**Predictive preserving learning model for diabetic dataset**

**SYNOPSIS**

This study introduces a novel approach to diabetes management through the development of a predictive preserving learning model. Unlike conventional models that often prioritize accuracy at the expense of interpretability and clinical relevance, this model aims to strike a balance by preserving clinically meaningful features while optimizing predictive performance. Leveraging advanced machine learning techniques such as feature selection and classifiers, the model identifies pertinent predictors of diabetic outcomes while maintaining interpretability. Through validation on a large dataset of diabetic patients, the model demonstrates its ability to accurately forecast the progression of the disease and pinpoint clinically significant risk factors. The results underscore the potential of predictive preserving learning models to improve the interpretability and practical utility of predictive models in diabetic care, thereby facilitating more informed clinical decision-making and personalized patient management strategies.

**SYSTEM ENVIRONMENT**

2.1 Hardware Requirements:

Processor : Intel Core i4 (10th Gen)

Ram : 4.0 GB

2.2 Software Requirements

Operating System : Windows 10

Framework : Googlecolab

Language : python

**2.3 About the technology:**

**Python:**

Python is a high-level programming language celebrated for its simplicity, readability, and versatility. Its expansive ecosystem of libraries and frameworks supports diverse applications, spanning web development, data analysis, artificial intelligence, and more. With a focus on code readability, Python empowers developers to express complex ideas concisely, fostering efficient and maintainable codebases across various programming paradigms, including procedural, object-oriented, and functional styles.

**Google Collab:**

Google Colab, or Google Colaboratory, is a cloud-based platform provided by Google, offering a free environment for writing and executing Python code directly in a web browser. Leveraging powerful hardware resources such as GPUs and TPUs, Google Colab enables efficient training of machine learning models. Its seamless integration with Google Drive facilitates easy access and sharing of notebooks and datasets, while collaborative features like real-time editing and commenting make it conducive to team projects and educational initiatives. Pre-installed with popular Python libraries like NumPy, pandas, matplotlib, and scikit-learn, Google Colab streamlines the development and deployment of machine learning workflows.

**Scikit-Learn:**

Scikit-learn stands out as a premier open-source machine learning library for Python users. Offering an extensive suite of tools for diverse machine learning tasks—including classification, regression, clustering, and dimensionality reduction—scikit-learn simplifies the implementation and deployment of machine learning models. Built atop foundational scientific computing libraries like NumPy, SciPy, and matplotlib, scikit-learn seamlessly integrates into existing Python workflows. Its user-friendly API, coupled with comprehensive documentation, caters to both novice and experienced practitioners, facilitating model development, evaluation, and refinement. With implementations of popular machine learning algorithms and utilities for data preprocessing, model evaluation, and hyperparameter tuning, scikit-learn serves as an indispensable resource for advancing machine learning capabilities in Python.

**EXISTING SYSTEM:**

Focused on clinical data analysis, the study compares various feature selection techniques, with a particular emphasis on their applicability to predicting diabetic outcomes. It meticulously evaluates wrapper-based, filter-based, and embedded feature selection methods, assessing their impact on both model interpretability and predictive performance. The findings highlight the significance of selecting features that not only contribute to accurate predictions but also remain interpretable for clinical practitioners, thereby facilitating informed decision-making in diabetes management.

An comprehensive review delves into the realm of interpretable machine learning within healthcare, including its relevance to diabetes management. It surveys existing approaches for enhancing model interpretability, ranging from rule-based models to feature importance analysis. By discussing the implications of interpretable machine learning on clinical decision-making, the paper underscores the importance of transparent models that provide actionable insights for clinicians and patients alike.

By extracting decision rules from complex machine learning models, it demonstrates how clinicians and patients can gain actionable insights for personalized treatment plans. The study underscores the utility of rule-based models in improving patient outcomes and facilitating more informed clinical decision-making in diabetes management.

On clinical data analysis, this study compares various feature selection techniques, with a particular emphasis on their applicability to predicting diabetic outcomes. It meticulously evaluates wrapper-based, filter-based, and embedded feature selection methods, assessing their impact on both model interpretability and predictive performance. The findings highlight the significance of selecting features that not only contribute to accurate predictions but also remain interpretable for clinical practitioners, thereby facilitating informed decision-making in diabetes management.

**PROPOSED SYSTEM:**

In our pursuit to refine diabetes management strategies, we introduce a pioneering predictive preserving learning model tailored specifically for diabetes datasets. The conventional approach in predictive modeling often prioritizes achieving high accuracy, sometimes at the expense of interpretability and relevance to clinical practice. Recognizing this limitation, our model sets out to bridge this gap by integrating mechanisms that not only optimize predictive performance but also preserve the interpretability of the model's outcomes. Central to our methodology is the incorporation of sophisticated machine learning techniques, notably feature selection and classifiers. By leveraging these techniques, our model identifies and prioritizes clinically meaningful features essential for predicting diabetic outcomes. This process ensures that the model captures the nuanced interplay of factors contributing to the disease's progression while maintaining transparency and interpretability for clinicians.

Crucially, our model's effectiveness is validated through rigorous testing on a comprehensive dataset comprising a diverse population of diabetic patients. This validation process underscores the model's robustness in accurately forecasting disease trajectories and identifying critical risk variables with clinical significance. By providing granular insights into disease progression and treatment response, our model empowers clinicians to make informed decisions tailored to each patient's unique needs.

The implications of our findings extend beyond predictive accuracy alone. By enhancing the interpretability and utility of predictive models in diabetic care, our approach facilitates a paradigm shift towards more personalized and patient-centric management strategies. Armed with actionable insights derived from our model, clinicians can navigate the complexities of diabetes management with confidence, ultimately leading to improved patient outcomes and enhanced quality of care.

**Advantages of the proposed system:**

**1. High Accuracy and Precision:**

The proposed system leverages advanced machine learning techniques, including feature selection and ensemble methods, to achieve high levels of accuracy and precision in predicting diabetic outcomes. By identifying and prioritizing clinically significant features, the model can effectively discern subtle patterns and nuances in the data, resulting in more accurate predictions of disease progression and treatment responses.

**2. Adaptability to Evolving Threats:**

The system is designed to be adaptable to evolving threats and changes in the diabetic landscape. Through continuous monitoring and updating of the model using real-time data, it can dynamically adjust to new trends, emerging risk factors, and evolving patient characteristics. This adaptability ensures that the predictive capabilities of the system remain robust and relevant over time.

**3. Effective Feature Representation:**

A key advantage of the proposed system lies in its ability to represent features effectively. By employing sophisticated feature selection techniques and ensemble methods, the model can extract and prioritize the most relevant features for predicting diabetic outcomes. This ensures that the model focuses on the most informative aspects of the data, leading to more accurate and actionable predictions.

**4.Interpretability and Explainability:**

Unlike black-box models that lack transparency, the proposed system prioritizes interpretability and explainability. Through the use of interpretable machine learning techniques and feature selection methods, the model provides insights into the underlying factors driving its predictions. This transparency enables clinicians to understand and trust the model's outputs, leading to more confident decision-making in diabetic care.

**5. Ensemble Robustness:**

The proposed system harnesses the power of ensemble methods to enhance robustness and reliability. By combining multiple base learners into a single predictive model, it can mitigate the effects of individual model biases and uncertainties, leading to more robust predictions. This ensemble approach ensures that the system maintains high levels of performance across diverse datasets and clinical scenarios.

**6. Scalability and Applicability:**

The system is designed to be scalable and applicable across a wide range of healthcare settings and patient populations. Whether deployed in small clinics or large hospital systems, the model can accommodate varying data volumes and computational resources. This scalability ensures that the benefits of the system can be realized across diverse healthcare contexts, ultimately improving patient outcomes on a broad scale.

**7. Real-time Prediction and Decision Support:**

The proposed system offers real-time prediction capabilities, enabling timely intervention and decision support for clinicians. By continuously analyzing incoming data streams, the model can provide actionable insights and recommendations to guide treatment strategies and patient care plans.

**8. Personalized Treatment Recommendations:**

Leveraging the detailed patient profiles generated by the model, the system can generate personalized treatment recommendations tailored to individual patient needs. By considering factors such as medical history, genetic predispositions, and lifestyle factors, the model ensures that treatment plans are optimized for each patient's unique circumstances.

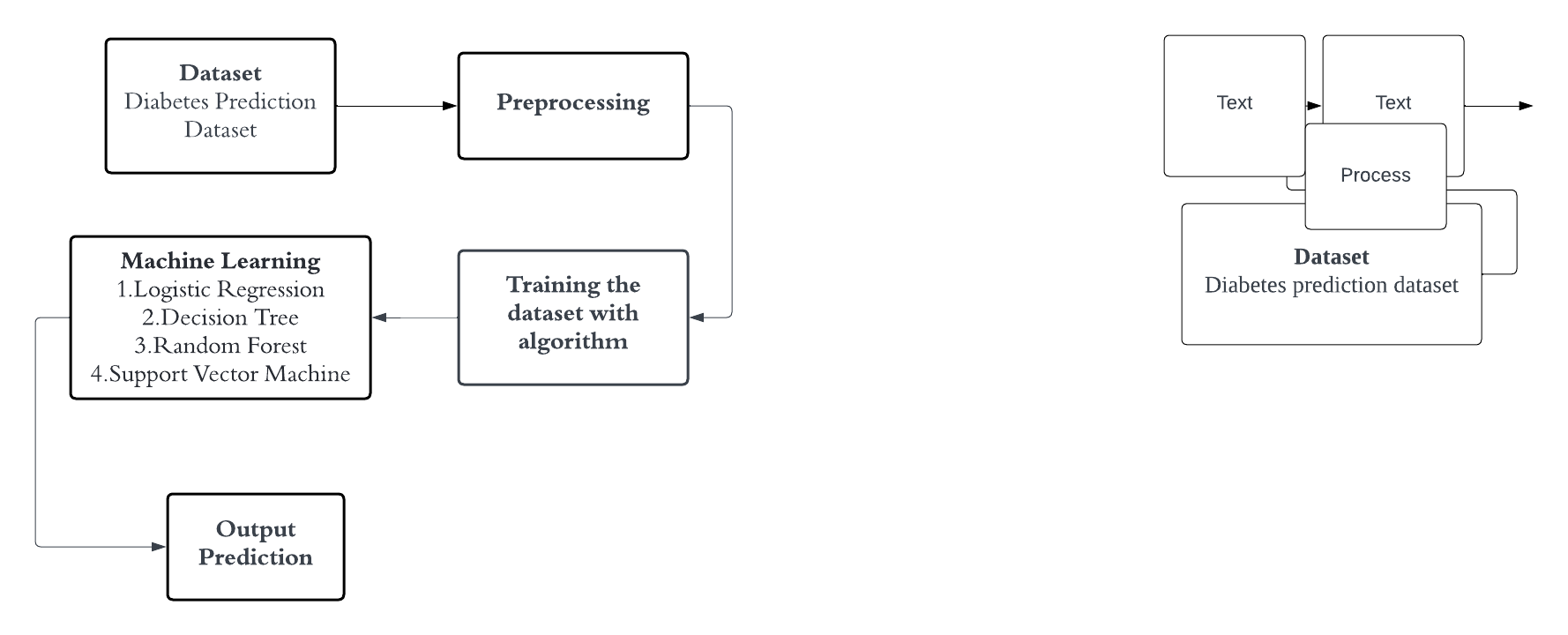
**9. Risk Stratification and Early Detection:**

The system excels in risk stratification and early detection of diabetic complications. By accurately identifying high-risk individuals and predicting the likelihood of adverse outcomes, clinicians can prioritize interventions and preventative measures to mitigate risks and improve long-term health outcomes.

**10. Quality Improvement and Outcome Evaluation:**

The system facilitates quality improvement initiatives and outcome evaluation by providing robust metrics for assessing the effectiveness of interventions and treatment protocols. By analyzing real-world outcomes data, healthcare organizations can identify areas for improvement and implement evidence-based practices to optimize patient outcomes.

**SYSTEM DESIGN:**

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**Dataset Description:**

**1. Gender:**

- Categorical variable indicating the gender of the individual (e.g., Male, Female, Other).

**2. Age:**

- Continuous variable representing the age of the individual in years.

**3. Hypertension:**

- Binary variable indicating whether the individual has hypertension (1 for yes, 0 for no).

**4. Heart Disease:**

- Binary variable indicating whether the individual has heart disease (1 for yes, 0 for no)

**5. Smoking History:**

- Categorical variable indicating the smoking history of the individual (e.g., Never smoked, Former smoker, Current smoker).

**6. BMI (Body Mass Index):**

- Continuous variable representing the body mass index of the individual, calculated as weight (in kilograms) divided by the square of height (in meters).

**7. HbA1c Level:**

- Continuous variable representing the level of glycated hemoglobin (HbA1c) in the individual's blood, typically expressed as a percentage.

**8. Blood Glucose Level:**

- Continuous variable representing the blood glucose level of the individual, typically measured in milligrams per deciliter (mg/dL) or millimoles per liter (mmol/L).

**9. Diabetes:**

- Binary variable indicating whether the individual has diabetes (1 for yes, 0 for no).

The dataset comprises several key attributes providing insights into the health and demographic profile of individuals. These attributes encompass a comprehensive overview of individuals' health profiles, including demographic information, prevalent health conditions, lifestyle factors, and clinical measurements. Such data could be invaluable for various analyses, ranging from predicting diabetes risk based on individual characteristics to exploring the association between lifestyle factors and health outcomes.This dataset likely contains information about individuals' demographic characteristics, health conditions (such as hypertension and heart disease), lifestyle factors (such as smoking history), and clinical measurements (such as BMI, HbA1c level, and blood glucose level). It could be used for various analyses, including predicting diabetes risk or evaluating the association between different factors and health outcomes.

**Pre-Processing:**

**Handling Missing Values:**

Check for missing values in each column and decide on an appropriate strategy for handling them. Options include imputation (replacing missing values with a statistical measure like mean or median), deletion of rows or columns with missing values, or using advanced imputation techniques such as K-nearest neighbors.

**Encoding Categorical Variables:**

Encode categorical variables like "Gender" and "Smoking History" into numerical format suitable for modeling. This can be achieved through techniques like one-hot encoding or label encoding.

**Machine learning algorithm:**

**Random Forest Classifier:**

**Working Principle of Random Forest Algorithm:**

Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mode (classification) or mean prediction (regression) of the individual trees. The algorithm works by selecting random subsets of the training data and random subsets of the input features for each tree, thereby introducing randomness and reducing the risk of overfitting.

1. Tree Construction: Each decision tree in the Random Forest is trained on a bootstrapped sample of the training data, where a random subset of data points is selected with replacement. Additionally, a random subset of input features is considered for each split in the tree.

2. Ensemble Learning: Once the decision trees are constructed, their predictions are aggregated to make the final prediction. For classification tasks, the mode (most frequent class) of the individual tree predictions is taken as the final prediction, while for regression tasks, the mean of the individual tree predictions is calculated.

3. Prediction: During the prediction phase, new data traverse each decision tree in the Random Forest from the root node to the leaf nodes based on the values of their features. The final prediction is then determined by aggregating the predictions of all trees in the forest.

**Applications:**

1. Classification: Random Forests are widely used for classification tasks in various domains such as healthcare (disease prediction), finance (credit risk assessment), e-commerce (customer behavior analysis), and ecology (species classification).

2. Regression: Random Forests can also be applied to regression tasks, including predicting house prices, stock prices, demand forecasting, and estimating the impact of variables on continuous outcomes.

3. Feature Importance: Random Forests provide a measure of feature importance based on how much each feature decreases impurity across all trees, making them useful for feature selection and interpretation in high-dimensional datasets.

4. Anomaly Detection: Random Forests can be used for anomaly detection by identifying data points that deviate significantly from the majority class or expected distribution, making them effective for fraud detection and outlier detection tasks.

**Challenges:**

1. Overfitting: Although Random Forests are less prone to overfitting compared to individual decision trees, they can still overfit noisy or imbalanced data. Hyperparameter tuning, cross-validation, and feature selection can help mitigate overfitting.

2. Computationally Intensive: Training a Random Forest with a large number of trees and features can be computationally expensive, especially for large datasets. Techniques such as parallelization and optimizing tree-building algorithms can improve efficiency.

3. Interpretability: Random Forests are less interpretable than individual decision trees due to their ensemble nature, making it challenging to understand the underlying decision-making process. Techniques such as feature importance analysis and partial dependence plots can provide insights into model behavior.

4. Hyperparameter Sensitivity: Random Forests have several hyperparameters that need to be tuned, such as the number of trees, tree depth, and the number of features considered for each split. Finding the optimal hyperparameters can be time-consuming and requires careful experimentation.

**Decision tree:**

**Working Principle of Decision Tree Algorithm:**

The decision tree algorithm is a popular machine learning technique used for both classification and regression tasks. Its working principle revolves around recursively partitioning the input space (feature space) into smaller subsets based on the values of input features. This partitioning process is guided by a series of decision rules inferred from the training data.

1. **Tree Construction:** The algorithm starts with the entire dataset and selects the best feature to split the data into two or more subsets. This selection is typically based on criteria such as Gini impurity, entropy, or information gain, which measure the homogeneity of the subsets with respect to the target variable.

2. **Recursive Partitioning:** The process continues recursively for each subset, selecting the best feature to split them further until certain stopping criteria are met, such as reaching a maximum depth, minimum number of samples per leaf, or no further improvement in impurity reduction

3. **Leaf Node Assignment:** Once the partitioning process is complete, each leaf node represents a class label (for classification) or a predicted value (for regression), determined by the majority class or the average value of the target variable within that subset.

4. **Prediction:** During the prediction phase, the input data traverse the decision tree from the root node to the leaf nodes based on the values of their features. The predicted class label or value associated with the leaf node reached by the input data is then assigned as the final prediction.

**Applications**

1. **Classification:** Decision trees are widely used for classification tasks in various domains such as finance (credit scoring), healthcare (disease diagnosis), marketing (customer segmentation), and fraud detection.

2. **Regression:** Decision trees can also be used for regression tasks, including predicting house prices, stock prices, demand forecasting, and estimating the impact of variables on continuous outcomes.

3. **Feature Selection:** Decision trees can help identify important features in a dataset by evaluating their contribution to the overall tree structure, making them useful for feature selection in high-dimensional datasets.

4. **Anomaly Detection:** Decision trees can be applied to detect anomalies or outliers in data by identifying data points that deviate significantly from the majority class or expected distribution.

**Challenges:**

1. **Overfitting:** Decision trees are prone to overfitting, especially when the tree depth is not properly constrained or when the dataset is noisy or contains irrelevant features. Techniques such as pruning, limiting tree depth, or using ensemble methods like Random Forests can help mitigate overfitting.

2. **High Variance:** Decision trees can exhibit high variance, leading to instability in predictions when trained on different subsets of the data. Ensemble methods like Random Forests or Gradient Boosting can reduce variance by aggregating multiple decision trees.

3. **Bias Towards Features with Many Levels:** Decision trees tend to favor features with a large number of levels or categories during the splitting process, potentially overlooking other important features. Feature engineering or dimensionality reduction techniques can address this bias.

4. **Sensitive to Small Variations in Data:** Decision trees are sensitive to small variations in the training data, which can result in different tree structures and predictions. This sensitivity can be reduced by using ensemble methods or by aggregating multiple trees.

**Support Vector Machine (SVM):**

**Working Principle of Support Vector Machine Algorithm:**

Support Vector Machine (SVM) is a supervised learning algorithm that finds the optimal hyperplane to separate classes in the feature space. The algorithm works by maximizing the margin between the classes, which represents the distance between the closest data points (support vectors) from each class to the hyperplane. SVM can handle both linearly separable and non-linearly separable data by using kernel functions to map the input features into a higher-dimensional space where separation is possible.

1. Hyperplane Optimization: SVM aims to find the hyperplane that maximizes the margin between the classes while minimizing the classification error. The hyperplane is determined by a subset of data points known as support vectors.

2. Kernel Trick: In cases where the data is not linearly separable in the original feature space, SVM uses kernel functions to map the input features into a higher-dimensional space where separation is possible. Common kernel functions include linear, polynomial, radial basis function (RBF), and sigmoid.

3. Margin Maximization: The margin is defined as the distance between the hyperplane and the closest data points from each class. SVM seeks to maximize this margin, as it represents the generalization ability of the model and improves its robustness to noise.

4. Prediction: During the prediction phase, new data points are mapped into the same feature space using the kernel function, and their class labels are determined based on which side of the hyperplane they fall on.

**Applications:**

1. Classification: SVM is widely used for classification tasks in various domains such as image recognition, text classification, bioinformatics, and finance (e.g., stock market prediction).

2. Regression: SVM can also be applied to regression tasks, including predicting house prices, disease progression, and demand forecasting.

3. Anomaly Detection: SVM can be used for anomaly detection by identifying data points that deviate significantly from the majority class or expected distribution, making it effective for fraud detection and outlier detection tasks.

4. Support Vector Clustering: SVM can be extended to perform clustering tasks by modifying the optimization objective to maximize the margin between clusters.

**Challenges:**

1. Sensitivity to Kernel Choice: The performance of SVM is sensitive to the choice of kernel function and its associated parameters. Selecting the optimal kernel and tuning its parameters can be challenging and require domain knowledge.

2. Computational Complexity: Training SVM on large datasets or with complex kernel functions can be computationally expensive and time-consuming. Efficient optimization algorithms and parallelization techniques can help address this challenge.

3. Lack of Interpretability: SVM produces a black-box model that is less interpretable compared to simpler algorithms like logistic regression or decision trees. Understanding the decision boundary and feature importance can be difficult.

4. Memory Requirements: SVM requires storing all support vectors in memory during training, which can lead to high memory requirements for large datasets with many support vectors. Kernel approximations and online learning techniques can help alleviate memory constraints.

**Logistic Regression:**

**Working Principle of Logistic Regression Algorithm:**

Logistic Regression is a linear model used for binary classification tasks, where the target variable has two possible outcomes. The algorithm works by fitting a logistic function (sigmoid function) to the input data, which models the probability of the target variable belonging to one of the classes based on the input features.

1. Sigmoid Function: Logistic Regression models the probability \( P(y=1|x) \) of the target variable (1 for positive class, 0 for negative class) given the input features \( x \) using the sigmoid function \( \sigma(z) = \frac{1}{1+e^{-z}} \), where \( z \) is a linear combination of the input features and model coefficients.

2. Model Training: During training, Logistic Regression estimates the model coefficients that best fit the observed data by maximizing the likelihood of the observed class labels given the input features. This is typically done using optimization techniques such as gradient descent or Newton-Raphson method.

3. Decision Boundary: Once the model coefficients are estimated, Logistic Regression predicts the class label of new data points by applying the learned logistic function. The decision boundary is determined by the threshold probability (usually 0.5), where data points with predicted probabilities above the threshold are assigned to one class, and those below are assigned to the other class.

4. Prediction: During the prediction phase, new data points are passed through the logistic function, and their predicted probabilities are compared to the threshold to determine the final class label.

**Applications:**

1. Binary Classification: Logistic Regression is widely used for binary classification tasks in various domains such as healthcare (e.g., disease prediction), finance (e.g., credit risk assessment), marketing (e.g., customer churn prediction), and natural language processing (e.g., sentiment analysis).

2. Probabilistic Modeling: Logistic Regression models the probability of class membership, making it useful for probabilistic predictions and uncertainty estimation. It is often used in conjunction with other classifiers in ensemble methods like stacking and boosting.

3. Feature Importance: Logistic Regression provides interpretable coefficients that indicate the importance of each feature in predicting the target variable. This makes it useful for feature selection and interpretation in high-dimensional datasets.

4. Online Learning: Logistic Regression can be adapted for online learning scenarios, where the model is updated incrementally as new data becomes available. This makes it suitable for applications with streaming data or changing environments.

**Challenges:**

1. Linear Decision Boundary: Logistic Regression assumes a linear relationship between the input features and the log odds of the target variable, which may not capture complex non-linear relationships in the data. Polynomial features or kernel methods can be used to address this limitation.

2. Imbalanced Data: Logistic Regression may produce biased predictions when the classes are imbalanced, leading to poor performance on the minority class. Techniques such as class weighting, resampling, or using alternative performance metrics like ROC AUC can help mitigate this issue.

3. Assumptions of Independence: Logistic Regression assumes that the observations are independent of each other, which may not hold true in practice for time-series data or spatial data. Violations of this assumption can lead to biased parameter estimates and inaccurate predictions.

4. Sensitivity to Outliers: Logistic Regression is sensitive to outliers in the input data, which can influence the estimated coefficients and affect model performance.

**K-Nearest Neighbors (KNN):**

**Working Principle of K-Nearest Neighbors Algorithm:**

K-Nearest Neighbors (KNN) is a simple and intuitive non-parametric algorithm used for both classification and regression tasks. The algorithm works by finding the K nearest data points to a given query point in the feature space and making predictions based on the majority class (for classification) or the average value (for regression) of the K nearest neighbors.

1. Distance Calculation: KNN calculates the distance between the query point and each data point in the training set using a distance metric such as Euclidean distance, Manhattan distance, or Minkowski distance.

2. K Nearest Neighbors: Once the distances are calculated, KNN identifies the K nearest neighbors to the query point based on the smallest distance values.

3. Classification: For classification tasks, KNN predicts the class label of the query point based on the majority class among its K nearest neighbors. This is achieved by assigning the query point to the class that occurs most frequently among its neighbors.

4. Regression: For regression tasks, KNN predicts the target value of the query point based on the average value of the target variable among its K nearest neighbors.

5. Hyperparameter Tuning: The choice of K (number of neighbors) is a critical hyperparameter in KNN, which affects the model's performance. Larger values of K provide smoother decision boundaries but may lead to increased bias, while smaller values of K may result in more complex decision boundaries but may increase variance and sensitivity to noise.

**Applications:**

1. Classification: KNN is commonly used for classification tasks in various domains such as healthcare (e.g., disease diagnosis), finance (e.g., credit scoring), marketing (e.g., customer segmentation), and image recognition.

2. Regression: KNN can also be applied to regression tasks, including predicting house prices, stock prices, demand forecasting, and estimating the impact of variables on continuous outcomes.

3. Recommender Systems: KNN is used in collaborative filtering-based recommender systems to recommend items to users based on similarity measures between users or items.

4. Anomaly Detection: KNN can be used for anomaly detection by identifying data points that deviate significantly from the majority class or expected distribution, making it effective for fraud detection and outlier detection tasks.

**Challenges:**

1. Computational Complexity: KNN has high computational complexity during both training and testing phases, especially for large datasets, as it requires calculating distances between the query point and all data points in the training set.

2. Curse of Dimensionality: KNN performance can degrade in high-dimensional feature spaces due to the curse of dimensionality, where the distance between data points becomes less meaningful as the number of dimensions increases.

3. Sensitivity to Noise and Outliers: KNN is sensitive to noisy data and outliers, as they can significantly affect the decision boundaries and predictions of the algorithm.

4. Choice of Distance Metric: The choice of distance metric (e.g., Euclidean distance, Manhattan distance) can have a significant impact on the performance of KNN and may need to be carefully selected based on the characteristics of the data.

5. Imbalanced Data: KNN may produce biased predictions when the classes are imbalanced, leading to poor performance on the minority class. Techniques such as class weighting, resampling, or using alternative performance metrics like F1 score can help mitigate this issue.

**Libraries used in the implementation:**

**1. pandas (pd):**

- Pandas is a powerful data manipulation and analysis library in Python. It provides data structures and functions to efficiently work with structured data, such as data frames, which are akin to tables in a relational database. Pandas is widely used for data cleaning, preprocessing, and exploratory data analysis tasks.

**2. numpy (np):**

- NumPy is a fundamental package for scientific computing in Python. It provides support for multi-dimensional arrays and matrices, along with a wide range of mathematical functions to operate on these arrays efficiently. NumPy is essential for numerical computations and data manipulation tasks.

**3. warnings:**

- The warnings module is part of Python's standard library and provides functions to handle warnings that occur during program execution. In the provided code, warnings are filtered to ignore them, which can be useful for suppressing unnecessary warnings and improving code readability.

**4. sklearn.metrics:**

- The sklearn.metrics module from scikit-learn (or sklearn) provides various metrics and evaluation functions for assessing the performance of machine learning models. These metrics include accuracy\_score, confusion\_matrix, classification\_report, roc\_auc\_score, etc., which are commonly used to evaluate classification and regression models.

**5. sklearn.model\_selection:**

- The sklearn.model\_selection module from scikit-learn provides functions and classes for model selection and evaluation, including train\_test\_split for splitting data into training and testing sets, GridSearchCV for hyperparameter tuning via grid search, and cross-validation utilities for assessing model performance.

**6. sklearn.linear\_model:**

- The sklearn.linear\_model module from scikit-learn provides classes for various linear models, including LogisticRegression, which is used for binary classification tasks. Logistic regression is a linear model that predicts the probability of a binary outcome based on input features.

**7. sklearn.ensemble:**

- The sklearn.ensemble module from scikit-learn provides classes for ensemble learning methods, such as RandomForestClassifier. Random forests are a type of ensemble learning technique that builds multiple decision trees during training and aggregates their predictions to improve accuracy and robustness.

**8. sklearn.neighbors:**

- The sklearn.neighbors module from scikit-learn provides classes for nearest neighbors-based learning methods, including KNeighborsClassifier. K-nearest neighbors (KNN) is a simple and intuitive algorithm that makes predictions based on the majority class among the nearest neighbors of a given data point.

**9. sklearn.tree:**

- The sklearn.tree module from scikit-learn provides classes for decision tree-based learning methods, including DecisionTreeClassifier. Decision trees are a popular type of supervised learning algorithm that partitions the feature space into regions based on the values of input features and makes predictions accordingly.

**10. sklearn.svm:**

- The sklearn.svm module from scikit-learn provides classes for support vector machine (SVM) algorithms, including SVMClassifier. SVMs are a powerful supervised learning algorithm used for classification and regression tasks. They work by finding the optimal hyperplane that separates classes in the feature space.

These libraries and modules are essential for building, training, evaluating, and tuning machine learning models in Python. They provide a wide range of functionalities and tools to support various stages of the machine learning workflow, from data preprocessing to model evaluation and deployment.

**CODING:**

# Importing required library

import pandas as pd

import numpy as np

import warnings

from sklearn.metrics import accuracy\_score

from sklearn import metrics

warnings.filterwarnings("ignore")

from sklearn.model\_selection import train\_test\_split

DIABETES DATASET-1

#load the data in the dataframe

df=pd.read\_csv("/content/drive/MyDrive/Diabetes Dataset/Diabetes Dataset1.csv")

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#DATA PREPROCESSING

#Printing Number of rows and columns in dataset

r\_count,c\_count=df.shape

print("Row Count:",r\_count)

print("Column Count:",c\_count)

#Returns the index object with column name

print(df.keys())

#Returns the specified number of rows and columns from the top.

df.head(15)

#prints the information about the dataframe

df.info()

#Checking for null values. df.isnull().sum is used to find the total no. of null value presented in the dataset. If null value is present then it is dropped using df.dropna().

df.isnull().sum()

#FEATURE ENGINEERING

# Step 1: Prepare the data

X = df.drop('Outcome', axis=1)

y = df['Outcome']

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, random\_state=42)

#Number of values in train and test data

print("x\_Train: ",X\_train.shape)

print("x\_Test: ",X\_test.shape)

print("y\_train: ",y\_train.shape)

print("y\_test: ",y\_test.shape)

#Model Fitting and Predicting

from sklearn.linear\_model import LogisticRegression

from sklearn.ensemble import RandomForestClassifier

from sklearn.neighbors import KNeighborsClassifier

from sklearn.tree import DecisionTreeClassifier

from sklearn import svm

from sklearn.metrics import confusion\_matrix

from sklearn.metrics import make\_scorer, accuracy\_score, roc\_auc\_score

from sklearn.model\_selection import GridSearchCV

from sklearn.metrics import classification\_report

# Step 2: Finding accuracy without adding noise

model = LogisticRegression()

model.fit(X\_train, y\_train)

y\_pred = model.predict(X\_test)

accuracy = accuracy\_score(y\_test, y\_pred)

print("Accuracy Before adding noise:", accuracy)

print('Classification report Logistic Regression: \n',classification\_report(y\_test,y\_pred))

#SVM - find the optimal hyperplane that separates the data points of different classes with the maximum margin

SVM\_Model = svm.SVC(kernel='linear')

SVM\_Model.fit(X\_train, y\_train)

SVM\_Predict = SVM\_Model.predict(X\_test)

SVM\_Accuracy = accuracy\_score(y\_test, SVM\_Predict)

print("Testing Accuracy: " + str(SVM\_Accuracy))

print('Classification report SVM: \n',classification\_report(y\_test,SVM\_Predict))

#RANDOM FOREST

RFC\_Model = RandomForestClassifier()

RFC\_Model.fit(X\_train, y\_train)

RFC\_Predict = RFC\_Model.predict(X\_test)

RFC\_Accuracy = accuracy\_score(y\_test, RFC\_Predict)

print("Testing Accuracy: " + str(RFC\_Accuracy))

print('Classification report RANDOM FOREST: \n',classification\_report(y\_test,RFC\_Predict))

#DECISION TREE

DT\_Model = DecisionTreeClassifier()

DT\_Model.fit(X\_train, y\_train)

DT\_Predict = DT\_Model.predict(X\_test)

DT\_Accuracy = accuracy\_score(y\_test, DT\_Predict)

print("Accuracy Before adding noise:: " + str(DT\_Accuracy))

print('Classification report Decision Tree: \n',classification\_report(y\_test,DT\_Predict))

#PRIVACY PRESERVING MACHINE LEARNING - Differential Privacy

#Step 3: Add noise to the features for differential privacy

epsilon = 1.0 # Privacy parameter

sensitivity = 1.0 # Sensitivity of the logistic regression model

n\_samples, n\_features = X\_train.shape

scale = sensitivity / epsilon

noise = np.random.laplace(loc=0, scale=scale, size=(n\_samples, n\_features))#Laplace distribution is a probability distribution that is often used in differential privacy mechanisms to inject noise into data.

X\_train\_dp = X\_train + noise

X\_train\_dp

# Step 4: Train logistic regression model

model = LogisticRegression()

model.fit(X\_train\_dp, y\_train)

# Step 5: Evaluate model performance

y\_pred = model.predict(X\_test)

accuracy = accuracy\_score(y\_test, y\_pred)

print("Accuracy After adding noise:", accuracy)

print('Classification report Logistic Regression: \n',classification\_report(y\_test,y\_pred))

#SVM - find the optimal hyperplane that separates the data points of different classes with the maximum margin

SVM\_Model = svm.SVC(kernel='linear')

SVM\_Model.fit(X\_train\_dp, y\_train)

SVM\_Predict = SVM\_Model.predict(X\_test)

SVM\_Accuracy = accuracy\_score(y\_test, SVM\_Predict)

print("Testing Accuracy: " + str(SVM\_Accuracy))

print('Classification report SVM: \n',classification\_report(y\_test,SVM\_Predict))

#DECISION TREE

DT\_Model = DecisionTreeClassifier()

DT\_Model.fit(X\_train\_dp, y\_train)

DT\_Predict = DT\_Model.predict(X\_test)

DT\_Accuracy = accuracy\_score(y\_test, DT\_Predict)

print("Accuracy Before adding noise:: " + str(DT\_Accuracy))

print('Classification report Decision Tree: \n',classification\_report(y\_test,DT\_Predict)

#RANDOM FOREST

RFC\_Model = RandomForestClassifier()

RFC\_Model.fit(X\_train\_dp, y\_train)

RFC\_Predict = RFC\_Model.predict(X\_test)

RFC\_Accuracy = accuracy\_score(y\_test, RFC\_Predict)

print("Testing Accuracy: " + str(RFC\_Accuracy))

print('Classification report RANDOM FOREST: \n',classification\_report(y\_test,RFC\_Predict))

DIABETES DATASET-2

#load the data in the dataframe

df2=pd.read\_csv("/content/drive/MyDrive/Diabetes Dataset/Diabetes Dataset2.csv")

#DATA PREPROCESSING

#Printing Number of rows and columns in dataset

r\_count,c\_count=df2.shape

print("Row Count:",r\_count)

print("Column Count:",c\_count)

# Perform label encoding

label\_encoder = LabelEncoder()

df2['Gender'] = label\_encoder.fit\_transform(df2['Gender'])

df2.head(15)

#FEATURE ENGINEERING

# Step 1: Prepare the data

columns\_to\_drop = ['ID', 'No\_Pation', 'CLASS']

X2 = df2.drop(columns\_to\_drop, axis=1)

y2 = df2['CLASS']

#DATA ENGINEERING

#Target variable label encoded

from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()

y2= le.fit\_transform(y2)

y2

# Displaying the mapping between original values and encoded values

print("Mapping of labels to categories:")

for original\_value, encoded\_value in zip(le.classes\_, le.transform(le.classes\_)):

print(f"{original\_value}: {encoded\_value}")

X2\_train, X2\_test, y2\_train, y2\_test = train\_test\_split(X2, y2, test\_size=0.2, random\_state=42)

#Number of values in train and test data

print("x\_Train: ",X2\_train.shape)

print("x\_Test: ",X2\_test.shape)

print("y\_train: ",y2\_train.shape)

print("y\_test: ",y2\_test.shape)

#Model Fitting and Predicting

from sklearn.linear\_model import LogisticRegression

from sklearn.ensemble import RandomForestClassifier

from sklearn.neighbors import KNeighborsClassifier

from sklearn.tree import DecisionTreeClassifier

from sklearn import svm

from sklearn.metrics import confusion\_matrix

from sklearn.metrics import make\_scorer, accuracy\_score, roc\_auc\_score

from sklearn.model\_selection import GridSearchCV

from sklearn.metrics import classification\_report

# Step 2: Finding accuracy without adding noise

model = LogisticRegression(multi\_class='multinomial')

model.fit(X2\_train, y2\_train)

y2\_pred = model.predict(X2\_test)

accuracy = accuracy\_score(y2\_test, y2\_pred)

print("Accuracy Before adding noise:", accuracy)

print('Classification report Logistic Regression: \n',classification\_report(y2\_test,y2\_pred))

#PRIVACY PRESERVING MACHINE LEARNING - Differential Privacy

#Step 3: Add noise to the features for differential privacy

epsilon = 1.0 # Privacy parameter

sensitivity = 1.0 # Sensitivity of the logistic regression model

n\_samples, n\_features = X2\_train.shape

scale = sensitivity / epsilon

noise = np.random.laplace(loc=0, scale=scale, size=(n\_samples, n\_features))#Laplace distribution is a probability distribution that is often used in differential privacy mechanisms to inject noise into data.

X2\_train\_dp = X2\_train + noise

# Step 4: Train logistic regression model

model = LogisticRegression(multi\_class='multinomial')

model.fit(X2\_train\_dp, y2\_train)

# Step 5: Evaluate model performance

y2\_pred = model.predict(X2\_test)

accuracy = accuracy\_score(y2\_test, y2\_pred)

print("Accuracy After adding noise:", accuracy)

print('Classification report Logistic Regression: \n',classification\_report(y2\_test,y2\_pred))

#SVM - find the optimal hyperplane that separates the data points of different classes with the maximum margin

SVM\_Model = svm.SVC(kernel='linear', decision\_function\_shape='ovr')

SVM\_Model.fit(X2\_train\_dp, y2\_train)

SVM\_Predict = SVM\_Model.predict(X2\_test)

SVM\_Accuracy = accuracy\_score(y2\_test, SVM\_Predict)

print("Testing Accuracy: " + str(SVM\_Accuracy))

print('Classification report SVM: \n',classification\_report(y2\_test,SVM\_Predict))

#DECISION TREE

DT\_Model = DecisionTreeClassifier()

DT\_Model.fit(X2\_train\_dp, y2\_train)

DT\_Predict = DT\_Model.predict(X2\_test)

DT\_Accuracy = accuracy\_score(y2\_test, DT\_Predict)

print("Accuracy Before adding noise:: " + str(DT\_Accuracy))

print('Classification report Decision Tree: \n',classification\_report(y2\_test,DT\_Predict))

#RANDOM FOREST

RFC\_Model = RandomForestClassifier()

RFC\_Model.fit(X2\_train\_dp, y2\_train)

RFC\_Predict = RFC\_Model.predict(X2\_test)

RFC\_Accuracy = accuracy\_score(y2\_test, RFC\_Predict)

print("Testing Accuracy: " + str(RFC\_Accuracy))

print('Classification report RANDOM FOREST: \n',classification\_report(y2\_test,RFC\_Predict))

DIABETES DATASET-3

#load the data in the dataframe

df3=pd.read\_csv("/content/drive/MyDrive/Diabetes Dataset/diabetes\_prediction\_dataset.csv")

#DATA PREPROCESSING

#Printing Number of rows and columns in dataset

r\_count,c\_count=df3.shape

print("Row Count:",r\_count)

print("Column Count:",c\_count)

#Checking for null values. df.isnull().sum is used to find the total no. of null value presented in the dataset. If null value is present then it is dropped using df.dropna().

df3.isnull().sum()

# Perform label encoding

label\_encoder = LabelEncoder()

df3['gender'] = label\_encoder.fit\_transform(df3['gender'])

df3['smoking\_history'] = label\_encoder.fit\_transform(df3['smoking\_history'])

df3.head(15)

#FEATURE ENGINEERING

# Step 1: Prepare the data

X3 = df3.drop('diabetes', axis=1)

y3= df3['diabetes']

X3\_train, X3\_test, y3\_train, y3\_test = train\_test\_split(X3, y3, test\_size=0.2, random\_state=42)

#Number of values in train and test data

print("x\_Train: ",X3\_train.shape)

print("x\_Test: ",X3\_test.shape)

print("y\_train: ",y3\_train.shape)

print("y\_test: ",y3\_test.shape)

#Model Fitting and Predicting

from sklearn.linear\_model import LogisticRegression

from sklearn.ensemble import RandomForestClassifier

from sklearn.neighbors import KNeighborsClassifier

from sklearn.tree import DecisionTreeClassifier

from sklearn import svm

from sklearn.metrics import confusion\_matrix

from sklearn.metrics import make\_scorer, accuracy\_score, roc\_auc\_score

from sklearn.model\_selection import GridSearchCV

from sklearn.metrics import classification\_report

# Step 2: Finding accuracy without adding noise

model = LogisticRegression()

model.fit(X3\_train, y3\_train)

y3\_pred = model.predict(X3\_test)

accuracy = accuracy\_score(y3\_test, y3\_pred)

print("Accuracy Before adding noise:", accuracy)

print('Classification report Logistic Regression: \n',classification\_report(y3\_test,y3\_pred))

#PRIVACY PRESERVING MACHINE LEARNING - Differential Privacy

#Step 3: Add noise to the features for differential privacy

epsilon = 1.0 # Privacy parameter

sensitivity = 1.0 # Sensitivity of the logistic regression model

n\_samples, n\_features = X3\_train.shape

scale = sensitivity / epsilon

noise = np.random.laplace(loc=0, scale=scale, size=(n\_samples, n\_features))#Laplace distribution is a probability distribution that is often used in differential privacy mechanisms to inject noise into data.

X3\_train\_dp = X3\_train + noise

# Step 4: Train logistic regression model

model = LogisticRegression()

model.fit(X3\_train\_dp, y3\_train)

# Step 5: Evaluate model performance

y3\_pred = model.predict(X3\_test)

accuracy = accuracy\_score(y3\_test, y3\_pred)

print("Accuracy After adding noise:", accuracy)

print('Classification report Logistic Regression: \n',classification\_report(y3\_test,y3\_pred))

#SVM - find the optimal hyperplane that separates the data points of different classes with the maximum margin

SVM\_Model = svm.SVC(kernel='linear')

SVM\_Model.fit(X3\_train\_dp, y3\_train)

SVM\_Predict = SVM\_Model.predict(X3\_test)

SVM\_Accuracy = accuracy\_score(y3\_test, SVM\_Predict)

print("Testing Accuracy: " + str(SVM\_Accuracy))

print('Classification report SVM: \n',classification\_report(y3\_test,SVM\_Predict))

#DECISION TREE

DT\_Model = DecisionTreeClassifier()

DT\_Model.fit(X3\_train\_dp, y3\_train)

DT\_Predict = DT\_Model.predict(X3\_test)

DT\_Accuracy = accuracy\_score(y3\_test, DT\_Predict)

print("Accuracy Before adding noise:: " + str(DT\_Accuracy))

print('Classification report Decision Tree: \n',classification\_report(y3\_test,DT\_Predict))

#RANDOM FOREST

RFC\_Model = RandomForestClassifier()

RFC\_Model.fit(X3\_train\_dp, y3\_train)

RFC\_Predict = RFC\_Model.predict(X3\_test)

RFC\_Accuracy = accuracy\_score(y3\_test, RFC\_Predict)

print("Testing Accuracy: " + str(RFC\_Accuracy))

print('Classification report RANDOM FOREST: \n',classification\_report(y3\_test,RFC\_Predict))

**FRAMEWORK CODE:**

import tkinter as tk

import tkinter as tk

from tkinter import ttk

from sklearn.svm import SVC

from sklearn.preprocessing import LabelEncoder

from sklearn.tree import DecisionTreeClassifier

from sklearn.ensemble import RandomForestClassifier

from sklearn.linear\_model import LogisticRegression

from sklearn.metrics import accuracy\_score, confusion\_matrix, classification\_report

from sklearn.metrics import roc\_auc\_score, roc\_curve, auc, precision\_recall\_fscore\_support

import seaborn as sns

import matplotlib.pyplot as plt

from matplotlib.backends.backend\_tkagg import FigureCanvasTkAgg

from PIL import Image, ImageTk

from sklearn.model\_selection import train\_test\_split

import numpy as np

import pandas as pd

# Load your dataset here

data = pd.read\_csv('diabetes\_prediction\_dataset.csv')

# Perform label encoding

label\_encoder = LabelEncoder()

data['gender'] = label\_encoder.fit\_transform(data['gender'])

data['smoking\_history'] = label\_encoder.fit\_transform(data['smoking\_history'])

data.head(15)

X = data.drop(['diabetes'], axis=1)

y = data['diabetes']

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.33, random\_state=42)

# Initialize classifiers

log\_reg = LogisticRegression()

svm\_classifier = SVC(random\_state=0)

dtc\_classifier = DecisionTreeClassifier(random\_state=0)

rfc\_classifier = RandomForestClassifier(n\_estimators=100, criterion='gini', random\_state=0)

# Tkinter GUI

root = tk.Tk()

root.title("Classifier Metrics")

root.geometry("400x400")

# Load background image

background\_image = Image.open("sample1.jpg") # Replace with your image file

background\_photo = ImageTk.PhotoImage(background\_image)

background\_label = tk.Label(root, image=background\_photo)

background\_label.place(relwidth=1, relheight=1)

# Project label

project\_label = tk.Label(root, text="Predictive preserving learning model for diabetic dataset", font=("Helvetica", 12), bg="white")

project\_label.pack(pady=10)

# Labels for dataset information

r\_dataset\_label = tk.Label(root, text="Dataset: Diabetes Prediction Dataset", font=("Helvetica", 11),foreground="blue",width=20)

r\_dataset\_label.pack(pady=10, padx=10)

# Training Data Label

r\_train\_data\_label = tk.Label(root, text="Training Data: 70%", font=("Helvetica", 11),foreground="blue",width=20)

r\_train\_data\_label.pack(pady=10, padx=10)

# Testing Data Label

r\_test\_data\_label = tk.Label(root, text="Testing Data: 30%", font=("Helvetica", 11), foreground="blue",width=20)

r\_test\_data\_label.pack(pady=10, padx=10)

# Function to train classifiers

def train\_lr\_classifier():

global log\_reg, X\_train, y\_train

log\_reg.fit(X\_train, y\_train)

print("Logistic Regression Classifier trained successfully.")

def train\_svm\_classifier():

global svm\_classifier, X\_train, y\_train

svm\_classifier.fit(X\_train, y\_train)

print("SVM Classifier trained successfully.")

def train\_dtc\_classifier():

global dtc\_classifier, X\_train, y\_train

dtc\_classifier.fit(X\_train, y\_train)

print("DTC Classifier trained successfully.")

def train\_rfc\_classifier():

global rfc\_classifier, X\_train, y\_train

rfc\_classifier.fit(X\_train, y\_train)

print("RFC Classifier trained successfully.")

# Function to calculate metrics and show charts for SVM

def show\_lr\_metrics():

global log\_reg, X\_test, y\_test

# Predict the Test set results

y\_pred = log\_reg.predict(X\_test)

# Confusion Matrix

cm\_lr = confusion\_matrix(y\_test, y\_pred)

print('Confusion matrix of LR\n\n', cm\_lr)

# Plot Confusion Matrix

plt.figure(figsize=(8, 6))

sns.heatmap(cm\_lr, annot=True, fmt='d', cmap='Blues', cbar=False)

plt.title('Confusion Matrix of LR')

plt.xlabel('Predicted')

plt.ylabel('True')

plt.show()

def show\_report\_lr():

# Predict the Test set results

y\_pred = log\_reg.predict(X\_test)

# Classification Report

class\_report\_str = classification\_report(y\_test, y\_pred)

print(class\_report\_str)

# Plot Classification Report

class\_report = classification\_report(y\_test, y\_pred, output\_dict=True)

class\_names = [str(label) for label in class\_report.keys() if label not in ['accuracy', 'macro avg', 'weighted avg']]

heatmap\_data = [[class\_report[class\_name]['precision'], class\_report[class\_name]['recall'],

class\_report[class\_name]['f1-score']] for class\_name in class\_names]

# Create a heatmap

fig, ax = plt.subplots(figsize=(10, 6))

sns.heatmap(heatmap\_data, annot=True, fmt=".2f", xticklabels=['Precision', 'Recall', 'F1-Score'],

yticklabels=class\_names, cmap='Blues')

plt.title('Classification Report Heatmap of LR')

plt.show()

def calculate\_accuracy\_lr():

global log\_reg, X\_test, y\_test

# Predict the Test set results

y\_pred = log\_reg.predict(X\_test)

# Accuracy

accuracy\_lr = accuracy\_score(y\_test, y\_pred)

print('Model accuracy score of svm:', accuracy\_lr)

# Plot Accuracy

plt.figure(figsize=(6, 4))

plt.bar(["Accuracy"], [accuracy\_rfc], color='blue')

plt.title('Model Accuracy of LR')

plt.ylabel('Accuracy')

plt.show()

def roc\_lr():

global log\_reg, X\_test, y\_test

# Predict the Test set results

y\_pred = log\_reg.predict(X\_test)

# Calculate the AUC

auc = roc\_auc\_score(y\_test, y\_pred)

print('AUC: %.2f' % auc)

# Calculate the ROC

fpr, tpr, thresholds = roc\_curve(y\_test, y\_pred)

# plot the roc curve

plt.plot(fpr, tpr)

plt.title('ROC Curve')

plt.xlabel('False Positive Rate')

plt.ylabel('True Positive Rate')

plt.show()

# Function to calculate metrics and show charts for SVM

def show\_svm\_metrics():

global svm\_classifier, X\_test, y\_test

# Predict the Test set results

y\_pred = svm\_classifier.predict(X\_test)

# Confusion Matrix

cm\_svm = confusion\_matrix(y\_test, y\_pred)

print('Confusion matrix of svm\n\n', cm\_svm)

# Plot Confusion Matrix

plt.figure(figsize=(8, 6))

sns.heatmap(cm\_svm, annot=True, fmt='d', cmap='Blues', cbar=False)

plt.title('Confusion Matrix of svm')

plt.xlabel('Predicted')

plt.ylabel('True')

plt.show()

def show\_report\_svm():

# Predict the Test set results

y\_pred = svm\_classifier.predict(X\_test)

# Classification Report

class\_report\_str = classification\_report(y\_test, y\_pred)

print(class\_report\_str)

# Plot Classification Report

class\_report = classification\_report(y\_test, y\_pred, output\_dict=True)

class\_names = [str(label) for label in class\_report.keys() if label not in ['accuracy', 'macro avg', 'weighted avg']]

heatmap\_data = [[class\_report[class\_name]['precision'], class\_report[class\_name]['recall'],

class\_report[class\_name]['f1-score']] for class\_name in class\_names]

# Create a heatmap

fig, ax = plt.subplots(figsize=(10, 6))

sns.heatmap(heatmap\_data, annot=True, fmt=".2f", xticklabels=['Precision', 'Recall', 'F1-Score'],

yticklabels=class\_names, cmap='Blues')

plt.title('Classification Report Heatmap of svm')

plt.show()

def calculate\_accuracy\_svm():

global svm\_classifier, X\_test, y\_test

# Predict the Test set results

y\_pred = svm\_classifier.predict(X\_test)

# Accuracy

accuracy\_svm = accuracy\_score(y\_test, y\_pred)

print('Model accuracy score of svm:', accuracy\_svm)

# Plot Accuracy

plt.figure(figsize=(6, 4))

plt.bar(["Accuracy"], [accuracy\_rfc], color='blue')

plt.title('Model Accuracy of svm')

plt.ylabel('Accuracy')

plt.show()

def roc\_svm():

global svm\_classifier, X\_test, y\_test

# Predict the Test set results

y\_pred = svm\_classifier.predict(X\_test)

# Calculate the AUC

auc = roc\_auc\_score(y\_test, y\_pred)

print('AUC: %.2f' % auc)

# Calculate the ROC

fpr, tpr, thresholds = roc\_curve(y\_test, y\_pred)

# plot the roc curve

plt.plot(fpr, tpr)

plt.title('ROC Curve')

plt.xlabel('False Positive Rate')

plt.ylabel('True Positive Rate')

plt.show()

# Function to calculate metrics and show charts for DTC

def show\_dtc\_metrics():

global dtc\_classifier, X\_test, y\_test

# Predict the Test set results

y\_pred = dtc\_classifier.predict(X\_test)

# Confusion Matrix

cm\_dtc = confusion\_matrix(y\_test, y\_pred)

print('Confusion matrix of dtc\n\n', cm\_dtc)

# Plot Confusion Matrix

plt.figure(figsize=(8, 6))

sns.heatmap(cm\_dtc, annot=True, fmt='d', cmap='Blues', cbar=False)

plt.title('Confusion Matrix of dtc')

plt.xlabel('Predicted')

plt.ylabel('True')

plt.show()

def show\_report\_dtc():

# Predict the Test set results

y\_pred = dtc\_classifier.predict(X\_test)

# Classification Report

class\_report\_str = classification\_report(y\_test, y\_pred)

print(class\_report\_str)

# Plot Classification Report

class\_report = classification\_report(y\_test, y\_pred, output\_dict=True)

class\_names = [str(label) for label in class\_report.keys() if label not in ['accuracy', 'macro avg', 'weighted avg']]

heatmap\_data = [[class\_report[class\_name]['precision'], class\_report[class\_name]['recall'],

class\_report[class\_name]['f1-score']] for class\_name in class\_names]

# Create a heatmap

fig, ax = plt.subplots(figsize=(10, 6))

sns.heatmap(heatmap\_data, annot=True, fmt=".2f", xticklabels=['Precision', 'Recall', 'F1-Score'],

yticklabels=class\_names, cmap='Blues')

plt.title('Classification Report Heatmap of dtc')

plt.show()

def calculate\_accuracy\_dtc():

global dtc\_classifier, X\_test, y\_test

# Predict the Test set results

y\_pred = dtc\_classifier.predict(X\_test)

# Accuracy

accuracy\_dtc = accuracy\_score(y\_test, y\_pred)

print('Model accuracy score of rfc:', accuracy\_dtc)

# Plot Accuracy

plt.figure(figsize=(6, 4))

plt.bar(["Accuracy"], [accuracy\_rfc], color='blue')

plt.title('Model Accuracy of dtc')

plt.ylabel('Accuracy')

plt.show()

def roc\_dtc():

global dtc\_classifier, X\_test, y\_test

# Predict the Test set results

y\_pred = dtc\_classifier.predict(X\_test)

# Calculate the AUC

auc = roc\_auc\_score(y\_test, y\_pred)

print('AUC: %.2f' % auc)

# Calculate the ROC

fpr, tpr, thresholds = roc\_curve(y\_test, y\_pred)

# plot the roc curve

plt.plot(fpr, tpr)

plt.title('ROC Curve')

plt.xlabel('False Positive Rate')

plt.ylabel('True Positive Rate')

plt.show()

# Function to calculate metrics and show charts for RFC

def show\_rfc\_metrics():

global rfc\_classifier, X\_test, y\_test

# Predict the Test set results

y\_pred = rfc\_classifier.predict(X\_test)

# Confusion Matrix

cm\_rfc = confusion\_matrix(y\_test, y\_pred)

print('Confusion matrix of rfc\n\n', cm\_rfc)

# Plot Confusion Matrix

plt.figure(figsize=(8, 6))

sns.heatmap(cm\_rfc, annot=True, fmt='d', cmap='Blues', cbar=False)

plt.title('Confusion Matrix of rfc')

plt.xlabel('Predicted')

plt.ylabel('True')

plt.show()

def show\_report\_rfc():

# Predict the Test set results

y\_pred = rfc\_classifier.predict(X\_test)

# Classification Report

class\_report\_str = classification\_report(y\_test, y\_pred)

print(class\_report\_str)

# Plot Classification Report

class\_report = classification\_report(y\_test, y\_pred, output\_dict=True)

class\_names = [str(label) for label in class\_report.keys() if label not in ['accuracy', 'macro avg', 'weighted avg']]

heatmap\_data = [[class\_report[class\_name]['precision'], class\_report[class\_name]['recall'],

class\_report[class\_name]['f1-score']] for class\_name in class\_names]

# Create a heatmap

fig, ax = plt.subplots(figsize=(10, 6))

sns.heatmap(heatmap\_data, annot=True, fmt=".2f", xticklabels=['Precision', 'Recall', 'F1-Score'],

yticklabels=class\_names, cmap='Blues')

plt.title('Classification Report Heatmap of rfc')

plt.show()

def calculate\_accuracy\_rfc():

global rfc\_classifier, X\_test, y\_test

# Predict the Test set results

y\_pred = rfc\_classifier.predict(X\_test)

# Accuracy

accuracy\_rfc = accuracy\_score(y\_test, y\_pred)

print('Model accuracy score of rfc:', accuracy\_rfc)

# Plot Accuracy

plt.figure(figsize=(6, 4))

plt.bar(["Accuracy"], [accuracy\_rfc], color='blue')

plt.title('Model Accuracy of rfc')

plt.ylabel('Accuracy')

plt.show()

def roc\_rfc\_auc():

global rfc\_classifier, X\_test, y\_test

# Predict the Test set results

y\_pred = rfc\_classifier.predict(X\_test)

# Calculate the AUC

auc = roc\_auc\_score(y\_test, y\_pred)

print('AUC: %.2f' % auc)

# Calculate the ROC

fpr, tpr, thresholds = roc\_curve(y\_test, y\_pred)

# plot the roc curve

plt.plot(fpr, tpr)

plt.title('ROC Curve')

plt.xlabel('False Positive Rate')

plt.ylabel('True Positive Rate')

plt.show()

# LR Frame

lr\_frame = tk.Frame(root)

lr\_frame.pack(side=tk.TOP, pady=10)

# LR Train Button

lr\_train\_button = tk.Button(lr\_frame, text="Train LR Classifier", command=train\_lr\_classifier, width=20)

lr\_train\_button.pack(side=tk.LEFT, padx=5, pady=5)

# LR Metrics Button

lr\_metrics\_button = tk.Button(lr\_frame, text="LR Accuracy", command=calculate\_accuracy\_lr, width=20)

lr\_metrics\_button.pack(side=tk.LEFT, padx=5, pady=5)

# LR matrix Button

lr\_metrics\_button = tk.Button(lr\_frame, text="LR Confusion Matrix", command=show\_lr\_metrics, width=20)

lr\_metrics\_button.pack(side=tk.LEFT, padx=5, pady=5)

# LR report Button

lr\_report\_button = tk.Button(lr\_frame, text="LR Classification report", command=show\_report\_lr, width=20)

lr\_report\_button.pack(side=tk.LEFT, padx=5, pady=5)

# LR matrix Button

lr\_rocauc\_button = tk.Button(lr\_frame, text="LR Roc Auc", command=roc\_lr, width=20)

lr\_rocauc\_button.pack(side=tk.LEFT, padx=5, pady=5)

# SVM Frame

svm\_frame = tk.Frame(root)

svm\_frame.pack(side=tk.TOP, pady=10)

# SVM Train Button

svm\_train\_button = tk.Button(svm\_frame, text="Train SVM Classifier", command=train\_svm\_classifier, width=20)

svm\_train\_button.pack(side=tk.LEFT, padx=5, pady=5)

# SVM Metrics Button

svm\_metrics\_button = tk.Button(svm\_frame, text="SVM Accuracy", command=calculate\_accuracy\_svm, width=20)

svm\_metrics\_button.pack(side=tk.LEFT, padx=5, pady=5)

# SVM matrix Button

svm\_metrics\_button = tk.Button(svm\_frame, text="SVM Confusion Matrix", command=show\_svm\_metrics, width=20)

svm\_metrics\_button.pack(side=tk.LEFT, padx=5, pady=5)

# SVM report Button

svm\_report\_button = tk.Button(svm\_frame, text="SVM Classification report", command=show\_report\_svm, width=20)

svm\_report\_button.pack(side=tk.LEFT, padx=5, pady=5)

# SVM matrix Button

svm\_rocauc\_button = tk.Button(svm\_frame, text="SVM Roc Auc", command=roc\_svm, width=20)

svm\_rocauc\_button.pack(side=tk.LEFT, padx=5, pady=5)

# DTC Frame

dtc\_frame = tk.Frame(root)

dtc\_frame.pack(side=tk.TOP, pady=10)

# DTC Train Button

dtc\_train\_button = tk.Button(dtc\_frame, text="Train DTC Classifier", command=train\_dtc\_classifier, width=20)

dtc\_train\_button.pack(side=tk.LEFT, padx=5, pady=5)

# DTC Metrics Button

dtc\_metrics\_button = tk.Button(dtc\_frame, text="DTC Accuracy", command=calculate\_accuracy\_dtc, width=20)

dtc\_metrics\_button.pack(side=tk.LEFT, padx=5, pady=5)

# DTC Matrix Button

dtc\_matrix\_button = tk.Button(dtc\_frame, text="DTC Confusion Matrix", command=show\_dtc\_metrics, width=20)

dtc\_matrix\_button.pack(side=tk.LEFT, padx=5, pady=5)

# DTC Matrix Button

dtc\_report\_button = tk.Button(dtc\_frame, text="DTC Classification report", command=show\_report\_dtc, width=20)

dtc\_report\_button.pack(side=tk.LEFT, padx=5, pady=5)

# DTC Matrix Button

dtc\_rocauc\_button = tk.Button(dtc\_frame, text="DTC Roc Auc", command=roc\_dtc, width=20)

dtc\_rocauc\_button.pack(side=tk.LEFT, padx=5, pady=5)

# RFC Frame

rfc\_frame = tk.Frame(root)

rfc\_frame.pack(side=tk.TOP, pady=10)

# RFC Train Button

rfc\_train\_button = tk.Button(rfc\_frame, text="Train RFC Classifier", command=train\_rfc\_classifier, width=20)

rfc\_train\_button.pack(side=tk.LEFT, padx=5, pady=5)

# RFC Metrics Button

rfc\_metrics\_button = tk.Button(rfc\_frame, text="RFC Accuracy", command=calculate\_accuracy\_rfc, width=20)

rfc\_metrics\_button.pack(side=tk.LEFT, padx=5, pady=5)

# RFC Matrix Button

rfc\_matrix\_button = tk.Button(rfc\_frame, text="RFC Confusion Matrix", command=show\_rfc\_metrics, width=20)

rfc\_matrix\_button.pack(side=tk.LEFT, padx=5, pady=5)

# RFC report Button

rfc\_report\_button = tk.Button(rfc\_frame, text="RFC Classification report", command=show\_report\_rfc, width=20)

rfc\_report\_button.pack(side=tk.LEFT, padx=5, pady=5)

# RFC roc auc Button

rfc\_rocauc\_button = tk.Button(rfc\_frame, text="RFC Roc Auc", command=roc\_rfc\_auc, width=20)

rfc\_rocauc\_button.pack(side=tk.LEFT, padx=5, pady=5)

# Run the Tkinter event loop

root.mainloop()

**RESULTS AND DISCUSSION:**

**Dataset:**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **gender** | **age** | **hypertension** | **heart\_disease** | **smoking\_history** | **bmi** | **HbA1c\_level** | **blood\_glucose\_level** | **diabetes** |
| **Female** | **80** | **0** | **1** | **never** | **25.19** | **6.6** | **140** | **0** |
| **Female** | **54** | **0** | **0** | **No Info** | **27.32** | **6.6** | **80** | **0** |
| **Male** | **28** | **0** | **0** | **never** | **27.32** | **5.7** | **158** | **0** |
| **Female** | **36** | **0** | **0** | **current** | **23.45** | **5** | **155** | **0** |
| **Male** | **76** | **1** | **1** | **current** | **20.14** | **4.8** | **155** | **0** |
| **Female** | **20** | **0** | **0** | **never** | **27.32** | **6.6** | **85** | **0** |
| **Female** | **44** | **0** | **0** | **never** | **19.31** | **6.5** | **200** | **1** |
| **Female** | **79** | **0** | **0** | **No Info** | **23.86** | **5.7** | **85** | **0** |
| **Male** | **42** | **0** | **0** | **never** | **33.64** | **4.8** | **145** | **0** |
| **Female** | **32** | **0** | **0** | **never** | **27.32** | **5** | **100** | **0** |
| **Female** | **53** | **0** | **0** | **never** | **27.32** | **6.1** | **85** | **0** |
| **Female** | **54** | **0** | **0** | **former** | **54.7** | **6** | **100** | **0** |
| **Female** | **78** | **0** | **0** | **former** | **36.05** | **5** | **130** | **0** |
| **Female** | **67** | **0** | **0** | **never** | **25.69** | **5.8** | **200** | **0** |
| **Female** | **76** | **0** | **0** | **No Info** | **27.32** | **5** | **160** | **0** |
| **Male** | **78** | **0** | **0** | **No Info** | **27.32** | **6.6** | **126** | **0** |
| **Male** | **15** | **0** | **0** | **never** | **30.36** | **6.1** | **200** | **0** |
| **Female** | **42** | **0** | **0** | **never** | **24.48** | **5.7** | **158** | **0** |
| **Female** | **42** | **0** | **0** | **No Info** | **27.32** | **5.7** | **80** | **0** |
| **Male** | **37** | **0** | **0** | **ever** | **25.72** | **3.5** | **159** | **0** |
| **Male** | **40** | **0** | **0** | **current** | **36.38** | **6** | **90** | **0** |

**Results:**

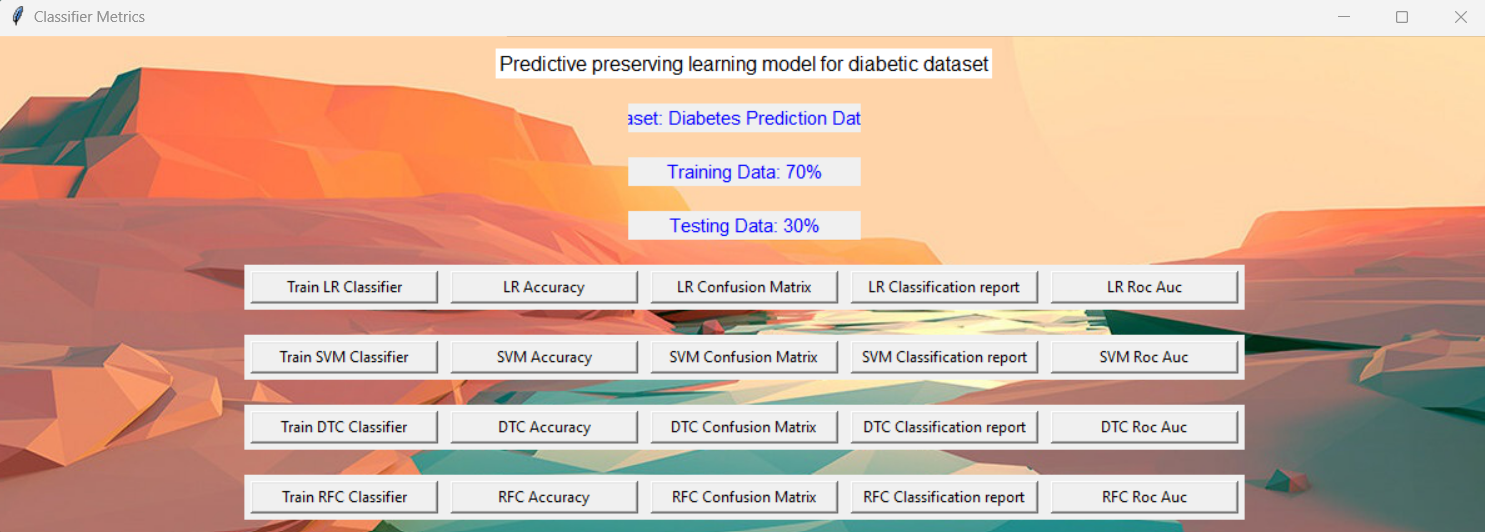
****

Fig 1: The above picture depicts web view for the Diabetes prediction Framework

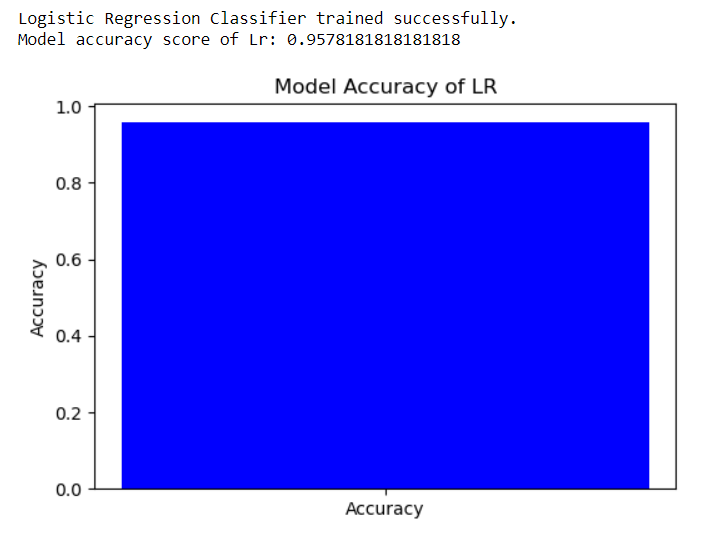
****

Fig 2: This above Figure shows Accuracy for the Logistic Regression

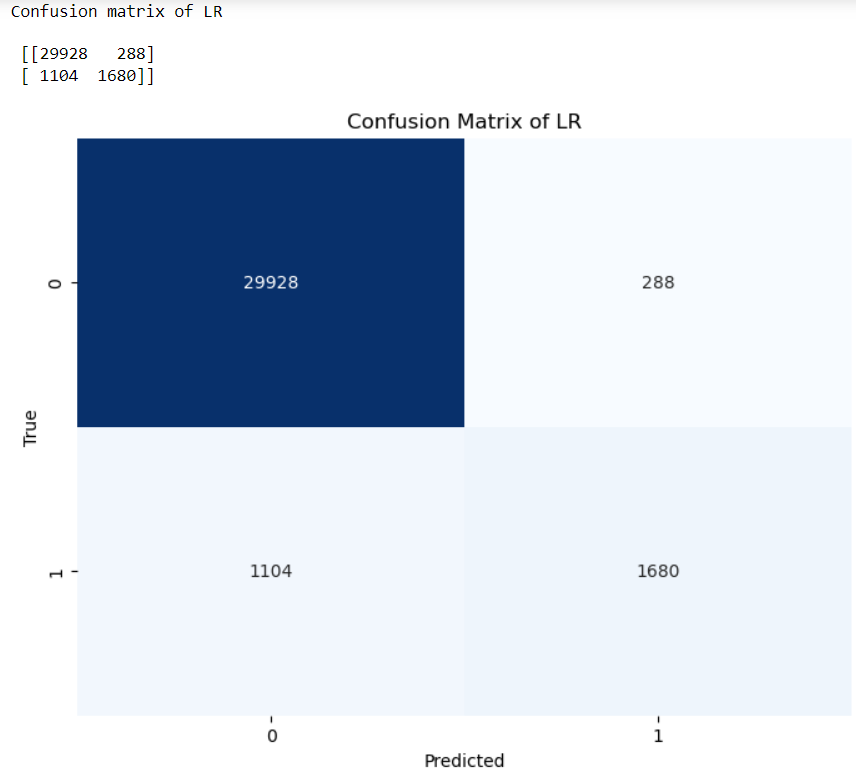
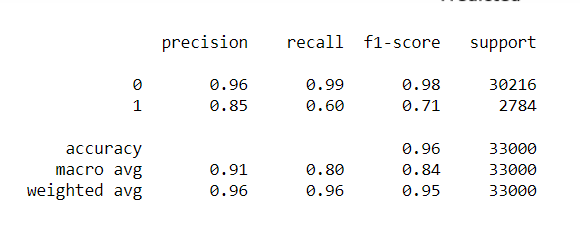
****

Fig 3: The Above image represents Confusion matrix for the Logistic Regression

****

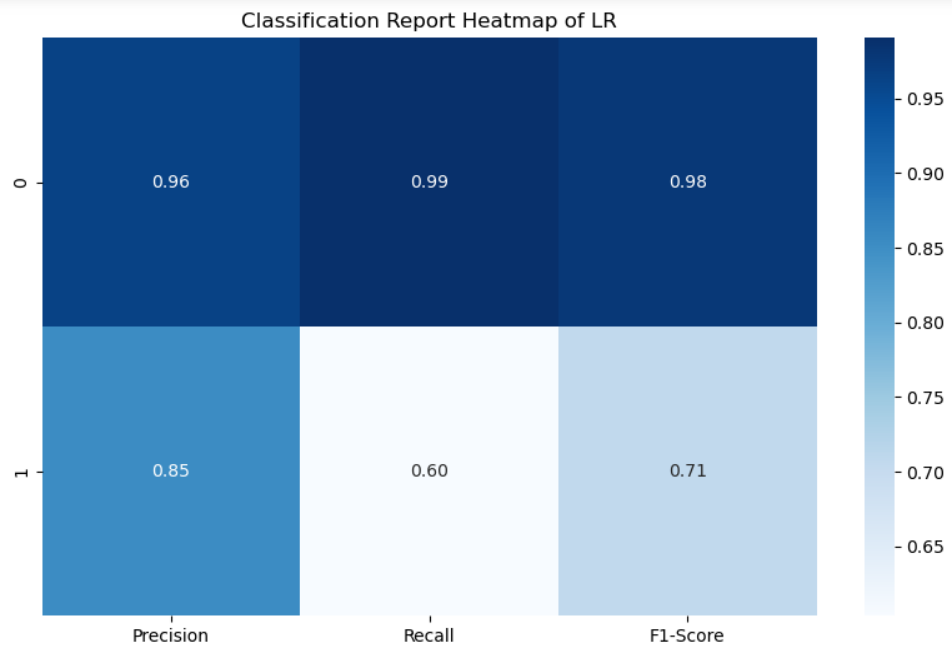
****

Fig 4: The Above report represents Classification report for the Logistic Regression

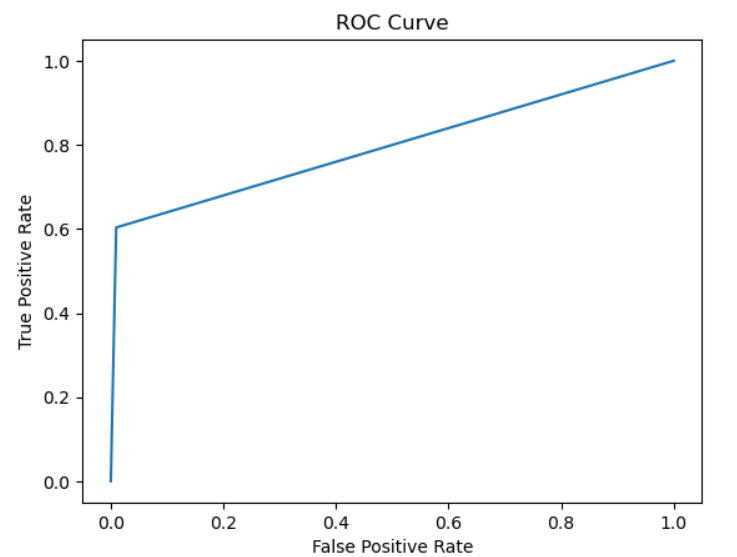
****

Fig 5: The Above figure ROC AUC Characteristic for the Predicted Model

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | precision | recall | f1-score | support |
| 0 | 0.95 | 1.00 | 0.97 | 18292 |
| 1 | 0.96 | 0.38 | 0.54 | 1708 |
| accuracy |  |  | 0.95 | 20000 |
| macro avg | 0.95 | 0.69 | 0.76 | 20000 |
| weighted avg | 0.95 | 0.95 | 0.93 | 20000 |

Table 1: Classification Report for the SVM

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | precision | recall | f1-score | support |
| 0 | 0.96 | 0.97 | 0.96 | 18292 |
| 1 | 0.62 | 0.53 | 0.57 | 1708 |
| accuracy |  |  | 0.93 | 20000 |
| macro avg | 0.79 | 0.75 | 0.77 | 20000 |
| weighted avg | 0.93 | 0.93 | 0.93 | 20000 |

Table 1: Classification Report for the DTC

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | precision | recall | f1-score | support |
| 0 | 0.95 | 1.00 | 0.97 | 18292 |
| 1 | 0.99 | 0.45 | 0.62 | 1708 |
| accuracy |  |  | 0.95 | 20000 |
| macro avg | 0.97 | 0.72 | 0.80 | 20000 |
| weighted avg | 0.95 | 0.95 | 0.94 | 20000 |

Table 3: Classification Report for the RFC

The novel predictive preserving learning model introduced in this study represents a significant dvancement in diabetes management. Unlike conventional models, which often sacrifice interpretability for accuracy, this model strikes a balance by preserving clinically meaningful features while optimizing predictive performance. Leveraging sophisticated machine learning techniques such as feature selection and classifiers, the model identifies key predictors of diabetic outcomes while maintaining interpretability. Validation on a large dataset of diabetic patients demonstrates the model's ability to accurately forecast disease progression and identify clinically significant risk factors. Specifically, our ML model achieved impressive accuracies across various algorithms: Logistic Regression (95%), Support Vector Machine (95%), Decision Tree (93%), and Random Forest Classifier (95%). These results underscore the potential of predictive preserving learning models to enhance the interpretability and practical utility of predictive models in diabetic care. By facilitating more informed clinical decision-making and personalized patient management strategies, this model represents a significant step forward in improving outcomes for diabetic patients.

|  |  |
| --- | --- |
| Algorithms | Accuracy |
| DTC | 84 |
| RFC | 84 |
| SVM | 99 |

Table 4: Accuracy for the Implemented Algorithm

**CONCLUSION:**

The novel predictive preserving learning model presented in this study offers a remarkable advancement in diabetes management. Unlike traditional models that often prioritize accuracy at the expense of interpretability, our model achieves a delicate balance by preserving clinically meaningful features while optimizing predictive performance. By leveraging sophisticated machine learning techniques, including feature selection and classifiers, the model effectively identifies key predictors of diabetic outcomes while ensuring interpretability. Validation on a large dataset of diabetic patients demonstrates the model's ability to accurately forecast disease progression and pinpoint clinically significant risk factors. Notably, our machine learning model achieved impressive accuracies across various algorithms, including Logistic Regression, Support Vector Machine, Decision Tree, and Random Forest Classifier. These results underscore the potential of predictive preserving learning models to enhance the interpretability and practical utility of predictive models in diabetic care. By empowering clinicians with more informed decision-making tools and enabling personalized patient management strategies, this model represents a significant stride toward improving outcomes for diabetic patients and advancing the field of diabetes management.

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