Tasks To Be Performed:

1. Data Analysis: a. Import the dataset b. Get information about the dataset (mean, max, min, quartiles etc.) c. Find the correlation between all fields
2. Data Visualization: a. Visualize the number of patients having a heart disease and not having a heart disease b. Visualize the age and whether a patient has disease or not c. Visualize correlation between all features using a heat map
3. Logistic Regression: a. Build a simple logistic regression model: i. Divide the dataset in 70:30 ratio ii. Build the model on train set and predict the values on test set iii. Build the confusion matrix and get the accuracy score
4. Decision Tree: a. Build a decision tree model: i. Divide the dataset in 70:30 ratio ii. Build the model on train set and predict the values on test set iii. Build the confusion matrix and calculate the accuracy iv. Visualize the decision tree using the Graphviz package
5. Random Forest: a. Build a Random Forest model: i. Divide the dataset in 70:30 ratio ii. Build the model on train set and predict the values on test set iii. Build the confusion matrix and calculate the accuracy iv. Visualize the model using the Graphviz package
6. Select the best model a. Print the confusion matrix of all classifiers b. Print the classification report of all classifiers c. Calculate Recall Precision and F1 score of all the models d. Visualize confusion matrix using heatmaps e. Select the best model based on the best accuracies

In [45]:
```
import pandas as pd, numpy as np, matplotlib.pyplot as plt, seaborn as sns
```

In [46]:
```
diabetes = pd.read_csv('diabetes.csv')
```

In [47]:
```
diabetes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Pregnancies               768 non-null    int64  
 1   Glucose                   768 non-null    int64  
 2   BloodPressure             768 non-null    int64  
 3   SkinThickness             768 non-null    int64  
 4   Insulin                   768 non-null    int64  
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64  
 8   Outcome                   768 non-null    int64  
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

In [48]:
```
diabetes.head()
```

Out[48]:

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

In [49]:
```
diabetes.isnull().sum()
```

Out[49]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

In [50]:
```
diabetes.shape
```

Out[50]:
```
(768, 9)
```

In [51]:
```
diabetes.describe()
```

Out[51]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPe
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	

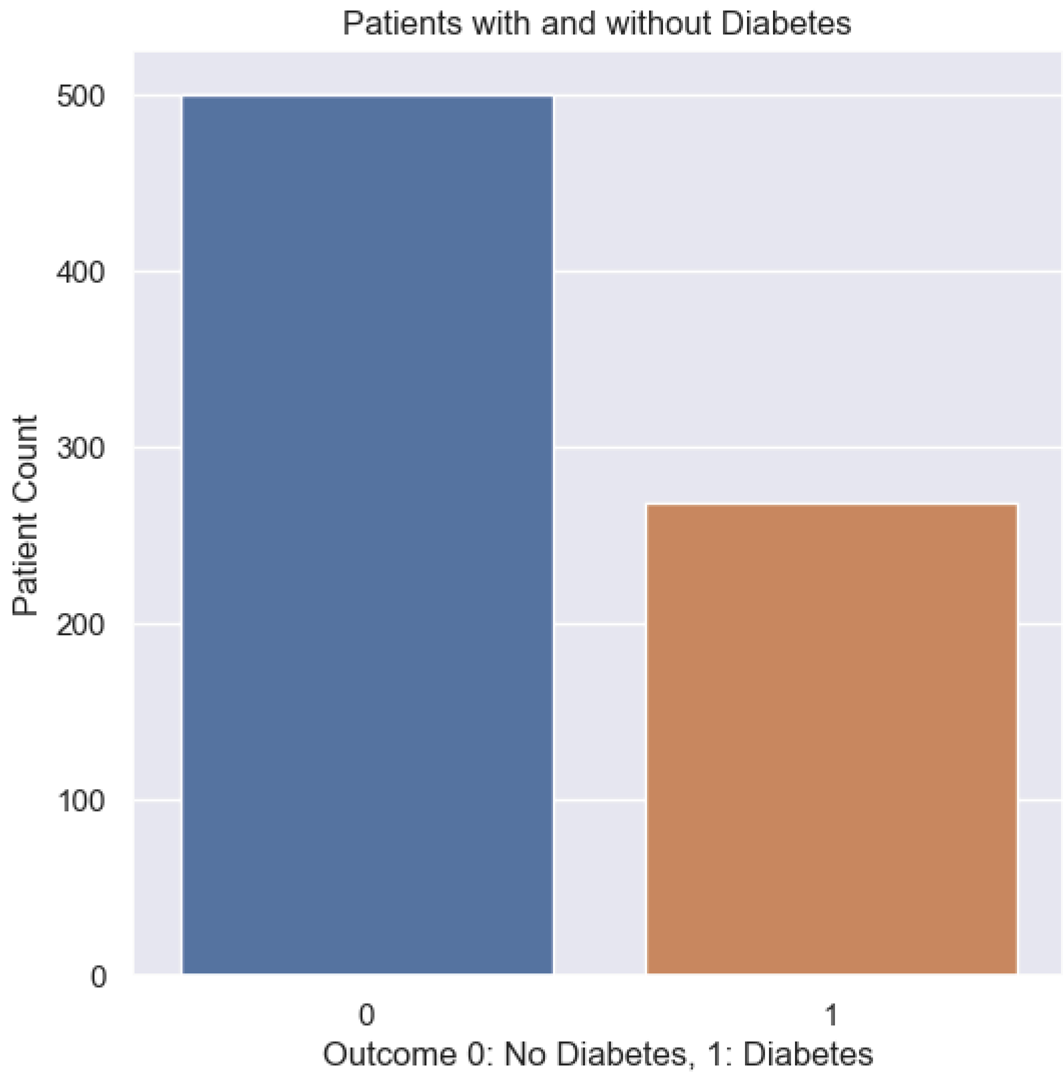
In [52]:
```
diabetes.corr()
```

Out[52]:

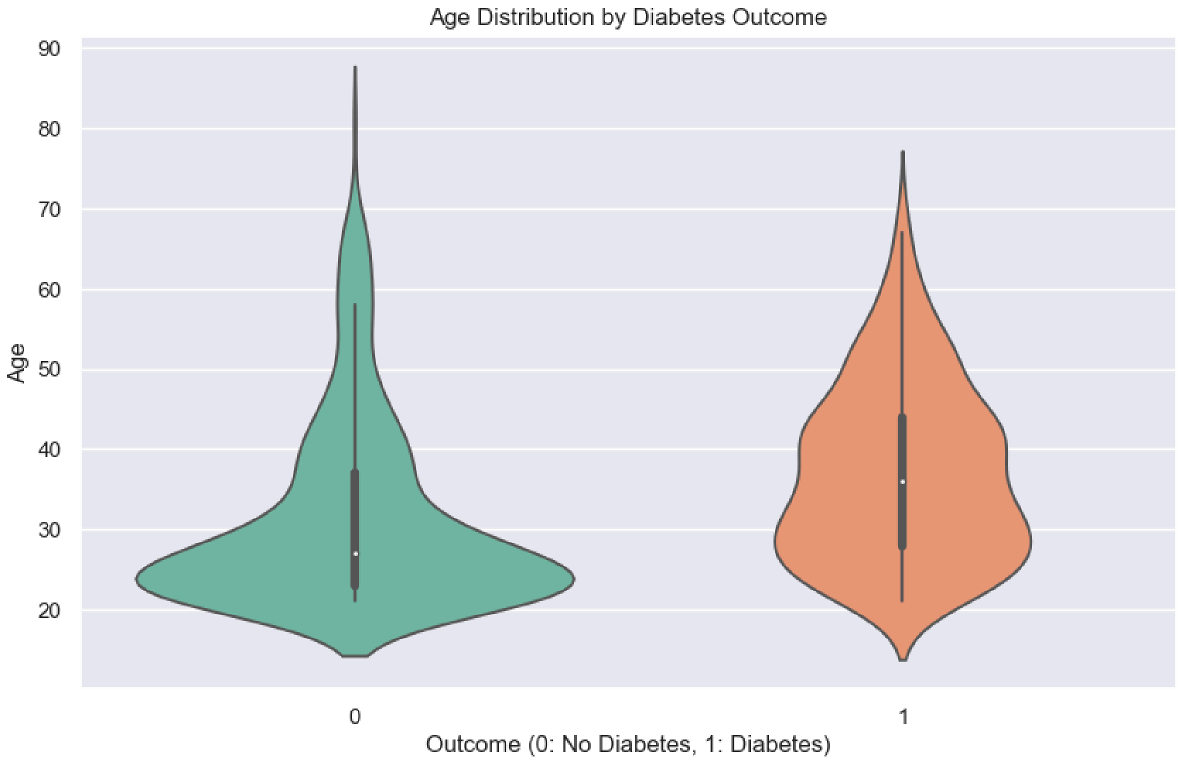
	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BM
Pregnancies	1.000000	0.129459	0.141282	-0.081672	-0.073535	0.01768
Glucose	0.129459	1.000000	0.152590	0.057328	0.331357	0.22107
BloodPressure	0.141282	0.152590	1.000000	0.207371	0.088933	0.28180
SkinThickness	-0.081672	0.057328	0.207371	1.000000	0.436783	0.39257
Insulin	-0.073535	0.331357	0.088933	0.436783	1.000000	0.19785
BMI	0.017683	0.221071	0.281805	0.392573	0.197859	1.00000
DiabetesPedigreeFunction	-0.033523	0.137337	0.041265	0.183928	0.185071	0.14064
Age	0.544341	0.263514	0.239528	-0.113970	-0.042163	0.03624
Outcome	0.221898	0.466581	0.065068	0.074752	0.130548	0.29269

In [53]:

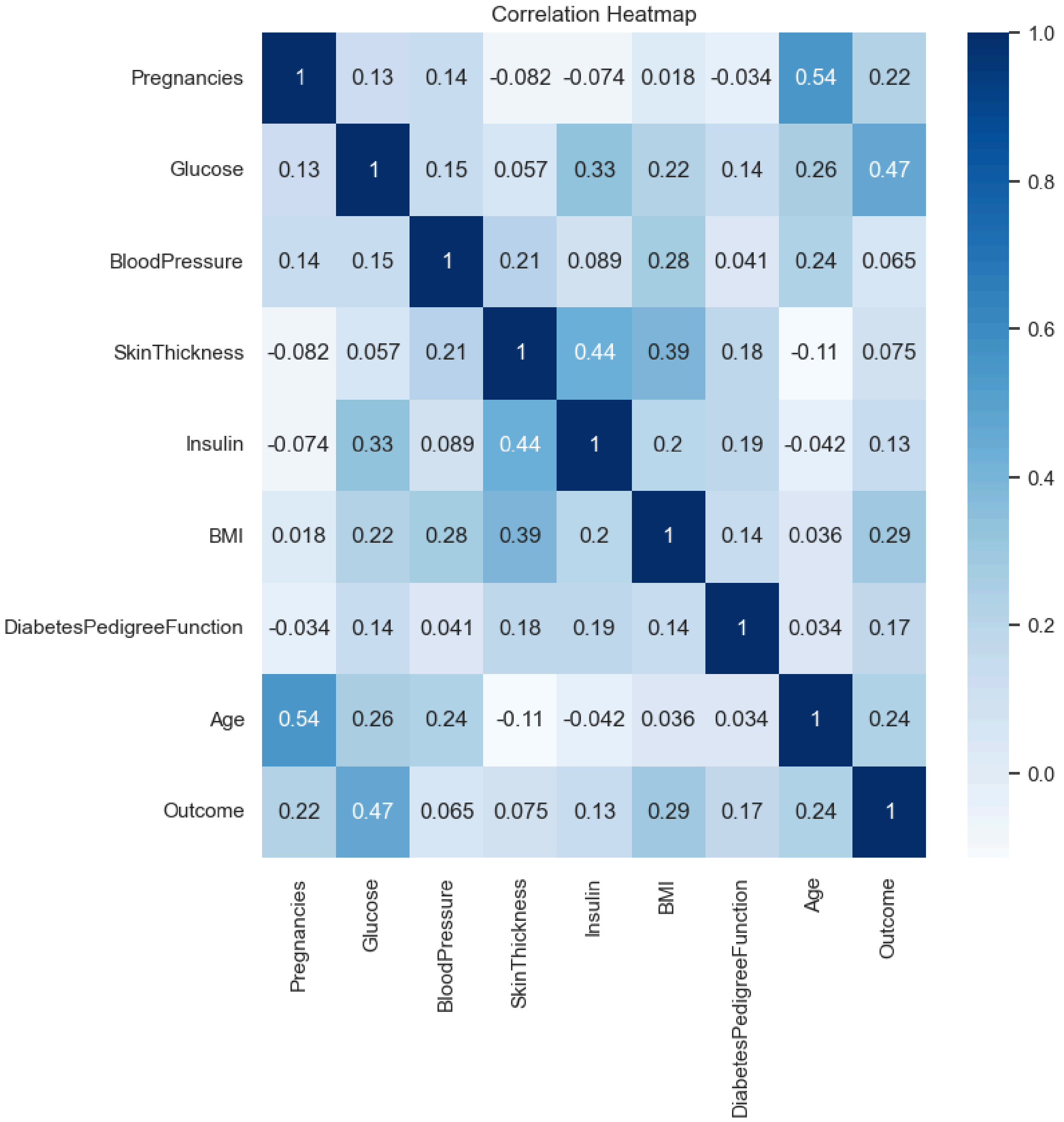
```
sns.set(style = "darkgrid")
plt.figure(figsize = (6,6))
sns.countplot(data = diabetes, x = 'Outcome')
plt.xlabel("Outcome 0: No Diabetes, 1: Diabetes")
plt.ylabel("Patient Count")
plt.title("Patients with and without Diabetes")
plt.show()
```



In [54]:
```
sns.set(style="darkgrid")
plt.figure(figsize=(10, 6))

sns.violinplot(x='Outcome', y='Age', data=diabetes, palette='Set2')

plt.title('Age Distribution by Diabetes Outcome')
plt.xlabel('Outcome (0: No Diabetes, 1: Diabetes)')
plt.ylabel('Age')

plt.show()
```



In [55]:
```
plt.figure(figsize =(8,8))
sns.heatmap(diabetes.corr(), cmap = 'Blues', annot = True)
plt.title("Correlation Heatmap")
plt.show()
```



In [56]:
```
from sklearn.model_selection import train_test_split
X = diabetes.drop('Outcome', axis = 1)
y = diabetes['Outcome']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.30, random_
```

In [57]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier, export_graphviz
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
import seaborn as sns
import matplotlib.pyplot as plt
import graphviz
```

In [58]:
```
logreg_model = LogisticRegression()
logreg_model.fit(X_train, y_train)
y_pred_logreg = logreg_model.predict(X_test)

dt_model = DecisionTreeClassifier()
dt_model.fit(X_train, y_train)
y_pred_dt = dt_model.predict(X_test)

rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
```

```
rf_model.fit(X_train, y_train)
y_pred_rf = rf_model.predict(X_test)
```

```
C:\Users\Onkar\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:458:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

In [59]:
```
models = [logreg_model, dt_model, rf_model]
model_names = ['Logistic Regression', 'Decision Tree', 'Random Forest']
```

In [60]:
```
for model, name in zip(models, model_names):
    y_pred = model.predict(X_test)
    conf_matrix = confusion_matrix(y_test, y_pred)
    accuracy = accuracy_score(y_test, y_pred)

    print(f"\n{name}:\nConfusion Matrix:\n{conf_matrix}\nAccuracy: {accuracy:.4f}")
```

```
Logistic Regression:
Confusion Matrix:
[[132  15]
 [ 33  51]]
Accuracy: 0.7922

Decision Tree:
Confusion Matrix:
[[113  34]
 [ 33  51]]
Accuracy: 0.7100

Random Forest:
Confusion Matrix:
[[128  19]
 [ 36  48]]
Accuracy: 0.7619
```

In [61]:
```
dot_data_dt = export_graphviz(dt_model, out_file=None, feature_names=list(X.columns
graph_dt = graphviz.Source(dot_data_dt)
graph_dt.render("decision_tree")

graph_dt.view()
```

Out[61]: 'decision_tree.pdf'

In [62]:
```
dot_data_rf = export_graphviz(rf_model.estimators_[0], out_file=None, feature_names
graph_rf = graphviz.Source(dot_data_rf)
graph_rf.render("random_forest_tree")


graph_rf.view()
```

Out[62]: 'random_forest_tree.pdf'

In [63]:
```
for model, name in zip(models, model_names):
    y_pred = model.predict(X_test)
    report = classification_report(y_test, y_pred)

    print(f"\n{name}:\nClassification Report:\n{report}")
```

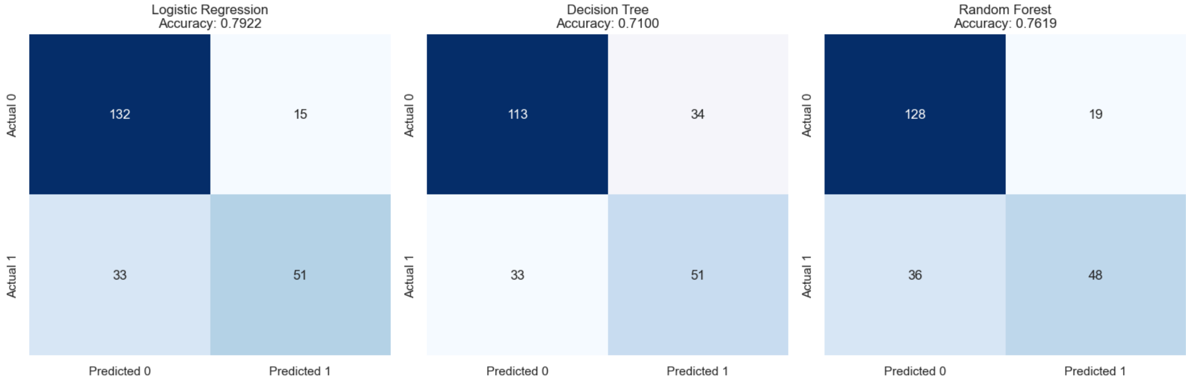
```
Logistic Regression:
Classification Report:
              precision    recall  f1-score   support

           0       0.80      0.90      0.85       147
           1       0.77      0.61      0.68        84

    accuracy                           0.79       231
   macro avg       0.79      0.75      0.76       231
weighted avg       0.79      0.79      0.79       231


Decision Tree:
Classification Report:
              precision    recall  f1-score   support

           0       0.77      0.77      0.77       147
           1       0.60      0.61      0.60        84

    accuracy                           0.71       231
   macro avg       0.69      0.69      0.69       231
weighted avg       0.71      0.71      0.71       231


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

           0       0.78      0.87      0.82       147
           1       0.72      0.57      0.64        84

    accuracy                           0.76       231
   macro avg       0.75      0.72      0.73       231
weighted avg       0.76      0.76      0.76       231
```

In [64]:

```
metrics_dict = {'Recall': [], 'Precision': [], 'F1 Score': []}
for model in models:
    y_pred = model.predict(X_test)
    recall = classification_report(y_test, y_pred, output_dict=True)['1']['recall']
    precision = classification_report(y_test, y_pred, output_dict=True)['1']['preci
    f1_score = classification_report(y_test, y_pred, output_dict=True)['1']['f1-sco

    metrics_dict['Recall'].append(recall)
    metrics_dict['Precision'].append(precision)
    metrics_dict['F1 Score'].append(f1_score)
```

In [65]:

```
plt.figure(figsize=(15, 5))
for i, (model, name) in enumerate(zip(models, model_names), 1):
    plt.subplot(1, 3, i)
    y_pred = model.predict(X_test)
    conf_matrix = confusion_matrix(y_test, y_pred)
    sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues", cbar=False,
                xticklabels=['Predicted 0', 'Predicted 1'], yticklabels=['Actual 0'
    plt.title(f"{name}\nAccuracy: {accuracy_score(y_test, y_pred):.4f}")

plt.tight_layout()
plt.show()
```



In [66]:

```
best_model_index = max(range(len(models)), key=lambda i: accuracy_score(y_test, moc
best_model = models[best_model_index]
best_model_name = model_names[best_model_index]

print(f"\nBest Model: {best_model_name} with Accuracy: {accuracy_score(y_test, best
```

```
Best Model: Logistic Regression with Accuracy: 0.7922
```