Assignment -8

By aditya verma

Dataset
https://drive.google.com/file/d/1UsBPqFUirQk-nLAXKyL001jMgCnrCt-W/view?usp=classroom_web&authuser=0

Aim
To perform the task in the
https://drive.google.com/file/d/1GINuvQfwEb_5rtbhbDuk6L0Ha1L7c4cI/view?usp=classroom_web&authuser=0

Collab file link : diabetesassignment_adityaverma.ipynb

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from skimpy import skim
import missingno as msno
import plotly.express as px
from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
init_notebook_mode(connected=True)

from sklearn.model_selection import train_test_split, cross_validate, cross_val_score, GridSearchCV,
StratifiedKFold
from sklearn.compose import make_column_transformer
from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder, LabelEncoder, StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import confusion_matrix, classification_report, ConfusionMatrixDisplay, make_scorer,
roc_curve, auc, precision_recall_curve, average_precision_score
from sklearn.metrics import f1_score, accuracy_score, recall_score, precision_score, RocCurveDisplay,
PrecisionRecallDisplay
from sklearn.preprocessing import label_binarize
from itertools import cycle
from sklearn.tree import plot_tree


import warnings
warnings.filterwarnings("ignore")
warnings.warn("this will not show")
```

Read csv

read csv

```python
df =  pd.read_csv('diabetes.csv')
```

✓ 0.0s

check dataset

```python
df.head()
```

✓ 0.0s

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

checking for the null values

```python
df.isnull().sum()
```

✓ 0.0s

```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

Getting the summary of the dataset

```
skim(df)
```
✓ 0.0s

skimpy summary

Data Summary

Dataframe	Values
Number of rows	768
Number of columns	9

Data Types

Column Type	Count
int64	7
float64	2

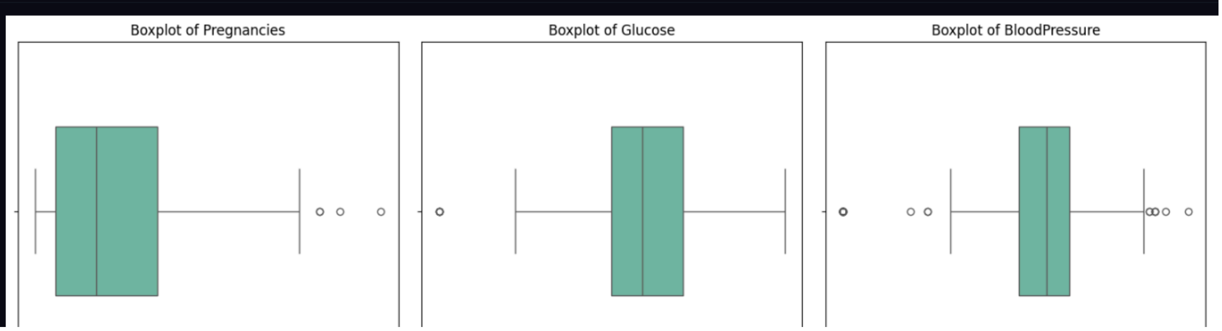
number

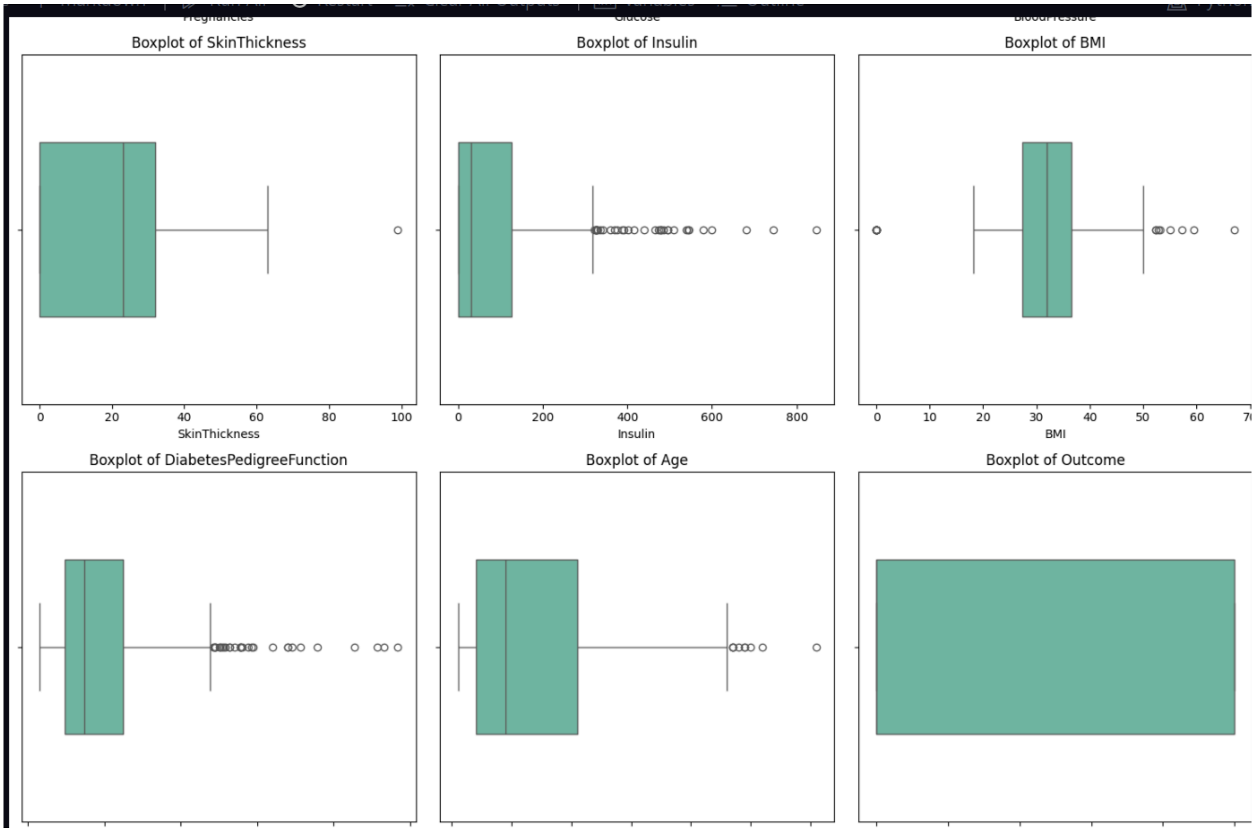
column	NA	NA %	mean	sd	p0	p25	p50	p75	p100	hist
Pregnancies	0	0	3.845	3.37	0	1	3	6	17	
Glucose	0	0	120.9	31.97	0	99	117	140.2	199	
BloodPressure	0	0	69.11	19.36	0	62	72	80	122	
SkinThickness	0	0	20.54	15.95	0	0	23	32	99	
Insulin	0	0	79.8	115.2	0	0	30.5	127.2	846	
BMI	0	0	31.99	7.884	0	27.3	32	36.6	67.1	
DiabetesPedigreeFuncti on	0	0	0.4719	0.3313	0.078	0.2437	0.3725	0.6262	2.42	
Age	0	0	33.24	11.76	21	24	29	41	81	
Outcome	0	0	0.349	0.477	0	0	0	1	1	

End

plotting histogram for all the attributes

```
numeric_cols = df.select_dtypes(include='number').columns
n_cols = 3
n_rows = (len(numeric_cols) + n_cols - 1) // n_cols
fig, axes = plt.subplots(n_rows, n_cols, figsize=(5*n_cols, 5 * n_rows))
axes = axes.flatten()
for  i , col in enumerate(numeric_cols):
    sns.boxplot(x=df[col], ax=axes[i] , palette='Set2', hue=None, width=0.5)
    axes[i].set_title(f'Boxplot of {col}')
for j in range(len(numeric_cols), len(axes)):
    fig.delaxes(axes[j])
    
plt.tight_layout()
```
✓ 1.3s





remove outliers from the whole dataset vith the median values

```python
# remove outliers fron the whole dataset
for col in numeric_cols:
    data = df[col]
    q1 = data.quantile(0.25)
    q3 = data.quantile(0.75)
    iqr = q3 - q1
    lower_bound = q1 - 1.5 * iqr
    upper_bound = q3 + 1.5 * iqr
    # Remove outliers with caps and replace them with the median
    df[col] = np.where(data < lower_bound, data.median(), df[col])
    df[col] = np.where(data > upper_bound, data.median(), df[col])
# check the shape of the dataframe after removing outliers


df.shape
```

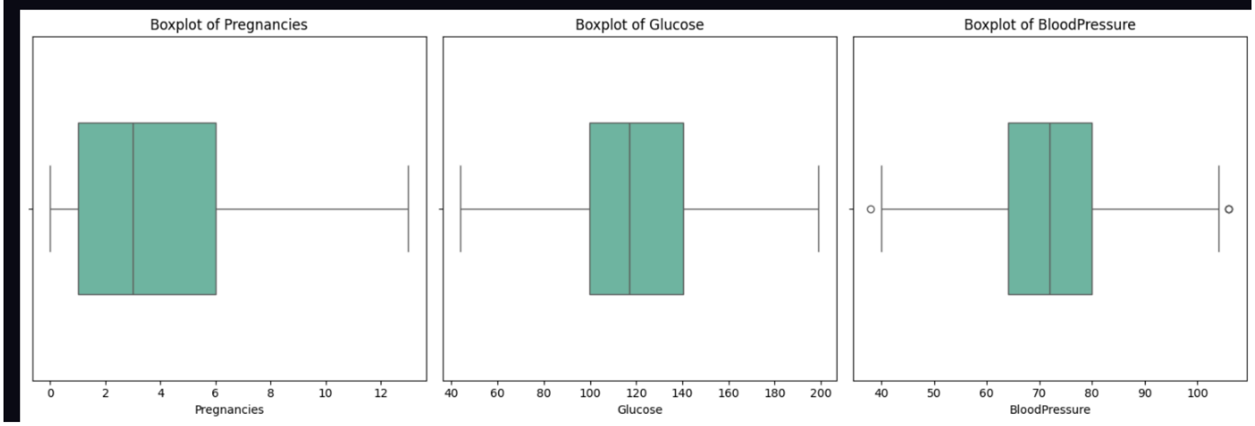
0.0s

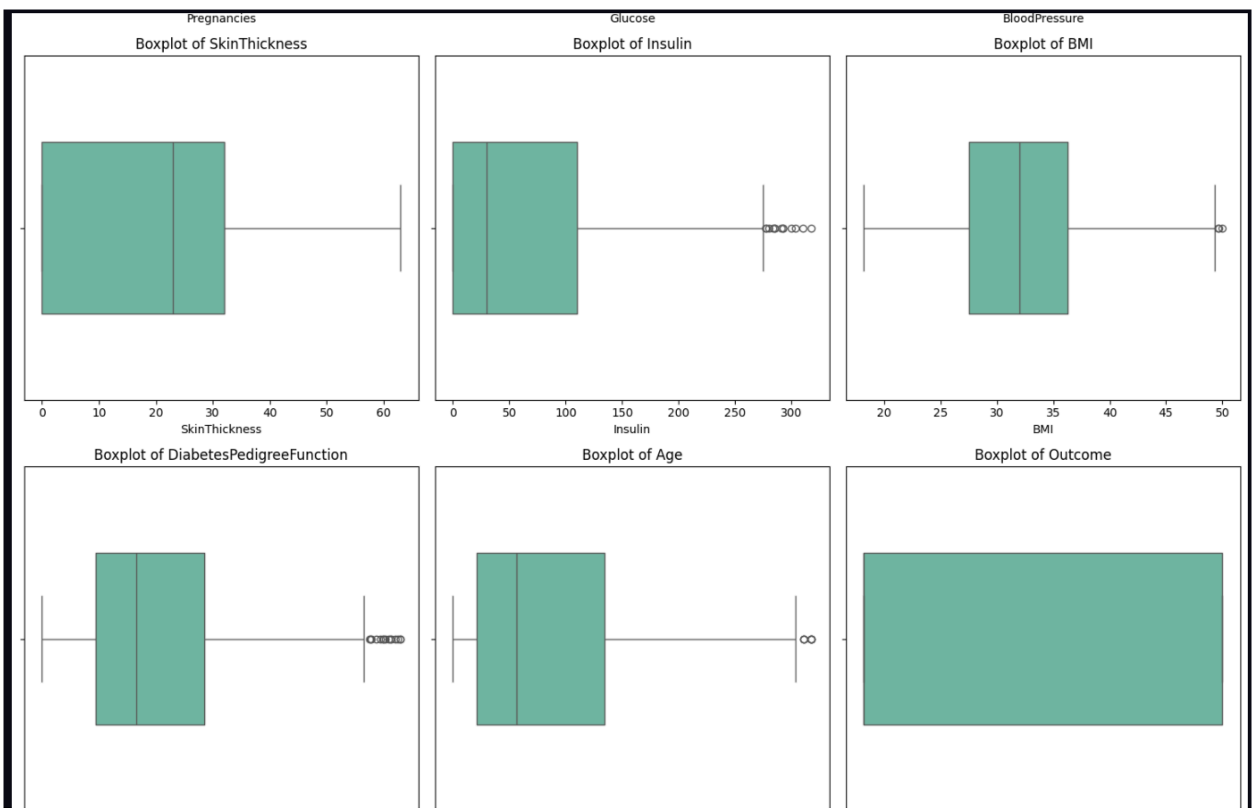
(768, 9)

+ Code + Markdown

```python
numeric_cols = df.select_dtypes(include='number').columns
n_cols = 3
n_rows = (len(numeric_cols) + n_cols - 1) // n_cols
fig, axes = plt.subplots(n_rows, n_cols, figsize=(5*n_cols, 5 * n_rows))
axes = axes.flatten()
for  i , col in enumerate(numeric_cols):
    sns.boxplot(x=df[col], ax=axes[i] , palette='Set2', hue=None, width=0.5)
    axes[i].set_title(f'Boxplot of {col}')
for j in range(len(numeric_cols), len(axes)):
    fig.delaxes(axes[j])

plt.tight_layout()
```

✓ 1.7s





plotting correlation matrics

```python
fig = px.imshow(df.corr(), text_auto=True, aspect="auto")
fig.show()
```

✓ 0.0s


```python
sns.pairplot(df, hue='Outcome', diag_kind='kde', markers=["o", "s"], height=2.5)
```

✓ 18.4s

<seaborn.axisgrid.PairGrid at 0x25ef65aa7d0>

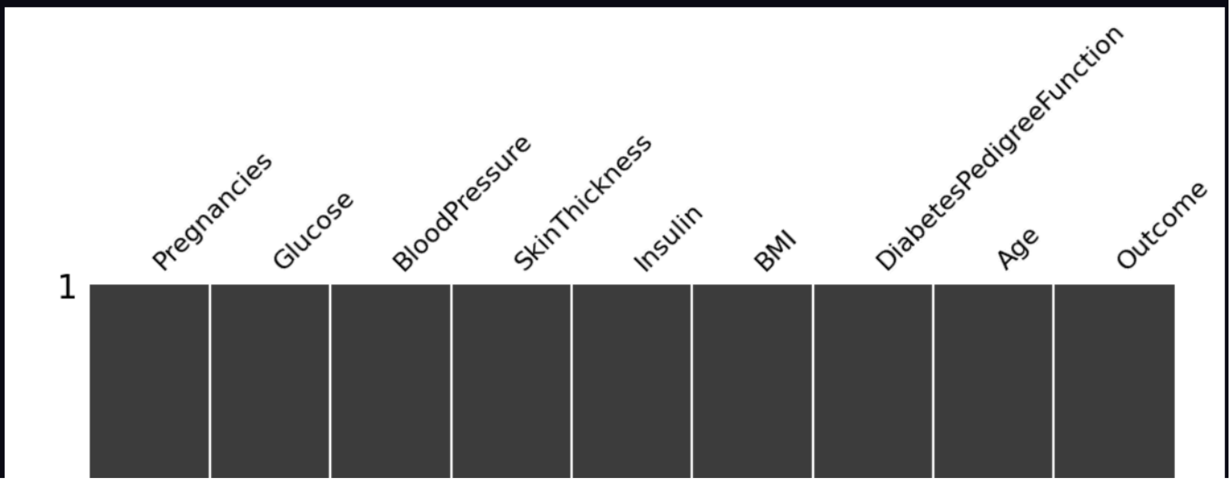
check the irregularities in the data

```python
msno.matrix(df, figsize=(12, 6), sparkline=False)
```

✓ 1.2s

Pyth

<Axes: >




```python
df.values_counts = df['Outcome'].value_counts()
print(df.values_counts)
```

✓ 0.0s

Python

```
Outcome
0.0    500
1.0    268
Name: count, dtype: int64
```

```python
df.describe()
```

✓ 0.0s

Python

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	O
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768
mean	3.782552	121.656250	72.196615	20.437500	60.919271	32.198958	0.427667	32.760417	0
std	3.270644	30.438286	11.146723	15.698554	77.635666	6.410558	0.245162	11.055385	0
min	0.000000	44.000000	38.000000	0.000000	0.000000	18.200000	0.078000	21.000000	0
25%	1.000000	99.750000	64.000000	0.000000	0.000000	27.500000	0.243750	24.000000	0
50%	3.000000	117.000000	72.000000	23.000000	29.750000	32.000000	0.371750	29.000000	0
75%	6.000000	140.250000	80.000000	32.000000	110.000000	36.300000	0.582250	40.000000	1
max	13.000000	199.000000	106.000000	63.000000	318.000000	50.000000	1.191000	66.000000	1

task 1

Train a Random Forest classifier and a Gaussian Naive Bayes model on the diabetes dataset. Compare their default accuracies using 5-fold cross-validation.

```python
# split the data into features and target variable
X = df.drop(columns=['Outcome'])
y = df['Outcome']
```

[72] ✓ 0.0s Python

```python
# split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)
```

[73] ✓ 0.0s Python

create a preprocessing pipeline

```python
# create a preprocessing pipeline
#random forest classiffier pipeline
rf_pipeline = Pipeline([('scaler', StandardScaler()),
                        ('model', RandomForestClassifier(random_state=42))])
# Gaussian Naive Bayes pipeline
nb_pipeline = Pipeline([('scaler', StandardScaler()),('model', GaussianNB())])


# evaluate  using 5-fold cross-validation
rf_scores = cross_val_score(rf_pipeline, X_train, y_train, cv=5, scoring='accuracy')
nb_scores = cross_val_score(nb_pipeline, X_train, y_train, cv=5, scoring='accuracy')
print(f"Random Forest Classifier Accuracy: {rf_scores.mean():.4f} ± {rf_scores.std():.4f}")
print(f"Gaussian Naive Bayes Accuracy: {nb_scores.mean():.4f} ± {nb_scores.std():.4f}")


# fit the models on the training data
rf_pipeline.fit(X_train, y_train)
nb_pipeline.fit(X_train, y_train)


# make predictions on the test data
rf_y_pred = rf_pipeline.predict(X_test)
nb_y_pred = nb_pipeline.predict(X_test)
```

+ Code + Markdown | Run All Restart Clear All Outputs | Variables Outline ...

```python
# evaluate the models
rf_accuracy = accuracy_score(y_test, rf_y_pred)
nb_accuracy = accuracy_score(y_test, nb_y_pred)
print(f"Random Forest Classifier Test Accuracy: {rf_accuracy:.4f}")
print(f"Gaussian Naive Bayes Test Accuracy: {nb_accuracy:.4f}")
```

[174] ✓ 1.9s

```
Random Forest Classifier Accuracy: 0.7573 ± 0.0187
Gaussian Naive Bayes Accuracy: 0.7622 ± 0.0166
Random Forest Classifier Test Accuracy: 0.7208
Gaussian Naive Bayes Test Accuracy: 0.7143
```

```python
# print classification report
print("Random Forest Classifier Classification Report:")
print(classification_report(y_test, rf_y_pred))
print("Gaussian Naive Bayes Classification Report:")
print(classification_report(y_test, nb_y_pred))
```

[175] ✓ 0.3s

```
Random Forest Classifier Classification Report:
              precision    recall  f1-score   support

         0.0       0.77      0.81      0.79       100
         1.0       0.61      0.56      0.58        54
```

Snipping Tool

Screenshot copied to clipboard
Automatically saved to screenshots f

Markup and share

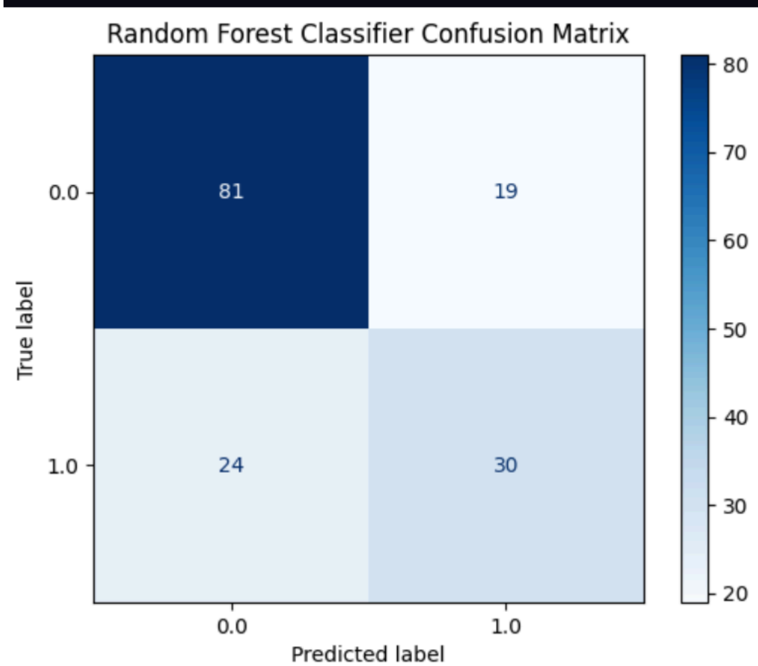

```
Random Forest Classifier Classification Report:
              precision    recall  f1-score   support

         0.0       0.77      0.81      0.79       100
         1.0       0.61      0.56      0.58        54
```

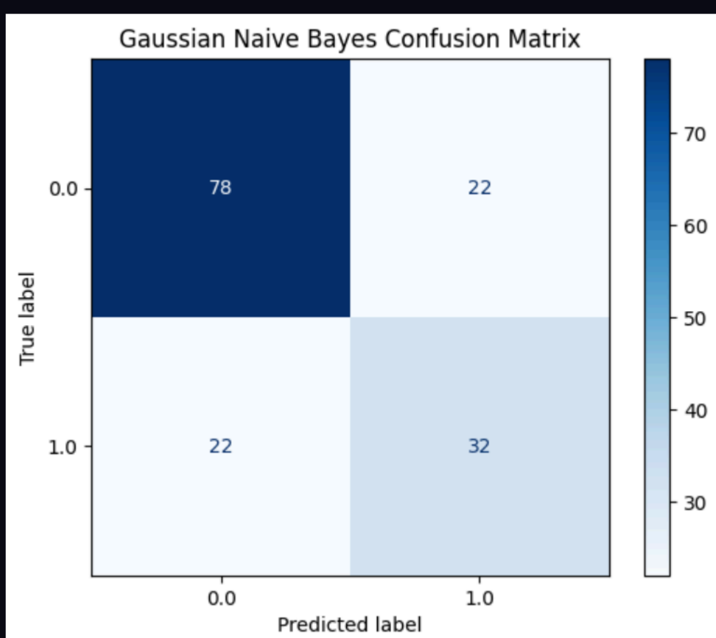

```
    accuracy                           0.72       154
   macro avg       0.69      0.68      0.69       154
weighted avg       0.72      0.72      0.72       154

Gaussian Naive Bayes Classification Report:
              precision    recall  f1-score   support

         0.0       0.78      0.78      0.78       100
         1.0       0.59      0.59      0.59        54

    accuracy                           0.71       154
   macro avg       0.69      0.69      0.69       154
weighted avg       0.71      0.71      0.71       154
```

```python
# confusion matrix
rf_cm = confusion_matrix(y_test, rf_y_pred)
nb_cm = confusion_matrix(y_test, nb_y_pred)
# plot confusion matrix for Random Forest Classifier
rf_disp = ConfusionMatrixDisplay(confusion_matrix=rf_cm, display_labels=rf_pipeline.classes_)
rf_disp.plot(cmap=plt.cm.Blues)
plt.title("Random Forest Classifier Confusion Matrix")
```

```
nb_disp = ConfusionMatrixDisplay(confusion_matrix=nb_cm, display_labels=nb_pipeline.classes_)
nb_disp.plot(cmap=plt.cm.Blues)
plt.title("Gaussian Naive Bayes Confusion Matrix")
plt.show()
```

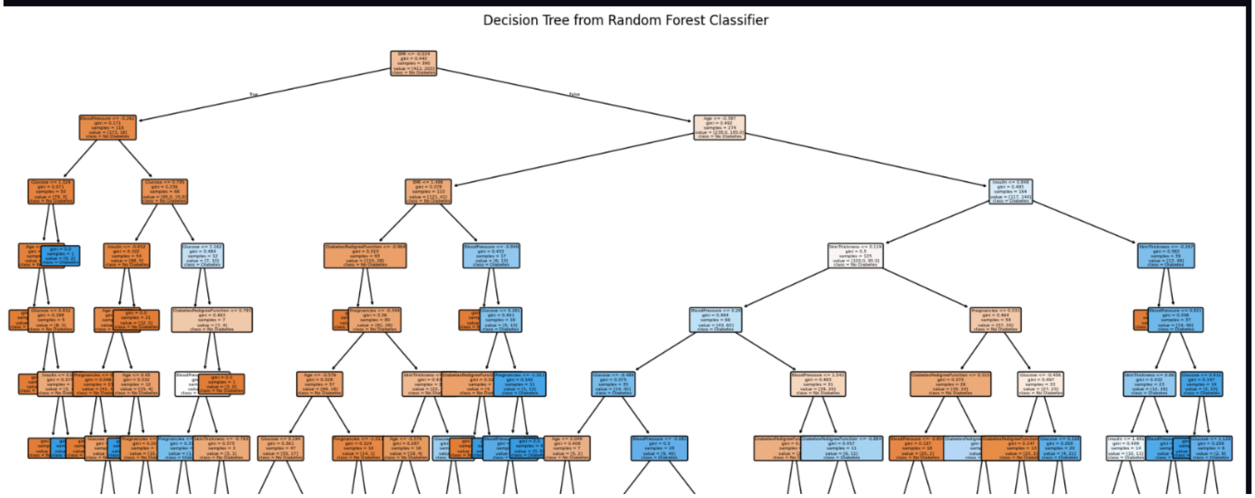
✓ 0.3s





```python
# PLOT A TEREE FOR RANDOM FOREST CLASSIFIER
plt.figure(figsize=(20, 15))
plot_tree(rf_pipeline.named_steps['model'].estimators_[0],
          feature_names=X.columns,
          class_names=['No Diabetes', 'Diabetes'],
          filled=True,
          rounded=True, fontsize=4)
plt.title("Decision Tree from Random Forest Classifier")
plt.show()
```

✓ 6.9s



Task-2

Identify the top 3 most important features using Random Forest and visualize their importance.

```python
importances = rf_pipeline.named_steps['model'].feature_importances_
feature_names = X_train.columns
feat_imp_df = pd.DataFrame({'Feature': feature_names, 'Importance': importances})
```

✓ 0.0s

```python
feat_imp_df
```

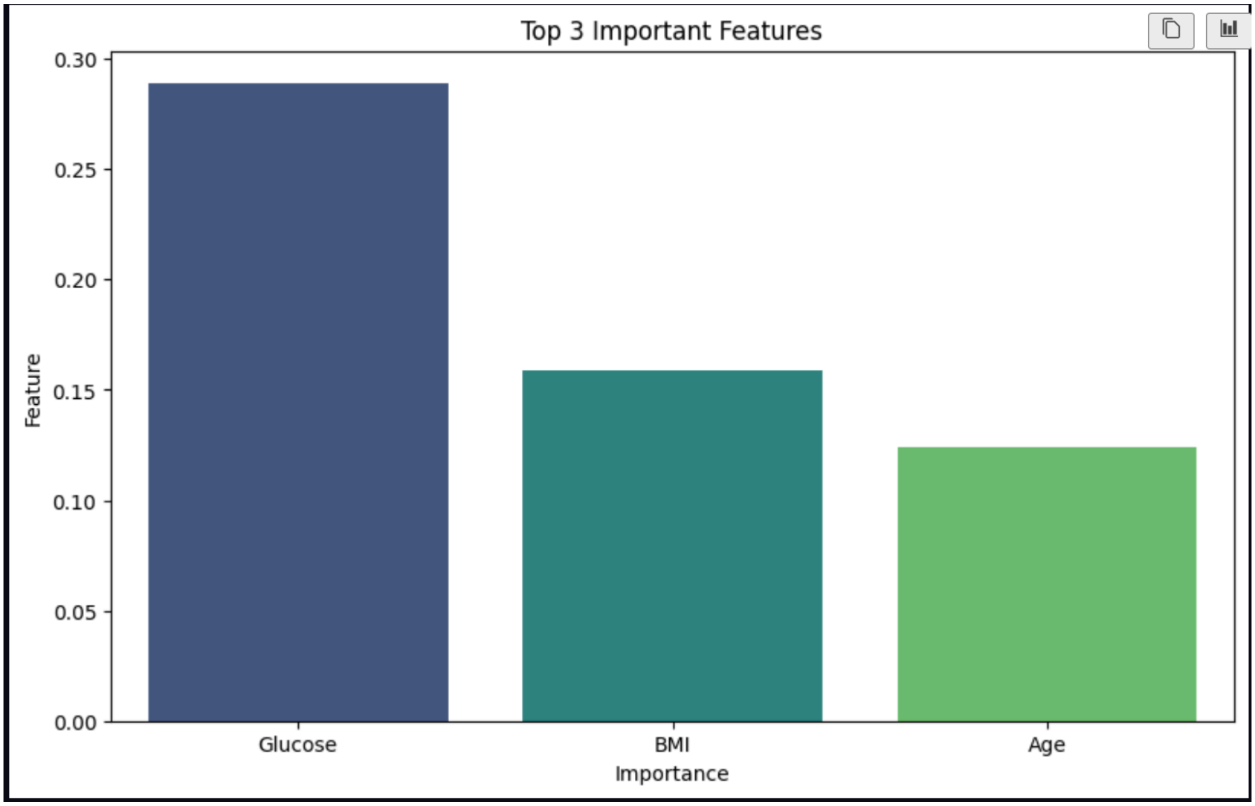
✓ 0.0s

	Feature	Importance
0	Pregnancies	0.084115
1	Glucose	0.289070
2	BloodPressure	0.084480
3	SkinThickness	0.075626
4	Insulin	0.064587
5	BMI	0.158495
6	DiabetesPedigreeFunction	0.119689
7	Age	0.123937

```python
top_3 = feat_imp_df.sort_values(by='Importance', ascending=False).head(3)
print(top_3)
plt.figure(figsize=(10, 6))
sns.barplot(y='Importance', x='Feature', data=top_3, palette='viridis')
plt.title('Top 3 Important Features')
plt.xlabel('Importance')
plt.ylabel('Feature')
```

✓ 0.3s Python

```
   Feature  Importance
1  Glucose    0.289070
5      BMI    0.158495
7      Age    0.123937

Text(0, 0.5, 'Feature')
```



Task-3

Use GridSearchCV to find the best hyperparameters (n_estimators, max_depth, min_samples_split) for Random Forest.

```
progam_grid ={
    'model__n_estimators': [50, 100, 150],
    'model__max_depth': [None, 10, 20],
    'model__min_samples_split': [2, 5, 10],

}

grid_search = GridSearchCV(estimator=rf_pipeline, param_grid=progam_grid, cv=5, scoring='accuracy', n_jobs=-1)
grid_search.fit(X_train, y_train)
```

✓ 29.6s Python

```
GridSearchCV

best_estimator_: Pipeline

StandardScaler
StandardScaler()

RandomForestClassifier
RandomForestClassifier(max_depth=10, min_samples_split=10, random_state=42)
```

```
#print the best parameters and score
print("Best Parameters:", grid_search.best_params_)
print("Best Score:", grid_search.best_score_)
```

✓ 0.0s Python

```
Best Parameters: {'model__max_depth': 10, 'model__min_samples_split': 10, 'model__n_estimators': 100}
Best Score: 0.7817672930827668
```

Task-4

The diabetes dataset is imbalanced. Modify the Random Forest to handle this using class_weight='balanced' and compare results.

```
def eval_metric(model, X_train, y_train, X_test, y_test):
    y_train_pred = model.predict(X_train)
    y_pred = model.predict(X_test)
    print("Test_Set")
    print(confusion_matrix(y_test, y_pred))
    print(classification_report(y_test, y_pred))
    print()
    print("Train_Set")
    print(confusion_matrix(y_train, y_train_pred))
    print(classification_report(y_train, y_train_pred))
```

✓ 0.0s Python

```
eval_metric(rf_pipeline, X_train, y_train, X_test, y_test,)
```

```python
eval_metric(rf_pipeline, X_train, y_train, X_test, y_test,)
```

✓ 0.1s

```
Test_Set
[[81 19]
 [24 30]]
              precision    recall  f1-score   support

         0.0       0.77      0.81      0.79       100
         1.0       0.61      0.56      0.58        54

    accuracy                           0.72       154
   macro avg       0.69      0.68      0.69       154
weighted avg       0.72      0.72      0.72       154


Train_Set
[[400   0]
 [  0 214]]
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00       400
         1.0       1.00      1.00      1.00       214

    accuracy                           1.00       614
   macro avg       1.00      1.00      1.00       614
weighted avg       1.00      1.00      1.00       614
```

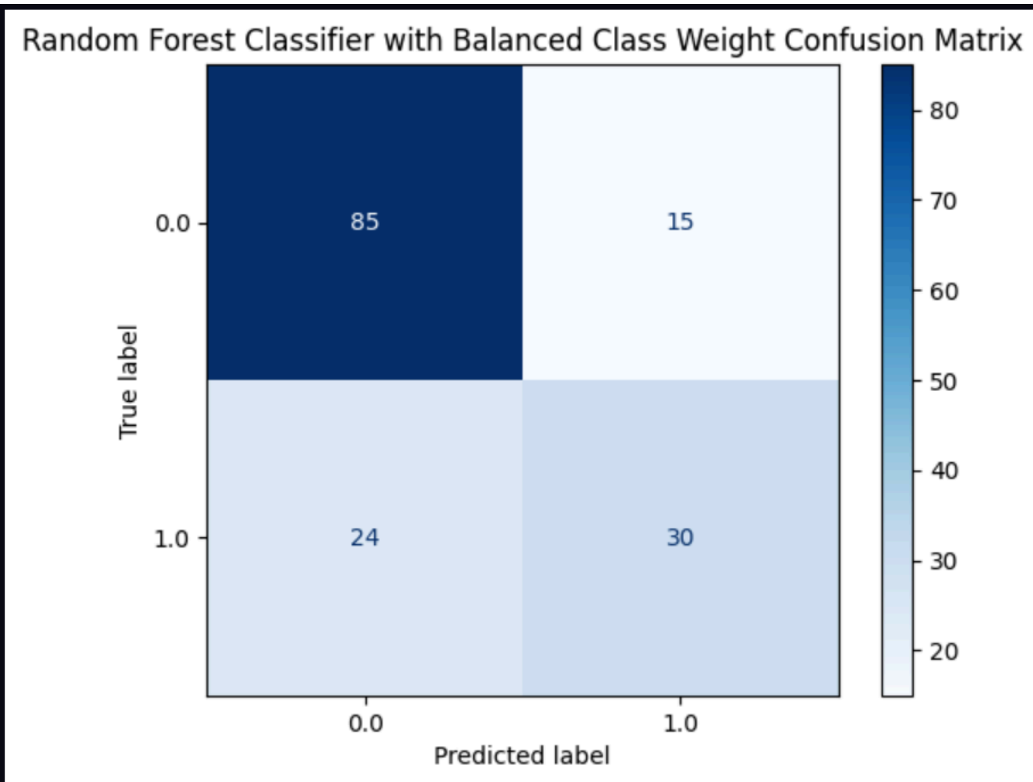
```python
rf_balanced = RandomForestClassifier(class_weight='balanced', random_state=42)
rf_balanced_pipeline = Pipeline([('scaler', StandardScaler()),
                                  ('model', rf_balanced)])
rf_balanced_pipeline.fit(X_train, y_train)
rf_balanced_y_pred = rf_balanced_pipeline.predict(X_test)

rf_balaced_cross_val_scores = cross_val_score(rf_balanced_pipeline, X_train, y_train, cv=5, scoring='accuracy')
print(f"Random Forest Classifier with Balanced Class Weight Cross-Validation Accuracy:
{rf_balaced_cross_val_scores.mean():.4f} ± {rf_balaced_cross_val_scores.std():.4f}")


rf_balanced_accuracy = accuracy_score(y_test, rf_balanced_y_pred)
print(f"Random Forest Classifier with Balanced Class Weight Test Accuracy: {rf_balanced_accuracy:.4f}")
```

✓ 3.4s Python

```
Random Forest Classifier with Balanced Class Weight Cross-Validation Accuracy: 0.7427 ± 0.0234
Random Forest Classifier with Balanced Class Weight Test Accuracy: 0.7468
```

```python
rf_balanced_cm = confusion_matrix(y_test, rf_balanced_y_pred)
rf_balanced_disp = ConfusionMatrixDisplay(confusion_matrix=rf_balanced_cm, display_labels=rf_balanced_pipeline.
classes_)
rf_balanced_disp.plot(cmap=plt.cm.Blues)
plt.title("Random Forest Classifier with Balanced Class Weight Confusion Matrix")
plt.show()
```

✓ 0.4s Python

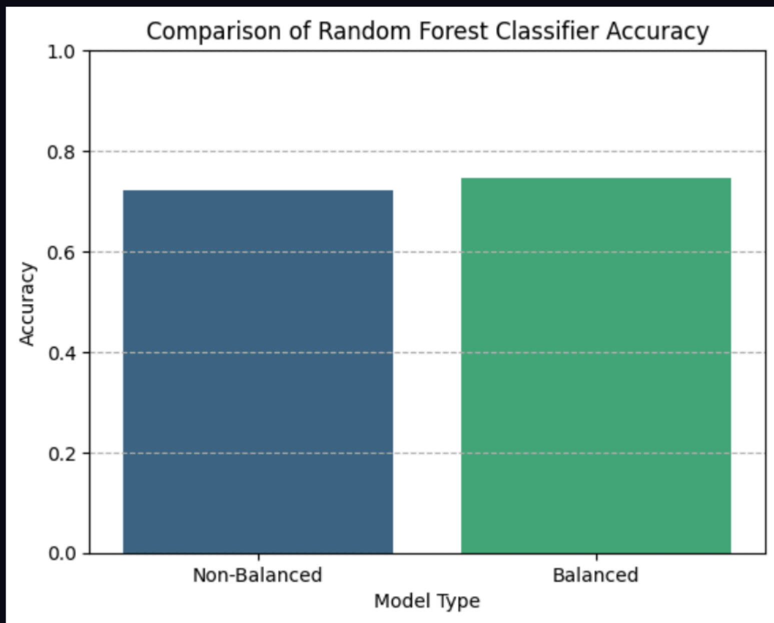


comparision between balanced and unbalanced rf scores

comparision between balanced and unbalanced rf scores

```python
# comparision belwwen balanced vs non-balanced random forest classifier
sns.barplot(x=['Non-Balanced', 'Balanced'], y=[rf_accuracy, rf_balanced_accuracy], palette='viridis')
plt.title('Comparison of Random Forest Classifier Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Model Type')
plt.grid(axis='y', linestyle='--')
plt.ylim(0, 1)
```

7] ✓ 0.4s Python



Task-5

Combine Random Forest and Naive Bayes predictions using a voting classifier and compare its performance with individu
models.

```
from sklearn.ensemble import VotingClassifier

# create a voting classifier with Random Forest and Gaussian Naive Bayes
voting_clf = VotingClassifier(
    estimators=[('rf', rf_pipeline),
                ('nb', nb_pipeline)],

    voting='soft')


# fit the voting classifier on the training data
voting_clf.fit(X_train, y_train)


# make predictions on the test data
voting_y_pred = voting_clf.predict(X_test)
```

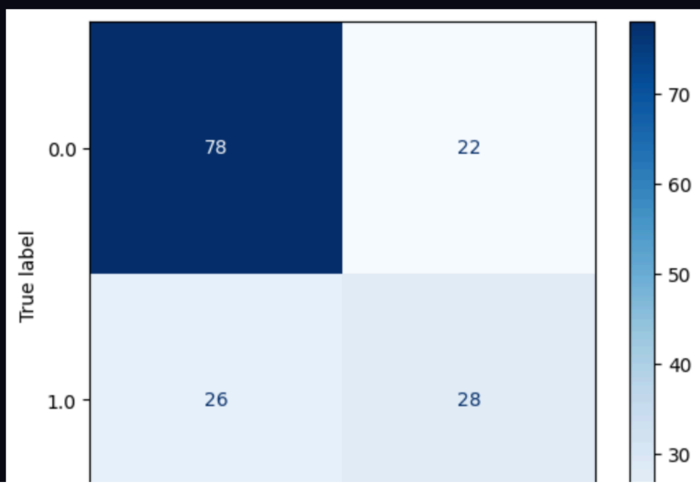
✓ 0.6s

```python
voting_accuracy = accuracy_score(y_test, voting_y_pred)
print(f"Voting Classifier Test Accuracy: {voting_accuracy:.4f}")
voting_cm = confusion_matrix(y_test, voting_y_pred)
voting_disp = ConfusionMatrixDisplay(confusion_matrix=voting_cm, display_labels=voting_clf.classes_)
voting_disp.plot(cmap=plt.cm.Blues)
```

0.4s

Voting Classifier Test Accuracy: 0.6883

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x25ef3ce0cd0>




```python
# COMPARISON OF VOTING CLASSIFIER WITH OTHER MODELS
plt.figure(figsize=(10, 6))
sns.barplot(x=['Random Forest', 'Gaussian Naive Bayes', 'Voting Classifier'],
            y=[rf_accuracy, nb_accuracy, voting_accuracy], palette='viridis')
plt.title('Comparison of Model Accuracies')
plt.ylabel('Accuracy')
plt.xlabel('Model Type')
plt.grid(axis='y', linestyle='--')
plt.ylim(0, 1)
```

0.4s

, 1.0)