniques and achieved the accuracy of 94.87% and miss rate of 5.13%.

V. CONCLUSION

Though different models had been used for the prediction of diabetes, the accuracy of the proposed models in disease prediction has always been the main concern of researchers. Therefore, a new model is required in order to achieve higher prediction accuracy in diabetes prediction. This research

proposed a machine learning based diabetes decision support system by using decision level fusion. Two widely used machine learning techniques are integrated in the proposed model by using the fuzzy logic. The proposed fuzzy decision system has achieved the accuracy of 94.87, which is higher than the other existing systems. Through this diagnosis model, we can save several lives. Moreover, the death ratio of diabetes can be controlled if the disease is diagnosed and preventative measures are taken in early-stage.

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