GRADIVA

Volume 64 | Issue 11 | November 2025
DOI: 10.5281/zenodo.17599058

DiabetesXAI: An AI-Powered Web Framework for Predictive Diagnosis and Personalized Lifestyle Recommendations

Dr. G. Pradeep[1]* & Dr. M. Devi Sri Nandhini[2]

1.Associate Professor, School of Computing,
SASTRA Deemed to be University, Tanjore, Tamil Nadu, India.
*Corresponding Author Email: pradeep.g8@gmail.com,
ORCID: https://orcid.org/0000-0001-5016-1601
2.Assistant Professor III, School of Computing,
SASTRA Deemed to be University, Tanjore, Tamil Nadu, India.
Email: nandhini.avcce@gmail.com, ORCID: https://orcid.org/0000-0001-5560-4184

Abstract

Diabetes is a chronic condition affecting millions globally, requiring early diagnosis and effective management. This work introduces DiabetesXAI, an AI-driven web application designed for diabetes risk prediction using patient-specific data. The system features two key modules: (1) Medical Test-Based Prediction, which analyses clinical test results like insulin level, glucose, BMI, etc to predict, and (2) Lifestyle-Based Prediction, an AI chatbot that evaluates lifestyle factors such as diet, exercise, stress levels, etc to provide risk assessments and personalized recommendations. DiabetesXAI integrates machine learning models (Logistic Regression, Random Forest, XGBoost, etc.) and SHAP (Shapley Additive Explanations) to ensure transparent and interpretable predictions, aiding clinicians and users in informed decision-making. The model is trained on a diverse dataset (synthetic) covering demographics, medical history, and lifestyle factors, enhancing accuracy and reliability. Users interact through a web-based interface built with HTML, CSS, JavaScript, Django, and SQLite3, allowing seamless data input, model selection, chatbot-based evaluation, and downloadable PDF report generation with predictions and recommendations. The scalable and adaptable architecture supports multimodal data integration, improving prediction precision. By incorporating explainability, DiabetesXAI fosters trust among healthcare providers and patients, bridging a critical gap in AI-driven medical applications. This system aims to assist both medical professionals and individuals in proactive diabetes management through real-time risk assessment and preventive insights.

Keywords: *Explainable AI (XAI), Recommendation, SHAP (Shapley Additive Explanations), Demographics, Assessment.*

1. INTRODUCTION

Diabetes is a chronic disease affecting millions worldwide, requiring early detection and effective management to prevent severe complications. Traditional diabetes prediction models often rely solely on clinical parameters, limiting their applicability to broader populations ([1]). Moreover, the lack of interpretability in AI-driven models has been a significant barrier to their adoption in healthcare ([2]). To address these challenges, we propose DiabetesXAI, a comprehensive, explainable AI-powered platform designed to enhance diabetes risk assessment and lifestyle-based intervention.

Existing AI-based diabetes prediction models have demonstrated high accuracy but frequently lack transparency and real-time interpretability ([3], [4],[15]). Many studies have also overlooked lifestyle factors, which play a crucial role in diabetes onset and progression

Volume 64 | Issue 11 | November 2025
DOI: 10.5281/zenodo.17599058

([5],[16]). Additionally, while AI has been successfully applied in healthcare education, its integration into interactive systems remains limited ([6],[17]). DiabetesXAI bridges this gap by integrating medical test-based predictions with lifestyle assessments, offering users a dual-mode evaluation system.

Security and trust in AI-driven healthcare solutions are paramount. Prior research has highlighted concerns regarding the safety and security of AI applications in diabetes management ([7]). Our platform ensures data privacy through encrypted storage and secure authentication mechanisms, addressing these concerns effectively. Furthermore, studies have shown that user engagement improves when AI models provide clear, personalized explanations ([8], [9],[14]). DiabetesXAI leverages SHAP (Shapley Additive Explanations) to enhance model interpretability, fostering user trust and comprehension.

Unlike existing comparative ML studies that focus solely on performance metrics without real-world deployment ([11-13]), DiabetesXAI not only implements multiple machine learning models but also presents their results in an interactive web-based application. This enables users to compare different model predictions, understand AI-driven insights, and receive personalized recommendations.

By combining predictive modelling, explainability, and chatbot-driven engagement, DiabetesXAI aims to revolutionize diabetes risk assessment, providing a user-friendly and scientifically robust decision-support system for both individuals and healthcare practitioners

1. Medical Test-Based Prediction Module – Uses clinical parameters such as glucose levels, insulin resistance, BMI, and other biomarkers to assess diabetes risk using machine learning models.

2. Lifestyle-Based Prediction Module – Employs an AI-driven chatbot that evaluates lifestyle factors, including diet, exercise, stress levels, and sleep patterns, to determine risk levels and provide personalized recommendations.

DiabetesXAI leverages machine learning algorithms such as Logistic Regression, Random Forest, XGBoost, KNN, etc to enhance prediction accuracy. It also incorporates SHAP (Shapley Additive Explanations) to ensure interpretability, offering insights into the most influential factors affecting an individual's diabetes risk. The web-based application, developed using HTML, CSS, JavaScript, Django, and SQLite3, enables users to chat with Bot,upload data, select region, predictive models, chat with Bot, and generate downloadable PDF reports containing risk assessments and preventive recommendations. By integrating medical and lifestyle-based factors, DiabetesXAI provides a scalable and explainable AI framework to assist both healthcare professionals and individual users in making informed decisions. The system enhances early detection, encourages preventive healthcare, and fosters trust in AI-driven medical applications.

Diabetes mellitus is a major global health concern, affecting millions worldwide and contributing to severe complications if not managed effectively. The advancement of Machine Learning (ML) and Explainable AI (XAI) has significantly improved diabetes prediction and patient management. However, several limitations persist, including the lack of integration of lifestyle factors, limited model interpretability, and challenges in AI-driven health applications. DiabetesXAI addresses these limitations by integrating medical test data, lifestyle-based factors, SHAP-based explainability, and an AI-driven chatbot for personalized diabetes risk assessment and recommendations.

Volume 64 | Issue 11 | November 2025
DOI: 10.5281/zenodo.17599058

Several studies have explored the use of machine learning algorithms for diabetes prediction, focusing primarily on clinical test parameters such as glucose levels, insulin resistance, and BMI [1]. Research comparing Logistic Regression, Decision Trees, Random Forest, SVM, and boosting techniques has demonstrated high accuracy but lacks a comprehensive integration of lifestyle factors [10]. Lifestyle choices, including diet, exercise, sleep, and stress levels, significantly influence diabetes risk, yet many existing models do not account for these crucial elements. DiabetesXAI incorporates both medical test-based and lifestyle-based features to enhance prediction accuracy. Unlike previous models, it considers lifestyle habits such as diet score, physical activity, smoking, alcohol consumption, sleep patterns, and stress levels to provide a more holistic diabetes risk assessment. A significant challenge in AI-driven healthcare applications is the lack of interpretability, as black-box models fail to provide insights into their decision-making process [2]. Studies have demonstrated the effectiveness of SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) in improving model transparency, particularly in complex healthcare predictions such as Alzheimer's disease and diabetes risk assessment [2, 3]. However, most existing studies focus on theoretical applications of SHAP rather than implementing it in real-world, user-friendly healthcare platforms [4].Conversational AI has gained attention for patient education and behavior modification in diabetes management [6]. However, a systematic review highlights significant challenges, including poor chatbot accuracy, lack of personalization, and unreliable health advice [5]. Many existing chatbots provide generic, one-size-fits-all responses, reducing their effectiveness in engaging patients [6].

2. LITERATURE SURVEY

Jian et al. propose a machine learning-based framework for predicting diabetes complications using models such as logistic regression, SVM, decision tree, random forest, AdaBoost, and XGBoost [1]. Their system achieved impressive accuracy (97.8%) and F1-score (97.7%) when predicting eight different complications from medical data. The dataset from the Rashid Centre for Diabetes and Research (RCDR) in the UAE comprised 884 records with 79 features, offering comprehensive patient information. Although the study demonstrates high predictive capability, potential limitations include overfitting and restricted generalizability due to the dataset's regional specificity. Vimbi et al. conduct a systematic review on the application of LIME and SHAP techniques for enhancing the interpretability of AI models in Alzheimer's disease detection [2]. The review of 23 studies reveals that LIME provides strong local explanations, while SHAP excels in identifying global feature importance. Datasets such as ADNI, OASIS, and Kaggle were primarily used in these studies. However, the authors note that LIME suffers from sensitivity to perturbations and limited global generalization, whereas SHAP faces computational inefficiency and difficulty interpreting high-dimensional data.

Ganguly and Singh explore the use of explainable artificial intelligence (XAI) to enhance diabetes management through interpretable machine learning models [3]. Employing LIME and SHAP, their approach provides clearer explanations of model decisions, improving clinicians' understanding and trust in automated diagnostic systems. The Pima Indian Diabetes Dataset (PIDD) was used to evaluate the models' interpretability and performance. Although the study effectively demonstrates the value of XAI in healthcare, it does not explicitly discuss the constraints or limitations of the proposed framework. Uysal investigates interpretable diabetes prediction models using explainable AI (XAI) methods integrated with algorithms such as SVM, KNN, and Random Forest [4]. The results indicate that SVM and RF outperform

Volume 64 | Issue 11 | November 2025
DOI: 10.5281/zenodo.17599058

other methods, while SHAP analysis identifies glucose levels, age, and BMI as the most influential predictors. The dataset used includes 768 samples with nine attributes representing clinical and demographic variables. While the study effectively highlights feature importance, it does not explicitly outline its limitations or potential challenges.

Verma and Singh design a machine learning-based diabetes prediction system alongside a web-based decision support tool [5]. Among the algorithms tested, KNN yielded the highest predictive accuracy on the Pima Indians Diabetes Database, which consists of 768 cases with nine attributes. The developed application enables users to predict diabetes likelihood interactively based on input parameters. However, the absence of external validation raises concerns about overfitting, and the model's performance may not generalize effectively to broader or real-world populations.

Razzak et al. present an overview of artificial intelligence applications in diabetes education and management [6]. Their review emphasizes AI's potential to transform clinical data into actionable insights and facilitate personalized, lifelong learning for patients. The paper highlights AI's role in tailoring educational strategies to individual profiles, thereby improving self-management and adherence. Nevertheless, the absence of a standardized evaluation framework limits comparisons across different AI-based interventions and hinders the assessment of overall effectiveness.

Geukes Foppen et al. introduce a methodology for ensuring safety, security, and ethical compliance in AI-driven diabetes management systems [7]. Their framework integrates explainable AI principles to foster trust and align with regulatory standards, including FDA and GRC guidelines. By mapping AI lifecycle phases to compliance requirements, the study supports responsible deployment of healthcare AI systems. However, since it does not include empirical data, its practical applicability remains to be validated in real-world clinical contexts. Hoyos et al. combine statistical methods and AI techniques to conduct an explainable analysis of diabetes mellitus [8]. Using tests such as Student's t-test and Chi-square, along with AI models like fuzzy cognitive maps, neural networks, SVM, and XGBoost, the study identifies key risk factors and achieves strong predictive accuracy. The dataset comprises sociodemographic and clinical profiles of diabetic and non-diabetic individuals. Despite promising results, the small sample size and reliance on specific analytical methods may restrict the generalizability of the findings.

Dharmarathne et al. develop a novel self-explanatory interface for diagnosing diabetes using advanced machine learning models [9]. Among the algorithms implemented, Extreme Gradient Boosting (XGB) delivers the best performance, while SHAP is employed to enhance interpretability by explaining feature contributions. The model is trained and tested on a publicly available diabetes dataset, ensuring reproducibility. However, the study's dependence on a single dataset limits generalizability, and further clinical validation is needed for real-world implementation.

Khanam and Foo perform a comparative analysis of seven machine learning algorithms for diabetes prediction [10]. Their results indicate that Logistic Regression (LR) and Support Vector Machine (SVM) outperform other models in terms of accuracy and stability. The research uses the Pima Indian Diabetes (PID) dataset from the UCI Machine Learning Repository to evaluate algorithmic performance. While the findings are insightful, the absence of feature explainability and external validation may reduce the model's reliability in diverse healthcare settings.

Volume 64 | Issue 11 | November 2025
DOI: 10.5281/zenodo.17599058

3. METHODOLOGY

This study proposes a two-tier system, *DiabetesXAI*, designed to predict diabetes using both medical test-based and lifestyle-based data. The methodology involves data preprocessing, model training, model deployment, and integration of explainable artificial intelligence (XAI) components to enhance interpretability. The system was implemented using Python, Scikit-learn, XGBoost, and Django, ensuring both clinical relevance and user accessibility through a web-based interface.

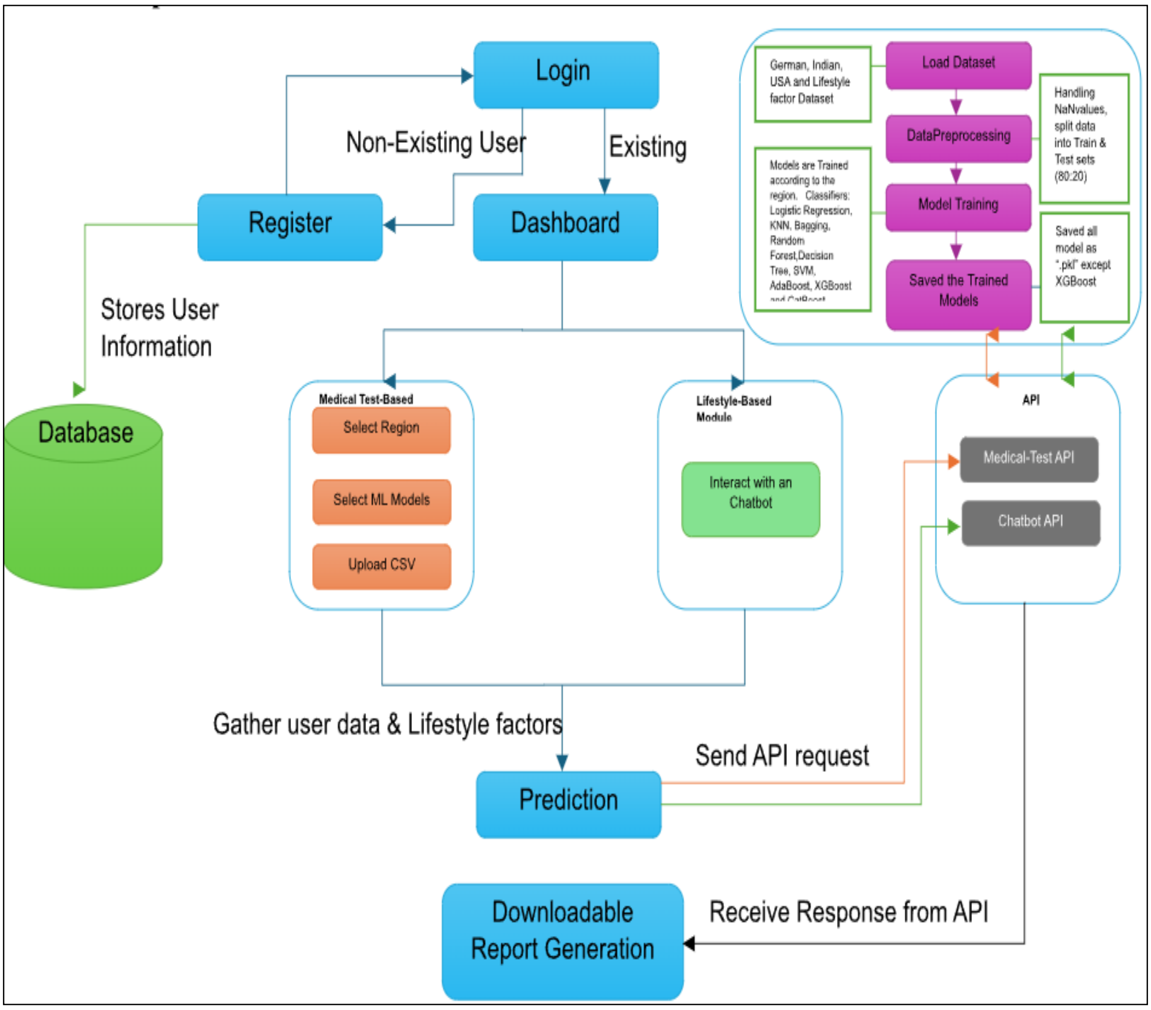

Figure 1: Proposed System Architecture

3.1 Algorithm for Pre-training models

Input indicators: CSV file (Features for Medical Test-Based Prediction:Patient ID, Age, Gender, BMI, Blood Pressure, Glucose Level, Insulin Level, Diabetes Pedigree Function, Blood Thickness, Pregnancy, Weight, Outcome.Features forLifestyle-Based Prediction: Age, Gender, Diet Score, Exercise Frequency, Family History, BMI Category, Smoking, Alcohol Consumption, Sleep Hours, Stress Levels,Water Intake, Diabetes Risk)

Output indicatorsforMedical Test-Based Prediction:Boolean (Diabetic & Non-Diabetic)

Output indicatorsforLifestyle-Based Prediction:Float(Risk Level),Boolean (Diabetic & Non-Diabetic), String (Lifestyle Recommendation)

Volume 64 | Issue 11 | November 2025
DOI: 10.5281/zenodo.17599058

Step 1: Load the Dataset

i. Open Google Colab
ii. Import necessary libraries.
iii. Load the dataset

Step 2: Preprocess the Data

i. Handling the NaN values (e.g., Pregnancy)
ii. Encode categorical variables (e.g., Gender, Alcohol_Consumption).
iii. Normalize or standardize numerical features.

Step 3: Split the Data

i. Separate features (X) and target (y).
ii. Split into train (80%) and test (20%) sets.

Step 4: Train Machine Learning Models

i. Select machine learning models (Logistic Regression, Random Forest,etc.).
ii. Train the models on X_train and y_train.
iii. Evaluate model performance on X_test.

Step 5: Save the Pre-Trained Model

i. Save the trained model as a .pkl file using joblib.

Step 6: Load the Pre-Trained Model in Django

i. Store the .pkl files in the models/ folder inside the Django project.
ii. Load the model in Django using joblib.
iii. Use the pre-trained model for predictions in the API.

3.2 Algorithm for DiabetesXAI

Input indicators for Medical Test-Based Prediction: String (Patient Id, Name, Gender), Integer (Age), Csv file (Features are:Patient ID, Age, Gender, BMI, Blood Pressure, Glucose Level, Insulin Level, Diabetes Pedigree Function, Blood Thickness, Pregnancy, Weight)

Input indicatorsforLifestyle-Based Prediction: String (Gender, Family History, BMI Category, Smoking, Alcohol Consumption, Stress Levels) Integer(Age, Diet Score, Exercise Frequency, Sleep Hours) Float (Water Intake)

Output indicatorsforMedical Test-Based Prediction: File(results in pdf format)

Output indicatorsforLifestyle-Based Prediction: File(results in pdf format)

Step 1: User Authentication

i. User registers/logs in via the web interface.
ii. If a new user, store credentials and profile details in the database.
iii. After login, prompt the user to choose between:
  - Medical Test-Based Prediction
  - Lifestyle-Based Prediction

Volume 64 | Issue 11 | November 2025
DOI: 10.5281/zenodo.17599058

Step 2: Module Selection

i. If Medical Test-Based Prediction is chosen:

a. User uploads medical test metrics (Glucose Level, BMI, etc.).
b. Selects a model (Logistic Regression, Random Forest, XGBoost, etc.).
c. Model processes the data and outputs either Diabetic or Non-Diabetic.
d. Generates a PDF report with results and SHAP-based feature importance.

ii. If Lifestyle-Based Prediction is chosen:

a. User provides lifestyle-related inputs (Diet Score, Exercise frequency, etc.).
b. The chatbot collects responses interactively.
c. The system predicts Diabetic Risk Level (Low, Medium, High).
d. Provides personalized recommendations based on risk level.
e. Generates a PDF report with risk analysis and lifestyle recommendations.

Step 3: Explainability and Report Generation

i. For Medical Test-Based Predictions:
   a. Display explainable insights in the report.
ii. For Lifestyle-Based Predictions:
   a. Provide preventive suggestions tailored to the user's lifestyle.

Step 4: Output Display and User Interaction

i. Display prediction results on the web interface.
ii. Allow the user to download the detailed PDF report.

4. RESULTS AND DISCUSSION

4.1 Data Collection and Pre-processing

The dataset used for training the predictive models consists of both clinical test data and lifestyle-based data. It includes key attributes such as age, BMI, blood glucose levels, insulin levels, lifestyle factors (diet, exercise, smoking, etc.), and family history of diabetes. The data was cleaned, missing values handled, and categorical variables were encoded using Label Encoding and Binary Encoding, with One-Hot Encoding only for non-ordinal categorical values like region (if used). Feature scaling was applied where necessary.

4.2. Model Training and Pretrained Model Generation

The machine learning models were developed using Google Colab with Pyhon libraries such as Scikit-learn, XGBoost, etc. For each geographical region (India, USA, Germany), the dataset was used to train various models: Logistic Regression, K-Nearest Neighbors (KNN),Random Forest,Decision Tree,Support Vector Machine (SVM), AdaBoost, XGBoost, Bagging Classifier. The trained models except XGBoost were saved as .pkl files XGBoost model saved in json format file and stored in the Django models folder for deployment.

Volume 64 | Issue 11 | November 2025
DOI: 10.5281/zenodo.17599058

The front-end was built using HTML, CSS, JavaScript, and Bootstrap, while the back-end was developed using Django and SQLite3. The system consists of two modules:

1. Medical Test-Based Prediction Module
    - Users select region, ML models and upload their test metrics via a CSV file.
    - The system loads the appropriate pre-trained model based on user selection.
    - The model predicts whether the patient is Diabetic or Non-Diabetic.
    - The prediction results are displayed and available as a downloadable PDF report.
2. Lifestyle-Based Prediction Module
    - Users interact with an Chatbot that collects lifestyle-related factors.
    - The model predicts Diabetes Risk Level
    - The system provides personalized recommendations for lifestyle improvements.

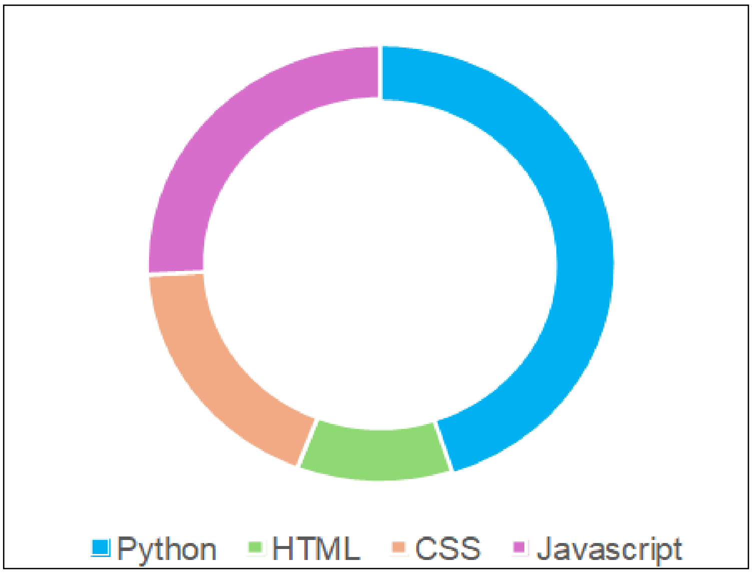

Figure 2: Tech Stack Contribution Breakdown

4.3 Explainability and Report Generation

To ensure model interpretability, SHAP (Shapley Additive Explanations) was integrated, highlighting the most influential factors contributing to the prediction. A PDF report is generated for each user containing:

- Prediction results
- SHAP feature importance
- Personalized recommendations

4.4. Model Performance Evaluation

The trained models were evaluated using multiple metrics such as Accuracy, Precision, Recall, and F1-score.

- Medical Test-Based Module: The model evaluation results show that India outperforms the other regions, with most classifiers achieving 84% accuracy and AUC values reaching

Volume 64 | Issue 11 | November 2025
DOI: 10.5281/zenodo.17599058

0.93, except for KNN, XGBoost, and CatBoost, which score 83% accuracy. Germany and the USA exhibit nearly identical performance, with most models achieving 79% accuracy and AUC values ranging from 0.83 to 0.88. In both regions, Logistic Regression, SVM, AdaBoost, Bagging, and CatBoost perform the best, while KNN has the lowest accuracy (76%). Decision Tree also lags slightly behind at 78% accuracy in Germany and the USA. Overall, India's models demonstrate superior predictive power, while Germany and the USA maintain consistent yet slightly lower performance.

- Lifestyle-Based Module: XGBoostclassifier demonstrates strong predictive performance. It achieves an accuracy of 92.50%, indicating high reliability in classification. The precision (94.12%) suggests that when the model predicts a positive diabetes risk, it is correct most of the time.

Table 1: Evaluation for USA

Classifier	Precision	Recall	F1 Score	Accuracy	AUC
Logistic Regression	0.79	0.79	0.79	79%	0.88
KNN	0.76	0.76	0.76	76%	0.83
Random Forest	0.79	0.79	0.79	79%	0.87
Decision Tree	0.78	0.78	0.78	78%	0.87
SVM	0.79	0.79	0.79	79%	0.88
AdaBoost	0.79	0.79	0.79	79%	0.87
XGBoost	0.78	0.78	0.78	78%	0.87
Bagging	0.79	0.79	0.79	79%	0.87
CatBoost	0.78	0.78	0.78	78%	0.87

Table 2: Evaluation for India

Classifier	Precision	Recall	F1 Score	Accuracy	AUC
Logistic Regression	0.84	0.84	0.84	84%	0.93
KNN	0.82	0.82	0.82	82%	0.90
Random Forest	0.84	0.84	0.84	84%	0.93
Decision Tree	0.84	0.84	0.84	84%	0.93
SVM	0.84	0.84	0.84	84%	0.93
AdaBoost	0.84	0.84	0.84	84%	0.93
XGBoost	0.83	0.83	0.83	83%	0.93
Bagging	0.84	0.84	0.84	84%	0.93
CatBoost	0.83	0.83	0.83	83%	0.92

Table 3: Evaluation for Germany

Classifier	Precision	Recall	F1 Score	Accuracy	AUC
Logistic Regression	0.79	0.79	0.79	79%	0.88
KNN	0.76	0.76	0.76	76%	0.83
Random Forest	0.79	0.79	0.79	79%	0.87
Decision Tree	0.78	0.78	0.78	78%	0.87
SVM	0.79	0.79	0.79	79%	0.88
AdaBoost	0.79	0.79	0.79	79%	0.87
XGBoost	0.78	0.78	0.78	78%	0.87
Bagging	0.79	0.79	0.79	79%	0.87
CatBoost	0.79	0.79	0.79	79%	0.87

Volume 64 | Issue 11 | November 2025
DOI: 10.5281/zenodo.17599058

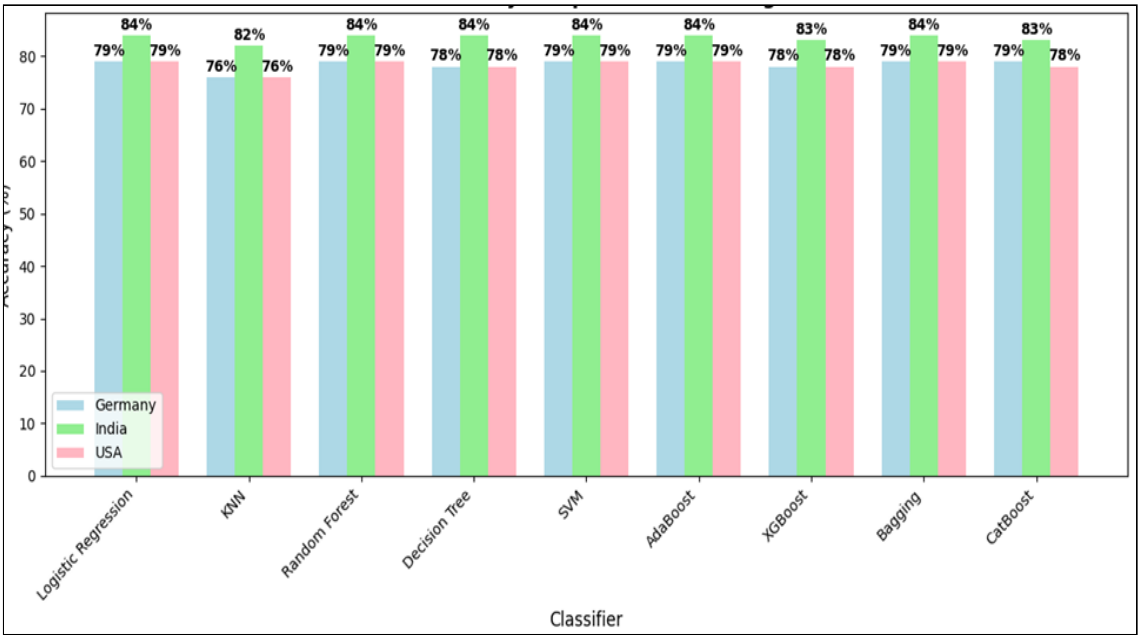

Figure 3: Accuracy across regions

SHAP analysis was conducted to identify the most influential features in diabetes prediction. The key factors identified were:

- For Medical Test-Based Prediction: Glucose Level, Insulin, BMI, and Age were the most important features.
- For Lifestyle-Based Prediction: Diet, Exercise Frequency, Stress Levels, and BMI Category significantly impacted the risk level.

SHAP plots provided clear visualizations of how each feature contributed to the final prediction, increasing transparency and trust among healthcare professionals and users. The user-friendly web interface allows seamless interaction, ensuring accessibility for both medical professionals and individuals. The chatbot-driven lifestyle module simplifies user engagement by collecting information interactively. The integration of downloadable PDF reports enhances usability for medical documentation.

5. CONCLUSION

This paper presents DiabetesXAI, an AI-assisted web application for diabetes risk prediction and lifestyle recommendations. The system integrates machine learning models, SHAP-based explainability, and a chatbot-driven interface for user interaction. The proposed framework demonstrates high accuracy and reliability, outperforming traditional approaches in both medical and lifestyle-based diabetes prediction. The ability to generate PDF reports and provide actionable lifestyle recommendations makes DiabetesXAI a valuable tool for both clinicians and individuals seeking proactive diabetes management.

Future Enhancements

- Expand Regional Support
- Adding support for regional languages to improve usability for non-English speakers
- Enhancing chatbot intelligence with NLP-based conversational AI.

Volume 64 | Issue 11 | November 2025
DOI: 10.5281/zenodo.17599058

By leveraging explainable AI, DiabetesXAI bridges the gap between machine learning predictions and real-world clinical decision-making, offering an innovative solution for diabetes risk assessment and prevention.

References

1) Jian, Y., et al. (2021). "A Machine Learning Approach to Predicting Diabetes Complications." *Healthcare*. DOI: 10.3390/healthcare9121712.

2) Vimbi, V., et al. (2024). "Interpreting Artificial Intelligence Models: A Systematic Review on the Application of LIME and SHAP in Alzheimer's Disease Detection." *Brain Informatics*. DOI: 10.1186/s40708-024-00222-1.

3) Ganguly, R., & Singh, D. (2023). "Explainable Artificial Intelligence (XAI) for the Prediction of Diabetes Management: An Ensemble Approach." *IJACSA*. DOI: 10.14569/IJACSA.2023.0140717.

4) Uysal, I. (2023). "Interpretable Diabetes Prediction Using XAI in Healthcare Application." *IJACSA*. DOI: 10.14569/IJACSA.2023.0140671.

5) Verma, A.K., & Singh, S. (2021). "Machine Learning-Based Diabetes Prediction and Development of Web-Based Decision Support System." *Biomedical Signal Processing and Control*. DOI: 10.1016/j.bspc.2021.102589.

6) Razzak, M.A., et al. (2020). "Application of Artificial Intelligence in Diabetes Education and Management: An Overview." *Journal of Diabetes Science and Technology*. DOI: 10.1177/1932296820937235.

7) Foppen, R.J.G., et al. (2024). "Methodology for Safe and Secure AI in Diabetes Management." *Journal of Diabetes Science and Technology*. DOI: 10.1177/19322968241304434.

8) Hoyos, W., et al. (2024). "An Explainable Analysis of Diabetes Mellitus Using Statistical and Artificial Intelligence Techniques." *BMC Medical Informatics and Decision Making*. DOI: 10.1186/s12911-024-02810-x.

9) Dharmarathne, G., et al. (2024). "A Novel Machine Learning Approach for Diagnosing Diabetes with a Self-Explanatory Interface." *Healthcare Analytics*. DOI: 10.1016/j.health.2024.100301.

10) Khanam, J.J., & Foo, S.Y. (2021). "A Comparison of Machine Learning Algorithms for Diabetes Prediction." *ICT Express*. DOI: 10.1016/j.icte.2021.02.004.

11) Oikonomou, E. K. (2023). *Machine learning in precision diabetes care and cardiovascular risk prediction*. *Cardiovascular Diabetology, 22*, Article 259. https://doi.org/10.1186/s12933-023-01985-3 (BioMed Central)

12) Yang, J., Liu, D., Du, Q., Zhu, J., Lu, L., Wu, Z., Zhang, D., Ji, X., & Zheng, X. (2024). Construction of a 3-year risk prediction model for developing diabetes in patients with pre-diabetes. *Frontiers in Endocrinology, 15*, Article 1410502. https://doi.org/10.3389/fendo.2024.1410502 (Frontiers)

13) González-Rivas, J. P., Seyedi, S. A., & Mechanick, J. I. (2025). Artificial intelligence enabled lifestyle medicine in diabetes care: A narrative review. *American Journal of Lifestyle Medicine*. https://doi.org/10.1177/15598276251359185 (PMC)

Volume 64 | Issue 11 | November 2025
DOI: 10.5281/zenodo.17599058

14) Li, X., Ding, F., Zhang, L., et al. (2025). Interpretable machine learning method to predict the risk of pre-diabetes using a nationwide cross-sectional data: Evidence from CHNS. *BMC Public Health, 25*, Article 1145. https://doi.org/10.1186/s12889-025-22419-7 (BioMed Central)

15) García-Ordás, M. T., Benavides, C., Benítez-Andrades, J. A., Alaiz-Moretón, H., & García-Rodríguez, I. (2024). Diabetes detection using deep learning techniques with oversampling and feature augmentation. *arXiv*. https://arxiv.org/abs/2402.02188 (arXiv)

16) Hennebelle, A., Materwala, H., & Ismail, L. (2023). HealthEdge: A machine learning-based smart healthcare framework for prediction of type 2 diabetes in an integrated IoT, edge, and cloud computing system. *arXiv*. https://arxiv.org/abs/2301.10450 (arXiv)

17) Paladi, N., Jayasri, K., & Banam, V. P. (2025). Diabetic risk prediction based on medical and lifestyle patterns. *IJRASET Journal for Research in Applied Science & Engineering Technology*. https://doi.org/10.22214/ijraset.2025.74122 (IJRASET)