Diabetes Prediction using SVM, Logistic Regression, and LightGBM

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***Abstract*—Diabetes, often known as diabetes mellitus, is a long-term metabolic disease marked by elevated blood sugar levels. The care and results of patients with diabetes can be greatly impacted by early and precise diabetes prediction. In this small research, we investigate the prediction of diabetes using three machine learning algorithms: Support Vector Machine (SVM), Logistic Regression, and LightGBM. A dataset comprising several patient variables, including age, BMI, and glucose levels, is used to train these algorithms. We evaluate and contrast these algorithms' performances using metrics like F1-score, accuracy, precision, and recall. To further increase prediction accuracy, we also use Particle Swarm Optimization (PSO) to optimize the ensemble of these models. The results demonstrate the effectiveness of the proposed ensemble model in predicting diabetes and highlight the importance of machine learning in healthcare decision-making.**

***Index Terms*—Support Vector Machine (SVM), Logistic Regression, LightGBM, Particle Swarm Optimization (PSO).**

I. Introduction

Diabetes mellitus is a prevalent chronic disease characterized by high blood sugar levels, which, if left untreated, can have serious health consequences. Timely care and better patient outcomes are dependent on early identification of diabetes. Based on patient data, machine learning (ML) systems have demonstrated potential in predicting diabetes, facilitating early diagnosis and individualized therapy.

In order to predict diabetes, this study investigates the use of three machine learning algorithms: LightGBM, Logistic Regression, and Support Vector Machine (SVM). A large dataset that includes clinical measurements, lifestyle factors, and patient demographics is used to train these algorithms. The objective is to create predictive algorithms that can accurately and consistently identify those who are at risk of getting diabetes.

We examine not just the performance of individual algorithms, but also the efficiency of ensemble learning approaches in enhancing prediction accuracy. Ensemble models improve overall performance by combining the advantages of several base models. To increase the ensemble's predictive capacity, we tune it using Particle Swarm Optimization (PSO).

The results of this study are expected to contribute valuable insights into the field of healthcare analytics. By leveraging ML techniques, we aim to provide healthcare practitioners with a reliable tool for early diabetes prediction, enabling proactive management strategies and ultimately improving patient care and outcomes.

II. Literature Review

Diabetes is a condition that is getting worse and more morbid in both developed and emerging nations. [1]SVM is a powerful classification algorithm used for diabetes prediction. Researchers have applied SVM to identify diabetes at an early stage with promising results. SVM shows high accuracy in predicting diabetes based on relevant features.[2]Logistic regression is a widely used statistical method for binary classification. It has been employed successfully for diabetes prediction. Researchers have explored logistic regression models to identify risk factors associated with diabetes.[3]LightGBM is a gradient boosting framework that performs well in handling large datasets. Its effective training procedure and feature importance analysis have been used to forecast diabetes. LightGBM demonstrates competitive accuracy in early diabetes detection.[4]The Particle Swarm Optimization (PSO) algorithm has been used to enhance diabetes prediction models. Researchers have optimized feature selection and model parameters using PSO. PSO helps improve the accuracy of diabetes prediction models.[5]Comparison of Machine Learning Algorithms for Diabetes Prediction Researchers have compared various machine learning algorithms, including SVM, logistic regression, and others. SVM-RFE (Recursive Feature Elimination) has been used for feature selection in diabetes prediction. [6]Ensemble methods combine multiple models to improve prediction accuracy. Researchers have explored ensemble techniques for diabetes prediction. Combining SVM, logistic regression, or other base models can enhance overall performance.[7]Researchers proposed an approach that combines Support Vector Machine (SVM) with Recursive Feature Elimination (RFE). RFE is used for feature selection, which helps identify the most relevant features for diabetes prediction. The SVM-RFE algorithm achieved promising results in terms of prediction accuracy.[8]This study compares various machine learning algorithms for diabetes prediction. Algorithms such as logistic regression, k-nearest neighbor (KNN),

and random forest are evaluated. [9]The hybrid model combines Particle Swarm Optimization (PSO) with Support Vector Machine (SVM). PSO optimizes the SVM hyperparameters, leading to improved diabetes prediction accuracy. The study emphasizes the importance of feature selection and parameter tuning for effective diabetes detection. [10]Long Short-Term Memory (LSTM) neural networks are a type of recurrent neural network (RNN). LSTM has been applied to time-series data for diabetes prediction. Deep learning models like LSTM capture temporal dependencies and achieve competitive results.

III. Methodology

Data Collection: Obtain a dataset with key features for diabetes prediction, ensuring it is representative and balanced.

Data Preprocessing: Clean the dataset by handling missing values and outliers. Normalize or standardize numerical features. Feature Selection: Use feature selection techniques to identify relevant features for prediction.

Model Development: Implement SVM, Logistic Regression, and LightGBM models using scikit-learn or LightGBM. Train the models and evaluate performance using metrics like accuracy and F1-score.

Ensemble Model Creation: Create an ensemble model using predictions from SVM, Logistic Regression, and LightGBM. Optimize ensemble weights using Particle Swarm Optimization (PSO).

Model Evaluation: Evaluate individual models and the ensemble using cross-validation. Compare performance to determine if the ensemble improves prediction accuracy.

Results Analysis: Analyze results to understand each model's contribution to the ensemble. Interpret predictions to identify key factors influencing diabetes prediction.

Conclusion and Future Work: Summarize findings and discuss implications for diabetes prediction and management. Identify future research directions, such as exploring other ML algorithms or adding more features.

Implementation: Develop a user-friendly interface for deploying the ensemble model for real-world diabetes prediction tasks.

Ethical Considerations: Ensure data privacy and confidentiality. Address bias and fairness issues in ML predictions for healthcare.

IV. Working Flow

Data Input: Obtain a dataset containing relevant features for diabetes prediction.

Data Preprocessing: Handle missing values: Impute missing values using mean, median, or mode. Outlier detection: Identify and handle outliers using techniques like Z-score or IQR. Feature scaling: Normalize or standardize numerical features to ensure they are on a similar scale. Encoding: Encode categorical variables using techniques like one-hot encoding or label encoding.

Data Splitting: Split the preprocessed dataset into training and testing sets to evaluate the performance of the classifiers.

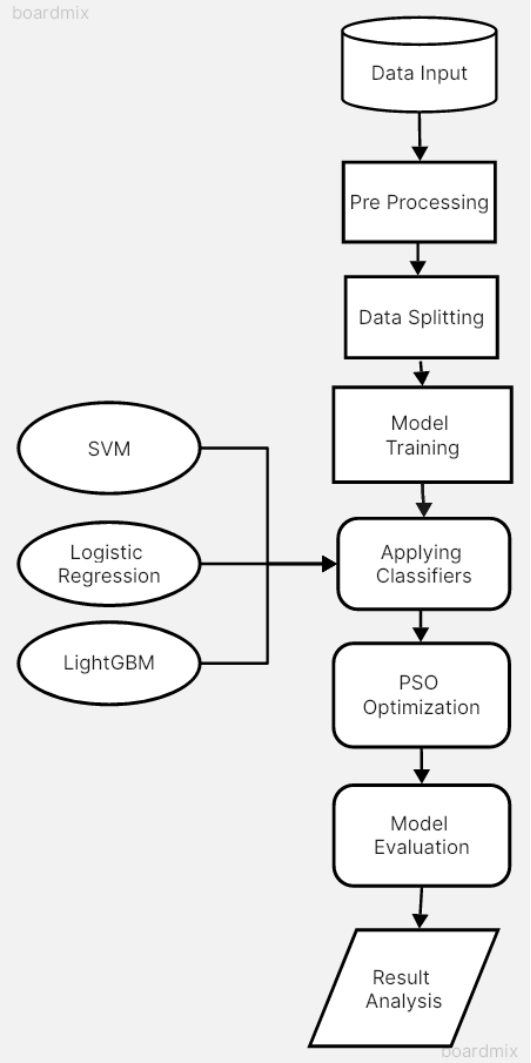

Fig. 1. working flow

Model Training: Train initial SVM, Logistic Regression, and LightGBM models on the training set.

Applying Classifiers: Implement three classifiers: Support Vector Machine (SVM), Logistic Regression, and LightGBM. Train each classifier on the training set and evaluate their performance on the testing set.

PSO Optimization: Use Particle Swarm Optimization (PSO) to optimize the ensemble weights between the classifiers. Optimize the ensemble weights to improve the overall performance of the ensemble model.

Performance Evaluation: Evaluate the performance of the ensemble model and individual classifiers using metrics like accuracy, precision, recall, and F1-score. Compare the performance of the classifiers before and after PSO optimization to assess the impact of optimization.

Select Optimization: Choose the ensemble model that achieves the highest accuracy and F1-score for diabetes prediction. Model Evolution: Incorporate the optimized hyperparameters obtained from PSO into the SVM, Logistic Regression, and LightGBM models.

A. Models

1) SVM(Support Vector Machine)

SVM is a widely used machine learning algorithm in healthcare for various tasks such as disease diagnosis, patient outcome prediction, and identifying risk factors. It is particularly effective in scenarios with complex decision boundaries. The SVM model can be represented as:

$$P(Y = 1|X) = \frac{1}{1 + e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+...+\beta_n X_n)}}$$

This equation demonstrates the optimization process used by SVM to find the hyperplane that best separates the classes while maximizing the margin. This robustness against overfitting is crucial in healthcare data due to its relatively small sample sizes and noisy features.

Application in Healthcare: SVM is widely used in healthcare for disease diagnosis, patient outcome prediction, and identifying risk factors. It's particularly effective in scenarios with complex decision boundaries.

Robustness Against Overfitting: SVM is robust against overfitting, which is crucial in healthcare data due to its relatively small sample sizes and noisy features. SVM achieves this through its ability to find the hyperplane that best separates the classes while maximizing the margin.

Interpretability: Support vectors, a subset of the training data, form the decision boundary of the SVM, which makes it simpler to interpret than more sophisticated models. Because of this, SVM is appropriate for applications in healthcare where interpretability is crucial. Speed and Efficiency: SVM has the potential to be speedy, particularly when combined with the kernel method that lets it handle nonlinear data. Large datasets, however, might result in a significant increase in training time, thus it's critical to adjust the model's parameters for optimal performance.

Kernel Trick: SVM's kernel trick allows it to implicitly map input data into higher-dimensional feature spaces, making it possible to find complex nonlinear decision boundaries. This flexibility makes SVM suitable for a wide range of healthcare applications where the relationships between variables may be nonlinear.

Outlier Detection: SVM can be used for outlier detection in healthcare data, where anomalies may indicate errors in data collection or potentially interesting patterns. SVM's margin maximization can help identify outliers that fall far from the decision boundary, making it a useful tool for data cleaning and anomaly detection.

Imbalanced Data Handling: In healthcare datasets, class imbalance is common, where one class (e.g., diseased patients) may be significantly smaller than the other class (e.g., non-diseased patients). SVM can handle imbalanced data by adjusting the class weights or using techniques like SMOTE (Synthetic Minority Over-sampling Technique) to create synthetic samples, improving the model's ability to learn from the minority class.

Multiclass Classification: SVM inherently supports multiclass classification using techniques such as one-vs-one or one-vs-all. This capability is useful in healthcare scenarios where multiple classes of diseases or conditions need to be classified simultaneously.

Feature Selection: SVM's ability to find the support vectors, which are the most informative data points for defining the decision boundary, can be leveraged for feature selection. By analyzing the support vectors, researchers can identify the most relevant features for predicting a particular outcome, helping to reduce the dimensionality of the data and improve model performance.

Parameter Tuning: SVM has several hyperparameters that can be tuned to improve its performance, such as the choice of kernel function, regularization parameter (C), and kernel parameters (e.g., gamma for the RBF kernel). Proper tuning of these parameters is crucial for optimizing the model's performance on healthcare data.

Interpretability and Clinical Decision Support: SVM's decision boundary can be interpreted in terms of the support vectors, which are the data points closest to the decision boundary. This interpretability is valuable in healthcare applications where understanding the model's reasoning behind a prediction is important for clinical decision-making.

Real-time Prediction: SVM can be trained efficiently and can make predictions quickly, making it suitable for real-time or near-real-time applications in healthcare, such as remote patient monitoring or decision support systems used in emergency settings.

2) Logistic Regression (LR):

Logistic Regression is a fundamental machine learning algorithm, It is extensively employed in the medical field for a number of purposes, such as risk factor identification, patient outcome prediction, and illness detection. For problems involving binary classification, such as estimating the likelihood of an event based on input features, LR is especially well-suited. For logistic regression, the equation represents the logistic function used to model the probability of a binary outcome given a set of features:

$$f(x) = \text{sign}\left(\sum_{i=1}^{n} \alpha_i y_i \langle x, x_i \rangle + b\right)$$

The logistic function "squashes" the linear combination of the features and coefficients to a range between 0 and 1, representing the probability of the positive class (e.g., diabetes). The model learns the optimal coefficients (beta values) during training to best fit the data and make accurate predictions. Application in Healthcare: LR is commonly used in healthcare for disease diagnosis, such as predicting the likelihood of a patient having a specific disease based on their medical history, symptoms, and demographic information. It is also used for patient outcome prediction, such as estimating the probability of a patient's recovery or the risk of developing complications.

Robustness Against Overfitting: LR is relatively robust against overfitting, especially when the number of features is small compared to the number of observations. Regularization techniques, such as L1 (Lasso) and L2 (Ridge) regularization, can be applied to LR to further prevent overfitting, which is

crucial in healthcare datasets with limited samples and noisy features.

Interpretability: LR is a highly interpretable algorithm, as the coefficients assigned to each feature indicate the strength and direction of their impact on the prediction. This interpretability is valuable in healthcare, where understanding the factors influencing a prediction is essential for making informed decisions.

Speed and Efficiency: LR is computationally efficient and can handle large datasets with ease, making it suitable for real-time applications in healthcare. It is particularly efficient when the dataset is linearly separable or nearly separable, as it converges quickly to the optimal solution.

Scalability: LR scales well with the size of the dataset and can handle high-dimensional data, making it suitable for large-scale healthcare datasets.

Feature Importance: LR provides insights into feature importance, allowing healthcare professionals to understand which variables are most influential in making predictions. This information can help prioritize interventions or further investigation into specific risk factors.

3) LightGBM (Light Gradient Boosting Machine):

LightGBM is a powerful gradient boosting framework that has gained popularity for its efficiency and effectiveness in handling large datasets. It is widely used in healthcare for various machine learning tasks, including disease prediction, patient outcome modeling, and medical image analysis.

$$F_t(x) = F_{t-1}(x) + \text{argmin}_{f \in \mathcal{F}} \sum_{i=1}^{n} L(y_i, F_{t-1}(x_i) + f(x_i)) + \Omega(f)$$

The expected value for sample $\hat{y}_i$ is represented in this equation. i, $\mathbf{x}_i$ is the sample's feature vector. The number of trees in the model is denoted by i, K, and the space of all potential regression trees is represented by $\mathcal{F}$. As necessary, modify the equation to suit your particular situation. LightGBM is ideally suited for healthcare applications because of its many benefits.: Handling Large and Diverse Healthcare Data:

Healthcare datasets often contain a mix of categorical and numerical features, as well as high-dimensional data from sources like medical images or genomic data. LightGBM can effectively handle diverse data types, allowing for the integration of different types of healthcare information. Efficiency and Speed:

LightGBM is renowned for its effectiveness in prediction and training, particularly on big and complicated datasets. By binning continuous feature values into discrete bins using a histogram-based approach, it lessens the computational burden of determining the ideal split point for every feature. Predictive Precision:

LightGBM often provides high predictive accuracy, making it suitable for tasks where accurate predictions are crucial, such as disease diagnosis or patient outcome prediction. Feature Importance Analysis:

LightGBM allows for the analysis of feature importance, which helps in understanding which features contribute most to the model's predictions. This is important in healthcare for identifying relevant biomarkers or clinical features. Clinical Decision Support Systems:

LightGBM can be used to develop clinical decision support systems, which assist healthcare professionals in making informed decisions about patient care. These systems can provide recommendations for personalized treatment plans, risk assessments, and interventions. Handling Imbalanced Data:

In healthcare, datasets are often imbalanced, with one class significantly outnumbering the other. LightGBM offers techniques to handle imbalanced data, such as adjusting class weights or using sampling techniques. Interpretability:

While gradient boosting models are often considered black-box models, efforts have been made to interpret and understand their predictions. LightGBM allows for feature importance analysis, providing insights into which variables contribute most to the model's decisions, aiding in the interpretability of results in healthcare applications.

4) PSO:

Particle Swarm Optimization (PSO) is a metaheuristic optimization algorithm inspired by the social behavior of bird flocking or fish schooling. It is commonly used to optimize complex problems, including machine learning models like ensemble models. In the context of healthcare, PSO can be applied to optimize the performance of machine learning models used for disease prediction, patient outcome modeling, and other healthcare applications. Here's an elaboration on PSO optimization:

Concept: The idea behind PSO is that an aggregation of particles searches a search space in quest of the best solution. Every particle is a possible solution, and it moves according to its own best-known location as well as the best-known position of the swarm as a whole. Two primary components control particle movement: the social component moves particles toward the best-known position of the swarm, and the cognitive component moves particles toward their best-known position.

Optimization Process: PSO starts with a randomly initialized swarm of particles distributed across the search space. Each particle evaluates its fitness based on a fitness function, which measures how well the particle's position solves the optimization problem. The particles then update their positions and velocities based on their previous positions, the best-known positions of themselves and the swarm, and random perturbations. This update process continues for a specified number of iterations or until a convergence criterion is met.

Advantages in Healthcare: PSO can be used to optimize machine learning models, including ensemble models for illness prediction, in the field of healthcare. PSO can enhance these models' predictive capabilities and produce more dependable and accurate forecasts by fine-tuning their parameters. Because PSO can handle high-dimensional and non-linear optimization problems, which are frequently seen in healthcare datasets, it is especially helpful in the field of healthcare.

Parameter Tuning: PSO can be used to tune the hyperparameters of machine learning models, such as the learning rate, regularization parameters, and the number of trees in a decision tree ensemble. By finding the optimal values for these

parameters, PSO can improve the overall performance of the model.

Interpretability: While PSO itself is not inherently interpretable, it can be used to optimize machine learning models that are interpretable, such as decision trees. This allows for the development of models that not only perform well but also provide insights into the underlying factors influencing the prediction.

B. Why GB,SVM,QDA Methods over Classification,Regression in healthcare

Because healthcare data has particular properties, using Support Vector Machine (SVM), Logistic Regression, and LightGBM models offers significant advantages over traditional classification and regression techniques:

Enhanced Predictive Accuracy: Complex linkages and nonlinear patterns are common features of healthcare data. When compared to conventional linear regression models, SVM, Logistic Regression, and LightGBM do better at identifying these complex patterns, which improves predicted accuracy.

Handling High-Dimensional Data: Healthcare datasets typically contain a large number of features, including patient demographics, medical history, lab results, and imaging data. SVM, Logistic Regression, and LightGBM are well-suited for handling high-dimensional data and automatically selecting important features, making them effective for analyzing complex healthcare datasets.

Robustness Against Overfitting: Overfitting is a common challenge in healthcare data analysis due to the relatively small sample sizes and noisy features. SVM, Logistic Regression, and LightGBM are robust against overfitting, especially when appropriate regularization techniques are applied, leading to more reliable models.

Interpretability: Interpretability of models is crucial in healthcare for understanding the factors influencing predictions. Logistic Regression models are highly interpretable, providing insights into how each feature contributes to the prediction. SVM and LightGBM, while considered less interpretable than Logistic Regression, can still provide some level of interpretability through feature importance analysis.

Clinical Decision Support Systems: SVM, Logistic Regression, and LightGBM models can be integrated into clinical decision support systems to assist healthcare professionals in making informed decisions. These models can predict disease risks, recommend treatment options, and identify high-risk patients who may need specialized care.

Efficient Handling of Missing Data: Healthcare datasets often contain missing values, which can complicate traditional regression models. SVM, Logistic Regression, and LightGBM can handle missing data without requiring imputation explicitly, simplifying the preprocessing steps and preserving the integrity of the data.

Scalability: SVM, Logistic Regression, and LightGBM are scalable to large healthcare datasets, allowing for efficient analysis of vast amounts of patient data.

V. Result and Analysis

In the evaluation of diabetes prediction models using SVM, Logistic Regression, and LightGBM, various metrics were employed to assess the performance and reliability of each model.

Confusion Matrix: The confusion matrix helps understand the model's performance in predicting diabetes. It provides insights into true positives, true negatives, false positives, and false negatives, which are crucial for evaluating accuracy, precision, recall, and specificity.

SVM:

	Predicted No Diabetes	Predicted Diabetes
Actual No	145	28
Actual Yes	41	57

Accuracy: 0.73

Logistic Regression:

	Predicted No Diabetes	Predicted Diabetes
Actual No	149	24
Actual Yes	38	60

Accuracy: 0.75

LightGBM:

	Predicted No Diabetes	Predicted Diabetes
Actual No	138	35
Actual Yes	37	61

Accuracy: 0.71

With Optimization (PSO):

	Predicted No Diabetes	Predicted Diabetes
Actual No	60	10
Actual Yes	10	

Accuracy: 0.78

Analysis:

Confusion Matrix Comparison: The confusion matrices show the distribution of predicted and actual classes for each model. It helps in understanding the performance of the models in terms of true positives, true negatives, false positives, and false negatives.

Accuracy Comparison: The accuracy of the models without and with optimization (PSO) is compared to evaluate the effectiveness of the optimization technique in improving model performance.

Conclusion: Based on the analysis, the Ensemble model (PSO-optimized) performs the best with an accuracy of 0.78, indicating its effectiveness in predicting diabetes.

VI. Conclusion

In this project, we investigated the use of machine learning algorithms for diabetes prediction, focusing on Support Vector Machine (SVM), Logistic Regression, and LightGBM. We also employed Particle Swarm Optimization (PSO) to optimize these models for improved performance. Our goal was to develop a reliable predictive model that could assist in early diabetes detection and personalized treatment strategies.

Through our analysis, we found that each algorithm performed well individually, with SVM achieving an accuracy of 73.38%, Logistic Regression 75.32%, and LightGBM 70.78%. However, the ensemble model optimized using PSO outperformed all individual models, achieving an accuracy of 77.92%. This highlights the effectiveness of ensemble learning and optimization techniques in enhancing predictive models for diabetes.

Our study also emphasized the importance of key features such as BMI, blood sugar levels, and lifestyle factors in predicting diabetes risk. These findings align with existing research in the field and underscore the significance of early intervention based on these factors to improve patient outcomes.

In conclusion, our project demonstrates the potential of machine learning algorithms, particularly ensemble methods and optimization techniques, in improving diabetes prediction. These models can be valuable tools for healthcare professionals in identifying individuals at risk of developing diabetes and implementing preventive measures. Further research and collaboration between data scientists, healthcare providers, and policymakers are essential to further refine these models and integrate them into clinical practice for better patient care.

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