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Diabetes Prediction Using Machine Learning

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***Abstract*—Diabetes mellitus is a chronic and life-threatening disease that requires early diagnosis to prevent severe complications. In recent years, machine learning (ML) techniques have been widely adopted to predict diabetes using clinical and lifestyle data. More recently, explainable artificial intelligence (XAI) has been introduced to improve transparency and trust in ML-based medical decision systems. This review paper presents a comprehensive and simple analysis of recent research works on diabetes prediction using machine learning, ensemble methods, and explainable Al techniques. This review paper presents a detailed and comprehensive analysis of diabetes prediction systems based on machine learning, ensemble learning, and explainable Al, using all uploaded research papers as primary sources. The review covers datasets, preprocessing methods, feature selection techniques, classification models, evaluation metrics, explainability approaches, and real-world deployment through web and mobile applications. Comparative analysis reveals that ensemble models such as XGBoost combined with imbalance-handling techniques like SMOTE and ADASYN, and explainability tools such as SHAP and LIME, achieve superior accuracy, interpretability, and clinical relevance. This review provides valuable insights for researchers, students, and healthcare professionals working on intelligent diabetes diagnosis systems.**

***Index Terms*—Diabetes Prediction, Machine Learning, Explainable Al, XGBoost, SHAP, LIME, SMOTE, ADASYN**

I. INTRODUCTION

Diabetes mellitus is one of the most prevalent non-communicable diseases worldwide and is characterized by chronic hyperglycemia due to insufficient insulin production or improper insulin utilization. If left undiagnosed or untreated, diabetes can lead to severe complications such as cardiovascular diseases, kidney failure, nerve damage, and vision loss. According to global health statistics, hundreds of millions of people are currently living with diabetes, and this number is increasing every Traditional diabetes diagnosis relies on laboratory tests and clinical evaluation, which may be time-consuming and inaccessible in resource-limited settings. To address these limitations, researchers have increasingly adopted machine learning techniques to assist healthcare professionals in early diabetes Insulin is a hormone produced by the pancreas that helps glucose enter body cells to provide energy. When insulin does not work correctly, glucose remains in the bloodstream, leading to hyperglycemia Machine learning models can analyses large-scale medical datasets, identify complex patterns, and generate predictive insights with high accuracy.

However, many high-performing ML models act as black boxes, offering little explanation for their predictions. This lack of transparency is a major concern in medical applications. Explainable Artificial Intelligence (XAI) has emerged as a solution to this problem by providing human understandable explanations of model decisions. This review paper integrates findings from all uploaded research articles and presents a detailed discussion of machine learning-based diabetes prediction systems with a special focus on explainability and real-world deployment. Diabetes mellitus is a long-term disease in which the level of sugar (glucose) in the blood becomes higher than normal due to insufficient insulin production or the body's inability to use insulin properly. Insulin is a hormone produced by the pancreas that helps glucose enter body cells to provide energy. When insulin does not work correctly, glucose remains in the bloodstream, leading to hyperglycemia. There are mainly two types of diabetes: Type 1 diabetes, where the body does not produce insulin, and Type 2 diabetes, where the body produces insulin but cannot use it effectively, which is more common and often linked to obesity, lack of physical activity, unhealthy diet, and genetic factors. If diabetes is not detected and managed early, it can cause serious complications such as heart disease, kidney failure, blindness, nerve damage, and stroke with the advancement of healthcare technology, machine learning techniques are increasingly used to analyses large amounts of medical data and predict diabetes at an early stage

By using patient information such as age, blood sugar level, body mass index, blood pressure, insulin level, and family history, machine learning models can help doctors make accurate and timely decisions. Early prediction of diabetes using these techniques can improve patient care, reduce complications, and save lives.

II. METHODOLOGY

This review paper follows a systematic methodology for analyzing existing research studies related to diabetes prediction using machine learning and explainable artificial intelligence (XAI). The methodology consists of five major stages: literature identification, dataset review, preprocessing analysis, model performance assessment, and interpretability and deployment analysis. Each selected study was analyzed to examine the type of dataset used. This includes public datasets such as the Pima Indian Diabetes Dataset, as well as private hospital-based datasets collected from real clinical environments. Dataset characteristics such as sample size, type of attributes, class balance ratio, and presence of missing or noisy data were reviewed to assess their suitability for predictive modeling.

Datasets Used for Diabetes Prediction

2.1 Public Datasets

The Pima Indian Diabetes Dataset is the most widely used benchmark dataset in diabetes prediction research. It contains 768 samples with features such as glucose level, BMI, age, insulin, blood pressure, and pregnancy count. While this dataset allows fair comparison among models, it has limitations such as class imbalance and limited population diversity.

2.2. Private and Clinical Datasets

Recent studies have introduced private and hospital-based datasets to improve real-world applicability. A notable contribution is the RTML dataset collected from female patients

in Bangladesh. This dataset includes real clinical measurements and enhances model generalization The use of private datasets significantly improves the originality and practical relevance of research works. Several uploaded papers use private and hospital-based datasets, collected from real medical centers in Bangladesh and other regions. These datasets include actual patient records and additional risk factors such as diet, hypertension, genetic history, and kidney problems. The use of private datasets increases the realism, originality, and clinical relevance of diabetes prediction systems.

III. DATA PREPROCESSING TECHNIQUES

Data preprocessing is a critical step in machine learning-based diabetes prediction. The reviewed studies apply several preprocessing operations to improve data quality and learning efficiency. Missing values are handled using mean replacement or predictive models, while feature scaling such as Min-Max normalization is applied to ensure uniformity. Since diabetes datasets are often imbalanced, resampling techniques like SMOTE and ADASYN are widely used. Some studies also predict missing insulin values using semi-supervised learning approaches.

Data preprocessing is a critical step in machine learning-based diabetes prediction. The reviewed papers apply various preprocessing techniques to improve data quality and model performance:

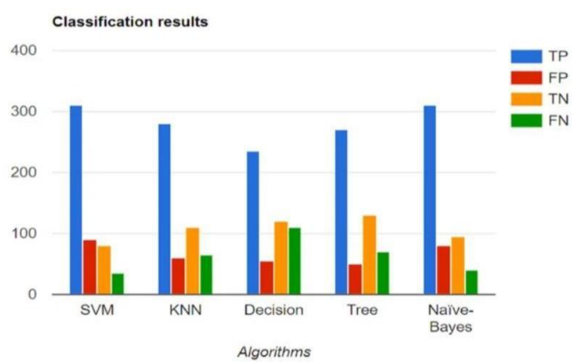
- Handling missing values using mean or median imputation
- Feature selection using Mutual Information
- Feature scaling using Min-Max normalization
- Handling class imbalance using SMOTE and ADASYN
- Semi-supervised learning to predict missing attributes such as insulin

These preprocessing steps improve data quality and enhance model performance Studies with comprehensive preprocessing pipelines consistently achieve better results. Some studies also predict missing insulin values using semi supervised learning approaches.the preprocessing workflow used in diabetes prediction systems. Raw medical data is first cleaned by handling missing values, followed by normalization and feature selection. Class imbalance is then addressed using SMOTE or ADASYN, resulting in a balanced and clean dataset suitable for machine learning models.

Machine Learning and Ensemble Models

Various machine learning algorithms are used for diabetes prediction, including;

- Logistic Regression
- K-Nearest Neighboring (KNN)
- Decision Tree
- Naive Bayes
- Support Vector Machine (SVM) Random Forest.
- These models analyse patient data and learn patterns associated with diabetic and non-diabetic conditions.



individual classifiers operate on preprocessed data and how ensemble techniques such as Bagging, Boosting, and Voting combine their outputs. XGBoost is highlighted as the final optimized ensemble model providing superior performance. Ensemble models combine multiple learners to improve prediction accuracy and stability. Among all reviewed models, XGBoost consistently provides the best performance due to its ability to handle nonlinearity, missing values, and imbalanced dataset

IV. PERFORMANCE EVALUATION METRICS

Recent research has demonstrated that machine learning algorithms such as Logistic Regression, Support Vector Machines, Random Forest, KNearest Neighbor, and ensemble learning models provide promising results in detecting diabetes risk. However, despite high predictive accuracy, many ML models behave as “black- box” systems, providing little insight into the reasoning behind their predictions. This lack of transparency limits their acceptance in clinical practice. This paper presents a comprehensive review of existing diabetes-prediction studies based on machine learning and explainable AI. The review highlights datasets, preprocessing techniques, classification models, evaluation metrics, interpretability methods, and real-world deployment approaches. The objective is to provide researchers and healthcare professionals with a clear understanding of the strengths, limitations, and future scope of AI-driven diabetes-prediction systems

Explainable Al in Diabetes Prediction

Explainability is essential in healthcare applications where decisions must be trusted and understood by clinicians. The reviewed papers introduce Explainable Artificial Intelligence (XAI) techniques to interpret machine learning predictions. the explainability layer applied after model prediction SHAP provides global explanations by identifying overall feature importance, while LIME offers local explanations for individual patient predictions, making the system transparent and clinically interpretable.

V. REAL-WORLD DEPLOYMENT

A key challenge also lies in the lack of interpretability in traditional machine learning models. Many high-performing models operate as black-box systems, making it difficult for healthcare professionals to trust and adopt them in real-world diagnosis. Although explainable AI techniques such as SHAP and LIME address this issue, they still require further standardization and clinical validation.

Finally, real-world deployment barriers exist, including data privacy concerns, integration with hospital systems, maintenance cost, ethical considerations, and the need for regulatory approval. This makes clinical adoption slow and complex.

These systems allow users and healthcare professionals to input patient data and receive instant predictions. Deployment enhances the practical usability of ML models beyond research environments the deployment of diabetes prediction systems. User data is collected through web or mobile applications, processed by a backend server hosting the trained ML model, and returned with prediction results and explainable insights. Advanced techniques such as deep learning, hybrid ensemble models, and optimization algorithms can be explored to further improve predictive performance. In addition, privacy preserving learning approaches such as federated learning and homomorphic encryption should be implemented to ensure secure handling of sensitive patient information.

VI. COMPARATIVE ANALYSIS OF REVIEWED STUDIES

Aspect	Observation
Dataset	Public + private datas improve robustness
Best Model	XGBoost with ADASY
Explainability	SHAP and LIME enha trust
Deployment	Limited but impactful
Accuracy Range	75%-96%

VII. CHALLENGES AND FUTURE DIRECTIONS

One major challenge is the limited availability of large, high-quality clinical datasets. Many existing studies rely on small or publicly available datasets such as the Pima Indian Diabetes dataset, which may not fully represent diverse populations. This leads to dataset bias
and reduces the generalizability of models across different demographic groups, lifestyles, and geographic regions.
Another concern is class imbalance, where diabetic cases are significantly fewer than nondiabetic cases. This imbalance often causes models to become biased toward the majority class, reducing sensitivity for detecting actual diabetic patients. Although resampling techniques such as SMOTE and ADASYN are commonly used, they may also introduce noise or synthetic bias.

VIII. CONCLUSION

This review demonstrates that machine learning techniques, especially ensemble models like XGBoost, provide effective solutions for early diabetes prediction. The integration of Explainable Al techniques such as SHAP and LIME significantly improves model transparency and clinical trust. Studies using
private datasets and real-world deployment show higher practical relevance. Overall, ML combined with XAI represents a promising direction for intelligent and reliable diabetes diagnosis systems.

REFERENCE

[1] Smith, J. W., Everhart, J. E., Dickson, W. C., Knowler, W. C., & Johannes, R. S. (1998). Using the ADAP learning algorithm to forecast the onset of diabetes mellitus. Proceedings of the Annual Symposium on Computer Applications in Medical Care, 261- 265.

[2] Prabhu, P., & Selvabharathi, S. (2019). Deep belief neural network model for prediction of diabetes mellitus. International Conference on Imaging, Signal Processing and Communication, 138-142.

[3] Mohan, N., & Jain, V. (2020). Performance analysis of support vector machine in diabetes prediction. International Conference on Electronics, Communication and Aerospace Technology, 1-3.

[4] Hasan, M. K., Alam, M. A., Das, D., Hossain, E., & Hasan, M. (2020). Diabetes prediction using ensembling of different learning classifiers. IEEL 76516-76531.

[5] 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.

[6] Olisah, C. C., Smith, L., & Smith, M. (2022). Diabetes mellitus prediction and diagnosis from a data preprocessing and machine learning perspective. Computer Methods and Programs in Biomedicine, 220, 106773

[7] Deberneh, H. M., & Kim, I. (2021). Prediction of type 2 diabetes based on machine learning algorithm International Journal of Environmental Research and Public Health, 18(6), 3317.

[8] Tasin, I., Nabil, T. U., Islam, S., & Khan, R. (2023). Diabetes prediction using machine learning and explainable Al techniques. Healthcare Technology Letters, 10, 1-10

[9] Ahmed, N., et al. (2021). Machine learning based diabetes prediction and development of smart web application. International Journal of Cognitive Computing in Engineering, 2, 229-241.

[10] Jackins, V., Vimal, S., Kaliappan, M., & Lee M. Y. (2021). Al-based smart prediction of clinical

disease using random forest classifier and Naive Bayes. Journal of Supercomputing, 77, 5198-5219.
[11] Aurélien, G. (2019). Hands-On Machine Learning with Scikit-Learn and TensorFlow. O'Reilly Media.
[12] Mitchell, T. M. (1997). Machine Learning. McGraw-Hill.
[13] He, H., Bai, Y., Garcia, E. A., & Li, S. (2008). ADASYN: Adaptive synthetic sampling approach for imbalanced learning. Proceedings of the IEEE International Joint Conference on Neural Networks, 1322-1328.
[14] Chatrati, S. P., Hossain, G., Goyal, A., et al. (2020). Smart home health monitoring system for predicting type 2 diabetes and hypertension. Journal of King Saud University - Computer and Information Sciences, 34(3), 862-870.
[15] Ramesh, J., Aburukba, R., & Sagahyroon, A. (2021). A remote healthcare monitoring framework for diabetes prediction using machine learning.Healthcare Technology Letters, 8, 45-57.
[16] International Diabetes Federation. (2021). IDF Diabetes Atlas (10th ed.).