Classification Takeaway Assignment

Import necessary libraries

In [104…
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans, AgglomerativeClustering, DBSCAN
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score, f1_score, precision_score, re
from sklearn.metrics import silhouette_score, davies_bouldin_score, calin

from imblearn.over_sampling import SMOTE
```

Load the dataset

In [105…
```
df = pd.read_csv('Dataset of Diabetes .csv')
```

Exploratory Data Analysis

In [106…
```
df.head()
```

Out[106…

	ID	No_Pation	Gender	AGE	Urea	Cr	HbA1c	Chol	TG	HDL	LDL	VLDL
0	502	17975	F	50	4.7	46	4.9	4.2	0.9	2.4	1.4	0.5
1	735	34221	M	26	4.5	62	4.9	3.7	1.4	1.1	2.1	0.6
2	420	47975	F	50	4.7	46	4.9	4.2	0.9	2.4	1.4	0.5
3	680	87656	F	50	4.7	46	4.9	4.2	0.9	2.4	1.4	0.5
4	504	34223	M	33	7.1	46	4.9	4.9	1.0	0.8	2.0	0.4

In [107…
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 14 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   ID         1000 non-null   int64  
 1   No_Pation  1000 non-null   int64  
 2   Gender     1000 non-null   object 
 3   AGE        1000 non-null   int64  
 4   Urea       1000 non-null   float64
 5   Cr         1000 non-null   int64  
 6   HbA1c      1000 non-null   float64
 7   Chol       1000 non-null   float64
 8   TG         1000 non-null   float64
 9   HDL        1000 non-null   float64
 10  LDL        1000 non-null   float64
 11  VLDL       1000 non-null   float64
 12  BMI        1000 non-null   float64
 13  CLASS      1000 non-null   object 
dtypes: float64(8), int64(4), object(2)
memory usage: 109.5+ KB
```

Check for null values

In [108…

```
print(df.isnull().sum())
```

```
ID           0
No_Pation    0
Gender       0
AGE          0
Urea         0
Cr           0
HbA1c        0
Chol         0
TG           0
HDL          0
LDL          0
VLDL         0
BMI          0
CLASS        0
dtype: int64
```

In [109…

```
print(df['CLASS'].value_counts())
```

```
CLASS
Y     840
N     102
P      53
Y       4
N       1
Name: count, dtype: int64
```

In [110…

```
df['CLASS'] = df['CLASS'].str.strip() #making sure there are only 3 class
```

In [111…

```
print(df['CLASS'].unique())
```

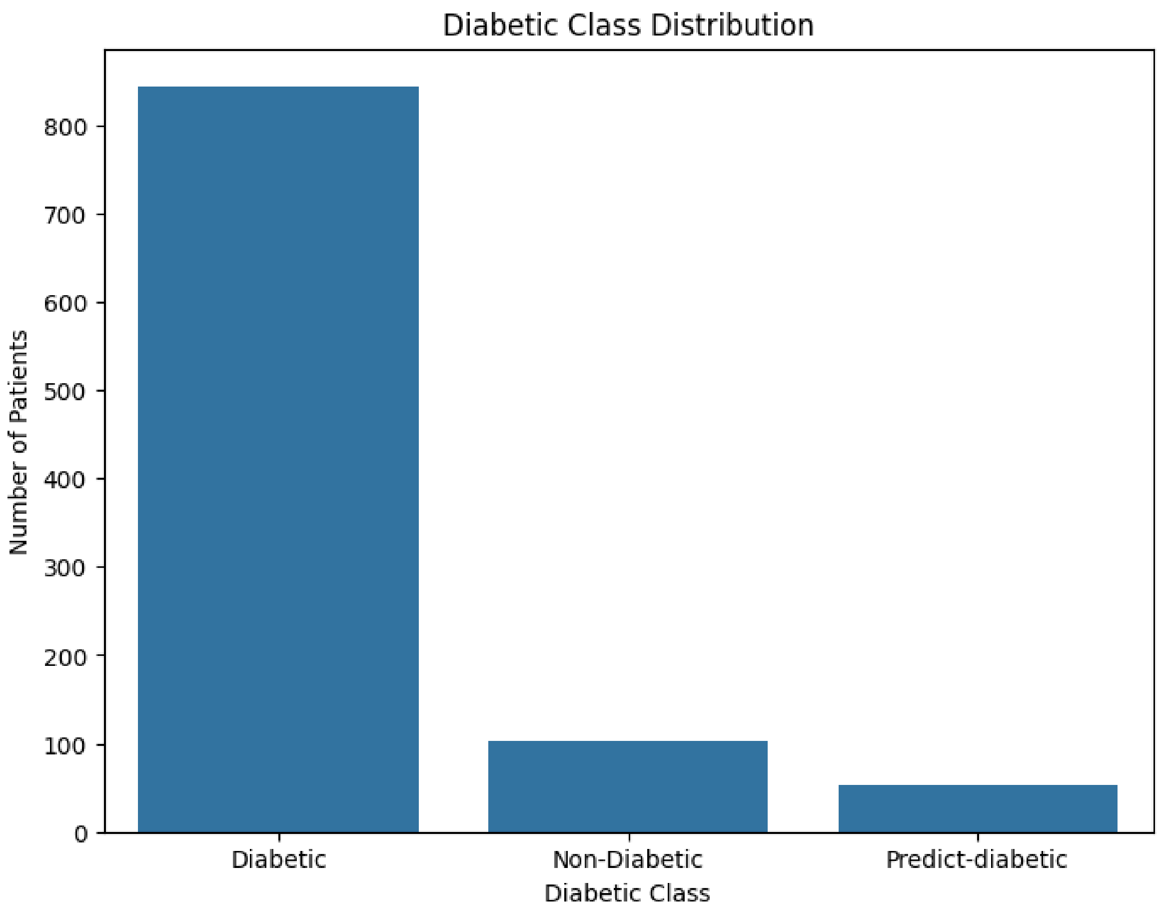
```
['N' 'P' 'Y']
```

In [112…

```
class_dist = df['CLASS'].value_counts()
class_dist = class_dist.rename({"Y":"Diabetic", "P":"Predict-diabetic", "
```

```
plt.figure(figsize=(8, 6))
ax = sns.barplot(x=class_dist.index, y=class_dist.values)
plt.title("Diabetic Class Distribution")
plt.ylabel("Number of Patients")
plt.xlabel("Diabetic Class")
```

Out[112… Text(0.5, 0, 'Diabetic Class')



In [113…
```
print(df['Gender'].value_counts())
```

```
Gender
M    565
F    434
f      1
Name: count, dtype: int64
```

In [114…
```
df['Gender'] = df['Gender'].str.upper()
```

In [115…
```
print(df['Gender'].unique())
```

```
['F' 'M']
```

In [116…
```
le = LabelEncoder()

# Fit and transform the categorical data
df['Gender']= le.fit_transform(df['Gender'])
df['CLASS']= le.fit_transform(df['CLASS'])
```

In [117…
```
df.describe()
```

Out[117…

	ID	No_Pation	Gender	AGE	Urea	
count	1000.000000	1.000000e+03	1000.000000	1000.000000	1000.000000	1000.(
mean	340.500000	2.705514e+05	0.565000	53.528000	5.124743	68.9
std	240.397673	3.380758e+06	0.496005	8.799241	2.935165	59.!
min	1.000000	1.230000e+02	0.000000	20.000000	0.500000	6.(
25%	125.750000	2.406375e+04	0.000000	51.000000	3.700000	48.(
50%	300.500000	3.439550e+04	1.000000	55.000000	4.600000	60.(
75%	550.250000	4.538425e+04	1.000000	59.000000	5.700000	73.(
max	800.000000	7.543566e+07	1.000000	79.000000	38.900000	800.(

In [118…

```
df.drop(columns=['ID','No_Pation'])
```

Out[118…

	Gender	AGE	Urea	Cr	HbA1c	Chol	TG	HDL	LDL	VLDL	BMI	CLASS
0	0	50	4.7	46	4.9	4.2	0.9	2.4	1.4	0.5	24.0	0
1	1	26	4.5	62	4.9	3.7	1.4	1.1	2.1	0.6	23.0	0
2	0	50	4.7	46	4.9	4.2	0.9	2.4	1.4	0.5	24.0	0
3	0	50	4.7	46	4.9	4.2	0.9	2.4	1.4	0.5	24.0	0
4	1	33	7.1	46	4.9	4.9	1.0	0.8	2.0	0.4	21.0	0
...	...	...	...	...	...	...	...	...	...	...	...	...
995	1	71	11.0	97	7.0	7.5	1.7	1.2	1.8	0.6	30.0	2
996	1	31	3.0	60	12.3	4.1	2.2	0.7	2.4	15.4	37.2	2
997	1	30	7.1	81	6.7	4.1	1.1	1.2	2.4	8.1	27.4	2
998	1	38	5.8	59	6.7	5.3	2.0	1.6	2.9	14.0	40.5	2
999	1	54	5.0	67	6.9	3.8	1.7	1.1	3.0	0.7	33.0	2

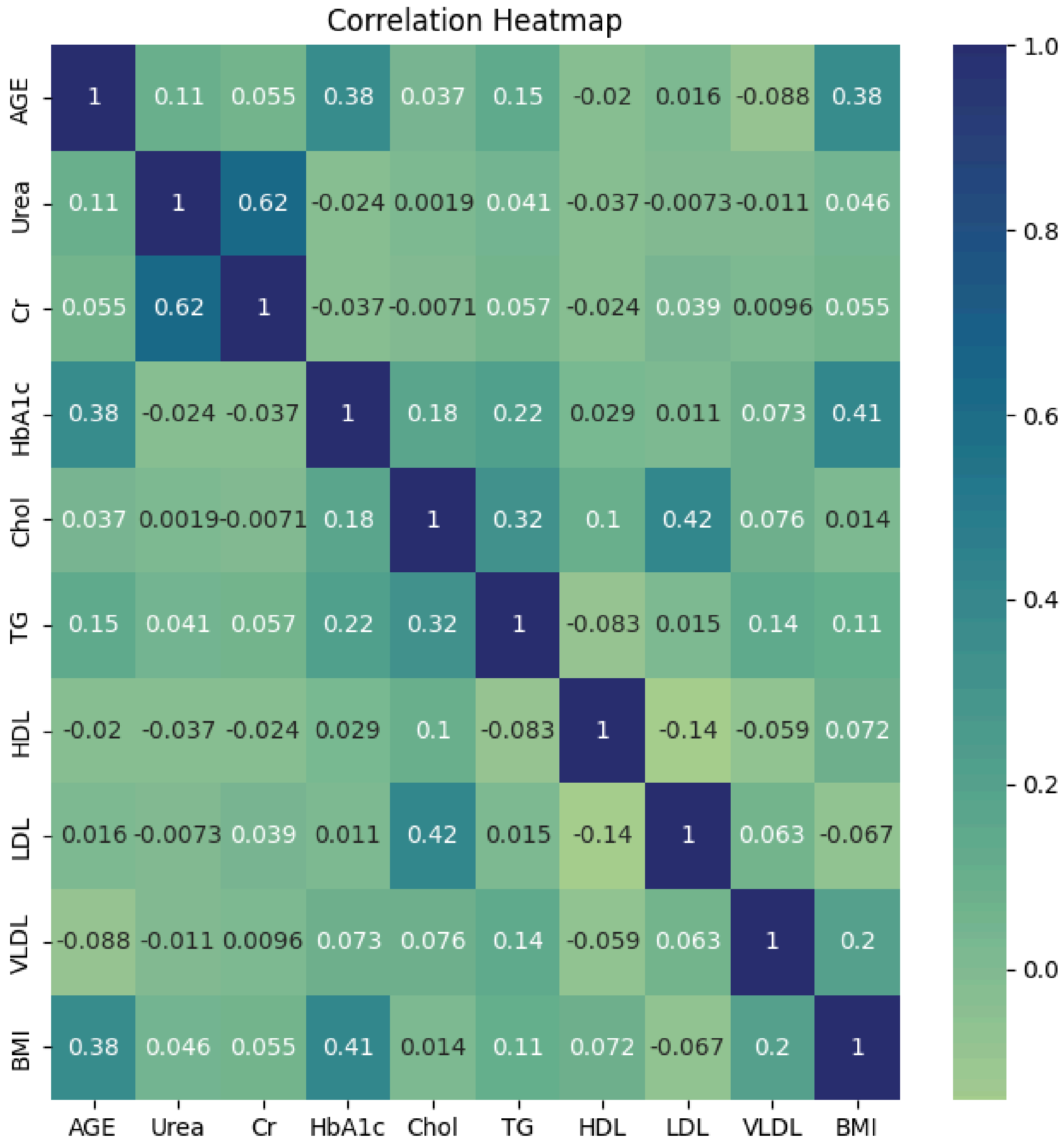
1000 rows × 12 columns

In [119…

```
attribute_columns = ['AGE', 'Urea', 'Cr', 'HbA1c', 'Chol','TG', 'HDL', 'L
corr_matrix = df[attribute_columns].corr()

plt.figure(figsize=(8, 8))
sns.heatmap(corr_matrix, annot=True, cmap='crest' )
plt.title('Correlation Heatmap')
```

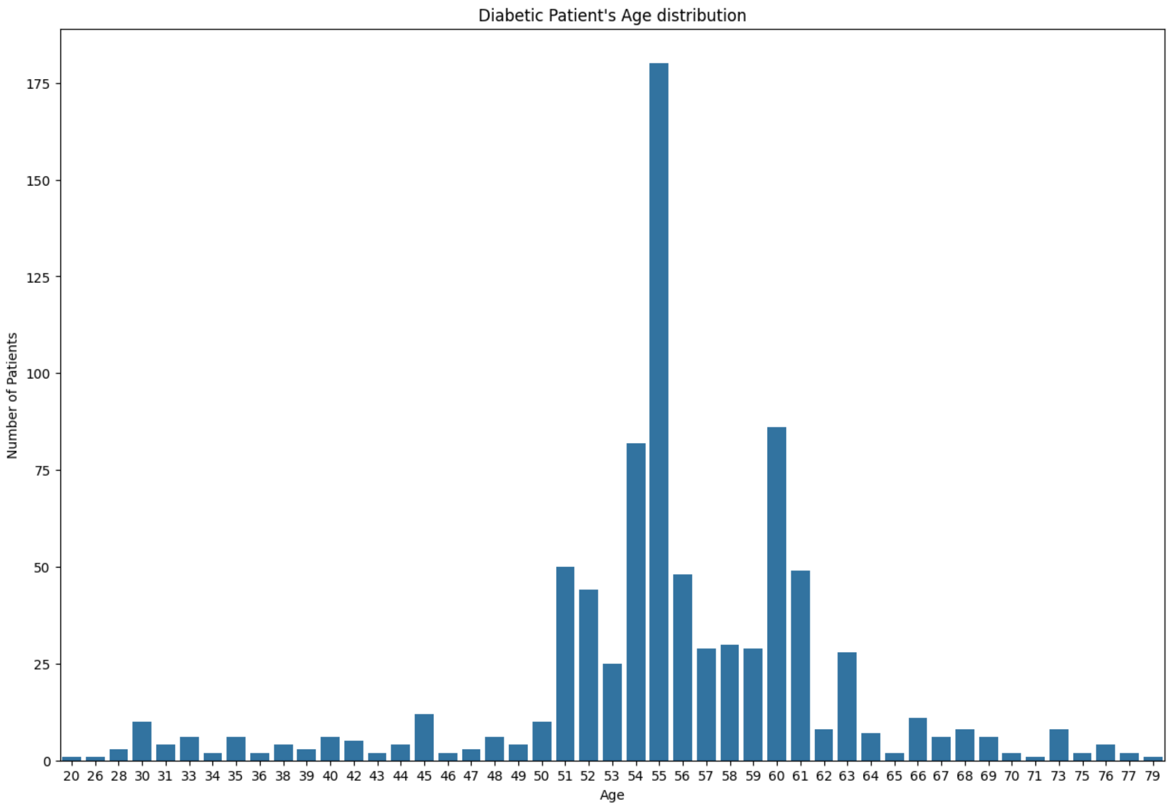
Out[119…

```
Text(0.5, 1.0, 'Correlation Heatmap')
```



In [120…
```
diabetic_patients = df.loc[df["CLASS"] == 2]
non_diabetic_patients = df.loc[df["CLASS"] == 0]
predict_diabetic_patients = df.loc[df["CLASS"] == 1]
```

In [121…
```
age_count = diabetic_patients['AGE'].value_counts()
age_count = age_count.sort_index()

plt.figure(figsize=(15, 10))
bax = sns.barplot(x=age_count.index, y=age_count.values)
plt.title("Diabetic Patient's Age distribution")
plt.ylabel("Number of Patients")
plt.xlabel("Age")
plt.show()
```



Model Building

In [122…

```
X = df.drop('CLASS', axis=1)  # Features
y = df['CLASS']  # Target variable
```

In [123…

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,

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

Classification Algorithms:

K Nearest Neighbour (KNN)

In [124…

```
training_accuracy = []
test_accuracy = []
training_f1 = []
test_f1 = []

neighbors_settings = range(2,20)

for n_neighbors in neighbors_settings:
    print(f'working on neighbors {n_neighbors}')
    knn = KNeighborsClassifier(n_neighbors=n_neighbors)
    knn.fit(X_train, y_train)

    y_train_pred=knn.predict(X_train)
    y_pred=knn.predict(X_test)

    training_accuracy.append(accuracy_score(y_train,y_train_pred))
```

```
    test_accuracy.append(accuracy_score(y_test, y_pred))

    training_f1.append(f1_score(y_train,y_train_pred, average='weighted')
    test_f1.append(f1_score(y_test, y_pred, average='weighted'))
```

```
working on neighbors 2
working on neighbors 3
working on neighbors 4
working on neighbors 5
working on neighbors 6
working on neighbors 7
working on neighbors 8
working on neighbors 9
working on neighbors 10
working on neighbors 11
working on neighbors 12
working on neighbors 13
working on neighbors 14
working on neighbors 15
working on neighbors 16
working on neighbors 17
working on neighbors 18
working on neighbors 19
```

In [125…

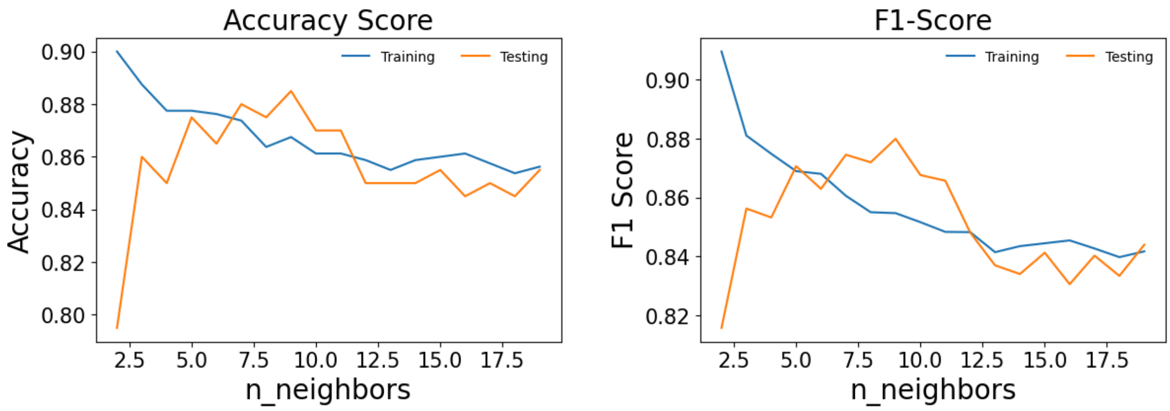
```
results_df = pd.DataFrame({
    'k': neighbors_settings,
    'Training Accuracy': training_accuracy,
    'Test Accuracy': test_accuracy,
    'Training F1 Score': training_f1,
    'Test F1 Score': test_f1
})

print(results_df)

best_k_accuracy = results_df.loc[results_df['Test Accuracy'].idxmax()]
print(f"\nBest k based on Test Accuracy: {best_k_accuracy['k']}")
print(f"Test Accuracy: {best_k_accuracy['Test Accuracy']}")
print(f"Training Accuracy: {best_k_accuracy['Training Accuracy']}")

best_k_f1 = results_df.loc[results_df['Test F1 Score'].idxmax()]
print(f"\nBest k based on Test F1 Score: {best_k_f1['k']}")
print(f"Test F1 Score: {best_k_f1['Test F1 Score']}")
print(f"Training F1 Score: {best_k_f1['Training F1 Score']}")
```

	k	Training Accuracy	Test Accuracy	Training F1 Score	Test F1 Score
0	2	0.90000	0.795	0.909521	0.815808
1	3	0.88750	0.860	0.881025	0.856264
2	4	0.87750	0.850	0.874846	0.853246
3	5	0.87750	0.875	0.868952	0.870631
4	6	0.87625	0.865	0.868044	0.862955
5	7	0.87375	0.880	0.860605	0.874531
6	8	0.86375	0.875	0.855023	0.871945
7	9	0.86750	0.885	0.854716	0.879932
8	10	0.86125	0.870	0.851648	0.867626
9	11	0.86125	0.870	0.848364	0.865702
10	12	0.85875	0.850	0.848273	0.848139
11	13	0.85500	0.850	0.841479	0.837011
12	14	0.85875	0.850	0.843524	0.834067
13	15	0.86000	0.855	0.844496	0.841294
14	16	0.86125	0.845	0.845471	0.830618
15	17	0.85750	0.850	0.842732	0.840303
16	18	0.85375	0.845	0.839795	0.833434
17	19	0.85625	0.855	0.841749	0.843980

```
Best k based on Test Accuracy: 9.0
Test Accuracy: 0.885
Training Accuracy: 0.8675

Best k based on Test F1 Score: 9.0
Test F1 Score: 0.8799319727891156
Training F1 Score: 0.8547156862473493
```

In [126…

```
fig = plt.figure(figsize=(14,10))
fig.subplots_adjust(hspace=0.5, wspace=0.3)

fig.add_subplot(2,2,1)
plt.plot(neighbors_settings, training_accuracy, label='training accuracy'
plt.plot(neighbors_settings, test_accuracy, label='test accuracy')
plt.ylabel('Accuracy',size=20)
plt.xticks(size=15)
plt.yticks(size=15)
plt.xlabel('n_neighbors',size=20)
plt.title('Accuracy Score',size=20)
plt.legend(['Training','Testing'],frameon=False, ncol=2);

fig.add_subplot(2,2,2)
plt.plot(neighbors_settings, training_f1)
plt.plot(neighbors_settings, test_f1)
plt.xticks(size=15)
plt.yticks(size=15)
plt.ylabel('F1 Score',size=20)
plt.xlabel('n_neighbors',size=20)
plt.title('F1-Score',size=20)
plt.legend(['Training','Testing'],frameon=False, ncol=2);
```



In [127…

```
knn = KNeighborsClassifier(n_neighbors=9).fit(X_train, y_train)
y_pred = knn.predict(X_test)

print(classification_report(y_test,y_pred))
```

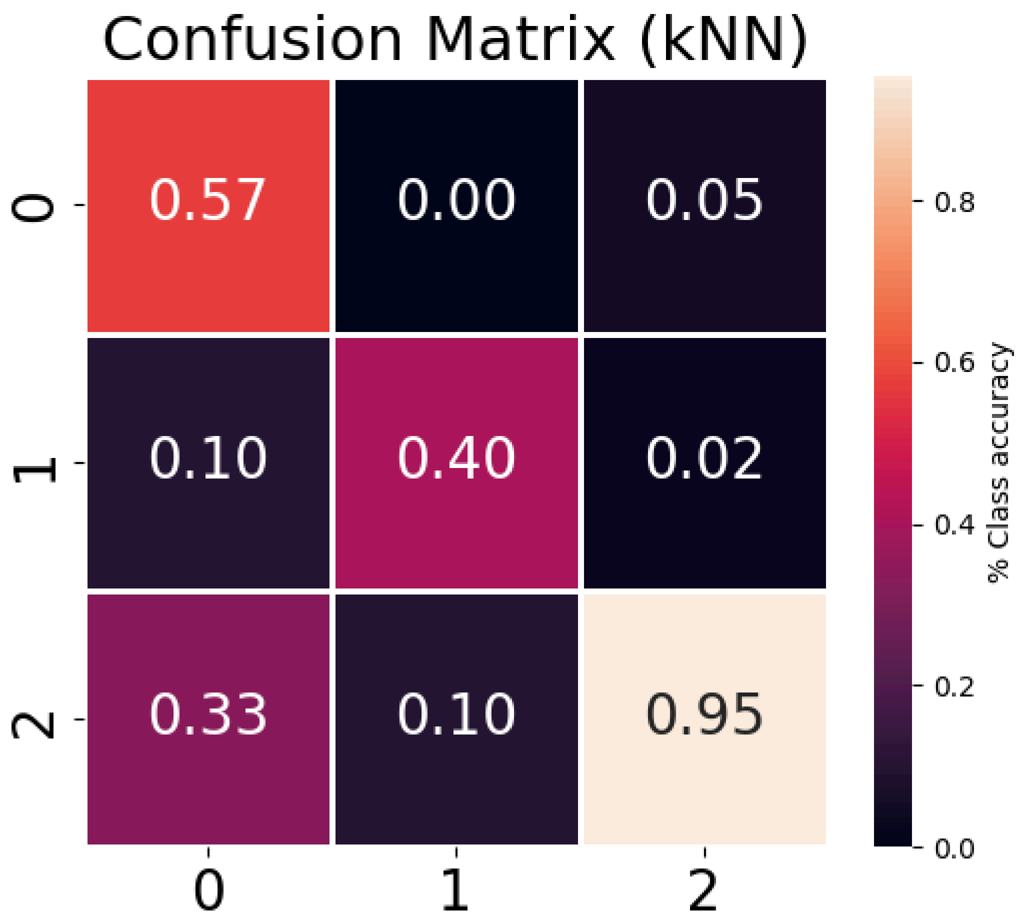
```
              precision    recall  f1-score   support

           0       0.57      0.57      0.57        21
           1       0.80      0.40      0.53        10
           2       0.93      0.95      0.94       169

    accuracy                           0.89       200
   macro avg       0.77      0.64      0.68       200
weighted avg       0.88      0.89      0.88       200
```

In [128…

```
def normalized_confusion_matrix(y_test, conf_mat, model):
    _ , counts = np.unique(y_test,return_counts=True)
    conf_mat = conf_mat/counts
    plt.figure(figsize=(6,5))
    ax=sns.heatmap(conf_mat,fmt='.2f',annot=True,annot_kws={'size':20},lw
    plt.title(f'Confusion Matrix ({model})',size=22)
    plt.xticks(size=20)
    plt.yticks(size=20)
```

In [129…

```
conf_mat = confusion_matrix(y_test,y_pred)
normalized_confusion_matrix(y_test,conf_mat, 'kNN')
```



Support Vector Machine (SVM)

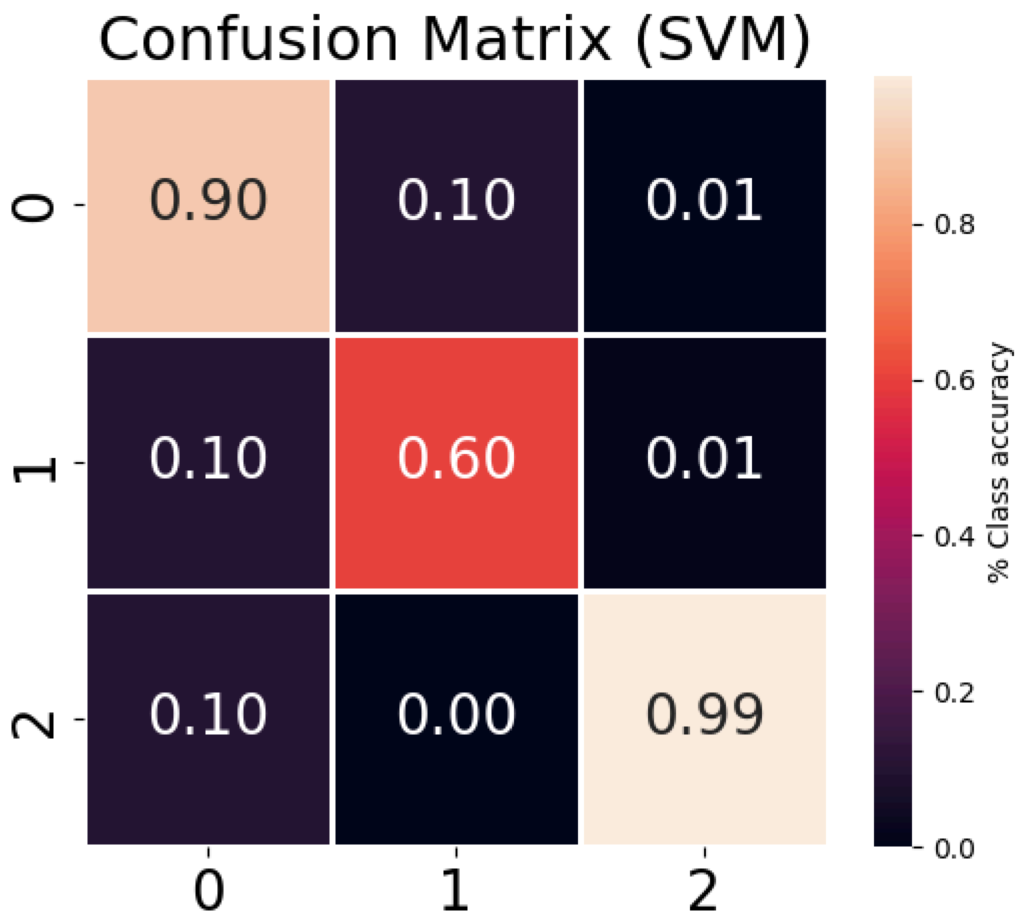
In [130…

```
svc = SVC(C=1000, gamma='auto').fit(X_train_scaled, y_train)
y_pred=svc.predict(X_test_scaled)

print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.83      0.90      0.86        21
           1       0.86      0.60      0.71        10
           2       0.98      0.99      0.99       169

    accuracy                           0.96       200
   macro avg       0.89      0.83      0.85       200
weighted avg       0.96      0.96      0.96       200
```

In [131…

```
conf_mat = confusion_matrix(y_test,y_pred)
normalized_confusion_matrix(y_test,conf_mat,'SVM')
```



Decision Tree

In [132…

```
max_depth=range(1,20)
training_accuracy = []
test_accuracy = []
training_f1 = []
test_f1 = []

for depth in max_depth :
    tree = DecisionTreeClassifier(random_state=0, max_depth=depth, min_sa
    y_train_pred = tree.predict(X_train)
    y_pred = tree.predict(X_test)

    training_accuracy.append(accuracy_score(y_train,y_train_pred))
    test_accuracy.append(accuracy_score(y_test, y_pred))

    training_f1.append(f1_score(y_train,y_train_pred,average='weighted'))
    test_f1.append(f1_score(y_test, y_pred,average='weighted'))
```

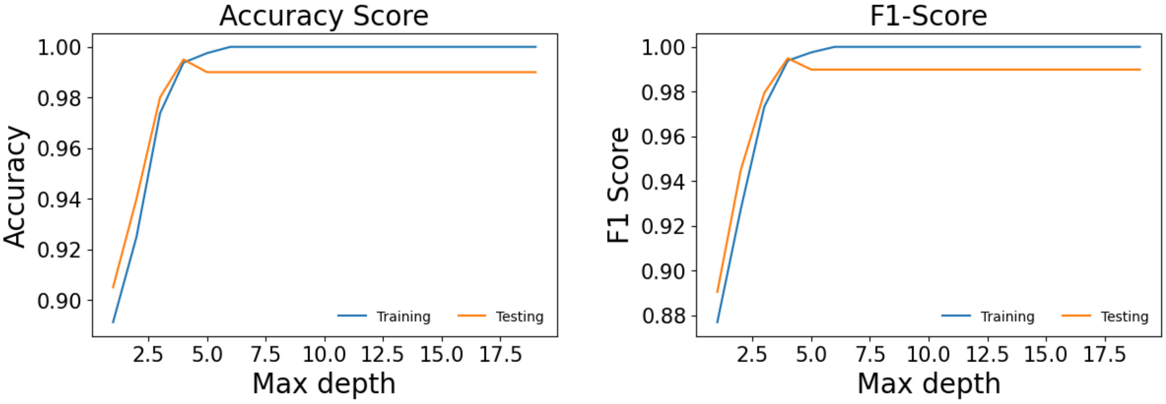
In [133…

```
best_max_depth = pd.DataFrame({
    "Max Depth": max_depth,
    "Train Accuracy": training_accuracy,
    "Test Accuracy": test_accuracy,
    "Train F1": training_f1,
    "Test F1": test_f1
})

print(best_max_depth.to_string(index=False))
```

```
    Max Depth  Train Accuracy  Test Accuracy  Train F1  Test F1
            1         0.89125          0.905  0.876988 0.890492
            2         0.92500          0.940  0.927530 0.945016
            3         0.97375          0.980  0.973217 0.979408
            4         0.99375          0.995  0.993831 0.994876
            5         0.99750          0.990  0.997513 0.989837
            6         1.00000          0.990  1.000000 0.989837
            7         1.00000          0.990  1.000000 0.989837
            8         1.00000          0.990  1.000000 0.989837
            9         1.00000          0.990  1.000000 0.989837
           10         1.00000          0.990  1.000000 0.989837
           11         1.00000          0.990  1.000000 0.989837
           12         1.00000          0.990  1.000000 0.989837
           13         1.00000          0.990  1.000000 0.989837
           14         1.00000          0.990  1.000000 0.989837
           15         1.00000          0.990  1.000000 0.989837
           16         1.00000          0.990  1.000000 0.989837
           17         1.00000          0.990  1.000000 0.989837
           18         1.00000          0.990  1.000000 0.989837
           19         1.00000          0.990  1.000000 0.989837
```

In [134…

```
fig = plt.figure(figsize=(14,10))
fig.subplots_adjust(hspace=0.5, wspace=0.3)

fig.add_subplot(2,2,1)
plt.plot(max_depth, training_accuracy, label='training accuracy')
plt.plot(max_depth, test_accuracy, label='test accuracy')
plt.ylabel('Accuracy',size=20)
plt.xlabel('Max depth',size=20)
plt.xticks(size=15)
plt.yticks(size=15)
plt.title('Accuracy Score',size=20)
plt.legend(['Training','Testing'],frameon=False, ncol=2);

fig.add_subplot(2,2,2)
plt.plot(max_depth, training_f1)
plt.plot(max_depth, test_f1)
plt.ylabel('F1 Score',size=20)
plt.xlabel('Max depth',size=20)
plt.xticks(size=15)
plt.yticks(size=15)
plt.title('F1-Score',size=20)
plt.legend(['Training','Testing'],frameon=False, ncol=2);
```



In [135…

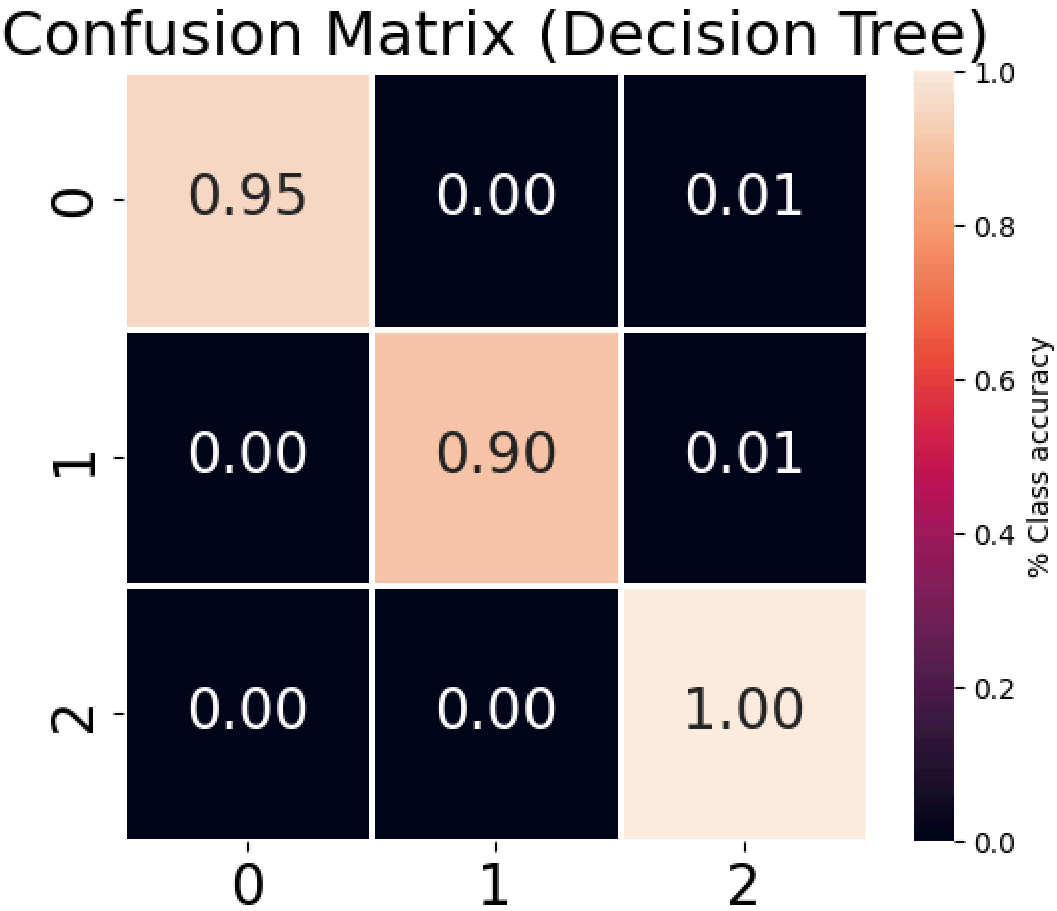
```
tree = DecisionTreeClassifier(max_depth=8, min_samples_leaf=1, random_sta
y_pred=tree.predict(X_test)
```

```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      0.95      0.98        21
           1       1.00      0.90      0.95        10
           2       0.99      1.00      0.99       169

    accuracy                           0.99       200
   macro avg       1.00      0.95      0.97       200
weighted avg       0.99      0.99      0.99       200
```

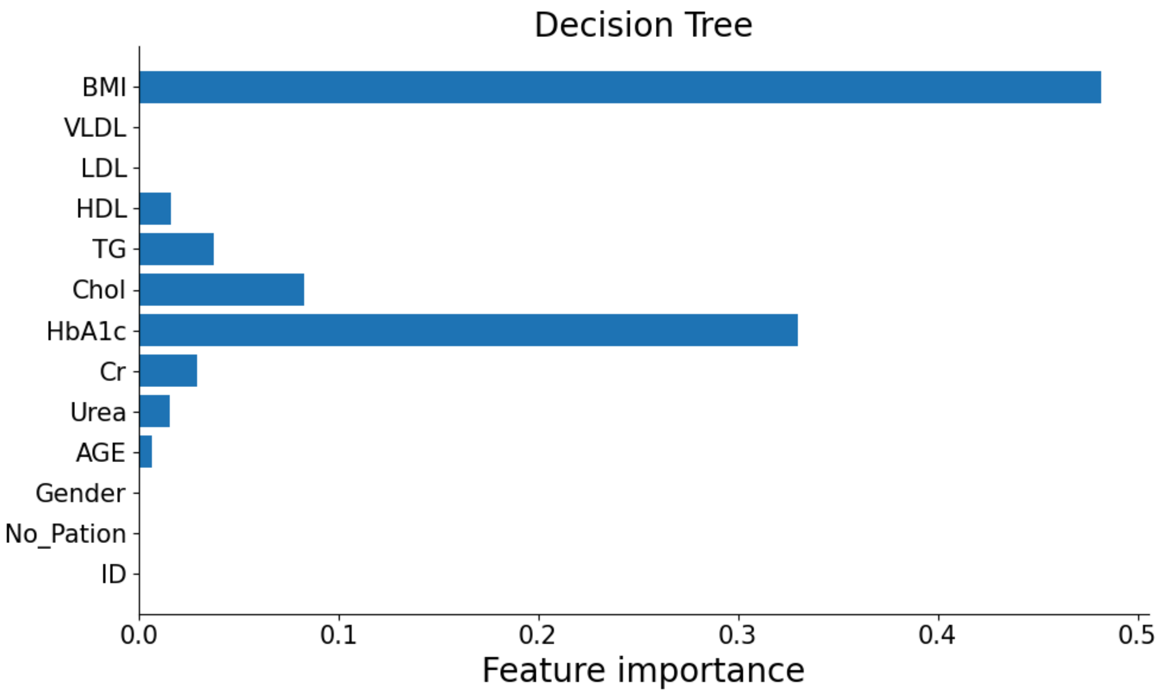
In [136…

```
conf_mat = confusion_matrix(y_test,y_pred)
normalized_confusion_matrix(y_test,conf_mat,'Decision Tree')
```



In [137…

```
n_features = 13
plt.figure(figsize=(10,6))
plt.barh(range(n_features), tree.feature_importances_, align='center')
plt.yticks(np.arange(n_features), X_train.columns, size=15)
plt.xticks(size=15)
plt.xlabel('Feature importance', size=20)
# plt.ylabel('Feature', size=20)
plt.ylim(-1, n_features)
sns.despine(top=True)
plt.title('Decision Tree', size=20)
plt.tight_layout()
```



We can see that BMI is the most important feature followed by HbA1c.

Logistic Regression

In [138…

```
logreg_cv = LogisticRegression(C=10, solver='lbfgs', max_iter=1000, class
cv_scores = cross_val_score(logreg_cv, X_train_scaled, y_train, cv=5, sco
print("Cross-validation accuracy (5-fold):", cv_scores.mean())

logreg_cv.fit(X_train_scaled, y_train)
y_pred = logreg_cv.predict(X_test)

print(classification_report(y_test, y_pred,zero_division=0))
```

```
Cross-validation accuracy (5-fold): 0.905
              precision    recall  f1-score   support

           0       0.11      1.00      0.19        21
           1       0.00      0.00      0.00        10
           2       1.00      0.01      0.02       169

    accuracy                           0.12       200
   macro avg       0.37      0.34      0.07       200
weighted avg       0.86      0.12      0.04       200
```

```
/Users/sushantneopane/Library/Python/3.9/lib/python/site-packages/sklearn/
utils/validation.py:2732: UserWarning: X has feature names, but LogisticRe
gression was fitted without feature names
  warnings.warn(
```

In [139…

```
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)

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

# Use SMOTE to address class imbalance
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_trai
```

```
# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_resampled)
X_test_scaled = scaler.transform(X_test)

parameters = {
    'C': [0.001, 0.01, 0.1, 1, 10],
    'penalty': ['l2'],
    'class_weight': [None, 'balanced']
}
```

In [140…

```
logreg_model = LogisticRegression(multi_class='multinomial', solver='lbfg

# Perform grid search with cross-validation
logreg_gs = GridSearchCV(logreg_model, parameters, cv=5)
logreg_gs.fit(X_train_scaled, y_train_resampled)
```

Out[140…

```
▸ GridSearchCV

▸ best_estimator_:
  LogisticRegression

  ▸ LogisticRegression
```

In [141…

```
print(f"Best Parameters: {logreg_gs.best_params_}")

y_pred = logreg_gs.predict(X_test_scaled)
```

```
Best Parameters: {'C': 10, 'class_weight': None, 'penalty': 'l2'}
```

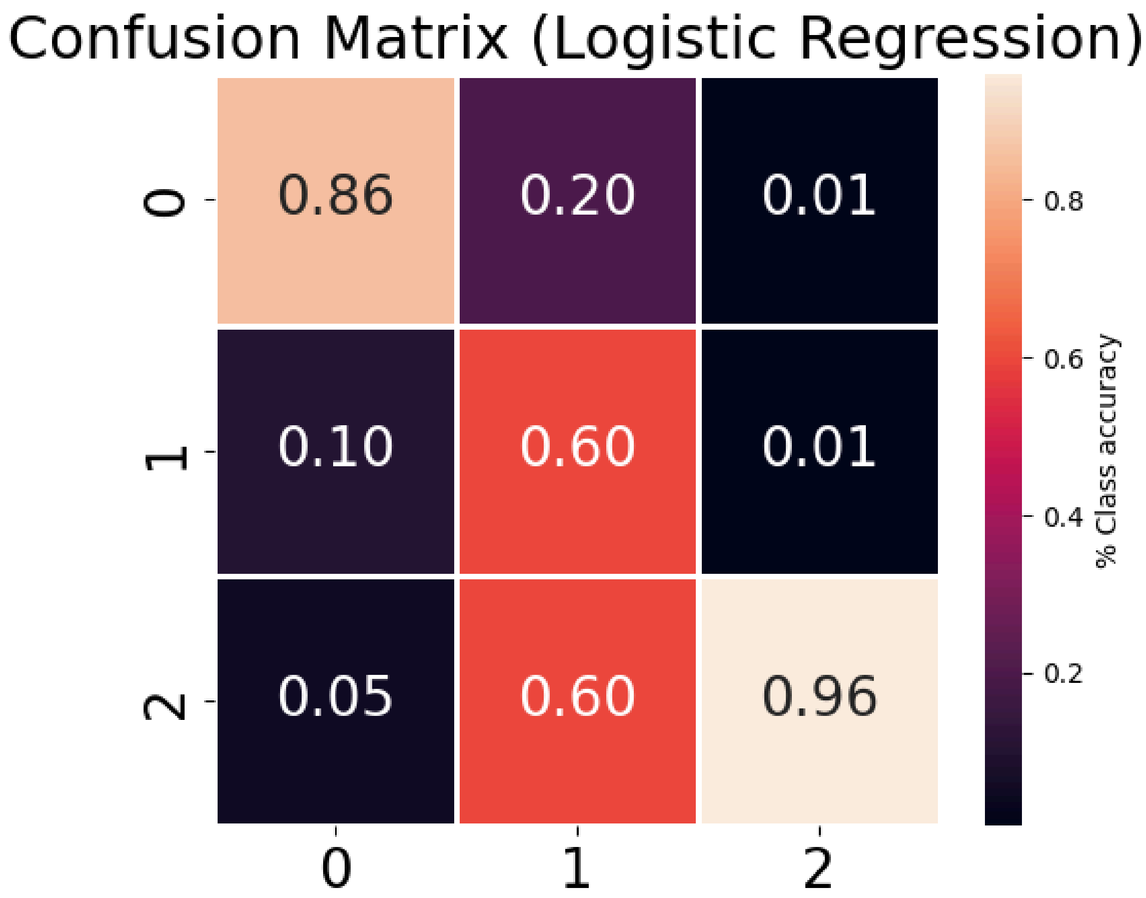
In [142…

```
print('Classification Report (Logistic Regression):\n', classification_re
```

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

           0       0.86      0.86      0.86        21
           1       0.43      0.60      0.50        10
           2       0.98      0.96      0.97       169

    accuracy                           0.93       200
   macro avg       0.76      0.81      0.78       200
weighted avg       0.94      0.93      0.93       200
```

In [143…

```
conf_mat = confusion_matrix(y_test,y_pred)
normalized_confusion_matrix(y_test,conf_mat,'Logistic Regression')
```



Clustering

In [144…

```
print(df)
```

```
       ID  No_Pation  Gender  AGE  Urea  Cr  HbA1c  Chol   TG  HDL  LDL  VL
DL  \
0    502      17975       0   50   4.7  46    4.9    4.2  0.9  2.4  1.4
0.5
1    735      34221       1   26   4.5  62    4.9    3.7  1.4  1.1  2.1
0.6
2    420      47975       0   50   4.7  46    4.9    4.2  0.9  2.4  1.4
0.5
3    680      87656       0   50   4.7  46    4.9    4.2  0.9  2.4  1.4
0.5
4    504      34223       1   33   7.1  46    4.9    4.9  1.0  0.8  2.0
0.4
..   ...        ...     ...  ...   ...  ..    ...    ...  ...  ...  ...
...
995  200     454317       1   71  11.0  97    7.0    7.5  1.7  1.2  1.8
0.6
996  671     876534       1   31   3.0  60   12.3    4.1  2.2  0.7  2.4  1
5.4
997  669      87654       1   30   7.1  81    6.7    4.1  1.1  1.2  2.4
8.1
998   99      24004       1   38   5.8  59    6.7    5.3  2.0  1.6  2.9  1
4.0
999  248      24054       1   54   5.0  67    6.9    3.8  1.7  1.1  3.0
0.7

       BMI  CLASS
0     24.0      0
1     23.0      0
2     24.0      0
3     24.0      0
4     21.0      0
..     ...    ...
995   30.0      2
996   37.2      2
997   27.4      2
998   40.5      2
999   33.0      2

[1000 rows x 14 columns]
```

In [145…

```
df.drop(columns=['ID','No_Pation'])
```

Out[145…

	Gender	AGE	Urea	Cr	HbA1c	Chol	TG	HDL	LDL	VLDL	BMI	CLASS
0	0	50	4.7	46	4.9	4.2	0.9	2.4	1.4	0.5	24.0	0
1	1	26	4.5	62	4.9	3.7	1.4	1.1	2.1	0.6	23.0	0
2	0	50	4.7	46	4.9	4.2	0.9	2.4	1.4	0.5	24.0	0
3	0	50	4.7	46	4.9	4.2	0.9	2.4	1.4	0.5	24.0	0
4	1	33	7.1	46	4.9	4.9	1.0	0.8	2.0	0.4	21.0	0
...	...	...	...	...	...	...	...	...	...	...	...	...
995	1	71	11.0	97	7.0	7.5	1.7	1.2	1.8	0.6	30.0	2
996	1	31	3.0	60	12.3	4.1	2.2	0.7	2.4	15.4	37.2	2
997	1	30	7.1	81	6.7	4.1	1.1	1.2	2.4	8.1	27.4	2
998	1	38	5.8	59	6.7	5.3	2.0	1.6	2.9	14.0	40.5	2
999	1	54	5.0	67	6.9	3.8	1.7	1.1	3.0	0.7	33.0	2

1000 rows × 12 columns

In [146…

```
y_true = df["CLASS"]
X = df.drop(columns=["CLASS"])
```

In [147…

```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

pd.DataFrame(X_scaled, columns=X.columns).head()
```

Out[147…

	ID	No_Pation	Gender	AGE	Urea	Cr	HbA1c	
0	0.672140	-0.074747	-1.139671	-0.401144	-0.144781	-0.382672	-1.334983	-0
1	1.641852	-0.069940	0.877446	-3.130017	-0.212954	-0.115804	-1.334983	-0
2	0.330868	-0.065869	-1.139671	-0.401144	-0.144781	-0.382672	-1.334983	-0
3	1.412950	-0.054126	-1.139671	-0.401144	-0.144781	-0.382672	-1.334983	-0
4	0.680463	-0.069939	0.877446	-2.334096	0.673299	-0.382672	-1.334983	C

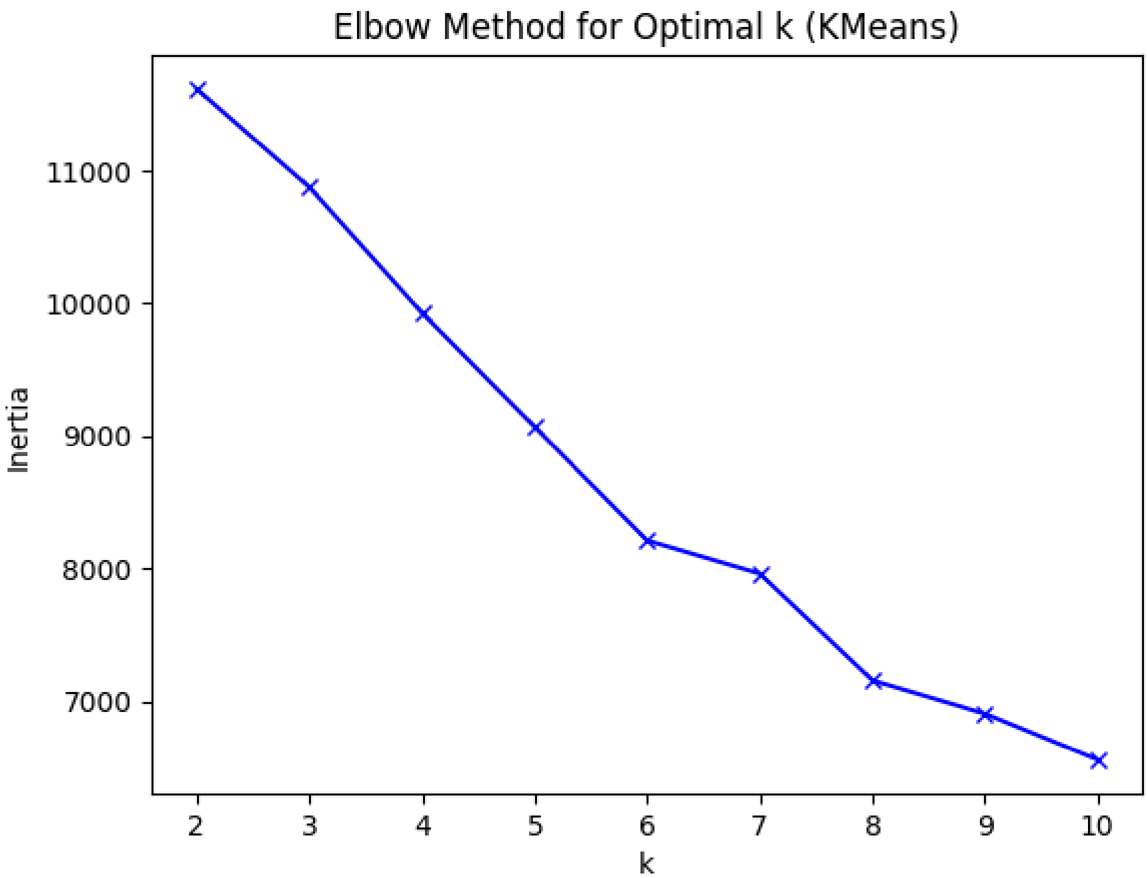
In [148…

```
# PCA for visualization
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)
```

In [149…

```
inertia = []
K = range(2, 11)
for k in K:
    km = KMeans(n_clusters=k, random_state=42)
    km.fit(X_scaled)
    inertia.append(km.inertia_)

plt.plot(K, inertia, 'bx-')
plt.xlabel('k')
plt.ylabel('Inertia')
```

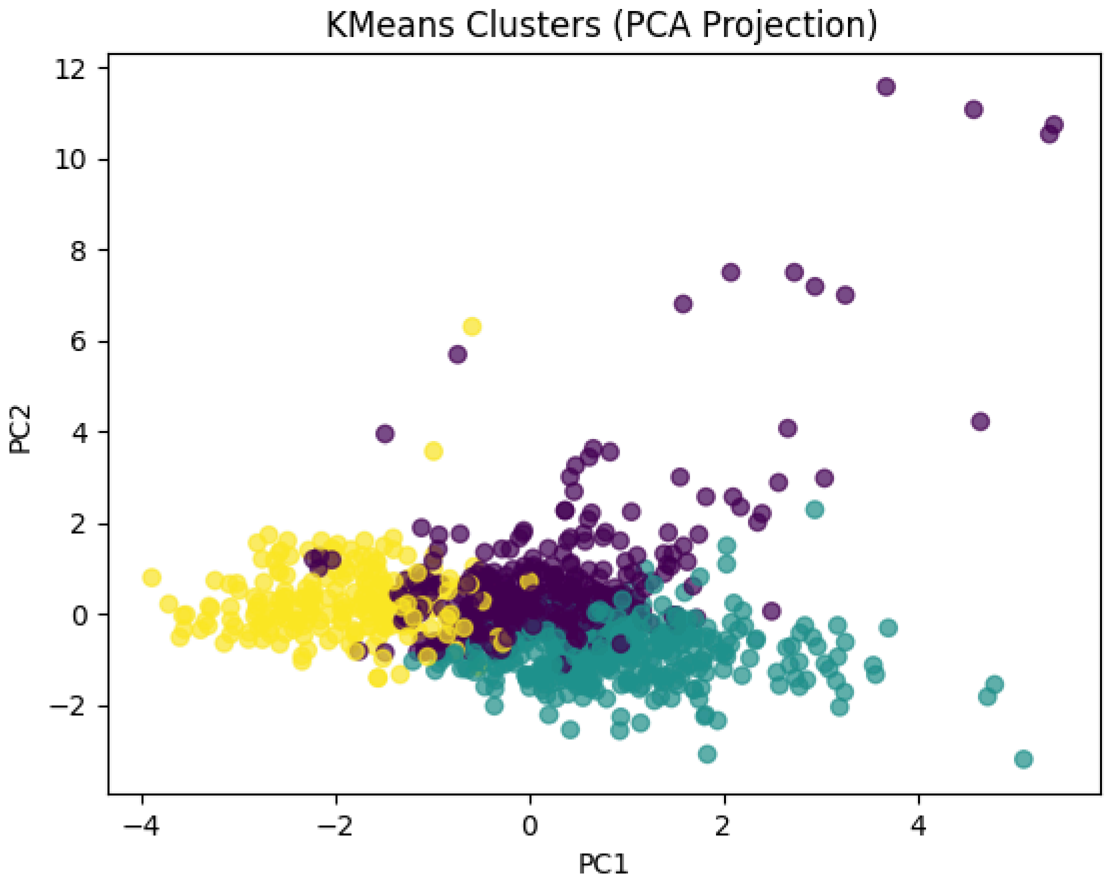
```
plt.title('Elbow Method for Optimal k (KMeans)')
plt.show()
```



In [150…

```
kmeans = KMeans(n_clusters=3, random_state=42)
labels_kmeans = kmeans.fit_predict(X_scaled)

print("KMeans Silhouette Score:", silhouette_score(X_scaled, labels_kmean
print("KMeans Davies-Bouldin Score:", davies_bouldin_score(X_scaled, labe
print("KMeans Calinski-Harabasz Score:", calinski_harabasz_score(X_scaled

plt.scatter(X_pca[:,0], X_pca[:,1], c=labels_kmeans, cmap='viridis', alph
plt.title("KMeans Clusters (PCA Projection)")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.show()
```

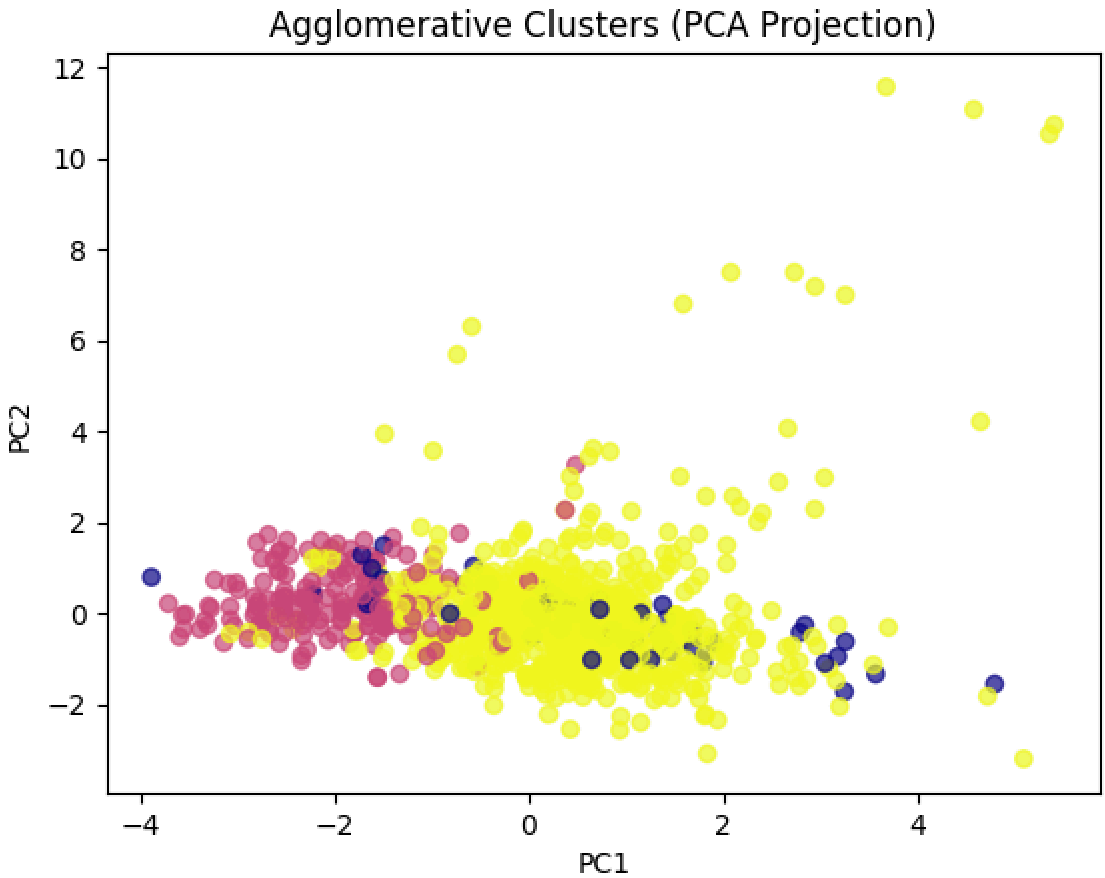
```
KMeans Silhouette Score: 0.10340177510924843
KMeans Davies-Bouldin Score: 2.5834372263333667
KMeans Calinski-Harabasz Score: 97.61959399467135
```



In [151…

```
agg = AgglomerativeClustering(n_clusters=3)
labels_agg = agg.fit_predict(X_scaled)

print("Agglomerative Silhouette Score:", silhouette_score(X_scaled, label
print("Agglomerative Davies-Bouldin Score:", davies_bouldin_score(X_scale
print("Agglomerative Calinski-Harabasz Score:", calinski_harabasz_score(X

plt.scatter(X_pca[:,0], X_pca[:,1], c=labels_agg, cmap='plasma', alpha=0.
plt.title("Agglomerative Clusters (PCA Projection)")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.show()
```

```
Agglomerative Silhouette Score: 0.13819106205375598
Agglomerative Davies-Bouldin Score: 1.860549541466516
Agglomerative Calinski-Harabasz Score: 96.8464672225151
```



Both K Means Clustering and Agglomerative Clustering perform poorly on the given dataset, based on the clustering evaluation metrics. This indicates that the dataset does not contain strong natural groupings. From the above visualizations, we can also see that there are tons of overlapped classes.

This suggests that unsupervised clustering may not be ideal for this dataset. Given that labels are available, the dataset is likely better suited for supervised learning approaches, where models can learn decision boundaries even in overlapping feature spaces.

Future Enhancements

- More hyperparameter tuning
- More classifiers such as Random Forest, Gradient Boosting, XGBoost
- Perform feature selection/engineering to reduce noise and redundancy
- Apply dimensionality reduction for better seperation and visualization
- Generating a Tableau Dashboard