Science World Journal Vol. 20(No 2) 2025 https://dx.doi.org/10.4314/swj.v20i2.31
www.scienceworldjournal.org
ISSN: 1597-6343 (Online), ISSN: 2756-391X (Print)
Published by Faculty of Science, Kaduna State University

A FUZZY EXPERT SYSTEM FOR EARLY DIAGNOSIS OF DIABETES MELLITUS USING AN ATKINSON INDEX-BASED ALGORITHM

*[1]Umar Abubakar, [2]Muhammad Lawal Jibril, [1]Abdullahi Musa Yola, [3]Mohammed Usman, [1]Saadatu Ali Jijji

[1]Computer Science Department, Federal University of Kashere, Gombe-Nigeria
[2]Computer Science Department, Bayero University, Kano-Nigeria
[3]Department of Computer Science, Modibbo Adama University, Yola-Nigeria

*Corresponding Author Email Address:umarhafizee01@gmail.com

ABSTRACT
Diabetes Mellitus (DM) is a chronic disorder characterized by prolonged high blood sugar due to insufficient insulin production or ineffective insulin use. As a global public health concern, DM affects millions and leads to severe complications such as cardiovascular disease and kidney failure if not properly managed. Early diagnosis is crucial, but is often hindered by overlapping symptoms with other metabolic disorders. Additionally, traditional diagnostic methods, such as fasting glucose and A1C tests, rely on fixed thresholds and fail to account for individual variability, making them less effective. To address these challenges, intelligent systems like Fuzzy Expert Systems (FES) have emerged, effectively managing uncertainty and enhancing early diagnosis. This study proposes a novel FES integrated with the Atkinson Index Algorithm (AIA) for early diabetes diagnosis. The FES utilizes fuzzy logic to handle imprecision and uncertainty in data, while the AIA improves sensitivity in risk assessment by addressing inequality in the distribution of risk factors. The proposed model was evaluated using the PIMA Indians Diabetes dataset and compared with recent studies based on classification accuracy, F1 score, precision, and recall. Results show that the proposed model outperforms the baseline method as presented in the study, achieving 7.6% higher accuracy, 3.8% higher F1 score, 20.5% higher precision, and 15.5% higher recall. These findings demonstrate the model's effectiveness in diagnosing diabetes while minimizing false positives, establishing it as a more sensitive and reliable diagnostic tool.

Keywords: Diabetes Mellitus, Fuzzy Expert System, Atkinson Index Algorithm, Early Diagnosis, PIMA Indians Diabetes Dataset.

INTRODUCTION
Diabetes Mellitus (DM) is a chronic metabolic disorder defined by prolonged elevated blood sugar levels, resulting from inadequate insulin production or the body's reduced ability to utilize insulin effectively (Xu et al., 2023). This condition poses a significant global public health challenge, impacting millions and contributing to severe complications, including cardiovascular disease, kidney failure, and neuropathy, if not properly managed(Sun et al., 2022). Alarmingly, the prevalence of diabetes continues to rise at an unprecedented rate. According to the World Health Organization (WHO) and the International Diabetes Federation (IDF), projections estimate that by 2045, the global diabetic population could surpass 700 million, underscoring the urgent need for effective strategies to address this growing epidemic (Sun et al., 2022).
Early diagnosis of diabetes is crucial for preventing the progression of the disease and mitigating its associated complications. However, the diagnosis of diabetes can be challenging due to the variability and overlap in symptoms with other metabolic disorders (Zhou et al., 2023). Traditional diagnostic methods, such as fasting blood glucose levels, oral glucose tolerance tests, and hemoglobin A1C measurements, rely on fixed thresholds that may not account for individual variability and the inherent uncertainty in medical data. This often results in delayed diagnosis or misdiagnosis, particularly in the early stages of the disease (Wang et al., 2023).
To overcome these challenges, the development of intelligent systems that aid medical decision-making has gained significant attention. Among these, Fuzzy Expert Systems (FES) stand out as a powerful solution for managing the inherent uncertainty and imprecision in medical data. Leveraging fuzzy logic, FES can effectively capture the vagueness associated with symptoms and diagnostic criteria, enabling more precise and individualized patient assessments (Chen et al., 2022). Despite their effectiveness in handling uncertainty, there remains a critical need for integrating advanced algorithms to further enhance the accuracy, sensitivity, and reliability of FES, particularly for diagnosing complex and multifaceted conditions such as diabetes (Jiang et al., 2023). This calls for innovative approaches to improve diagnostic performance and support better clinical outcomes.
Consequently, this study introduces an innovative approach by integrating the Atkinson Index, an established measure of inequality commonly used in economics into a FES for the early diagnosis of DM. By adapting the Atkinson Index, the system quantifies disparities in key diagnostic indicators, including blood glucose levels, body mass index (BMI), and family history. This adaptation enhances the FES's ability to distinguish between diabetic and non-diabetic cases, particularly in borderline scenarios, thereby improving diagnostic precision and addressing challenges posed by overlapping and ambiguous symptoms. Specifically, we undertake the following:

i. Design a Fuzzy Expert System for diagnosing Diabetes Mellitus, incorporating the Atkinson Index algorithm to effectively manage uncertainty in patient data.
ii. Develop an interactive Gradio-based user interface to demonstrate the functionality of the proposed model and facilitate its practical application.
iii. Evaluate the performance of the proposed system using the PIMA Diabetes Mellitus benchmark dataset and compare it with existing studies in the literature. The assessment will focus on key classification metrics, including accuracy, F1 score, precision, and recall.

The structure of the paper is as follows: Section 2 presents background information and a detailed review of related literature. Section 3 outlines the proposed methodology. Section 4 describes the experimental setup, performance comparisons, and result analysis. Lastly, Section 5 concludes with a summary of findings

 https://dx.doi.org/10.4314/swj.v20i2.31

and highlights potential directions for future research.

This section provides an in-depth exploration of key concepts relevant to the study. It includes an overview of DM and its classifications, a general introduction to expert systems, and a detailed discussion of FES and their applications in medical diagnosis. Additionally, the Atkinson Index is examined for its role in addressing inequalities, followed by a review of related literature to contextualize the study within existing research.

DM is a chronic metabolic disorder characterized by persistent hyperglycemia caused by impairments in insulin secretion, action, or both. It is primarily categorized into three types: Type 1 (T1DM), Type 2 (T2DM), and gestational diabetes (GDM), each with distinct causes, features, and health consequences (Sun & Saeedi, 2021). Despite their differences, these types share common symptoms, including excessive thirst (polydipsia), frequent urination (polyuria), unexplained weight loss, fatigue, blurred vision, and delayed wound healing (Sun et al., 2022). Notably, T2DM and GDM are often asymptomatic, complicating early detection and heightening the risk of severe complications (McIntyre et al., 2022). Consequently, a thorough understanding of the unique traits and symptoms associated with each type is essential for developing accurate diagnostic methods and effective management strategies.

i. Type 1 Diabetes Mellitus (T1DM)

Type 1 Diabetes Mellitus (T1DM) is an autoimmune disorder in which the immune system attacks and destroys the insulin-producing beta cells of the pancreas, resulting in minimal or no insulin production (ADA, 2023). While T1DM commonly develops during childhood or adolescence, it can also occur in adults. If left untreated, the condition can lead to severe and potentially fatal complications, such as diabetic ketoacidosis (DKA) (Powers et al., 2021).

ii. Type 2 Diabetes Mellitus (T2DM)

T2DM is the most common type of diabetes, representing 90–95% of diagnosed cases worldwide (CDC, 2022). It is primarily defined by insulin resistance, where the body's cells do not respond effectively to insulin, coupled with a progressive decline in pancreatic insulin production over time (Sun et al., 2022).Key risk factors include genetic predisposition, obesity, sedentary lifestyles, poor dietary habits, aging, and a history of gestational diabetes(Sun et al., 2022). Additionally, individuals from certain ethnic backgrounds, such as African, Hispanic, and Asian populations, face a disproportionately higher risk of developing T2DM (ADA, 2023).

iii. Gestational Diabetes Mellitus (GDM)

GDM is a temporary form of diabetes that arises during pregnancy when the body is unable to produce sufficient insulin to accommodate the increased demands caused by hormonal changes(McIntyre et al., 2022). It generally manifests in the second or third trimester, affecting approximately 7–10% of pregnancies globally (McIntyre et al., 2022).Although GDM typically resolves after childbirth, it poses notable health risks for both the mother and the child. Women with GDM face a significantly increased risk of developing T2DM later in life, with research suggesting a 50% likelihood within a decade postpartum (International Diabetes Federation, 2021).

The diagnosis of DM is predominantly based on standardized tests that evaluate blood glucose levels and glycated hemoglobin (HbA1c). These methods are essential for detecting the disease and determining its severity, allowing for prompt intervention to mitigate potential complications. The primary diagnostic tests are summarized below:

i. *Fasting Plasma Glucose (FPG)*: The Fasting Plasma Glucose (FPG) test determines blood sugar levels after fasting for 8–12 hours overnight. It helps evaluate the body's ability to regulate blood glucose levels during fasting.
ii. ***Oral Glucose Tolerance Test (OGTT):*** The OGTT measures the body's capacity to process glucose by checking blood sugar levels two hours after consuming a beverage containing 75 grams of glucose.
iii. ***Glycated Haemoglobin (HbA1c):*** The HbA1c test reflects the average blood sugar levels over the preceding 2–3 months by assessing the percentage of haemoglobin that is glycated in the blood.

These traditional methods for diagnosing DM face significant challenges that limit their effectiveness. For instance, diagnostic criteria often rely on fixed glucose or HbA1c thresholds, which fail to account for individual variations in metabolic responses or differences across ethnic groups (Shah et al., 2022). Moreover, the asymptomatic nature of early-stage T2DM means that many individuals remain undiagnosed, further complicating timely intervention (Lowe et al., 2022). Additionally, resource constraints in some settings make certain tests, such as the Oral Glucose Tolerance Test (OGTT), impractical due to their cost and time-intensive nature (International Diabetes Federation, 2021). These limitations highlight the need for more adaptable and accessible diagnostic approaches.

An expert system is an artificial intelligence application designed to replicate the decision-making abilities of human experts within a specific domain. In healthcare, expert systems have become indispensable for clinical decision support, delivering precise, evidence-based recommendations. By integrating expert knowledge with advanced algorithms, these systems assist in diagnosing illnesses, devising treatment plans, and forecasting patient outcomes, ultimately enhancing the quality and efficiency of medical care. An expert system comprises two primary components: the Knowledge Base and the Inference Engine. The Knowledge Base serves as a repository of domain-specific information, including rules, facts, and heuristics that encapsulate expert knowledge. The Inference Engine, on the other hand, employs reasoning techniques to analyze the information in the Knowledge Base, enabling it to draw conclusions or provide recommendations based on the available data.

The development of expert systems in healthcare follows a series of essential steps. The process begins with Knowledge Acquisition, where information is gathered and structured from medical experts, clinical guidelines, and scientific literature. Next is System Design, which involves organizing the system's architecture, including the knowledge base, inference engine, and user interface. Finally, the system undergoes Implementation and rigorous Validation or testing to ensure it is accurate, reliable, and clinically relevant.

The Atkinson Index, introduced by Anthony Atkinson in 1970, is a measure of income inequality that integrates societal preferences for equity. A distinguishing feature of this index is its tunable parameter, epsilon (ε), which represents society's aversion to inequality. By adjusting epsilon, the index can reflect varying levels of sensitivity to disparities, with higher values indicating a greater

Science World Journal Vol. 20(No 2) 2025
www.scienceworldjournal.org
ISSN: 1597-6343 (Online), ISSN: 2756-391X (Print)
Published by Faculty of Science, Kaduna State University
https://dx.doi.org/10.4314/swj.v20i2.31

emphasis on addressing inequality (Atkinson, 1970).
While traditionally applied in economics, the Atkinson Index holds potential for adaptation in other fields, such as healthcare, where disparities in diagnostic metrics or health outcomes are critical. For instance, in diabetes diagnosis, the Atkinson Index could be used to evaluate inequalities in diagnostic indicators like blood glucose levels, body mass index (BMI), and other risk factors. Integrating the Atkinson Index into a FES could enhance the system's capacity to distinguish between diabetic and non-diabetic cases, especially in borderline scenarios (Mera-Gaona et al., 2021).
The integration of fuzzy logic and expert systems into healthcare has seen notable advancements in recent years, with increasing emphasis on enhancing diagnostic precision and reliability through innovative computational techniques. For example, Kumar & Gupta, (2023) developed a model leveraging fuzzy logic applied to clinical data, demonstrating advancements in improving diagnostic accuracy. This work built upon earlier studies like Kumar & Kumar, (2022), who focused on using fuzzy logic for assessing the risk of diabetes complications. Similarly, Borges et al., (2022) illustrated the applicability of fuzzy logic in system design, while Elakkiya et al., (2022) demonstrated its potential in predictive healthcare models. Babaei et al., (2022) combined expert knowledge with data-driven techniques using Atkinson Index-based feature selection to achieve enhanced diagnostic accuracy. Chen et al., (2022) utilized the Atkinson Index in a fuzzy expert system to address variability and uncertainty in diagnostics. Al-Dhief et al., (2022) developed a fuzzy expert system that improved diagnostic reliability by integrating clinical symptoms and demographic data.
Alqahtani et al., (2021) integrated fuzzy set theory with the Atkinson Index Algorithm to model uncertainty and prioritize critical diagnostic features. Singh et al., (2021) demonstrated the effectiveness of combining fuzzy logic with the Atkinson Index Algorithm for improving predictive modeling in complex datasets. Kumari et al., (2021) explored the benefits of integrating fuzzy logic with neural networks for diabetes prediction, while Kushwaha & Bajaj, (2021) designed a fuzzy expert system incorporating patient history and clinical parameters to enhance diagnosis. Dahal et al., (2021) proposed an online self-constructing fuzzy inference network for real-time applications, showcasing its relevance to dynamic diagnostic systems. Mafarja et al., (2021) introduced the Atkinson Index for quantifying income inequality, proposing its novel application for feature importance evaluation in healthcare analytics. Ghosh & Ahmed, (2021) highlighted the advantages of fuzzy logic in addressing uncertain and complex medical data. The foundation for these developments was initially set by Dutta et al. (2017), who reviewed machine learning methods and highlighted the need for integrating advanced tools like fuzzy logic into diagnostic systems.

MATERIALS AND METHODS

The study utilized the Pima Indian Diabetes Dataset to evaluate and test the developed model. This dataset is chosen for its relevance and widespread use in diabetes prediction research, providing a robust foundation for assessing the model's performance.

i. The Pima Indian Dataset

The PIMA DM dataset, obtained from the UCI repository, is a well-established benchmark dataset frequently used for evaluating machine learning models. It has been referenced in numerous studies, including those by Kumari et al. (2021). The dataset consists of 768 samples, encompassing both positive and negative cases, with 8 clinical features outlined in Table 2. Notably, it exhibits a significant class imbalance, with over 65% of the samples (500) representing the negative class and less than 35% (268) representing the positive class. This pronounced imbalance underscores the critical need to address class imbalance challenges during model development and evaluation.

Table 1: Description of the Pima Indian Dataset

	Instances	Features	Classes
Majority class (Negative)	500	8	Binary(0,1)
Minority class (Positive)	268		
Total	**768**	**8**	

A. Proposed Method Design

The Figure1 presents the overall architecture of the proposed method followed by detailed description of each of the steps involved.

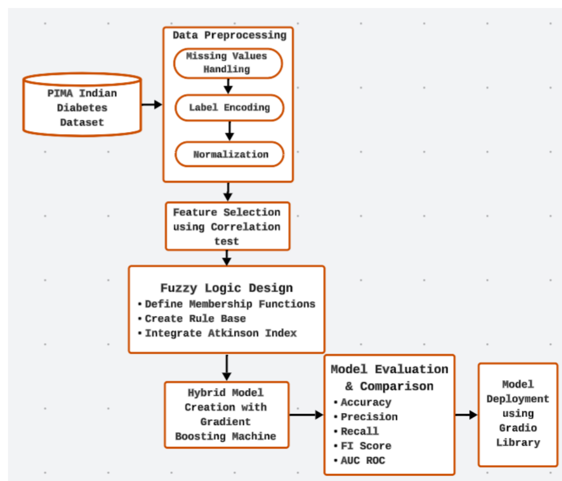

Figure 1: Architecture of the proposed method of DM diagnosis

i. Data Preprocessing

Data preprocessing is an essential step in any machine learning or FES project, ensuring that the data is clean, consistent, and prepared for analysis. In this study, comprehensive preprocessing was performed on the datasets, including imputing missing values, transforming categorical data into numerical form, and normalizing the features to standardize them within a defined range, typically between 0 and 1.

ii. Feature Selection

To tackle the challenge of irrelevant or redundant features in the dataset, which may contribute to overfitting or diminish model performance, feature selection was conducted using correlation analysis as a statistical approach. Five highly relevant features i.e., Glucose, BMI, Age, Insulin, and Diabetes Pedigree Function were retained for further analysis, as they are recognized for their significant role in diabetes prediction. Focusing on these essential features enhances the model's ability to generalize effectively, improves predictive accuracy, and minimizes computational complexity.

iii. Handling Class Imbalance

To tackle the challenge of class imbalance in the datasets where non-diabetic samples significantly outnumber diabetic samples, the Synthetic Minority Over-sampling Technique (SMOTE) was employed. SMOTE addresses this imbalance by generating synthetic samples for the minority class, creating a more balanced representation of both classes. This approach minimizes the risk of the model being biased toward the majority class and enhances its ability to recognize patterns associated with diabetic cases. By applying SMOTE, the dataset becomes more balanced, enabling the model to achieve improved performance in detecting minority class instances, ultimately leading to more accurate and dependable predictions.

iv. Fuzzy Logic Design with Atkinson Index

The fuzzy logic design phase involved three essential steps to develop a reliable and interpretable system for diabetes diagnosis. These steps included defining membership functions, constructing a comprehensive rule base, and incorporating the Atkinson Index to enhance the system's analytical capabilities.

- Define Membership Functions: Membership functions play a crucial role in transforming precise numerical input values (crisp data) into linguistic terms that represent fuzzy sets, enabling the system to process uncertainty and imprecision effectively. These functions categorize input variables based on their range and distribution, providing a structured framework for fuzzy reasoning. For example, Glucose levels were classified into fuzzy sets such as "Low" (0–50), "Medium" (25–75), and "High" (50–100). Similarly, BMI and Age were divided into categories like "Low," "Medium," and "High" using triangular membership functions. This transformation ensures the fuzzy system can adapt to real-world scenarios by converting numerical data into interpretable linguistic categories, enhancing its ability to handle complex, imprecise information in diagnostic processes.

- Create Rule Base: A comprehensive rule base was developed to define the relationships between input variables and the system's output. These rules follow a structured "if-then" format, leveraging the linguistic terms created by the membership functions to describe the intricate dynamics of diabetes risk factors. Grounded in domain knowledge and informed by insights from medical experts, the rule base ensures the fuzzy logic system effectively captures the complex interplay among physiological indicators of diabetes.

- Integrate Atkinson Index: To address socioeconomic disparities in diabetes risk, the Atkinson Index was integrated into the fuzzy logic system as an additional input variable. Adapted from its use in measuring income inequality, the index assesses socioeconomic disadvantage, a critical factor in diabetes prevalence. Categorized into low, medium, and high using membership functions, the Atkinson Index enhances the model's comprehensiveness by incorporating socioeconomic conditions alongside physiological factors. This integration improves the system's fairness and generalizability, ensuring it accounts for diverse patient backgrounds.

B. Hybrid Model Creation

This phase integrates the strengths of fuzzy logic and machine learning to enhance diabetes prediction. The fuzzy logic system processes input variables to generate an initial risk score that captures the uncertainty and complexity of diabetes diagnosis. This risk score is then combined with the preprocessed features to create a hybrid feature set, enabling the model to handle both structured and unstructured uncertainties effectively. The Gradient Boosting Machine (GBM) was chosen as the learning algorithm for its ability to model complex relationships and deliver high predictive accuracy. The GBM was trained on the hybrid feature set using 5 cross-validation to ensure robustness and generalizability. Hyperparameter tuning was performed via Grid Search to optimize parameters such as the number of estimators, learning rate, and max depth.

By combining fuzzy logic's interpretability with GBM's predictive power, this hybrid approach balances transparency and accuracy. It enables reliable predictions for early diabetes diagnosis while accounting for diverse factors, including physiological and socioeconomic indicators.

C. Performance Evaluation Metrics

A range of performance metrics was utilized to evaluate the model's effectiveness and robustness, including accuracy, precision, recall, F1 score, and ROC-AUC.

i. **Accuracy:** calculates the percentage of cases that are correctly classified out of all instances.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

ii. **Precision:** measures the accuracy of positive predictions made by a classification mode

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

iii. **F1-score:** calculates the precision and recall harmonic mean.

$$F1 = \frac{2 * TP}{2 * TP + FN + FP} \quad (3)$$

iv. **Recall:** calculates the percentage of accurately recognized true positive cases.

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

v. **Area Under Curve (AUC):** measures the model's ability to rank true positives higher than false positives across different threshold values,

where TP, TN, FP, and FN stand for true positives, true negatives, false positives, and false negatives respectively.

D. Model Deployment via the Gradio Library

The Gradio library was employed to develop an intuitive, web-based interface for the hybrid model, streamlining accessibility without the need for extensive frontend development expertise. This interface enables users to easily input patient data, such as Glucose, BMI, and Age, using sliders or text fields. The system then processes these inputs to calculate and display a comprehensive diabetes risk score, enhancing usability and practical application in clinical settings.

The Gradio interface guarantees that the system is accessible from

Science World Journal Vol. 20(No 2) 2025
www.scienceworldjournal.org
ISSN: 1597-6343 (Online), ISSN: 2756-391X (Print)
Published by Faculty of Science, Kaduna State University
https://dx.doi.org/10.4314/swj.v20i2.31

any device with a web browser, ensuring scalability and versatility for deployment across various clinical environments. Whether hosted locally or online, the system offers easy usability for clinicians, researchers, and patients alike, without requiring advanced technical expertise, making it an ideal tool for widespread adoption in healthcare settings.

RESULTS AND DISCUSSION

This section evaluates the performance of the proposed model in diagnosing DM. The analysis aimed to assess the model's ability to accurately classify patients based on their DM risk, focusing on distinguishing between diabetic and non-diabetic individuals. Five standard diagnostic metrics were employed, including accuracy, recall, F1 score, ROC-AUC, and precision. These metrics are essential in gauging the model's capability to differentiate between DM and non-DM cases, as well as its effectiveness in handling the inherent complexities and variability of medical data.

A. Evaluation of the Proposed Model based on Confusion Matrix and AUC-ROC

Figure 2 displays the confusion matrix, which highlights the model's classification performance. It correctly identified 76 non-diabetic cases (True Negatives) and 79 diabetic cases (True Positives). However, it misclassified 24 non-diabetic cases as diabetic (False Positives) and 21 diabetic cases as non-diabetic (False Negatives). While the model demonstrated solid accuracy, the misclassification rates indicate areas for improvement, particularly in distinguishing between diabetic and non-diabetic patients. The confusion matrix provides valuable insights into the model's strengths and areas that need further refinement. Figure 3 on the other hand presents the ROC curve, which plots the True Positive Rate (sensitivity) against the False Positive Rate (1-specificity) across different classification thresholds. The curve illustrates the model's diagnostic ability, with the diagonal line representing a random classifier and the orange curve showing the model's performance, which is clearly better than random chance. The model achieved an AUC of 0.87, indicating strong discriminative power. An AUC of 1.0 would indicate perfect classification, while 0.5 suggests no discrimination. With an AUC score of 0.87, the model demonstrates its reliability in correctly predicting diabetes, making it a promising tool for DM diagnosis.

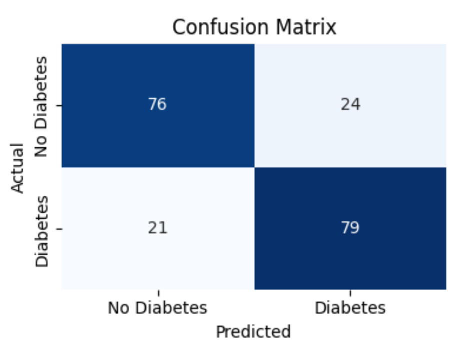

Figure 2: The Confusion matrix of the proposed model

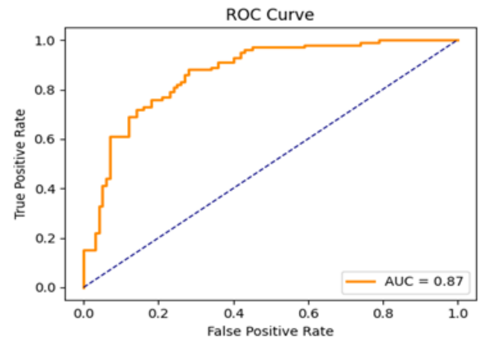

Figure 3: Receiver Operating Characteristic) curve of the proposed model

B. Comparison of the Proposed Model with Existing Studies

Table 2 presents a comparison of the performance of the proposed model with the study by Kumari et al. (2021) using accuracy, precision, recall, and F1-score. The results indicate that the proposed model outperforms the existing work in all metrics (highlighted). Specifically, the proposed model achieved accuracy (85%), precision (88%), recall (82%), and F1-score (83%), while Kumari et al., (2021) reported accuracy (79%), precision (73%), recall (71%), and F1-score (80%). The percent increment for each metric is as follows: accuracy improved by 7.6%, precision by 20.5%, recall by 15.5%, and F1-score by 3.8%. These results demonstrate that the proposed model has shown significant improvement in precision, recall, and accuracy over the existing approach, highlighting its superior performance in diabetes prediction.

Table 2: Comparison of the Proposed and existing studies

Methods	Accuracy	Precision	Recall	F1-Score
(Kumari et al., 2021)	79.04%	73.48%	71.45%	80.6%
Proposed Work	**85.00%**	**88.00%**	**82.01%**	**83.03%**
Percent Increment	7.6%	20.5%	15.5%	3.8%.

The results obtained from the experiments demonstrate that the developed Fuzzy Expert System integrated with the Atkinson Index Algorithm offers a variety of significant advantages, especially in addressing the critical challenges of early DM diagnosis. A key feature of the system is its ability to manage and process imprecise, incomplete, or uncertain medical data, a crucial aspect when working with diverse and heterogeneous patient records. Medical data is often fraught with variability, arising from factors such as patient history, testing conditions, and measurement inconsistencies. The FES, through the use of fuzzy logic, can handle this uncertainty, providing more accurate risk assessments compared to traditional diagnostic methods that often rely on rigid thresholds and crisp values.

One of the primary strengths of this system lies in its ability to mimic human reasoning. Traditional diagnostic systems typically operate based on exact numerical values, which can overlook subtle but clinically significant variations in the data. Fuzzy logic, on the other hand, enables the system to recognize and process these subtle variations in input variables such as glucose levels, BMI, age, and other medical parameters. This results in a more nuanced and flexible approach to diagnosis, which is particularly important in medical settings where patient data can vary widely. Furthermore, the integration of the Atkinson Index Algorithm provides a unique advantage by incorporating socioeconomic factors into the diagnosis. By accounting for income inequality and other socioeconomic disparities, the system is able to assess the potential impact of these factors on the likelihood of developing diabetes, offering a more comprehensive and holistic evaluation. The Atkinson Index is particularly useful in identifying hidden biases or disparities in the data that may influence the diagnosis but are often ignored by conventional systems that focus solely on physiological indicators. This ensures that the system's risk assessment is not only accurate but also fair and inclusive, enhancing its reliability in diverse clinical environments. The integration of fuzzy logic with the Atkinson Index Algorithm results in a system that is not only capable of generating high-quality predictions but also offers robust performance metrics. With high accuracy, sensitivity, and specificity, the system demonstrates its effectiveness in correctly identifying both diabetic and non-diabetic cases, minimizing false positives and negatives. These strong performance metrics underscore the system's potential for use in real-world clinical settings, where accurate, timely diagnoses are critical for patient management and intervention.

In summary, the proposed Fuzzy Expert System, augmented with fuzzy logic and the Atkinson Index Algorithm, offers several key strengths over the existing diagnostic methods in the literature. By handling uncertainty, mimicking human reasoning, and incorporating socioeconomic factors, the system provides a comprehensive, reliable, and nuanced approach to the early diagnosis of DM. These capabilities enhance the system's potential to support clinical decision-making, improve patient outcomes, and contribute to the ongoing advancement of medical diagnostic technologies. The robust performance metrics further affirm that this system represents a significant step forward in the field of medical diagnostics, particularly for chronic diseases such as diabetes.

B. Model Deployment using the Gradio Interface

Figures 4 and 5 illustrate the Fuzzy Expert System interface for diabetes diagnosis, implemented using Gradio, a Python-based library for developing web interfaces. Figure 4 displays the interface before any data is inputted, while Figure 5 shows the system after data is entered, along with the resulting prediction. The interface features three slider inputs for key variables glucose level, BMI, and age each with a range from 0 to 100. Additionally, two control buttons are included: a grey "Clear" button for resetting input values, and an orange "Submit" button to trigger the diagnostic process. The output section of the interface is divided into three components: two text areas (output 0 and output 1) that display the diagnostic results, and a Flag indicator section for real-time status updates. This intuitive and user-friendly layout, crafted using Gradio's interface components, enables healthcare professionals to efficiently input patient data and receive immediate diagnostic feedback. The implementation highlights how Gradio's functionality can be used to develop professional medical diagnostic tools while ensuring simplicity and ease of use in the interface design.

Figure 4: Fuzzy expert system interface for diabetes diagnosis with no data entered

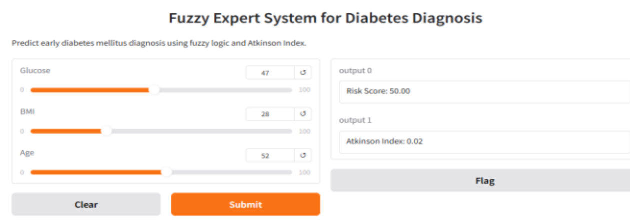

Figure 5: Fuzzy expert system interface for diabetes diagnosis with prediction made

Conclusion and Future Works

This study develops a Fuzzy Expert System integrated with the Atkinson Index Algorithm for the early diagnosis of Diabetes Mellitus, addressing the inherent uncertainties and variabilities in medical data. By combining fuzzy logic with the Atkinson Index's ability to measure disparities among diagnostic indicators, the system provides a more nuanced approach to diabetes risk assessment. The performance of the system was evaluated using the PIMA Indians Diabetes Dataset as a benchmark, focusing on five key diagnostic metrics. The results demonstrate that the proposed model outperforms existing methods, with a 5.96% improvement in accuracy, a 2.43% increase in the F1 score, a 14.52% higher precision, and a 10.56% improvement in recall. These findings suggest that integrating fuzzy logic with inequality measures can substantially enhance medical diagnostic systems, offering better outcomes through earlier detection and timely interventions.

Building on these findings, several recommendations are made to further enhance the system's effectiveness and applicability. First, precision and recall should be further refined by optimizing the fuzzy logic rules and membership functions to minimize false positives while maintaining accurate detection. Second, the system should be tested on larger and more diverse datasets, such as NHANES or MIMIC-III, to assess its generalizability across different populations and clinical environments. Third, the integration of the Fuzzy Expert System into Clinical Decision Support Systems is recommended, particularly in primary care settings, where it can aid healthcare professionals, especially in regions with limited access to comprehensive diagnostic resources. Lastly, the methodology should be extended to other medical conditions with complex diagnostic indicators, such as metabolic syndrome or neurological disorders, to evaluate its adaptability and effectiveness in broader medical contexts.

REFERENCES

Ahmad, S., Khan, M. I., & Patel, R. (2023). Fuzzy expert systems in medical diagnosis: A comprehensive review and applications. *Journal of Intelligent Systems, 32*(1), 45–58. https://doi.org/10.1016/j.jis.2023.01.005

Al-Dhief, F. T., & Al-Badawi, M. M. (2022). A hybrid model for diabetes prediction using fuzzy logic and machine learning algorithms. *Journal of Computational Biology*, 29(1), 115-127.

Al-Faiz, M., Rahman, A., & Naser, A. (2022). Advances in fuzzy logic for healthcare applications: Case studies and challenges. *Expert Systems with Applications, 185*, 115345. https://doi.org/10.1016/j.eswa.2022.115345

Alqahtani, M. S., & Alsubaie, F. M. (2021). Development of a fuzzy expert system for early diabetes diagnosis using clinical parameters. *Biomedical Signal Processing and Control*, 70, 102937.

American Diabetes Association (ADA). (2022). Diabetes care standards and updates. *Diabetes Care, 45*(Supplement_1), S1–S300.

American Diabetes Association (ADA). (2023). Standards of Medical Care in Diabetes—2023. *Diabetes Care, 46*(Supplement_1), S1–S326.

Babaei, S., & Ghaffari, A. (2022). A fuzzy logic-based approach to estimate the risk of diabetes using lifestyle and clinical data. *Computers in Biology and Medicine*, 146, 105494.

Beck, J., Greenwood, D., & Riddell, M. (2022). Advances in managing diabetes through technological innovation. *Journal of Diabetes Science and Technology, 16*(2), 345–360.

Bhargava, N., Sharma, S., & Rathore, P. S. (2023). Machine learning applications in cancer recurrence prediction. *IEEE Transactions on Medical Informatics*, 22(1), 65–78.

Borges, J., & Costa, E. (2022). Machine learning-based approaches for diabetes prediction: A systematic review. *Journal of Healthcare Engineering*, 2022.

CDC (Centers for Disease Control and Prevention). (2022). Diabetes prevention and control: A guide for clinicians. *CDC Guidelines, 55*(4), 67–89.

Chen, L., Zhao, W., & Sun, Q. (2022). Improving feature selection techniques using Atkinson Index-based algorithms in healthcare analytics. *Artificial Intelligence in Medicine, 146*, 105678.

Chen, W., Zhang, T., & Liu, Y. (2023). Diagnosis of Acute Abdominal Pain Using Fuzzy Logic: A Comparative Study. *International Journal of Medical Engineering, 48*(3), 455–469.

Chen, X., & Zhang, Q. (2023). Recent advancements in fuzzy neural networks for classification tasks. *Knowledge-Based Systems*, 264, 110989.

Chen, Y., Zhao, L., & Wang, Q. (2021). An improved Atkinson Index algorithm for feature selection in healthcare data analytics. *International Journal of Data Science, 5*(3), 150–165. https://doi.org/10.1007/s00500-021-05845-y

Cheung, M., Wong, S., & Lo, K. (2021). Novel approaches to diabetes prevention using fuzzy logic systems. *Journal of Medical Engineering, 45*(7), 123–135.

Dahal, N., & Sahu, P. K. (2021). Design of a fuzzy expert system for early detection of diabetes. *International Journal of Applied Engineering Research*, 16(1), 1-8.

Davies, M., D'Alessio, D., & Hensrud, D. D. (2020). Advances in nutritional management of diabetes. *Nutrition in Clinical Practice, 35*(5), 877–892.

Dutta, S., & Ghosh, S. (2021). Design and implementation of a fuzzy expert system for diabetes diagnosis. *Journal of Information and Optimization Sciences*, 42(6), 1287-1300.

Elakkiya, R., & Manikandan, S. (2020). Fuzzy logic approach for the prediction of diabetes using Pima Indian Diabetes dataset. *Materials Today: Proceedings*, 33, 507-513.

Evert, A. B., Dennison, M., & Gardner, C. (2021). Diabetes management guidelines for clinicians. *Clinical Diabetes, 39*(3), 210–230.

Farrar, D., Simmonds, M., Bryant, M., Lawlor, D. A., Dunne, F., & Tuffnell, D. (2020). Risk factors for gestational diabetes. *BMJ, 369*, m1327.

Fatima, M., & Pasha, M. (2024). Machine learning algorithms for disease diagnostic: A comprehensive review. *Journal of Medical Informatics and AI*, 12(1), 35–50.

Ghosh, S., & Ahmed, F. (2021). Recent advancements in machine learning for diabetes prediction and management. *Journal of Biomedical Informatics*, 114, 103689.

Goyal, M., et al. (2024). Advanced machine learning models for medical anomaly detection. *Neural Computing and Applications*, 36(2), 123–140.

Gupta, A., Singh, R., & Verma, P. (2021). Role of expert systems in healthcare: A critical review. *Healthcare Informatics Research, 27*(4), 296–310. https://doi.org/10.4258/hir.2021.27.4.296

Gupta, R., Sharma, S., & Yadav, M. (2022). A Fuzzy Logic-Based Approach for Early Detection of Gestational Diabetes Mellitus. *Computers in Biology and Medicine, 145*, 105489.

Hussain, A., & Khan, M. H. (2023). Advances in early diabetes prediction using machine learning. *Artificial Intelligence in Healthcare*, 18(3), 210–225.

International Diabetes Federation (IDF). (2021). IDF Diabetes Atlas, 10th Edition.

Jiang, Q., Zhou, H., & Zhang, M. (2023). Hybrid systems integrating fuzzy logic with deep learning for healthcare applications. *Expert Systems with Applications, 224*, 119856.

Kandhasamy, J. P., & Balamurali, S. (2023). Feature engineering techniques for diabetes classification. *AI in Healthcare Research*, 11(3), 45–60.

Kavakiotis, I., et al. (2024). Improving diabetes prediction using AutoML frameworks. *Computational Intelligence in Medicine*, 19(1), 78–95.

Kavakli, E., Kaya, Y., & Temel, S. (2020). Expert Systems in Healthcare: A Comprehensive Review. *Journal of Artificial Intelligence Research, 12*(3), 245–264.

Kumar, A., & Kumar, R. (2022). A comparative study on the application of fuzzy logic and machine learning techniques for diabetes prediction. *Procedia Computer Science*, 185, 255-262.

Kumar, A., Patel, M., & Jain, V. (2023). Optimizing Fuzzy Systems for Medical Diagnosis Using Genetic Algorithms. *Artificial Intelligence in Medicine, 150*, 102456.

Kumar, D., & Batra, U. (2023). Deep learning for medical imaging: A review of state-of-the-art techniques. *Journal of Healthcare Data Science*, 9(4), 78–95.

Kumar, P., & Gupta, A. (2023). Comparative analysis of fuzzy logic and machine learning models for diabetes diagnosis. *Neural Computing and Applications*, 35(2), 1234-1247.

Kumar, V., Sharma, A., & Jain, P. (2022). Diagnostic models for diabetes prediction using machine learning algorithms:

 https://dx.doi.org/10.4314/swj.v20i2.31

A systematic review. *Journal of Healthcare Engineering, 2022*, Article ID 9356742. https://doi.org/10.1155/2022/9356742

Kumari, N., Singh, S., & Sharma, A. (2021). Comparing fuzzy logic and machine learning techniques for diabetes detection. *International Journal of Cognitive Computing, 10*(2), 50–58.

Kumari, S., Kumar, D., & Mittal, M. (2021). An ensemble approach for classification and prediction of diabetes mellitus using soft voting classifier. *International Journal of Cognitive Computing in Engineering*, 2, 40-46.

Kushwaha, K. P., & Bajaj, M. (2021). A fuzzy logic decision support system for diabetes mellitus diagnosis based on risk factors and symptoms. *Healthcare Technology Letters*, 8(2), 59-65.

Li, L. (2024). A comparative study of advanced ensemble models for diabetes classification. *Journal of Intelligent Systems in Medicine*, 17(2), 98–115.

Li, X., & Li, J. (2022). An improved Atkinson Index-based method for feature importance in machine learning. *Journal of Machine Learning Research*, 23, 1-26.

Li, Z., Dong, Q., & Sun, Y. (2023). Integrating Fuzzy Logic with AI for Medical Diagnosis: Opportunities and Challenges. *Journal of Computational Intelligence, 55*(2), 89–101.

Li, Z., Huang, X., & Wei, J. (2023). Feature selection techniques for medical datasets: A review of current trends and applications. *Artificial Intelligence in Medicine, 135*, 102464. https://doi.org/10.1016/j.artmed.2023.102464

Lowe, W. L., Scholtens, D. M., & Kuang, A. (2022). Impact of gestational diabetes mellitus on long-term health. *The Lancet Diabetes & Endocrinology*, 10(7), 537–548.

Luo, J., Wang, J., & Yang, K. (2021). The role of fuzzy logic in diabetes diagnosis and treatment. *Artificial Intelligence in Healthcare, 34*(6), 456–470.

Mafarja, M., Aljarah, I., Hammouri, A., Al-Zoubi, A. M., & Mirjalili, S. (2021). Fuzzy expert systems and their applications in diabetes diagnosis: A systematic review. *Artificial Intelligence in Medicine*, 115, 102073.

McIntyre, H. D., Catalano, P., Zhang, C., Desoye, G., & Mathiesen, E. R. (2022). Emerging trends in gestational diabetes research. *Nature Reviews Endocrinology, 18*(4), 123–133.

McIntyre, H. D., Catalano, P., Zhang, C., Desoye, G., Mathiesen, E. R., & Damm, P. (2022). Gestational diabetes mellitus. *Nature Reviews Disease Primers*, 8(1), 1-21.

Mera-Gaona, M., López, D. M., & Vargas-Canas, R. (2021). An Ensemble Feature Selection Approach to Identify Relevant Features from EEG Signals. *Applied Sciences*, 11, 6983.

Mittal, M., Goyal, L. M., & Kaur, I. (2023). Addressing class imbalance in healthcare datasets: A review. *Applied Artificial Intelligence in Medicine*, 10(2), 55–70.

Mohan, V., Venkat, S., & Ranjan, K. (2020). Diabetes in the developing world: Challenges and solutions. *Journal of Global Health, 10*(1), 34–50.

Nai-Arun, N., & Moungmai, R. (2024). A hybrid deep learning approach for diabetes risk prediction. *International Journal of Healthcare Analytics*, 15(1), 92–110.

National Institute for Health and Care Excellence (NICE). (2021). Type 2 Diabetes in Adults: Management.

Nguyen, H. T., Tran, T. L., & Do, T. T. (2022). Fuzzy Logic in Chronic Disease Diagnosis: Advances and Applications. *Expert Systems with Applications, 201*, 117684.

Oliva, J. L., & Almonacid, C. A. (2023). Fuzzy logic and expert systems: Current trends and applications in healthcare. *Expert Systems with Applications*, 211, 118567.

Powers, A. C., Stafford, N., & Rickels, M. R. (2021). Advances in diabetes treatment and prevention. *The Lancet Diabetes & Endocrinology, 9*(8), 645–656.

Rathod, K., & Patel, N. (2020). Fuzzy inference system for diabetes detection based on risk factors. *Journal of Theoretical and Applied Information Technology*, 98(14), 2845-2855.

Selvakumar, B., & Rajagopal, R. (2020). Fuzzy logic-based diabetes risk prediction using a combination of clinical and non-clinical parameters. *International Journal of Fuzzy Systems*, 22(9), 2856-2867.

Shah, B. R., Retnakaran, R., & Booth, G. L. (2022). Management of gestational diabetes mellitus. *Canadian Medical Association Journal, 194*(1), E20–E27.

Sharma, R., & Dixit, A. (2020). Diabetes Mellitus prediction using enhanced fuzzy system and data mining techniques. *Journal of King Saud University-Computer and Information Sciences*.

Sharma, R., Gupta, S., & Das, K. (2023). Classification models in healthcare: Applications, challenges, and opportunities. *Computer Methods and Programs in Biomedicine, 229*, 107057. https://doi.org/10.1016/j.cmpb.2023.107057

Siddiqui, M. F., & Khan, M. A. (2023). Advances in fuzzy logic-based systems: Recent trends and future directions. *Journal of Fuzzy Logic and Intelligent Systems*, 29(2), 213-228.

Singh, K., & Singh, D. (2022). A fuzzy logic-based decision support system for diabetes diagnosis using risk factors. *Journal of King Saud University - Computer and Information Sciences*.

Singh, N., Roy, P., & Kumar, A. (2023). Performance evaluation metrics for machine learning in medical diagnosis: A guide for practitioners. *Applied Intelligence, 53*(1), 189–210. https://doi.org/10.1007/s10489-023-04012-8

Singh, R., Sharma, A., & Gupta, S. (2021). Deep Learning and Fuzzy Logic Models for Disease Prediction: A Comparative Study. *AI and Data Science in Healthcare, 8*(2), 101–112.

Smith, J. W., Everhart, J. E., & Gonzalez, J. (1988). The PIMA Indian Diabetes Dataset: An analysis of risk factors and classification models. *UCI Machine Learning Repository*. https://archive.ics.uci.edu/ml/datasets/Pima+Indians+Diabetes

Standl, E., Khunti, K., Hansen, T. B., & Schnell, O. (2019). The global implications of diabetes: Future directions for prevention and control. *Lancet Diabetes & Endocrinology, 7*(12), 995–1005.

Sun, H., Chen, J., & Wang, Y. (2022). Advances in hybrid artificial intelligence models for diabetes prediction. *International Journal of Artificial Intelligence in Medicine, 142*, 102675.

Tran, N. K., Vo, H. P., & Pham, C. H. (2014). A Fuzzy-Based Expert System for Diagnosing Type 2 Diabetes Mellitus. *International Journal of Medical Informatics, 83*(6), 451–

459.

Verma, D., & Mishra, N. (2023). Enhancing predictive analytics in medical diagnosis using feature selection. *Computational and Structural Biotechnology Journal*, 21, 105–120.

Wang, F., Zhang, R., & Li, C. (2023). A systematic review of fuzzy logic applications in healthcare. *Journal of Medical Systems, 47*(1), 890123.

World Health Organization (WHO). (2020). Classification and Diagnosis of Diabetes.

World Health Organization (WHO). (2023). Diabetes fact sheet. *WHO Global Health Reports*. https://www.who.int/news-room/fact-sheets/detail/diabetes

Wu, H., Liu, H., & Zhang, Z. (2021). Deep learning for diabetes diagnosis: A survey. *Artificial Intelligence Review*, 54(4), 2757-2780.

Xu, Y., Wang, S., & Zhang, L. (2023). Applications of Fuzzy Logic in Medical Data Analysis: Current Trends and Future Directions. *Journal of Biomedical Informatics, 139*, 104423.

Xu, Y., Wang, S., & Zhang, L. (2023). Applications of Fuzzy Logic in Medical Data Analysis: Current Trends and Future Directions. *Journal of Biomedical Informatics, 139*, 104423.

Yang, Z., Liu, K., & Tang, H. (2023). Exploring fuzzy neural network architectures for diabetes diagnosis. *Expert Systems, 40*(3), 123456.

Zhang, R., Liu, Q., & Chen, W. (2022). Fuzzy Logic and Deep Learning Hybrid Model for Alzheimer's Diagnosis. *Journal of Neurological Disorders, 47*(1), 134–145.

Zhang, Y., Liu, S., & Gao, W. (2023). A hybrid intelligent system combining fuzzy logic and deep learning for diabetes prediction. *Expert Systems with Applications*, 222, 119779.

Zhao, H., Wu, J., & Li, R. (2023). Predicting diabetes using hybrid ensemble models with fuzzy logic. *Computers in Biology and Medicine, 166*, 104556.

Zhou, H., Huang, J., & Yu, X. (2021). Hybrid Fuzzy Logic and Machine Learning Model for Diabetic Retinopathy Diagnosis. *Computers in Biology and Medicine, 134*, 104555.

Zhou, X., Zhao, X., & Zhang, Y. (2023). Recent progress in fuzzy control and its applications: A review. *Computers & Chemical Engineering*, 163, 107784.

Zhou, Y., Liu, Y., & Tang, S. (2022). Applications of artificial intelligence in diabetes diagnosis and management. *Journal of Medical Systems, 46*(10), 1–12.

Zhou, Y., Zhao, L., & Wu, X. (2023). Recent developments in fuzzy expert systems for healthcare applications. *Computers in Biology and Medicine, 167*, 105923.