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MACHINE LEARNING
(CBCS – MDA 471)

Continuous Internal Assessment - 2
Classification using Ensemble Methods

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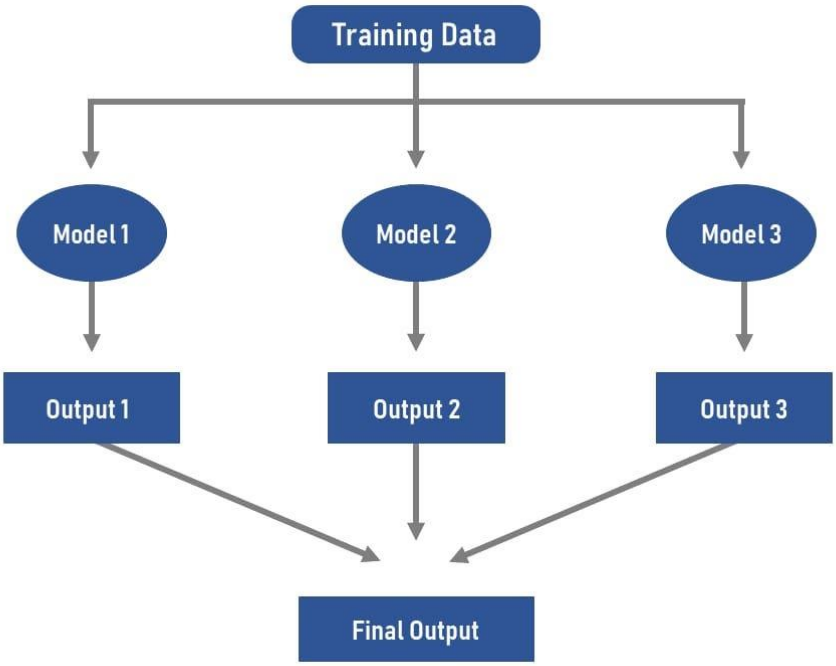
CLASSIFICATION USING ENSEMBLE TECHNIQUES

Ensemble techniques are a class of machine learning methods that combine the predictions of multiple base models (learners) to produce a single, more accurate prediction. The idea behind ensemble techniques is that by aggregating the opinions of multiple models, the ensemble can often achieve better performance than any individual model. Ensemble techniques are widely used in machine learning and are effective in improving the robustness and generalization of models.

Characteristics of Ensemble Techniques

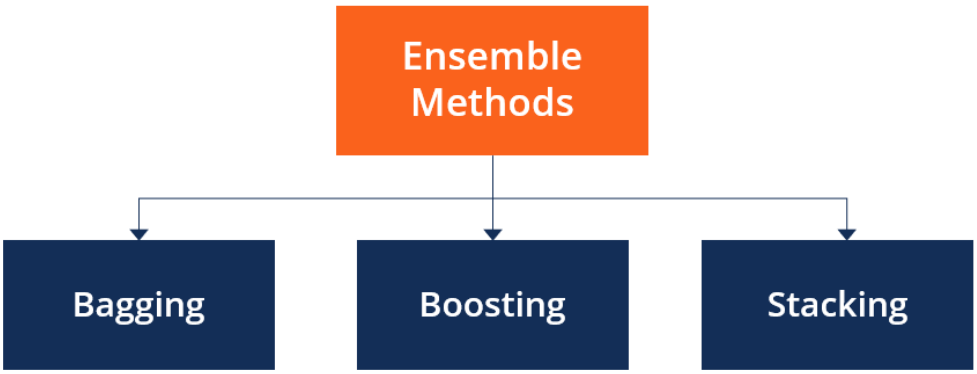
- **Base Models (Learners):** These are the individual models that make up the ensemble. They can be any machine learning algorithms, such as decision trees, support vector machines, or neural networks.
- **Aggregation:** Ensemble techniques use different aggregation methods to combine the predictions of base models. The choice of aggregation method depends on the type of ensemble technique being used.
- **Diversity:** A critical factor in the success of ensemble techniques is the diversity of base models. Diverse models make different errors on different parts of the data, and when combined, they can compensate for each other's weaknesses.



Pipeline of Ensemble Techniques

Types of Ensemble Techniques

There are several ensemble techniques, and they can be broadly categorized into three main types:



Bagging (Bootstrap Aggregating):

Bagging is an ensemble technique that aims to reduce the variance of a base model by training multiple instances of the model on bootstrapped subsets of the training data and then aggregating their predictions.

Key Characteristics:

- Base models are trained independently on random subsets of the training data.
- Typically, the subsets are generated by randomly sampling the training data with replacement (bootstrap samples).
- Predictions from individual models are combined through majority voting (for classification) or averaging (for regression).
- Bagging helps to reduce overfitting and improve model stability.
- Examples of bagging algorithms include Random Forest and Bagged Decision Trees.

Random Forest:

- Random Forest is a popular bagging algorithm that uses a collection of decision trees as base models.
- Each decision tree is trained on a different bootstrap sample of the data.
- During tree construction, a random subset of features is considered at each split, adding an extra layer of randomness.
- The final prediction is made by averaging the predictions of all the trees (regression) or taking a majority vote (classification).

Boosting:

Boosting is an ensemble technique that combines multiple weak base models sequentially, with each model focusing on correcting the mistakes made by its predecessor

Key Characteristics:

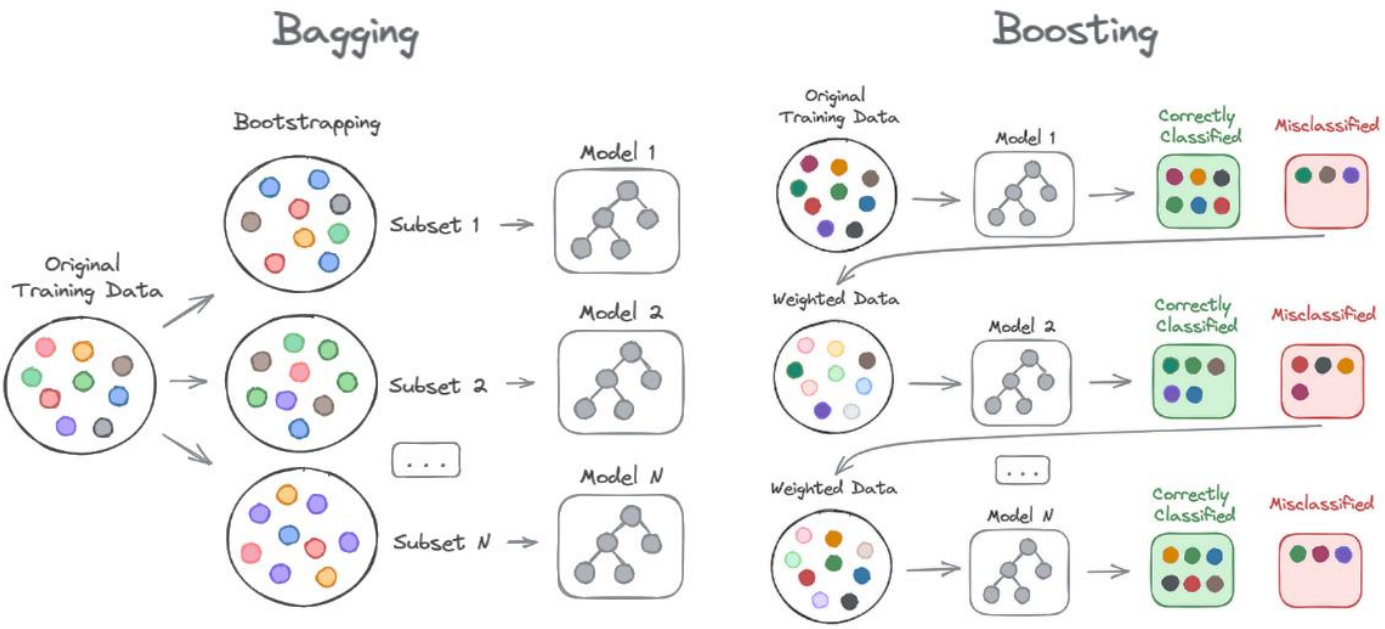
- Base models are trained iteratively, with each subsequent model giving more weight to the misclassified instances from the previous round.
- The final prediction is often a weighted sum of individual model predictions.
- Boosting aims to reduce bias and improve model accuracy.
- It is sensitive to outliers and noisy data.
- Example Algorithms: AdaBoost, Gradient Boosting, XGBoost

AdaBoost (Adaptive Boosting):

- AdaBoost is one of the earliest boosting algorithms.
- Base models (often shallow decision trees or "stumps") are trained sequentially.
- Misclassified instances are assigned higher weights, so subsequent models focus on these instances.
- The final prediction is a weighted combination of individual model predictions.

Gradient Boosting:

- Gradient Boosting builds an ensemble of decision trees sequentially.
- It uses gradient descent to minimize a loss function, such as mean squared error (for regression) or log loss (for classification).
- Trees are added iteratively, with each tree addressing the residuals (errors) of the previous trees.
- Gradient Boosting is known for its high predictive accuracy.



Stacking (Stacked Generalization):

Stacking is an ensemble technique that combines the predictions of multiple base models by training a meta-model on top of their predictions.

Key Characteristics:

- Base models make predictions independently.
- A meta-model (often a linear regression or neural network) is trained on the predictions of base models as features.
- Stacking allows models with diverse strengths to complement each other.
- It can involve multiple layers of base models and meta-models.
- Example Algorithm: Stacking with Regression

Stacking with Regression:

- Here, multiple regression models (e.g., linear regression, support vector regression) serve as base models.
- Each base model makes predictions on the same dataset.
- A higher-level meta-regression model is trained on the base models' predictions to make the final prediction.

Advantages of using Ensemble Techniques

- **Improved Accuracy:** Ensemble techniques can significantly improve predictive accuracy compared to using a single model.
- **Reduced Overfitting:** Ensembles can help reduce overfitting because they rely on the consensus of multiple models rather than a single model's predictions.
- **Robustness:** Ensembles are more robust to noisy data and outliers because they can "smooth out" individual model errors.
- **Generalization:** Ensembles tend to generalize well to new, unseen data.

Challenges and Considerations

- **Computational Cost:** Training multiple models and aggregating their predictions can be computationally expensive.
- **Interpretability:** Ensembles can be more challenging to interpret compared to individual models.
- **Hyperparameter Tuning:** Ensembles often have more hyperparameters to tune, making the optimization process more complex.
- **Data Size:** Ensembles benefit from large datasets; in some cases, they may not be as effective with small datasets.

In conclusion, ensemble techniques are a powerful approach to improving the performance and robustness of machine learning models. They are widely used in practice and have contributed to the success of various machine learning applications. The choice of ensemble technique and the design of diverse base models depend on the specific problem and dataset characteristics.

Diabetes Prediction Model

Data Description

The Behavioral Risk Factor Surveillance System (BRFSS) is a health-related telephone survey that is collected annually by the CDC. Each year, the survey collects responses from over 400,000 Americans on health-related risk behaviors, chronic health conditions, and the use of preventative services. It has been conducted every year since 1984. For this project, a csv of the dataset available on Kaggle for the year 2015 was used. This original dataset contains responses from 441,455 individuals and has 330 features. These features are either questions directly asked of participants, or calculated variables based on individual participant responses.

This dataset, diabetes _ 012 _ health _ indicators _ BRFSS2015.csv, is a clean dataset of 253,680 survey responses to the CDC's BRFSS2015. The target variable Diabetes_012 has 3 classes. There is class imbalance in this dataset. This dataset has 21 feature variables

- 0 is for No Diabetes or only during pregnancy
- 1 is for Prediabetes, and
- 2 is for Diabetes.

Features - Important Risk Factors

Research in the field has identified the following as important risk factors for diabetes and other chronic illnesses like heart disease (not in strict order of importance):

- Blood Pressure (high)
- Cholesterol (high)
- Smoking
- Diabetes
- Obesity
- Age
- Sex
- Race
- Diet
- Exercise
- Alcohol Consumption
- BMI
- Household Income
- Marital Status
- Sleep
- Time since last checkup
- Education
- Health Care Coverage
- Mental Health

Here, Diabetes_012 is our target variable and we will try to predict whether a person has diabetes or not based on the 21 features using bagging, specifically the Random Forest algorithm, which is an ensemble method based on bagging.

Importing Libraries and Reading Data

In [23]:
```
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import joblib
from time import time
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import SelectFromModel
from sklearn.metrics import accuracy_score, classification_report, confusion_

# Load the dataset
data=pd.read_csv("C:/Users/rishu/OneDrive/Desktop/Divyanshi/MSc DA/Machine Le
data.head(3)
```

Out[23]:

	Diabetes_012	HighBP	HighChol	CholCheck	BMI	Smoker	Stroke	HeartDiseaseorAttack	F
0	0.0	1.0	1.0	1.0	40.0	1.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	25.0	1.0	0.0	0.0	
2	0.0	1.0	1.0	1.0	28.0	0.0	0.0	0.0	

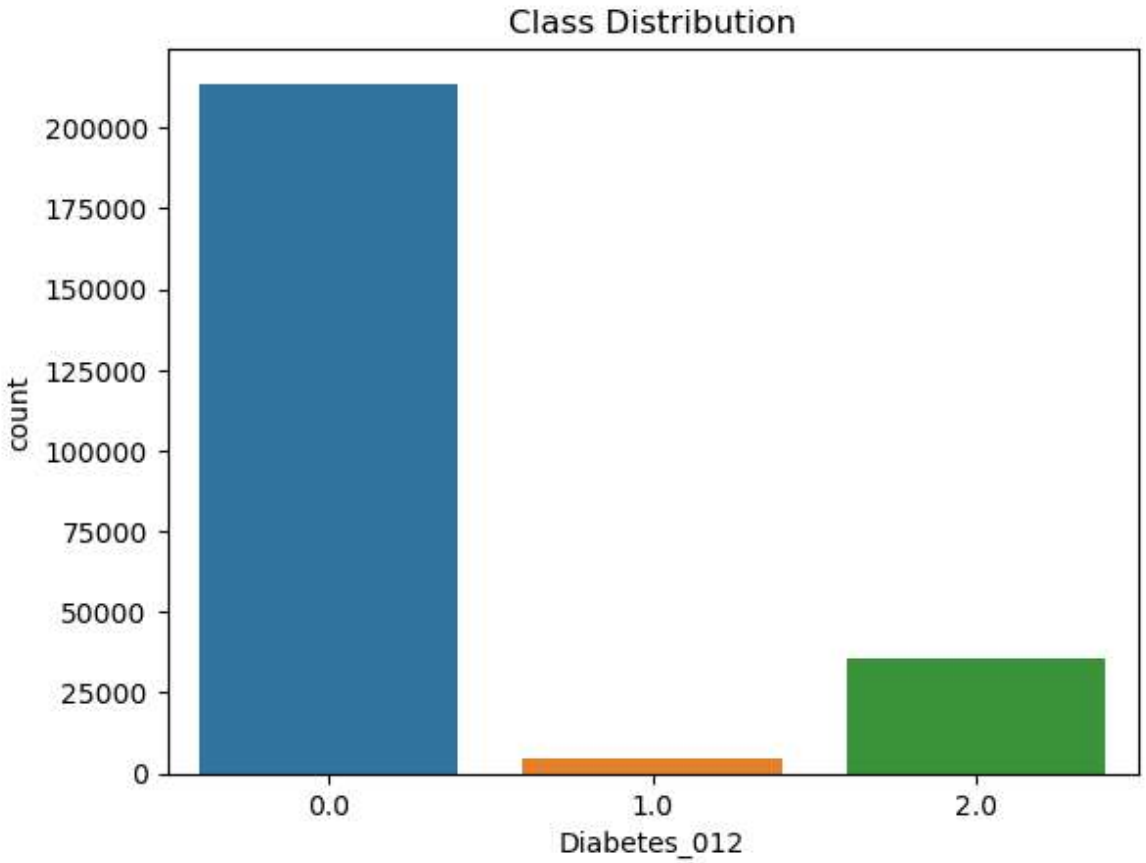
3 rows × 22 columns

Data Exploration and Visualization

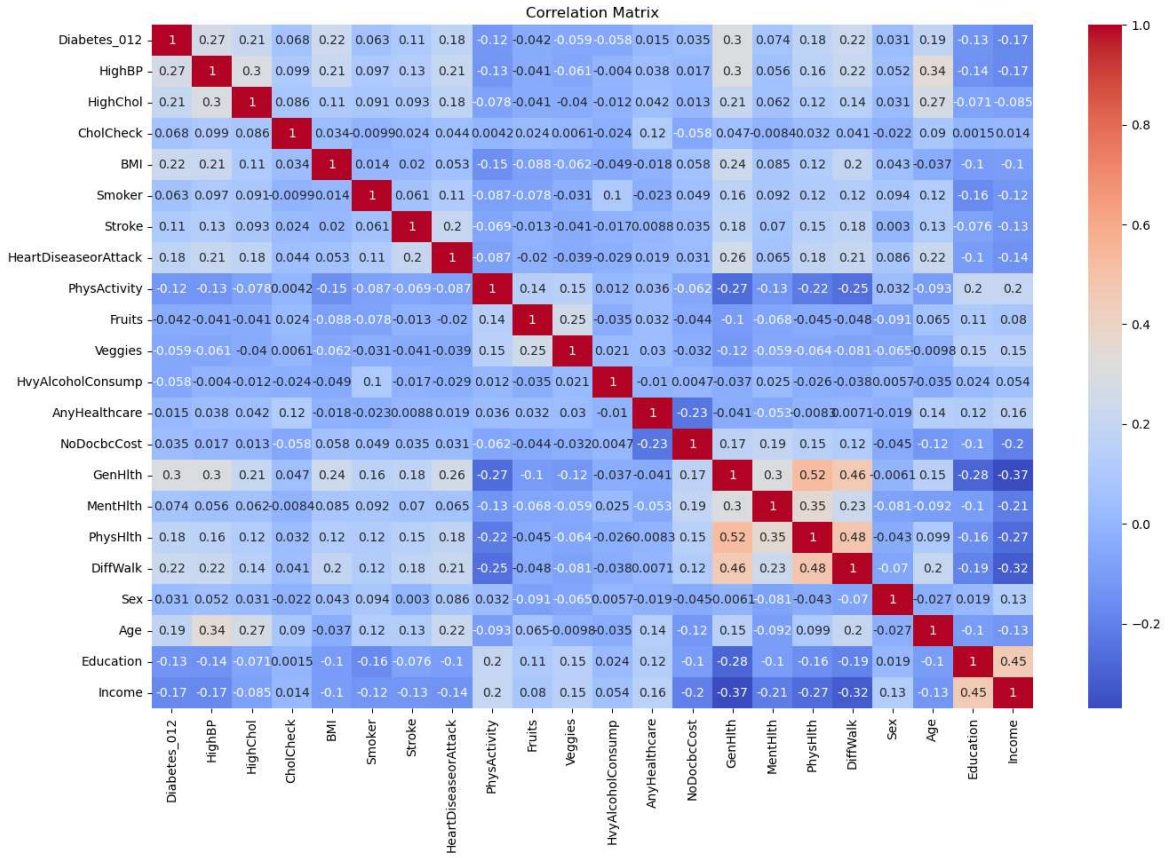
In [24]:
```
# Explore the dataset
print("Dataset Info:")
data.info()
```

```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 253680 entries, 0 to 253679
Data columns (total 22 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   Diabetes_012          253680 non-null  float64
 1   HighBP                253680 non-null  float64
 2   HighChol              253680 non-null  float64
 3   CholCheck             253680 non-null  float64
 4   BMI                   253680 non-null  float64
 5   Smoker                253680 non-null  float64
 6   Stroke                253680 non-null  float64
 7   HeartDiseaseorAttack  253680 non-null  float64
 8   PhysActivity          253680 non-null  float64
 9   Fruits                253680 non-null  float64
 10  Veggies               253680 non-null  float64
 11  HvyAlcoholConsump     253680 non-null  float64
 12  AnyHealthcare         253680 non-null  float64
 13  NoDocbcCost           253680 non-null  float64
 14  GenHlth               253680 non-null  float64
 15  MentHlth              253680 non-null  float64
 16  PhysHlth              253680 non-null  float64
 17  DiffWalk              253680 non-null  float64
 18  Sex                   253680 non-null  float64
 19  Age                   253680 non-null  float64
 20  Education             253680 non-null  float64
 21  Income                253680 non-null  float64
dtypes: float64(22)
memory usage: 42.6 MB
```

In [10]:
```
# Visualize class distribution
sns.countplot(x='Diabetes_012', data=data)
plt.title("Class Distribution")
plt.show()
```



In [13]:
```
# Visualize correlation matrix
corr_matrix = data.corr()
plt.figure(figsize=(16, 10))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title("Correlation Matrix")
plt.show()
```



Feature Selection

In [14]:
```
# Feature Selection
features = data.drop('Diabetes_012', axis=1)
labels = data['Diabetes_012']
```

In [15]:
```
# Perform feature selection using Random Forest feature importance
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)
rf_classifier.fit(features, labels)

feature_importances = pd.DataFrame({'Feature': features.columns, 'Importance'
feature_importances.sort_values(by='Importance', ascending=False, inplace=Tru
selected_features = feature_importances[feature_importances['Importance'] > 0

X_selected = features[selected_features]
```

Split into Train, Test and Validation Sets

In [16]:
```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features, labels, test_si
X_val, X_test, y_val, y_test = train_test_split(X_test, y_test, test_size=0.5
```

In [17]:
```
for dataset in [y_train, y_val, y_test]:
    print(round(len(dataset) / len(labels), 2))
```

```
0.6
0.2
0.2
```

Hyperparameter Tuning using Grid Search

In [18]:
```
param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

rf_classifier = RandomForestClassifier(random_state=42)
grid_search = GridSearchCV(rf_classifier, param_grid, cv=5, n_jobs=-1, verbos
grid_search.fit(X_train, y_train)

# Best hyperparameters
best_params = grid_search.best_params_
print("Best Hyperparameters:", best_params)
```

```
Fitting 5 folds for each of 54 candidates, totalling 270 fits
Best Hyperparameters: {'max_depth': None, 'min_samples_leaf': 4, 'min_sampl
es_split': 10, 'n_estimators': 200}
```

Training and Prediction

In [20]:
```
# Train the Random Forest Classifier with the best hyperparameters
rf_classifier = RandomForestClassifier(random_state=42, **best_params)
rf_classifier.fit(X_train, y_train)

# Make predictions on the validation set
rf_predictions = rf_classifier.predict(X_val)
```

Model Evaluation

In [21]:

```
# Evaluate the Random Forest Classifier on the validation set
rf_accuracy = accuracy_score(y_val, rf_predictions)
print("\nRandom Forest Classifier Accuracy on Validation Set:", rf_accuracy)
print("Classification Report on Validation Set:\n", classification_report(y_v
print("Confusion Matrix on Validation Set:\n", confusion_matrix(y_val, rf_pre
```

```
Random Forest Classifier Accuracy on Validation Set: 0.847839798170924
Classification Report on Validation Set:
               precision    recall  f1-score   support

         0.0       0.86      0.98      0.92     42704
         1.0       0.00      0.00      0.00       941
         2.0       0.56      0.16      0.25      7091

    accuracy                           0.85     50736
   macro avg       0.47      0.38      0.39     50736
weighted avg       0.80      0.85      0.81     50736

Confusion Matrix on Validation Set:
 [[41884     0   820]
 [  857     0    84]
 [ 5959     0  1132]]

C:\Users\rishu\anaconda3\Lib\site-packages\sklearn\metrics\_classification.
py:1469: UndefinedMetricWarning: Precision and F-score are ill-defined and
being set to 0.0 in labels with no predicted samples. Use `zero_division` p
arameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\rishu\anaconda3\Lib\site-packages\sklearn\metrics\_classification.
py:1469: UndefinedMetricWarning: Precision and F-score are ill-defined and
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py:1469: UndefinedMetricWarning: Precision and F-score are ill-defined and
being set to 0.0 in labels with no predicted samples. Use `zero_division` p
arameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Exporting as .pkl file

In [22]:

```
# Export the trained model as a .pkl file
model_filename = 'Diabetes_Prediction_Model.pkl'
joblib.dump(rf_classifier, model_filename)
print(f"Model saved as {model_filename}")
```

```
Model saved as Diabetes_Prediction_Model.pkl
```

Conclusion

In this notebook, we have learnt about the ensemble models namely Boosting, Bagging and Stacking. We have built a Bagging model using the Diabetes dataset and evaluated the accuracy, precision and recall of the model. From the above, we can conclude that:

1. **Accuracy**: The accuracy of the classifier on the validation set is approximately 0.848 or **84.8%**. This metric measures the overall correctness of the classifier's predictions.
2. **Classification Report**: The classification report provides additional metrics such as precision, recall, and F1-score for each class. Here's a breakdown:
    - For Class 0 (Non-diabetic):
        - Precision is approximately 0.86, which means that among the instances predicted as class 0, **86% are actually class 0.**
        - Recall is approximately 0.98, which means that among all the actual class 0.0 instances, **98% are correctly predicted as class 0.**
        - **F1-score is approximately 0.92**, which is the harmonic mean of precision and recall.
    - For Class 1 (Pre-diabetic):
        - Precision is 0.0, which means that **no instances are correctly predicted as class 1.** This might indicate an issue with class imbalance or data quality.
        - Recall is 0.0, indicating that **none of the actual class 1.0 instances are correctly predicted.**
        - **F1-score is 0.0 due to the lack of correct predictions for class 1.0.**
    - For class 2.0 (Diabetec):
        - Precision is approximately 0.56, indicating that **56% of the instances predicted as Class 2 are actually Class 2.**
        - Recall is approximately 0.16, indicating that **only 16% of the actual class 2 instances are correctly predicted.**
        - **F1-score is approximately 0.25.**
3. **Confusion Matrix**: The confusion matrix provides a detailed breakdown of true positives, true negatives, false positives, and false negatives for each class. It allows you to see how the classifier's predictions match with the actual classes.
    - For Class 0: There are 41,884 true positives (correctly predicted), 0 false positives, and 820 false negatives.
    - For Class 1: There are 0 true positives, 0 false positives, and 941 false negatives.
    - For Class 2: There are 1,132 true positives, 0 false positives, and 5,959 false negatives.

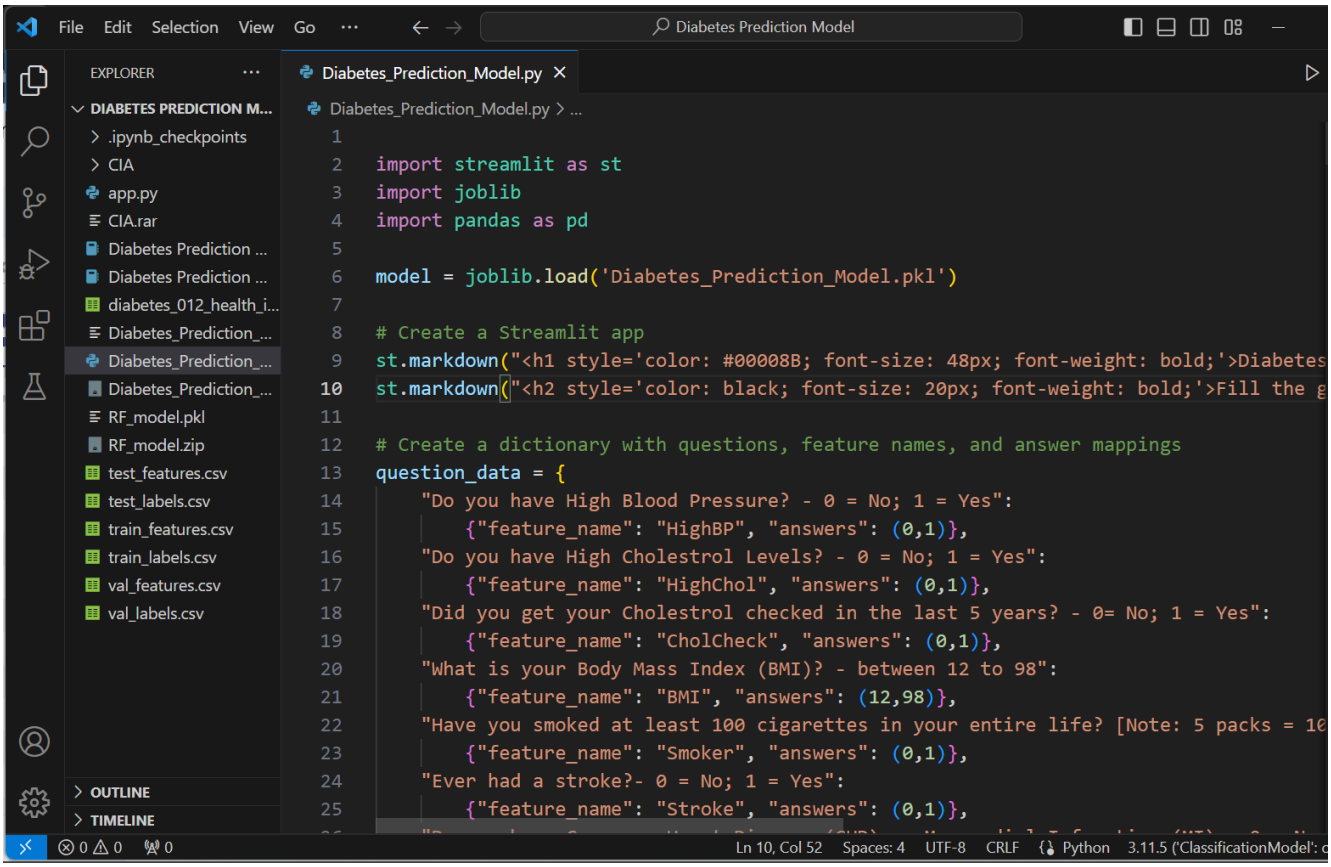
The "UndefinedMetricWarning" indicates that precision and F1-score are ill-defined for Class 1 because there are no predicted samples for this class, likely due to a lack of Class 1 instances in the validation set or an issue with class imbalance.

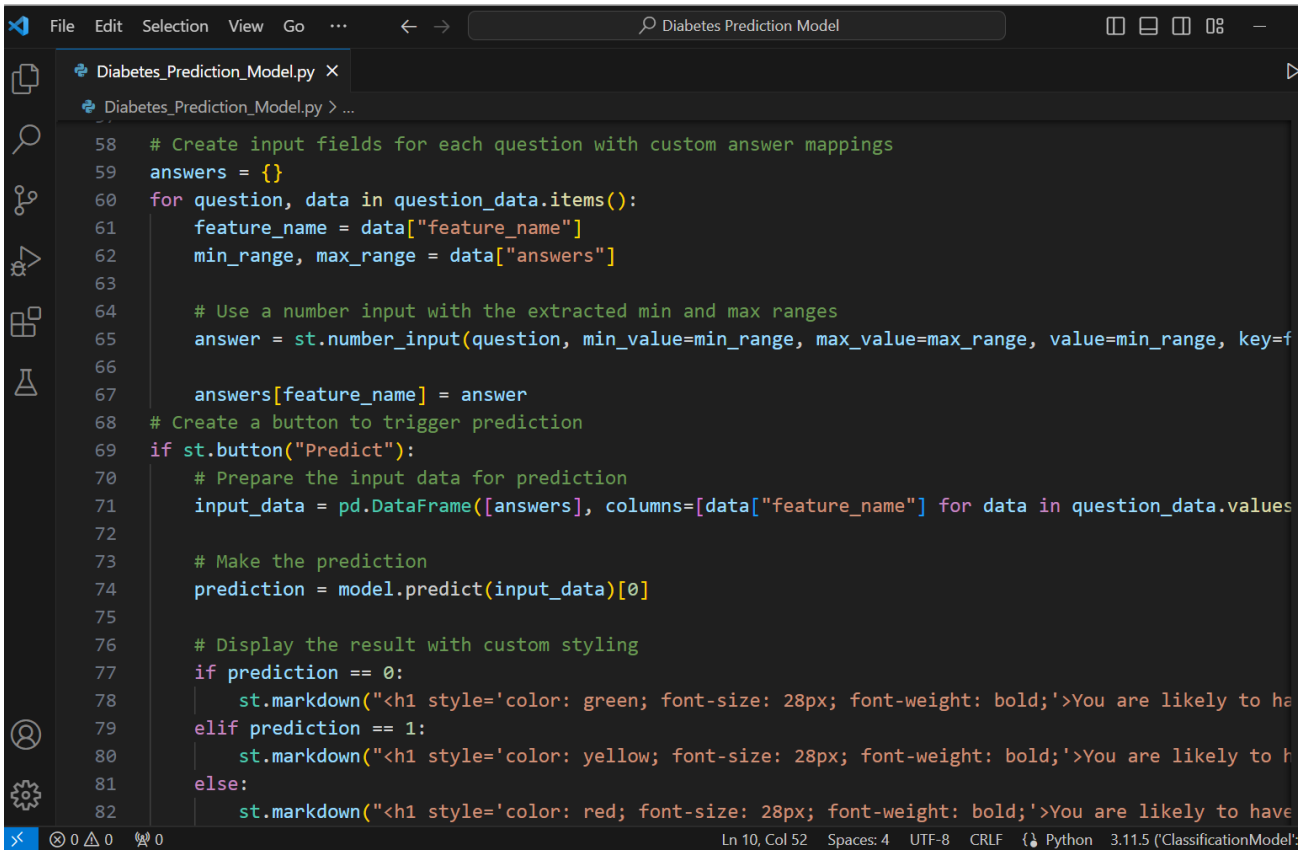
Overall, the model appears to perform well for Class 0 but struggles with Class 1, possibly due to data imbalance or data quality issues for that class. Further analysis and data preprocessing may be needed to improve performance on Class 1.

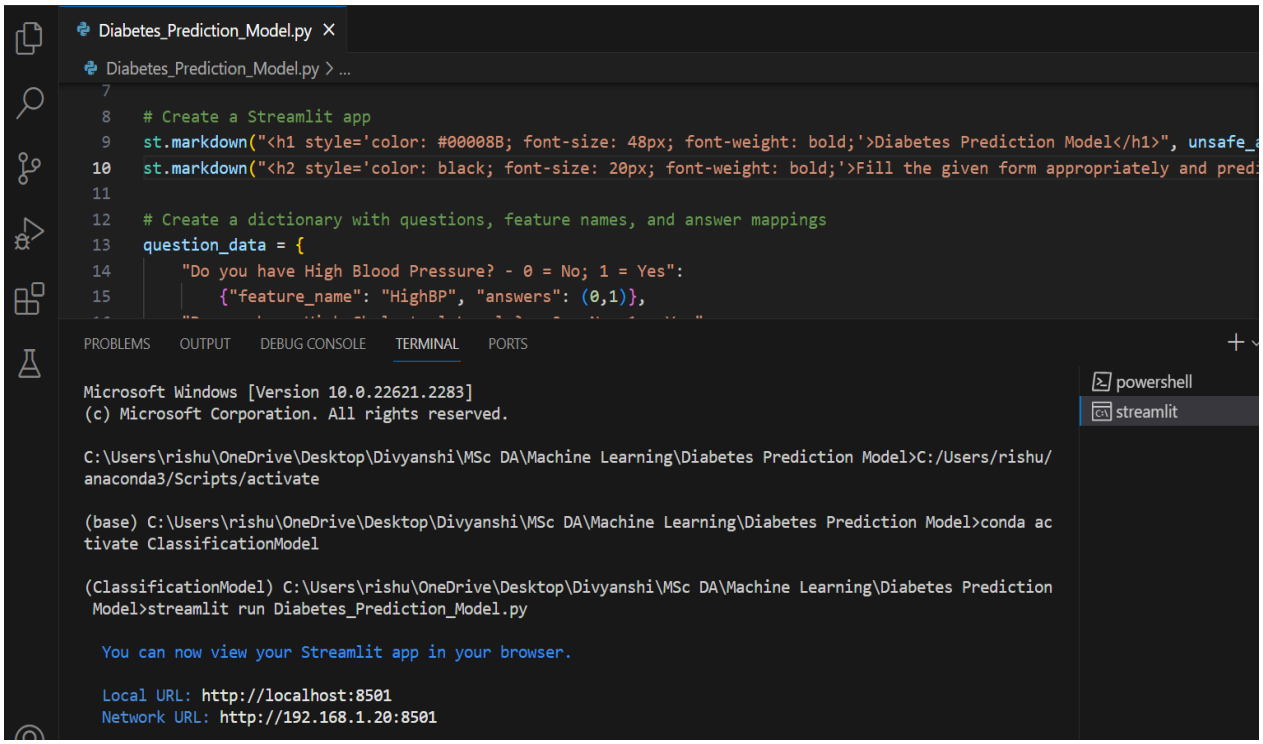
Hosting Model on Web using Streamlit

```
Step 1: Extract the Diabetes_Prediction_Model.zip file in downloads

Step 2: Open Anaconda prompt
       Creat new virtal environment
              Use following code: "conda create -n new_env"
              Activate new_env  : "activate new_env"

Step 3: Navigate to file location
       Use cd command:
"C:\Users\<user_name>\Downloads\Diabetes_Prediction_Model"

Step 4: Install Streamlit
              > pip install streamlit

Step 5: Run the web application
              > streamlit run app.py
```

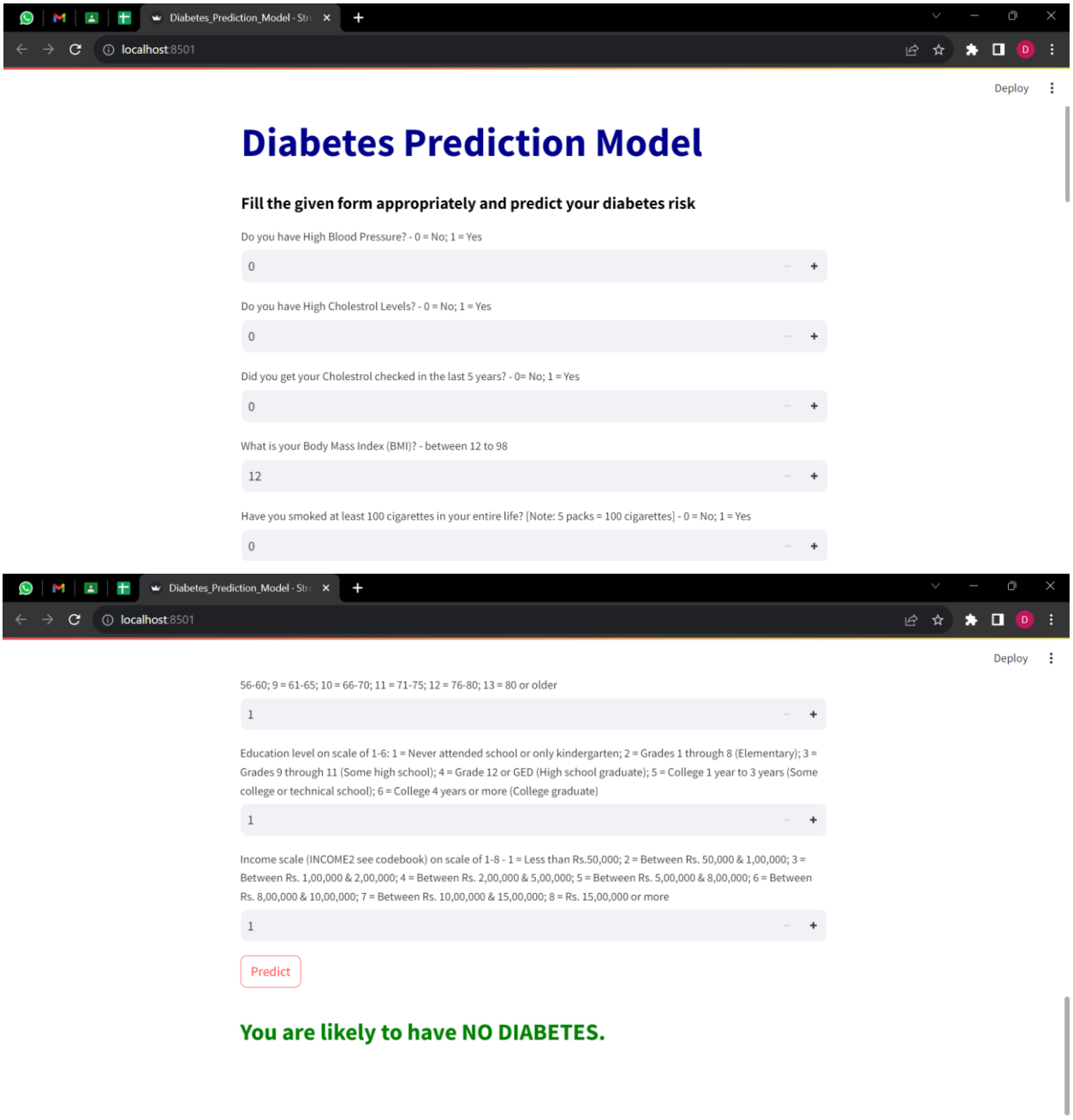
App.py File




File Edit Selection View Go ···
Diabetes Prediction Model
Diabetes_Prediction_Model.py
Diabetes_Prediction_Model.py > ...
58 # Create input fields for each question with custom answer mappings
59 answers = {}
60 for question, data in question_data.items():
61 feature_name = data["feature_name"]
62 min_range, max_range = data["answers"]
63
64 # Use a number input with the extracted min and max ranges
65 answer = st.number_input(question, min_value=min_range, max_value=max_range, value=min_range, key=f
66
67 answers[feature_name] = answer
68 # Create a button to trigger prediction
69 if st.button("Predict"):
70 # Prepare the input data for prediction
71 input_data = pd.DataFrame([answers], columns=[data["feature_name"] for data in question_data.values
72
73 # Make the prediction
74 prediction = model.predict(input_data)[0]
75
76 # Display the result with custom styling
77 if prediction == 0:
78 st.markdown("<h1 style='color: green; font-size: 28px; font-weight: bold;'>You are likely to ha
79 elif prediction == 1:
80 st.markdown("<h1 style='color: yellow; font-size: 28px; font-weight: bold;'>You are likely to h
81 else:
82 st.markdown("<h1 style='color: red; font-size: 28px; font-weight: bold;'>You are likely to have
Ln 10, Col 52 Spaces: 4 UTF-8 CRLF Python 3.11.5 ('ClassificationModel'


Diabetes_Prediction_Model.py
Diabetes_Prediction_Model.py > ...
8 # Create a Streamlit app
9 st.markdown("<h1 style='color: #00008B; font-size: 48px; font-weight: bold;'>Diabetes Prediction Model</h1>", unsafe_a
10 st.markdown("<h2 style='color: black; font-size: 20px; font-weight: bold;'>Fill the given form appropriately and predi
12 # Create a dictionary with questions, feature names, and answer mappings
13 question_data = {
14 "Do you have High Blood Pressure? - 0 = No; 1 = Yes":
15 {"feature_name": "HighBP", "answers": (0,1)},
PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS
powershell
streamlit
Microsoft Windows [Version 10.0.22621.2283]
(c) Microsoft Corporation. All rights reserved.
C:\Users\rishu\OneDrive\Desktop\Divyanshi\MSc DA\Machine Learning\Diabetes Prediction Model>C:/Users/rishu/anaconda3/Scripts/activate
(base) C:\Users\rishu\OneDrive\Desktop\Divyanshi\MSc DA\Machine Learning\Diabetes Prediction Model>conda activate ClassificationModel
(ClassificationModel) C:\Users\rishu\OneDrive\Desktop\Divyanshi\MSc DA\Machine Learning\Diabetes Prediction Model>streamlit run Diabetes_Prediction_Model.py
You can now view your Streamlit app in your browser.
Local URL: http://localhost:8501
Network URL: http://192.168.1.20:8501

Output using Streamlit



THANK YOU