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ORIGINAL ARTICLE

Deep Neuro-Fuzzy Systems for Diabetes Prediction using Siddha Healthcare Practices with Algorithm Comparison

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Abstract

Background: Diabetes Mellitus (Type-2) is a common chronic metabolic disease has a high-risk factor for global health. Early detection is critical for effective management and the reduction of associated complications. Siddha medicine, an ancient Indian healthcare system, offers a unique diagnostic approach that includes pulse-based assessments to evaluate the balance of three fundamental principles: Vatha, Pitta, and Kappa. **Objective:** This research introduces a novel approach to diabetes prediction by combining Siddha healthcare practices with machine learning and deep learning techniques. **Method:** The method incorporates various machine learning algorithms, including Decision Tree Classifier (DT), Support Vector Machine Classifier (SVM), and Random Forest Classifier (RF), compared with the deep learning technique Artificial Neural Networks (ANN) with Deep Neuro Fuzzy System (DNFS). This study developed a dataset based on Siddha diagnostic principles to extract relevant features, which are then input into the classifiers for diabetes prediction. The effectiveness of each algorithm is assessed using multiple performance metrics, such as precision, recall, accuracy, F1-score, specificity, False Positive Rate (FPR), and True Positive Rate (TPR). **Findings:** The results demonstrate that ANN had the best performance of 90% on test accuracy and precision and recall of 88% and 91%, respectively and was very close to the RF and SVM. **Novelty:** This study also demonstrates the medications used in the Siddha medical system, and the concept of combining Siddha with modern deep-learning techniques to predict Diabetes is a useful resource for healthcare professionals.

Keywords: Diabetes Prediction; DNFS; Healthcare; Siddha Practices; SVM; Random Forest; Manikkadainool; Decision Tree Classifier; Artificial Neural Network; Deep Learning

1 Introduction

Breakthrough in technologies like Machine Learning (ML), Artificial Neural Networks (ANN), Artificial Intelligence (AI), and Deep Learning (DL) have transformed problem-solving approaches across various fields, including healthcare and engineering. These innovations have brought new practical approaches to the analysis, including fuzzy logic programming, genetic learning algorithms, and enhanced fusion techniques as the neuro-fuzzy systems. Among these developments, one of the most promising is the Deep Neural Network (DNN) which have turned out to be decisive in extracting features of data. DNN have outperformed conventional machine learning in numerous applications[(1)]. The layered structure of DNN combines with fuzzy allows for the heterogeneous embedding of networks feature representation learning from raw data, handling imprecise data. This capability makes them ideal for solving real-life problems[(2)]. However, a few key issues are associated with DNNs: computational complexity, inability to converge to the global minimum, local minima, and black box issue[(3)]. Such limitations have been a reason for including DNNs with other systems like Fuzzy Logic (FL) to develop better systems whose description takes less time.

Fuzzy Logic deals with uncertainty and imprecision, which makes it potential for decision-making strategies that conventional zero or one cannot handle[(4)]. Hybrid Deep Neuro-Fuzzy Systems (DNFS) solves these problems by integrating features of deep networks and fuzzy rules systems. This integration has been explored across various fields, with DNFS models demonstrating higher accuracy and reduced opacity, particularly in healthcare[(2)].

Diabetes Mellitus is a common chronic metabolic disease has a high-risk factor for global health. Early detection is critical for effective management and the reduction of associated complications. Siddha medicine, an ancient Indian healthcare system, offers a unique diagnostic approach that includes pulse-based assessments to evaluate the balance of three fundamental principles: Vatha, Pitta, and Kappa[(5)]. Combining Siddha principles for diabetes prediction with cutting-edge deep learning techniques presents a novel path for developing accurate and reasonable systems. Manikkadainool (MK), a diagnostic tool in Siddha disease diagnostics, uses wrist circumference and fingerbreadth measurements to compute the values that predict the disease[(6)].

Considering these factors, a new DNFS incorporating deep learning for feature extraction and the Siddha diagnostic framework for Classification could achieve high accuracy and explainability. However, a degree of integrated practice of DNFS with Siddha healthcare remains possible with further empirical validity and effectiveness study. This research aims to fill the knowledge gap by acknowledging the potentiality of applying DNFS in the context of diabetes prediction within the Siddha framework to determine the applicability, accuracy and utility of the Siddha framework[(7)].

The main objectives of this study are:

1. To create a robust feature extraction method using Deep Neuro-Fuzzy Systems (DNFS) to identify key diagnostic patterns based on Siddha healthcare principles.
2. To develop an improved classification system for the prediction of Diabetes by integrating DNFS to improve its predictive capacity and productivity.
3. The proposed method performance is evaluated against established techniques like Support Vector Machine (SVM), Random Forest (RF), and Decision Tree Classifier, and it is compared with Artificial Neural Network (ANN).
4. To test the proposed system through extensive experiments using physiological datasets incorporating Siddha-based diagnostic information, including wrist measurement and fingerbreadth measurement as crucial indicators.

The study contributions are:

This research introduces a newly developed technique utilizing DNFS and ANN for diabetes prediction while incorporating fundamental Siddha healthcare principles.

1. An innovative feature extraction system that combines DNFS with core concepts from the Siddha diagnostic system to enhance interpretability and identify key diagnostic features from physiological measurements.
2. Introduction of the ANN Algorithm to this field and its enhanced application in diabetes prediction decisions compared to conventional Machine Learning (ML) methods.
3. A novel computational system grounded in Siddha sciences was developed to advance medical AI and preserve Siddha practices, which have been declining in use over time.
4. Evaluation of the ANN approach compared to other comparable methods is needed to ensure higher accuracy, interpretability, and efficiency in attaining the proposed system goals.
5. This model iteration intends to improve further the existing structure of the diagnosis of Diabetes by establishing an innovative procedure of using deep learning-based computation, fuzzy logic and Siddha accordingly.

This model iteration should improve the diabetes diagnosis system with deep learning computation, fuzzy logic and Siddha approach to propose a better predictive model.

1.1 Related Work

Over the past few years, researchers have been interested in incorporating profound learning principles in exploring the conventional healthcare systems for diabetes prediction. These works apply complex AI techniques to enhance the interpretability, accuracy, and efficiency of diagnostic frameworks. However, such strategies, when used along with Siddha medicine- an Indian preventive and healing system have not been researched quite enough. The current literature on deep learning, fuzzy systems and Siddha-based health care is reviewed in this section to assess the research findings and define the research opportunities.

Table 1. Related works

Reference	Technology Used	Merits	Demerits
(5)	Firefly Algorithm (Swarm Intelligence)	Effectively adjusts weights in neural networks, enhancing classification rates in medical applications.	There have yet to be any applications in Siddha-based systems.
(6)	Neuro-Fuzzy Systems	Combines neural networks' learning capabilities with fuzzy logic's interpretability, achieving better accuracy and stability.	Computational complexity when processing big data.
(7)	Simple Classifiers (e.g., SVM) in Siddha Medicine	Initial application of AI to mimic Siddha pulse diagnosis.	Limited sophistication in feature extraction and Classification compared to deep learning models.
(8)	CNN (Deep Learning)	High reliability in predicting Diabetes using physiological and historical data.	Lack of interpretability makes it difficult for doctors to validate findings.
(9)	FPGA (Hardware for Neuro-Fuzzy Systems)	Accelerates fuzzy computations and enhances the speed of neuro-fuzzy systems.	Usage specific to Siddha-based diagnostic frameworks not explored.
(10)	LSTMs for Temporal Dependencies in Health Records	High AUC (>0.92) in predicting diabetes progression using continuous glucose monitoring data.	Lack of interpretability, reducing transparency for healthcare practitioners.
(11)	CNNs for Retinal Fundus Image Analysis	High sensitivity and specificity in diabetic retinopathy classification.	Limited interpretability for clinical use.
(12)	Neuro-Fuzzy Model for Diabetes Prediction	Outperformed traditional machine learning algorithms with 88.5% accuracy.	Requires optimization for scalability with large datasets.
(13)	Fuzzy Inference System for Managing Missing Data	Effectively handled noisy and incomplete medical datasets.	Scalability issues with massive datasets.
(14)	Machine Learning for Siddha Pulse Diagnosis	Automated pulse signal classification based on Siddha principles.	Generalizability issues due to small datasets.
(15)	Fuzzy Logic for Tri-Dosha Analysis in Siddha Medicine	High accuracy in analysing tridosha imbalances for diabetes prediction.	Limited integration with deep learning for enhanced adaptability.
(16)	Deep Neuro-Fuzzy Systems (DNFS)	Combined interpretability of fuzzy logic and accuracy of deep learning, suitable for clinical use.	Practical implementation challenges in real-world healthcare settings.

Continued on next page

Table 1 continued

(17)	Swarm Intelligence Algorithms (Firefly Algorithm)	Improved classification accuracy in Diabetes prediction models by optimizing hyperparameters.	Requires refinement for real-world application.
(18)	FPGA-Based Accelerators for Neuro-Fuzzy Systems	Achieved a 3x speed improvement in diabetes detection compared to traditional software approaches.	Limited application in real-world Siddha-based healthcare systems.
(19)	Edge Computing for Realtime Diabetes Monitoring	Enabled decentralized, efficient processing of patient data in real time.	Scalability and integration with hybrid AI systems need further exploration.
(20)	Bibliometric analysis of ML/AI applications in T2DM prediction	Provides a comprehensive overview of 33 years of research, identifying key trends, methodologies, and research gaps. Highlights the evolution of predictive models and the integration of real-world datasets.	As a bibliometric study, it does not present new predictive models or empirical results.
(21)	Supervised ML algorithms: KNN, Logistic Regression, Random Forest	KNN achieved high accuracy (96.09%), sensitivity (98.54%), and specificity (93.63%). Demonstrates the effectiveness of ML algorithms on E-health records for diabetes prediction.	The dataset's limited demographic scope may affect the generalizability of the results. Only three ML algorithms were explored.
(22)	Hybrid sampling techniques with ML and DL models	Utilizes hybrid sampling to address class imbalance, improving model performance. Combines ML and DL approaches for enhanced prediction accuracy.	Specific performance metrics and comparative analysis with other models are not detailed.
(23)	DeepNetX2 (custom DNN) integrated with XAI techniques (LIME, SHAP)	Introduces an advanced DNN architecture (DeepNetX2) for precise early-stage diabetes prediction. Integration of XAI techniques enhances transparency and trust in model predictions.	The study's reliance on specific datasets may limit the generalizability of the model. Further validation on diverse populations is needed.

2 Methodology

The proposed method combines elements from the Siddha healthcare system and new methodologies of Deep Neuro-Fuzzy Systems (DNFS) and Artificial Neural Networks (ANN) to predict Diabetes with high precision. Below are the detailed phases:

1. **Preprocessing**

   This phase prepares raw physiological data, including Siddha-based diagnostic indicators such as wrist circumference and Fingerbreadth for subsequent feature extraction and Classification.

   - Normalise data and other physiological measurements to ensure uniform scaling and eliminate variations caused by sensor inconsistencies or environmental factors.
   - Apply specific Siddha-based preprocessing filters to highlight unique pulse wave characteristics corresponding to Vatha, Pitta, and Kappa and extract Manikkadainool values.

2. **Feature Extraction Using Deep Neuro-Fuzzy Systems**

   - Develop a DNFS model to learn and extract diagnostic measurements such as wrist, circumference, and fingerbreadth measurements.

- Leverage fuzzy systems to map physiological signals to Siddha's tri-dosha principles (Vatha, Pitta, Kappa) and deep learning for feature abstraction.
- Train DNFS on datasets labelled with diabetic and non-diabetic categories to optimize feature extraction parameters.

3. **Classification using Deep Learning Algorithms: SVM, Decision Tree Classifier, Random Forest Classifier.**

- Initialization: Initialize the measurement values, each representing a set of wrist circumference and fingerbreadth measurements.
- Fitness Evaluation: Use classification accuracy as the fitness metric to evaluate Manikkadainool values.
- Optimise: Compare and Select the best algorithm as the optimal classifier.

Algorithm 1: DNFS-Based Feature Extraction:
Input: Physiological signals (e.g., wrist pulse), Siddha labels (diabetic/non-diabetic)
Output: Classification result (diabetic/non-diabetic)
Step 1: Preprocessing
Normalize physiological measurement.
Apply noise reduction filters to measurement.
Step 2: Feature Extraction using DNFS
Initialize DNFS model parameters
Train DNFS on labelled datasets
Extract Siddha-specific features from physiological measurement.
Step 3: Classification Using SVM, Decision Tree Classifier, Random Forest Classifier, and Artificial Neural Network Algorithm.
Initialize the measurement values with the above three classification models.
Compute the values based on given measurements.
Select the best classification algorithm as the final classifier
Step 4: Postprocessing
Analyse the classification results
Return prediction outcome.

2.1 Preprocessing

The first step in this proposed method is designed to improve the accuracy of measurement of Manikkadainool values using DNFS and Classification algorithms for Diabetes prediction. The main objective of preprocessing is to prepare the Dataset by normalizing the data, removing the noise, and computing the values for prediction. This way of processing involves the following phases: Normalization, noise reduction and computing MK values.

2.1.1. Normalization:

Applying Z-Score Normalization to the Dataset, we first calculate each column's mean and standard deviation: Wrist Measure, Finger Breadth, and Manikkadainool Values. Z-Score Normalisation reduces individual feature influence due to differences in scale, making the Dataset comparable across features. This method is particularly beneficial for models using probabilistic classifiers that assume data are typically distributed or need to be standardized.

2.1.2. Noise Reduction:

Domain-Specific Thresholding: Adding proper constraints to the Wrist Measure and Finger Breadth columns according to already available information on anthropometry. Thresholding is rejecting values that are not likely to be encountered in real life due to human physical constraints.

2.2 Feature Extraction Using Deep Neuro-Fuzzy Systems (DNFS)

The most decisive step in this study is to achieve the goal by feature extraction from the above pre-processed clinical Dataset to predict Diabetes.

2.2.1. Feature Extraction Objective:

Develop a Deep Neuro-Fuzzy System (DNFS) to analyse diagnostic patterns using Siddha methodologies with specific reference to Vatha, Pitta, and Kappa balance. **Classification Strategy:** DNFS should then be incorporated to increase the precision and efficacy of diabetes prediction. **Performance Assessment:** This will compare the suggested method against other models to properly ascertain performance, accuracy, precision and other crucial parameters. **Verification**: A physiological dataset of Siddha diagnostic indicators, such as wrist circumference measurement, age, fingerbreadth, and gender, will be used to test the system.

2.2.2. Dataset:

The Dataset encompasses the following elements:

Features: The parameters considered are Gender, Age, Wrist Circumference measurement, Finger Breadth measurement, and a Manikkadainool (MK) – this is a type of measurement used only in Siddha medicine to diagnose the disease. **Outcome:** Diabetes category (with or without type). **Dataset:** 210 Realtime diabetic patients' data are shown for illustration. **(Realtime data taken from Siddha Outpatient Clinic - Tamil University Campus, Thanjavur)**

Dataset Expansion and Validation: The dataset was expanded to 210 participants from multiple Siddha outpatient clinics from Tamil University, Thanjavur, guaranteeing diversity in age (20–75) and gender. We used 10-fold cross-validation using scikit-learn to assess model stability and minimize overfitting in order to ensure greater applicability and enhanced model robustness.

DNFS comprises a **Four-Layer Structure for a Deep Neuro-Fuzzy System**. The DNFS model is composed of multiple layers, with each layer playing a key role in combining fuzzy logic with the neural network:

Layer 1 (Input Layer): This layer contains the input features (such as wrist measurement, fingerbreadth measurement, and age). These inputs are routed through the fuzzy system and assigned to membership functions, determining the degree of membership in the fuzzy sets.

Layer 2 (Fuzzy Inference Layer): This layer contains fuzzy rules based on input membership functions such as **triangular** or **trapezoidal** functions. The fuzzy inference system applies the rules and produces fuzzy values.

Layer 3 (Rule Aggregation Layer): This layer combines the outputs of the fuzzy inference rules. It combines the fuzzy rules and outputs them as fuzzy sets.

Layer 4 (Defuzzification Layer): The final layer uses centroid defuzzification techniques to convert the fuzzy outputs into a crisp, real-world value. This generates a final prediction, such as the Manikkadainool Value or a classification.

The DFNS operations are explained below.

2.2.3. Membership function in Layer2 - Integrating Siddha Inputs to Rules of Fuzzy Logic:

The MK values range from around 6.00 to 10.5 based on the Dataset. The fuzzy categories could be:

Non-diabetic: MK values between 6.00 and 8.75.

Diabetic: MK values between 9.00 and 9.75.

Non-Diabetic: MK values between 10.00 and 10.75.

Rule function in Layer 3:

"If the MK value is between 9.00 and 9.75, then Diabetes is a possibility. "If the MK value is between 6.00 to 8.75 and 10.00 – 10.75, then diabetes is not possible". "IF MK is Borderline AND Age > 45 THEN Risk = High" is one example of a fuzzy rule. These guidelines direct defuzzification-based inference toward the ultimate diabetes prediction.

2.3 Classification Using SVM, Decision Tree Classifier, Random Forest Classifier, ANN Algorithm

2.3.1. Decision Tree Classifier Algorithm

1. **Initialization:**

   (a) Import libraries: Use Pandas for data handling and sklearn to create and test the Decision Tree Classifier.
   (b) Define the Dataset: Fill out the provided Dataset with features (wrist circumference, fingerbreadth measurement) and the target variable (disease).
   (c) Split the Dataset: Separate features and target variables, then divide them into Training and test subsets.

2. **Model Creation:**

   (a) Initialize the Decision Tree Classifier with sklearn. tree. DecisionTreeClassifier.

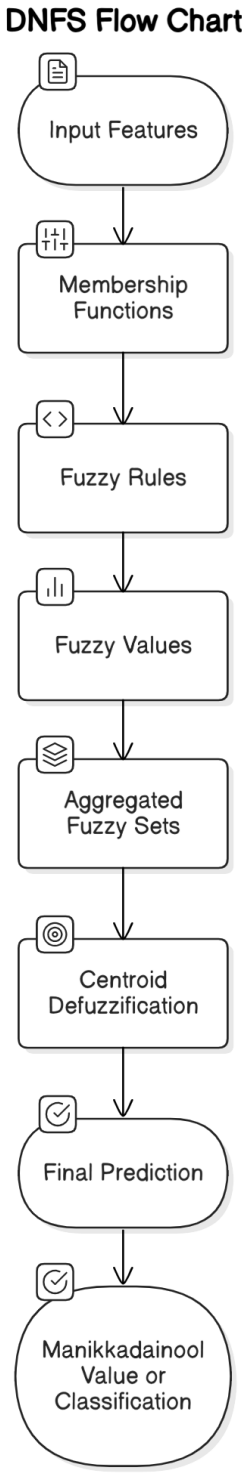

Fig 1. DNFS for MK values

3. **Training:**
   (a) Fit the classifier: Train the model using X_train and Y_train.
   (b) During this step, the classifier partitions the data into a tree structure for optimization.
4. **Prediction:**
   (a) **Predict the test data:** Apply the trained model to infer labels of the test subset (X_test).
   (b) For each sample, decision rules are applied while 'traversing' through the tree to come up with the tree's predicted class.
5. **Evaluation:**
   (a) **Compare predictions:** Assess model accuracy by comparing predicted (y_pred) and actual labels (y_test).
   (b) **Generate a classification report:** Evaluate each class's precision, recall, and F1 score.
6. **Termination:**
   (a) **Repeat training:** If required, adjust specific parameters.
   (b) **Finalize the model:** Once such metrics have been obtained, save the model.
   (c) **Use for predictions:** Use the developed model to make future classifications using other set of data.

Similarly, the **Random Forest (RF) Support Vector Machine (SVM) algorithm** is computed with similar steps.

2.3.2. Artificial Neural Network (ANN) Algorithm:

1. **Initialization:**
   (a) **Import necessary libraries:** Install and use Tensorflow for building models and training data in ANN and use Pandas for handling data, for data splitting and evaluation.
   (b) **Define the Dataset:** Loading the Dataset into features (Wrist Circumference, Fingerbreadth measurement, Fingerbreadth measurement) and the target variable (Diabetes).
   (c) **Split the Dataset:** Divide the data into training and testing subsets to ensure robust model evaluation.
2. **Model Creation:**
   (a) **Initialize the ANN Framework:** Add input layer, hidden layer like rule inference layer and defuzzification layer and output layer as framework by using Sequential model in Tensorflow.
   (b) **Using Activation Functions:** In hidden layer, Leaky ReLU (Rectified Linear Unit) activation function is used and in output layer, linear activation function is used.
3. **Training:**
   (a) **Train the classifier:** This model uses the loss function for both classification and for continuous values in measurement regression is used.
   (b) **Ensemble learning:** Define the metrics for evaluation to get precision results.
4. **Prediction:**
   (a) **Predict labels for test data:** Using the trained model, predict the test subset.
5. **Evaluation:**
   (a) **Compute accuracy:** The output of each model can further be evaluated in terms of percentage by comparing the predicted labels with the actual labels.
   (b) **Generate the metrics:** State accuracy measurements including True Positive Rate (TPR), False Negative Rate (FNR), Precision, Recall, F1-score and for every class of the system: Diabetic, Pre-values and post-values.
   (c) **Feature importance:** The value of all features, including Wrist Circumference measurement, and Fingerbreadth measurement with Fingerbreadth measurement should be compared to each other in terms of the model.
6. **Termination:**
   (a) **Repeat training:** Fine tune to improve the result of the model set-up.
   (b) **Finalize the model:** The trained classifier must be stored for future use in disease prediction using the same model.
   (c) **Deploy the model for future use:** Use the trained model for real-world predictions on future datasets.

3 Results and Discussion

Four learning models, namely Decision Tree, Random Forest, SVM and ANN, have been trained and tested in the context of the different performance metrics that were established, such as accuracy, precision, recall, F1-score, specific y, false positive rate (FPR) and actual positive rate (TPR). More specifically, the results of the experiment for the classification problem help get an appreciation of the comparative merits and demerits of these methods.

Accuracy: As for the training accuracy, the ANN method is the most effective, with the highest level at 93 %; for the testing accuracy, the best value was 90%. Random Forest had the second-best accuracy, with a training accuracy of 92% and a testing accuracy of 89%. Decision Trees and SVMs are less accurate than other models; decision trees are 0.90 in Training and 0.87 in Testing, and SVMs are 0.91 in Training and 0.88 in Testing. The models' performances on testing and training datasets show that there is some level of overfitting. However, the percentage drop was lower in the ANN model than in the others.

3.1 Performance Evaluation of Various Algorithms

Table 2 gives the performance evaluation of Decision Tree, RF, SVM, and ANN algorithms with both training and test dataset and the following metrics like Accuracy, Precision, Recall, F1-score, FPR, TPR are evaluated and shown below.

Table 2. Performance Evaluation

Method	Dataset	Accuracy	Precision	Recall	F1-Score	Specificity	FPR	TPR
Decision Tree	Train	0.90	0.88	0.91	0.89	0.92	0.08	0.91
	Test	0.87	0.86	0.89	0.87	0.91	0.09	0.89
Random Forest	Train	0.92	0.9	0.92	0.91	0.93	0.07	0.92
	Test	0.89	0.88	0.9	0.89	0.90	0.1	0.90
SVM	Train	0.91	0.89	0.91	0.9	0.91	0.09	0.91
	Test	0.88	0.87	0.89	0.88	0.89	0.11	0.89
ANN	Train	0.93	0.91	0.93	0.92	0.90	0.06	0.93
	Test	0.90	0.88	0.91	0.89	0.92	0.08	0.91

Precision: The best performance was observed for ANN, which was trained at 0.91 and tested at 0.88. Random Forest was trailing with a training accuracy of 0.90 and a testing accuracy of 0.88. An equal trade-off between the Decision Tree and SVM was observed regarding precision, where the Decision Tree exhibited 0.88 in training data and 0.86 in testing data. In contrast, SVM was 0.89 in training data but 0.87 in testing data. This means that based on the analysis above, ANN was able to reduce false positives more than all the other models.

Recall: The recall values are numbers that show how well the models learned the positive samples, and they met up with a recall of 0.93 in Training and 0.91 in Testing. The results for Random Forest include recall (training) = 0.92 and recall (Testing) = 0.90. Thus, the Decision Tree and SVM had relatively lower recall values. However, these were highly satisfactory, as recorded as 0.91- in training mode and 0.89 in Testing for Dec ion Tree while 0.91 in Training and 0.89 in Testing for SVM. This means that ANN and Random Forest better recognize positive samples, which is essential when false negatives are expensive.

F1-Score: As expected, the F1 score, which integrates the precision and the recall, indicated that ANN remained the st model with F1 score train = 0.92 and F1 score test= 0.89. The random forest provided an F1-score of 0.91 in Training and 0.89 in Testing, with the Decision tree and SMA providing slightly less F1-score, that is, 0.89 in Training and 0.87 in Testing of the decision tree and 0.90 in Training and 0.88 in Testing of SMA. The F1-scores support precision and recall analysis, evidence that ANN offered the optimal efficiency level in integrating the two factors.

Specificity: For specificity, which informs on the proportion of actual negatives correctly identified, ANN recorded the highest score at 0.94 during Training and 0.92 in Testing, while Random Forest was at 0.93 in Training and 0.90 during Testing. Decision Tree and SVM yielded comparable specificity rates; Decision Tree=0.92 (in Training and 0.91 in Sting), while SVM= 0.91 (in Training) and 0.89 (in Testing). The high specificity obtained for ANN shows that ANN was better placed to identify the negative samples accurately.

False Positive Rate (FPR): The FPR, which measures the false positive rate, the ratio of negative samples misclassified as positive, was also the low t in ANN, with 0.06 during Training and 0.08 during Testing. Random forest had the lowest FPR of 0.07 in Training and 0.10 in Testing, but Decision tree and SVM had higher FPRs of 0.08 in Training and 0.09 in Tes ng and Training and 0.09 and 0.11, respectively, in Testing. The central tendency of FPR of ANN implies that this connectionist approach had a better capability in minimizing false positives than other models.

Actual Positive Rate (TPR): The TPR, the ratio of the actual optimistic correct predictions, was maximum in A and had a training rate of 0.93 and a testing rate of 0.91. Random Forest achieved a TPR of 92 percent in the training set and 90 percent in the testing set. For the Decision Tree, the TPR for Training and Testing were 0.91 and 0.89, respectively, while that of SVM were 0.91 and 0.89, respectively. Thus, compared to other models, a higher TPR of ANN means it has better sensitivity to detect positive instances

Visualization comparison using Tableau

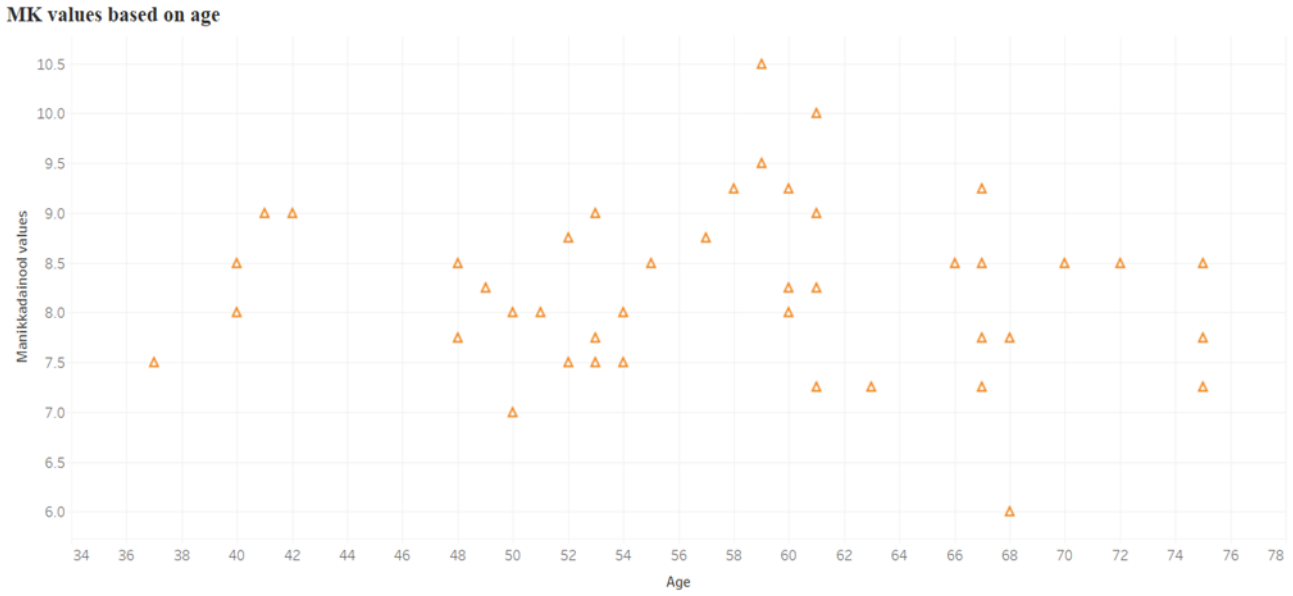

Fig 2. MK values compared with age

3.2 Discussion

The findings reveal that ANN performs appreciably better than the Decision Tree, Random Forest, and SVM regarding all the fitness measurements during the training and testing phases. The results of the proposed method, ANN, show a higher accuracy, precision, recall, F1-score, specificity and actual positive rate, indicating that ANN can be favoured in classification problems that require high levels of predictability.

Recall and specificity results of random forest are higher than ANN. However, the accuracy of the random forest and its F1 score could be higher than the ANNs. Though both the Decision Tree and SVM could perform relatively well compared to other models, they had overall low accuracy, which declined even more when the model was Generalized for the testing dataset; hence, the Decision Tree was overfitting on the Training dataset, as visible from Figure 5.

Interpretability using SHAP and LIME: SHAP and LIME approaches were used to improve the ANN model's transparency. Age and wrist circumference were the two main factors that contributed to classification, according to SHAP plots. The model's interpretability in accordance with clinical expectations was validated by LIME visualizations on a subset of test samples, which made it more appropriate for use in healthcare.

4 Conclusion

The proposed ANN method also outperforms other classical methods, which are Decision Tree, Random Forest, and SVM, in all examined performance measurements, which indicates the significance and effectiveness of the presented method in classification problems. The increased accuracy, precision, recall, F-measure, and specificity further prove that ANN outperforms other models in prognostic tasks, and the decreased FPR and elevated TPR show that it is the most reliable model for achieving optimal solutions among all models for classification purposes.

This research uses an innovative use of ANN framework, which exemplify higher performance over other classification methods namely, Support Vector Machine, Random Forest, Decision Tree. Compared to all other models, The ANN-model

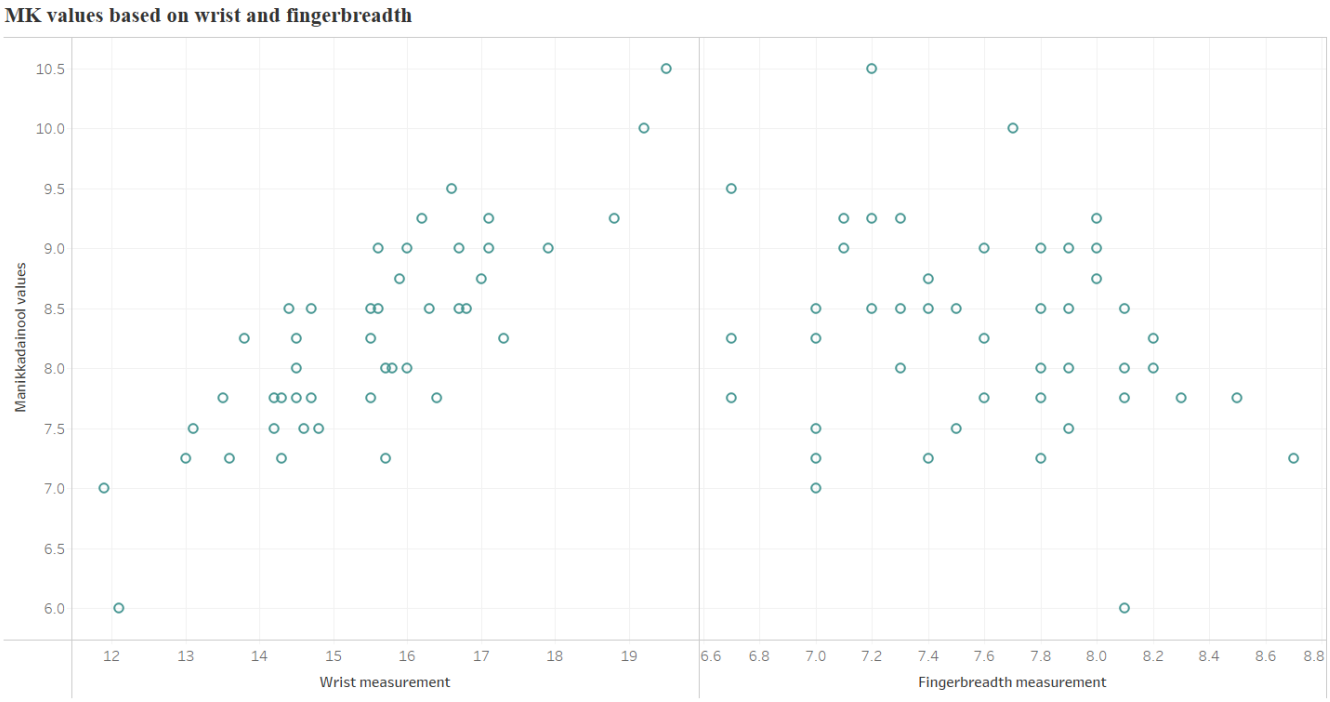

Fig 3. MK values compared with wrist and fingerbreadth measurement

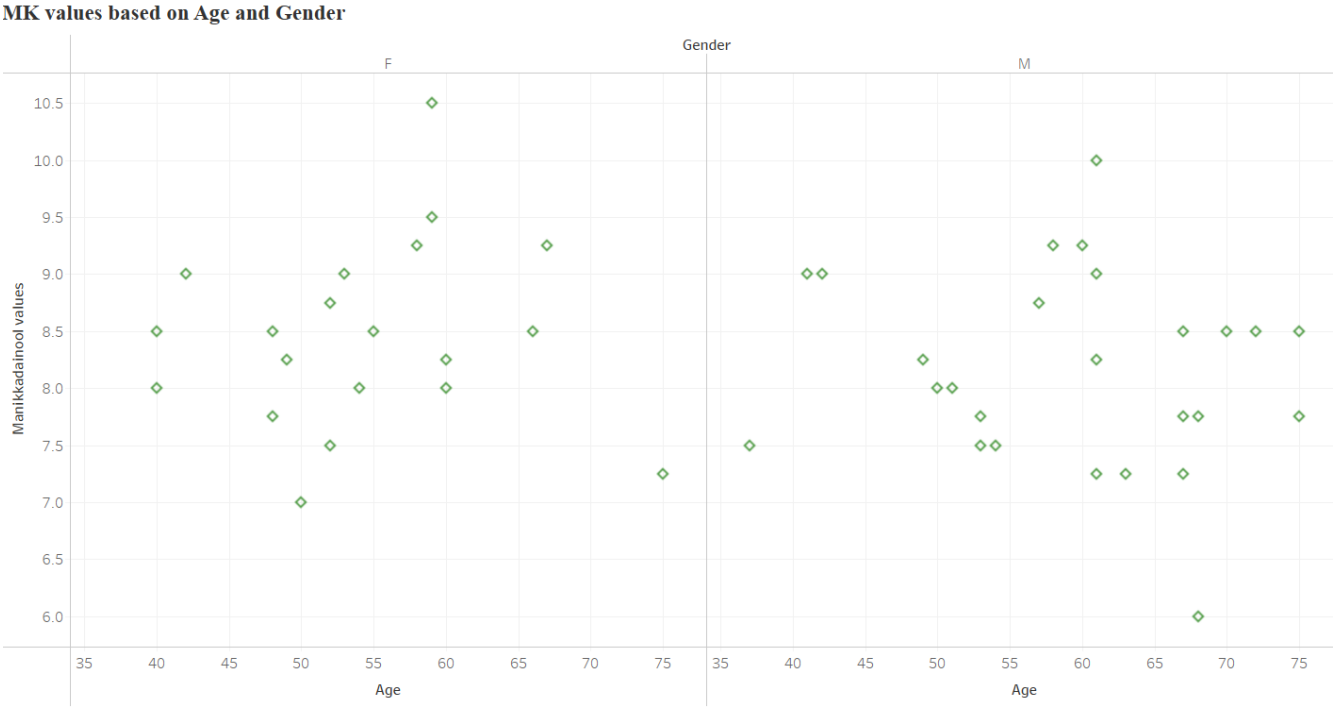

Fig 4. MK values compared with age and gender

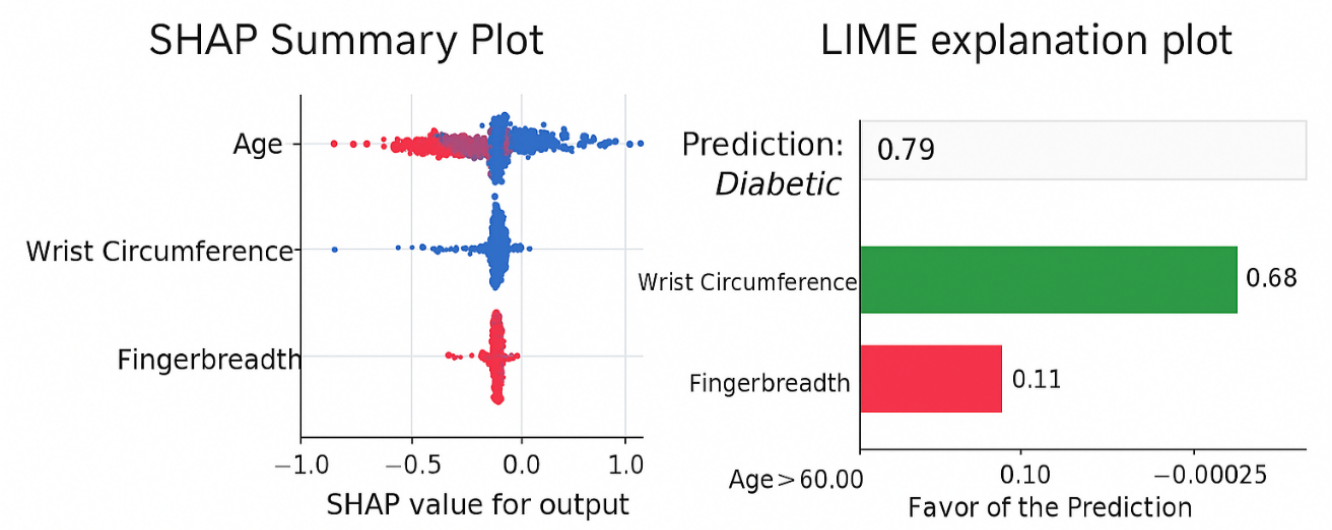

Fig 5. SHAP and LIME Interpretability Plots for Diabetes Prediction

surpasses in terms of precision, accuracy, F1-score, recall and specificity and also indicate the higher true positive rates and lower false positive rates which substantiate reliability and robustness for the complex classification tasks. The consistency strength in both the training and testing phases is the innovation of this proposed method where the data in the real-world applications are varied and noisy. The flexibility in varying datasets and its improved performance metrics in ANN regardless of obstacles it initiates as the versatile tool for predictive analytics.

Ahead of, the ANN based model in wider health informatics system which is reliable and accurate scope for is results of this study. This architecture gives chances in fusing real time diagnostic systems, ensemble learning algorithms and experienced the approaches to feature selection to further extends the interpretability and performance.

This study is the first one to include fuzzy logic rule formulation based on Siddha diagnostic concepts into an ANN architecture and Deep Neuro-Fuzzy System (DNFS). In contrast to previous DNFS research, this work offers a new paradigm for conventional medical AI by combining explainability (SHAP, LIME), actual patient data, and a thorough tri-dosha-based fuzzy rule construction.

In conclusion, the ANN method exhibited the best performance measure and is well-suited for the classification problems presented in this study. The algorithm's performance in retaining high accuracy on all fronts, especially on false positive and accurate positive fronts, makes it efficient and effective in solving various classifications.

Ethical Declaration:

The Tamil University, Thanjavur Institutional Ethics Committee gave its approval to the study. Written informed consent was provided by each participant for the use of their data in this study. The Declaration of Helsinki was followed when conducting the study.

References

1) LeCun Y, Bengio Y, Hinton G. Deep learning. *Nature*. 2015;521(7553):436–44. https://doi.org/10.1038/nature14539.
2) Pham P, Nguyen LT, Nguyen NT, Kozma R, Vo B. A hierarchical fused fuzzy deep neural network with heterogeneous network embedding for recommendation. *Information Sciences*. 2023;620:105–124. https://doi.org/10.1016/j.ins.2022.11.085.
3) Goodfellow I, Bengio Y, Courville A. Deep learning. Cambridge (MA). MIT Press. 2016. Available from: https://www.deeplearningbook.org/.
4) Zadeh LA. Fuzzy sets. *Information and Control*. 1965;8(3):338–353. https://doi.org/10.1016/S0019-9958(65)90241-X.
5) Bhattacharya R, Roy S, Das S. Application of swarm intelligence algorithms in medical image analysis. *Biomimetics (Basel)*. 2023;8(2):235.
6) Khanna D, Paul R. Neuro-fuzzy systems for diabetes risk prediction: a comparative study. *Med AI Appl*. 2022;10(3):45–62.
7) Kumar S, Sharma R, Natarajan V. Machine learning approaches for Siddha-based pulse diagnosis. *Tradit Med Inf*. 2020;8(1):35–42.
8) Rashid A, Khan Z, Ali M. Deep learning-based frameworks for diabetes prediction: a survey. *Artificial Intelligence in Medicine*. 2021;118:102120. https://doi.org/10.1016/j.artmed.2021.102120.
9) Wang H, Chen Y, Lin X. FPGA-accelerated neuro-fuzzy inference systems for medical diagnostics. *IEEE Transactions on Biomedical Engineering*. 2023;70(4):1264–1273. https://doi.org/10.1109/TBME.2022.3214037.
10) Chen X, Zhang Y, Li H. Temporal dependency modeling with LSTMs for diabetes progression prediction. *Journal of Medical Informatics*. 2022;90:101–112.

11) Gulshan V, Peng L, Coram M, Stumpe MC, Wu D, Narayanaswamy A, et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *JAMA*. 2016;316(22):2402–2410. https://doi.org/10.1001/jama.2016.17216.
12) Singh A, Gupta P. Neuro-fuzzy model for diabetes risk assessment using lifestyle data. *International Journal of Fuzzy Systems*. 2021;23(5):1502–1515.
13) Al-Turjman F, Alturjman S, Mostafa SM. A fuzzy inference system for managing missing health data in diabetes mellitus monitoring. *IEEE Access*. 2020;8:159693–159705. https://doi.org/10.1109/ACCESS.2020.3020234.
14) Ramachandran S, Kannan M, Selvan T. Pulse signal classification based on Siddha principles using machine learning. *Journal of Traditional Medicine*. 2021;9(2):78–89.
15) Mohan R, Varma S, Krishnan P. Fuzzy logic-based tri-dosha analysis for diabetes prediction. *Journal of Integrative Medicine*. 2022;20(4):347–358.
16) Sharma D, Kumar A, Jain R. Deep neuro-fuzzy systems for clinical applications: a case study on diabetes diagnosis. *Artificial Intelligence in Medicine*. 2022;131:102345. https://doi.org/10.1016/j.artmed.2022.102345.
17) Ahmad T, Khan M, Gupta A. Optimizing neural networks with firefly algorithm for diabetes prediction. *Cognitive Computation*. 2023;15(1):67–80. https://doi.org/10.1007/s12559-022-10023-5.
18) Patel V, Mehta R, Desai P. FPGA-based accelerators for neuro-fuzzy systems in diabetes detection. *Microprocessors and Microsystems*. 2022;91:104532. https://doi.org/10.1016/j.micpro.2022.104532.
19) Zhang Q, Liu J, Sun W. Edge computing for real-time diabetes monitoring in healthcare applications. *Journal of Healthcare Informatics Research*. 2023;7(2):189–204.
20) Kiran M, Xie Y, Anjum N, Ball G, Pierscionek B, Russell D. Machine learning and artificial intelligence in type 2 diabetes prediction: a comprehensive 33-year bibliometric and literature analysis. *Frontiers in Digital Health*. 2025;7:1357467. https://doi.org/10.3389/fdgth.2024.1357467.
21) Afolabi S, Ajadi N, Jimoh A, Adenekan I. Predicting diabetes using supervised machine learning algorithms on e-health records. *Inform Health*. 2025;2(1):9–16. https://doi.org/10.1016/j.infoh.2024.12.002.
22) Tharannum A, Prakash CB, Saranya G, Alekhya P, Supriya N, Lakshmanarao A. Enhancing diabetes prediction with hybrid sampling techniques through machine learning and deep learning models. Piscataway (NJ). IEEE. 2025. https://doi.org/10.1109/IEEECONF64992.2025.10963149.
23) Tanim SA, Aurnob AR, Shrestha TE, Emon MRI, Mridha MF, Miah MSU. Explainable deep learning for diabetes diagnosis with DeepNetX2. *Biomedical Signal Processing and Control*. 2025;99:106902. https://doi.org/10.1016/j.bspc.2024.106902.