PART A: CLASSIFICATION TASK

Import Libraries

In [75]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score,
f1_score, classification_report

from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import RFE

from sklearn.neural_network import MLPClassifier
```

Load Dataset

In [76]:
```
import pandas as pd
df = pd.read_csv("/diabetes.csv")
df.head()
```

Out[76]:

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

Data Understanding

In [77]:

```
df.info()
df.describe()
```

```
<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
```

Out[77]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insu
count	768.000000	768.000000	768.000000	768.000000	768.000
mean	3.845052	120.894531	69.105469	20.536458	79.7994
std	3.369578	31.972618	19.355807	15.952218	115.244
min	0.000000	0.000000	0.000000	0.000000	0.00000
25%	1.000000	99.000000	62.000000	0.000000	0.00000
50%	3.000000	117.000000	72.000000	23.000000	30.5000
75%	6.000000	140.250000	80.000000	32.000000	127.250
max	17.000000	199.000000	122.000000	99.000000	846.000

In [78]:
```
df.isnull().sum()
```

Out[78]:

	0
Pregnancies	0
Glucose	0
BloodPressure	0
SkinThickness	0
Insulin	0
BMI	0
DiabetesPedigreeFunction	0
Age	0
Outcome	0

dtype: int64

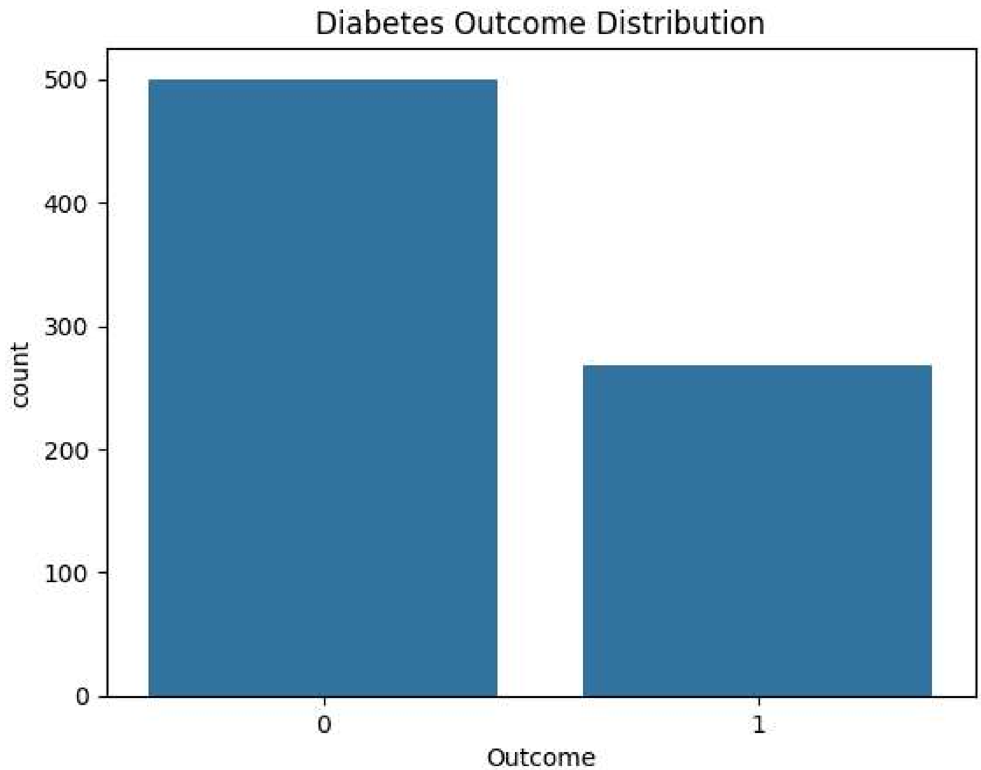
Data Cleaning

In [79]:
```
cols_with_zero = ['Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
'BMI']

for col in cols_with_zero:
    df[col] = df[col].replace(0, df[col].median())
```

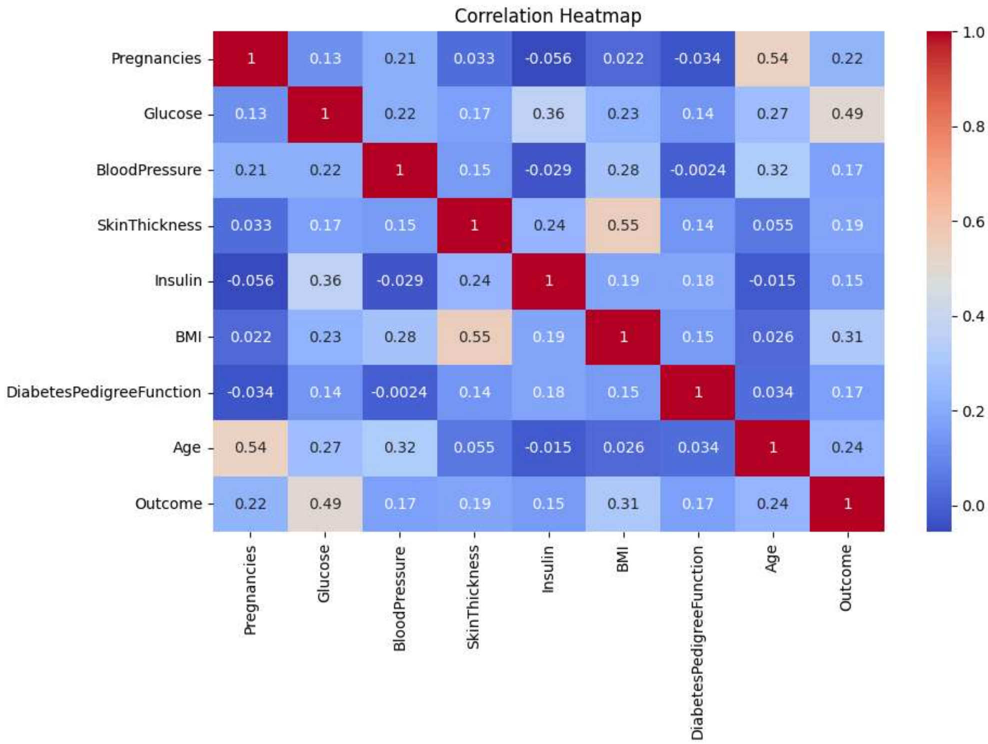
Exploratory Data Analysis (EDA)

In [80]:
```
sns.countplot(x='Outcome', data=df)
plt.title("Diabetes Outcome Distribution")
plt.show()
```



Correlation Heatmap

In [81]:
```
plt.figure(figsize=(10,6))
sns.heatmap(df.corr(), annot=True, cmap="coolwarm")
plt.title("Correlation Heatmap")
plt.show()
```



Train–Test Split & Scaling

In [82]:
```
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, stratify=y
)

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Neural Network Model (MLP)

In [83]:
```
mlp = MLPClassifier(
    hidden_layer_sizes=(64,32),
    activation='relu',
    solver='adam',
    max_iter=500,
    random_state=42
)

mlp.fit(X_train, y_train)

y_pred_mlp = mlp.predict(X_test)

print("Neural Network Performance")
print(classification_report(y_test, y_pred_mlp))
```

```
Neural Network Performance
              precision    recall  f1-score   support

           0       0.84      0.85      0.85       100
           1       0.72      0.70      0.71        54

    accuracy                           0.80       154
   macro avg       0.78      0.78      0.78       154
weighted avg       0.80      0.80      0.80       154
```

```
/usr/local/lib/python3.12/dist-
packages/sklearn/neural_network/_multilayer_perceptron.py:691:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (500)
reached and the optimization hasn't converged yet.
  warnings.warn(
```

Classical Model 1: Logistic Regression

In [84]:
```
log_reg = LogisticRegression(max_iter=1000)
log_reg.fit(X_train, y_train)

y_pred_lr = log_reg.predict(X_test)

print("Logistic Regression Performance")
print(classification_report(y_test, y_pred_lr))
```

```
Logistic Regression Performance
              precision    recall  f1-score   support

           0       0.75      0.82      0.78       100
           1       0.60      0.50      0.55        54

    accuracy                           0.71       154
   macro avg       0.68      0.66      0.67       154
weighted avg       0.70      0.71      0.70       154
```

Classical Model 2: Random Forest

In [85]:
```
rf = RandomForestClassifier(random_state=42)
rf.fit(X_train, y_train)

y_pred_rf = rf.predict(X_test)

print("Random Forest Performance")
print(classification_report(y_test, y_pred_rf))
```

```
Random Forest Performance
              precision    recall  f1-score   support

           0       0.79      0.85      0.82       100
           1       0.68      0.59      0.63        54

    accuracy                           0.76       154
   macro avg       0.74      0.72      0.73       154
weighted avg       0.75      0.76      0.76       154
```

Hyperparameter Tuning (GridSearchCV)
Logistic Regression

In [86]:
```
param_lr = {
    'C': [0.01, 0.1, 1, 10]
}

grid_lr = GridSearchCV(LogisticRegression(max_iter=1000),
                       param_lr, cv=5, scoring='f1')
grid_lr.fit(X_train, y_train)

grid_lr.best_params_
```

Out[86]:
```
{'C': 10}
```

Random Forest

In [87]:
```
param_rf = {
    'n_estimators': [100, 200],
    'max_depth': [None, 5, 10]
}

grid_rf = GridSearchCV(RandomForestClassifier(random_state=42),
                       param_rf, cv=5, scoring='f1')
grid_rf.fit(X_train, y_train)

grid_rf.best_params_
```

Out[87]:
```
{'max_depth': 10, 'n_estimators': 200}
```

Feature Selection (RFE – Logistic Regression)

In [88]:
```
rfe = RFE(LogisticRegression(max_iter=1000), n_features_to_select=5)
rfe.fit(X_train, y_train)

selected_features = X.columns[rfe.support_]
selected_features
```

Out[88]:
```
Index(['Pregnancies', 'Glucose', 'BMI', 'DiabetesPedigreeFunction',
       'Age'], dtype='object')
```

Final Model Evaluation

In [89]:

```
final_lr = LogisticRegression(C=grid_lr.best_params_['C'], max_iter=1000)
final_lr.fit(X_train[:, rfe.support_], y_train)

final_pred = final_lr.predict(X_test[:, rfe.support_])

print("Final Logistic Regression Model")
print(classification_report(y_test, final_pred))
```

```
Final Logistic Regression Model
              precision    recall  f1-score   support

           0       0.75      0.81      0.78       100
           1       0.59      0.50      0.54        54

    accuracy                           0.70       154
   macro avg       0.67      0.66      0.66       154
weighted avg       0.69      0.70      0.70       154
```

PART B: REGRESSION TASK

Import Libraries

In [90]:

```
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.neural_network import MLPRegressor
```

Load Dataset

In [91]:

```
df = pd.read_csv("/kc_house_data.csv")
df.head()
```

Out[91]:

	id	date	price	bedrooms	bathrooms	s
0	7129300520	20141013T000000	221900.0	3	1.00	1
1	6414100192	20141209T000000	538000.0	3	2.25	2
2	5631500400	20150225T000000	180000.0	2	1.00	7
3	2487200875	20141209T000000	604000.0	4	3.00	1
4	1954400510	20150218T000000	510000.0	3	2.00	1

5 rows × 21 columns

Data Cleaning

In [92]:
```
df.drop(['id', 'date'], axis=1, inplace=True, errors='ignore')
```

EDA

In [93]:
```
plt.figure(figsize=(8,5))
sns.scatterplot(x='sqft_living', y='price', data=df)
plt.title("Price vs Living Area")
plt.show()
```

Train–Test Split & Scaling

In [94]:
```
X = df.drop("price", axis=1)
y = df["price"]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Neural Network Regressor

In [95]:
```
mlp_reg = MLPRegressor(hidden_layer_sizes=(64,32),
                       max_iter=500,
                       random_state=42)

mlp_reg.fit(X_train, y_train)

pred_mlp = mlp_reg.predict(X_test)

print("NN RMSE:", np.sqrt(mean_squared_error(y_test, pred_mlp)))
print("NN R2:", r2_score(y_test, pred_mlp))
```

```
NN RMSE: 181207.8370064435
NN R2: 0.782795380966062
```

```
/usr/local/lib/python3.12/dist-
packages/sklearn/neural_network/_multilayer_perceptron.py:691:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (500)
reached and the optimization hasn't converged yet.
  warnings.warn(
```

Linear Regression

In [96]:
```
lr = LinearRegression()
lr.fit(X_train, y_train)

pred_lr = lr.predict(X_test)

print("LR RMSE:", np.sqrt(mean_squared_error(y_test, pred_lr)))
print("LR R2:", r2_score(y_test, pred_lr))
```

```
LR RMSE: 212539.51663817756
LR R2: 0.7011904448878412
```

Random Forest Regressor

In [97]:
```
rf_reg = RandomForestRegressor(random_state=42)
rf_reg.fit(X_train, y_train)

pred_rf = rf_reg.predict(X_test)

print("RF RMSE:", np.sqrt(mean_squared_error(y_test, pred_rf)))
print("RF R2:", r2_score(y_test, pred_rf))
```

```
RF RMSE: 148684.3214107646
RF R2: 0.8537669783701961
```

Hyperparameter Tuning

In [98]:
```
param_rf = {
    'n_estimators': [100,100],
    'max_depth': [50, 50]
}

grid_rf = GridSearchCV(
    RandomForestRegressor(
        random_state=42
    ),
    param_rf,
    cv=2,
    scoring='r2',
    n_jobs=2,
    verbose=1
)

grid_rf.fit(X_train, y_train)

grid_rf.best_params_
```

```
Fitting 2 folds for each of 4 candidates, totalling 8 fits
```

Out[98]:
```
{'max_depth': 50, 'n_estimators': 100}
```

Feature Importance

In [99]:
```
importances = rf_reg.feature_importances_
features = X.columns

feat_imp = pd.Series(importances,
index=features).sort_values(ascending=False)
feat_imp.head()
```

Out[99]:

	0
grade	0.314274
sqft_living	0.274926
lat	0.153213
long	0.063410
yr_built	0.032626

dtype: float64

Feature Selection

In [100]:
```
best_rf = RandomForestRegressor(
    n_estimators=grid_rf.best_params_['n_estimators'],
    max_depth=grid_rf.best_params_['max_depth'],
    random_state=42
)

best_rf.fit(X_train, y_train)

importances = best_rf.feature_importances_
features = X.columns

feature_importance = pd.Series(importances, index=features)
feature_importance = feature_importance.sort_values(ascending=False)

selected_features = feature_importance.head(8).index.tolist()
selected_features
```

Out[100]:
```
['grade',
 'sqft_living',
 'lat',
 'long',
 'yr_built',
 'waterfront',
 'sqft_living15',
 'sqft_above']
```

Rebuild FINAL MODELS with Selected Features

In [101]:
```
X_train_sel = X_train[:, [X.columns.get_loc(f) for f in selected_features]]
X_test_sel = X_test[:, [X.columns.get_loc(f) for f in selected_features]]
```

Final Model 1: Linear Regression

In [102]:
```
final_lr = LinearRegression()
final_lr.fit(X_train_sel, y_train)

lr_pred = final_lr.predict(X_test_sel)

lr_rmse = np.sqrt(mean_squared_error(y_test, lr_pred))
lr_r2 = r2_score(y_test, lr_pred)
```

Final Model 2: Random Forest Regressor

In [103]:

```
final_rf = RandomForestRegressor(
    n_estimators=grid_rf.best_params_['n_estimators'],
    max_depth=grid_rf.best_params_['max_depth'],
    random_state=42
)

final_rf.fit(X_train_sel, y_train)

rf_pred = final_rf.predict(X_test_sel)

rf_rmse = np.sqrt(mean_squared_error(y_test, rf_pred))
rf_r2 = r2_score(y_test, rf_pred)
```

Cross-Validation Scores

In [104]:

```
from sklearn.model_selection import cross_val_score

lr_cv = cross_val_score(final_lr, X_train_sel, y_train, cv=3,
scoring='r2').mean()
rf_cv = cross_val_score(final_rf, X_train_sel, y_train, cv=3,
scoring='r2').mean()
```

FINAL COMPARISON TABLE OF BOTH

In [105]:

```
final_results = pd.DataFrame({
    "Model": ["Linear Regression", "Random Forest Regressor"],
    "Features Used": [f"Selected ({len(selected_features)})", f"Selected
({len(selected_features)})"],
    "CV Score": [round(lr_cv, 3), round(rf_cv, 3)],
    "Test RMSE": [round(lr_rmse, 2), round(rf_rmse, 2)],
    "Test R-squared": [round(lr_r2, 3), round(rf_r2, 3)]
})

final_results
```

Out[105]:

	Model	Features Used	CV Score	Test RMSE	Test R-squared
0	Linear Regression	Selected (8)	0.675	219859.00	0.680
1	Random Forest Regressor	Selected (8)	0.869	144185.13	0.862