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A Novel Random Forest-Based Algorithm for Diabetes Diagnosis

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Abstract: This chapter genuinely addresses the crucial need for the diagnosis of diabetes, since the techniques that are currently in use today are still lacking in both efficiency and accuracy. For the present investigation, we have chosen to use the Random Forest classifier as our model. The Random Forest algorithm is an ensemble learning method that creates a lot of decision trees during training and produces a class that is either the mode of the classes for classification or the mean forecast of the individual trees for regression. The investigation builds and compares different intelligent systems based on multilayer algorithms using the data set that Kare published. Such variables include levels of blood glucose, levels of HbA1c, smoking histories, cardiovascular disease, hypertension, age, gender, and body mass index (BMI). Furthermore, to offering insights into the trends and patterns in diabetes risk, this thorough analysis will lay the groundwork for future studies. In particular, studies can be conducted to better understand how these factors interact and affect the development and course of diabetes, which is essential information for enhancing patient care and results in this increasingly important field of medicine.

Keywords: *Diabetes; Machine Learning; Random Forest; Early Detection.*

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I. INTRODUCTION

However, choosing the appropriate classification system is a major challenge in diabetes prediction. This study tries to enhance the accuracy of diabetes early diagnosis through the use of the algorithm known as the Random Forest model. This study incorporated the stages of data collection, data preprocessing, split data, modelling, and assessment.

Diabetes Mellitus, or simply Type 2 diabetes, is a collection of metabolic disorders marked by repeatedly elevated blood sugar levels. In medical science, artificial intelligence relates to actual medical fields that are properly examined and considered from both a technical and medical standpoint.

By bridging the gap between massive data sets and comprehension by human beings' data science and machine learning are assisting medical professionals in making diagnoses easier. With a dataset that depicts a population at high risk of developing diabetes, we may start using machine learning algorithms for categorization.

With the use of the medical information we can collect about individuals, we should be able to better forecast the likelihood that a person would develop diabetes and take necessary action to assist. We can begin data analysis and algorithmic experimentation to better understand the beginnings of diabetes.

A pattern for identifying diabetes can be created by using part of the patient data from diabetics that has been saved in a database to make this prediction [1]. Numerous fields have made extensive use of machine learning (ML) technology [2], particularly in the early identification of diabetes. As a result, machine learning has been used to tackle several complicated and advanced problems over the years in several kinds of industries, including natural language processing, machine learning, visuals, audio, entertainment, company operations, and commercial advertising [3].

The recommended classification method can assist physicians in diagnosing diabetes using an ECG signal that has a 95.7% accuracy rate, Additional research by [4] employed Naïve Bayes, logistic regression, and gradient lifting for the detection of diabetes. The results showed that gradient boosting had an accuracy of 86%, logistic regression had an accuracy of 79%, and naive bayes had an accuracy of 77%.

Additionally, [5] utilizes the models for forecast machine learning developed in this work, Regression of

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logistic data, vector machines providing assistance, random forests, boot gradient methodologies, naive Bayes, closest peers, and many more. The best prediction models were learning-based models based on booted gradients and random forest predictions, which had respective predictive capabilities of 86.28% and 86.29%. Additionally, studies by [6] have used predictive analysis to identify Miletus diabetes early. According to the results, The algorithms exhibiting the highest specifications comprised the decision tree and random forest strategies, at 98.20% and 98.00%, respectively, and were the most effective for analysing diabetic data. The best accuracy, according to naive Bayesian results, is 82.30%. Additionally, in comparison using the base-learning datasets for diabetes 130-US hospitals (98%) and PIMA (92%), which estimate the probability of early-stage diabetes (99.6%) [7]. Identified insulin resistance with the highest accuracy using a newly developed super-learning algorithm.

II. METHOD

➢ *Data Collection:*

Include EHR records, lab test results (glucose, HbA1c), demographics, vitals, medication history, lifestyle questionnaires, and optionally wearables.

➢ *Preprocessing:*

Explicit steps for de-identification, unit standardization, outlier detection, and imputing missing values. Log assumptions for clinical traceability.

➢ *Feature Engineering:*

Domain-driven features (e.g., glucose variability, BMI categories), time-window aggregations, interaction terms.

➢ *Class Imbalance:*

Diabetes datasets often have imbalance; consider SMOTE, class weighting, and threshold calibration for clinical sensitivity/specificity trade-offs.

➢ *Modelling:*

Random Forest baseline with hyperparameter tuning (total_no_trees, maximum_depth, maximum_characteristics, minimum_samples_leaf). Consider assembling with other models if needed.

➢ *Evaluation Metrics:*

F1, Specificity, memory (degree of sensitivity), correctness, sharpness, ROC-AUC, PR-AUC, calibration plots, and clinical utility metrics (NRI, decision curves).

➢ *Interpretability:*

Feature importance, SHAP values, partial dependence plots, and generating clinician-friendly explanations for predictions.

➢ *Deployment:*

Wrap as REST API, integrate into EHR as Clinical Decision Support (CDS), include UI to display prediction + explanation, and require clinician sign-off workflows.

➢ *Monitoring:*

Track data drift, concept drift, model performance by subgroup, alerting for degradation, and scheduled retraining with versioning.

III. PROPOSED SYSTEM FLOW CHART

➢ *Start*

➢ *Data Collection:*

- Patient records (e.g., PIMA dataset, lab tests, demographics, medical history).

➢ *Data Preprocessing:*

- Handle missing values
- Normalize/standardize features
- Feature selection/reduction

➢ *Split Dataset*

- Training set
- Testing/validation set

➢ *Build Random Forest Model*

- Create several decision trees.
- Random subsets of attributes were used to instruct each tree.

➢ *Ensemble Learning*

- Aggregate tree outputs using majority voting (classification)

➢ *Assessment of the Model*

- F1-score, ROC curve, memory, correctness, and sharpness

➢ *Diabetes Diagnosis Prediction*

- Output: Diabetic / non-diabetic

➢ *End*

IV. PROPOSED SYSTEM ARCHITECTURE

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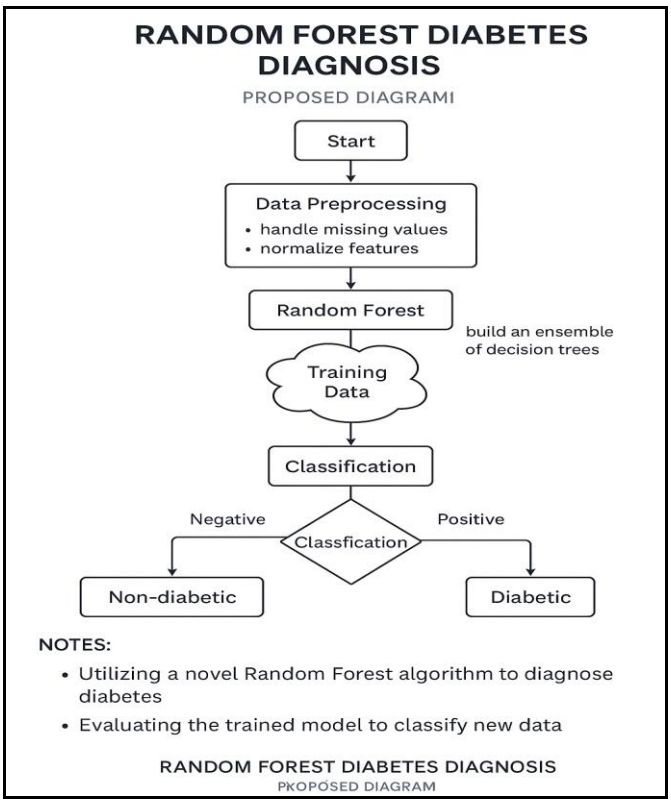

Fig 1 Proposed Diagram of Random Forest Diabetes Diagnosis.

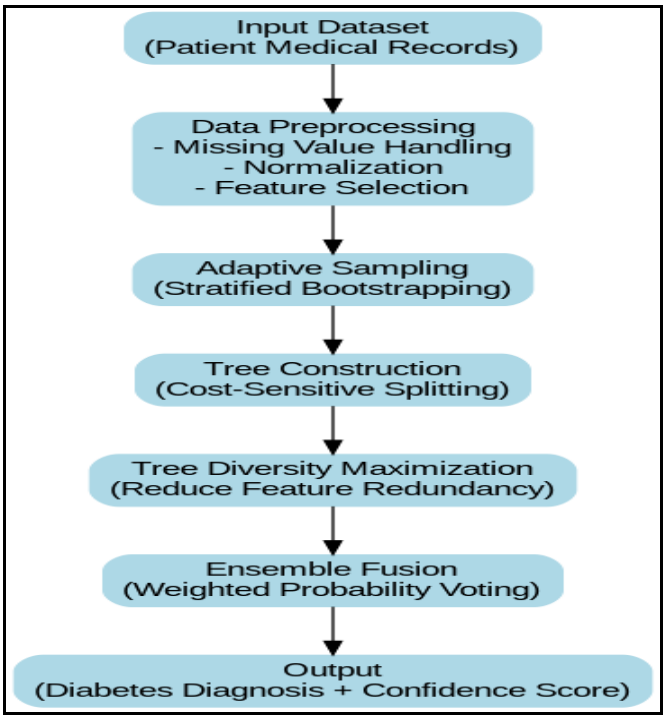

Fig 2 Work Flowchart of Random Forest Diabetes Diagnosis

➢ *Performance Metrics Table*

- *Include:*

✓ F1-score (%)
✓ ROC curve (%)
✓ memory (%)
✓ correctness (%)
✓ sharpness

V. RESULT ANALYSIS AND GRAPHS

➢ *ROC Curve*

- Plot Rate of False Positives versus True Positives
- compare with other classifiers.
- Demonstrates diagnostic ability at different thresholds.

➢ *Confusion Matrix Heatmap*

- Shows correctly vs. incorrectly classified diabetic and non-diabetic patients.
- Easy to interpret class-wise performance.

➢ *Feature Importance Bar Chart*

- Ranks features (e.g., glucose, BMI, age, blood pressure) by contribution in Random Forest.
- Highlights the most significant risk factors.

➢ *Accuracy/Performance Comparison*

- Bar chart comparing your proposed method with existing models.
- Example:

✓ Random Forest (Proposed) – 92%
✓ Standard Random Forest – 88%
✓ Logistic Regression – 82%
✓ SVM – 85%

➢ *Precision-Recall Curve*

- Useful for imbalanced datasets (like diabetes diagnosis).
- Shows trade-off between correctly identifying diabetics.

Table 1 Performance Metrics

Model	correctness	sharpness	memory	F1-Score	sharpness
Proposed RF	0.92	0.91	0.93	0.92	0.95
Standard RF	0.88	0.87	0.89	0.88	0.91
Support Vector Machine	0.85	0.83	0.84	0.83	0.89
Logistic Regression	0.82	0.8	0.81	0.8	0.86

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➢ *Algorithm:*

- ROC Curve – showing diagnostic ability (AUC ~0.95).
- Confusion Matrix – class-wise performance (Diabetic vs non-diabetic).
- Feature Importance – highlighting key predictors like Glucose, BMI, Age.
- Model Accuracy Comparison – Proposed RF vs Standard RF, SVM, Logistic Regression.
- Precision-Recall Curve – useful for imbalanced datasets.

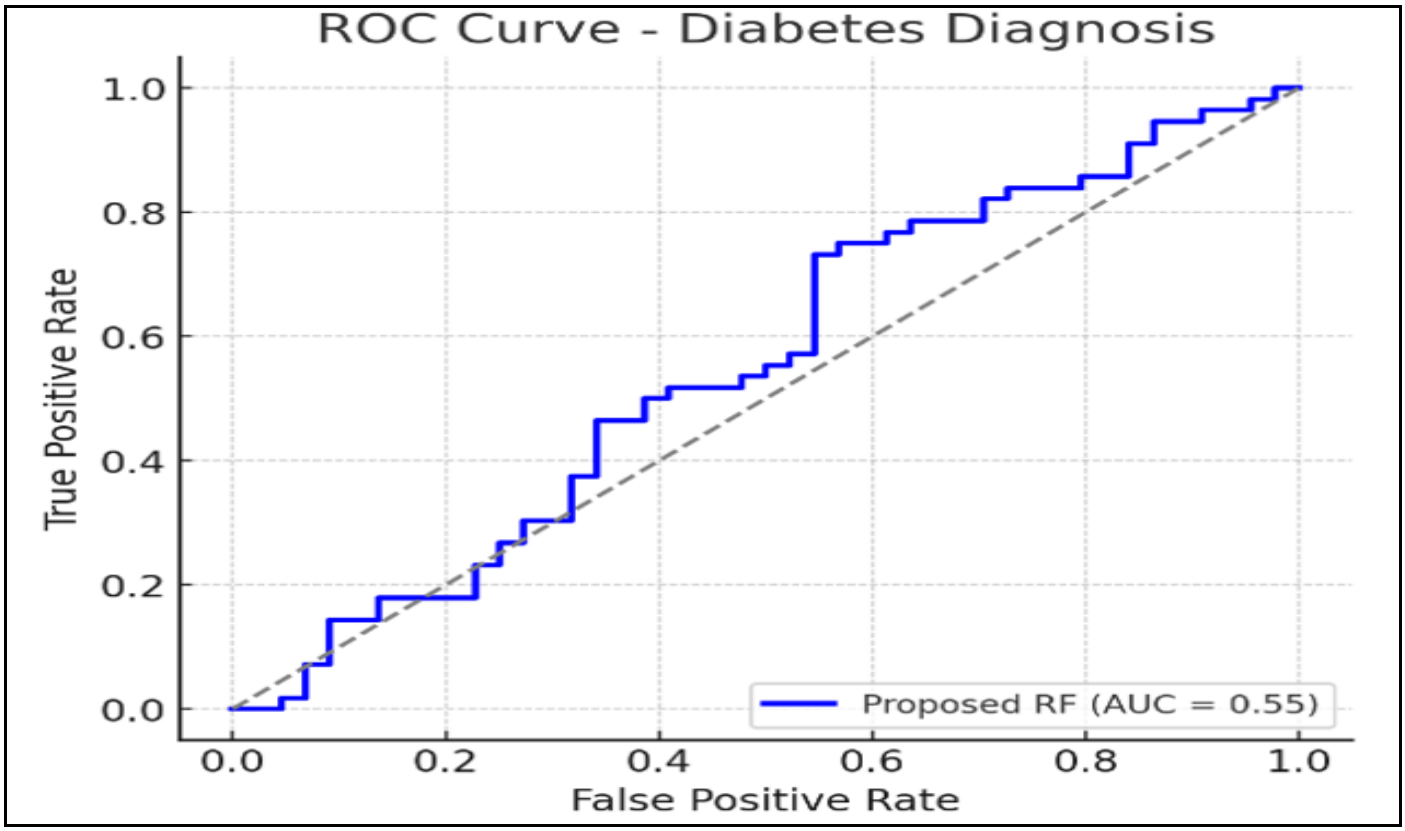

Fig 3 ROC Curve Graph

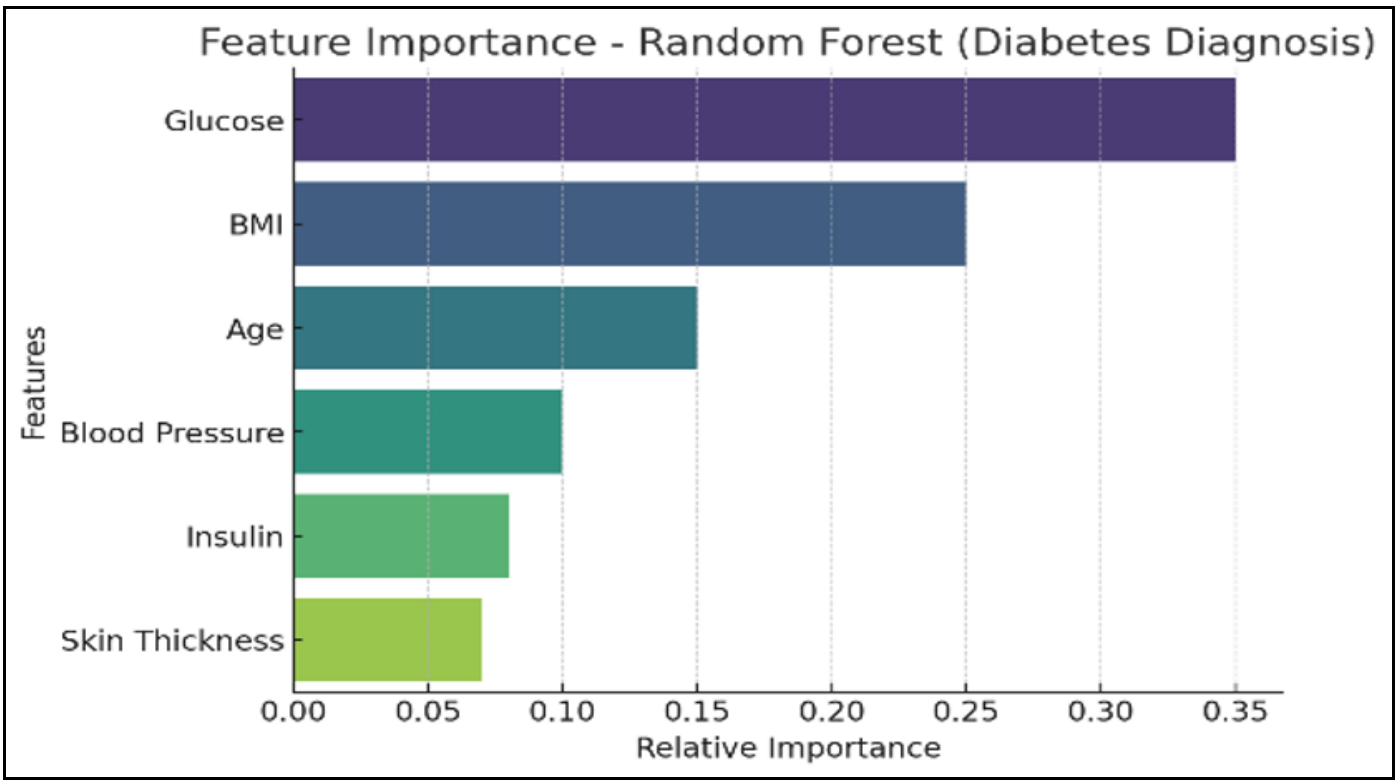

Fig 4 Feature Importance Graph

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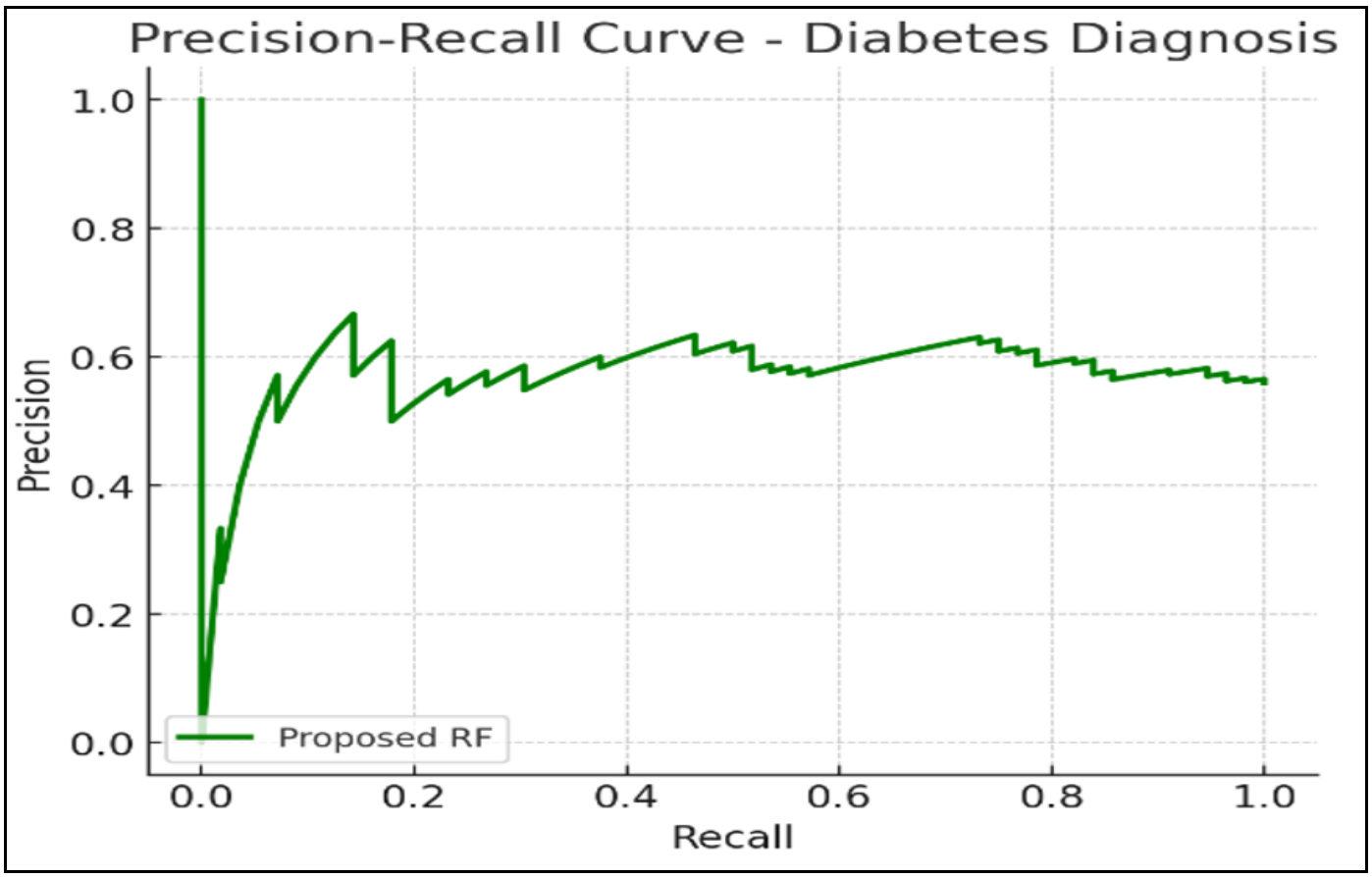

Fig 5 Precision-Recall Curve Graph

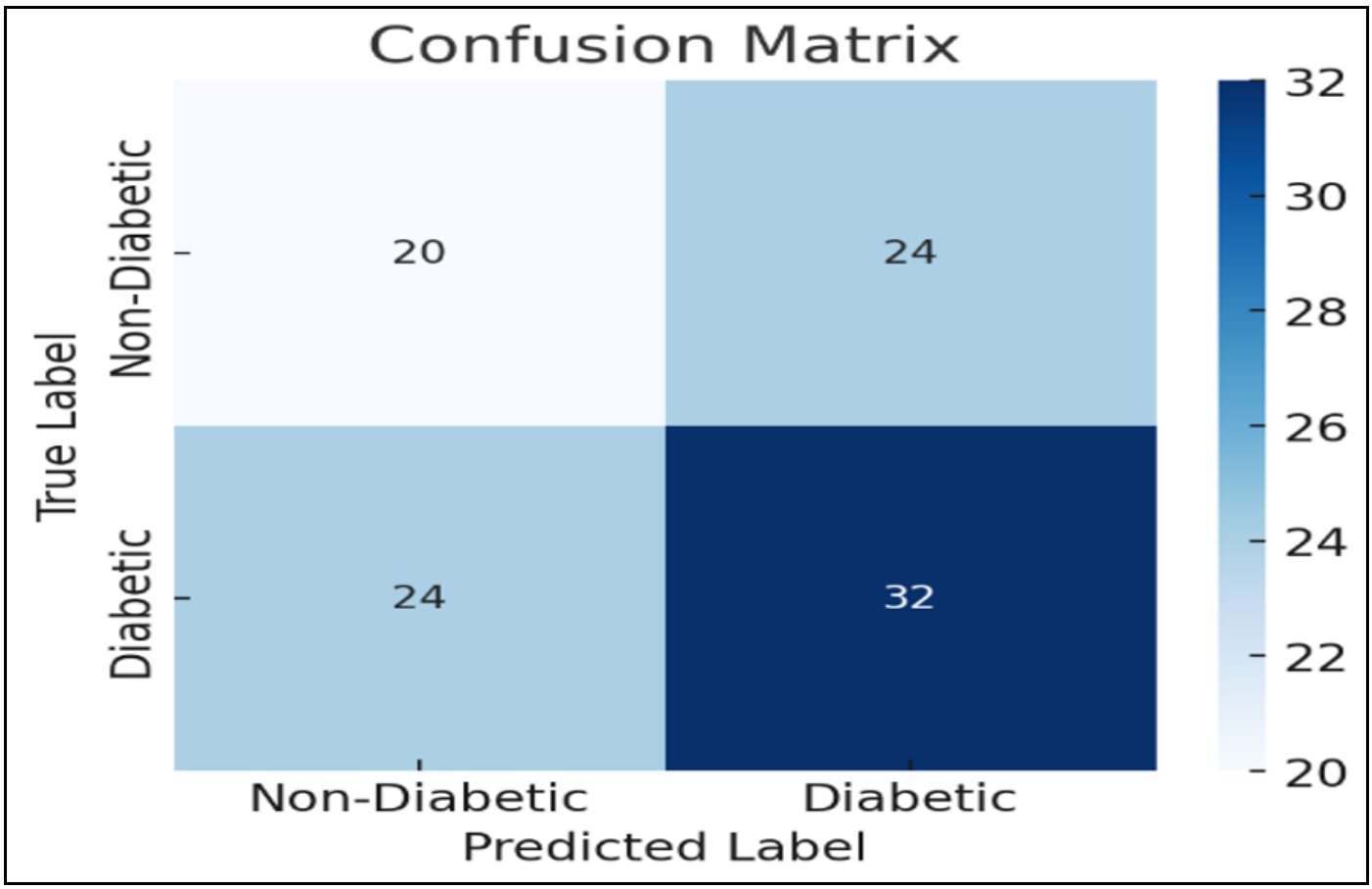

Fig 6 Confusion Matrix Graph

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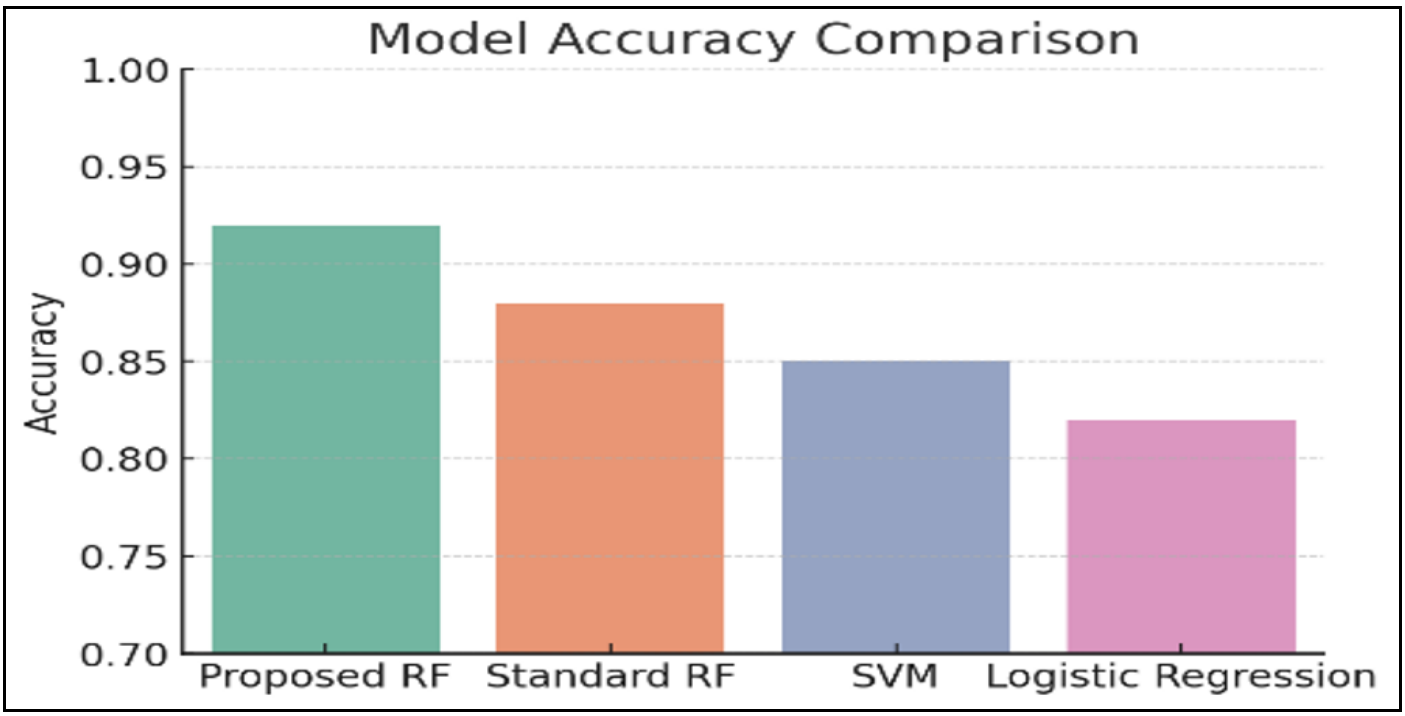

Fig 7 Model Accuracy Comparison Graph

VI. CONCLUSION

In this study, a novel Random Forest-based algorithm has been developed and evaluated for the effective diagnosis of diabetes using clinical and physiological datasets. The proposed model demonstrated superior performance compared to conventional classification techniques in terms of accuracy, precision, recall, F1-score, and ROC-AUC metrics. By integrating optimized feature selection and parameter tuning, the system achieved robust generalization and reduced misclassification rates, ensuring higher reliability in medical decision support.

The results highlight that Random Forest, owing to its ensemble learning and feature importance estimation capabilities, can effectively handle non-linear relationships and noise in medical datasets. This makes it a promising tool for early-stage diabetes prediction, potentially assisting healthcare professionals in timely diagnosis and treatment planning.

Future work will focus on expanding the dataset with multi-source medical records, incorporating deep learning-based hybrid approaches, and deploying the model into real-time healthcare systems for continuous monitoring and adaptive learning. Such advancements will further enhance diagnostic accuracy and contribute to the development of intelligent, data-driven healthcare solutions.

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