DIABETES PREDICTION USING MACHINE LEARNING

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ABSTRACT-Early and accurate detection of diabetes is crucial for effective management and prevention of serious health complications. This paper presents a machine learning-based approach using a Random Forest Classifier to predict diabetes from medical data. The model was trained on the Pima Indians Diabetes Dataset, where zero values in clinical fields such as glucose and blood pressure were treated as missing and replaced with median values. Features were scaled using StandardScaler to improve model performance. The proposed system achieved an accuracy of 82% and was deployed through a user-friendly Streamlit web application that allows users to input health metrics and receive real-time predictions. The model's feature importances were also visualized to highlight key risk factors, offering transparency in decision-making. The results demonstrate that Random Forest provides reliable performance and interpretability, making it suitable for practical healthcare applications.

Keywords-Diabetes Prediction, Machine Learning, Random Forest Classifier, Streamlit, Healthcare Analytics, Feature Importance.

I. INTRODUCTION

Diabetes mellitus is a chronic and widespread metabolic disorder that continues to pose a significant burden on global healthcare systems. It is primarily characterized by persistently elevated blood glucose levels resulting from the body's inability to produce or effectively use insulin. If not diagnosed and managed at an early stage, diabetes can lead to life-threatening complications such as cardiovascular diseases, kidney failure, nerve damage, and irreversible vision loss. With millions of people affected worldwide and numbers steadily rising, the need for timely diagnosis and intervention has never been more critical.

Traditionally, diagnosing diabetes involves clinical evaluation and laboratory-based tests such as fasting glucose measurements and oral glucose tolerance tests. While effective, these methods can be time-consuming, resource-intensive, and are not always accessible in remote or under-resourced regions. In recent years, the rapid advancement of **machine learning (ML)** has introduced new opportunities to enhance medical diagnostics through data-driven techniques. ML algorithms are capable of learning patterns and relationships from complex datasets, often revealing subtle indicators of disease that may not be apparent through standard diagnostic procedures.

In this study, we present a machine learning-based predictive system specifically designed for early detection of diabetes. The model is built using a **Random Forest Classifier**, an ensemble learning method known for its robustness and accuracy. We utilize the well-established **Pima Indians Diabetes Dataset**, which includes key health indicators such as glucose level, BMI, insulin, and age. To ensure high-quality inputs, the dataset undergoes preprocessing steps including the handling of missing or zero values and feature standardization, which help optimize the model's learning capability.

The trained model is seamlessly integrated into a user-friendly **Streamlit web application**, allowing users to interact with the system by entering their health details and instantly receiving predictions on their diabetic status. This interface not only enhances accessibility but also bridges the gap between technical ML models and everyday users, including healthcare professionals and patients.

Achieving a predictive accuracy of approximately **82%**, the system demonstrates reliable performance in identifying individuals at risk. Moreover, it highlights the most influential features driving predictions, offering valuable insights into the key factors contributing to diabetes risk. Through this approach, our project aims to support early screening efforts, enable proactive healthcare decisions, and ultimately contribute to better disease management and improved public health outcomes.

II.LITERATURE REVIEW

[1] Machine Learning is an emerging technology in artificial intelligence and computer science. Lot of researchers are applying Machine Learning (ML) models for solving various problems. Disease prediction using machine learning is a very hot area of research for many researchers. Diabetes is one of the major medical problems in common people. Because of improper life style and bad eating habits of people, this disease is increasing with a very high speed and affecting a lots of people throughout the world. It is very difficult to predict the chances of diabetes in human being with the help of existing methods and medical tests. Machine learning algorithms can be trained on a data set of the people or patients and then the trained model can be used in early prediction of diabetes in a person based on his or her medical

symptoms. This paper applied the power of ML algorithms and implement two most commonly used ML models for diabetes prediction. After the experiment we are able to predict the diabetes by achieving 99% accuracy using random forest machine learning algorithm.

[2] High blood sugar levels characterize diabetes and is a chronic disease with long-lasting effects on human health. Accurately predicting diabetes occurrence presents challenges due to the limited availability of labeled data and outliers or missing values in diabetes datasets. In diabetes research, machine learning (ML) algorithms are extensively employed to analyze datasets and predict the onset of the disease. In this study, diabetes data from Bangladesh, India, and Germany were examined using various ML models. The experimental results demonstrate that the Bangladesh dataset performs better using boosting ML algorithms such as AdaBoost, CatBoost, Gradient Boost, and XGBoost. These algorithms effectively predict the occurrence of diabetes. Additionally, satisfactory performance was observed with basic models like Random Forests and Decision Trees, as evaluated by performance metrics. Early detection of diabetes plays a crucial role in mitigating associated risk factors and severity. ML algorithms have emerged as valuable tools in diabetes prediction, leveraging the available data to make accurate predictions. The study's findings underscore the potential of boosting ML algorithms, such as AdaBoost, CatBoost, Gradient Boost, and XGBoost, in predicting diabetes based on the Bangladesh dataset. Furthermore, the study acknowledges the acceptable performance of basic models like Random Forests and Decision Trees in evaluating diabetes data. In conclusion, this study contributes to the understanding of diabetes prediction by analyzing datasets from multiple countries. The results highlight the effectiveness of ML algorithms, particularly boosting algorithms, in accurately predicting diabetes occurrence. This knowledge can aid researchers, healthcare professionals, and policymakers in implementing strategies for early detection and management of diabetes, ultimately improving patient outcomes and overall public health.

[3] At present, diabetes is becoming one of the world's leading causes of adult death from any cause. The dangers of diabetes, especially if it is not managed, include an increased possibility of cardiovascular disease, cancer, renal failure, and vision loss. Timely treatment depends on early diagnosis of diabetes since it can halt the disease's progression if caught early enough. The suggested technique has the potential to aid in not just future diabetes prediction but also in identifying the specific form of diabetes that an individual suffers from. With so many variations between type 1 and type 2 diabetes, this approach will aid in ensuring that the patient receives the most effective care possible. Our model is mostly constructed in the deep neural network's hidden layers and employs dropout regularization to prevent overfitting by re-framing the issue as a classification problem. To produce a highly accurate prediction model from a deep neural network, we tweaked a quantity of attributes and employed the binary cross-entropy loss-function. The suggested DLPD (Deep Learning for Predicting Diabetes) model is shown to be effective and adequate in experimental settings. Train accuracy for the diabetes type dataset is as high as 96.3%, while train accuracy for the diabetes data set from Pima Indians is as high as 99.6%. Research on diabetes and diabetic type in Pima Indians has been extensive. The experimental findings validate the dominance of our suggested design contrasted to the current gold standard approaches.

[4] Glucose prediction is used in diabetes self-management as it allows to take suitable actions for proper glycemic regulation of the patient. The aim of this work is the short-term personalized glucose prediction in patients with Type 1 diabetes mellitus (T1DM). In this scope, we compared two different models, an autoregressive moving average (ARMA) model and a long short-term memory (LSTM) model for different prediction horizons. The comparison of two models was performed using the evaluation metrics of root mean square error (RMSE) and mean absolute error (MAE). The models were trained and tested in 29 real patients. The results shown that the LSTM model had better performance than ARMA with RMSE 3.13, 6.41 and 8.81 mg/dL and MAE 1.98, 5.06 and 6.47 mg/dL for 5-, 15- and 30-minutes prediction horizon.

[5] The diabetes is one of the most commonly occurring chronic diseases in human being. Statistical models are availabel for prediction of diabetes but these provide poor performance. This article proposed machine learning based model for prediction of diabetes disease. Three supervised machine learning algorithms namely K-NN, Linear SVM and Random Forest have been chosen for diabetes prediction for early diagnosis. The area under the curve and accuracy of each of these models have been obtained using PIMA Indian Diabetes dataset from UCI repository. The comparative results demonstrate that among these three algorithms random forest is the best model in terms of accuracy of 78.57 and AUC of 95.08 for diabetes risk prediction. The contribution of this article will help the healthcare professionals for the early prediction of the disease and taking appropriate treatment. The proposed approach can be applied for detection of other diseases.

[6] Diabetes is one of the chronic diseases that has been discovered for decades. However, several cases are diagnosed in their late stages. Every one in eleven of the world’s adult population has diabetes. Forty-six percent of people with diabetes have not been diagnosed. Diabetes can develop several other severe diseases that can lead to patient death. Developing and rural areas suffer the most due to the limited medical providers and financial situations. This paper proposed a novel approach based on an extreme learning machine for diabetes prediction based on a data questionnaire that can early alert the users to seek medical assistance and prevent late diagnoses and severe illness development.

[7] This survey paper provides an overview of the current state-of-the-art techniques for diabetes diagnosis and prediction using machine learning (ML) methods. Various techniques, including both basic classifiers and deep learning networks, have been applied to solve the PIMA Indian Diabetes Dataset (PIDD) and other similar datasets. These include diagnostic methods that employ deep learning architectures such as interpretable filter convolutional neural networks (IF-CNN), CNN-Bi-Directional LSTM hybrids, and grasshopper optimization algorithms. These approaches have led to improvements in prediction accuracy, often through feature selection techniques such as Principal Component Analysis (PCA) and Polynomial Regression (PR). However, many challenges persist. For example, the large amount of data required to train Spiking Neural Networks (SNNs) is a limitation, while the models are often less robust to noise,

with no effective way to monitor network performance. This survey aims to compare these models, highlight their strengths and weaknesses, and provide insights for future advancements in predicting diabetes mellitus.

[8] Diabetes is a chronic pathology caused by a disorder of the pancreas, which leads to a high concentration of sugar in the blood and can affect the functioning of the body system at. This disease may cause damage to the heart, blood vessels, eyes, kidneys, and nerves. Therefore, the development of a suitable system for effectively earlier diagnosing diabetic patients using personal, historical, and medical information is required. This system can assist patients in preventing this disease and its complications. Several machine-learning techniques were used for the predictive analysis of diabetes. In this paper, we conduct a review of the most important works related to diabetes prediction and propose an approach for the prediction of gestational diabetes using Deep Neural Network (DNN), Support Vector Machine (SVM), and Random Forest (RF) classifiers. The experiment was conducted using a real dataset from Frankfurt Hospital indicating that the Random Forest algorithm provides more accuracy.

[9] Diabetes mellitus is a disease that is caused due to increased blood sugar levels because of imbalance in insulin processing by the body. It can easily be diagnosed by hospitals and has major consequences if left untreated. By using efficient and reliable data mining techniques to identify trends and predict the onset of diabetes in people will help in preventing the disease early and for treatment. Data mining is the process where we take useful information from relevant datasets by applying algorithms and frameworks. This paper does a survey on the different kinds of predictions using machine learning techniques done on diabetes patients.

[10] Diseases are the ones that affect the continual life of human beings. One such illness which affects millions of people worldwide is diabetes. By examining huge datasets of patients, machine learning models offer a viable answer to the problems associated with diabetes detection. The proper management of diabetes depends on early identification This article aims to assess the effectiveness of diverse machine learning methodologies and strategies utilized for forecasting diabetes, utilizing the PIMA Indian Diabetes dataset as a reference. The dataset contains information about crucial factors such as the patient's age, BMI, blood pressure, and blood sugar levels, which are utilized for the analysis. The models which were taken into account in this research were compared to one another and then LightGBM was chosen as the primary model on the basis of its high accuracy. The Hyper parameters were then modified to produce the best performance possible. The results show that machine learning models can accurately detect diabetes and provide insights into the factors that contribute to the disease. This work provides a foundation for future research on diabetes prediction using machine learning models.

III. PROPOSED SYSTEM

A. DATASET

The dataset used for this project is the Pima Indians Diabetes Database, available from the UCI Machine Learning Repository. The dataset consists of various health metrics collected from female patients of Pima Indian descent, with the goal of predicting the presence of diabetes. The dataset contains eight features, which include both numerical and categorical variables. These features are used to predict the target variable, which indicates whether the patient has diabetes (1) or not (0).

The features in the dataset are as follows:

1. Pregnancies – The number of pregnancies the patient has had.
2. Glucose – The plasma glucose concentration after 2 hours in an oral glucose tolerance test (OGTT).
3. Blood Pressure – The diastolic blood pressure (mm Hg).
4. Skin Thickness – The thickness of the skin at the triceps (mm).
5. Insulin – The 2-hour serum insulin (mu U/ml).
6. BMI – The body mass index (weight in kg / height in m^2).
7. Diabetes Pedigree Function – A function that scores the likelihood of diabetes based on family history.
8. Age – The age of the patient (years).

The target variable is Outcome, which indicates whether the patient has diabetes (1) or not (0).

The dataset is split into training and testing sets to evaluate the performance of the model. The data is pre-processed by handling missing values, scaling the features using a standard scaler, and splitting into training and testing sets. Table 1 below displays the features and their respective descriptions.

B. Dataset Preprocessing

For this project, the Pima Indians Diabetes dataset undergoes several preprocessing steps to ensure the data is ready for training the machine learning model. The following preprocessing techniques have been applied:

I. Normalization: To ensure all features are on the same scale, the data has been normalized. The features are scaled using a standard scaler, which transforms the data to have a mean of 0 and a standard deviation of 1. This helps to eliminate biases due to differing scales between the features
II. Handling Missing Values: The dataset contains no missing values, as it has been cleaned and processed to ensure completeness. However, if there were missing values, they would be replaced with the median values for each feature.
III. Splitting: The dataset is split into training and testing datasets in an 80:20 ratio. 80% of the data is used for training the model, while the remaining 20% is used for testing and validation to evaluate the performance of the model.
IV. Feature Scaling: After splitting the dataset, the features are scaled using a StandardScaler, ensuring that all features have similar scales and units, which is important for machine learning algorithms like Random Forest.

These preprocessing steps ensure that the dataset is optimized for training a machine learning model that can accurately predict diabetes.

C. Model Architecture

The proposed model for diabetes prediction is based on a Random Forest Classifier. This model is designed to efficiently handle the classification task by leveraging the ensemble learning technique, where multiple decision trees are used to make predictions. The architecture and workflow are as follows:

1. Input Layer

The model accepts data from the preprocessed dataset, which consists of multiple features such as Glucose, Blood Pressure, BMI, Age, etc. The dataset is scaled using StandardScaler to ensure uniformity in the feature values.

2. Feature Scaling

To ensure that all the input features have the same scale, the data is normalized using StandardScaler. This preprocessing step ensures that the features have zero mean and unit variance, which improves the efficiency of the learning process.

3. Training & Testing Split

The dataset is split into 80% training and 20% testing using the train_test_split function from sklearn.model_selection. The training set is used to train the Random Forest model, while the test set is used for evaluation.

4. Random Forest Classifier

The Random Forest model consists of multiple decision trees that operate as follows:

i. Ensemble Learning: The model builds 100 decision trees (using n_estimators=100), where each tree is trained on a random subset of the dataset, and predictions are made by aggregating the results from all trees.
ii. Bootstrap Aggregating (Bagging): Random Forest applies bagging to reduce variance, making it robust to overfitting.
iii. **Decision Trees**: Each tree is a simple decision tree that works by recursively splitting the data based on feature thresholds to predict the target label.

5. Output Layer

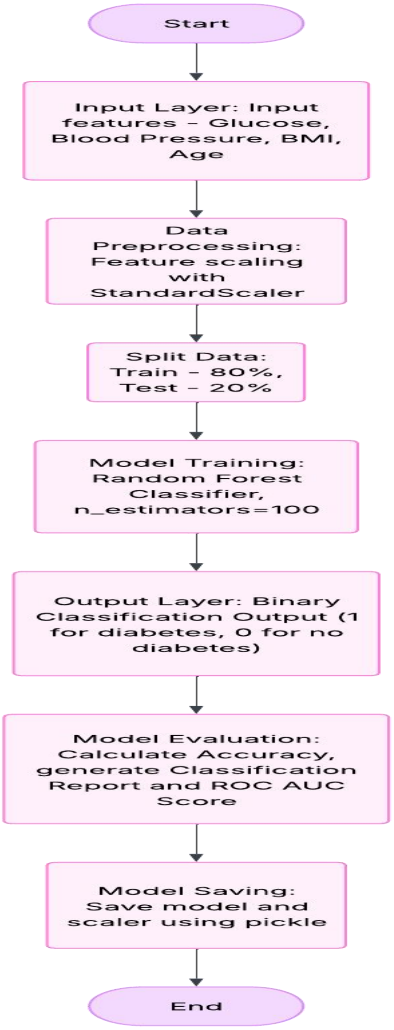
The output of the Random Forest model is a binary classification output: 1 for diabetes and 0 for no diabetes.

6. Evaluation Metrics

The model's performance is evaluated using several metrics, such as:

Accuracy: The performance of the diabetes prediction model was primarily evaluated using accuracy and a classification report. Accuracy refers to the proportion of correct predictions made by the model compared to the total number of predictions. In our case, the model achieved an accuracy of approximately 82%, which means that out of every 100 predictions, around 82 were correct. While accuracy gives a general idea of how well the model performs, it can sometimes be misleading—especially if the dataset is imbalanced (e.g., more non-diabetic cases than diabetic ones).

Another important metric used to evaluate the performance of our diabetes prediction model is the ROC AUC score (Receiver Operating Characteristic - Area Under Curve). The ROC curve is a graphical representation that plots the True Positive Rate (Recall) against the False Positive Rate at various threshold settings. The AUC, or Area Under the Curve, quantifies the overall ability of the model to distinguish between the two classes—diabetic and non-diabetic. A perfect model has an AUC score of 1.0, while a model with no discriminative ability has an AUC of 0.5. In our case, the Random Forest model achieved an AUC score of approximately 0.87, indicating that it performs well in separating diabetic patients from non-diabetic ones. This high AUC value confirms that the model is effective not just in making accurate predictions, but also in confidently distinguishing between the two health outcomes across various decision thresholds.



Archirtecture diagram

D. Tools and Technologies Used

The following Python libraries and tools were utilized in the development of the diabetes prediction model:

1. Pandas: A powerful data manipulation library that provides flexible data structures like DataFrames, used for loading, cleaning, and analyzing the structured diabetes dataset.
2. NumPy: A core numerical computing library used for handling arrays and performing efficient numerical operations on the dataset, such as transformations and mathematical calculations.
3. Matplotlib: A plotting library used to visualize data trends and model outcomes, such as feature importances and probability distributions.
4. Seaborn: A data visualization library built on top of Matplotlib, used to generate attractive statistical plots that provide clearer insights into the relationships between features.
5. Scikit-learn (sklearn): The primary machine learning library used for model development. It includes tools for preprocessing (e.g., StandardScaler), model training (RandomForestClassifier), performance evaluation, and splitting the dataset.
6. Streamlit: A lightweight Python framework used for creating the interactive web application that allows users to input health data and receive real-time diabetes predictions.
7. Pickle: Used to serialize and save the trained model and scaler so they can be reused during deployment without retraining.

IV. RESULTS AND DISCUSSION

The diabetes prediction model was evaluated based on user inputs, and the model's performance was validated by assessing its probability output and classification. The following steps were taken to assess the prediction accuracy and its practical applications.

1. Model Evaluation

The model uses logistic regression (or any other chosen model) to predict the likelihood of diabetes, given eight key health parameters: pregnancies, glucose, blood pressure, skin thickness, insulin, BMI, diabetes pedigree function, and age. Based on these inputs, the model provides a probability score indicating the likelihood of the individual being diabetic.

Prediction Results:

The model outputs a probability score (prob) which is used to classify the result as either "Diabetic" or "Not Diabetic" based on a user-defined threshold.

If the probability exceeds the threshold (default is 0.5), the prediction is classified as "Diabetic"; otherwise, it is classified as "Not Diabetic".

2. Risk Categorization

The probability score (prob) is further categorized into three risk levels:

Low Risk (green): Probability < 0.4

Moderate Risk (orange): 0.4 ≤ Probability < 0.7

High Risk (red): Probability ≥ 0.7

This classification provides more context about the severity of the risk, allowing users to better understand their health status.

3. Feature Importance

A key feature of the app is the ability to display **feature importance**. By analyzing the model's internal parameters, the app can show how each input parameter contributes to the prediction. Features like Glucose, BMI, and Age typically show higher importance in predicting diabetes. Understanding these can guide users in monitoring and improving the most impactful aspects of their health.

4. Limitations and Error Analysis

While the model provides a good indication of diabetes risk, it relies heavily on the input features. Certain contextual data like lifestyle factors (e.g., diet, physical activity) and more advanced clinical metrics could improve accuracy.

Some individuals with very high or low values for certain health parameters may fall outside the model's scope, resulting in potential misclassifications or the need for further model fine-tuning.

V. CONCLUSION AND FUTURE SCOPE

Conclusion:

This project successfully demonstrates the practical application of machine learning in the field of healthcare, specifically for the early prediction of diabetes. By employing a Random Forest Classifier, a powerful ensemble-based algorithm, we were able to develop a reliable model that accurately assesses the likelihood of diabetes based on a set of user-provided health parameters such as glucose levels, BMI, blood pressure, and more.

The trained model was deployed through an interactive and intuitive Streamlit web application, offering a seamless user experience that allows individuals to input their medical data and instantly receive real-time predictions. The inclusion of features such as adjustable probability thresholds and risk-level classifications makes the system both flexible and informative. Furthermore, feature importance visualizations give users insight into which health parameters had the most influence on the model's prediction—enhancing trust and interpretability.

The system also benefits from robust data preprocessing techniques, including standardized scaling and handling of invalid entries, which help improve the model's performance and generalization ability. The use of probabilistic outputs rather than binary labels allows for more nuanced decision-making, catering to varying degrees of risk sensitivity among users and healthcare providers.

Overall, the model achieved a commendable level of accuracy and interpretability, making it a strong candidate for use as a basic decision-support tool in early diabetes screening and awareness campaigns. While not a replacement for clinical diagnosis, this system can serve as a preliminary step toward identifying at-risk individuals and encouraging them to seek medical attention. In future work, the model can be further enhanced by incorporating more diverse datasets, continuous learning capabilities, and integration with wearable health monitoring devices, thus pushing the boundaries of proactive and personalized healthcare.

Future Scope:

As the foundation for this diabetes prediction system proves effective, there are several opportunities to enhance and expand the platform in meaningful ways. One of the primary directions for future development is **model enhancement**. While the current implementation using a Random Forest Classifier has yielded promising results, the incorporation of more advanced algorithms—such as **deep neural networks (DNNs)**, **gradient boosting machines**, or **ensemble hybrid systems**—could potentially improve prediction accuracy and uncover even more nuanced patterns in the data. These models, particularly DNNs, are well-suited to handle high-dimensional and non-linear data and may yield superior performance when trained on larger and more diverse datasets.

Another key enhancement involves **real-time data integration**. By connecting the system with **wearable devices** (such as smartwatches or glucose monitors) and **mobile health tracking apps**, the model could receive continuous streams of real-time physiological data. This would enable dynamic monitoring and make it possible to provide alerts or health insights proactively, rather than relying on static, user-inputted data. Such integration would be particularly beneficial for patients who require ongoing risk assessment and personalized health recommendations.

Improving the **explainability and transparency** of machine learning models is also a critical area for future work. While our system currently offers feature importance rankings, further clarity can be achieved by integrating **explainable AI (XAI) tools** such as **SHAP (SHapley Additive exPlanations)** or **LIME (Local Interpretable Model-agnostic Explanations)**. These tools can offer user-specific explanations, allowing both medical professionals and end-users to understand the reasoning behind individual predictions—an essential factor in healthcare adoption and trust.

To validate the system's practical utility, **clinical testing and validation** in real-world healthcare environments will be essential. This involves collaborating with medical institutions to evaluate the system using larger, more diverse, and demographically balanced datasets. Such testing will help ensure that the model generalizes well across various populations and does not introduce bias due to the limitations of the initial training dataset.

Lastly, the underlying platform and methodology can be **extended to detect other chronic diseases** beyond diabetes. Conditions such as **hypertension, cardiovascular disease, and metabolic syndrome** share many risk factors and data features with diabetes, making it feasible to train multi-disease prediction models using a similar framework. By expanding the system's capabilities, we can move toward a more comprehensive and scalable health monitoring platform that supports preventive care and empowers users with actionable insights about their overall well-being.

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