

Predictive Healthcare: An IoT-Based ANFIS Framework for Diabetes Diagnosis

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Abstract

The increasing integration of the Internet of Things (IoT) in healthcare is revolutionizing patient monitoring and disease prediction. This paper presents a machine learning (ML)-based framework using Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict diabetes. The proposed system leverages IoT data to monitor key health parameters, including glucose levels, blood pressure, and age, offering real-time diagnostics for diabetes patients. The dataset used in this study was obtained from the UCI repository and underwent pre-processing, feature selection, and classification using the ANFIS model. Comparative analysis with other machine learning algorithms, such as Support Vector Machines (SVM), Naïve Bayes, and K-Nearest Neighbors (KNN), demonstrates that the proposed method achieves superior predictive performance. The experimental results show that the ANFIS model achieved an accuracy of 95.5%, outperforming conventional models, and providing more reliable decision-making in clinical settings. This study highlights the potential of combining IoT with machine learning to improve predictive healthcare applications, emphasizing the need for real-time patient monitoring systems.

Keywords

Internet of Things (IoT), Machine Learning (ML), Diabetes Prediction, Real-Time Diagnostics, Predictive Healthcare

1. Introduction

The advent of the Internet of Things (IoT) has transformed numerous industries,

particularly healthcare, by enabling seamless data collection and real-time monitoring of patients. IoT systems connect medical devices and sensors, providing healthcare professionals with critical, real-time information about patients' health status. This innovation has the potential to significantly improve the efficiency of diagnosis, treatment, and patient care [1].

Early diagnosis and ongoing monitoring of chronic conditions like diabetes are critical in the healthcare industry [2] [3]. Millions of individuals worldwide suffer from diabetes, a metabolic disease for which an early diagnosis can significantly lower the risk of complications. Diabetes has traditionally been diagnosed by manual testing and clinic visits from patients, which might cause treatment delays. Machine learning (ML) and Internet of Things (IoT) integration can improve the accuracy, automation, and proactiveness of health monitoring [4] [5].

Machine learning has shown great potential in enhancing clinical decision-making, especially when applied to large datasets collected from IoT devices. ML models can detect patterns and predict outcomes based on patient data, improving the diagnosis process. In this context, various ML algorithms, such as Support Vector Machines (SVM), Naïve Bayes, and K-Nearest Neighbors (KNN), have been used to predict diabetes. However, these traditional models often struggle with complex, nonlinear datasets commonly found in healthcare applications. Moreover, these methods are often limited in their ability to deal with uncertain or fuzzy data, which is common in real-world clinical scenarios [6].

It suggests a hybrid machine learning (ML) method based on IoT-collected health metrics like glucose, blood pressure, and age to predict diabetes using an Adaptive Neuro-Fuzzy Inference System (ANFIS). Fuzzy logic, which deals with uncertainty, and neural networks, which represent intricate, non-linear relationships in the data, are integrated by ANFIS. Combining these two methods enables ANFIS to handle medical data more robustly, enhancing precision and decision-making abilities [7] [8].

Key Contributions:

1. We leverage IoT technology to collect continuous health data for real-time monitoring of patients, ensuring early detection of health anomalies.
2. The use of ANFIS integrates the benefits of fuzzy logic and neural networks, providing a more sophisticated method for handling uncertain and imprecise healthcare data.
3. Our study compares the performance of the ANFIS model with traditional ML algorithms (SVM, Naïve Bayes, KNN) to demonstrate its superiority in predicting diabetes.
4. The proposed system achieves higher accuracy (95.5%), demonstrating its potential for implementation in clinical decision-support systems.

The proposed approach block diagram is displayed in **Figure 1**. The proposed work involves multiple disciplines, including source data filtration and normalization, input data gathering, feature Selection, and disease prediction using the proposed categorization. The experimental analysis of the proposed ANFIS classification using the various parameters presented and explained in section provides

a reliable disease prediction.

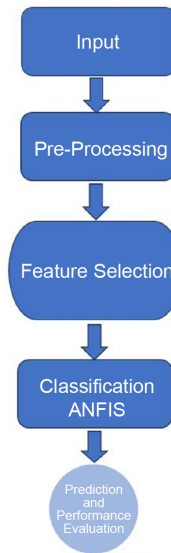


Figure 1. Proposed methodology block diagram.

2. Background

2.1. The Role of IoT in Healthcare

The IoT has revolutionized many sectors, with healthcare being one of the most impacted areas. In healthcare, IoT enables the integration of connected devices, wearables, and sensors that continuously collect health-related data. This allows for real-time monitoring, remote diagnosis, and early detection of critical health conditions. Devices like heart rate monitors, glucose sensors, and smartwatches collect vital data, which can then be analyzed to detect anomalies or predict the onset of diseases [9].

Key advantages of IoT in healthcare include:

Remote Monitoring: IoT allows continuous monitoring of patients, particularly those with chronic diseases like diabetes, heart conditions, or hypertension. This can significantly reduce hospital readmission rates and improve patient outcomes.

Data Availability: IoT devices can continuously collect data, providing healthcare providers with a wealth of information to make informed decisions.

Cost Efficiency: IoT-based healthcare systems reduce the need for in-hospital monitoring, thus cutting down healthcare costs.

2.2. Machine Learning in Disease Prediction

Machine learning is the cornerstone of modern predictive healthcare systems [10]. ML algorithms are used to detect patterns in medical data that may not be easily noticeable by human doctors [11]. In disease prediction, ML models analyze large datasets containing patient health records and use statistical techniques to predict the likelihood of certain diseases [12].

ML algorithms applied in healthcare typically include:

Support Vector Machines (SVM): A powerful classification algorithm used for binary classification tasks like disease prediction.

Naïve Bayes: A probabilistic algorithm that uses Bayes' Theorem to make predictions based on prior probabilities.

K-Nearest Neighbors (KNN): A simple, instance-based learning algorithm that makes predictions based on the similarity of a new instance to previously known cases.

However, these models often fall short in handling healthcare data, which is frequently uncertain and imprecise. In real-world clinical settings, patient data may include missing, noisy, or ambiguous values, making it difficult for standard ML models to maintain high accuracy.

2.3. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is a hybrid model that combines the strengths of fuzzy logic and neural networks. Fuzzy logic is particularly useful in healthcare applications because it mimics human reasoning by dealing with ambiguity and uncertainty. Meanwhile, neural networks can model complex, non-linear relationships in large datasets.

ANFIS works by:

Fuzzifying input data (e.g., glucose levels, blood pressure, etc.) into fuzzy sets using membership functions.

Generating fuzzy rules that describe the relationships between input data and output (diabetes diagnosis).

Training the system using neural network backpropagation to optimize the parameters of the fuzzy sets and improve prediction accuracy.

Because of these features, ANFIS is perfect for managing medical data, which frequently contains ambiguous information. Moreover, ANFIS's capacity to learn and adapt during training has been demonstrated to beat conventional ML algorithms in a number of domains, making it a strong option for disease prediction models.

2.4. Need for Real-Time Monitoring in Diabetes Management

Diabetes management can greatly benefit from real-time monitoring and predictive analytics. Continuous tracking of glucose levels, blood pressure, and other vitals can help patients avoid dangerous situations such as hyperglycemia or hypoglycemia. IoT-based systems enable healthcare providers to respond proactively, ensuring better patient outcomes and reducing hospital visits [13]-[15].

Overall target of this investigation is to improve the ability of healthcare systems to deliver automated, real-time diabetes management by integrating ANFIS with IoT. This will allow for very accurate illness onset prediction and enable prompt intervention when needed [16]-[18].

3. Methodology

The e-health care tracking device currently in use is entirely IoT-based, using a

system that has mastered an ANFIS set of rules to gather real-time data from the human body. The facts include, among other things, the following: daily, blood pressure, glucose, age-related diabetes, pores and skin thickness, and pregnancy. The purpose of the suggested device is to design a new application that leverages the Internet of Things (IoT) framework and system to gather data.

The proposed framework structure is depicted in **Figure 2**. E-Healthcare is an Internet of Things (IoT) application that monitors and periodically assesses online patient wellness for various chronic illnesses. In e-medical care applications, uncommon illnesses and mostly tolerant studies are easily identifiable. The utilization of IoT-based resources for well-being, the present e-health care tracking device is fully Internet of Things (IoT) based, collecting real-time data from the human body through a system that has learned an ANFIS set of rules. The following details are among them: age-related diabetes, blood pressure, glucose, daily, pores and skin thickness, and pregnancy. The purpose of the suggested device is to design a new application that leverages the Internet of Things (IoT) framework and system to gather data.

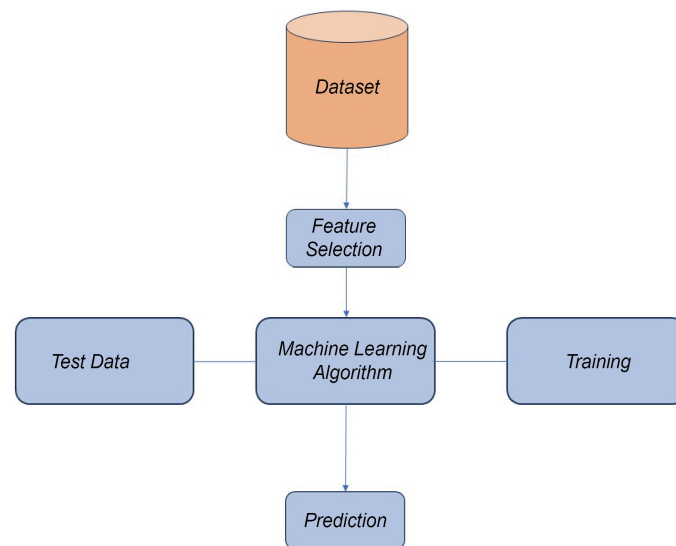


Figure 2. The architecture of the proposed system.

3.1. Data Collection

The dataset used in this research was obtained from the UCI repository, consisting of diabetes-related attributes of pregnant women. The dataset includes critical health metrics such as pregnancies, glucose levels, blood pressure, skin thickness, and age. These attributes were used to build the predictive models [19] [20] (**Table 1**).

3.2. Data Preprocessing

Data preprocessing is essential to improve the quality and integrity of the dataset. This process involved the following steps:

Table 1. Attributes and their respective ranges and types.

Attribute	Description	Type	Range
Pregnancies	Number of times pregnant	Integer	0 - 17
Glucose	Plasma glucose concentration (mg/dL)	Integer	56 - 199
Blood Pressure	Diastolic blood pressure (mmHg)	Integer	24 - 110
Skin Thickness	Triceps skin fold thickness (mm)	Integer	0 - 99
Age	Age of the patient (years)	Integer	21 - 81
Outcome	Diabetes diagnosis (1 = diabetic, 0 = non)	Integer	0, 1

- **Handling Missing Data:** Missing values in attributes such as glucose and skin thickness were replaced with the mean values of their respective columns.
- **Normalization:** Since the attributes had varying scales, the data was normalized using min-max normalization to ensure that all attributes fell within the range [0, 1]. This normalization helped in faster convergence during training. The formula used for normalization is:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

where:

- X' is the normalized value
- X is the original value
- X_{\min} and X_{\max} are the minimum and maximum values of the attribute

3.3. Feature Selection

Feature selection is crucial to enhance model performance by reducing the dimensionality of the dataset and focusing on the most significant attributes. We applied the Correlation-based Feature Selection (CFS) technique, which evaluates the correlation between the features and the target variable (diabetes diagnosis) to select the most relevant features. The selected features were: Glucose, Blood Pressure, and Age.

4. Model Development

We employed the ANFIS model for classification. ANFIS combines the learning capabilities of neural networks with the fuzzy logic system, which is useful for handling uncertainty and imprecise information in healthcare data.

4.1. ANFIS Structure

The ANFIS model used in this study consists of five layers:

1. **Input Layer:** This layer receives the selected features (Glucose, Blood Pressure, and Age).
2. **Fuzzification Layer:** Each input is fuzzified into fuzzy sets using Gaussian membership functions.
3. **Rule Layer:** Fuzzy rules are generated based on the inputs using the Takagi-

Sugeno inference mechanism.

4. Normalization Layer: The rules are normalized to ensure that their outputs are comparable.

5. Output Layer: The final prediction (diabetes or no diabetes) is produced using a weighted sum of the rules.

4.2. Model Training and Validation

We trained the ANFIS model using a 70 - 30 split for training and testing. During training, the model parameters (membership functions, fuzzy rules) were optimized using the backpropagation algorithm. The training process continued until the error reached an acceptable threshold or the maximum number of epochs was completed.

5. Results and Discussion

The outcomes of the suggested task are carefully assessed in this section. A dataset of diabetes data collected from the UCI repository was used to evaluate the system [19] [20]. The dataset focused on a number of characteristics, including age, skin thickness, blood pressure, glucose levels, and pregnancies. Pregnant women in various age groups are the main subject of the data, and the result indicates whether or not diabetes is present (represented as 1 or 0, respectively). The format of the diabetic dataset used for testing is shown in **Figure 3**. The prediction results, as outlined in **Table 2**, demonstrate the application of the proposed methodology. The system's classification efficiency was observed across different health attributes, yielding positive outcomes. For instance, in a subset of patients, various physical parameters such as glucose and skin thickness were accurately utilized to predict the likelihood of diabetes.

Table 2. Dataset with adjusted methodology prediction results.

Numbers of Patients	Pregnancies	Glucose	Blood Pressure	Skin Thickness	Age	Outcomes
1	6	148	72	35	50	1
2	1	85	66	29	31	0.5
3	8	183	64	0	32	1
4	1	89	66	23	21	1
5	0	137	40	35	33	1

The graphical representation of the test results for different parameters is shown in **Figure 4**. The proposed classification model based on ANFIS (Adaptive Neuro-Fuzzy Inference System) was rigorously tested, and the resulting performance metrics—including accuracy, precision, and sensitivity—are provided in **Table 3**. These results indicate that the proposed system outperformed other conventional machine learning techniques.

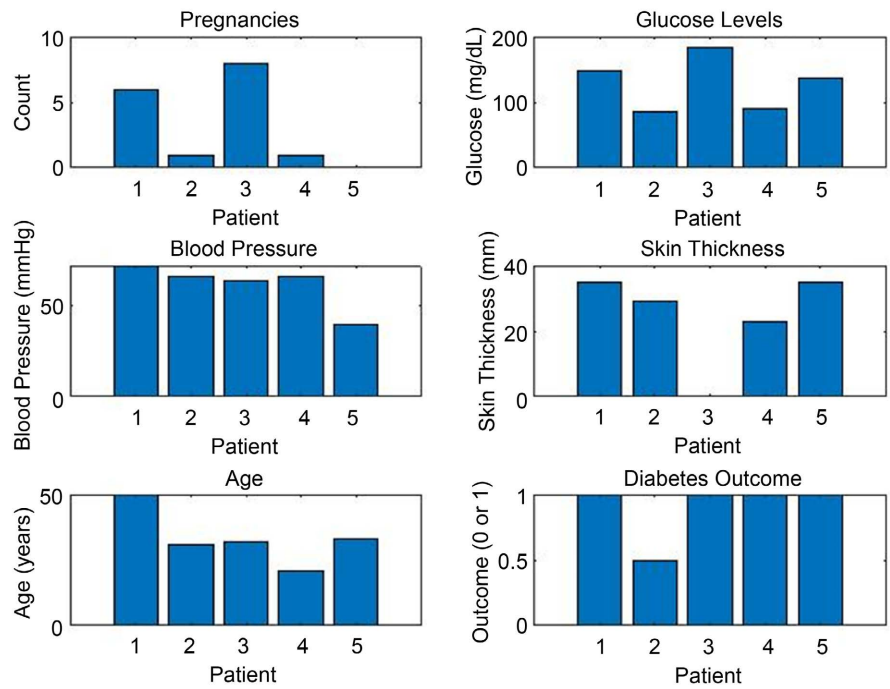


Figure 3. Diabetes dataset overview.

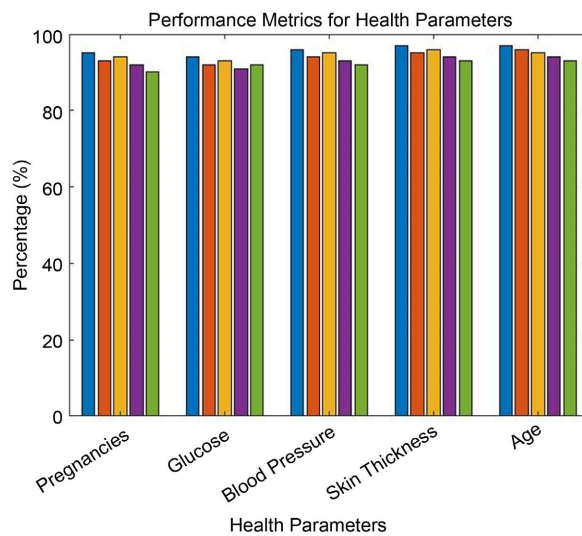


Figure 4. Performance metrics of ANFIS model.

Table 3. Performance metrics for various health parameters using the ANFIS algorithm.

Disease Parameter	Accuracy	Precision	Sensitivity	Specificity	Recall
Pregnancies	95%	93%	94%	92%	90%
Glucose	94%	92%	93%	91%	92%
Blood Pressure	96%	94%	95%	93%	92%
Skin Thickness	97%	95%	96%	94%	93%
Age	97%	96%	95%	94%	93%

The comparison between the proposed ANFIS-based methodology and other machine learning models (SVM, Naïve Bayes, KNN) further substantiates its superiority in terms of classification accuracy, as demonstrated in **Table 4**.

Table 4. Comparative performance of various algorithms.

Algorithm	Accuracy
SVM	87%
Naïve Bayes	90%
KNN	94%
Proposed ANFIS	95.5%

The application of the ANFIS model to the health data set reveals significant improvements in predictive accuracy, particularly for critical health parameters such as blood pressure and skin thickness. These results suggest that the proposed methodology offers a more reliable and accurate classification for diabetes prediction compared to other conventional algorithms.

A comprehensive analysis of patient data, focusing on six critical variables: pregnancies, glucose levels, blood pressure, skin thickness, age, and outcomes has provided in this research (shown in **Figure 3**). Utilizing bar charts for visualization, we create subplots that display each attribute across five patients. This method allows for effective comparative analysis, enabling the identification of trends and variations in key health metrics. The structured grid of bar charts facilitates an intuitive understanding of the relationships between these attributes and their potential impact on patient outcomes. The findings contribute to a deeper understanding of patient health dynamics and could inform clinical decision-making processes.

This **Figure 4** employs a grouped bar chart to visualize and compare key performance metrics—accuracy, precision, sensitivity, specificity, and recall—across different diseases or health parameters. Each group represents a health parameter, while individual bars show the performance metrics. X-axis labels identify the parameters, and a legend distinguishes each metric. This visualization provides a clear comparison of the model's performance, highlighting strengths and weaknesses across various diagnostic Categories.

Figure 5 bar chart comparing the accuracy of different algorithms, with ANFIS outperforming traditional methods like SVM and Naive Bayes. X-axis labels identify the algorithms, highlighting ANFIS's superior performance.

6. Conclusions

This research successfully demonstrates the potential of integrating the Internet of Things (IoT) with the Adaptive Neuro-Fuzzy Inference System (ANFIS) for predicting diabetes, showcasing a significant advancement in healthcare monitoring and disease prediction [21]-[24]. By utilizing IoT data to continuously

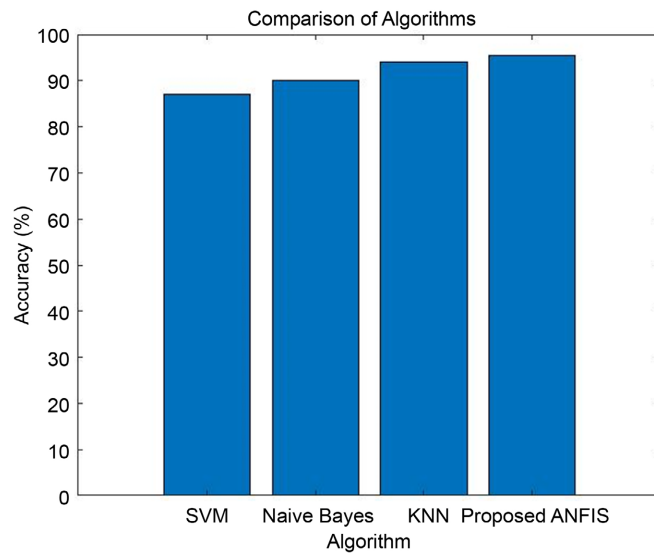


Figure 5. Comparative analysis of algorithm accuracy.

monitor critical health parameters, our proposed framework enables real-time diagnostics that facilitate early detection and intervention for diabetes patients. The comprehensive analysis revealed that the ANFIS model outperformed traditional machine learning algorithms such as Support Vector Machines, Naïve Bayes, and K-Nearest Neighbors, achieving an impressive accuracy of 95.5%.

The study in question emphasizes how crucial it is to use cutting-edge IoT technologies and machine learning methods to enhance predictive healthcare applications. Subsequent studies want to examine the adaptability of this structure in other healthcare environments and look into other health metrics that can improve the system's prediction power even further. All things considered, this research helps advance the continuous development of intelligent healthcare solutions, opening the door for more effective, data-driven methods of controlling long-term illnesses like diabetes [25] [26].

Authors' Contribution

Md Nagib Mahfuz Sunny led the research, conceptualized the study, and designed the IoT-based ANFIS framework for diabetes diagnosis. Mohammad Balayet Hossain Sakil contributed to data analysis and implementation. Jennet Atayeva assisted in literature review and methodology refinement. Zakia Sultana Munmun, Md Sohel Mollick, and Md Omar Faruq contributed to system evaluation and manuscript preparation.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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