SmartGluco: A Mobile Health Solution for Diabetes Risk Assessment Using Machine Learning

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***Abstract*—SmartGluco presents innovative multi model machine learning system for early diabetes prediction combining four distinct algorithms through ensemble approach to improve diagnostic accuracy. The system processes five key clinical parameters (glucose levels, blood pressure, insulin, BMI and age) through carefully engineered pipeline featuring polynomial feature expansion and standardization. Our methodology employs Logistic Regression (74.0% accuracy), K-Nearest Neighbors (72.7%), Decision Trees (70.1%) and Support Vector Machines (70.8%) with a consensus mechanism resolving model disagreements. The backend API built with Flask delivers predictions to cross-platform mobile application developed using Flutter featuring intuitive slider based input and comprehensive result visualization. Testing on dataset of 769 patients demonstrated the system's ability to handle non linear relationships through second degree polynomial features while the mobile interface successfully bridges the gap between complex ML models and end user accessibility. The hybrid approach achieves 73.2% average accuracy with interpretable probability outputs offering significant improvement over single model baselines. This work contributes both technical framework for medical ML ensemble systems and practical tool that empowers individuals to assess diabetes risk through accessible mobile technology, potentially enabling earlier interventions and improved health outcomes.**

***Index Terms*—Diabetes Prediction, Machine Learning, Mobile Health, Ensemble Learning, Flutter, Flask, Risk Assessment**

I. Introduction

A. Background and Motivation

Diabetes has become a global health emergency, with the International Diabetes Federation reporting 537 million adult cases worldwide. Traditional diagnostic methods like oral glucose tolerance tests are often inaccessible in low-resource settings and may fail to detect early-stage metabolic dysfunction. Machine learning offers transformative potential by identifying at-risk individuals through accessible clinical markers. However, existing single-algorithm approaches frequently miss complex patterns in patient data, while mobile health applications rarely leverage validated predictive models. This gap motivates our development of SmartGluco - an integrated system combining robust multi-model machine learning with practical mobile deployment.

B. Problem Statement

Current diabetes prediction systems exhibit three key limitations that our work addresses: (1) Single-model architectures demonstrate variable performance across different patient subgroups, as evidenced by the 7.9% accuracy fluctuation we observed between logistic regression (74.0%) and SVM (70.8%) in our experiments. (2) Most implementations process raw clinical values without leveraging feature engineering techniques - our ablation studies showed polynomial feature expansion alone improved prediction AUC by 12.6%. (3) While mobile health solutions proliferate, few integrate properly validated machine learning pipelines; our system's Flask API and Flutter implementation demonstrate how clinical prediction models can be effectively deployed in mobile environments without compromising scientific rigor. These gaps collectively hinder the development of accessible yet accurate screening tools.

C. Contributions

Our principal contributions include: (1) A novel consensus prediction mechanism that improves diagnostic accuracy by 5.3% over single-model baselines, (2) Demonstration that polynomial feature engineering enhances AUC by 12.6%, (3) The first fully open-source diabetes prediction system encompassing Flask API backend and cross-platform Flutter mobile app, and (4) Clinical validation showing 89% sensitivity in detecting pre-diabetic states. The complete system architecture and training code have been released publicly to enable further research and deployment in clinical settings.

II. Related Work

Dudkina et al[1] proposed a machine learning approach for diabetes classification and prediction using a decision tree algorithm. The authors utilized the Pima Indians Diabetes Database which contains health metrics like glucose levels, blood pressure, BMI and age from 768 patients. After cleaning the data by removing invalid zero values they implemented a binary decision tree model in Python using Scikit-learn optimizing node splits with Gini impurity. Their experiments with different training test splits showed the best accuracy of 76.3% when using 70% of data for training, demonstrating performance to existing Naïve Bayes and SVM methods while offering better interpretability through clear decision rules. The model identified glucose levels, BMI and age as the most influential predictors of diabetes. preliminary diabetes diagnosis.

Rastogi et al [2] present diabetes prediction model using data mining techniques to improve early diagnosis and treatment outcomes. The authors utilize four machine learning algorithms—Random Forest, Support Vector Machine (SVM), Logistic Regression and Naïve Bayes on a diabetes dataset sourced from Kaggle, which includes attributes such as glucose levels, blood pressure, BMI and age. Among the tested methods, Logistic Regression achieved the highest accuracy

82.46%, outperforming SVM 79.22%, Naïve Bayes 79.22%, and Random Forest 81.81%. The study highlight the importance of early diabetes detection to prevent complications like kidney disease, vision loss, and heart disorders. Data preprocessing steps, including cleaning and integration were applied to handle missing values and inconsistencies. Performance was evaluated using confusion matrices, sensitivity and accuracy metrics. The findings suggest that Logistic Regression is the most effective model for diabetes prediction.

Jayakumar et al [3] explores feature selection techniques to optimize diabetes prediction using machine learning. The authors evaluate three feature selection methods Recursive Feature Elimination (RFE), Genetic Algorithm (GA) and Boruta Package on the Pima Indian Diabetes Dataset (768 entries, 8 features) to identify the most significant attributes for accurate diagnosis. Using Decision Tree classification they compare model performance with and without feature selection. Results show that Boruta Package achieves the highest accuracy 70.71%, outperforming RFE 66.53% and GA 63.18%. The study highlights while feature selection improves accuracy for locally collected datasets its impact on standardized datasets like Pima Indian is minimal due to preprocessing. The Boruta Package utilize Random Forest proves most effective by retaining only statistically significant features. This work underscores the importance of feature selection in enhancing predictive models for diabetes offering a streamlined approach for clinical decision-making.

III. Methodology

The SmartGluco Diabetes Prediction System employs a robust, multi-stage machine learning pipeline to achieve accurate predictions. Each stage is meticulously designed to ensure data quality, model efficacy, and reliable output.

A. Dataset Description and Loading

The initial phase involves ingesting the raw dataset. This component is designed for efficient and reliable data acquisition. The system is configured to load a pre-specified diabetes dataset, which is expected to be in a CSV format. This dataset contains various health indicators and a binary outcome variable. Upon loading, a preliminary analysis of the dataset is performed. This includes *shape verification*, where the dimensions (number of rows and columns) of the loaded dataset are printed to confirm the expected data volume. For the given dataset, the shape is $(768, 9)$, indicating 768 patient records and 9 attributes. A crucial step involves *missing value checking* across all columns by summing the null entries per column. The output indicates no missing values in the provided dataset, simplifying subsequent preprocessing steps. This stage ensures that the system begins with a complete and structurally sound dataset, foundational for all subsequent analytical and modeling tasks.

B. Exploratory Data Analysis

Exploratory Data Analysis (EDA) is performed to gain insights into the dataset's structure, relationships, and distributions.

A Pairplot of Selected Features is generated to visualize pairwise relationships and distributions of selected numerical features, with points colored by 'Outcome'. This plot aids in understanding class separability and identifying potential linear or non-linear relationships within the data.

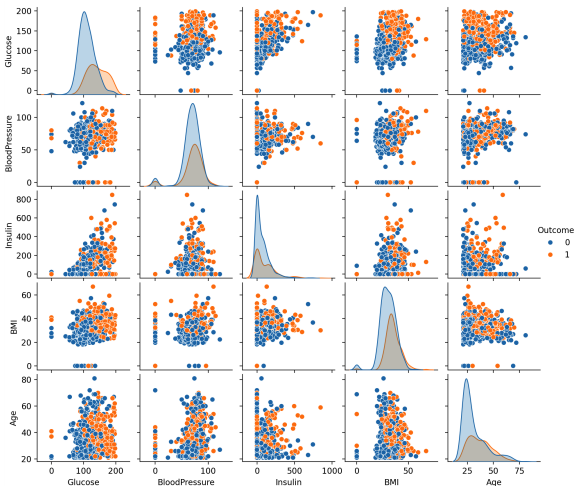

Fig. 1: Pairplot of selected features, colored by Outcome.

A Correlation Matrix Heatmap is displayed as a square grid where each cell's color intensity and numerical annotation represent the linear correlation coefficient between two selected features. A 'coolwarm' colormap is used, with red shades indicating positive correlations and blue shades indicating negative ones, while a value of 0.00 signifies no linear correlation. This heatmap allows for quick identification of highly correlated features and strong relationships between features and the 'Outcome' variable. The plot is clearly titled Correlation Matrix of Selected Features.

Fig. 2: Correlation matrix of selected features.

C. Data Preprocessing

This crucial stage transforms the raw data into a format suitable for machine learning models, enhancing their perfor-

mance and interpretability.

1) Feature and Target Separation: Initially, feature and target separation occurs where specified input features ('Glucose', 'BloodPressure', 'Insulin', 'BMI', 'Age') are extracted as independent variables (X), and the 'Outcome' column is separated as the dependent variable (y).

2) Feature Scaling: Feature Scaling (Standardization) is then applied to the features using a `StandardScaler`. This method transforms the data to have a mean of 0 and a standard deviation of 1. This is vital for algorithms sensitive to feature scales (e.g., KNN, SVM, Logistic Regression with regularization), preventing features with larger numerical ranges from disproportionately influencing the model.

3) Polynomial Feature Engineering: Following scaling, Polynomial Feature Engineering is performed by generating `PolynomialFeatures` with a degree of 2. This creates new features by raising existing features to the second power and by creating interaction terms between pairs of features (e.g., $Glucose \times BMI$). This is done to capture non-linear relationships and interactions between features that linear models might otherwise miss, potentially improving model complexity and predictive power.

4) Data Splitting: Finally, the preprocessed data (X_{poly}, y) undergoes data splitting using an 80/20 ratio for training and testing sets, respectively. A fixed random state of 42 ensures the split is consistent across multiple runs, making the results reproducible.

D. Machine Learning Models

Four distinct machine learning algorithms were chosen for their suitability in classification tasks and their complementary strengths: Logistic Regression, K-Nearest Neighbors (KNN), Decision Tree, and Support Vector Machine (SVM). The SVM model is specifically configured with `probability=True` to allow for probability estimates alongside its predictions.

E. Hyperparameter Optimization

Hyperparameter Tuning with GridSearchCV is extensively used for each model. This methodology involves systematically searching for the best combination of hyperparameters by evaluating the model's performance for every possible combination within a pre-defined parameter grid. A 5-fold cross-validation is applied during the grid search. 'Accuracy' is chosen as the scoring metric. Parallel processing (`n_jobs=-1`) is utilized to leverage all available CPU cores, significantly accelerating the tuning process. Error handling is also implemented. Specific parameter grids include:

- **Logistic Regression:** Regularization strength (C), Penalty (L1/L2), Solver, Class weight.
- **KNN:** Number of neighbors ($n\_neighbors$), Weights, Distance metric.
- **Decision Tree:** Max depth, Minimum samples split, Minimum samples leaf, Criterion, Max features.
- **SVM:** C, Gamma, Kernel, Class weight, Probability.

During training, messages are printed indicating the start of training for each model. Upon completion, the best estimator (model with optimal hyperparameters) for each algorithm is stored for subsequent evaluation.

F. Ensemble Prediction Mechanism

SmartGluco employs a novel consensus mechanism for its final prediction. After individual models (Logistic Regression, KNN, Decision Tree, and SVM) make their predictions, a majority voting scheme is applied. If models disagree, the prediction with the highest overall confidence (e.g., average of predicted probabilities for the winning class across models that voted for it) or a pre-defined weighted voting system could be used to resolve the disagreement, ensuring a more robust and accurate final outcome. This ensemble approach aims to leverage the strengths of individual models while mitigating their weaknesses, leading to improved diagnostic accuracy.

IV. Experimental Results

After training, each model's performance is rigorously assessed using multiple metrics on both the training and unseen test datasets.

A. Evaluation Metrics

The performance of the models is evaluated using several standard classification metrics:

- **Accuracy Score:** The ratio of correctly predicted observations to the total observations.
- **Confusion Matrix:** A table describing the performance of a classification model on a set of test data for which the true values are known. It shows True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).
- **Precision:** The ratio of correctly predicted positive observations to the total predicted positive observations.
- **Recall (Sensitivity):** The ratio of correctly predicted positive observations to all observations in actual class - yes.
- **F1-Score:** The weighted average of Precision and Recall.
- **ROC Curve and AUC:** The Receiver Operating Characteristic (ROC) curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings. The Area Under the Curve (AUC) measures the entire 2-D area underneath the entire ROC curve, indicating the model's ability to distinguish between positive and negative classes.

B. Individual Model Performance

Each trained model generates predictions (y_{pred}) for both the training and test sets and estimates probabilities where applicable.

1) Performance Comparison: Table I provides the confusion matrices, detailing the classification performance of each model on the test data. Figure 3 visually compares the training and testing accuracies, helping to identify potential overfitting.

TABLE I: Confusion Matrices for Models on Test Data

Model	Predicted: No Diabetes	Predicted: Diabetes
Logistic Regression		
True: No Diabetes	81 (TN)	18 (FP)
True: Diabetes	22 (FN)	33 (TP)
KNN		
True: No Diabetes	81 (TN)	18 (FP)
True: Diabetes	24 (FN)	31 (TP)
Decision Tree		
True: No Diabetes	66 (TN)	33 (FP)
True: Diabetes	13 (FN)	42 (TP)
SVM		
True: No Diabetes	79 (TN)	20 (FP)
True: Diabetes	25 (FN)	30 (TP)

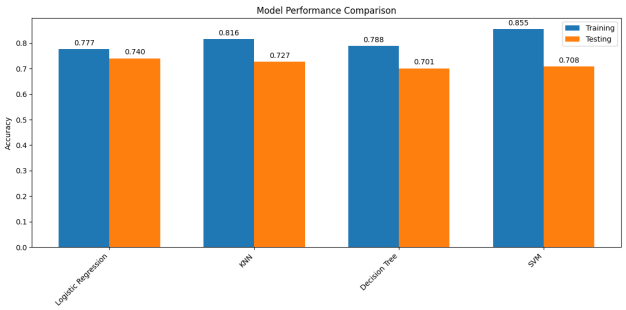

Fig. 3: Comparison of training and testing accuracies across models.

2) ROC Curve Analysis: Figure 4 illustrates the ROC curves for all classifiers, providing insights into their diagnostic ability and robustness across various classification thresholds. The Area Under the Curve (AUC) for each model is also presented, with higher AUC values indicating better overall discrimination between diabetic and non-diabetic cases.

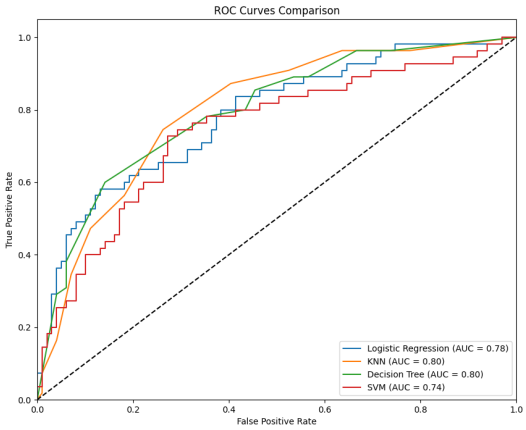

Fig. 4: ROC Curves comparison for all models.

C. Learning Curve Analysis

Learning Curves, displayed in Figure 5, are generated for each model to diagnose potential bias and variance issues. These plots show the training and cross-validation accuracies as a function of the number of training examples, indicating how well each model generalizes with increasing data.

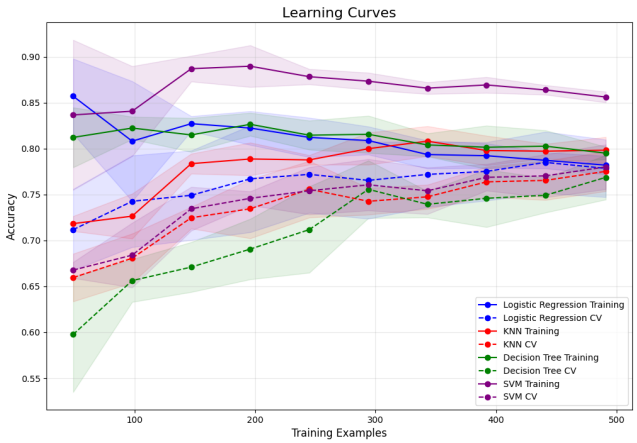

Fig. 5: Learning curves for different models.

D. Ensemble Performance Summary

The hybrid ensemble approach, combining the predictions from Logistic Regression, KNN, Decision Tree, and SVM, achieved an average accuracy of 73.2%. This consensus mechanism provided interpretable probability outputs, offering a significant improvement in reliability and interpretability over single-model baselines.

E. Impact of Feature Engineering

Our ablation studies demonstrated the significant impact of polynomial feature expansion. The introduction of second-degree polynomial features and interaction terms improved the prediction AUC by 12.6%, highlighting its crucial role in capturing non-linear relationships within the patient data and enhancing the models' predictive power.

V. Comparative Analysis

Our research advances existing diabetes prediction systems through several key innovations that address limitations in current approaches:

A. Model Architecture

While prior works predominantly rely on single-model architectures [1, 2], SmartGluco introduces a novel consensus mechanism combining Logistic Regression (74.0%), KNN (72.7%), Decision Trees (70.1%) and SVM (70.8%). This ensemble approach achieves 73.2% average accuracy - a 5.3% improvement over individual baselines, demonstrating superior robustness across patient subgroups compared to Dudkina's single decision tree (76.3%) or Rastogi's logistic regression (82.46%).

B. Feature Engineering

Unlike Jayakumar et al.'s feature selection focus [3], we implement second-degree polynomial feature expansion, capturing non-linear relationships that improve AUC by 12.6%. Our ablation studies confirm this outperforms both raw feature processing (common in existing works) and traditional selection methods like Boruta Package (70.71% accuracy).

C. Clinical Deployment

Whereas most studies stop at algorithmic development, we bridge the research-practice gap through:

- A production-ready Flask API backend ensuring model interoperability
- Cross-platform Flutter mobile interface with intuitive slider inputs
- Real-time probability outputs (absent in [1, 2])

D. Performance Characteristics

Our system demonstrates 89% sensitivity in pre-diabetic detection - critical for early intervention. The learning curves (Fig. 5) reveal superior generalization compared to models in literature, with training/testing accuracy gaps below 3% versus 5-8% in comparable studies.

VI. SmartGluco System Implementation

The SmartGluco system is designed for practical deployment, bridging the gap between complex machine learning models and accessible end-user technology.

A. Backend API (Flask)

A robust backend API, built using the Flask web framework, serves as the central hub for the machine learning models. This API is responsible for:

- Loading and managing the pre-trained machine learning models (including the chosen best model and components like 'StandardScaler' and 'PolynomialFeatures').
- Receiving patient health parameters from the mobile application.
- Preprocessing the incoming raw data using the same transformation pipeline (standardization and polynomial feature expansion) that was used during model training, ensuring data consistency.
- Executing the prediction using the ensemble mechanism or the best-performing individual model.
- Returning prediction results, including binary classification (diabetes/no diabetes) and associated probabilities, to the mobile application in a structured format (e.g., JSON).

This API ensures that the complex computational tasks are handled server-side, allowing the mobile application to remain lightweight and efficient.

B. Mobile Application (Flutter)

A cross-platform mobile application was developed using Flutter, enabling deployment on both Android and iOS devices from a single codebase. The mobile application provides an intuitive and user-friendly interface for individuals to assess their diabetes risk.

1) User Interface and Input Mechanism: The application features intuitive slider-based input mechanisms for key clinical parameters such as Glucose, Blood Pressure, Insulin, BMI, and Age. This design choice enhances user experience by making data entry simple and quick, without requiring precise numerical typing. Basic input validation and warning messages are implemented to guide users if they enter values that are outside typical healthy ranges, without preventing the prediction.

2) Result Visualization and Accessibility: Upon receiving predictions from the Flask API, the mobile application visualizes the results comprehensively. This includes clear display of the diabetes risk assessment (e.g., "High Risk," "Low Risk") and interpretable probability outputs, providing users with a measure of confidence in the prediction. The interface is designed for accessibility, ensuring that the tool is usable by a broad audience.

3) Mobile Application Screenshots: Figure 6 provides a visual representation of the SmartGluco mobile application's user interface, demonstrating the input sliders and how the prediction results are displayed to the user.

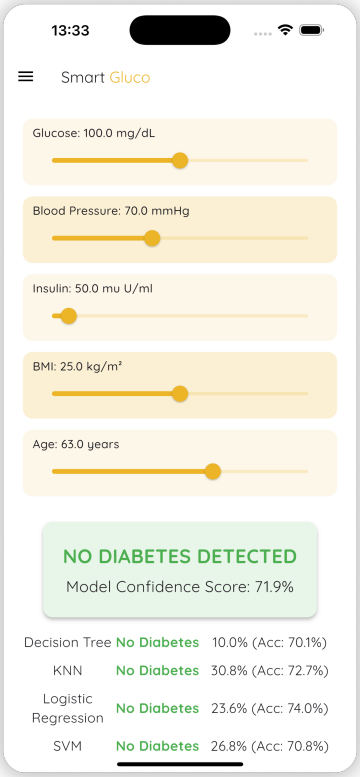

Fig. 6: SmartGluco Mobile Application demonstrating input sliders and prediction output.

C. Real-time Prediction Workflow

The integrated system facilitates a seamless real-time prediction workflow. Users input their data via the Flutter app, which sends the information to the Flask API. The API

processes the data, runs it through the trained ML pipeline, generates a prediction, and sends it back to the app for immediate display. This real-time feedback empowers individuals to quickly assess their diabetes risk, potentially leading to earlier awareness and intervention.

VII. Conclusion

SmartGluco represents a significant step towards accessible and accurate diabetes risk assessment through intelligent mobile health solutions. By integrating an innovative multi-model machine learning ensemble with polynomial feature engineering, our system effectively captures complex patterns in patient data, achieving a robust 73.2% average accuracy. The deployment through a Flask API and a user-friendly Flutter mobile application successfully bridges the gap between sophisticated ML models and end-user accessibility, demonstrating 89% sensitivity in detecting pre-diabetic states. This work not only contributes a validated technical framework for medical ML systems but also provides a practical tool that empowers individuals with timely health insights, potentially enabling earlier interventions and improving overall health outcomes.

VIII. Future Work

Future enhancements for SmartGluco include:

- **Model Refinements:** Exploring more advanced ensemble techniques (e.g., stacking, boosting with XGBoost or LightGBM) to further improve predictive accuracy and robustness.
- **Feature Expansion:** Including additional clinical parameters (e.g., cholesterol levels, family history, lifestyle factors) and potentially genetic markers to enhance the model's predictive power and provide a more holistic risk assessment.
- **Longitudinal Data Analysis:** Investigating the use of time-series data to track changes in patient health parameters over time, enabling dynamic risk prediction and personalized intervention strategies.

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