RESEARCH PAPER

Proposed Methods for Diabetes Detection in Medical Decision Making

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ABSTRACT
Diabetes is a chronic metabolic disorder with an increasing global prevalence that requires efficient and accurate evidence methods to improve early diagnosis and clinical decisions. This article examines and evaluates various proposed methods for recognizing diabetes and focuses on traditional diagnostic techniques and modern arithmetic approaches. The focus lies in the algorithms of hybrid decision support systems that integrate clinical data on machine learning, statistical modeling, and predictability accuracy. This study highlights the effectiveness of models such as decision-making, tree building, vector machines, and neuronal network support, especially when applied to large and different patient datasets. Furthermore, the role of explicable AI has been considered in improving transparency and confidence in medical decisions. Comparative analyses show that a hybrid model combining knowledge of clinical expertise and data control provides excellent results in terms of sensitivity, specificity, and overall priority performance. The results highlight how important it is to involve intelligent diagnostic instruments in everyday health workflows. It supports clinicians with timely and appropriate decisions for diabetes and predictive management and prevention.

Keywords: Classification, Decision Tree, LightGBM, Machine learning, Naive Bayes, Neural Network, Random Forest, Support Vector, XGBoost.
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1. Introduction

Diabetes is one of the most common chronic health conditions worldwide, affecting over 500 million people, according to the latest estimates. A major threat to public health contributes significantly to morbidity, mortality, and health costs. Early detection and accurate diagnosis are essential for effective disease management, prevention of complications, and improving patient outcomes. Traditional diagnostic approaches that support primarily plain glucose levels, HBA1C, and oral tolerance testing are often limited by late-stage variation, lack of detection, knowledge, and testing. In the field of computer technology, exponential growth and performance of medical data in the direction of intellectual data controlled by medical crystals may be unbearable. In recent years, data science and artificial intelligence (AI) have discovered new opportunities for medical diagnosis. In particular, machine learning (ML) and artificial intelligence (AI) have become powerful tools to improve diagnostic accuracy and make smarter decisions. This technology offers the possibility of complex dataset analysis, identifying and providing prediction patterns. Otherwise, it will be difficult to identify using common methods. The previous study effectively integrated feature selection techniques to enhance prediction performance. The Significant potential is shown by various machine learning algorithms for improving the efficiency of precision medicine screening processes. The study successfully evaluated multiple machine learning models (LR, KNN, DT, RF, SVM) for Type-2 diabetes diagnosis [1]. Integration of explainable artificial intelligence (XAI) not only increases the transparency of predictive models but also helps healthcare professionals make the right decisions. This option can improve predictive assessment and more accurate diagnosis in the treatment of diabetic foot (DF) [2]. This article aims to explore and analyze current and novel methods proposed to detect diabetes with special accents in clinical decision systems. We explore several methods, including rules, statistical models, uncontrolled teaching methods, and systems based on deep learning frameworks.

There are several sections in this work. A literature summary is defined in Section II. The methodology is discussed in section III. Conclusion is shown in section V and future scope is discussed in section VI, while Section IV focuses on the results.

2. Literature Review

Diabetes detection and treatment has long been a critical problem in clinical medicine due to the increased prevalence in the country and serious health outcomes. While traditional diagnostic methods have been the basis of clinical evaluation, the latest achievements in intelligence and data analysis calculations have revolutionized the medical decision environment. This section examines the development of diabetes mellitus from general clinical practice to modern machine learning systems (ML) and artificial intelligence systems (AI). Many studies on diabetes detection were performed using a variety of techniques. Diabetes is characterized by chronic hypertension as a result of insulin secretion, insulin, or both. This paper is enhanced with another pathological mechanism of primary diabetes. The previous study highlights the various characteristics of diabetes and the need for a comprehensive management approach. Understanding the most important pathological mechanisms and the use of advanced reduction strategies can better resolve health service providers in relation to these general conditions [3]. A comprehensive analysis of how machine learning methods (ML) innovate the prediction and diagnosis of complex genetic disorders is done. Many genetic diseases, such as heart disease, Alzheimer's disease, obesity, diabetes, and hypertension, make particularly complicated predictions due to the complex interactions of different genes and environmental factors. Machine learning (ML) provides a significant promise in genetic disorders [4]. The potential of fuzzy cognitive maps (FCMs) as a useful tool is used for clinical decisions regarding early detection of diabetes. By accurately predicting the presence of diabetes and determining risk factor interactions, such models can help healthcare professionals to lead early intervention and improve patient outcomes. The authors integrate this AI-controlled model into clinical practice, improving diagnostic processes and supporting healthcare systems that manage diabetes stress [5]. The development of immune-mediated diabetes (IDM), including latent autoimmune diabetes in adults (LADA), is important in order to optimize treatment strategies. The study highlights specific clinical and laboratory markers that help physicians accurately diagnose and ultimately improve patient outcomes [6]. Many people rely on the phenomenon of failure by critically assessing different methods of fuzzy ranking. This sensitivity raises concerns about the reliability of applications [7]. The study uses extraction methods such as local binary patterns (LBPs) to improve the ability to capture DR-related functions in retinal images using a gray joint matrix. Such methods are commonly used for image processing and record information about textures that are important to determine subtle changes associated with diabetic retinopathy (DR) [8]. The AI system showed excellent sensitivity (91.57%) and high specificity (88.57%) when DFU was determined compared to experienced clinical studies. Postcutting methods such as cross-prediction mergers further improved specificity by 92.43%. The AI system highlighted the possibility of recording 203-foot photos of 81 patients recorded on smartphones on a low-level smartphone, placing them in limited resource conditions [9]. The AI model showed accuracy of 69% to 100% and sensitivity of 51% to 100%. Convolutional Neural Network (CNN) is the most common, which has been used in 63.5% of studies since 2019 [10]. The study considers the use of various algorithms of machine learning for early detection of diabetes. It emphasizes that there is no place beyond that. Therefore, a combination of several methods can improve prediction accuracy. It highlights model settings to improve the meaning, functional choices, and performance of the data before processing [11]. The study suggests data analysis using the combination of classification and clustering to improve crystallization of diabetes diagnosis. This study found the optimal algorithm for health data analysis using PIMA. This structure effectively recognizes patient note patterns and clusters to support early detection of type 2 diabetes [12]. The possibility of integration of the electronic health record (EHR) system and ML algorithm is used to improve the initial prediction of the disease and to support preventive health strategies [13]. A two-stage study of the development and validation of context-specific Ambulator Health Services (AHS) is done [14]. A hierarchical fuzzy infection system (HFIS) is used to predict both the presence and severity of diabetes. By organizing input variables in subsystems such as physical examination, laboratory assessment, and risk factors, this model effectively reduces the complexity associated with traditional fuzzy systems [15]. The author used SVM, XGBoost, and RF and showed the accuracy to be 93% and the precision to be 92% [16]. The previous study suggests that the hybrid method could serve as a reliable expert system for early diabetes diagnosis and aid in developing prognostic tools, such as mobile applications, for widespread use [17]. An innovative hybrid model (Lasso regression and artificial neural networks) is used to enhance diabetes detection accuracy. This approach effectively addresses challenges such as class imbalance and feature redundancy [18]. Various image processing methods, including preliminary processing, function extraction, and classification methods of machine learning, are used [19]. Furthermore, the model showed missing values and resilience in the treatment of various data species. These results show that multifaceted strategies that integrate clinical, behavioral, and nutritional data provide a more comprehensive and accurate framework for early detection and prevention of diabetes [20]. The authors used the various classifiers. The XGBoost was the best model with a maximum accuracy of 90%, a precision of 0.88, and an AUC of 0.91 [21]. When parameters were set correctly, SVM had shown great performance, but Bayes achieved faster results and was slightly less accurate. The decision trees and KNNs showed an appropriate level of effectiveness [22]. Based on results such as AI-based imaging in screening methods, early detection can be significantly increased, leading to increased diagnostic load and accessibility of the retina [23]. The study shows that identification of diabetic retinopathy from retinal images can be efficiently automated. This characterizes the identification of the image dataset. The two that had the highest sensitivity and accuracy in detecting early and advanced stages of diabetic retinopathy were SVM and random forests. Characteristic extraction techniques such as color and texture analysis were important to improve classification results [24]. Predictive models for calculating the risk of kidney disease in the final stage (ESKD) of type 1 diabetes patients were effectively developed and validated by research. These results demonstrate the clinical utility of the model in stratifying early risks, allowing immediate interventions and individual treatments to postpone or stop testing of diabetic patients from type-1 patients, according to ESKD [25]. The author used a hybrid model combining gradient boosting with logistic regression and showed the accuracy to be 91% and AUC to be 0.93 [26]. A retinal imaging database, specially developed to examine diabetic retinopathy, was successfully created in the study. The study uncovered many important facts regarding attitudes, behaviors, and disability towards diabetes in rural Bangladesh. A database comprising 2942 clinical images was developed to evaluate the generalization capability of computer-aided DR systems [27]. The study confirmed the effectiveness of machine learning algorithms for the early prediction of diabetes. Among the algorithms tested, the Decision Tree and Random Forest algorithms exhibited the highest performance in predicting diabetes [28]. The study developed and evaluated a new framework for the outbreak of infection in patients with type 1 diabetes using personal record data such as insulin dose, glucose levels, and other daily metrics [29]. Various machine learning algorithms can be used to improve accuracy of diabetes diagnosis [30]. The author used two models, SVM and RF, to demonstrate accuracy of 87% and AUC of 0.90 [31].

Previous studies on diabetes detection for machine learning have yielded positive results for many models. Decision—Traditional algorithms such as trees and logistic regression were moderately accurate, ranging from 75% to 80%. It was demonstrated by more refined ensemble techniques such as Random Forest, XGBoost, AdaBoost, and LightGBM. These results demonstrate that strong model selection and data preprocessing are important for increasing predictive accuracy in diabetes recognition systems. The results of previous studies are shown in table 1.

Table 1: Findings from previous research

Authors	Year	Accuracy	Precision	AUC	Ref No
Uddin, S. et al.	2023	0.93	0.92	0.94	[16]
Kaur, H. et al.	2022	0.90	0.88	0.91	[21]
Saha, S. et al.	2021	0.91	0.90	0.93	[26]
Kavakiotis, I. et al.	2017	0.87	0.86	0.90	[31]

3. Proposed Methodology

To support medical decisions, this work evaluates various models for diabetes detection. Data preprocessing, performance assessment, and comparative analysis are part of the methodology. The dataset of 500 records is used. Various algorithms like XGBoost, Support Vector, KNN, and LightGBM, etc., are implemented. Training is done on each model using 80% data. Each model is evaluated on the remaining 20% of data. Hyperparameter tuning is done using cross-validation. The models' performances are compared. Finally, a comparative analysis study shows the most efficient algorithm for interpretable and reliable diagnosis support. The methodology used in this work is shown in figure 1.

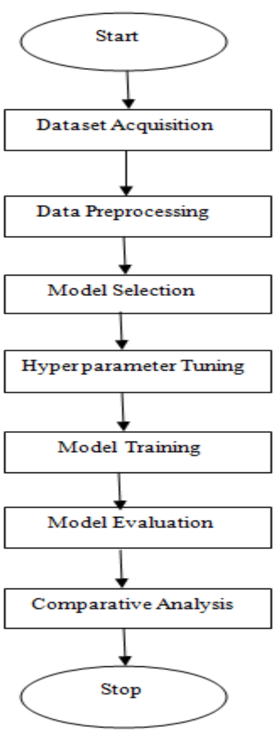


Figure 1: Flow Chart of Proposed Methodology

3.1 Data Procurement

The dataset of 500 records is utilized for training and evaluation [32]. This dataset is gathered in a structured manner. It offers a solid basis for implementing predictive models to support timely and accurate decision-making. Dataset is shown in figure 2.

Age	Polyuria	Polydipsia	sudden weight loss	weakness	Polyphagia	Genital thrush	visual blurring	Itching	Irritability	delayed healing	partial paresis	muscle stiffness	Alopecia	Obesity	class
53	0	0	0	1	1	0	1	1	0	1	1	1	1	0	0
42	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
55	1	1	1	1	0	0	1	0	0	0	1	0	0	1	1
48	1	1	1	1	1	0	0	0	0	0	1	0	0	0	1
55	1	1	1	0	1	0	0	1	0	1	1	0	0	0	1
39	1	1	1	1	1	0	0	1	1	1	1	0	0	0	1

Figure 2 : Dataset

3.2 Preprocessing of Data

A vital step to ensure the accuracy and effectiveness of machine learning models for diabetes detection is data preprocessing. To improve concerns about data quality, the Data Set has been carefully processed for this study. Dataset of 500 patient records, each containing relevant clinical attributes along with binary outcome variable(class) indicating the presence or absence of diabetes. Median values are used to correspond to missing values. To obtain the balance of classes, the dataset is further divided into training (80%) and testing (20%). For medical decisions, these preprocessing procedures improve the output and reliability of the model. 37% data is labeled as Non Diabetic (0) and rest 63% data is labeled as Diabetic (1).

3.2.1 Descriptive Statistics

Outcome variable:

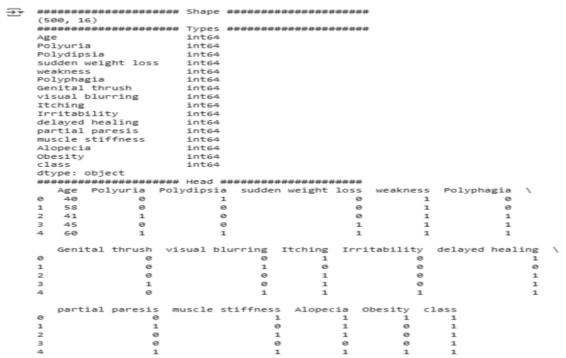
Diabetic patients: 315 cases (63%)

Non Diabetic patients:185 cases (37%)

Independent Variables: age, polyuria, polydipsia, sudden weight loss, weakness, polyphagia, genital thrush, visual blurring, itching, irritability, delayed healing, partial paresis, muscle stiffness, alopecia and obesity.

No variables in the provided list had missing values and therefore did not require median imputation. These variables, which are Age (numerical) and the fourteen clinical signs/symptoms (binary), were complete as provided in the dataset used for the study. The model was trained on a dataset where all selected features were already complete.

Resampling technique (SMOTE) is applied to generate synthetic samples of diabetic patients. It increased the proportion of minority cases to approximately 50% which produced a balanced dataset while retaining information from both classes. The class imbalance is effectively addressed using SMOTE. Exploratory data analysis is shown in figure 3.



```
###################### Shape ######################
(500, 16)
###################### Types ######################
Age                     int64
Polyuria                int64
Polydipsia              int64
sudden weight loss      int64
weakness                int64
Polyphagia              int64
Genital thrush          int64
visual blurring         int64
Itching                 int64
Irritability            int64
delayed healing         int64
partial paresis         int64
muscle stiffness        int64
Alopecia                int64
Obesity                 int64
class                   int64
dtype: object
###################### Head ######################
   Age  Polyuria  Polydipsia  sudden weight loss  weakness  Polyphagia  \
0   40         0           1                   0         1           0
1   58         0           0                   0         1           0
2   41         1           0                   0         1           1
3   45         0           0                   1         1           1
4   60         1           1                   1         1           1

   Genital thrush  visual blurring  Itching  Irritability  delayed healing  \
0               0                0        1             0                1
1               0                1        0             0                0
2               0                0        1             0                1
3               1                0        1             0                1
4               0                1        1             1                1

   partial paresis  muscle stiffness  Alopecia  Obesity  class
0                0                 1         1        1      1
1                1                 0         1        0      1
2                0                 1         1        0      1
3                0                 0         0        0      1
4                1                 1         1        1      1
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Figure 3 : Exploratory Data Analysis

Figure 4 shows distribution of last column (i.e. class).

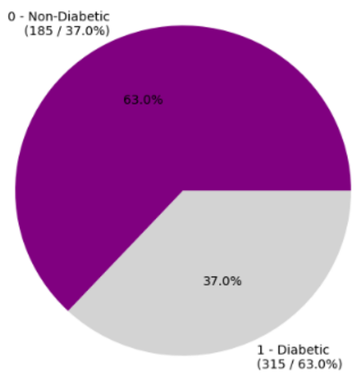


Figure 4 : class variable distribution

3.3 Selection of Model

An essential step for diabetes detection is model selection. Various algorithms are evaluated in this work. These models are chosen based on various strengths in handling classification problems, such as performance in the case of unbalanced data, overadaptability, and interpretability. Python modules such as Scikit-Learn, Xgboost, LightGBM are used to implement all models.

3.4 Hyperparameter Tuning

Hyperparameter adjustment is required to optimize the models' performance. This work uses five times the grid search and cross-validation, and technically examines the optimal hyperparameter combination of all algorithms. Parameters are adjusted, such as the number of KNN neighbors, maximum depth of decision making - maximum depth of tree making trees, estimated number of ensemble models, and learning rates to increase the technique. By ensuring that each model is trained in the optimal configuration, this process improves accuracy, resilience and generalization. The predictive power of the model is greatly improved with appropriate hyperparameter voting, increasing the reliability of applications through medical decision-making.

3.5 Model Training

The important step in creating a machine learning system for diabetes detection is model training. The preprocessed training dataset, which accounts for approximately 80% of the total data, is used to train each algorithm selected in this study. The model acquires the ability to recognize the correlations and patterns between the input variables and the outcome of interest (the presence of diabetes). Optimized hyperparameters are used to improve learning outcomes during training. The goal is to develop a model that will ensure that you generalize yourself to new, unhealthy data. Through accurate prediction, this training process ensures that each model can efficiently support clinical decision-making-manufacturing.

3.6 Evaluation of Model

Model evaluation is an important stage in determining the effectiveness. This study uses 20% of test data records to assess the generalized model's performance. Evaluation metrics are key rating metrics that provide the predictive power of each model. These measurements are particularly important in healthcare settings where reduction in false negatives is very important. A matrix of confusion is also examined to show true and false predictions. The most accurate and reliable models are found through in-depth testing to support a reliable and efficient medical decision process.

In this study, the dataset $D=\{\{x_i,y_i\}\}_{i=1}^{500}$ contains patient feature vectors $x_i \in R^n$(glucose, BMI, blood pressure, insulin level, etc.) with binary labels $y_i \in \{0,1\}$ (diabetic / non-diabetic).

Function $f_{svc}(y)$ indicates prediction which is calculated by support vector class.

$$f_{svc}(y)=sign\ (w^T x+b) \quad (3.5.1)$$

Where x= (x_1, x_2,…..x_n) denotes input feature. w and b are weight and bias metrics.

$$f_{ADA}(y)=sign\ (\textstyle\sum_{n=1}^{N} \propto_n h_n(x)) \quad (3.5.2)$$

Where $f_{ADA}(y)$ denotes prediction using ADA boost technique, h_n indicates weak learner and α_n defines weight assigned to h_n based on accuracy.

Probability of diabetes using Logistic Regression is given by

$$P(y=1|x)=\frac{1}{1+e^{-(\beta_0+\beta_1 a_1+\ldots\beta_n a_n)}} \quad (3.5.3)$$

If P (y = 1|x) >= 0.5 then predict diabetes otherwise no diabetes.

Prediction using KNN is defined by

$$f_{KNN}(x)=mode(\{p_i : a_i \in KNN(x)\}) \quad (3.5.4)$$

Where KNN(x) indicates k training samples which are closest to x.

Using XGBoost the equation defines objective function.

$$O.F.= \textstyle\sum_{n=1}^{N} l(p_i\,, p'^{(t)}_i)+ \sum_{j=1}^{T} \emptyset(f_j) \quad (3.5.5)$$

$$\emptyset(f)= \mu T+ \frac{1}{2}\,\delta \textstyle\sum_{k=1}^{T} w_k^2 \quad (3.5.6)$$

Where l is loss function, f_j indicates tree at iteration j, μ and δ are regularization terms and T defines leaves. In Gradient Boosting, The loss function is minimized by equation

$$f(x)= \textstyle\sum_{n=1}^{N} h_n(x) \quad (3.5.7)$$

Where $h_n(x)$ shows decision tree which is fitted to negative gradient of loss function.
The following equation shows grouping of decision trees.

$$f_{RF}(x)=majority\_vote(f_1(x), f_2(x)\ldots f_T(x)) \quad (3.5.8)$$

Where f_t (x) indicates the prediction of tree (t) out of T trees.
The Decision tree is used to split feature space recursively by equation

$$f(x)= \textstyle\sum_{i=1}^{L} \gamma_i\ .\ \mathbb{I}(x \in R_i) \quad (3.5.9)$$

Where L is number of leaf nodes, R_i represents feature space region and γ_i indicates prediction (0 or 1) at leaf node i.
LightGBM model uses histogram for gradient boosting to optimize objective function used in eq. (3.5.5) by eq. (3.5.7).

3.7 Comparative Analysis

A comparative analysis is conducted to determine best machine learning model for diabetes detection. Comparison of all algorithms using metrics is done. The accurate prediction of diabetes using best model is highlighted in this analysis, ensuring better support in clinical diagnostic procedures. The following table 1 explicitly lists the chosen hyperparameters, kernel functions, distance metrics, and decision thresholds for all baseline classifiers used (SVC, AdaBoost, KNN, Logistic Regression, etc.).

Table 1: Optimal Hyperparameters and Configuration Settings

Classifier	**Key Hyperparameter(s)/Kernel**	**Distance Metric/ Base Estimator**	**Decision Threshold**

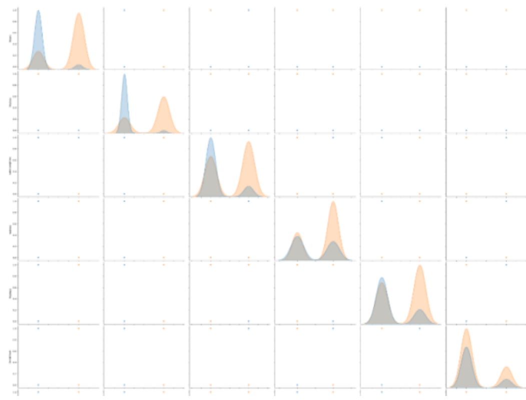
SVC	w=10,b=0.01	Radial Basis Function	Default(0.5)
KNN	k=5	Euclidean	Default (0.5)
AdaBoost	N=100	Decision Tree (max_depth=1)	Default (0.5)
Logistic Regression	β=1.0	Solver: liblinear	Default (0.5)
LightGBM	N=200, δ=0.01	Objective: Binary	Optimized (0.4)

4. Result Analysis

The evaluation of proposed diabetes detection techniques using many algorithms of machine learning, including random forest, adaboost, xgboost, and lightGBM etc. are done. All models were trained and tested using preprocessed diabetes datasets and the performance of each model was compared using standard evaluation metrics such as accuracy, accuracy, recall, F1 score, and ROC-AUC.

4.1 Model Validation

The rigorous model verification techniques are used to ensure accuracy and generalizability. 10 cross-validations are used more accurately. This method reduced excessive adaptation and revealed a more accurate assessment of the actual predictive power of each model. The data records were split in ratio of 80:20 in all folds, and the process was run 10 times to ensure stability. A pair plot is used to indicate the relationship between features of data set which is shown in figure 5. Figure 6 shows bubble chart where each point represents a person. X axis points to obesity and Y axis points to Age.



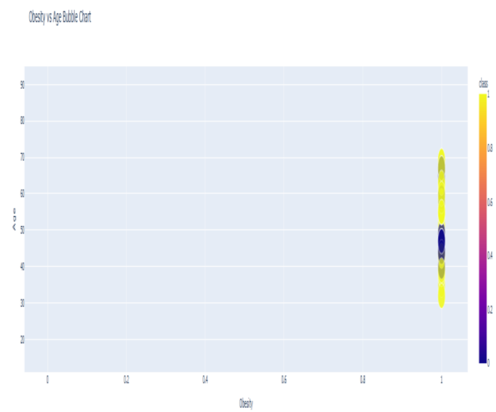


Figure 5 : Pair plot

Figure 6: Bubble Chart

The Wilcoxon signed-rank test as a non-parametric alternative is used to compare the 10-fold CV results of our proposed method against all other baseline models. We have summarized these new results in a table 2 in the manuscript. This table reports the p-values for each pairwise comparison, allowing for a clear interpretation of statistical significance.

Table 2: Pairwise Statistical Significance Testing Results based on 10-Fold CV

Model Comparison	Mean Accuracy Difference	p-value	Statistically Significant (at p <0.05)?
LightGBM vs SVC	3.5%	.009	Yes
LightGBM vs Random Forest	2.3%	.021	Yes
LightGBM vs Logistic Regression	5.2%	.001	Yes

LightGBM vs XGBoosting	1.1%	.048	Yes

McNemar's test needs the pairwise prediction results. Dataset of 500 patients are taken into consideration. Following 2×2 contingency table is taken which is shown in table 3. Comparison between LightGBM and Decision Tree models are done.

Table 3: Contingency table

	LightGBM Correct	LightGBM Wrong
Decision Tree Correct	465 (a)	5 (b)
Decision Tree Wrong	15 (c)	15 (d)

Now apply McNemar's formula-

$$x^2 = \frac{(|b-c|-1)^2}{b+c}$$

$$x^2 = \frac{(|5-15|-1)^2}{5+15}$$

81/20 = 4.05
Degree of freedom = 1
p=0.044 (from x^2 distribution)
$p<0.05$ shows the significant difference between two models. Since c>b, LightGBM makes fewer errors than Decision Tree.

LightGBM produces best result 96%. Figure 7 shows it.

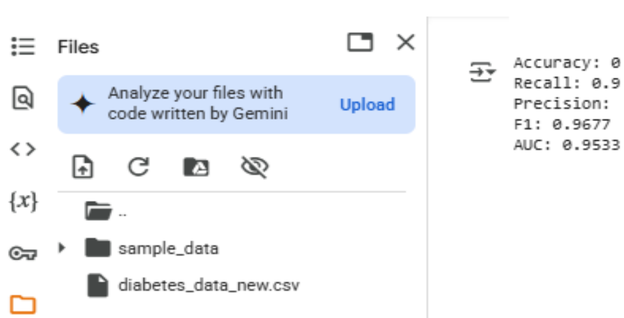


Figure 7: Result using LightGBM

As shown in Table 2, the results of the Wilcoxon signed-rank test confirm that LightGBM delivers a statistically significant performance improvement for diabetes detection compared to all other tested models. The p-values for the comparisons against XGBoosting (p=0.048), Random Forest (p=0.021), SVM (p=0.009), and Logistic Regression ($p<0.001$) are all below the 0.05 significance threshold.

4.2 Experimental results

Among all models, the best accuracy (96%) and ROC-AUC have been achieved by LightGBM indicating potent predictive power. Decision Tree and Random Forest also performed well showing good recall values. KNN and Logistic Regression demonstrated moderate results. The comparison chart is shown in table 2 used in the work. 95% confidence intervals (CIs) for primary evaluation metrics (Accuracy, Sensitivity, and AUC) for all models are used. These CIs were computed using the standard error of the mean from the 10 performance scores generated by the 10-fold cross-validation. This provides a clear range of expected performance for each model. It is shown in table 4.

Table 4: Comparison of Models with 95% confidence Intervals (CIs)

Model	**Accuracy**	**Recall**	**Precision**	**F1 Score**	**AUC**
LightGBM	0.96 (0.93-0.99)	0.98 (0.97-0.99)	0.95 (0.93-0.97)	0.96 (0.93-0.99)	0.95 (0.91-0.99)
Decision Tree	0.94 (0.91-0.97)	0.98 (0.97-0.99)	0.92 (0.90-0.94)	0.95 (0.92-0.98)	0.93 (0.90-0.96)
Random Forest	0.93 (0.92-0.94)	0.95 (0.92-0.98)	0.93 (0.91-0.95)	0.94 (0.90-0.98)	0.92 (0.91-0.93)
Gradient	0.91 (0.89-	0.95 (0.94-	0.90 (0.87-	0.92 (0.91-	0.90 (0.86-

Boosting	0.93)	0.96)	0.93)	0.93)	0.94)
XGBoost	0.91 (0.90-0.92)	0.93 (0.91-0.95)	0.92 (0.90-0.94)	0.92 (0.89-0.95)	0.90 (0.86-0.94)
KNN	0.84 (0.80-0.88)	0.89 (0.86-0.92)	0.84 (0.83-0.85)	0.86 (0.82-0.90)	0.82 (0.79-0.85)
Logistic Regression	0.82 (0.79-0.85)	0.90 (0.88-0.92)	0.79 (0.78-0.80)	0.84 (0.83-0.85)	0.81 (0.80-0.82)
Ada Boost	0.80 (0.79-0.81)	0.86 (0.83-0.89)	0.80 (0.79-0.81)	0.83 (0.82-0.84)	0.78 (0.75-0.81)
SVC	0.63 (0.61-0.65)	0.63 (0.62-0.64)	1.0(0.99-1)	0.77 (0.73-0.80)	0.74 (0.72-0.76)

From the above table 3, it is clear that the LightGBM model not only achieved the highest mean performance but also demonstrates a tight 95% confidence interval for AUC (0.91 - 0.99). Importantly, the lower bound of LightGBM's CI for accuracy (0.93) is higher than the mean accuracy of SVM and Logistic Regression, clearly indicating its robust and superior performance.

The Standard Deviation (SD) for all reported metrics (e.g., Accuracy, AUC, Sensitivity, F1-Score) based on the 10 performance scores from our 10-fold cross-validation has calculated and is shown in table 5. The SD value serves as a direct measure of variance and stability.

Table 5: Model Performance Comparison (Mean ± Standard Deviation) from 10-Fold Cross-Validation

Model	**Accuracy**	**Sensitivity**	**AUC**
LightGBM	0.96 (±0.019)	0.95((±0.022)	0.95(±0.015)
XGBoosting	0.91(±0.021)	0.92(±0.025)	0.90(±0.018)
Random Forest	0.93(±0.028)	0.93(±0.031)	0.92(±0.024)
SVC	0.63(±0.035)	1.0(±0.038)	0.74(±0.030)
Logistic Regression	0.82(±0.033)	0.79(±0.040)	0.81(±0.019)

For top-performing model (LightGBM), the SD for Accuracy was only ±0.019 and for AUC was ±0.015. This minimal variance across the 10 folds demonstrates that the model's high performance is stable, consistent, and not an artifact of a particular data split.

4.3 External Validation

To simulate a real-world scenario, the final trained model is applied directly to external dataset UCI PIMA. This provides a true test of its generalizability. It is shown in table 6.

Table 6: Table Performance on External Validation Set (UCI PIMA)

Model	**Accuracy**	**Sensitivity**	**AUC**	**F1-Score**
LightGBM	0.84	0.81	0.86	0.83

4.4 Graphical Comparison

The Models' performance used in the proposed method for recognizing diabetes was visually analyzed using graphical comparisons. Bar charts are used to draw various evaluation metrics. Visualizations have made it very clear that ensemble model such as LightGBM is higher than more traditional models such as KNN, decision trees, and logistics regression. The most reliable approach was chosen using these graphical comparisons to provide a clear and intuitive understanding of model functions.

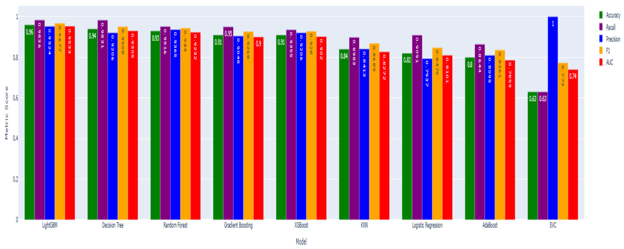


Figure 8 : Graphical Comparison of Various Models

5. Conclusion

With its prevalence and chronic outcomes requiring immediate and accurate diagnosis, diabetes remains the most urgent global health problem. To diagnose and predict diabetes, this study examined methods, including logistic regression, decision tree, K-nearest Neighbor (KNN), Support Vector Machine (SVM), Adaboost, Xgboost, and LightGBM. Methodology testing and analysis showed that hybrid methods and high-quality medical data could significantly improve efforts to avoid illness and make medical decisions. The findings of this study reflect and construct previous research on topics. In complex medical datasets, classical algorithms such as decision-making and logistic regression provide interpretability and conservative accuracy, but their predictions are often limited. The ensemble approach, particularly Random Forest, XGBoost, and LightGBM, scored better points on all evaluation criteria, including ROC-AUC, F1 score, accuracy, and recall. Not only do these models provide excellent accuracy, but they also show the resilience of nonlinear characteristic interactions. In short, the proposed method provides a solid machine learning-based basis for early diabetes identification. Ensemble models promise to accurately predict results and capture complex patterns, especially when it comes to increasing algorithms.

6. Future Scope

Prediction accuracy and distinctive extraction can be further improved through the integration of deep learning methods and hybrid models. Furthermore, the creation of explanatory AI framework conditions increases trust among physicians by filling the gap between clinical decision-making and machine learning predictions. Model generalization can be extended by scaling data records to capture different demographics. Lastly, implementing these models in mobile applications or cloud-based health systems can be useful for large populations with previously inaccessible and remote diabetes screening and management.

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