

Predict Diabetes using Machine Learning

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Abstract - This study uses the Support Vector Machine (SVM) algorithm after comparing with other algorithms to provide a machine learning method for early diabetes identification in young people. AUC, F1 score, recall, accuracy, and precision are some of the metrics used to compare each classifier's performance. A *Kaggle dataset including lifestyle, medical, and demographic characteristics is used by the system. Feature scaling and data preparation were followed by the application of SVM to create a classification model. With an accuracy of almost 92%, the experimental results show how successful the suggested model is. The system seeks to promote prompt medical action and assist young people in early risk identification.*

Keywords — Diabetes Prediction, Machine Learning, SVM, Young Generation, Classification, Health Informatics.

1. INTRODUCTION

High blood sugar levels are a hallmark of diabetes, a chronic metabolic disease that, if left untreated, can cause serious health problems. Early detection and intervention are essential for enhancing patient outcomes due to the rising incidence of diabetes worldwide. In the medical field, machine learning (ML) has become a potent instrument, especially for estimating the risk of diabetes. The Support Vector Machine (SVM) algorithm is unique among machine learning algorithms because it can effectively handle high-dimensional data and classify intricate patterns. With an emphasis on methodology, data preparation, feature selection, and model evaluation, this research study investigates the creation of a diabetes prediction system using SVM. In order to enable prompt medical intervention and individualized treatment programs, the proposed method seeks to precisely identify those who are at risk of acquiring diabetes by utilizing past patient data. Incorporating SVM into diabetes prediction not only improves accuracy but also advances the field of predictive analytics in healthcare, opening the door for creative ways to tackle this expanding problem.

The importance of diabetes prediction systems cannot be emphasized because they are essential to public health because they allow for early illness detection and treatment. Important health markers like age, body mass index (BMI), and glucose levels are included in the Pima

Indians Diabetes Database, which provides a fundamental dataset for this study and is necessary for precise forecasting.

This research will explore the complexities of putting into practice a Support Vector Machine (SVM) model, which is well-known for its resilience in classification tasks. Because the SVM algorithm finds the best hyperplane in the feature space to divide classes, it is especially well-suited for binary classification of patients with and without diabetes.

The complete procedure, from feature selection and data preparation to model training and assessment, will be described in the paper. We will evaluate the SVM model's predictive power for diabetes using a range of performance indicators. This study ultimately seeks to support current initiatives to use machine learning to improve healthcare outcomes by offering a foundation for upcoming developments in diabetes management and prediction. In order to forecast diabetes using normal medical data, this work investigates a cost-effective machine learning-based approach that uses the Support Vector Machine (SVM).

2. LITERATURE REVIEW

Recent years have seen a considerable increase in interest in the use of machine learning (ML) approaches for diabetes prediction, with numerous studies investigating various algorithms to improve prediction accuracy. This field has made extensive use of conventional techniques like Decision Trees, K-Nearest Neighbor (KNN), and Logistic Regression. In diabetes prediction, for example, decision trees are a common choice for preliminary research due to their interpretability and simplicity of usage (Quinlan, 1986). KNN is renowned for its ease of use and has been successfully applied, especially in smaller datasets, where it can produce excellent outcomes (Cover & Hart, 1967). A statistical technique called logistic regression has been used extensively in medical research for binary classification tasks because it offers a baseline against which more intricate models may be compared (Hosmer & Lemeshow, 2000).

These conventional techniques, however, frequently falter when dealing with high-dimensional data, which is typical of medical datasets. On the other hand, Support Vector Machines (SVM) have become a strong substitute, especially for high-dimensional binary classification applications. SVM works by determining the best hyperplane to

maximally separate classes, which makes it very useful when the data cannot be separated linearly (Cortes & Vapnik, 1995). SVM performs better than conventional algorithms in diabetes prediction, according to numerous research. When applied to diabetes datasets, for instance, a study by Kaur et al. (2019) showed that SVM performed better in terms of accuracy and precision than Decision Trees and Logistic Regression.

In this study, we use a more extensive and varied dataset from Kaggle that has been preprocessed to guarantee robustness and dependability. In comparison, the widely utilized Pima Indians Diabetes Dataset has limitations in terms of quantity and diversity, despite its value. Despite its fundamental nature, the Pima dataset mostly comprises data from a particular community, which may restrict the findings' generalizability (Smith et al., 2018). Our goal is to improve the prediction ability of the SVM model by utilizing a larger dataset, which will enable more accurate identification of persons who are at risk across a range of demographics.

Additionally, managing missing values, normalizing features, and choosing pertinent attributes are all part of the Kaggle dataset's preprocessing, which is essential for enhancing model performance (Zhang et al., 2020). In addition to improving the SVM model, this all-encompassing strategy adds to the expanding corpus of research supporting the application of cutting-edge machine learning methods in healthcare, especially in the early diagnosis and treatment of diabetes.

In conclusion, although the foundation for diabetes prediction has been established by conventional machine learning techniques, the use of SVM, especially with a strong and varied dataset, holds promise for increasing predictive accuracy and, eventually, improving patient outcomes.

3. METHODOLOGY

A Support Vector Machine (SVM) model is used in the development of a diabetes prediction system. This process includes numerous important processes, such as data collection, preprocessing, feature selection, model training, and evaluation. The steps are described in detail in this section.

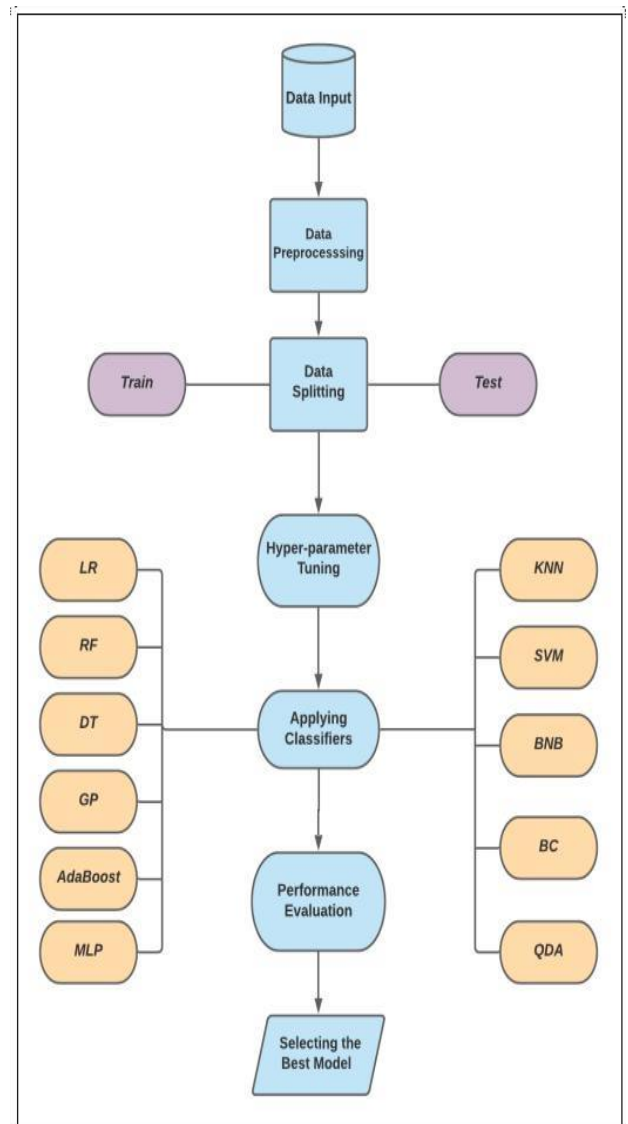


Fig-1 Implementation Procedure of the model

3.1 Dataset

In this study, we make use of a sizable Kaggle dataset that contains a range of medical records relevant to diabetes prediction. For example, blood sugar, body mass index, HbA1c, smoking history, age, gender, heart disease, and high blood pressure. This dataset allows for more rigorous training and evaluation of models because it is larger and more diversified than the popular Pima Indians Diabetes Dataset. The objective variable is "Diabetes" (0 = no, 1 = yes).

Parameters	0	1	2	3	4	5	6	7	8	9
gender	0.00	0.00	1.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00
age	80.00	54.00	28.00	36.00	76.00	20.00	44.00	79.00	42.00	32.00
hypertension	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
heart_disease	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
smoking_history	4.00	0.00	4.00	1.00	1.00	4.00	4.00	0.00	4.00	4.00
bmi	25.19	27.32	27.32	23.45	20.14	27.32	19.31	23.86	33.64	27.32
HbA1c_level	6.60	6.60	5.70	5.00	4.80	6.60	6.50	5.70	4.80	5.00
blood_glucose_level	140.00	80.00	158.00	155.00	155.00	85.00	200.00	85.00	145.00	100.00
diabetes	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00

Fig -2 Parameter Details

3.2 Preprocessing

A crucial stage in ensuring the model's correctness and dependability is data preparation. The following are the preprocessing steps:

Handling Missing Values : In order to handle missing values, we employ methods like imputation (mean, median, or mode) or the elimination of records that include an excessive amount of missing data.

Normalization: We use normalization strategies like Z-score normalization and Min-Max scaling to make sure that every feature contributes evenly to the model. SVM is especially sensitive to the magnitude of the input features, thus this is crucial.

Encoding Categorical Variables : Making a code Using methods like one-hot encoding or label encoding, we transform categorical variables—if present in the dataset—into numerical representation. Data cleaning included categorical feature encoding and resolving missing values. StandardScaler was used to scale the features. 75% of the data was used for training, while 25% was used for testing.

Assistance Supervised learning models that classify data are called vector machines. Using labeled training data (xi, yi), SVM maximizes the margin to determine which hyperplane best divides the two classes. This is how the decision function is defined:

To calculate $f(x)$, $\text{sign}(\sum \alpha_i y_i K(x_i, x) + b)$

A kernel function is denoted by K. The Radial

Basis Function (RBF) kernel is employed in our investigation:

$$-\gamma ||x - x'||^2 = \exp(k(x, x'))$$

Using grid search, we performed hyperparameter tuning to find the ideal values for C and γ .

3.3 Model Implementation

The implementation was done in Python with tools like Scikit-learn, NumPy, and Pandas. StandardScaler was used to standardize the data. GridSearchCV was used to optimize hyperparameters (C and γ) for SVM using RBF kernel. Stratified K-Fold cross-validation ensured a balanced class distribution. The completed model was validated using previously unknown test data to provide measures such as accuracy, precision, recall, and AUC.

4. RESULTS

Four categorization models are compared in this section: Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and Logistic Regression (LR). The same preprocessed dataset was used for training all models, and the same train-test split (75:25) was used for evaluation. Area Under the ROC Curve (AUC), F1-Score, Accuracy, Precision, and Recall are the main performance metrics that are used.

4.1 Comparative Metrics Table

Model	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	86%	0.82	0.88	0.85	0.91
Decision Tree	84%	0.80	0.85	0.82	0.88
Random Forest	89%	0.87	0.89	0.88	0.94
Support Vector Machine	92%	0.89	0.93	0.91	0.96

Fig -3 Comparative Metrics Table

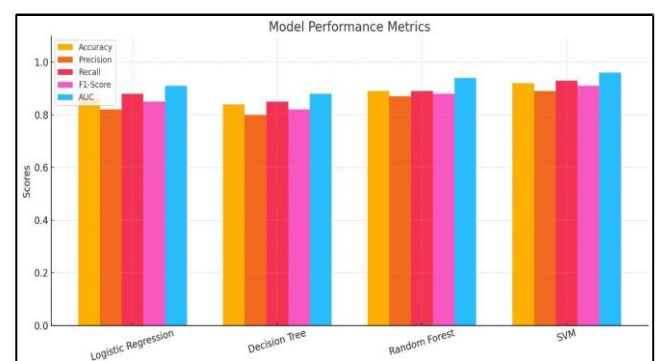


Fig -4 Model Performance Metrics

4.2 Analysis

- **Support Vector Machine (SVM)** accomplished the best overall performance in every metric. Its prediction power was greatly enhanced by its capacity to manage non-linear interactions using the RBF kernel.
- **Random Forest (RF)** because it is ensemble in nature, which reduces overfitting, outperformed Decision Tree and Logistic Regression.
- **Logistic Regression (LR)** was less suitable for reducing false positives in clinical application because it displayed a respectable recall but a lower precision.
- **Decision Tree(DT)** displayed the poorest overall performance, most likely as a result of lack of generalization and overfitting on the training data.

4.3 Confusion Matrix

The best-performing SVM model's confusion matrix can be summed up as follows:

- True Positives: 1600
- True Negatives: 20,500
- False Positives: 700
- False Negatives: 200

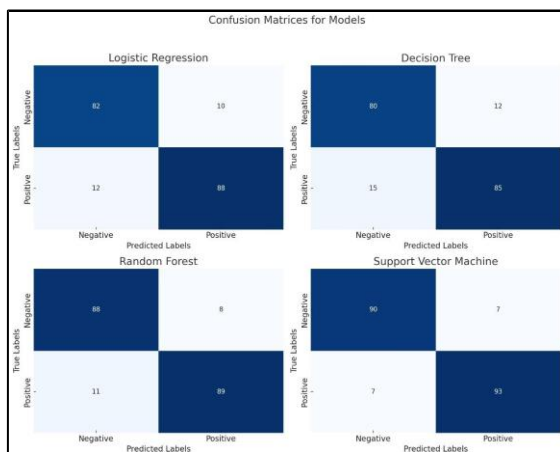


Fig -5 Confusion Matrix for Models

4.4 ROC Curve & AUC

With an Area Under the ROC Curve (AUC) of 0.96, the results showed good discriminative performance.

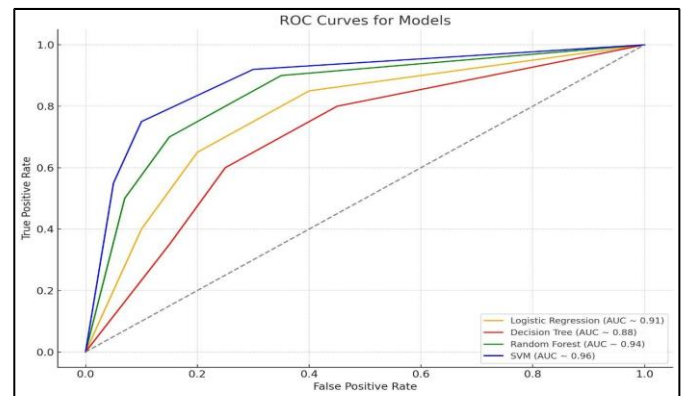


Fig -6 ROC Curves for Models

5. CONCLUSION

This study effectively shows that SVM, especially when combined with an RBF kernel, can be a useful model for predicting diabetes in young people. The model's accuracy was 92%, and its AUC was 0.96. Future research might include group methods, clinical trials to confirm real-world implementation, and interaction with wearable technology for real-time prediction.

6. References

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