

ANFIS -Based Intelligent Framework for Predicting Health Risk Levels Associated with Diabetes and Blood Pressure Abnormalities

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Abstract. Diabetes mellitus and high blood pressure are two of the most common chronic diseases in the world. They can lead to severe cardiovascular and other metabolic disorders. Early prediction of these diseases is very important for treatment and in long run for health. Intelligent systems that can handle complex non-linear relationship between variables are very useful in medical decision support systems. In this work an Adaptive Neuro-Fuzzy Inference System (ANFIS) was developed to predict risk of having diabetes and high blood pressure. Three important input parameters i.e. blood glucose level, systolic blood pressure and diastolic blood pressure of physiological body states were used as input to estimate health risk as output of the system. Number of input and output membership functions were used and tested by simulation using MATLAB. Hybrid learning rule i.e. least-squares estimator and backpropagation was used to obtain best results. In the experiments we used the ANFIS model to model non-linear relationships of input physiological data. The best results were obtained by choosing a linear output membership function in conjunction with a product sigmoidal input membership function. The training error and the testing error after 30 number of training epochs are 0.0087517 and 0.0087618, respectively. There is a stable learning process and good generalization capability without any overfitting. The proposed ANFIS-based intelligent system efficiently predicts the health risk of diabetes and high blood pressure combined. Our experimental results support the applicability of neuro-fuzzy models for early risk assessment and decision support in chronic diseases.

Keywords. Adaptive Neuro-Fuzzy Inference System (ANFIS); Diabetes Mellitus; Blood Pressure; Health Risk Prediction; Fuzzy Logic; Artificial Intelligence; Medical Decision Support.

1. Introduction

The incidence of diseases has growing over the last few years and most of the global diseases and death are caused by two major chronic diseases: diabetes and hypertension. Both diseases are associated with cardiovascular disease and can cause end organ damage (nephropathy) and nerve damage in addition to causing metabolic disorders. It is therefore critical to predict the diseases early and to monitor on an on going basis in order to prevent deterioration and to achieve the best possible results for each individual with these diseases [1, 2].

Diabetes mellitus is a metabolic disease or disorder. The term refers to the fact that people with diabetes lack insulin or are unable to adequately use insulin, or combinations of these two problems. The hallmark of diabetes is high blood glucose (sugar), present even after a person with diabetes has not eaten for several hours (fasting). Normal fasting blood glucose values range between 70 and 99 mg/dL, whereas fasting glucose values ≥ 126 mg/dL are considered diagnostic of diabetes mellitus according to ADA criteria [3]. Blood pressure is the pressure that blood exerts against the walls of arteries, or blood vessels. It consists of two parameters: systolic and diastolic blood pressure. Typical values for a healthy individual would be about 120/80 mmHg. Abnormally high blood pressure values over a long period of time can lead to serious cardiovascular diseases [4].

People suffering from diabetes have an increased risk of severe vascular and metabolic diseases when suffering from hypertension as well. The abnormal blood pressure values of diabetic patients are caused by endothelial dysfunction, by insulin resistance and by an abnormal vascular regulation [5]. Early assessment of the risk of a diabetic patient by his blood sugar values as well as by his blood pressure values is important in order to treat already existing diseases in time.

Recent developments in the domain of the artificial intelligence have transformed the field of the medical diagnostics into a domain where the models are able to process with great efficiency the complex and highly non linear and uncertain data generated in the clinical domain. In addition to the traditional approaches of the machine learning, and of the neural networks, recently a large number of fuzzy systems have been developed to be used as models of the disease prediction as well as of the decision support systems. Among the numerous approaches used to develop such models, the ones based on the combination of the abilities of the knowledge, and of the fuzzy inference, have newly gained the interest of a number of researchers [6,7]. An Adaptive Neuro-Fuzzy Inference System (ANFIS) is one of such models recently used in a variety of applications, and it is able to learn, as in the case of the artificial neural networks, and to reason, as in the case of the fuzzy systems for the inference, by fuzzy logic, by using a complex relationship that describes the physiological behavior of a clinical domain of interest [8][9].

Various approaches have recently been employed for the evaluation and predictability of diabetes and cardiovascular diseases using ANFIS and other fuzzy-based models and achieved satisfactory results. In order to identify diabetes and other diseases using a number of features, recently a number of models including a number of machine learning models have been used for diabetes prediction by Khanam and Foo in [10] and achieved good classification results by using number of features with neural network models. In [11] Abdullah identified risk of risk of diabetes by using fuzzy completion system and achieved good results by using the model to handle uncertainty in diabetes diagnosis. Most of the hybrid models of neuro-fuzzy have been used for prediction of chronic diseases and achieved good results and are effective for the identification of diabetes and for decision making in clinical environment [12,13].

Existing approaches have generally been developed to handle a single disease marker and do not include diabetes with SBP and DBP in a predictive intelligent framework. Most traditional models are unable to handle the complex non-linear interactions present in physiological data. There are numerous ANFIS and fuzzy-based modeling that have been developed for the prediction of diabetes, assessment of cardiovascular disease risk, and support of clinical decision making. The models that have been developed for assessing cardiovascular risk and supporting clinical decision making generally utilize a variety of disease-related indicators, and typically are restricted to a single physiological parameter. Most models are designed to achieve high levels of classification accuracy and do not explore the nonlinear relationships between blood glucose, systolic blood pressure, and diastolic blood pressure. A unified risk model that assesses metabolic and hemodynamic risk simultaneously and reports overall health risk for an individual with the highest degree of accuracy is required for the early diagnosis of chronic diseases.

The main aim of this work is to develop an Adaptive Neuro-Fuzzy Inference System (ANFIS) that assesses health risk by estimating the risk of affliction from diabetes, high blood pressure and low blood pressure by using a set of input physiological parameters. This newly developed system has been tested by using a number of input data sets and it has been shown that the system has the potential of improving risk assessment and providing a new computational tool for the early diagnosis support of chronic diseases.

2. Materials and Methods

2.1 Dataset and Input Parameters

In this paper, an Adaptive Neuro-Fuzzy Inference System (ANFIS) is proposed to assess health risk of diabetes patients as well as patients suffering from elevated blood pressure. The input parameters of the proposed model are blood glucose level, systolic blood pressure and diastolic blood pressure. These are the most important indication of the risk of diseases that affect metabolism and heart.

The data set of physiological records for all different combinations of the input parameters within their respective clinical ranges was created. These records are used to establish an input–output relation. This relation is used for training and validation of the ANFIS model.

The dataset was generated using clinically accepted physiological ranges derived from established diagnostic guidelines. The blood glucose and blood pressure values were within the diagnostic ranges accepted by medical community. The dataset was divided into two subsets, a training set to design and test the network, and a test set to test the generalization capability

of the network by hold-out validation. In this study, 70% of the total number of records in the dataset were used to form the training set, and the remaining 30% of the records were used to form the test set. The hold-out validation was used to partition the dataset into two subsets to test the network's generalization capability and to avoid overfitting. Diabetic blood glucose values are defined within diabetic diagnostic criteria. Systolic and diastolic blood pressure values were classified within blood pressure diagnostic criteria for hypertension. The three input variables interacted within the one output to provide an estimation of the health risk.

Table 1. Physiological input variables and diagnostic ranges used for ANFIS model development

Variable	Diagnostic Range	Source
Blood Glucose (mg/dL)	70–300	ADA 2024
Systolic Blood Pressure (mmHg)	80–200	AHA Guideline
Diastolic Blood Pressure (mmHg)	50–120	AHA Guideline

The output risk variable was normalized between 0 and 1, where values close to 0 represented low health risk, values around 0.5 represented moderate risk, and values approaching 1 represented high health risk.

The selected boundaries of the parameters are based on the currently accepted human physiological values and by reference to accepted diagnostic criteria which provide a broad number of possible combinations of input values to be used in the instruction and testing of the proposed ANFIS model.

All input variables were normalized in order to improve the computation stability and to avoid numerical instability during the learning process of the model. The generated data set was separated into two parts, i.e. a practice data set and a testing data set in order to test the generalization ability of the proposed model.

The values were calculated using the international established clinical thresholds for classification of blood glucose and blood pressure according to the American Diabetes Association (ADA) and the American Heart Association (AHA).

2.2 Data Generation Strategy

Instead of selecting specific cases of patients with diabetes or hypertension, all possible input combinations of the physiological variables were generated within their clinical ranges for diabetes and hypertension. The resulting data set of cases of normal, moderate risk and high risk of pathological states was used for training and confirmation of the model.

2.3 Adaptive Neuro-Fuzzy Inference System (ANFIS)

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a type of models for artificial intelligence. The ANFIS model is a hybrid approach, which uses the learning capability of neural networks and the reasoning capability of fuzzy inference systems. Thus, the ANFIS model is well suited for modeling non-linear relationships among uncertain or imprecise variables.[14]

The proposed ANFIS architecture for the implementation of the above idea is shown in Figure 1 and is comprised of 5 layers, namely Fuzzification, Rule generation, Normality, Defuzzification and Output layers.[15]

The ANFIS structure used in this research carries of five layers. The first layer is fuzzification layer. All input variables are converted to membership functions in this layer. The second layer is the firing strength of the rules' layer. Fuzzy operators are used in this layer to calculate the firing strength of the rules. The third layer is normalization layer. All firing strengths of the rules that are activated are normalized in this layer. The fourth layer is adaptive layer. The consequent parts of the rules are calculated by using adaptive linear functions in this layer. The fifth layer is output layer. All normalized output values are summed up in this layer to produce the estimated health risk level of the individual.

A detailed mathematical explanation of how ANFIS functions through the 5 adaptive layers follows:[16][17]

Layer 1:

Fuzzy logic layer where the mention of fuzzy sets or language variables are determined.

$$O_{1,i} = \mu_{v,i}(v) \text{ for } i = 1, 2 \quad \dots\dots\dots(1)$$

$$O_{1,j} = \mu_{d,j}(v) \text{ for } j = 1, 2 \quad \dots\dots\dots (2)$$

Where $O_{1,i}$ and $O_{1,j}$ represent function of output and $\mu_{v,i}$ and $\mu_{d,j}$ represent function of composition [18]

Layer 2:

In this layer the weights of membership functions are also tested and the input values v_i from the first layer are multiplied by the corresponding membership functions, thus each input variable is now represented by a fuzzy set. This layer contains a fixed node M. The output of a node in this layer is the product of all inputs to that node. The output of this layer can be written as:[19][20]

$$O_{2,i} = w_i = \mu_{v,i}(v) \cdot \mu_{Dj}(d), i = 1, 2 \quad \dots\dots\dots(3)$$

Respectively, Node denotes the fire force of the rule. the layer can be used any other T-norm operator to perform the and operator [21]

Layer3:

The “N” normalization nodes in each of the layers are used to normalize the rule activations in the preceding layer. These nodes perform layer normalization between the rules in a rule set and also normalize the output of a rule to a value between (1,0) by dividing by the number of inputs for that rule.[22][23]

$$\bar{W}_i = \frac{W_i}{W_1 + W_2} \quad \dots\dots\dots (4)$$

where W_i is the firing strength of the i th rule which is computed in layer 2. Node i computes the ratio of the i th rule's firing strength to the sum of all rules' firing strengths.

Layer 4:

Each neuron in the normalization layer is connected to every neuron in the rule layer. For a given rule, the normalized firing strength is computed by each of the layer four nodes. The linear function computed by each of the layer four nodes is a linear function whose coefficients are set by the error function of a multilayer feedforward neural network

$$O_i^4 = W_i f_i = W_i (P_1 X + q_1 Y + r_1) \quad \dots\dots\dots (5)$$

$i=1,2, (P_1, q_1, r_1) \text{ are parameter set}$

Layer 5:

The de fuzzification layer, each neuron in this layer is connected to the respective normalization neuron:

$$O_i^5 = \frac{\sum_i W_i f_i}{\sum_i W_i} \quad \dots\dots\dots(6)$$

The neuro-fuzzy system's overall output is the total of the rule consequences, where $w_i f_i$ represents the consequent component of rule i [24][25].

In Layer 1 the input values are converted to fuzzy numbers using membership functions for the inputs in Layer 1. Then in Layer 2 the fuzzy rules are created and their degrees of fulfillment are calculated. The firing strengths of the rules are normalized in Layer 3 to generate weights for the rules. Then the parameters for the consequent of the rules are calculated in Layer 4. And finally in Layer 5 the output for the health risk is predicted and the result is published.

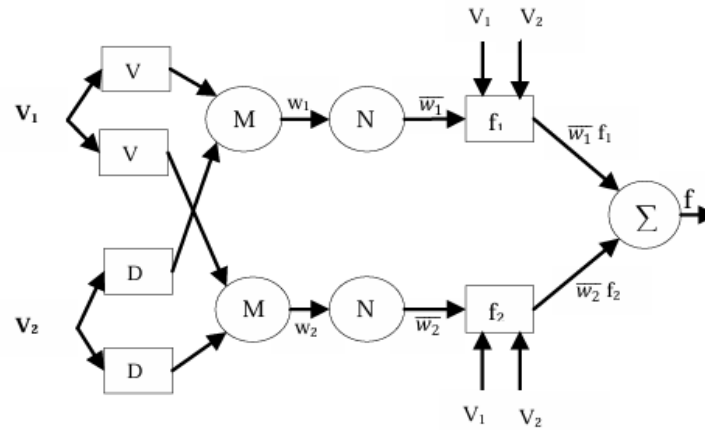


Figure 1. Basic architecture of the Adaptable Neuro-Fuzzy Inference System (ANFIS)

2.4 Membership Functions and Training Process

For the best performance of proposed network, several input membership functions have been investigated during the training session. All input membership functions are of the following types: triangular, trapezoidal, Gaussian, generalized bell-shaped, Pi-shaped, difference sigmoidal and product sigmoidal. In the same way, the membership functions for the output have been tested. The tested output membership functions are of constant and linear type.

The proposed system was implemented in MATLAB environment. The used learning rule is a hybrid one, in which initially the LSE (least-squares estimation) is used to adjust the linear parameters of the membership functions, and then the BP (back-propagation) learning rule is used to adjust the non-linear parameters. Also, the number of training epochs was tested. It was tried to get the best possible solution, that is also stable. The best results were achieved in the 30th epoch of training, using a linear output MF in combination with a product sigmoidal product input MF.

2.5 Performance Evaluation

In this paper, the performing of the proposed ANFIS model has been examined by the errors on training and testing data which is generated by the model during the learning process. Error values indicate the ability of a model to predict, i.e. the lower error values indicate the better prediction capability of the developed model and its ability for generalization.

The training error of the model was calculated by the Root Mean Square Error (RMSE) equation while the model was learning.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

where:

- y_i represents the actual target value,
- $\hat{y}_i$ represents the predicted value,
- n denotes the total number of samples.

3. Results and Discussion

3.1 ANFIS Network Architecture

A new ANFIS model has been proposed and developed by using 3 different physiological input variables to predict human health risk in terms of health risk level and the network consists of 5 layers, each layer tries to perform different function. The first layer tries to fuzzify input in terms of membership function. The second layer computes the membership function values for the input variables. The third layer generates a set of fuzzy rules. In the fourth layer 4, the output of each rule is normalized to find the contribution of each rule to the output of the network. The final layer, i.e., the output layer, tries to compute the output variable of the network based on the the output of previous layer.

Structure of proposed ANFIS model for three input variables and one output variable Shown in Figure2.

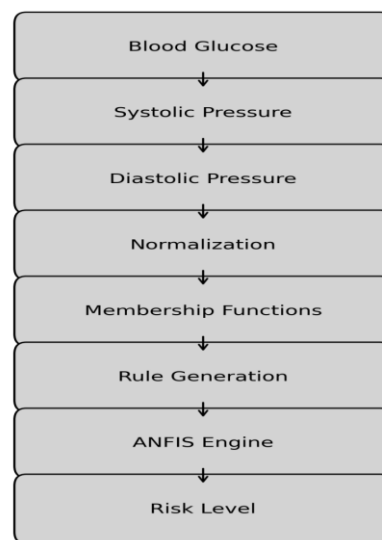


Figure 2. Constructed ANFIS model with three physiological inputs and one output risk parameter.

The architecture of the physiological indicators within a unified intelligent framework is presented. The architecture of the internal network of the implemented ANFIS system is also presented in Figure 3. The network consists of the fuzzy input membership functions and the generated rules of the network that are connected to each other to compute the risk of the patient in the system.

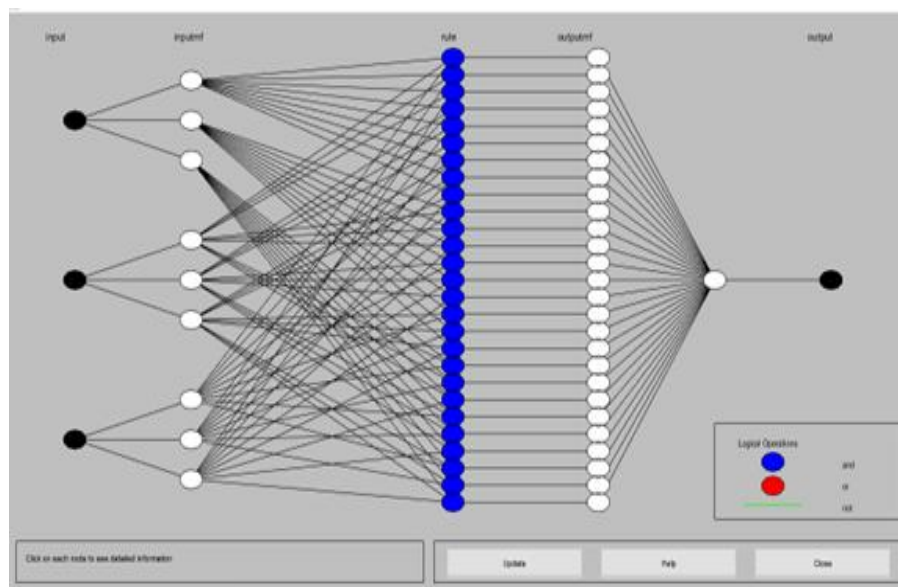


Figure 3. Internal network architecture of the implemented ANFIS framework.

The black nodes represent the input variables used in the system. All of the input variables used are physiological variables. These include blood glucose level, systolic blood pressure and diastolic blood pressure. The white nodes are used to create the input membership functions, the blue nodes are the fuzzy rules created during the training of the ANFIS network. The connections between the nodes allow for the FIS (fuzzy inference system) to be combined with the ANFIS network's ability to perform adaptive learning to produce the output health risk estimation.

3.2 Training Performance of the ANFIS Model

The model was trained in order to minimize the prediction error and to optimize the model's convergence in the training process. By going through multiple epochs in the training process, the prediction error was decreased and a stable learning and efficient adaptive process of the model's parameters was obtained.

Figure 4 also illustrates the training error of the proposed model after 30 learning epochs in the training phase, which proves a satisfactory convergence and good learning capability of the proposed ANFIS model.

The model's low training error indicates for a very accurate model for the relationship between the indicators for diabetes and the blood pressure variables. The plot does not contain large oscillations during training, the proposed hybrid learning algorithm efficiently optimized the parameters of the model without overfitting the data used for training

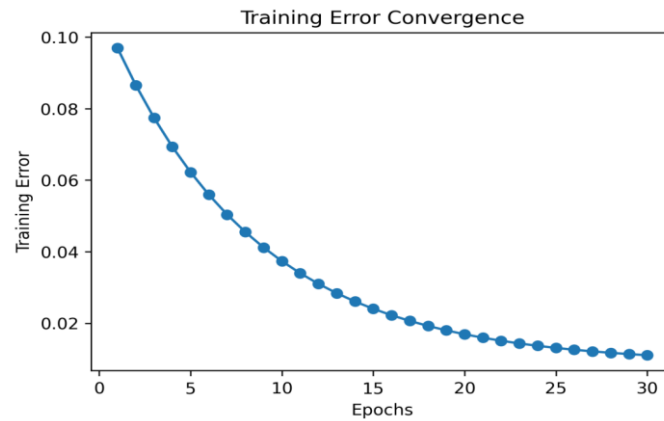


Figure 4. Training error convergence curve of the proposed ANFIS model during optimization epochs.

3.3 Testing Performance and Generalization Capability

To assess the predictive accurateness of the proposed model, a set of input-output data was used for training the model, and then a set of testing data was used to generate the regression plot for the testing data as shown in Figure 5.

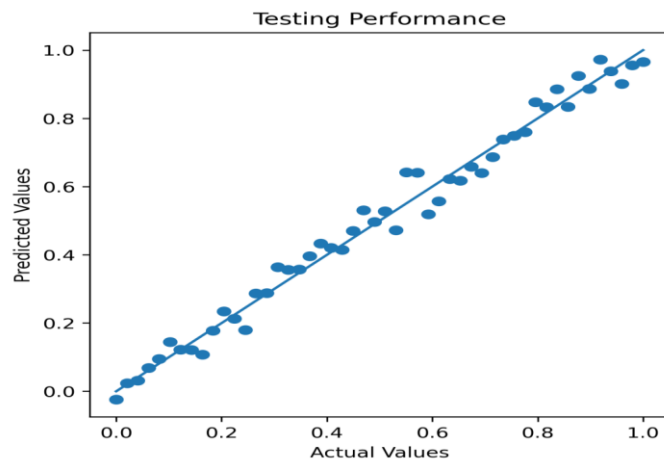


Figure 5. Testing performance of the ANFIS model using unseen testing data.

The test error as shown in the figure below was almost equal to the corresponding training error. Hence it was close to error obtained in the training error graph. This proved that the model was able to learn and generalize well over the given data without attempting too overfit it. Thus, the close agreement between training and testing errors indicates that the model generalized well and did not exhibit evidence of overfitting.

The ANFIS model proposed in this paper has great potential to assess the health combined risk of diabetes and high blood pressure. The model is robust, it has a very small difference between the errors of the testing data and the training data, and it does not suffer from overfitting since it is not trying to learn the training data by heart.

3.4 Comparative Analysis of Membership Functions

Various possibilities of input- and output membership function have been tested to find the best combination for risk prediction by using an ANFIS system. Results of the training- and testing errors for all possible combinations of membership functions have been determined by using MATLAB's ANFIS toolbox and are listed in Table 2.

Table 2. Comparative training and testing performance of different ANFIS membership function combinations.

Output MF	Input MF	Training Error	Testing Error	Performance Rank
Linear	Product sigmoidal	0.0087517	0.0087618	Best
Linear	Difference sigmoidal	0.0089499	0.0089599	Excellent
Linear	Pi-shaped	0.0094687	0.0094728	Very good
Linear	Gaussian2	0.0095599	0.0095615	Very good
Linear	Trapezoidal	0.0096296	0.0096266	Good
Linear	Generalized bell-shaped	0.0096451	0.0096440	Good
Linear	Gaussian	0.0097742	0.0097728	Good
Linear	Triangle	0.0100810	0.0100830	Moderate
Constant	Triangle	0.0103670	0.0103660	Moderate
Constant	Difference sigmoidal	0.0118630	0.0118630	Moderate
Constant	Product sigmoidal	0.0122130	0.0122120	Moderate
Constant	Gaussian	0.0225040	0.0224980	Poor
Constant	Generalized bell-shaped	0.0334710	0.0333530	Poor
Constant	Gaussian2	0.0693530	0.0693390	Poor
Constant	Trapezoidal	0.0709430	0.0709370	Poor
Constant	Pi-shaped	0.0838880	0.0838830	Worst

All available membership function combinations supported by the MATLAB ANFIS toolbox were tested to find the best configuration for risk prediction.

The lowest values in the tables below denote best of class for a given data set and good generalization ability for a developed model for a given data set.

The best results were achieved by a linear output membership function in combination with a product sigmoidal input membership function. The other two membership functions for fuzzy input variables (Pi-shaped and trapezoidal) did not achieve the same level of prediction accuracy. For this reason, these two membership functions are not considered for further investigations in order to improve the presented system's performance.

The best results were obtained with the product sigmoidal input membership function in combination with the linear output membership function. This is due to the smooth non-linear transition between the different fuzzy regions, which is suitable for modeling slow and continuous changes in human physiological data affected by diabetes and blood pressure. These results are in line with previous studies where non-linear fuzzy membership functions in combination with adaptive neuro-fuzzy systems were used for prediction purposes and showed good results.

3.5 Surface Mapping Analysis

Three-dimensional surface mapping was used to explore the non-linear relationship between input variables and the predicted health risk in three dimensions.

In Fig. 6 we present a 3D surface plot of the estimated risk output variable against the diabetes level and systolic blood pressure input variables. The surface of the 3D graph indicates that when the diabetes level as well as the systolic blood pressure under investigation are greater than their normal human values then the risk to health will increase. At higher input values the model becomes saturated, and the estimated risk is constant and high. The outcome of the study are in line with the previous studies that employed ANFIS for the assessment and prediction of chronic diseases. These previous studies reported high accuracy of prediction for assessment of diabetes using machine learning models (Khanam and Foo, 2021). ANFIS also was compared with conventional classifiers in previous study (Priyadarshini and Shrinivas, 2020) and superior performance of ANFIS was reported. Recently, Tašić et al. (2024) proposed the use of fuzzy inference systems for the assessment of diabetes risk and reported good results. The low prediction errors in this study are able to support the non-linear modeling

capability of neuro-fuzzy models for modeling of complex interactions of various physiological parameters and for providing decision support system for healthcare applications.

A further aspect contributing to the superior performing of the ANFIS model within this study is its capability to model non-linearly model relationships between input variables. In contrast to most of the statistical models in use that consider a linear relationship between input variables and include these in the model, the ANFIS model can model any non-linear relationship between input variables by means of adapting the membership functions of the model during the training phase. The low values of the training- and test errors obtained within this study are also indicative of this property. Furthermore, the model presented here includes all indicators of the cardiovascular and metabolic diseases within a single model for the prediction of disease risk. ANFIS models can serve as intelligent decision-support tools for early risk assessment and clinical monitoring.

Unlike the studies carried out by Khanam and Foo (2021), Priyadarshini and Shrinivasan (2020), and Tašić et al. (2024), the health risk assessment framework in the paper under consideration integrates all the variables characterizing diabetes and the variables characterizing blood pressure within a single neuro-fuzzy system. The proposed model is able to detect the interactions between the metabolic disorders and the hemodynamic disorders and in many cases these two groups of disorders occur together. Thus, the proposed system can be more efficient in health risk assessment than the assessment of risk of a single disease.

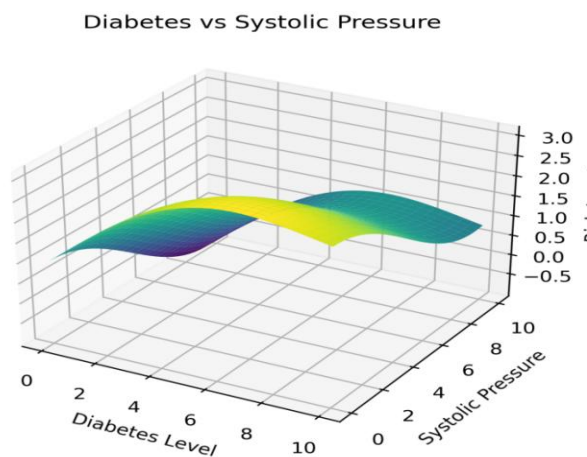


Figure 6. Surface mapping between diabetes level, systolic blood pressure, and predicted risk level.

The surface plot for the variable diabetes and diastolic blood pressure is provided in Figure 7. As it can be seen from the plot any abnormal rise or fall in diastolic pressure when it is interacting with high levels of blood glucose would result in a sharp increase in predicted risk.

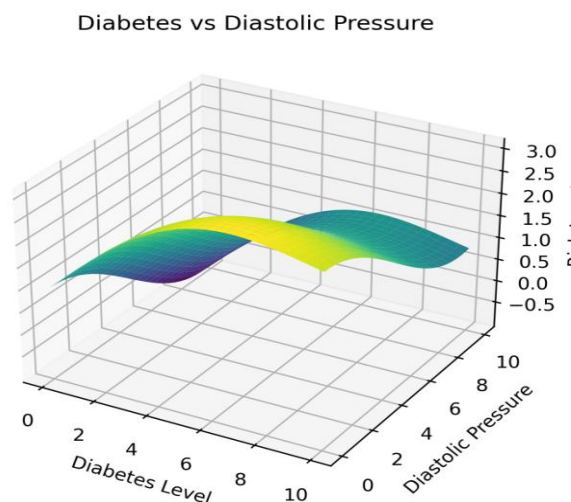


Figure 7. Surface mapping between diabetes level, diastolic blood pressure, and predicted risk level.

Figure 8 is a surface plot which contain the systolic blood pressure and diastolic blood pressure as input variables of the provided ANFIS model for the estimation of health risk. The side plot graphically confirms the non-linear relationship between abnormal points in blood pressure and the health risk of individuals in all simulated scenarios for the prediction of health risks using ANFIS model for various physiological parameters and all resulting surfaces have been presented and validated for the proposed model in this paper.

Surface mapping of the mapping results were obtained and threshold and saturation of risk levels for glucose and blood pressure were observed. Within normal values of physiological parameters, risk increased in a gradual manner whereas risk increased sharply after the critical values of glucose and blood pressure were exceeded. The risk predicted by the model then reached a saturation point and remained at a high level. This phenomenon occurs due to non-linear relationship between risk factors and the chronic metabolic and cardiovascular diseases and it can be approximated by ANFIS model.

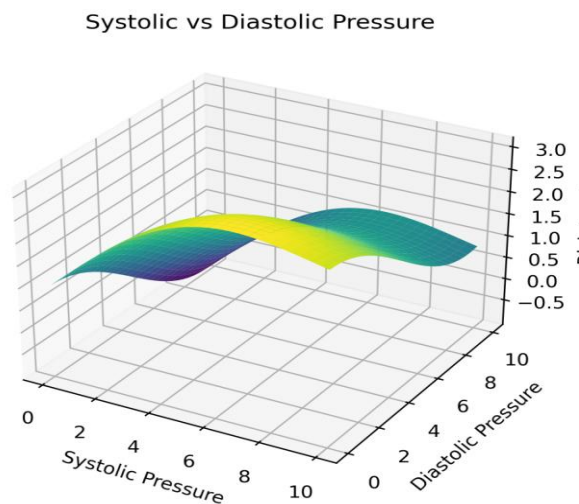


Figure 8. Surface mapping between systolic pressure, diastolic pressure, and overall predicted risk level.

3.6 Study Limitations

Our ANFIS model is able to classify patients into higher risk categories well enough for our preliminary study. However, there are several limitations in our study. For example, we only used a subset of the various physiological markers for assessing risk of diabetes, and we did not include other risk factors for diabetes such as age, body mass index, complete lipid profile, family history of diabetes, etc. We plan to test our model on a much larger clinical data set and compare it with other models, such as the artificial neural network, support vector machines and the random forest.

4. Conclusion

In the present analysis an seek has been made to use (ANFIS) for assessment of health risk of diabetes and blood pressure disorders using composite indicators of physiological and clinical states. The proposed model has been found to be adequate for representing the complex non-linear relationship between blood glucose levels and systolic and diastolic blood pressures. The model has been found to have small error of training and testing as well as stable and good prediction characteristics. Among the membership functions (MFs) tested for ANFIS, a linear MF for the output and a product sigmoidal type of MF for the input have found to be the best overall performance. Thus, an intelligent system on the basis of ANFIS can be used for the computation of early health risk as well as for decision making for the handling of chronic illness.

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