Diabetes Prediction - Project 2

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MeriSKILL!

- This dataset is originally from the National Institute of Diabetes and Digestive and Kidney Diseases.
- The objective of the dataset is to diagnostically predict whether a patient has diabetes based on certain diagnostic measurements included in the dataset.
- Several constraints were placed on the selection of these instances from a larger database. In particular, all patients here are females at least 21 years old of Pima Indian heritage

  The accuracy and f1_score is considered as the evaluation metrics

In [1]:
```
# importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score,accuracy_score
```

In [2]:
```
data = pd.read_csv('diabetes.csv')
```

In [3]:
```
data.head()
```

Out[3]:

	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 [4]:
```
# dataset information
data.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
```

- The total number of observations are **768**
- The shape of the data is **768*9**
- There are no null values present in the dataset

In [5]:

```
# more details of data
data.describe()
```

Out[5]:

	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	

- The range of pregnancies is from 0 to 17 with 3.84 as mean value
- The age group of the dataset is from 21 years to 81 years
- We can observe that columns like Glucose, BloodPressure, Skin,Thickness,Insulin and BMI are having 0 as their minimum value, which is not appropriate

---

In [6]:

```
data.isnull().sum()
```

Out[6]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

- There are no null values but the values are taken as 0 hence let us change the values to NaN

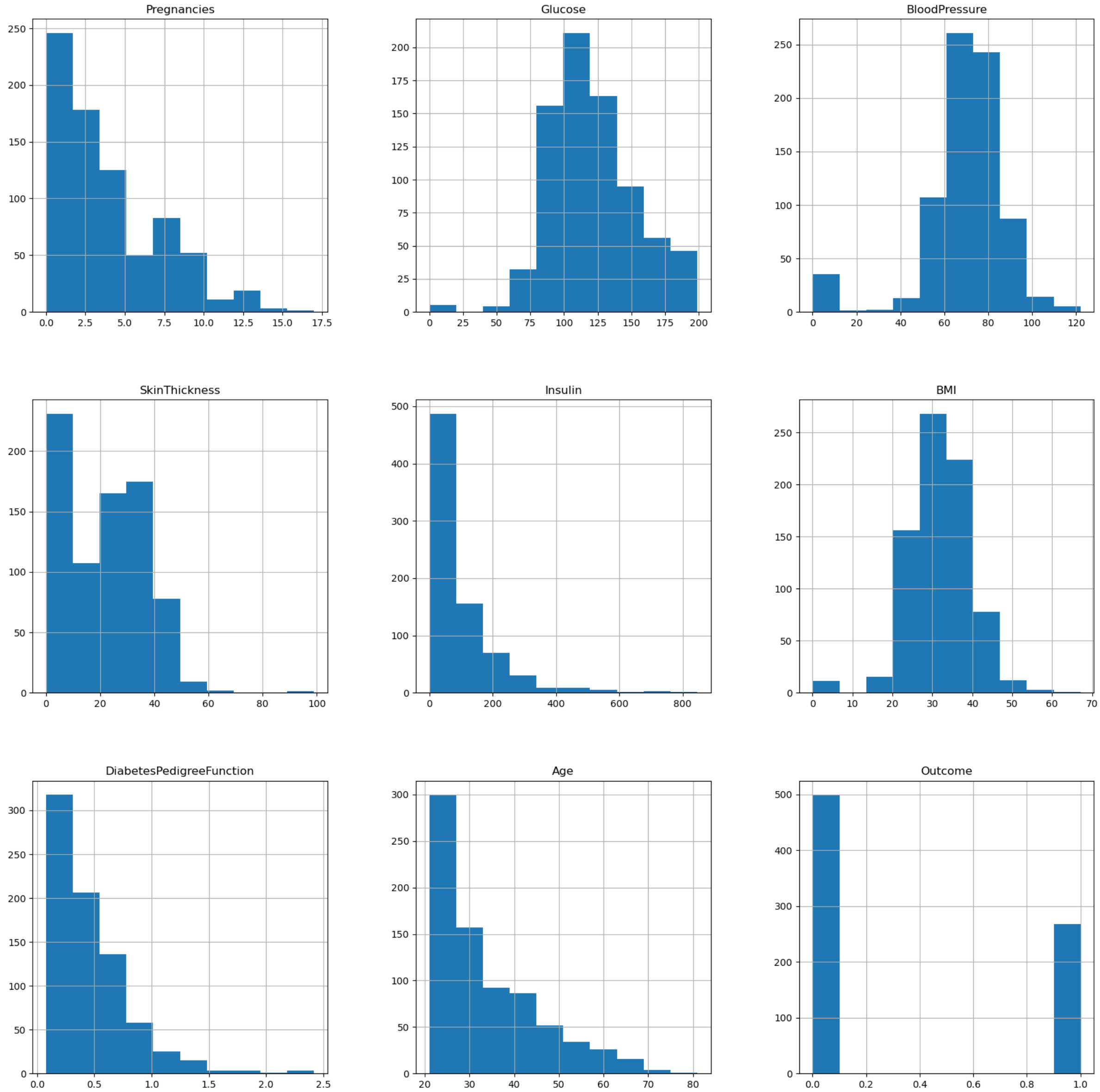
In [7]:
```
data_copy = data.copy(deep = True)
data_copy[['Glucose','BloodPressure','SkinThickness','Insulin','BMI']] = data_copy[

# Showing the Count of NANs
print(data_copy.isnull().sum())
```

```
Pregnancies                   0
Glucose                       5
BloodPressure                35
SkinThickness               227
Insulin                     374
BMI                          11
DiabetesPedigreeFunction      0
Age                           0
Outcome                       0
dtype: int64
```

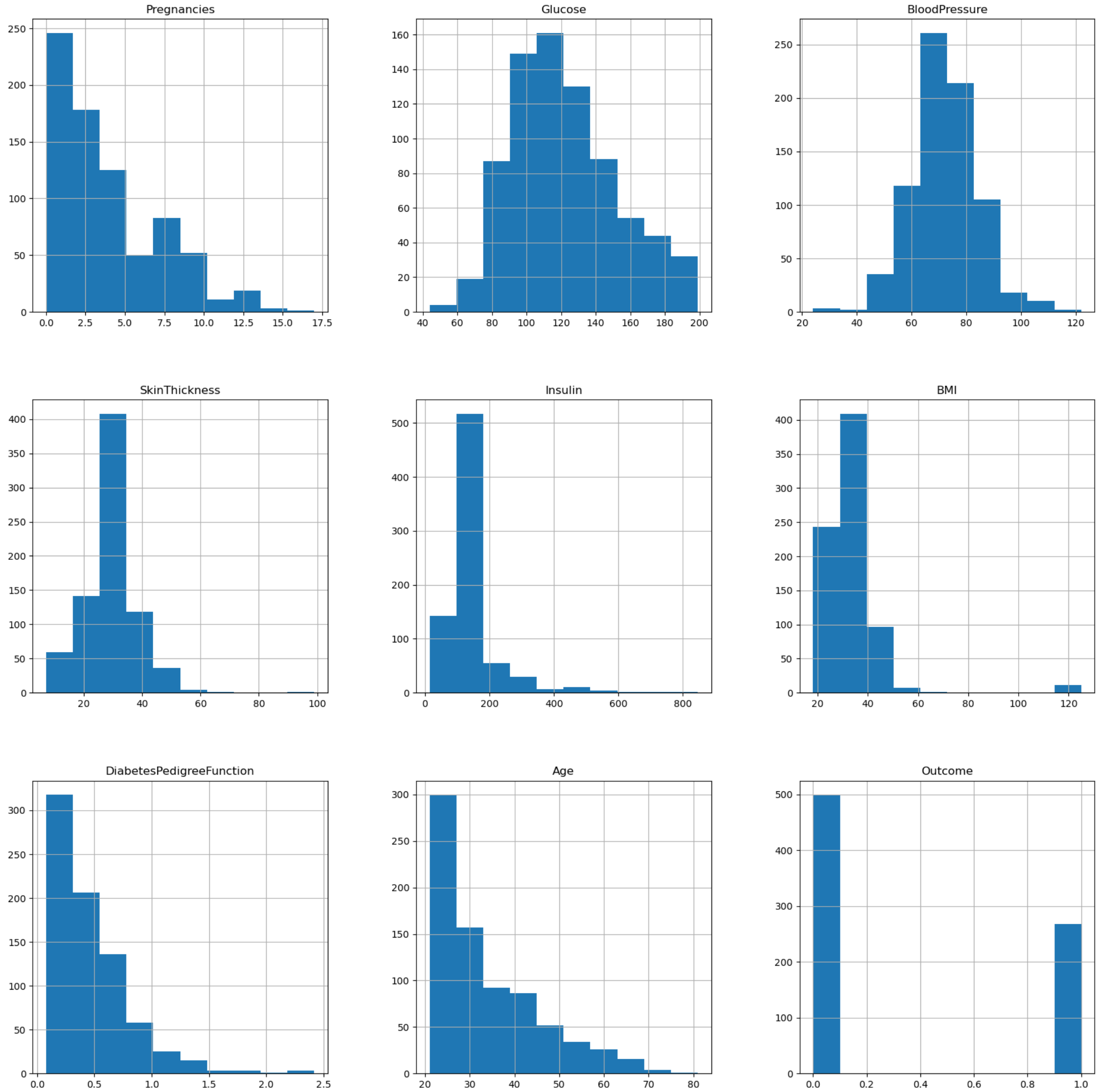
- Now we can see the null values in the columns like Glucose, BloodPressure, SkinThickness, Insulin and BMI

In [8]:
```
data.hist(figsize=(20,20))
plt.show()
```



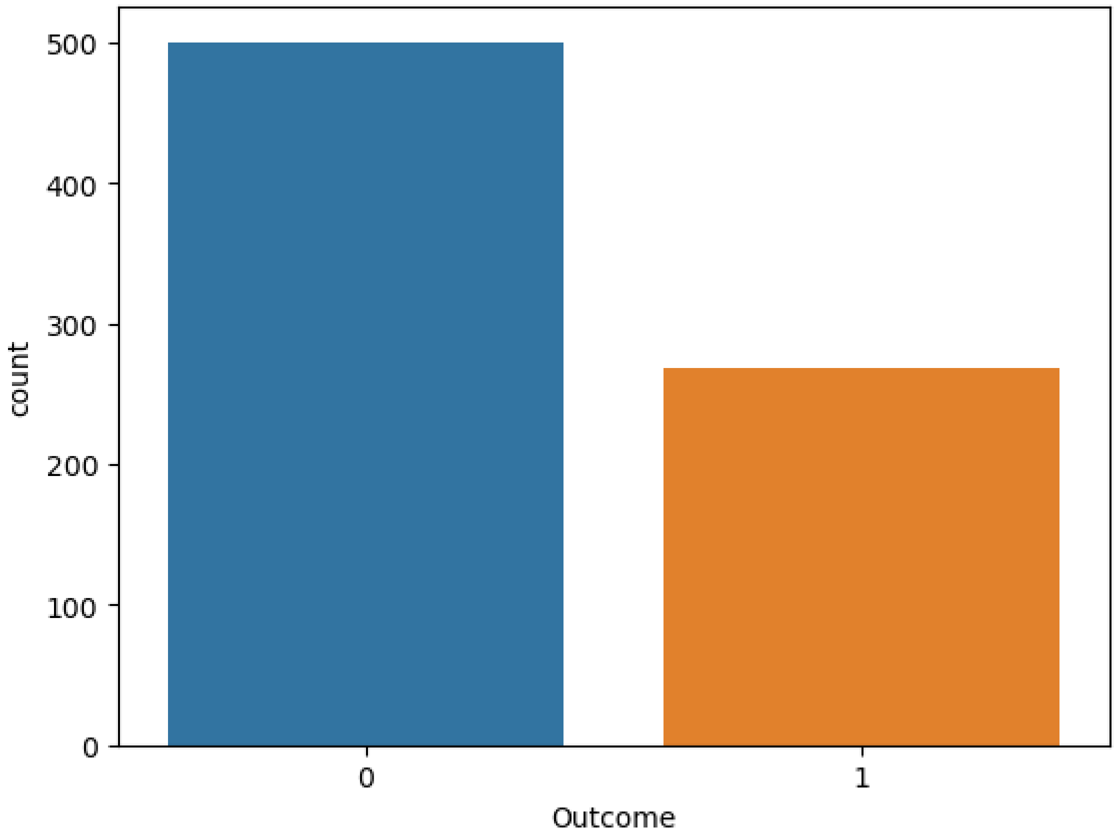
In [9]:
```
# imputing the null values as follows
data_copy['Glucose'].fillna(data_copy['Glucose'].mean(),inplace=True)
data_copy['BloodPressure'].fillna(data_copy['BloodPressure'].mean(),inplace=True)
data_copy['SkinThickness'].fillna(data_copy['SkinThickness'].median(),inplace=True)
data_copy['Insulin'].fillna(data_copy['Insulin'].median(),inplace=True)
data_copy['BMI'].fillna(data_copy['Insulin'].median(),inplace=True)
```

In [10]:
```
data_copy.hist(figsize=(20,20))
plt.show()
```



In [11]:
```
sns.countplot(x=data_copy['Outcome'])
data_copy['Outcome'].value_counts()
```

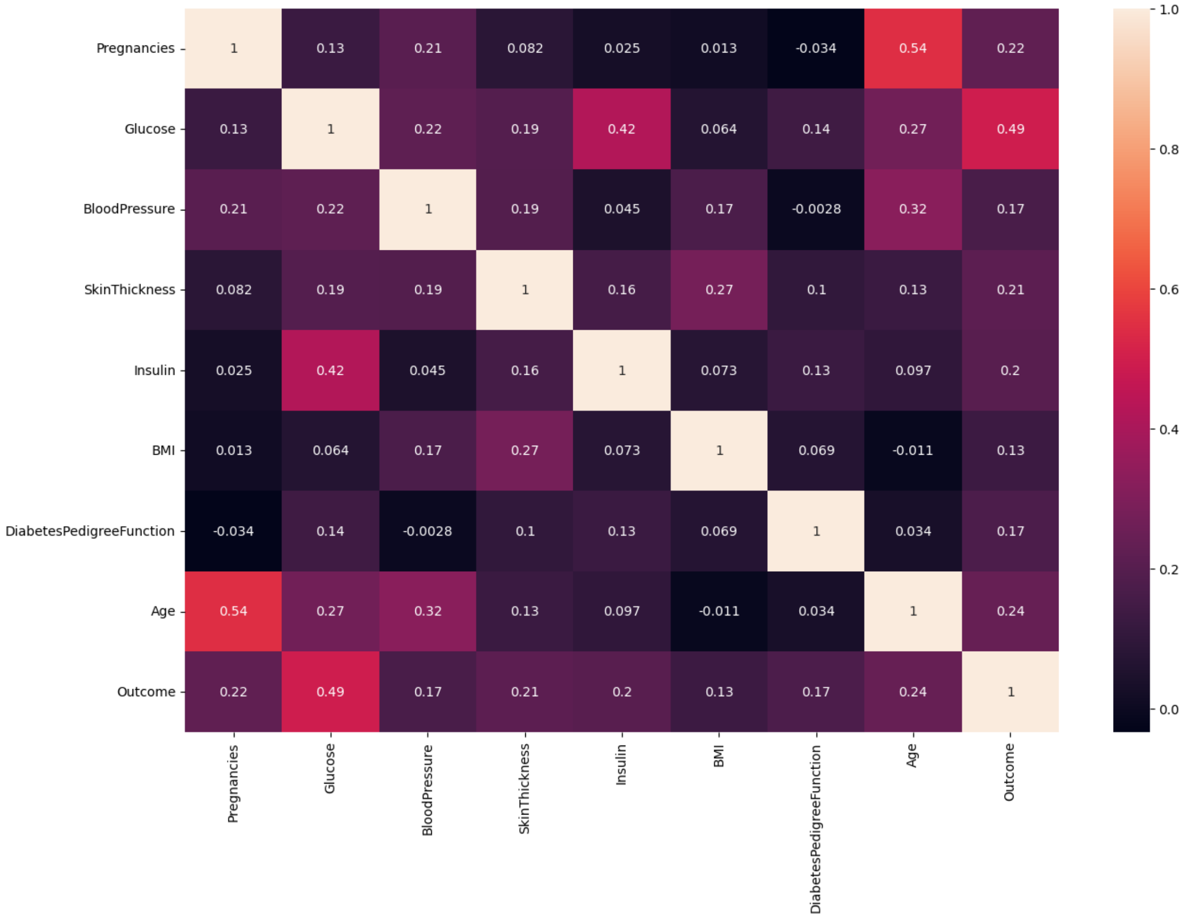
Out[11]:
```
0    500
1    268
Name: Outcome, dtype: int64
```



- From above visulaization the Outcome is imbalaced, the patients who are diabetic are only half of non-diabetic patients

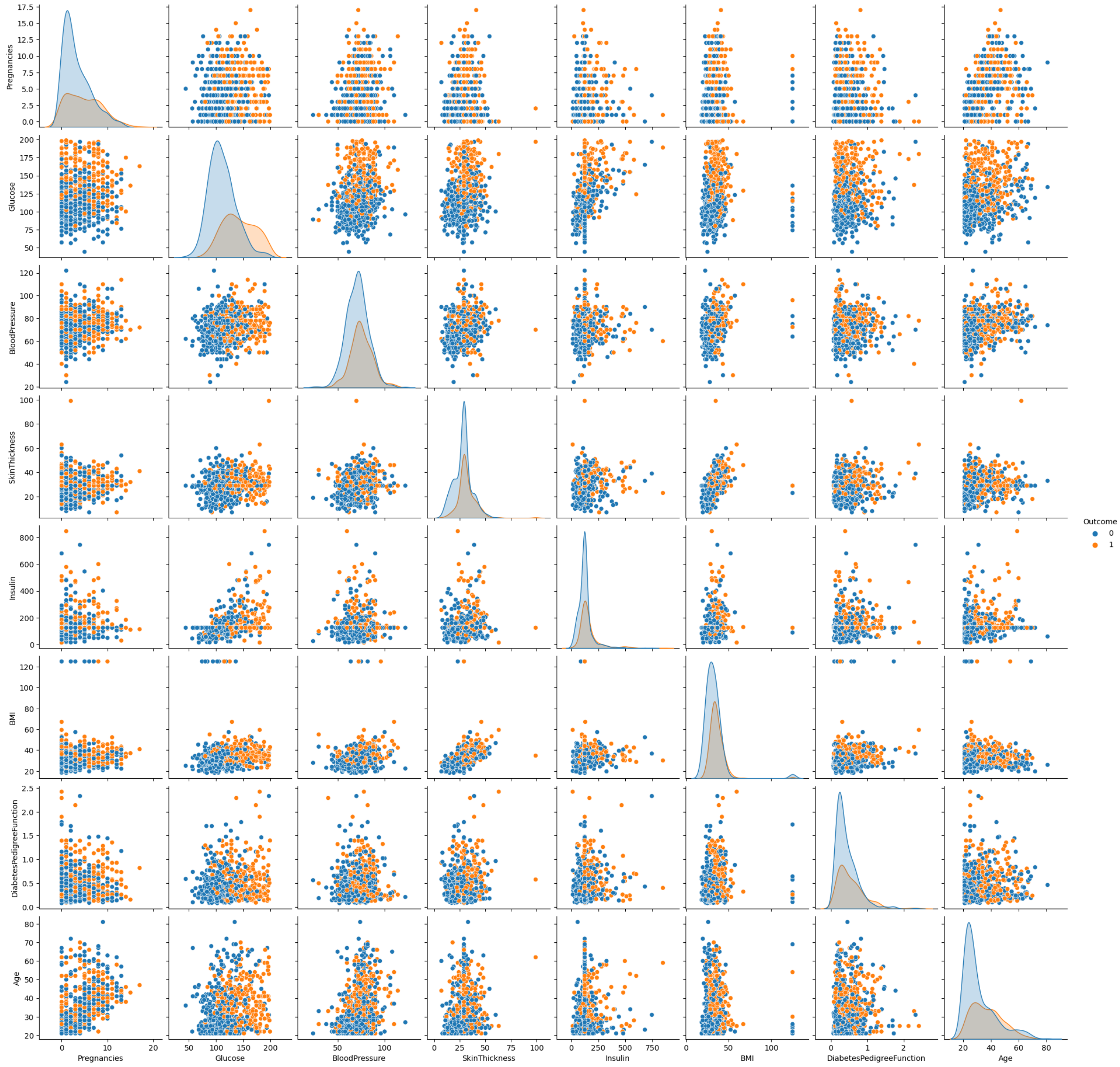
---

In [12]:
```
plt.figure(figsize=(15,10))
sns.heatmap(data_copy.corr(),annot=True)
plt.show()
```



In [13]:

```
sns.pairplot(data_copy,hue='Outcome')
plt.show()
```



Model Building

In [14]:
```
# splitting the data into features and target variables
X = data_copy.drop('Outcome',axis=1)
y = data_copy['Outcome']
```

In [15]:
```
# splitting the data into test and train columns
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_sta
```

In [16]:
```
# scaling the data using Standard scalar
scalar = StandardScaler()
X_train_scaled = scalar.fit_transform(X_train)
X_test_scaled = scalar.transform(X_test)
```

In [17]:
```
# shape of x train and X test datasets
X_train_scaled.shape,X_test_scaled.shape
```

Out[17]:
```
((537, 8), (231, 8))
```

In [18]:
```
# creating an instance of Logistic regression
logistic_model = LogisticRegression(random_state=101)
logistic_model.fit(X_train_scaled,y_train)
```

Out[18]:
```
LogisticRegression(random_state=101)
```

In [19]:
```
# predicting on the test data by logistic regression
test_predict_log=logistic_model.predict(X_test_scaled)
print('The accuracy score on test data is',accuracy_score(y_test,test_predict_log))
```

```
The accuracy score on test data is 0.7662337662337663
```

In [20]:
```
print('The f1 score on test data is',f1_score(y_test,test_predict_log))
```

```
The f1 score on test data is 0.6301369863013698
```

In [21]:
```
# imporitng libraries
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

Decision Tree Classifier

In [22]:
```
# decision tree classifier model for prediction
decision_tree = DecisionTreeClassifier(random_state=101)
decision_tree.fit(X_train_scaled,y_train)
test_predict_decision = decision_tree.predict(X_test_scaled)
```

In [23]:
```
print('The accuracy score for decision tree classifier is',accuracy_score(y_test,te
print('The f1_score for decision tree classifier is',f1_score(y_test,test_predict_d
```

```
The accuracy score for decision tree classifier is 0.7316017316017316
The f1_score for decision tree classifier is 0.6265060240963856
```

Gradient Boost Classifier

In [24]:
```
# gradient boost classifier model for prediction
gradient_boost =GradientBoostingClassifier(random_state=101)
gradient_boost.fit(X_train_scaled,y_train)
test_predict_gradient = gradient_boost.predict(X_test_scaled)
```

In [25]:
```
print('The accuracy score for gradient boost classifier is',accuracy_score(y_test,t
print('The f1_score for gradient boost classifier is',f1_score(y_test,test_predict_
```

```
The accuracy score for gradient boost classifier is 0.7489177489177489
The f1_score for gradient boost classifier is 0.6506024096385542
```

Random Forest Classifier

In [26]:
```
# random forest classifier model for prediction
random_forest = RandomForestClassifier(random_state=101)
random_forest.fit(X_train_scaled,y_train)
test_predict_rf = random_forest.predict(X_test_scaled)
```

In [27]:
```
print('The accuracy score for gradient boost classifier is',accuracy_score(y_test,t
print('The f1_score for gradient boost classifier is',f1_score(y_test,test_predict_
```

```
The accuracy score for gradient boost classifier is 0.7575757575757576
The f1_score for gradient boost classifier is 0.6455696202531646
```

- The accuracy score of
  ```
  Logistic Regression is 0.766
  Decision Tree classifier is 0.731
  Gradient Boost Classifier is 0.748
  Random Forest Classifier is 0.7575
  ```

- The F1_score of
  ```
  Logistic Regression is 0.630
  Decision Tree classifier is 0.626
  Gradient Boost Classifier is 0.650
  Random Forest Classifier is 0.645
  ```

- The accuracy score is best for **logistic model** and f1 score is best for **gradient boost classifier model**

Grid Search

In [28]:
```
from sklearn.model_selection import GridSearchCV
```

In [29]:
```
def grid_search(classifier, param_grid, X, y, scoring = 'f1_weighted'):

    # split the data in training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, rando

    # Scaling the train data by Standard scalar
    scalar = StandardScaler()
    X_train_scaled = scalar.fit_transform(X_train)
    X_test_scaled = scalar.transform(X_test)

    # Perform Grid Search
    grid_search = GridSearchCV(classifier, param_grid, cv=5, scoring=scoring, n_job
    grid_search.fit(X_train_scaled, y_train)

    # Print the Best Parameters
    print("Best Parameters:", grid_search.best_params_)






def model_evaluation(ml_model,X,y):

     # Split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, rando

    # Scaling the train data by Standard scalar
    scalar = StandardScaler()
    X_train_scaled = scalar.fit_transform(X_train)
    X_test_scaled = scalar.transform(X_test)

    # creating a model instance
    model = ml_model
    model.fit(X_train_scaled,y_train)

    # Make Predictions
    y_train_pred = model.predict(X_train_scaled)
    y_test_pred = model.predict(X_test_scaled)

    # Evaluate the Model
    train_accuracy = accuracy_score(y_train, y_train_pred)
    test_accuracy = accuracy_score(y_test, y_test_pred)
    train_f1_score = f1_score(y_train, y_train_pred, average='weighted')
```

```
    test_f1_score = f1_score(y_test, y_test_pred, average='weighted')

    print("Training Accuracy:", train_accuracy)
    print("Testing Accuracy:", test_accuracy)
    print('-'*50)
    print("Training F1 Score (weighted):", train_f1_score)
    print("Testing F1 Score (weighted):", test_f1_score)

    return train_accuracy,test_accuracy,train_f1_score,test_f1_score
```

Decision Tree

In [30]:
```
X = data_copy.drop('Outcome',axis=1)
y = data_copy['Outcome']

# Define the Decision Tree Classifier and hyperparameter grid for grid search
decision_tree = DecisionTreeClassifier(random_state=101)
param_grid = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [5, 10, 20, 30, 40],
    'min_samples_split': [2, 5, 10, 15, 20],
    'min_samples_leaf': [1, 2, 4, 8, 10]
}
grid_search(classifier=decision_tree,param_grid=param_grid,scoring='f1_weighted',X=
```

```
Best Parameters: {'criterion': 'gini', 'max_depth': 5, 'min_samples_leaf': 8, 'min
_samples_split': 2}
```

In [31]:
```
dt_score = model_evaluation(DecisionTreeClassifier(criterion='gini',max_depth=5,mir
```

```
Training Accuracy: 0.8229166666666666
Testing Accuracy: 0.7447916666666666
--------------------------------------------------
Training F1 Score (weighted): 0.8252848487977833
Testing F1 Score (weighted): 0.7492527167476717
```

Random Forest

In [32]:
```
X = data_copy.drop('Outcome',axis=1)
y = data_copy['Outcome']

# Define the Random Forest Classifier and hyperparameter grid for grid search
rf_classifier = RandomForestClassifier(random_state=101)
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [5, 10, 20],
    'max_features': ['auto', 'sqrt']
}

# grid_search function
best_random_search = grid_search(rf_classifier, param_grid, X, y)
```

```
Best Parameters: {'max_depth': 10, 'max_features': 'auto', 'n_estimators': 100}
```

In [33]:
```
rf_score = model_evaluation(RandomForestClassifier(max_depth=10,max_features='auto'
```

```
Training Accuracy: 0.9878472222222222
Testing Accuracy: 0.765625
--------------------------------------------------
Training F1 Score (weighted): 0.9878254495174441
Testing F1 Score (weighted): 0.7634681531545123
```

Gradient Boost

In [34]:
```
X = data_copy.drop('Outcome',axis=1)
y = data_copy['Outcome']

# Define the Gradient boosting Classifier and hyperparameter grid for grid search
gbm_classifier = GradientBoostingClassifier(random_state=101)
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [5, 10, 20],
    'max_features': ['auto','sqrt']
}

# grid_search function
best_gradient_boost = grid_search(gbm_classifier, param_grid, X, y)
```

```
Best Parameters: {'max_depth': 20, 'max_features': 'sqrt', 'n_estimators': 100}
```

In [35]:
```
gb_score = model_evaluation(GradientBoostingClassifier(n_estimators=100,max_depth=2
```

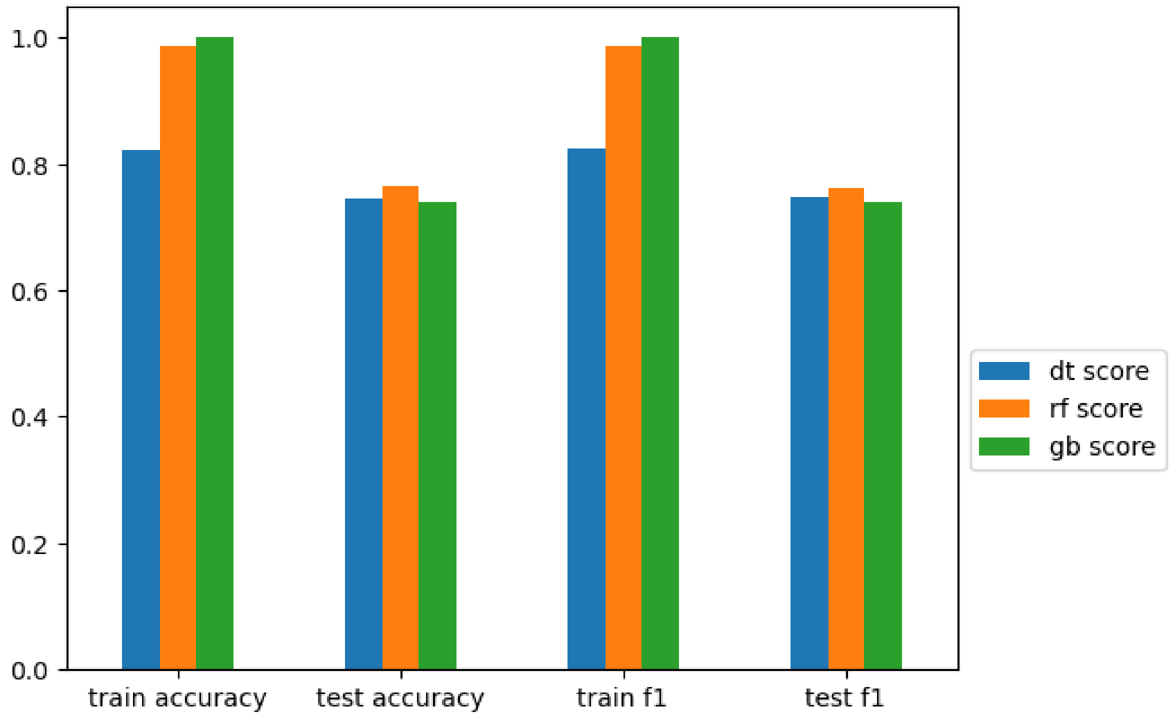
```
Training Accuracy: 1.0
Testing Accuracy: 0.7395833333333334
--------------------------------------------------
Training F1 Score (weighted): 1.0
Testing F1 Score (weighted): 0.7395833333333334
```

In [36]:
```
scores_data = pd.DataFrame({'dt score':dt_score,'rf score':rf_score,'gb score': gb_
                           index=['train accuracy','test accuracy','train f1','test
scores_data
```

Out[36]:

	dt score	rf score	gb score
train accuracy	0.822917	0.987847	1.000000
test accuracy	0.744792	0.765625	0.739583
train f1	0.825285	0.987825	1.000000
test f1	0.749253	0.763468	0.739583

In [37]:
```
score_plot=scores_data.plot(y=['dt score','rf score','gb score'],kind='bar',rot=0)
score_plot.legend(loc='upper left', bbox_to_anchor=(1.0, 0.5))
plt.show()
```



- From above graph the Gradient boost model is best performer on the training data and Random Forest is best performer on testing data

In [38]:
```
decision_tree = DecisionTreeClassifier(criterion='gini',max_depth=5,min_samples_lea
decision_tree.fit(X_train_scaled,y_train)
decision_tree.feature_importances_
```

Out[38]:
```
array([0.00281798, 0.51609451, 0.03144362, 0.0343589 , 0.03943707,
       0.11887285, 0.06917896, 0.18779611])
```

In [39]:
```
gradient_boost = GradientBoostingClassifier(n_estimators= 100, max_depth= 20, max_f
gradient_boost.fit(X_train_scaled,y_train)
gradient_boost.feature_importances_
```

Out[39]:
```
array([0.07670188, 0.24598665, 0.08622578, 0.08799447, 0.09185457,
       0.15884433, 0.11162447, 0.14076784])
```

In [40]:
```
random_forest =RandomForestClassifier(n_estimators = 100, max_depth = 10,max_featur
random_forest.fit(X_train_scaled,y_train)
random_forest.feature_importances_
```

Out[40]:
```
array([0.07755259, 0.26504731, 0.07670062, 0.08288426, 0.09660141,
       0.15315546, 0.11825831, 0.12980004])
```

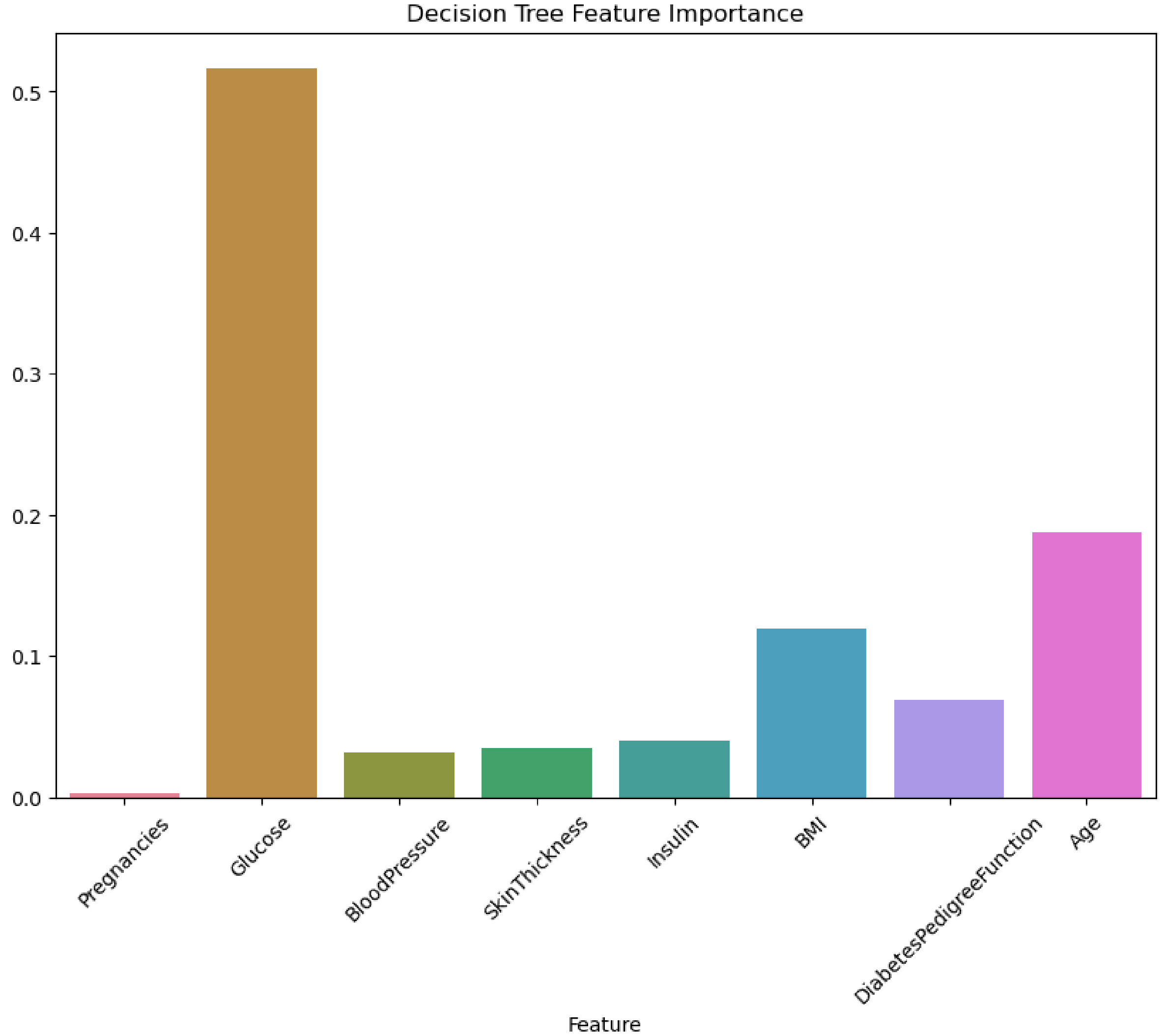
In [41]:
```
importance_df = pd.DataFrame({"Feature": X.columns,
                              "Decision Tree": decision_tree.feature_importances_,
                              "Random Forest": random_forest.feature_importances_,
                              "Gradient Boost": gradient_boost.feature_importances_
                              })
importance_df
```

Out[41]:

	Feature	Decision Tree	Random Forest	Gradient Boost
0	Pregnancies	0.002818	0.077553	0.076702
1	Glucose	0.516095	0.265047	0.245987
2	BloodPressure	0.031444	0.076701	0.086226
3	SkinThickness	0.034359	0.082884	0.087994
4	Insulin	0.039437	0.096601	0.091855
5	BMI	0.118873	0.153155	0.158844
6	DiabetesPedigreeFunction	0.069179	0.118258	0.111624
7	Age	0.187796	0.129800	0.140768

In [42]:

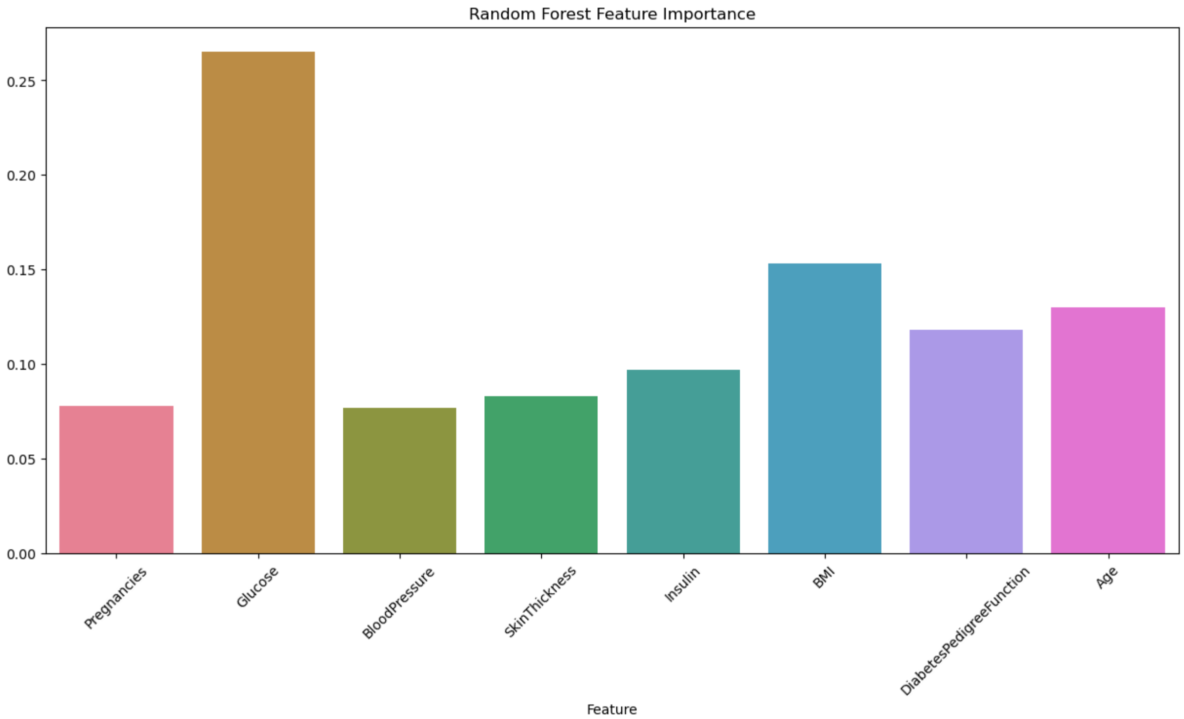
```
# Important features by Decision tree classifier
plt.figure(figsize=(10,7))
sns.barplot(x=importance_df['Feature'], y=importance_df['Decision Tree'], palette='
plt.xticks(rotation=45)
plt.ylabel(None)
plt.title('Decision Tree Feature Importance')
plt.show()
```



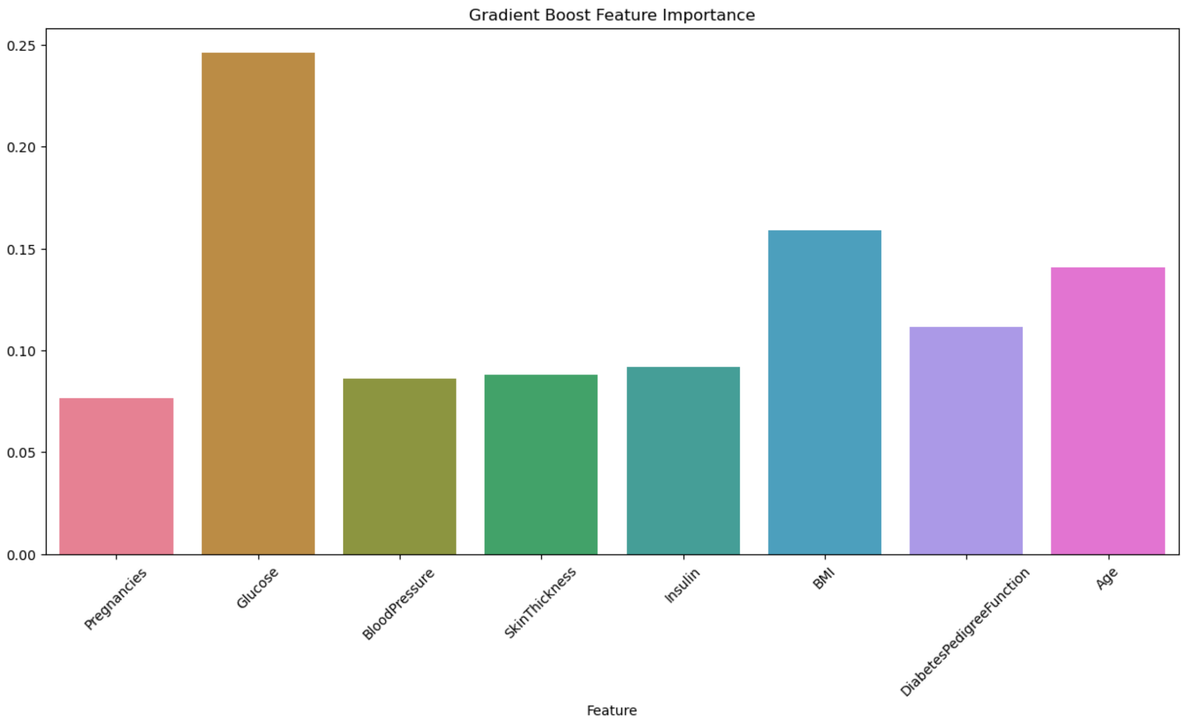
In [43]:

```
# Important features by Random forest classifier
plt.figure(figsize=(15,7))
sns.barplot(x=importance_df['Feature'], y=importance_df['Random Forest'], palette='
plt.xticks(rotation=45)
plt.ylabel(None)
```

```
plt.title('Random Forest Feature Importance')
plt.show()
```



In [44]:
```
# Important features by Gradient boost classifier
plt.figure(figsize=(15,7))
sns.barplot(x=importance_df['Feature'], y=importance_df['Gradient Boost'], palette=
plt.xticks(rotation=45)
plt.ylabel(None)
plt.title('Gradient Boost Feature Importance')
plt.show()
```



- From above graphs it is clear that, in decision tree the more importance is given to Glucose itself resulting in less f1_score
- In the Random forest the importance is distributed according to features weights

- In Gradient boost the importance is of features is increased by decreasing the Glucose which resulting in less f1 score

```
In [ ]:
```