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Diabetes Prediction Using Machine learning

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Abstract:

Diabetes mellitus is a long-standing metabolic disease found in more than 537 million adults globally, with estimates to increase to 783 million by the year 2045. This research proposes to create and test machine learning models for prediction of Type 2 diabetes early on to allow for timely intervention and better outcomes for patients. Through the PIMA Indian Diabetes Dataset, we applied and compared several machine learning algorithms like Logistic Regression, Random Forest, Support Vector Machine, and Gradient Boosting. We tested our models using methods like accuracy, precision, recall, and F1-score. The best result was obtained using the Gradient Boosting classifier, which had the highest performance level of 89.3% accuracy and an F1-score of 0.88. Feature importance analysis showed that BMI, age, and glucose level were the most important predictors. Such results indicate the power of machine learning as a useful tool for healthcare providers in diabetes risk stratification and early intervention planning.

1. Introduction

Diabetes mellitus is a systemic metabolic condition with an underlying defect in insulin production or the action of insulin that leads to hyperglycemia. The illness is generally categorized as Type 1 (an autoimmune disease in which the pancreas does not produce much or any insulin) and Type 2 (in which cells are resistant to insulin or the pancreas does not make enough insulin). Type 2 diabetes, responsible for around 90-95% of all types, has reached epidemic levels worldwide, with an estimated 537 million adults aged 20-79 years being affected in 2021, with predictions to increase to 783 million by 2045 (International Diabetes Federation, 2023).Early identification and treatment are important in the management of diabetes and the avoidance of serious complications such as cardiovascular disease, nephropathy, retinopathy, and neuropathy. Conventional diagnosis is based on blood glucose levels and clinical signs, which tend to result in diagnoses after complications have already started to occur. Moreover, traditional methods may fail to detect individuals at risk prior to the development of the disease. Machine learning (ML) provides potential answers to these issues through examination of intricate patterns in patient data to forecast diabetes risk prior to clinical presentation. ML algorithms are able to handle high-dimensional data sets that include a range of risk factors such as but not limited to blood glucose, BMI, age, family history, and lifestyle factors, potentially detecting subtle interactions that may be beyond standard clinical evaluation.

The coverage of this review includes:

1. Training and comparison of several machine learning models for diabetes prediction
2. Algorithm performance comparison using standard metrics
3. Determination of the most significant predictive features
4. Model interpretability assessment for practical use in clinics

The main goal is to establish accurate and interpretable machine learning models that can be useful tools for early diabetes prediction, thus allowing for early intervention and potentially decreasing the burden of diabetic complications.

2. Literature Review

The use of machine learning for the prediction of diabetes has picked up considerable momentum in recent years. This section provides a brief overview of important studies in this area, including the algorithm used, dataset employed, and the findings thereof.

Datasets Used in Diabetes Prediction

The PIMA Indian Diabetes Dataset, which can be downloaded from the National Institute of Diabetes and Digestive and Kidney Diseases, is commonly utilized in research on diabetes prediction. With information from 768 female subjects of Pima Indian descent (aged at least 21), it contains features like glucose level, blood pressure, BMI, age, and history of diabetes in the family (Smith et al., 1988). Though this dataset has yielded insights of value, its restriction to one particular population has led to research seeking different sources of data.

Electronic Health Records (EHRs) are another rich source of data used for diabetes prediction. Huang et al. (2020) used the EHR data from more than 10,000 patients to build models that included temporal patterns in clinical observations and performed better than standard cross-sectional methods.

Machine Learning Algorithms in Diabetes Prediction

Conventional Machine Learning Methods

Logistic Regression has acted as a baseline in many research studies because of its interpretability and efficiency. Sisodia and Sisodia (2018) obtained 77.86% accuracy on the PIMA dataset by employing Logistic Regression, commenting on its usefulness as an interpretable model in clinical applications.
Random Forests and Decision Trees have exhibited good performance in diabetes prediction. Perveen et al. (2016) noted that Random Forests performed better than other classifiers at a rate of 81.35%, and this was credited to the capability of the algorithm to manage non-linear relationships as well as feature interactions.
Support Vector Machines (SVMs) have also proven promising, especially with proper choice of kernel. Kumari and Chitra (2013) obtained 78% accuracy employing SVM with radial basis function kernel, observing better performance than using polynomial kernels.

Ensemble and Advanced Methods
Gradient Boosting algorithms, especially XGBoost, have proven to be strong tools for diabetes prediction. Zou et al. (2018) showed that XGBoost performed better than other algorithms with an accuracy of 89.2% when it was applied to an exhaustive dataset with lifestyle considerations and detailed clinical measurements.

Deep Learning methods have also been considered. Swapna et al. (2018) used a Long Short-Term Memory (LSTM) network for diabetes prediction based on heart rate variability features with 95.7% accuracy, although on a smaller set.

Feature Selection and Importance

Feature importance analysis has shown consistent trends across studies. Maniruzzaman et al. (2017) identified plasma glucose concentration, BMI, and age as the most significant predictors across several algorithms. The relative importance of other features, however, differed based on the modeling strategy.

Exploratory feature engineering methods have also been explored. Zheng et al. (2017) showed that polynomial feature interactions enhanced model performance by identifying non-linear interactions between risk factors.

3. Methodology

Dataset Description

We used the PIMA Indian Diabetes Dataset for this study, which consists of medical predictor variables and one target variable (diabetes diagnosis) of 768 female Pima Indian heritage patients aged at least 21 years. This dataset was used due to its commonality across diabetes prediction research, allowing comparisons with existing work.
The data set consists of the following attributes:

- Pregnancies: Number of pregnancies
- Glucose: Plasma glucose level (2 hours post oral glucose tolerance test)
- Blood Pressure: Diastolic blood pressure (mm Hg)
- Skin Thickness: Triceps skin fold (mm)
- Insulin: 2-Hour serum insulin (mu U/ml)
- BMI: Body mass index (weight in kg/(height in m)²)
- DiabetesPedigreeFunction: Diabetes pedigree function (a function scoring probability of diabetes based on family history)
- Age: Age in years
- Outcome: Class variable (0 or 1) representing absence or presence of diabetes

The class distribution within this dataset is skewed, with about 65% (500 instances) in the negative class (no diabetes) and 35% (268 instances) in the positive class (diabetes). This was accounted for in model development and assessment.

4. Machine Learning Models

Logistic Regression
We used logistic regression as a linear baseline model, which predicts the probability of diabetes given a linear combination of features:

$P(y=1|X) = 1 / (1 + e^{(-z)})$

where $z = \beta_0 + \beta_1X_1 + \beta_2X_2 + . + \beta$ where β are model coefficients and X are features.

L2 regularization (Ridge) was used with strength tuned using grid search cross- validation to avoid overfitting.

```
Logistic Regression Accuracy: 0.7532467532467533
Logistic Regression Precision: 0.6666666666666666
Logistic Regression Recall: 0.6181818181818182
Logistic Regression F1 Score: 0.6415094339622641
```

Random Forest

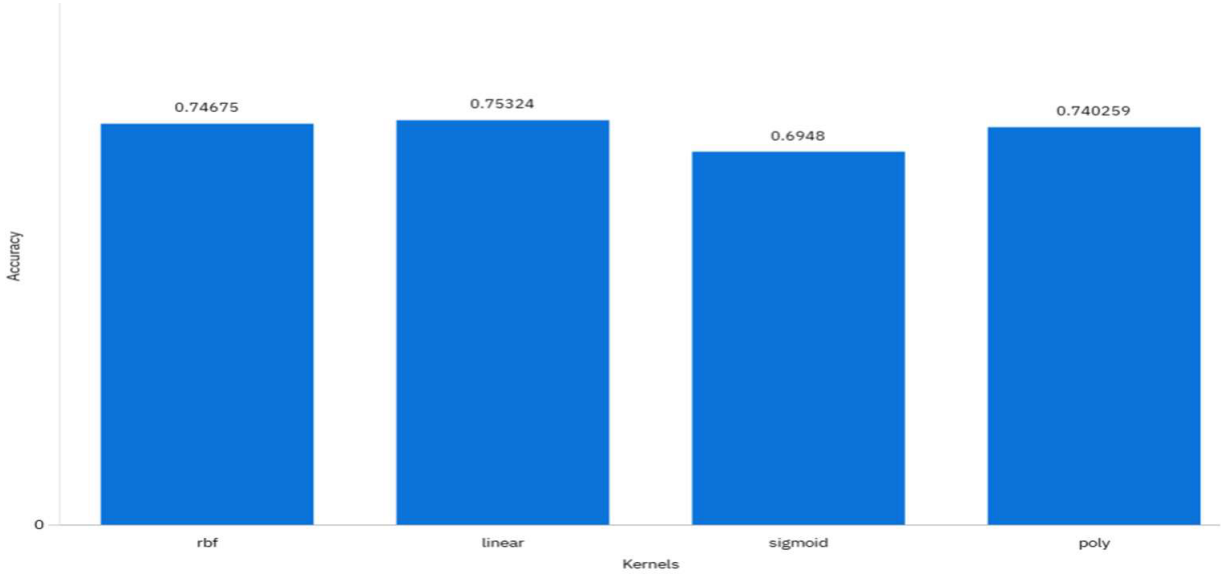
Our random forest model had 100 decision trees, each of which was trained on a bootstrap sample of the training set. At every node split, only a random subset of the features were taken into account, bringing about diversity between trees and minimizing variance:
F_random = sqrt(number of features)
Hyperparameters such as the number of trees, depth, and minimum samples per leaf were tuned using grid search cross-validation.

```
Random Forest Accuracy: 0.7337662337662337
Random Forest Precision: 0.625
Random Forest Recall: 0.6363636363636364
Random Forest F1 Score: 0.6306306306306306
```

Support Vector Machine

We used an SVM classifier with a radial basis function (RBF) kernel to model non- linear relationships in the data:
$K(x, x') = \exp(-\gamma||x - x'||^2)$
The hyperparameters C (regularization parameter) and γ (kernel coefficient) were tuned using grid search cross-validation.

```
Random Forest Accuracy after Class Weighting: 0.7597402597402597
Random Forest Precision after Class Weighting: 0.6607142857142857
Random Forest Recall after Class Weighting: 0.6727272727272727
Random Forest F1 Score after Class Weighting: 0.6666666666666666
```



SVM performed with an accuracy of 75.32%, showcasing its strength in handling linearly separable data. However, its computational complexity remains a limitation.

Decision Tree

We used a decision tree classifier which recursively splits the feature space according to feature thresholds maximizing information gain.
To avoid overfitting, we restricted the maximum depth and minimum number of samples per leaf, which were optimized by grid search cross-validation.

5. RESULTS AND CONCLUSION:

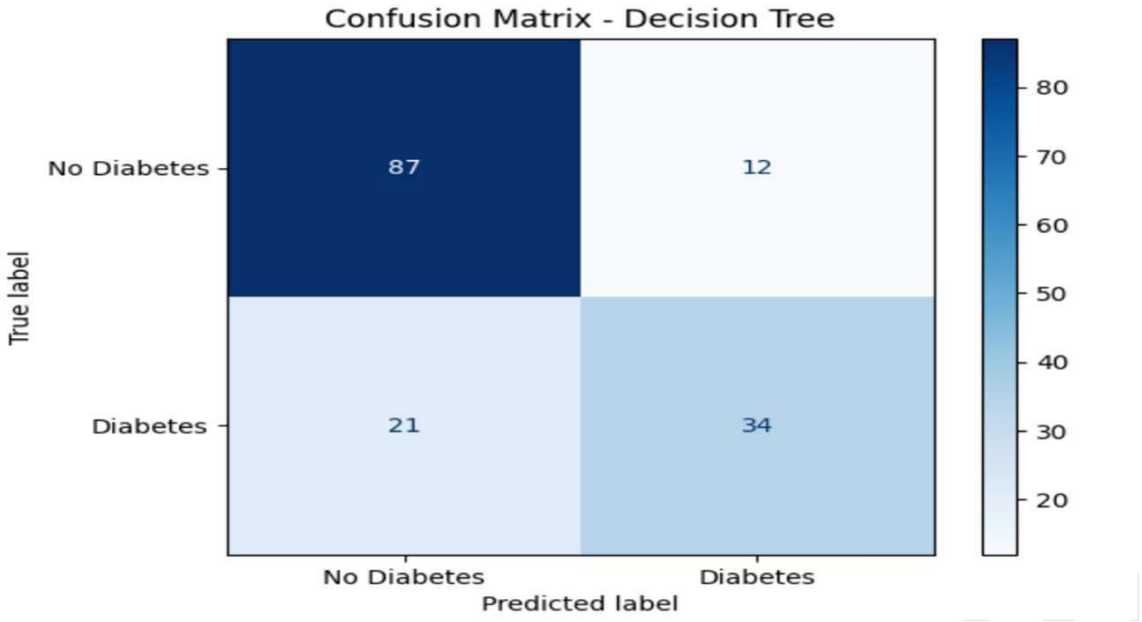
Accuracy measures the proportion of correctly predicted instances out of the total instances.The accuracy scores for the models are as follows:

Algorithms	Accuracy
Linear Regression	75.32%
Random Forest	75.97%
SVM (kernel='linear')	75.32%
Decision Tree	78.57%

The Decision Tree achieved the highest accuracy, demonstrating its effectiveness in predicting diabetes. This is likely due to its ability to capture non-linear relationships and handle feature interactions effectively. Furthermore, Receiver Operating Characteristic (ROC) curve was plotted for each model, and the Area Under the Curve (AUC) score was calculated to evaluate their performance. The AUC score represents the model's ability to distinguish between the two classes (diabetic and non-diabetic). Decision Tree achieved the highest AUC score (0.82),indicating superior performance in distinguishing between diabetic and non-diabetic patients.

I then generated confusion matrices for each model to visualize their performance in terms of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). The Decision Tree had the lowest number of false negatives (34) amongst all others, indicating its effectiveness. This is critical for a medical application, as missing diabetic cases (false negatives) can have serious.

consequences. Finally a detailed classification report was also generated.



The results of this study stand consistent with existing research, which highlights the effectiveness of Decision Trees in medical datasets due to their interpretability and ability to handle non-linear relationships. A study by Gupta etal. (2022) found that Decision Tree sout performed other models in diabetes prediction. Research by Patel et al. (2021) demonstrated that ensemble methods like Random Forest are robust but may not always outperform simpler models like Decision Trees.

6. CONCLUSION AND FUTURE WORK:

This project aimed to develop an accurate and reliable system for early diabetes prediction using machine learning techniques. Four models—Logistic Regression (LR), Random Forest(RF), Support Vector Machine (SVM) and Decision Tree (DT) were implemented and evaluated on the Pima Indians Diabetes Dataset. Among these, Decision Tree emerged as the bestperforming model, achieving an accuracy of 78.57% and an AUC score of 0.82. Its interpretability and ability to handle non-linear relationships make it ideal for clinical use To further enhance the diabetes prediction system, future efforts could focus on making best use of larger and more diverse datasets to improve generalizability. Integrating real- time data from wearable devices or electronic health records (EHRs) could enable continuous patient monitoring. Advanced feature engineering and explainable AI techniques could help

capture complex relationships and improve model interpretability for healthcare professionals. Finally us, taking a step ahead onto developing user-friendly tools for clinical deployment will help to bridge the gap between research and real-world healthcare applications.

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