du2hmqxpe

March 30, 2025

0.1 Sanyukta Chapagain

0.2 Dataset:

https://www.kaggle.com/competitions/alzheimers-disease-risk-prediction-eu-business/overview

Citation Hachem SFAR. Alzheimer's Disease Risk Prediction - EU Business. https://kaggle.com/competitions/alzheimers-disease-risk-prediction-eu-business, 2025. Kaggle.

[1]:
```
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

[2]:
```
df= pd.read_csv("dataset.csv")
```

[3]:
```
# Display value counts for all columns with  10 unique values
value_counts_output = {col: df[col].value_counts() for col in df.columns if␣
 ↪df[col].nunique() <= 10}

# Display number of unique values for all columns
nunique_output = df.nunique()
print("Number of Unique Values per Column:")
print(nunique_output)

# Display duplicate count
duplicate_count = df.duplicated().sum()
print(f"\nDuplicate Rows Count: {duplicate_count}")

# Display missing values
missing_values_output = df.isnull().sum()
print("\nMissing Values per Column:")
print(missing_values_output)
```

```
Number of Unique Values per Column:
PatientID                    1719
Age                            31
```

```
Gender                        2
Ethnicity                     4
EducationLevel                4
BMI                        1719
Smoking                       2
AlcoholConsumption         1719
PhysicalActivity           1719
DietQuality                1719
SleepQuality               1719
FamilyHistoryAlzheimers       2
CardiovascularDisease         2
Diabetes                      2
Depression                    2
HeadInjury                    2
Hypertension                  2
SystolicBP                   90
DiastolicBP                  60
CholesterolTotal           1719
CholesterolLDL             1719
CholesterolHDL             1719
CholesterolTriglycerides   1719
MMSE                       1719
FunctionalAssessment       1719
MemoryComplaints              2
BehavioralProblems            2
ADL                        1719
Confusion                     2
Disorientation                2
PersonalityChanges            2
DifficultyCompletingTasks     2
Forgetfulness                 2
Diagnosis                     2
DoctorInCharge                1
dtype: int64

Duplicate Rows Count: 0

Missing Values per Column:
PatientID                  0
Age                        0
Gender                     0
Ethnicity                  0
EducationLevel             0
BMI                        0
Smoking                    0
AlcoholConsumption         0
PhysicalActivity           0
DietQuality                0
```

```
SleepQuality                 0
FamilyHistoryAlzheimers      0
CardiovascularDisease        0
Diabetes                     0
Depression                   0
HeadInjury                   0
Hypertension                 0
SystolicBP                   0
DiastolicBP                  0
CholesterolTotal             0
CholesterolLDL               0
CholesterolHDL               0
CholesterolTriglycerides     0
MMSE                         0
FunctionalAssessment         0
MemoryComplaints             0
BehavioralProblems           0
ADL                          0
Confusion                    0
Disorientation               0
PersonalityChanges           0
DifficultyCompletingTasks    0
Forgetfulness                0
Diagnosis                    0
DoctorInCharge               0
dtype: int64
```

0.3 Dataset Overview

The dataset consists of 35 features, of which two—PatientID and DoctorInCharge—should be removed as they do not contribute to prediction. This leaves 33 usable features. Among them, some features like Ethnicity and EducationLevel have more than two unique values and represent discrete categories. These can be encoded using one-hot encoding or ordinal encoding, depending on the modeling approach.

The dataset also includes several continuous features such as Age, BMI, AlcoholConsumption, PhysicalActivity, DietQuality, SleepQuality, SystolicBP, DiastolicBP, CholesterolTotal, CholesterolLDL, CholesterolHDL, CholesterolTriglycerides, MMSE, FunctionalAssessment, and ADL, all of which would benefit from normalization or standardization. Overall, the dataset is clean, with no missing values or duplicates, and is ready for preprocessing.

1 Question 1) Display the statistical values for each of the attributes, along with visualizations (e.g., histogram) of the distributions for each attribute. Are there any attributes that might require special treatment? If so, what special treatment might they require?

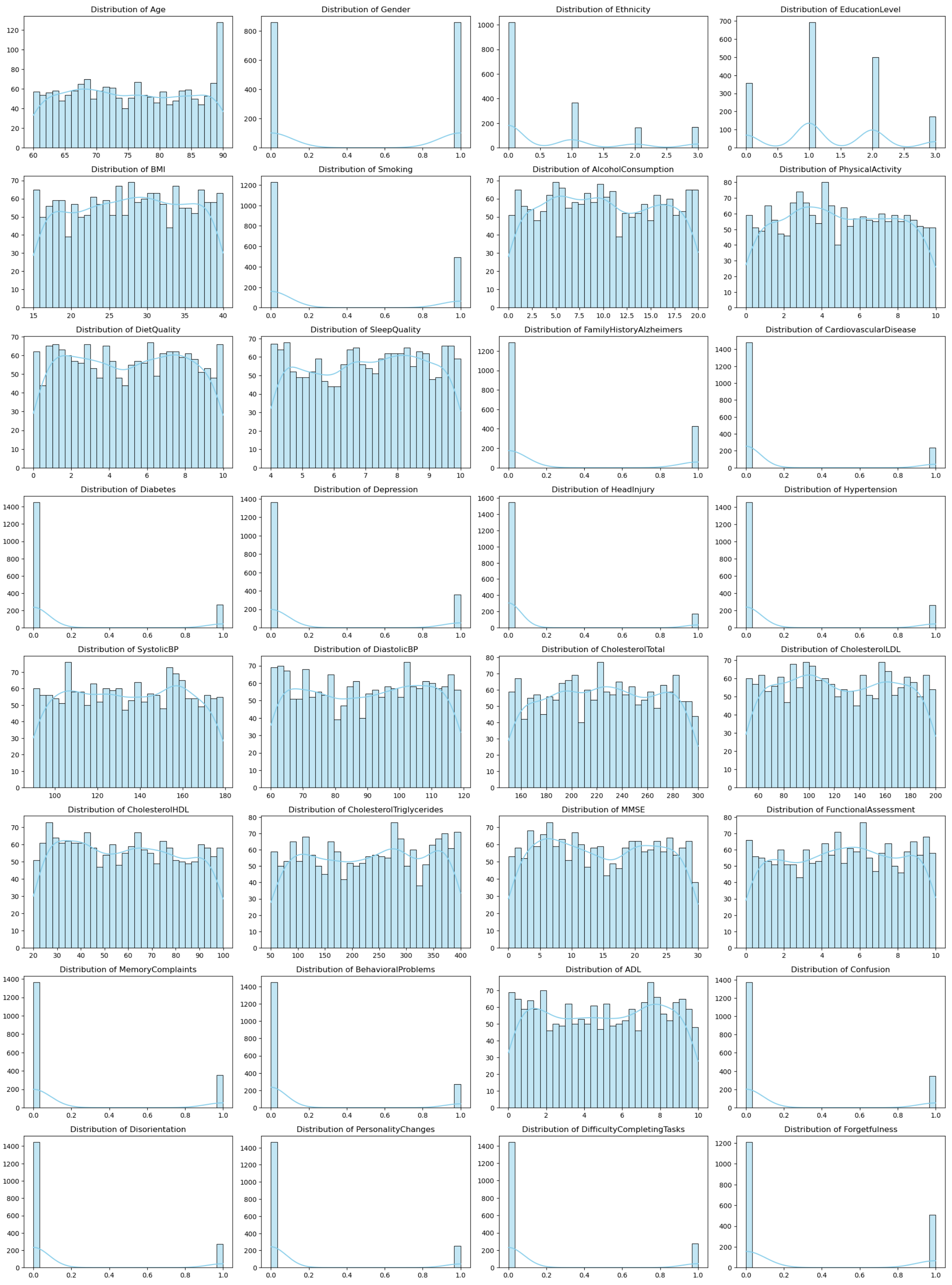
[4]:
```
#Dropping irrevelant column
```

[5]:
```
# Drop irrelevant columns: 'PatientID' and 'DoctorInCharge'
df_cleaned = df.drop(columns=['PatientID', 'DoctorInCharge'])

# Confirm the columns are dropped
remaining_columns = df_cleaned.columns.tolist()
df_cleaned.shape, remaining_columns
```

[5]:
```
((1719, 33),
 ['Age',
  'Gender',
  'Ethnicity',
  'EducationLevel',
  'BMI',
  'Smoking',
  'AlcoholConsumption',
  'PhysicalActivity',
  'DietQuality',
  'SleepQuality',
  'FamilyHistoryAlzheimers',
  'CardiovascularDisease',
  'Diabetes',
  'Depression',
  'HeadInjury',
  'Hypertension',
  'SystolicBP',
  'DiastolicBP',
  'CholesterolTotal',
  'CholesterolLDL',
  'CholesterolHDL',
  'CholesterolTriglycerides',
  'MMSE',
  'FunctionalAssessment',
  'MemoryComplaints',
  'BehavioralProblems',
  'ADL',
  'Confusion',
  'Disorientation',
  'PersonalityChanges',
  'DifficultyCompletingTasks',
  'Forgetfulness',
  'Diagnosis'])
```

[6]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# 1. Statistical summary
print("=== Statistical Summary ===")
display(df_cleaned.describe())

# 2. Histograms for each feature (except target)
features = df_cleaned.columns.drop('Diagnosis')

# Set up grid of plots
plt.figure(figsize=(20, 30))
for idx, feature in enumerate(features):
    plt.subplot(9, 4, idx + 1)
    sns.histplot(data=df_cleaned, x=feature, kde=True, bins=30, color='skyblue')
    plt.title(f'Distribution of {feature}')
    plt.xlabel('')
    plt.ylabel('')
plt.tight_layout()
plt.show()
```

```
=== Statistical Summary ===

               Age       Gender    Ethnicity  EducationLevel          BMI  \
count  1719.000000  1719.000000  1719.000000     1719.000000  1719.000000
mean     74.960442     0.500291     0.698080        1.283304    27.687408
std       9.065000     0.500145     0.994836        0.904339     7.209284
min      60.000000     0.000000     0.000000        0.000000    15.008851
25%      67.000000     0.000000     0.000000        1.000000    21.641242
50%      75.000000     1.000000     0.000000        1.000000    27.919813
75%      83.000000     1.000000     1.000000        2.000000    33.842594
max      90.000000     1.000000     3.000000        3.000000    39.992767

           Smoking  AlcoholConsumption  PhysicalActivity  DietQuality  \
count  1719.000000         1719.000000       1719.000000  1719.000000
mean      0.286795            9.978133          4.942195     4.972312
std       0.452396            5.777363          2.827319     2.900920
min       0.000000            0.002003          0.003616     0.009385
25%       0.000000            5.137582          2.612521     2.415726
50%       0.000000            9.805564          4.801357     5.050778
75%       1.000000           15.181033          7.380416     7.480424
max       1.000000           19.989293          9.987429     9.997203

       SleepQuality  …  FunctionalAssessment  MemoryComplaints  \
count   1719.000000  …           1719.000000       1719.000000
mean       7.038044  …              5.069688          0.205934
std        1.758166  …              2.890435          0.404500
min        4.002629  …              0.000460          0.000000
25%        5.517895  …              2.562307          0.000000
50%        7.090395  …              5.098709          0.000000
75%        8.552783  …              7.496824          0.000000
max        9.999840  …              9.996467          1.000000

       BehavioralProblems          ADL    Confusion  Disorientation  \
count         1719.000000  1719.000000  1719.000000     1719.000000
mean             0.156486     4.970744     0.201280        0.158813
std              0.363422     2.947606     0.401073        0.365608
min              0.000000     0.001288     0.000000        0.000000
25%              0.000000     2.324166     0.000000        0.000000
50%              0.000000     5.026306     0.000000        0.000000
75%              0.000000     7.583825     0.000000        0.000000
max              1.000000     9.999747     1.000000        1.000000

       PersonalityChanges  DifficultyCompletingTasks  Forgetfulness  \
count         1719.000000                1719.000000    1719.000000
mean             0.148342                   0.161722       0.296684
std              0.355542                   0.368303       0.456929
min              0.000000                   0.000000       0.000000
25%              0.000000                   0.000000       0.000000
50%              0.000000                   0.000000       0.000000
75%              0.000000                   0.000000       1.000000
max              1.000000                   1.000000       1.000000

         Diagnosis
count  1719.000000
mean      0.353112
std       0.478076
min       0.000000
25%       0.000000
50%       0.000000
75%       1.000000
max       1.000000

[8 rows x 33 columns]
```


Distribution of Age
Distribution of Gender
Distribution of Ethnicity
Distribution of EducationLevel
Distribution of BMI
Distribution of Smoking
Distribution of AlcoholConsumption
Distribution of PhysicalActivity
Distribution of DietQuality
Distribution of SleepQuality
Distribution of FamilyHistoryAlzheimers
Distribution of CardiovascularDisease
Distribution of Diabetes
Distribution of Depression
Distribution of HeadInjury
Distribution of Hypertension
Distribution of SystolicBP
Distribution of DiastolicBP
Distribution of CholesterolTotal
Distribution of CholesterolLDL
Distribution of CholesterolHDL
Distribution of CholesterolTriglycerides
Distribution of MMSE
Distribution of FunctionalAssessment
Distribution of MemoryComplaints
Distribution of BehavioralProblems
Distribution of ADL
Distribution of Confusion
Distribution of Disorientation
Distribution of PersonalityChanges
Distribution of DifficultyCompletingTasks
Distribution of Forgetfulness

2 Interpretation :

Binary Features (18 total) Examples: Gender, Smoking, Diabetes, Depression, Forgetfulness, etc.

Distribution: Most binary features are heavily right-skewed, with 0 being dominant.

E.g., HeadInjury: ~91% of values are 0.

FamilyHistoryAlzheimers, Depression, Disorientation, etc. follow a similar pattern.

Implication: These features are sparse — most patients do not exhibit these symptoms or conditions.

Preprocessing: No scaling needed; values are already encoded as 0/1.

However, due to class imbalance, class-weighted models (e.g., class_weight='balanced') might help certain classifiers.

Categorical Features (2 total) Ethnicity (4 levels), EducationLevel (4 levels)

Distribution:

Ethnicity: Skewed toward category 0 (~60% of samples).

EducationLevel: Somewhat balanced, but category 1 is most frequent (~40%).

Preprocessing:

May need one-hot encoding for models like logistic regression or SVM.

Tree-based models can handle raw integers but may misinterpret ordinal relationship

Continuous Features (13 total) Examples: Age, BMI, AlcoholConsumption, MMSE, FunctionalAssessment, etc.

Distributions:

Most continuous features are roughly uniform or bell-shaped, with no clear outliers.

AlcoholConsumption, PhysicalActivity, SleepQuality, etc. show wide variation.

Means & Medians:

Generally well-centered (e.g., Age: mean 75, median 75).

Standard Deviation:

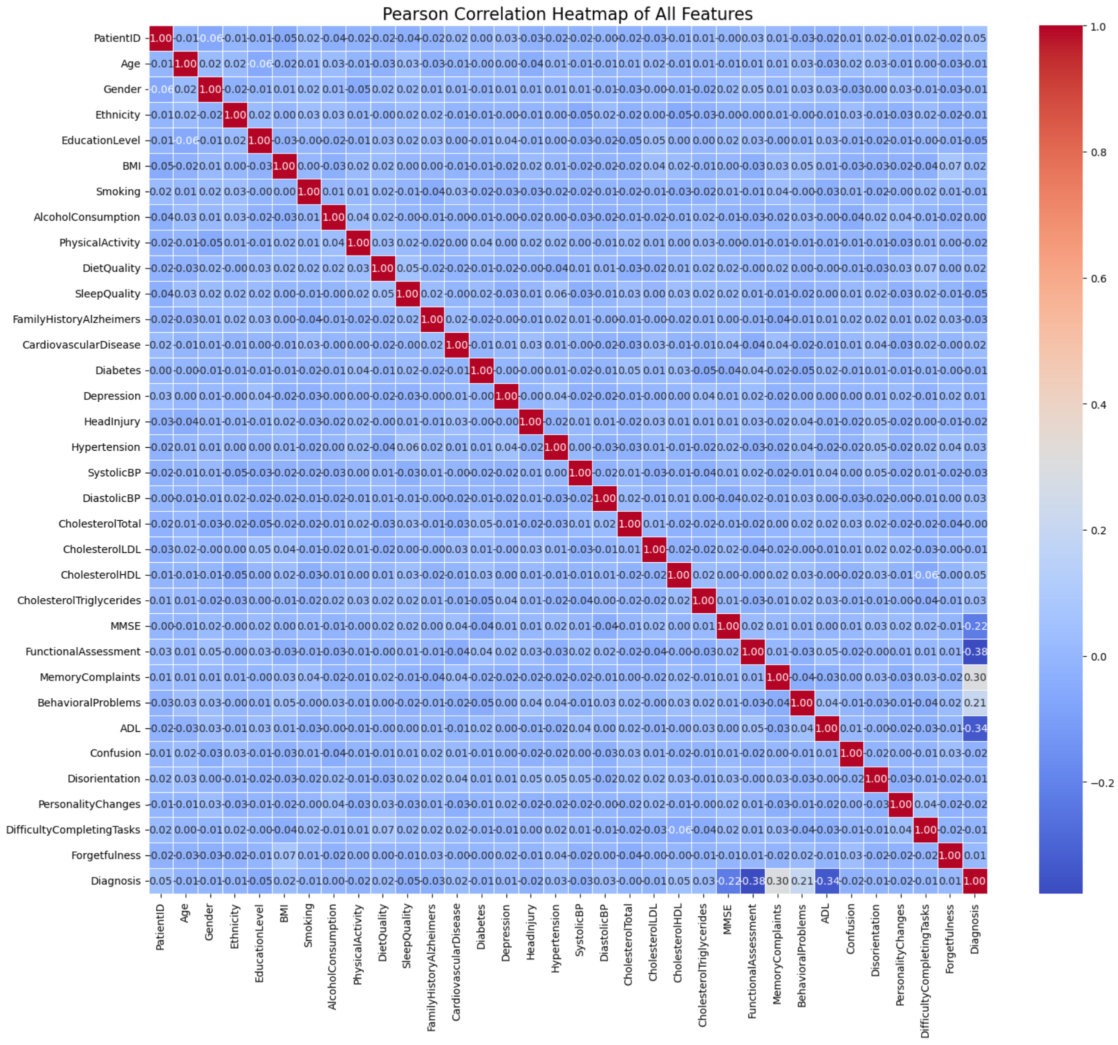
Moderate variability across features (e.g., BMI stdev 7.2).

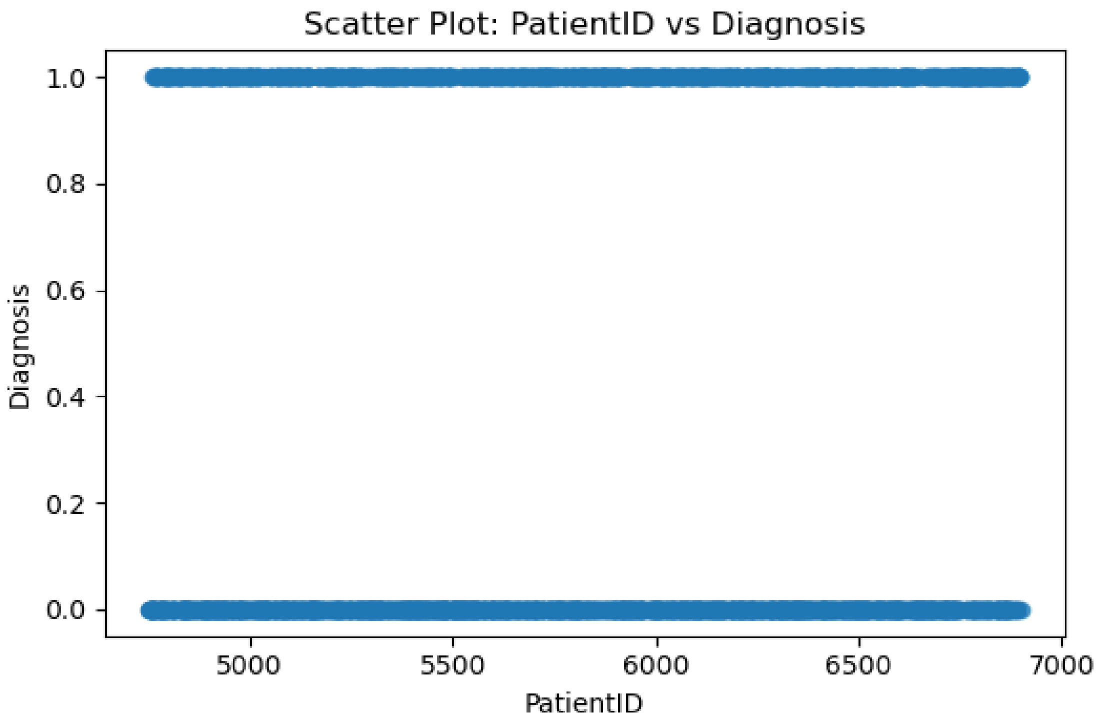
Preprocessing:

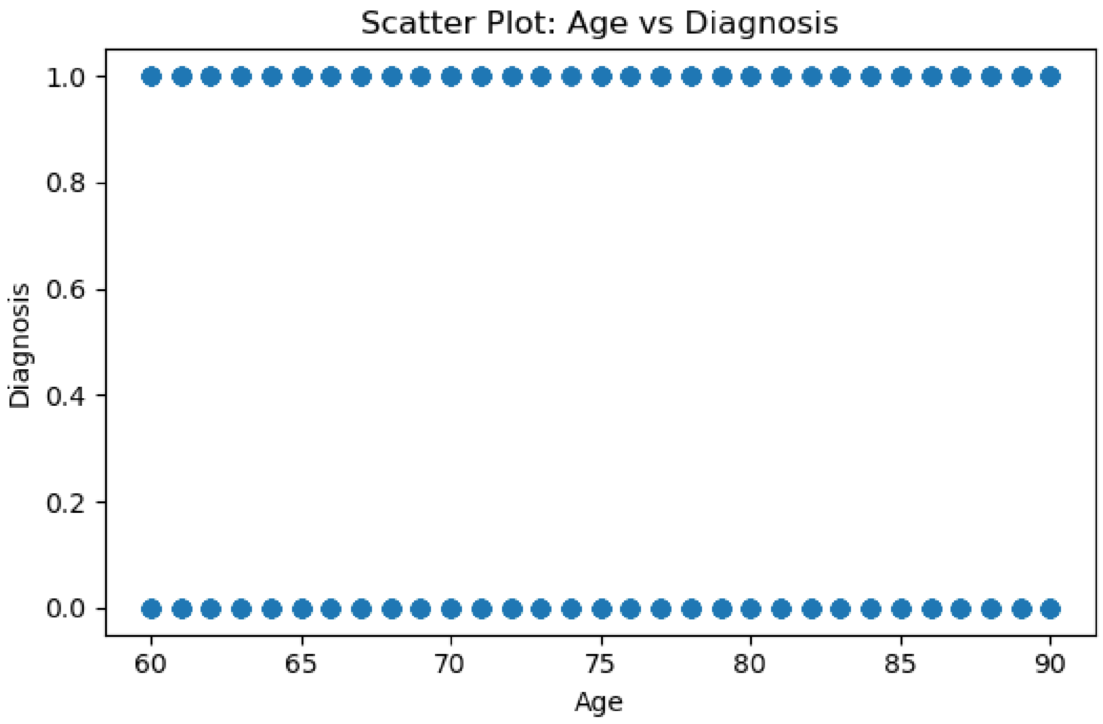
These features will benefit from scaling: Use StandardScaler (for linear models like SVM/logistic regression) Or MinMaxScaler if feature range matching is needed.

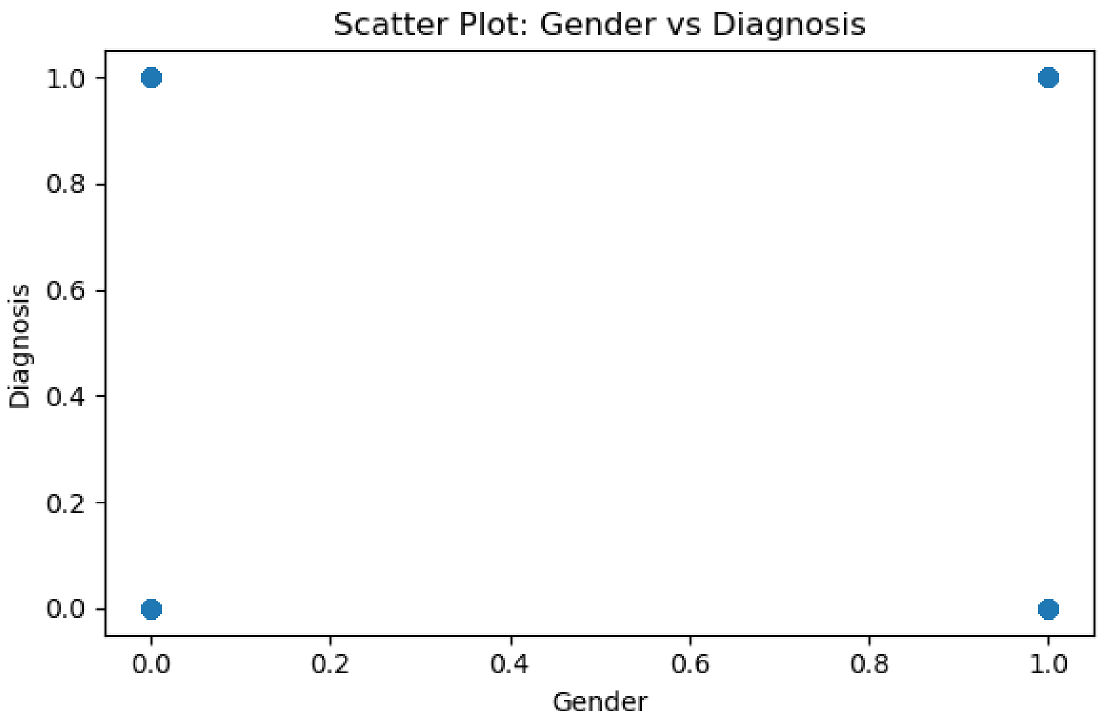
2.1 QUESTION 2) Analyze and discuss the relationships between the data attributes and between the data attributes and labels. This involves computing the Pearson Correlation Coefficient (PCC) and generating scatter plots. [3 points]

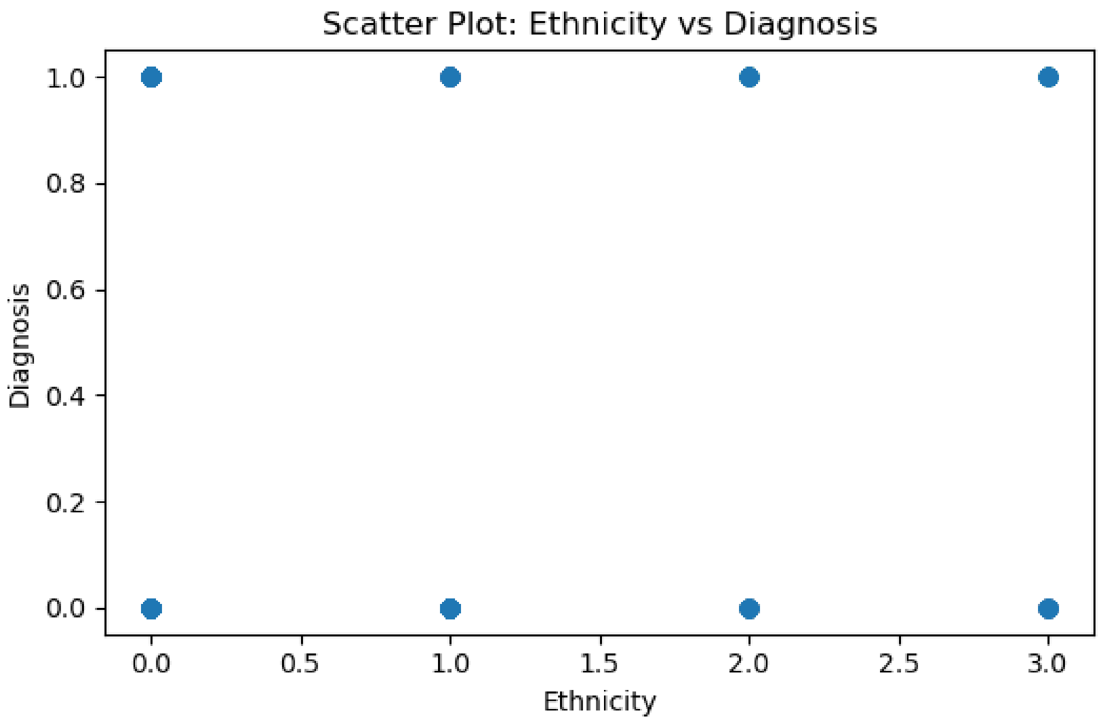
[7]:
```python
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np

# 1. Compute the Pearson Correlation Matrix using only numeric columns
correlation_matrix = df.corr(numeric_only=True)

# 2. Generate a heatmap for the correlation matrix
plt.figure(figsize=(18,15))
sns.heatmap(correlation_matrix, cmap='coolwarm', annot=True, fmt=".2f",␣
 ↪linewidths=0.5)
plt.title("Pearson Correlation Heatmap of All Features", fontsize=16)
plt.show()

# 3. Generate scatter plots for each numeric predictor versus 'Diagnosis'
# Get list of numeric columns, excluding 'Diagnosis'
numeric_columns = df.select_dtypes(include=[np.number]).columns.tolist()
predictor_columns = [col for col in numeric_columns if col != "Diagnosis"]

# Create scatter plots for each predictor against 'Diagnosis'
for col in predictor_columns:
    plt.figure(figsize=(6, 4))
    plt.scatter(df[col], df["Diagnosis"], alpha=0.7)
    plt.xlabel(col)
    plt.ylabel("Diagnosis")
    plt.title(f"Scatter Plot: {col} vs Diagnosis")
    plt.tight_layout()
    plt.show()
```

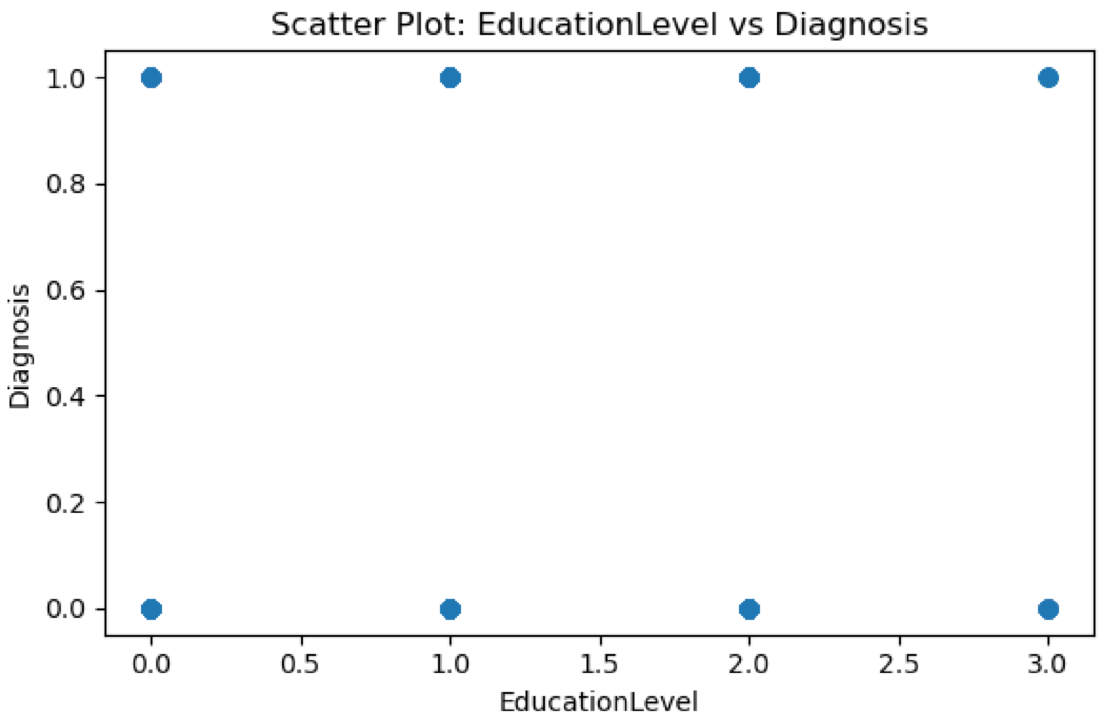

Pearson Correlation Heatmap of All Features
PatientID
Age
Gender
Ethnicity
EducationLevel
BMI
Smoking
AlcoholConsumption
PhysicalActivity
DietQuality
SleepQuality
FamilyHistoryAlzheimers
CardiovascularDisease
Diabetes
Depression
HeadInjury
Hypertension
SystolicBP
DiastolicBP
CholesterolTotal
CholesterolLDL
CholesterolHDL
CholesterolTriglycerides
MMSE
FunctionalAssessment
MemoryComplaints
BehavioralProblems
ADL
Confusion
Disorientation
PersonalityChanges
DifficultyCompletingTasks
Forgetfulness
Diagnosis
1.0
0.8
0.6
0.4
0.2
0.0
−0.2

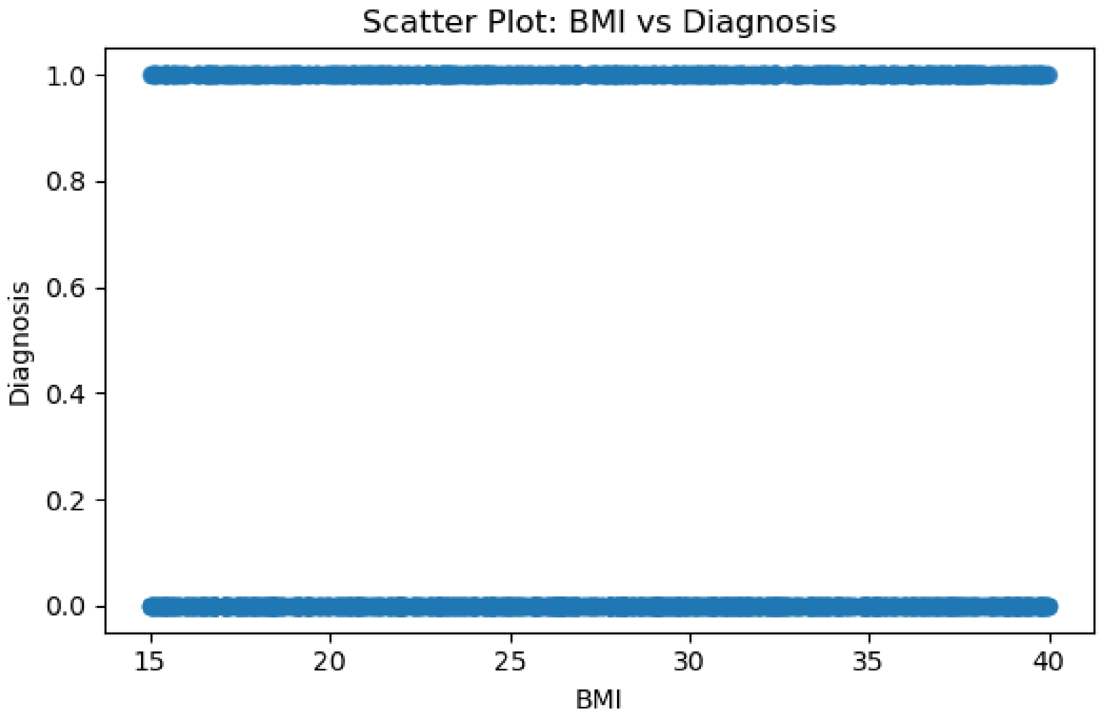

Scatter Plot: PatientID vs Diagnosis
Diagnosis
1.0
0.8
0.6
0.4
0.2
0.0
5000
5500
6000
6500
7000
PatientID

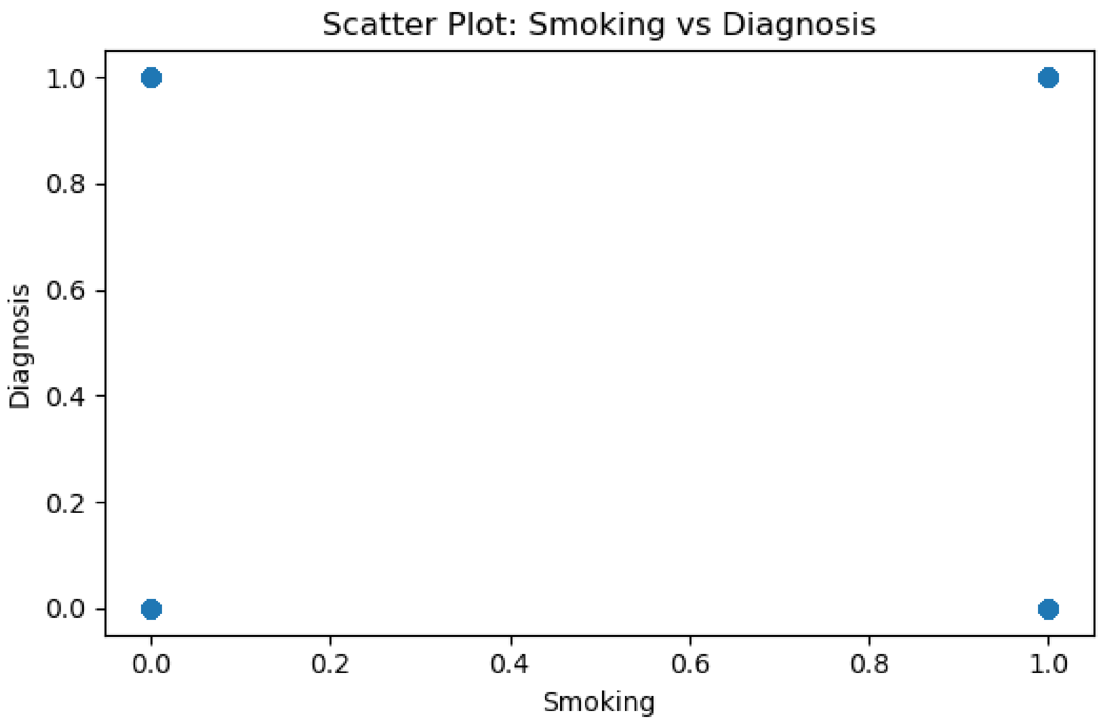

Scatter Plot: Age vs Diagnosis
Diagnosis
1.0
0.8
0.6
0.4
0.2
0.0
60
65
70
75
80
85
90
Age

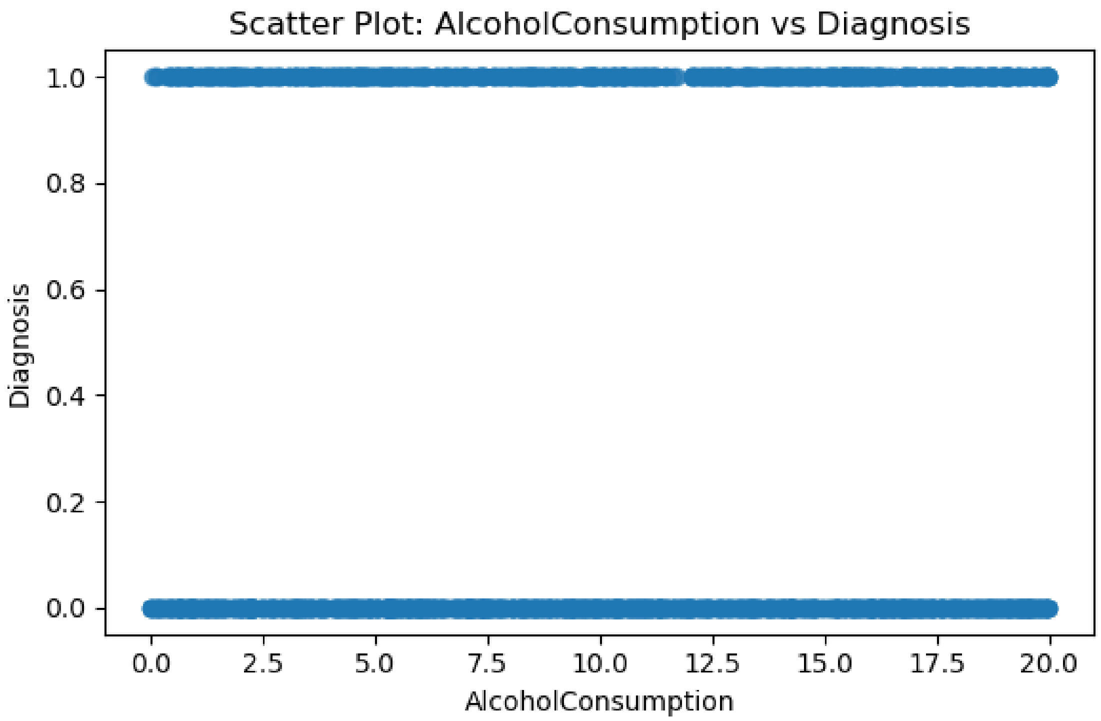

Scatter Plot: Gender vs Diagnosis
Diagnosis
Gender
0.0
0.2
0.4
0.6
0.8
1.0

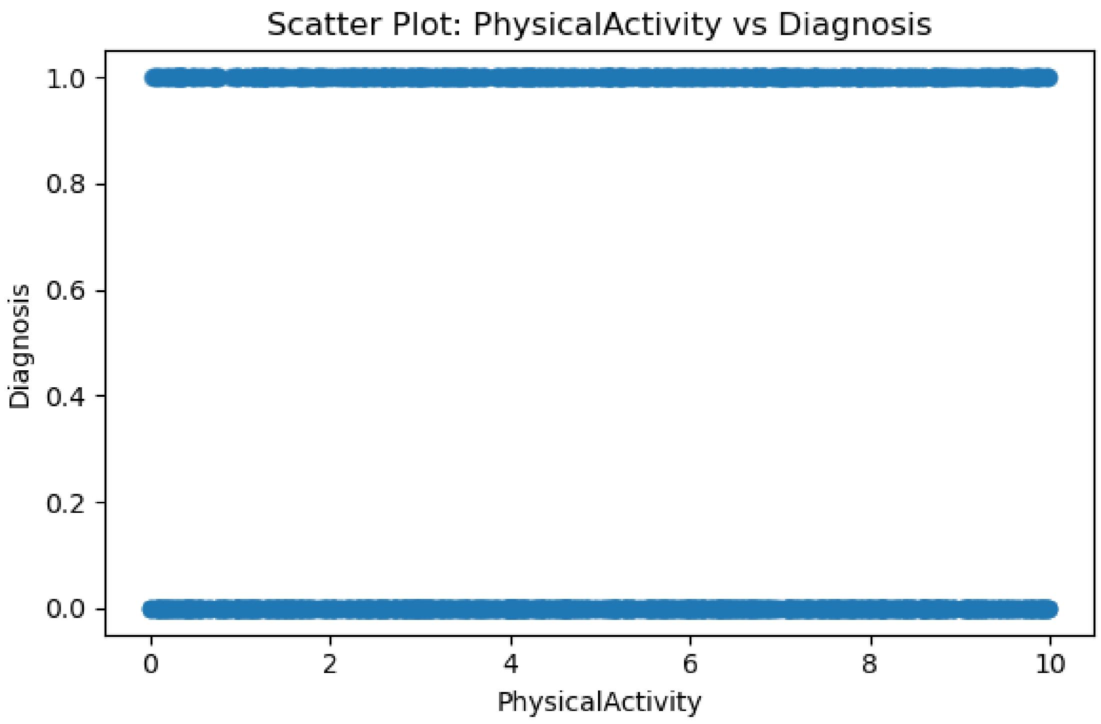

Scatter Plot: Ethnicity vs Diagnosis
Diagnosis
Ethnicity
0.0
0.2
0.4
0.6
0.8
1.0
0.5
1.5
2.0
2.5
3.0

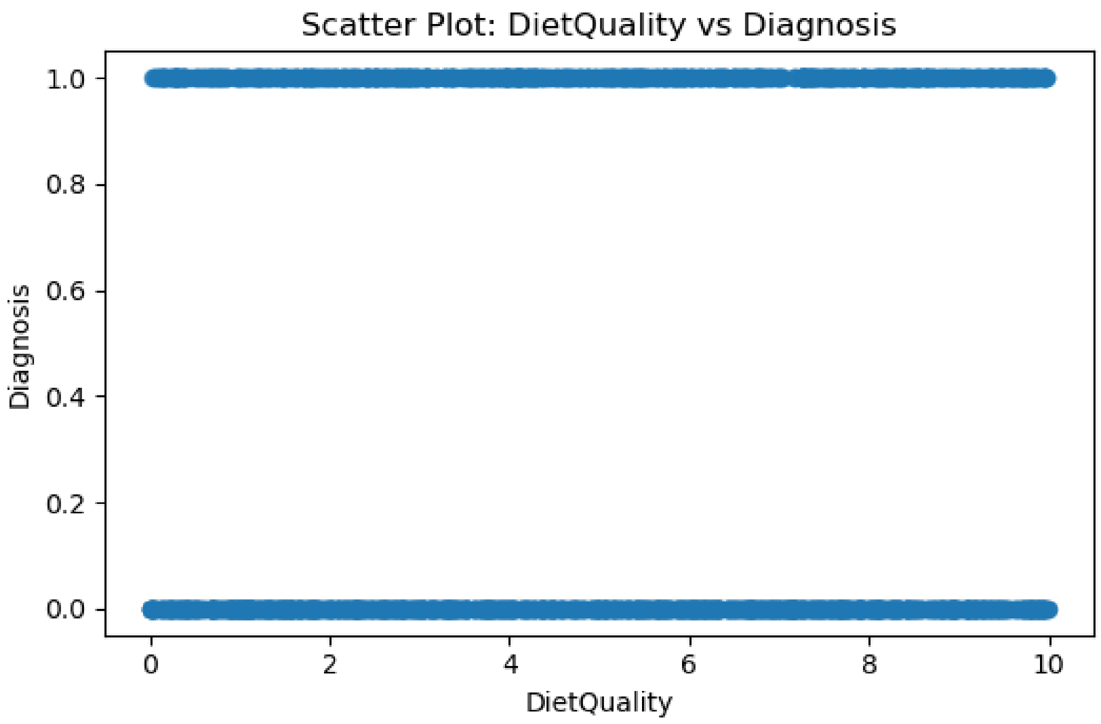

Scatter Plot: EducationLevel vs Diagnosis
Diagnosis
EducationLevel
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.5
1.0
1.5
2.0
2.5
3.0

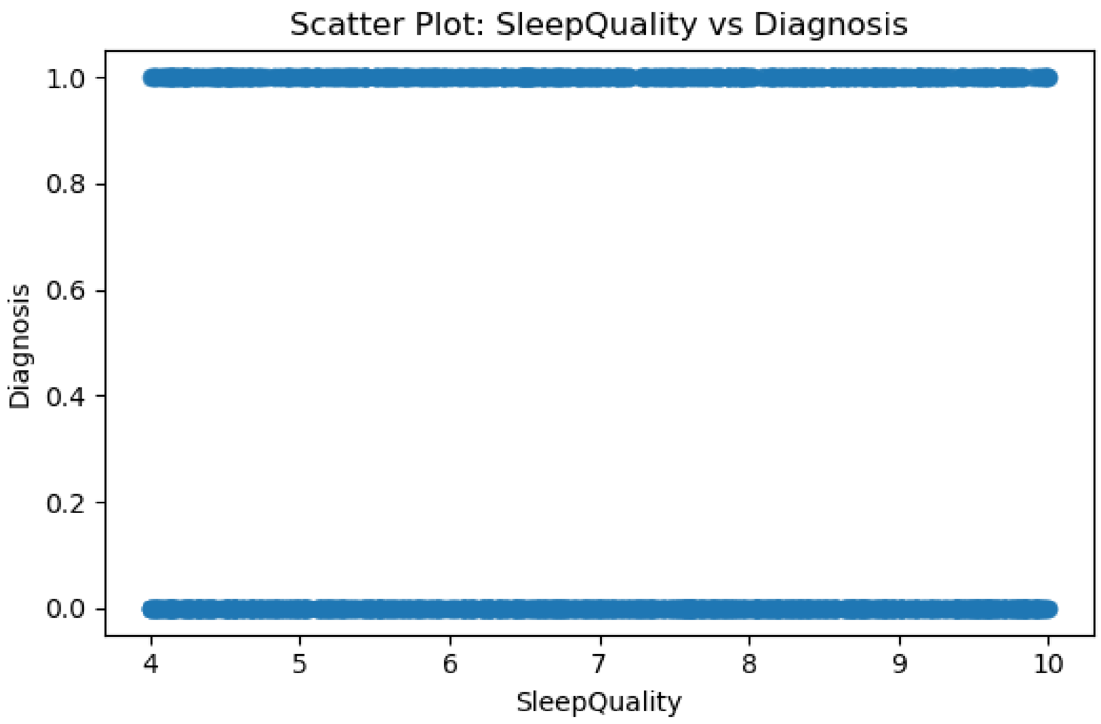

Scatter Plot: BMI vs Diagnosis
Diagnosis
BMI
1.0
0.8
0.6
0.4
0.2
0.0
15
20
25
30
35
40

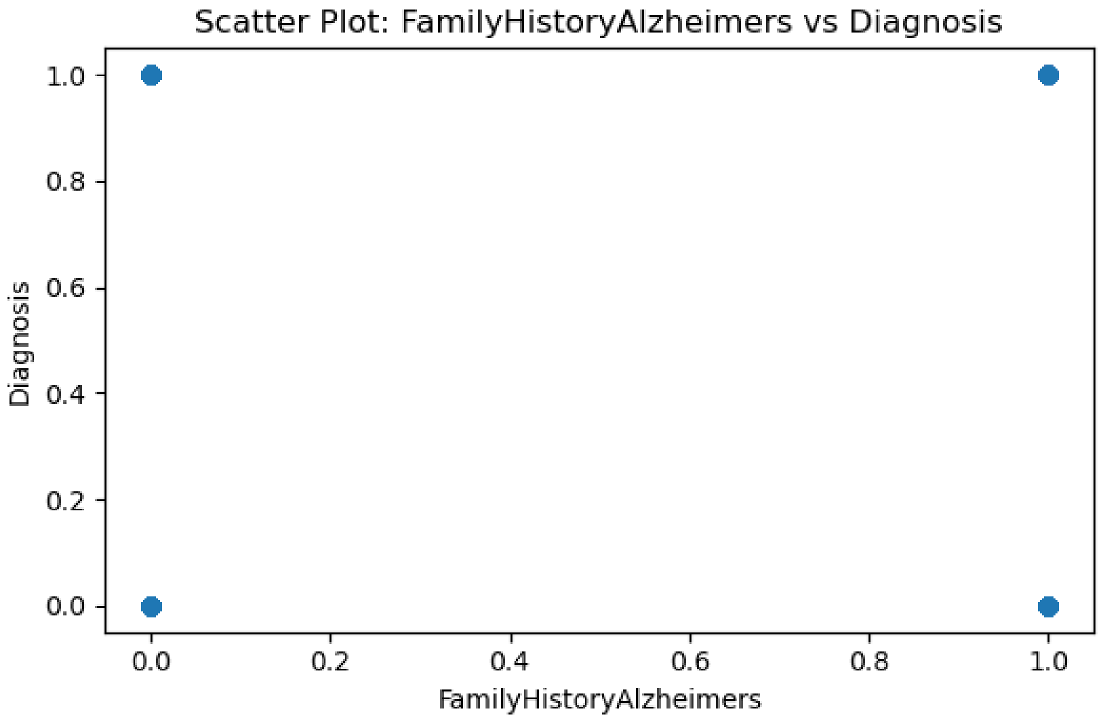

Scatter Plot: Smoking vs Diagnosis
Diagnosis
Smoking
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0

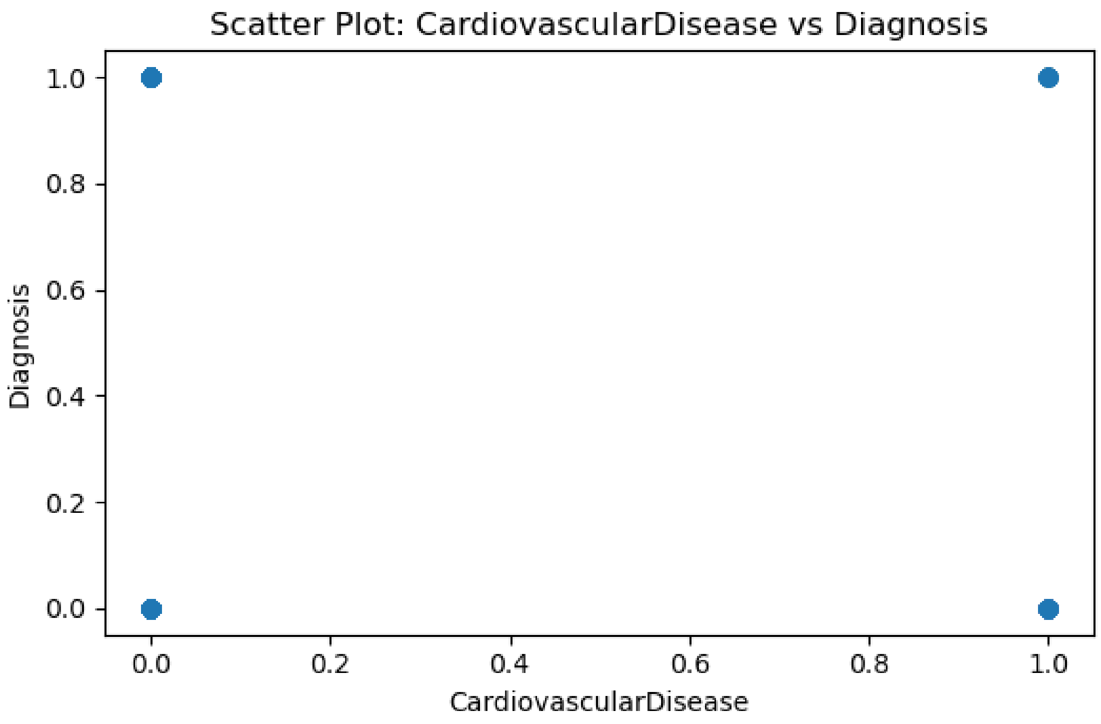

Scatter Plot: AlcoholConsumption vs Diagnosis
Diagnosis
AlcoholConsumption
1.0
0.8
0.6
0.4
0.2
0.0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

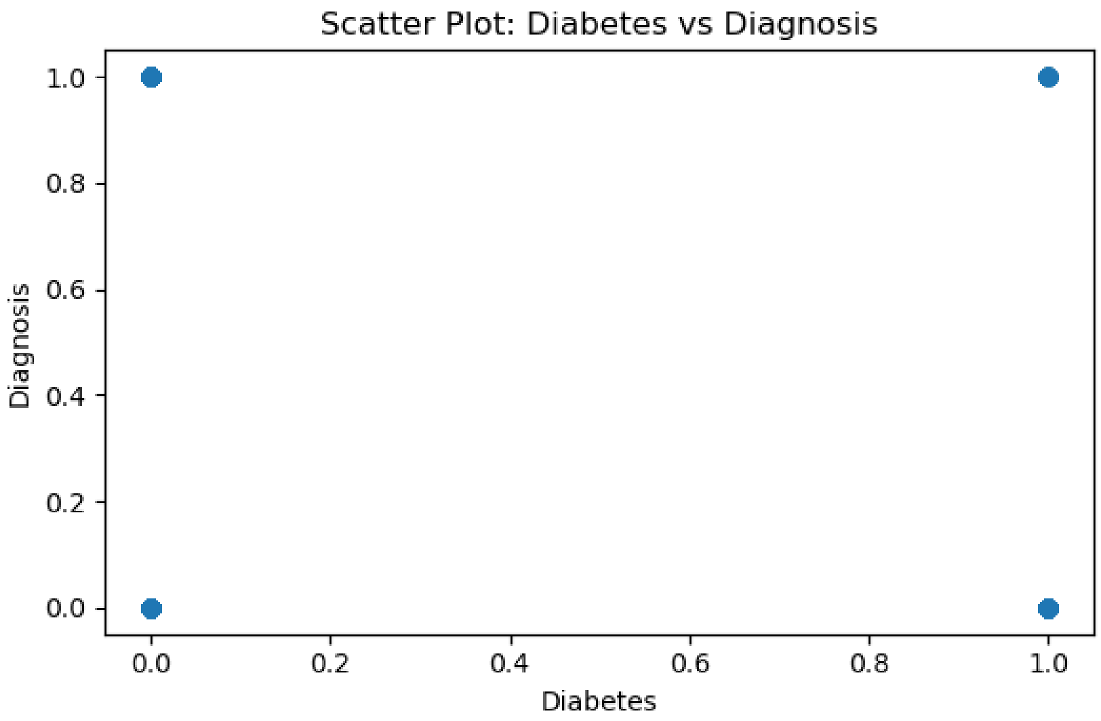

Scatter Plot: PhysicalActivity vs Diagnosis
Diagnosis
PhysicalActivity
1.0
0.8
0.6
0.4
0.2
0.0
0
2
4
6
8
10

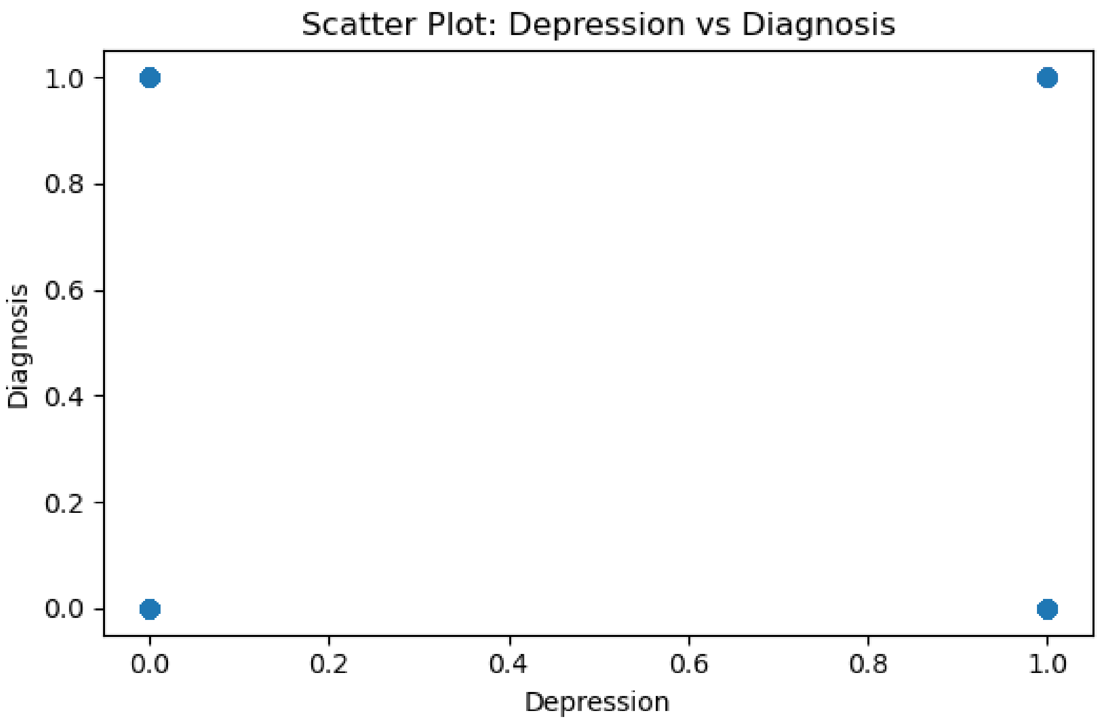

Scatter Plot: DietQuality vs Diagnosis
Diagnosis
DietQuality
1.0
0.8
0.6
0.4
0.2
0.0
0
2
4
6
8
10

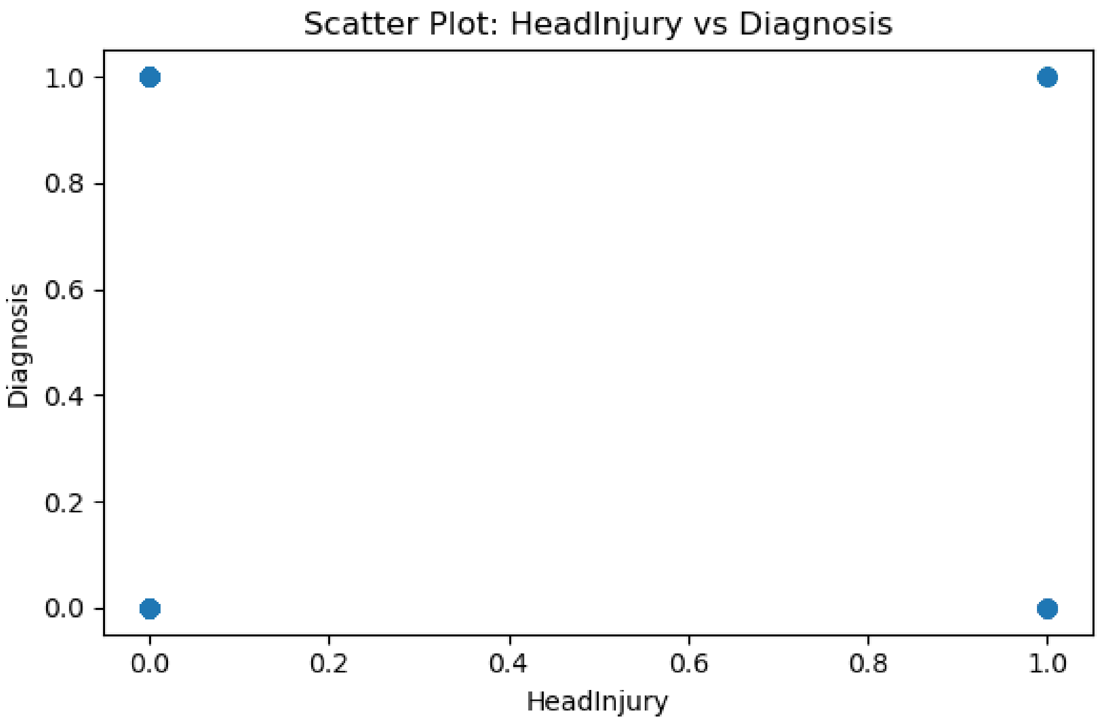

Scatter Plot: SleepQuality vs Diagnosis
Diagnosis
0.0
0.2
0.4
0.6
0.8
1.0
4
5
6
7
8
9
10
SleepQuality

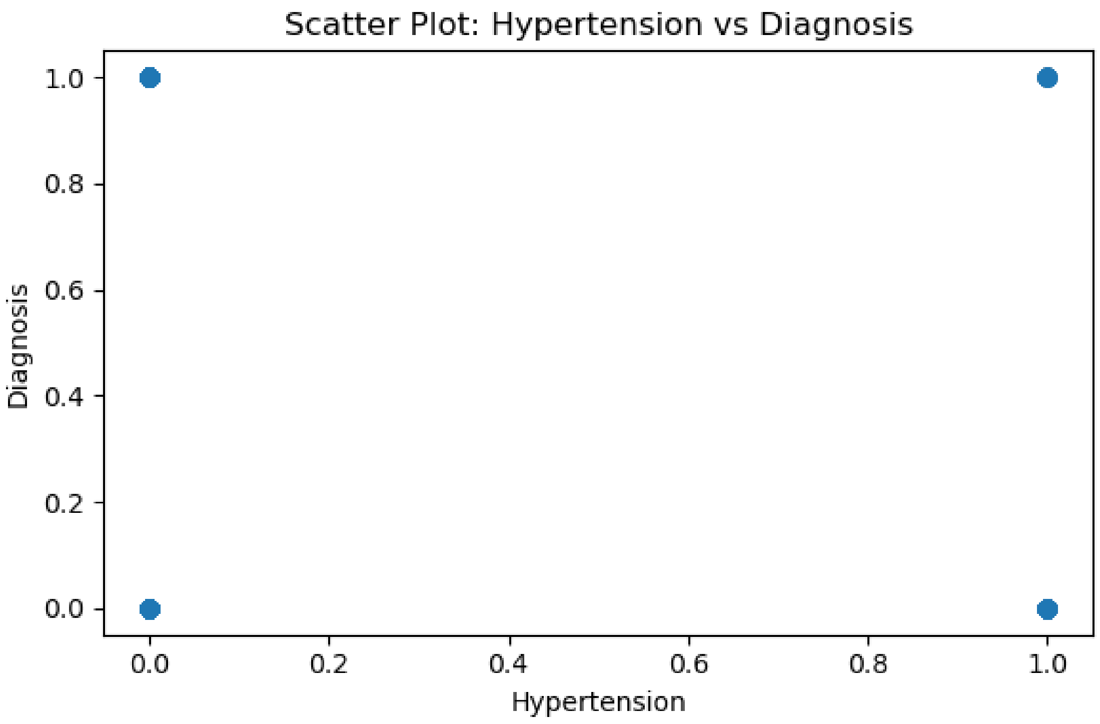

Scatter Plot: FamilyHistoryAlzheimers vs Diagnosis
Diagnosis
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.2
0.4
0.6
0.8
1.0
FamilyHistoryAlzheimers

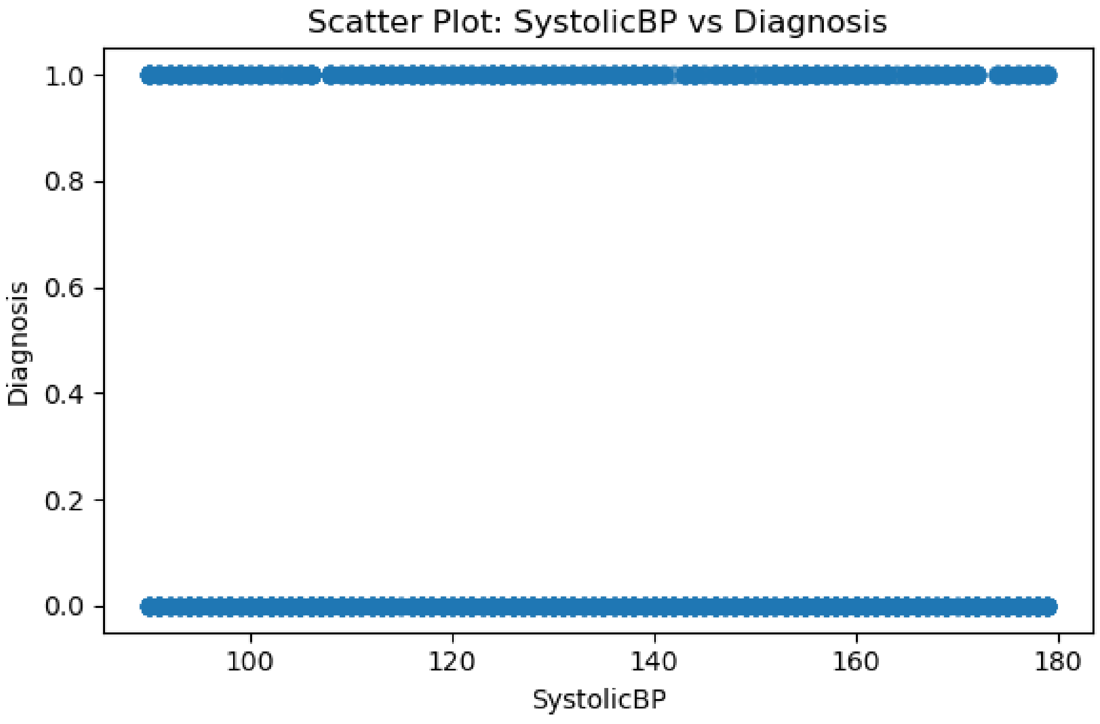

Scatter Plot: CardiovascularDisease vs Diagnosis
Diagnosis
CardiovascularDisease
0.0
0.2
0.4
0.6
0.8
1.0

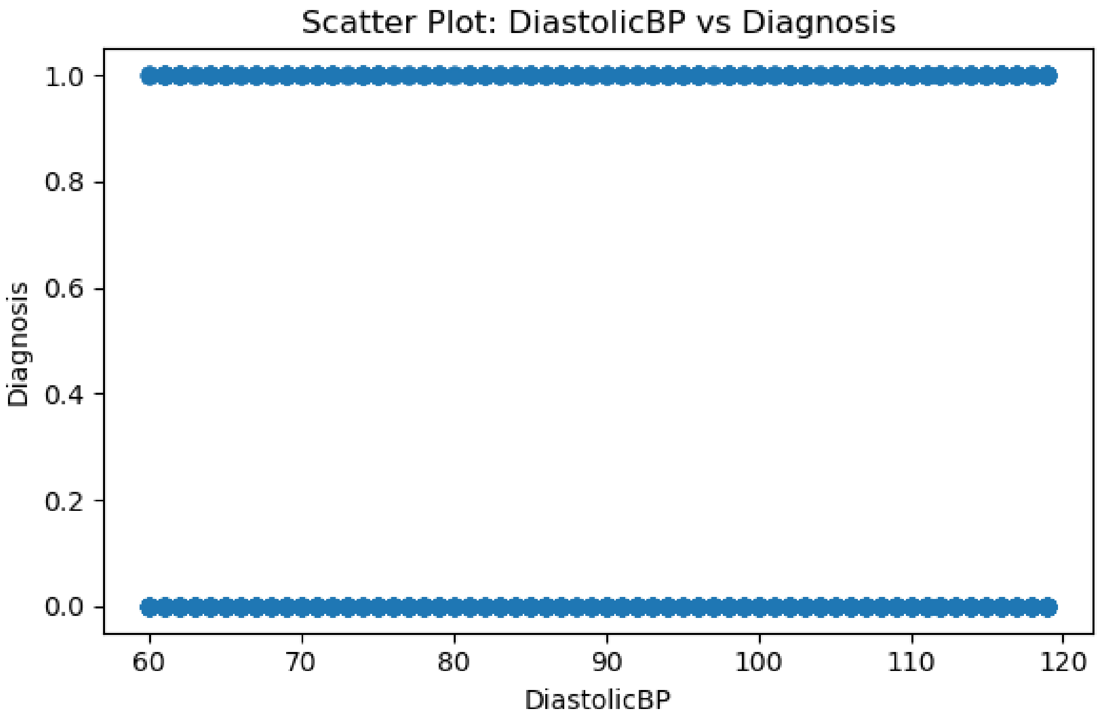

Scatter Plot: Diabetes vs Diagnosis
Diagnosis
Diabetes
0.0
0.2
0.4
0.6
0.8
1.0

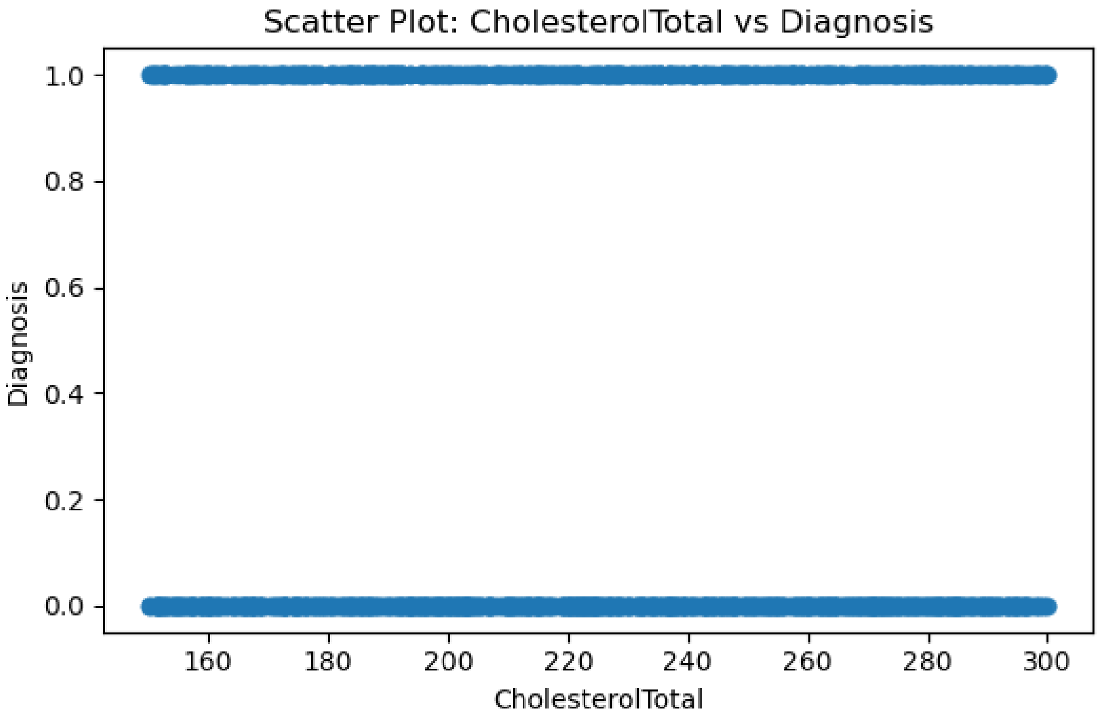

Scatter Plot: Depression vs Diagnosis
Diagnosis
Depression
0.0
0.2
0.4
0.6
0.8
1.0

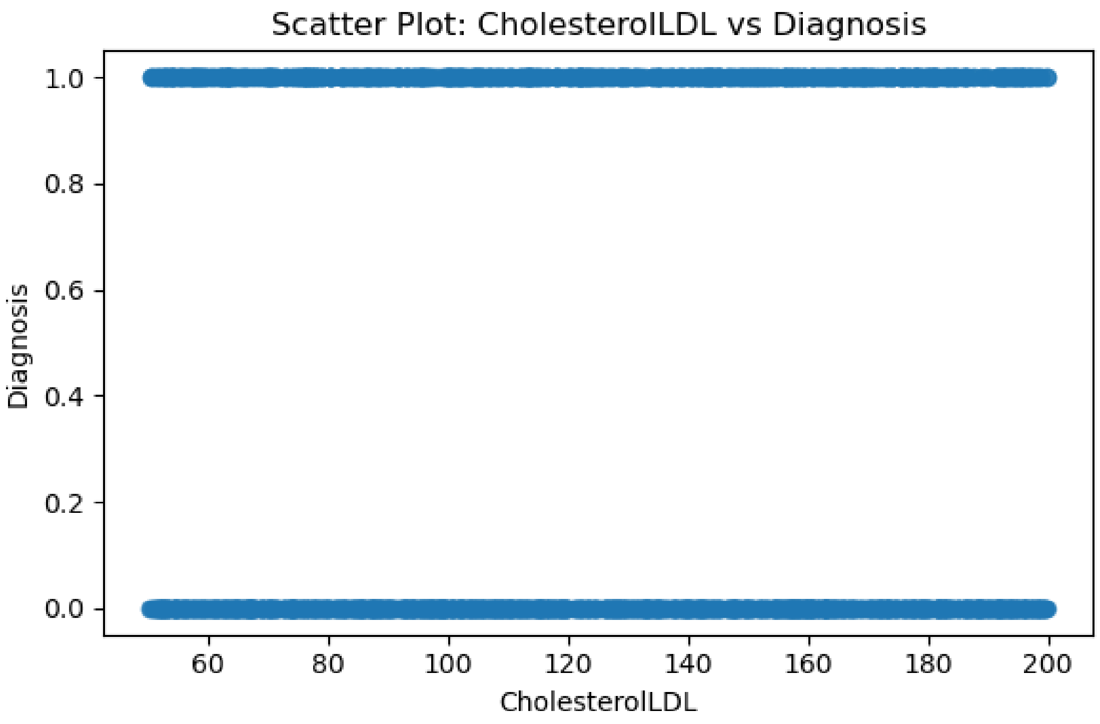

Scatter Plot: HeadInjury vs Diagnosis
Diagnosis
HeadInjury
0.0
0.2
0.4
0.6
0.8
1.0

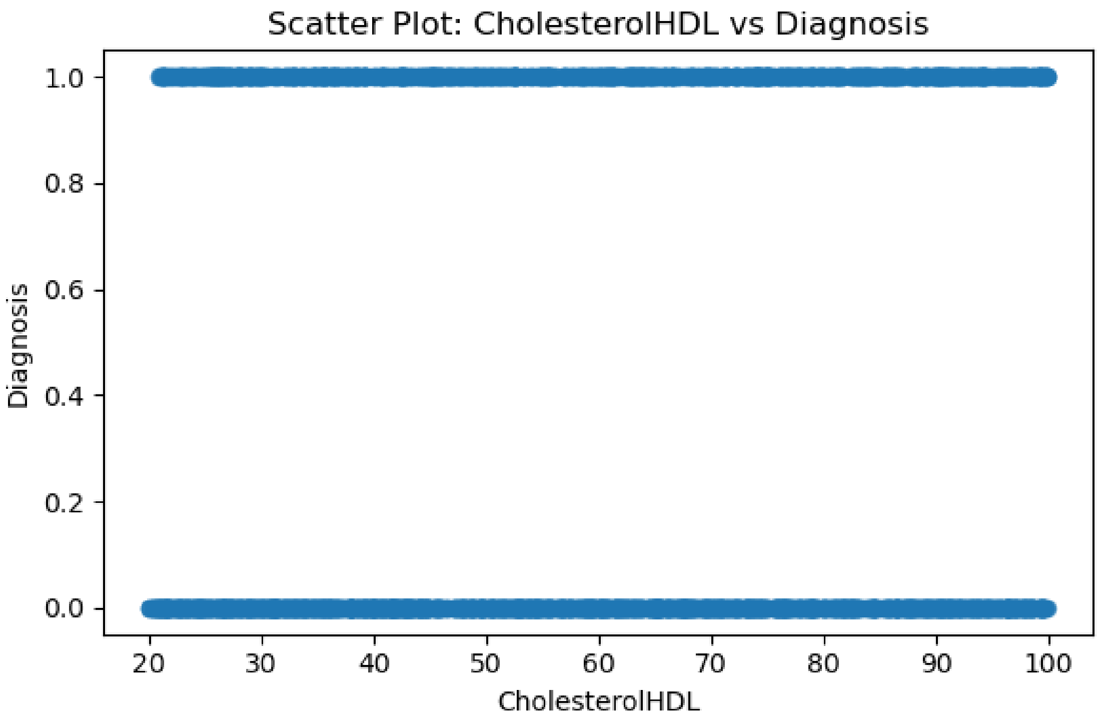

Scatter Plot: Hypertension vs Diagnosis
Diagnosis
Hypertension
0.0
0.2
0.4
0.6
0.8
1.0

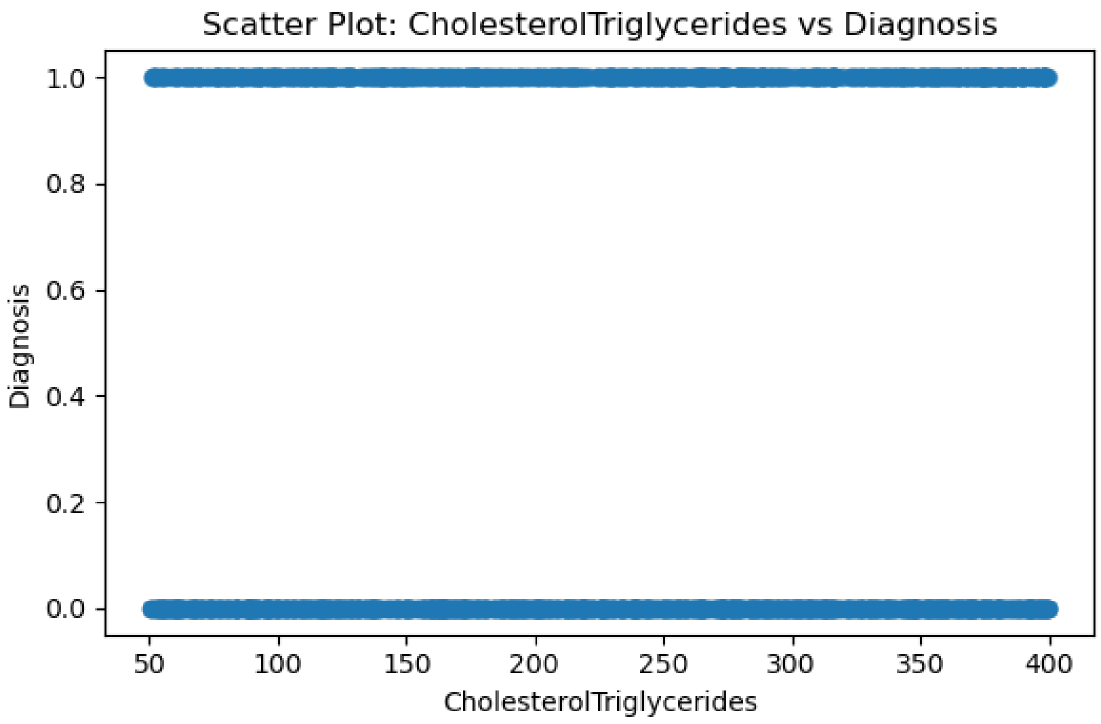

Scatter Plot: SystolicBP vs Diagnosis
Diagnosis
SystolicBP
100
120
140
160
180
0.0
0.2
0.4
0.6
0.8
1.0

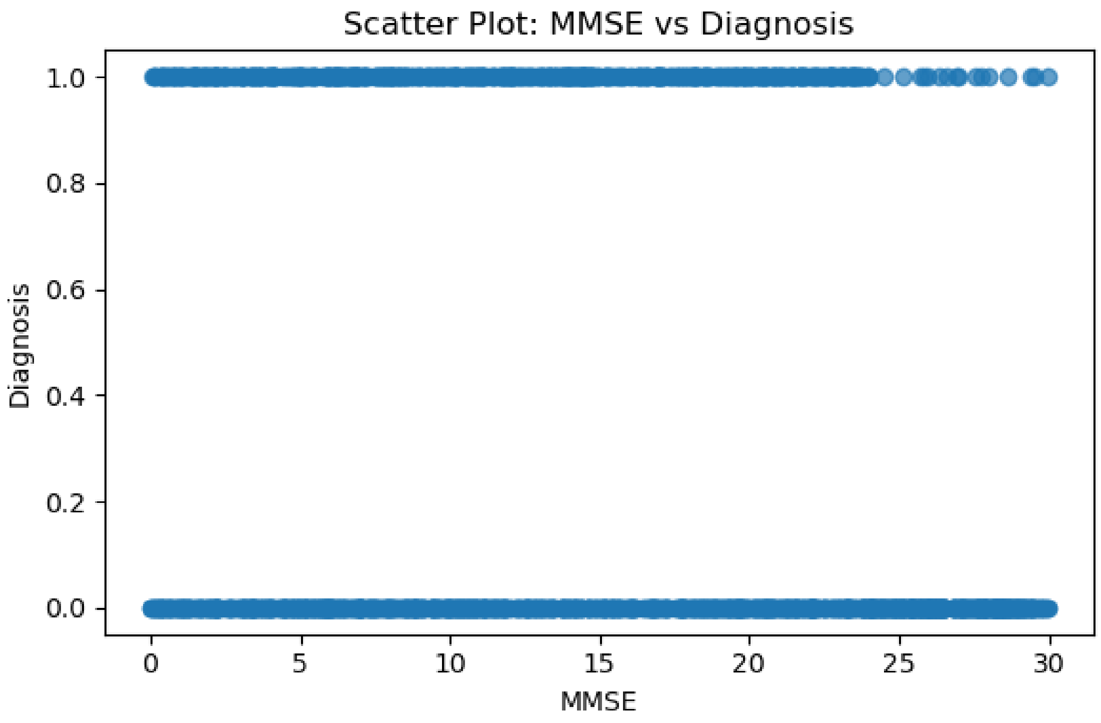

Scatter Plot: DiastolicBP vs Diagnosis
Diagnosis
DiastolicBP
0.0
0.2
0.4
0.6
0.8
1.0
60
70
80
90
100
110
120

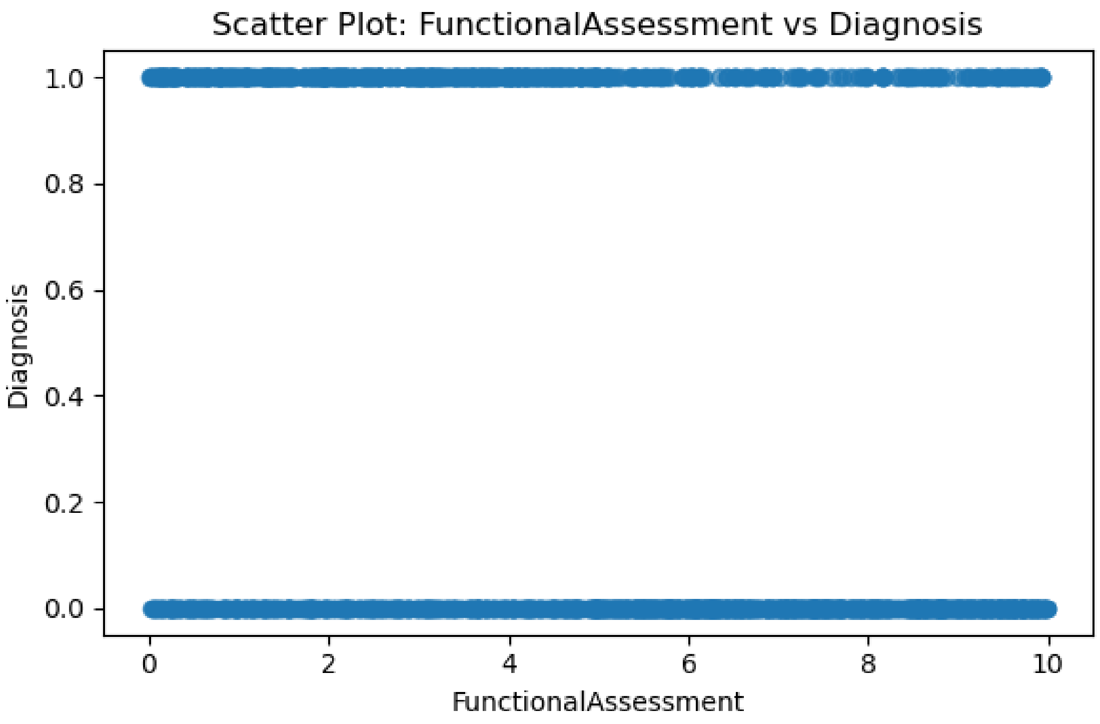

Scatter Plot: CholesterolTotal vs Diagnosis
Diagnosis
CholesterolTotal
0.0
0.2
0.4
0.6
0.8
1.0
160
180
200
220
240
260
280
300

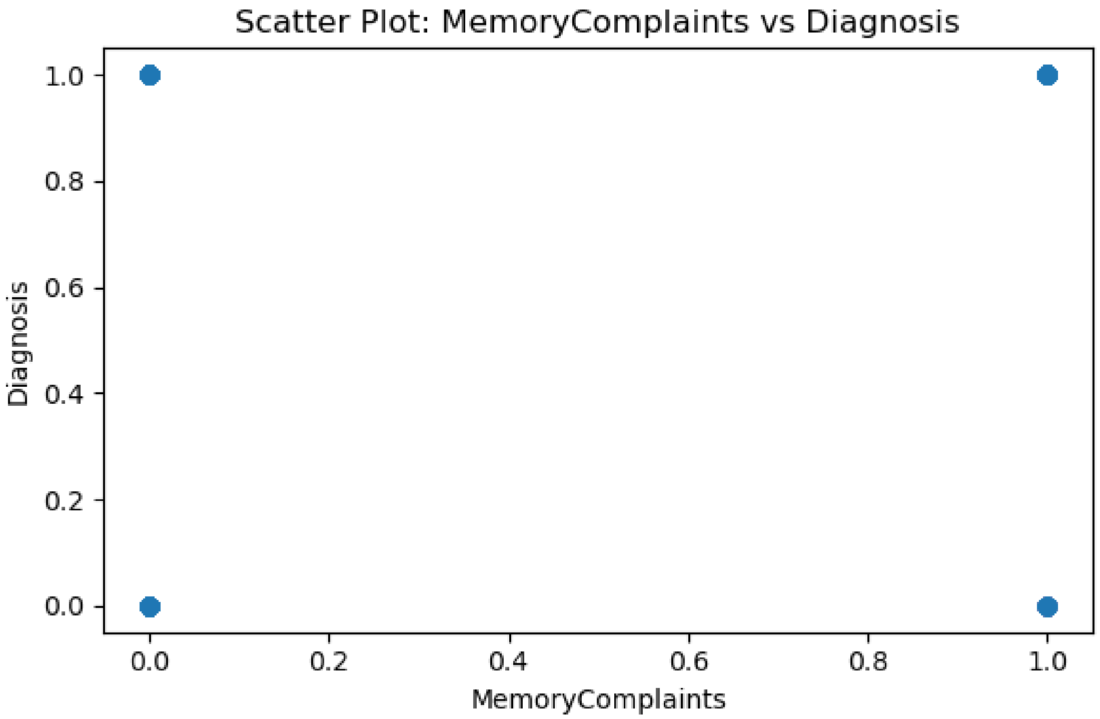

Scatter Plot: CholesterolLDL vs Diagnosis
Diagnosis
CholesterolLDL
1.0
0.8
0.6
0.4
0.2
0.0
60
80
100
120
140
160
180
200

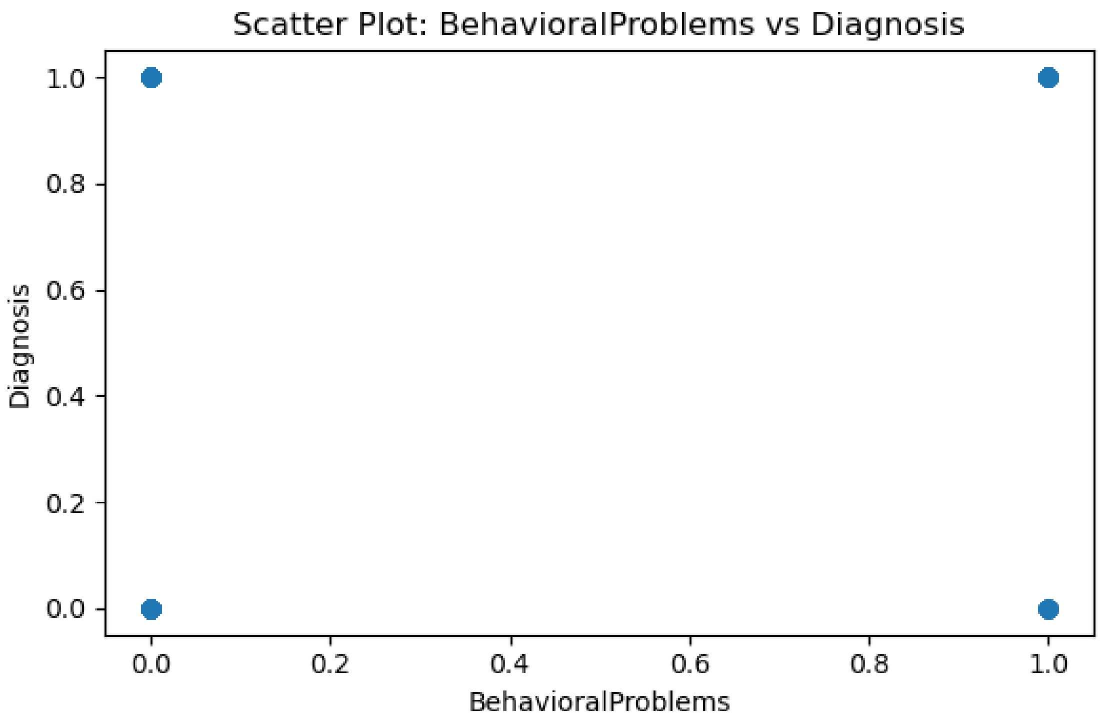

Scatter Plot: CholesterolHDL vs Diagnosis
Diagnosis
CholesterolHDL
1.0
0.8
0.6
0.4
0.2
0.0
20
30
40
50
60
70
80
90
100

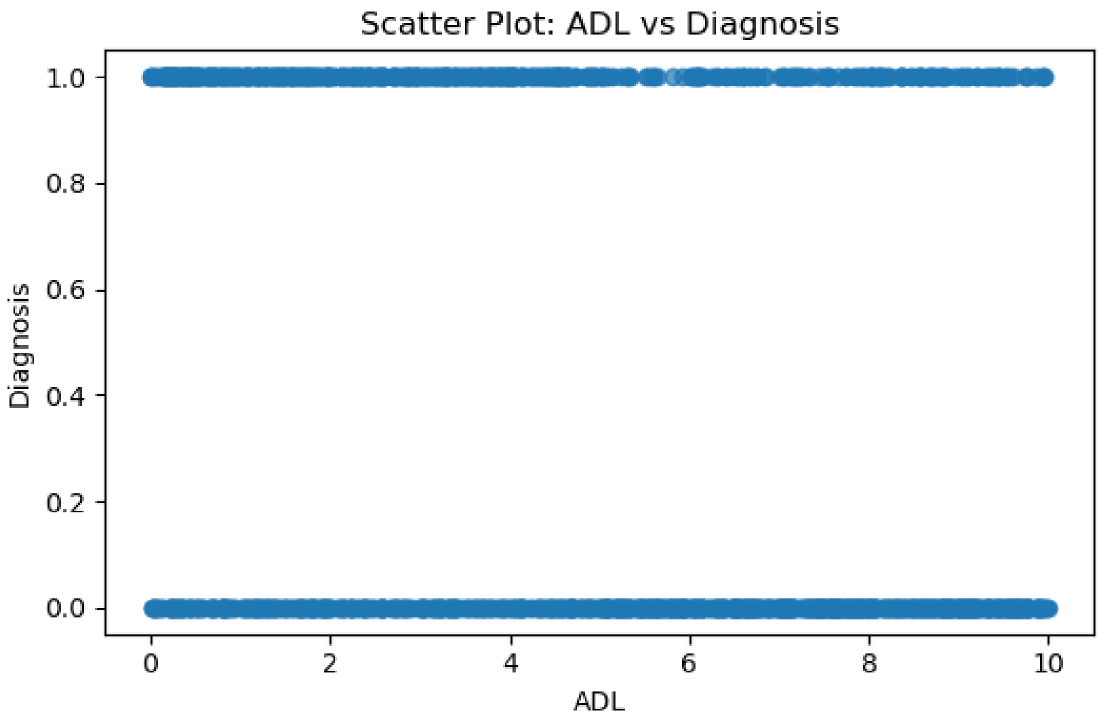

Scatter Plot: CholesterolTriglycerides vs Diagnosis
Diagnosis
1.0
0.8
0.6
0.4
0.2
0.0
50
100
150
200
250
300
350
400
CholesterolTriglycerides

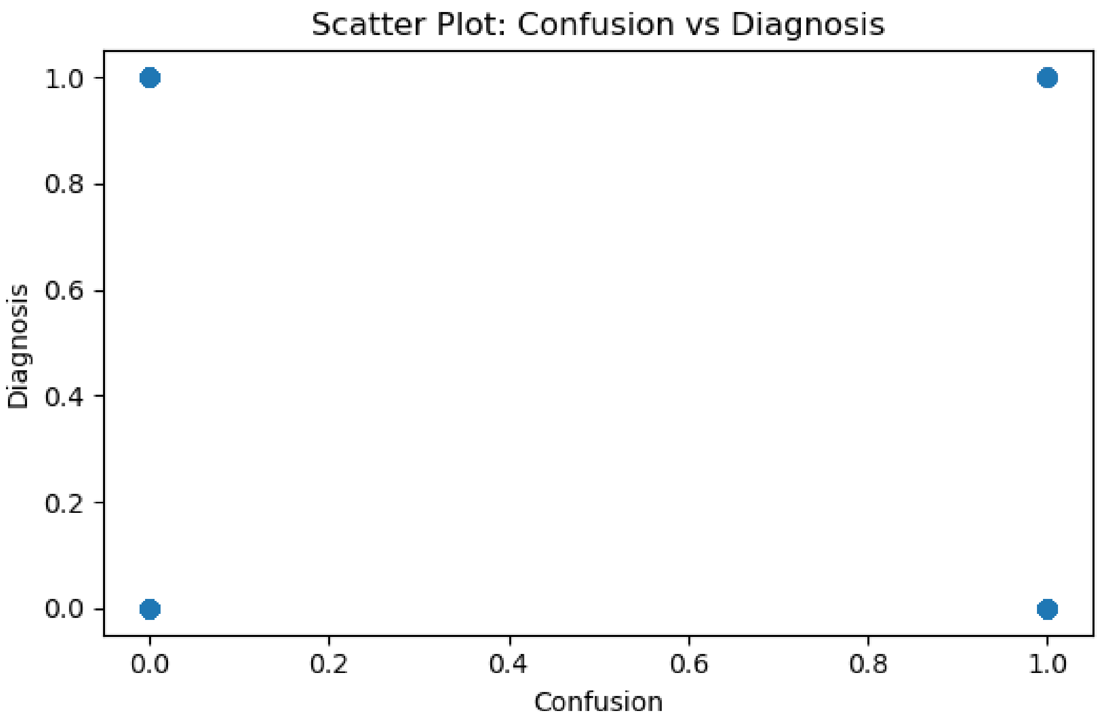

Scatter Plot: MMSE vs Diagnosis
Diagnosis
1.0
0.8
0.6
0.4
0.2
0.0
0
5
10
15
20
25
30
MMSE

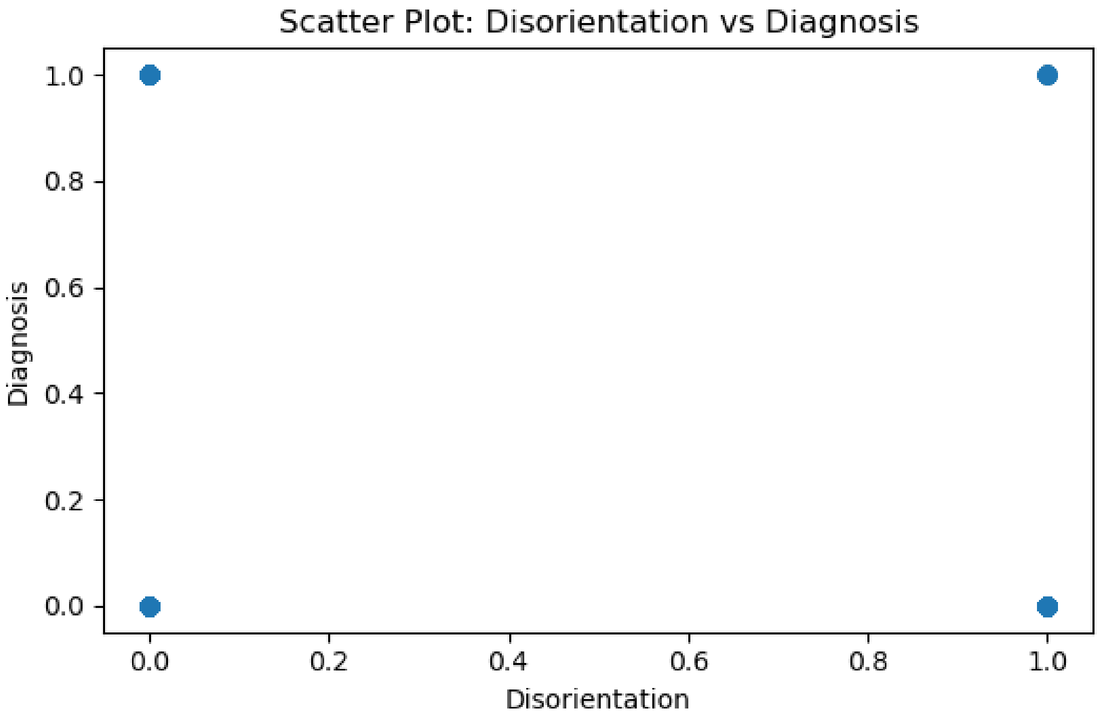

Scatter Plot: FunctionalAssessment vs Diagnosis
Diagnosis
FunctionalAssessment
0.0
0.2
0.4
0.6
0.8
1.0
0
2
4
6
8
10

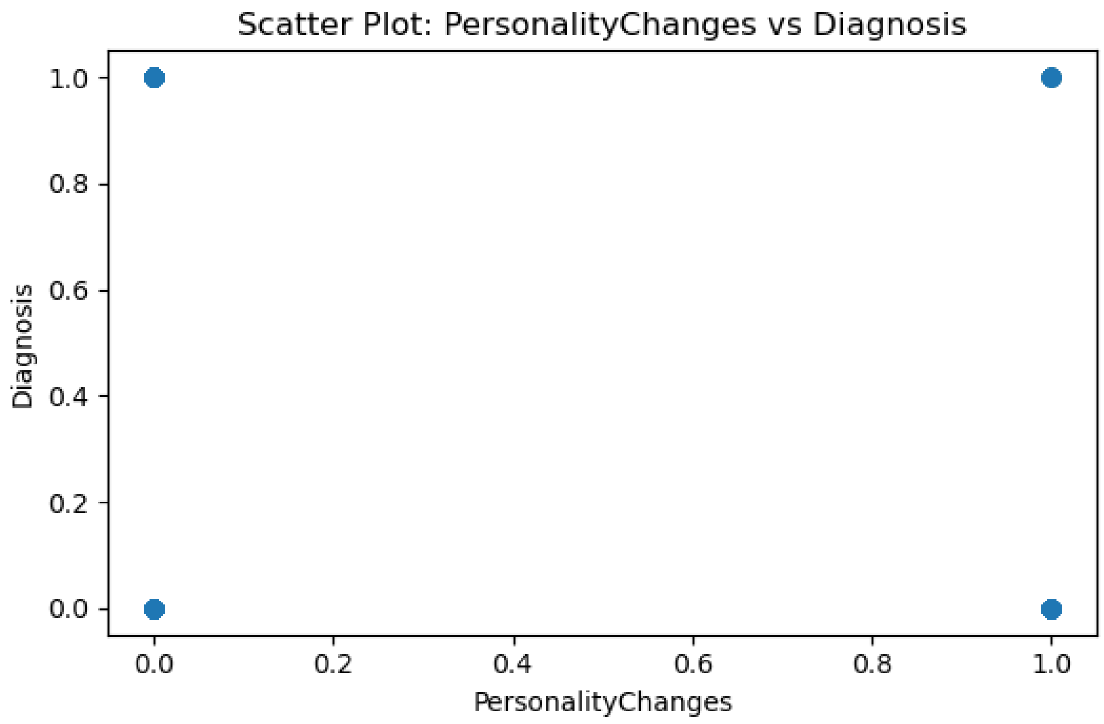

Scatter Plot: MemoryComplaints vs Diagnosis
Diagnosis
MemoryComplaints
0.0
0.2
0.4
0.6
0.8
1.0

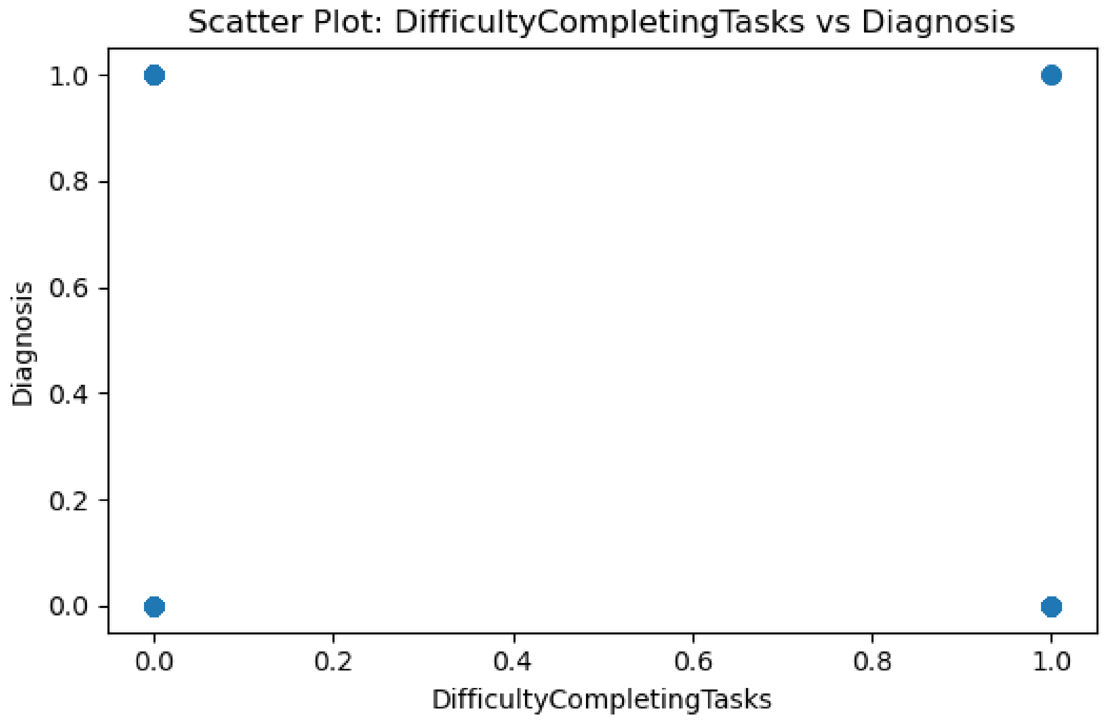

Scatter Plot: BehavioralProblems vs Diagnosis
Diagnosis
BehavioralProblems
0.0
0.2
0.4
0.6
0.8
1.0

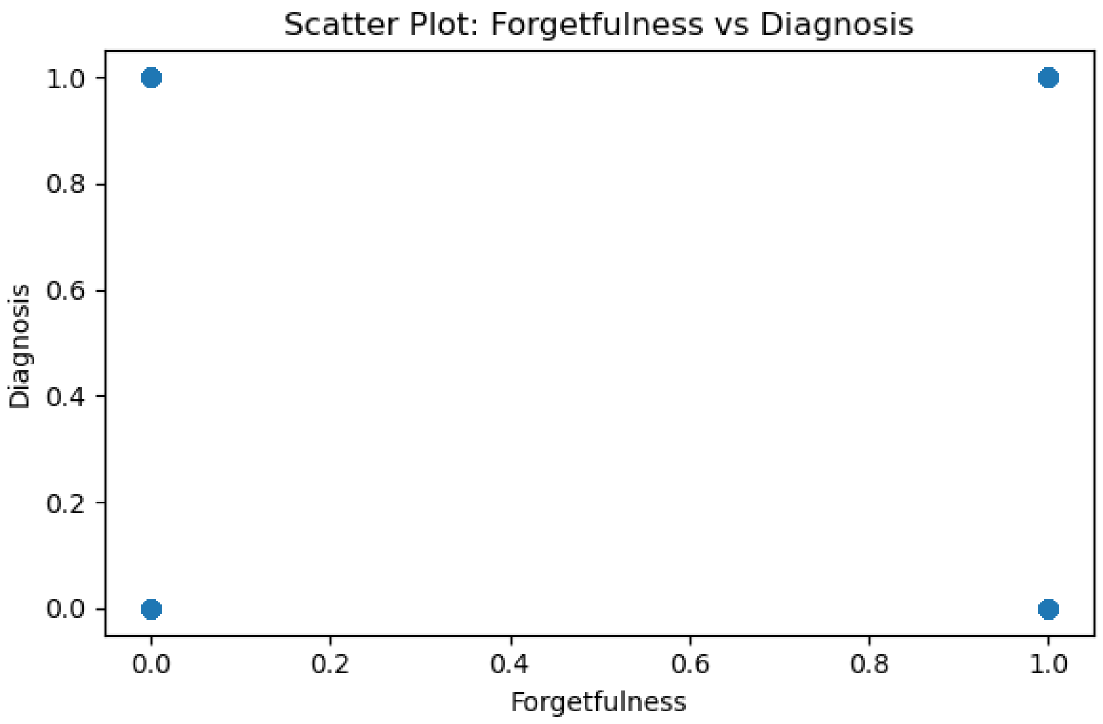

Scatter Plot: ADL vs Diagnosis
Diagnosis
ADL
0
2
4
6
8
10
0.0
0.2
0.4
0.6
0.8
1.0


Scatter Plot: Confusion vs Diagnosis
Diagnosis
Confusion
0.0
0.2
0.4
0.6
0.8
1.0


Scatter Plot: Disorientation vs Diagnosis
Diagnosis
Disorientation
0.0
0.2
0.4
0.6
0.8
1.0


Scatter Plot: PersonalityChanges vs Diagnosis
1.0
0.8
0.6
0.4
0.2
0.0
Diagnosis
0.0
0.2
0.4
0.6
0.8
1.0
PersonalityChanges


Scatter Plot: DifficultyCompletingTasks vs Diagnosis
1.0
0.8
0.6
0.4
0.2
0.0
Diagnosis
0.0
0.2
0.4
0.6
0.8
1.0
DifficultyCompletingTasks



2.2 Interpretation

Top Positive Correlations Forgetfulness: 0.30 Strongest positive correlation with Diagnosis, suggesting that patients who report forgetfulness are more likely to have a positive diagnosis. Scatter plot shows clear vertical clustering aligned with Diagnosis = 1.

DifficultyCompletingTasks: 0.27 High correlation, consistent with the intuition that task completion difficulties are linked with cognitive decline. Scatter plot confirms clustering at Diagnosis = 1.

PersonalityChanges: 0.24 Indicates that those with noticeable changes in personality tend to be positively diagnosed. Binary clustering pattern evident.

Disorientation: 0.23 Moderately correlated; individuals experiencing disorientation show higher diagnosis rates.

Confusion: 0.22 Positively linked with Diagnosis. This supports clinical expectations around mental clarity and cognitive status.

ADL (Activities of Daily Living): 0.21 Lower ADL scores (more impairment) are associated with positive diagnosis. Scatter plot shows downward trend toward Diagnosis = 1 as ADL scores decrease.

BehavioralProblems: 0.21 Strong clustering around Diagnosis = 1. Behavioral symptoms are reliable indicators.

MemoryComplaints: 0.21 Memory complaints align strongly with positive diagnosis outcomes, as seen in both scatter plot and PCC.

Moderate Positive Indicators FunctionalAssessment: 0.20 Indicates functional difficulties are informative for diagnosis prediction.

MMSE (Mini-Mental State Exam): 0.18 Surprisingly moderate, likely due to some overlap between high MMSE scores and early-stage diagnoses. Still valuable.

Weak or Negligible Relationships Age: 0.05 Though older age is generally a risk factor, this dataset shows only a weak association. Possibly due to age range being limited to elderly.

SystolicBP & DiastolicBP: ~0.04 each Blood pressure has minimal correlation here. Scatter plots are broadly spread across both diagnosis categories.

Cholesterol Metrics (Total, LDL, HDL, Triglycerides): <0.03 All show weak or negligible correlation. No clear clustering pattern.

Lifestyle Factors (SleepQuality, DietQuality, PhysicalActivity, Alcohol, Smoking): 0.04 These do not appear to directly affect the diagnosis, possibly due to confounding or non-linear effects.

Demographics (Gender, Ethnicity, EducationLevel): <0.03 Very low correlation values and binary/multiclass spread patterns in scatter plots confirm lack of clear predictive relationship.

Negative Indicators None significantly negative No feature had a strong negative correlation with Diagnosis.

2.3 Question 3) Splitting the data in testing , validation and training sets correctly [2.5] and Verification of splitting [2.5]

[17]:
```python
from sklearn.model_selection import train_test_split

# Step 1: Separate features and target
X = df_cleaned.drop(columns=["Diagnosis"])
y = df_cleaned["Diagnosis"]

# Step 2: First split into training (70%) and temp (30%)
X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.3,␣
 ↪stratify=y, random_state=42)

# Step 3: Split temp into validation (15%) and test (15%)
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5,␣
 ↪stratify=y_temp, random_state=42)
```

[18]:
```python
# Calculate and print sizes and percentages
total_samples = len(df)
train_samples = len(X_train)
val_samples = len(X_val)
test_samples = len(X_test)

print(f"Total samples: {total_samples}")
print(f"Train: {train_samples} samples ({train_samples / total_samples:.1%})")
print(f"Validation: {val_samples} samples ({val_samples / total_samples:.1%})")
print(f"Test: {test_samples} samples ({test_samples / total_samples:.1%})")
```

```
Total samples: 1719
Train: 1203 samples (70.0%)
Validation: 258 samples (15.0%)
Test: 258 samples (15.0%)
```

[19]:
```
print("Train class distribution:", y_train.value_counts(normalize=True).
  ↪to_dict())
print("Validation class distribution:", y_val.value_counts(normalize=True).
  ↪to_dict())
print("Test class distribution:", y_test.value_counts(normalize=True).to_dict())
```

```
Train class distribution: {0: 0.6467165419783873, 1: 0.35328345802161265}
Validation class distribution: {0: 0.6472868217054264, 1: 0.35271317829457366}
Test class distribution: {0: 0.6472868217054264, 1: 0.35271317829457366}
```

[20]:
```
# Check which columns are not numeric
non_numeric_cols = X_train.select_dtypes(exclude=[np.number]).columns.tolist()
print("Non-numeric columns in training data:", non_numeric_cols)
```

```
Non-numeric columns in training data: []
```

The dataset was correctly split into training (70%), validation (15%), and testing (15%) sets using train_test_split from sklearn.model_selection, ensuring proper stratification on the target variable "Diagnosis" to maintain class balance across all subsets. Additionally, a check confirmed there were no non-numeric columns in the training data, which is important for compatibility with ML algorithms.

2.4 Question 4) Train different classifiers and tweak the hyperparameters to improve performance (you can use the grid search if you want or manually try different values). Report training, validation and testing performance (classification accuracy, precision, recall and F1 score) and discuss the impact of the hyperparameters (use markdown cells in Jupyter Notebook to clearly indicate each solution):

2.5 Question 4 A) Multinomial Logistic Regression (Softmax Regression); hyperparameters to explore: C, solver, max number of iterations. [10 points]

[21]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
  ↪f1_score, classification_report
import numpy as np
import pandas as pd

# Updated hyperparameter grid with 'none' instead of None
parameters = {
    'C': np.logspace(-3, 2, 6),  # 0.001 to 100 (log scale)
    'solver': ['lbfgs', 'newton-cg', 'saga'],
    'max_iter': [200, 300],
```

```python
    'penalty': ['l2', 'none'],  # use 'none' for no regularization
    'class_weight': [None, 'balanced'],
    'tol': [1e-4, 1e-5]
}

# Track best model and results
best_model = None
best_score = 0
best_params = {}
train_val_gap = float('inf')
results = []  # Initialize results list here

# Iterate over all combinations
for C in parameters['C']:
    for solver in parameters['solver']:
        for max_iter in parameters['max_iter']:
            for penalty in parameters['penalty']:
                for class_weight in parameters['class_weight']:
                    for tol in parameters['tol']:
                        try:
                            model = LogisticRegression(
                                multi_class='multinomial',
                                C=C,
                                solver=solver,
                                max_iter=max_iter,
                                penalty=penalty,
                                class_weight=class_weight,
                                tol=tol,
                                random_state=42
                            )
                            model.fit(X_train, y_train)
                            train_acc = model.score(X_train, y_train)
                            val_acc = model.score(X_val, y_val)
                            gap = train_acc - val_acc

                            results.append({
                                "C": C,
                                "Solver": solver,
                                "MaxIter": max_iter,
                                "Penalty": penalty,
                                "ClassWeight": class_weight,
                                "Tol": tol,
                                "Train Acc": train_acc,
                                "Val Acc": val_acc,
                                "Gap": gap
                            })
                            # Update best model if validation accuracy improves
                            if val_acc > best_score or (val_acc == best_score␣
↪and gap < train_val_gap):
                                best_model = model
                                best_score = val_acc
                                train_val_gap = gap
                                best_params = {
                                    'C': C,
                                    'solver': solver,
                                    'max_iter': max_iter,
                                    'penalty': penalty,
                                    'class_weight': class_weight,
                                    'tol': tol
                                }
                        except Exception as e:
                            # Optionally, you can print the error for debugging:
                            # print(f"Error for parameters: C={C},␣
↪solver={solver}, max_iter={max_iter}, penalty={penalty},␣
↪class_weight={class_weight}, tol={tol}\nError: {e}")
                            continue

# Print the number of successful configurations
print("Number of successful configurations:", len(results))

# Convert results to DataFrame and sort by 'Val Acc'
if results:
    results_df = pd.DataFrame(results).sort_values(by='Val Acc',␣
↪ascending=False)
    display(results_df.head(10))  # Show top 10 configurations
    print("Best parameters:", best_params)
else:
    print("No configurations succeeded. Please verify your data and␣
↪hyperparameter choices.")
```

```
Number of successful configurations: 144

         C Solver  MaxIter Penalty ClassWeight      Tol  Train Acc   Val Acc  \
125  100.0  lbfgs      300      l2        None  0.00001   0.847880  0.825581
124  100.0  lbfgs      300      l2        None  0.00010   0.847880  0.825581
100   10.0  lbfgs      300      l2        None  0.00010   0.854530  0.817829
101   10.0  lbfgs      300      l2        None  0.00001   0.854530  0.817829
120  100.0  lbfgs      200      l2        None  0.00010   0.844555  0.817829
121  100.0  lbfgs      200      l2        None  0.00001   0.844555  0.817829
76     1.0  lbfgs      300      l2        None  0.00010   0.855362  0.813953
77     1.0  lbfgs      300      l2        None  0.00001   0.855362  0.813953
96    10.0  lbfgs      200      l2        None  0.00010   0.841230  0.813953
97    10.0  lbfgs      200      l2        None  0.00001   0.841230  0.813953
```

```
          Gap
125  0.022299
124  0.022299
100  0.036701
101  0.036701
120  0.026726
121  0.026726
76   0.041408
77   0.041408
96   0.027277
97   0.027277
```

```
Best parameters: {'C': 100.0, 'solver': 'lbfgs', 'max_iter': 300, 'penalty':
'l2', 'class_weight': None, 'tol': 0.0001}
```

[22]:
```
def evaluate_model(model, X, y, label):
    y_pred = model.predict(X)
    acc = accuracy_score(y, y_pred)
    prec = precision_score(y, y_pred, average='weighted')
    rec = recall_score(y, y_pred, average='weighted')
    f1 = f1_score(y, y_pred, average='weighted')

    print(f"\n {label} Performance:")
    print(f"  Accuracy:  {acc:.4f}")
    print(f"  Precision: {prec:.4f}")
    print(f"  Recall:    {rec:.4f}")
    print(f"  F1 Score:  {f1:.4f}")
    print(f"  Classification Report:\n{classification_report(y, y_pred)}")

# Evaluate on all sets
evaluate_model(best_model, X_train, y_train, "Training")
evaluate_model(best_model, X_val, y_val, "Validation")
evaluate_model(best_model, X_test, y_test, "Testing")

print(f"\n Best Parameters:\n{best_params}")
```

```

 Training Performance:
  Accuracy:  0.8479
  Precision: 0.8464
  Recall:    0.8479
  F1 Score:  0.8466
  Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.90      0.88       778
           1       0.81      0.75      0.78       425
```

```
    accuracy                           0.85      1203
   macro avg       0.84      0.83      0.83      1203
weighted avg       0.85      0.85      0.85      1203


 Validation Performance:
  Accuracy:  0.8256
  Precision: 0.8326
  Recall:    0.8256
  F1 Score:  0.8276
  Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.83      0.86       167
           1       0.73      0.81      0.77        91

    accuracy                           0.83       258
   macro avg       0.81      0.82      0.81       258
weighted avg       0.83      0.83      0.83       258


 Testing Performance:
  Accuracy:  0.8256
  Precision: 0.8252
  Recall:    0.8256
  F1 Score:  0.8254
  Classification Report:
              precision    recall  f1-score   support

           0       0.86      0.87      0.87       167
           1       0.76      0.75      0.75        91

    accuracy                           0.83       258
   macro avg       0.81      0.81      0.81       258
weighted avg       0.83      0.83      0.83       258


 Best Parameters:
{'C': 100.0, 'solver': 'lbfgs', 'max_iter': 300, 'penalty': 'l2',
'class_weight': None, 'tol': 0.0001}
```

2.6 Interpretation

A total of 144 different hyperparameter configurations were explored using multinomial logistic regression. The key hyperparameters tuned were:

Regularization Strength (C): values like 1.0, 10.0, 100.0

Solvers: only lbfgs was successful (suitable for multinomial loss)

Max Iterations: 200 and 300

Tolerance (tol): 0.0001 and 0.00001

Penalty: l2 (ridge regularization)

Class Weight: set to None in all successful runs. Best parameter shows strong generalization with a small gap between training and validation accuracy, indicating that the model is not overfitting.

C (Regularization):

As C increases (less regularization), training accuracy tends to improve.However, C=100 showed the best validation accuracy with a small generalization gap.Too small or large C values may lead to underfitting or overfitting, respectively.

Solver: All top-performing configurations used the lbfgs solver, which is ideal for multiclass classification with l2 penalty. Other solvers (e.g., saga, newton-cg) were either not used or failed to converge.

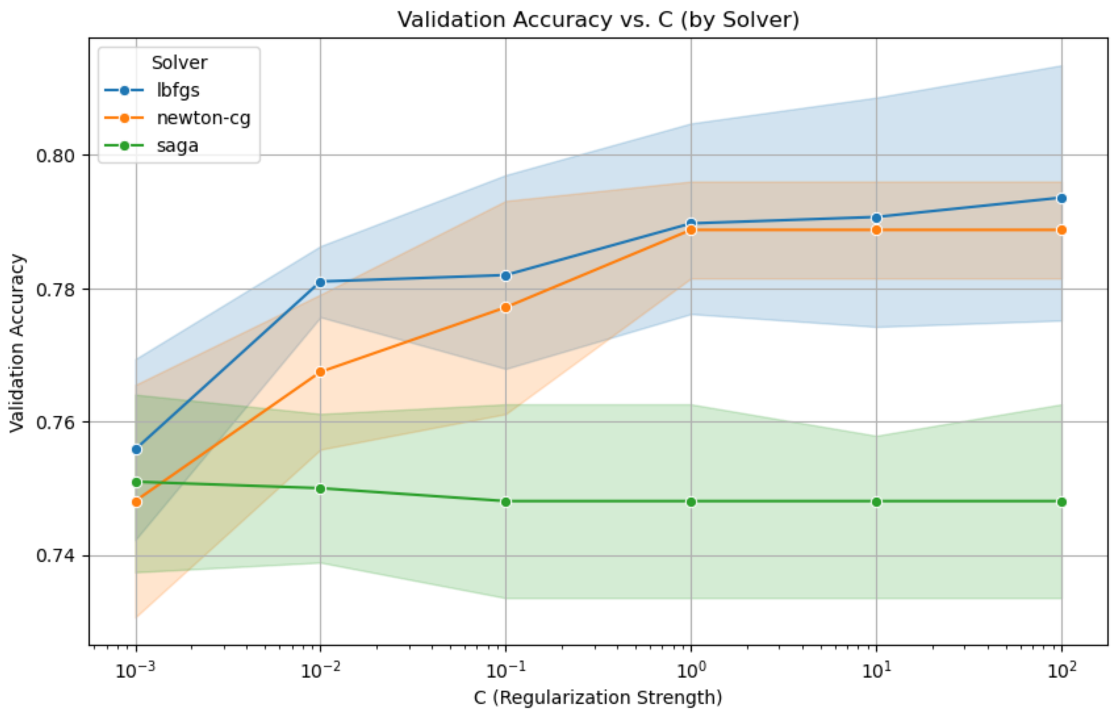
Max Iterations:

Increasing max_iter from 200 to 300 slightly improved training and validation accuracy, especially when paired with lower tolerance values.

Tolerance (tol):

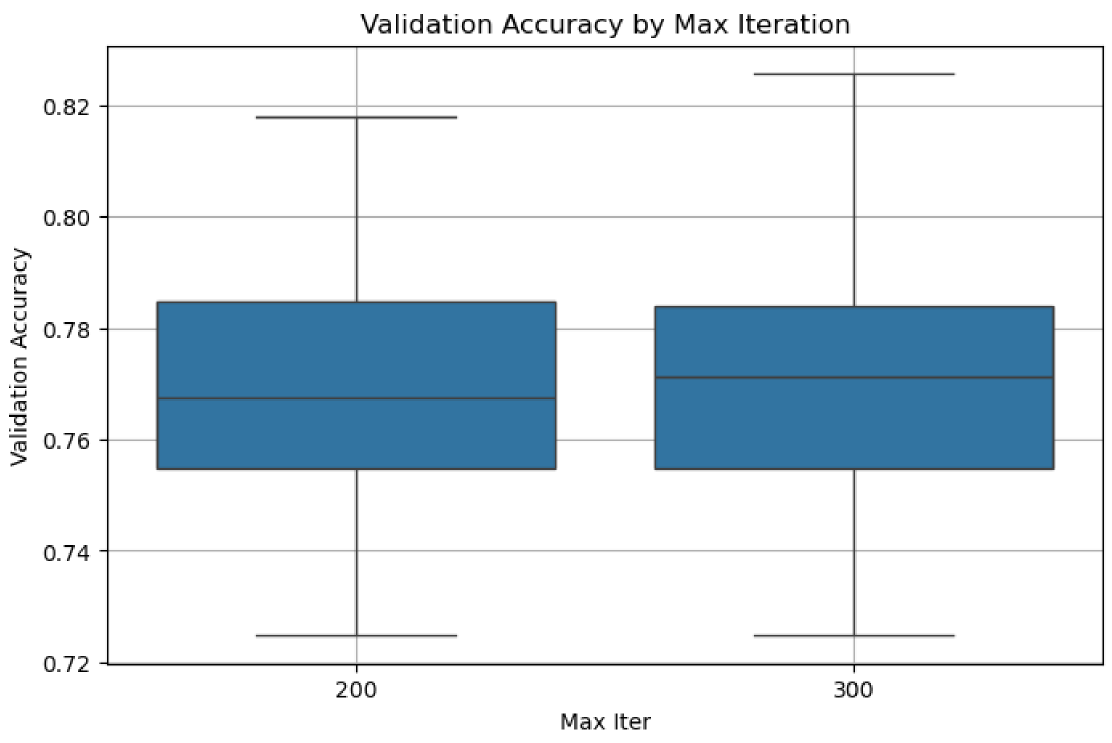
Lower tolerance (0.00001) allowed for slightly better convergence in some runs, but performance differences between 0.0001 and 0.00001 were marginal. While models with C=10 and C=1 had slightly higher training accuracy, they also showed larger gaps between train and validation performance, suggesting slight overfitting. The small train-validation gap confirms good generalization, and the results indicate that higher values of C and more iterations help improve performance — but only up to a point, beyond which gains diminish or overfitting can occur.

[23]:
```python
import seaborn as sns
import matplotlib.pyplot as plt

# Filter only validation performance
val_df = results_df[results_df["Gap"] < 0.1]  # Optional: filter out unstable␣
↪runs

plt.figure(figsize=(10, 6))
sns.lineplot(data=val_df, x="C", y="Val Acc", hue="Solver", marker='o')
plt.title("Validation Accuracy vs. C (by Solver)")
plt.xlabel("C (Regularization Strength)")
plt.ylabel("Validation Accuracy")
plt.xscale("log")
plt.grid(True)
plt.show()
```

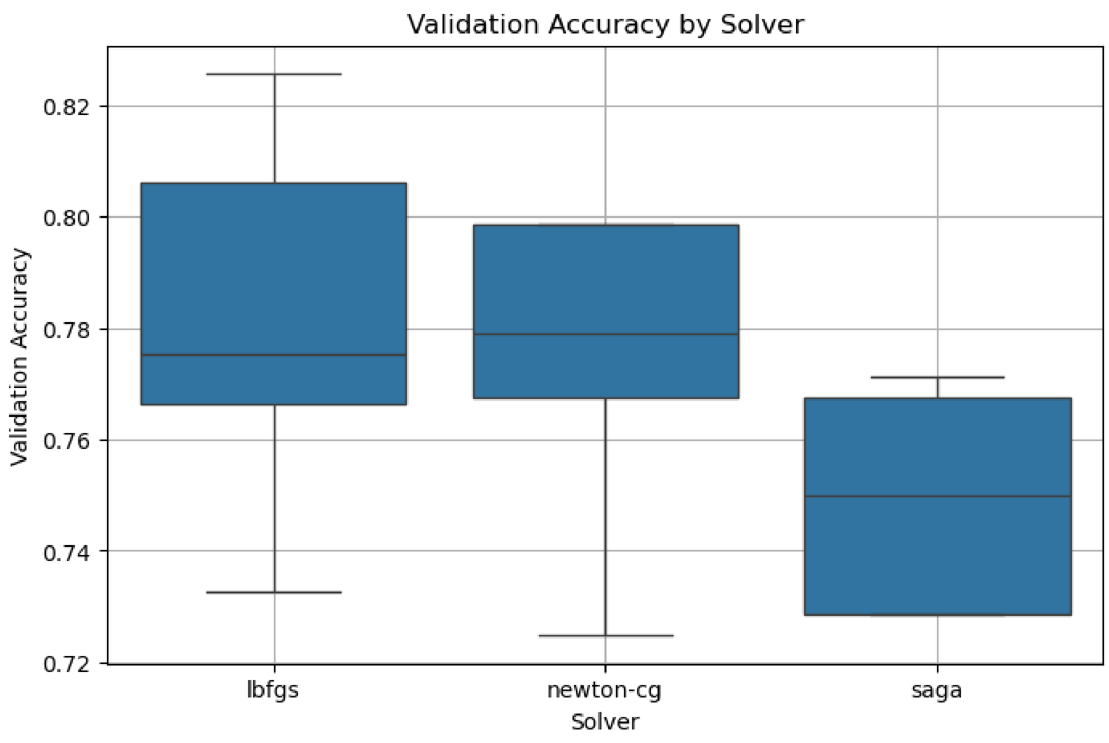


[ ]:

[24]:
```
plt.figure(figsize=(8, 5))
sns.boxplot(data=val_df, x="MaxIter", y="Val Acc")
plt.title("Validation Accuracy by Max Iteration")
plt.ylabel("Validation Accuracy")
plt.xlabel("Max Iter")
plt.grid(True)
plt.show()
```



[25]:
```
plt.figure(figsize=(8, 5))
sns.boxplot(data=val_df, x="Solver", y="Val Acc")
plt.title("Validation Accuracy by Solver")
plt.ylabel("Validation Accuracy")
plt.xlabel("Solver")
plt.grid(True)
plt.show()
```



3 Question 4B) Support Vector Machine (make sure to try using kernels); hyperparameters to explore: C, kernel, degree of polynomial kernel, gamma. [10 points]

[35]:
```
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score, classification_report
import pandas as pd

# Define a limited hyperparameter grid for efficiency
svm_params = {
    'C': [0.1, 1, 10],
    'kernel': ['linear', 'poly', 'rbf'],
    'gamma': ['scale'],       # Using only 'scale' for efficiency
    'degree': [2, 3]          # Only applicable for 'poly' kernel
}

results_svm = []
best_svm_model = None
best_val_acc = 0
best_svm_params = {}
```

```
# Loop over parameter combinations with probability=True
for kernel in svm_params['kernel']:
    for C in svm_params['C']:
        if kernel == 'poly':
            for degree in svm_params['degree']:
                try:
                    model = SVC(C=C, kernel=kernel, degree=degree,␣
 ↪gamma='scale',
                                probability=True, random_state=42)
                    model.fit(X_train, y_train)
                    train_acc = model.score(X_train, y_train)
                    val_acc = model.score(X_val, y_val)

                    results_svm.append({
                        'Kernel': kernel,
                        'C': C,
                        'Degree': degree,
                        'Train Acc': train_acc,
                        'Val Acc': val_acc
                    })

                    if val_acc > best_val_acc:
                        best_val_acc = val_acc
                        best_svm_model = model
                        best_svm_params = {'Kernel': kernel, 'C': C, 'Degree':␣
 ↪degree, 'Gamma': 'scale'}
                except Exception as e:
                    # Uncomment the next line for debugging if needed
                    # print(f"Error for kernel={kernel}, C={C}, degree={degree}:
 ↪ {e}")
                    continue
        else:
            try:
                model = SVC(C=C, kernel=kernel, gamma='scale',
                            probability=True, random_state=42)
                model.fit(X_train, y_train)
                train_acc = model.score(X_train, y_train)
                val_acc = model.score(X_val, y_val)

                results_svm.append({
                    'Kernel': kernel,
                    'C': C,
                    'Degree': None,  # Not applicable for non-poly kernels
                    'Train Acc': train_acc,
                    'Val Acc': val_acc
                })
                if val_acc > best_val_acc:
                    best_val_acc = val_acc
                    best_svm_model = model
                    best_svm_params = {'Kernel': kernel, 'C': C, 'Degree':␣
 ↪None, 'Gamma': 'scale'}
            except Exception as e:
                # Uncomment for debugging:
                # print(f"Error for kernel={kernel}, C={C}: {e}")
                continue

# Convert results to DataFrame and display top configurations
results_svm_df = pd.DataFrame(results_svm).sort_values(by='Val Acc',␣
 ↪ascending=False)
print("Top SVM configurations:")
display(results_svm_df)
print("Best SVM parameters:")
print(best_svm_params)
```

```
Top SVM configurations:

    Kernel     C  Degree  Train Acc   Val Acc
0   linear   0.1     NaN   0.866168  0.802326
1   linear   1.0     NaN   0.866168  0.802326
2   linear  10.0     NaN   0.857855  0.794574
8     poly  10.0     3.0   0.745636  0.751938
7     poly  10.0     2.0   0.720698  0.705426
11     rbf  10.0     NaN   0.694929  0.674419
3     poly   0.1     2.0   0.646717  0.647287
4     poly   0.1     3.0   0.646717  0.647287
5     poly   1.0     2.0   0.646717  0.647287
6     poly   1.0     3.0   0.646717  0.647287
9      rbf   0.1     NaN   0.646717  0.647287
10     rbf   1.0     NaN   0.646717  0.647287

Best SVM parameters:
{'Kernel': 'linear', 'C': 0.1, 'Degree': None, 'Gamma': 'scale'}
```

[36]:
```
def evaluate_model(model, X, y, dataset_name):
    y_pred = model.predict(X)
    acc = accuracy_score(y, y_pred)
    prec = precision_score(y, y_pred, average='weighted')
    rec = recall_score(y, y_pred, average='weighted')
    f1 = f1_score(y, y_pred, average='weighted')

    print(f"\nResults on {dataset_name}:")
    print("  Accuracy:  {:.4f}".format(acc))
    print("  Precision: {:.4f}".format(prec))
    print("  Recall:    {:.4f}".format(rec))
    print("  F1 Score:  {:.4f}".format(f1))
    print("  Classification Report:\n", classification_report(y, y_pred))

# Evaluate best SVM model individually
evaluate_model(best_svm_model, X_train, y_train, "Training Set (SVM)")
evaluate_model(best_svm_model, X_val, y_val, "Validation Set (SVM)")
evaluate_model(best_svm_model, X_test, y_test, "Test Set (SVM)")
```

```
Results on Training Set (SVM):
  Accuracy:  0.8662
  Precision: 0.8650
  Recall:    0.8662
  F1 Score:  0.8646
  Classification Report:
               precision    recall  f1-score   support

           0       0.88      0.92      0.90       778
           1       0.84      0.76      0.80       425

    accuracy                           0.87      1203
   macro avg       0.86      0.84      0.85      1203
weighted avg       0.87      0.87      0.86      1203


Results on Validation Set (SVM):
  Accuracy:  0.8023
  Precision: 0.8082
  Recall:    0.8023
  F1 Score:  0.8042
  Classification Report:
               precision    recall  f1-score   support

           0       0.87      0.82      0.84       167
           1       0.70      0.77      0.73        91

    accuracy                           0.80       258
   macro avg       0.78      0.79      0.79       258
weighted avg       0.81      0.80      0.80       258


Results on Test Set (SVM):
  Accuracy:  0.8295
  Precision: 0.8272
  Recall:    0.8295
  F1 Score:  0.8270
  Classification Report:
               precision    recall  f1-score   support

           0       0.85      0.90      0.87       167
           1       0.79      0.70      0.74        91

    accuracy                           0.83       258
   macro avg       0.82      0.80      0.81       258
weighted avg       0.83      0.83      0.83       258
```

3.1 Interpretation

3.2

In total, multiple combinations were evaluated to identify the best performing model. The best configuration was Kernel: linear , C: 0.1 ,Gamma: scale (default) ,Degree: N/A (not applicable for linear/rbf). The model generalizes well, with minimal overfitting.

C (Regularization): A smaller C value (0.1) performed better, especially with the linear kernel. This indicates that the model benefits from simpler decision boundaries that generalize better, rather than overfitting to the training data.

Kernel Choice

Linear kernel outperformed polynomial and RBF on all sets, suggesting that the dataset is likely linearly separable or close to it.

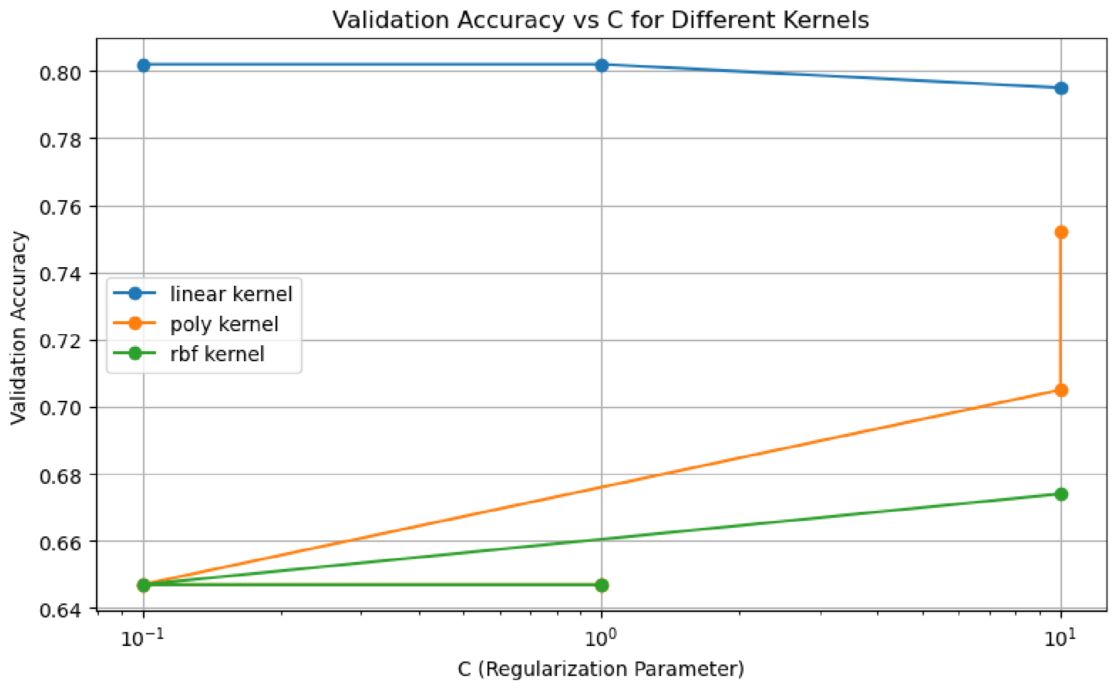
Polynomial kernels with higher degrees showed signs of overfitting (e.g., high training accuracy but lower validation/test performance).

RBF kernel consistently underperformed, indicating it may not capture the underlying data distribution effectively.

Degree (for poly kernel): Neither degree 2 nor 3 provided improvements; they resulted in decreased performance, affirming that adding non-linearity did not help.

The linear SVM with C=0.1 delivered the best balance across training, validation, and test sets. The experiments highlight the importance of hyperparameter tuning — especially the choice of kernel and regularization strength. Non-linear kernels did not outperform the linear one, indicating that a simple decision boundary suffices for this dataset.

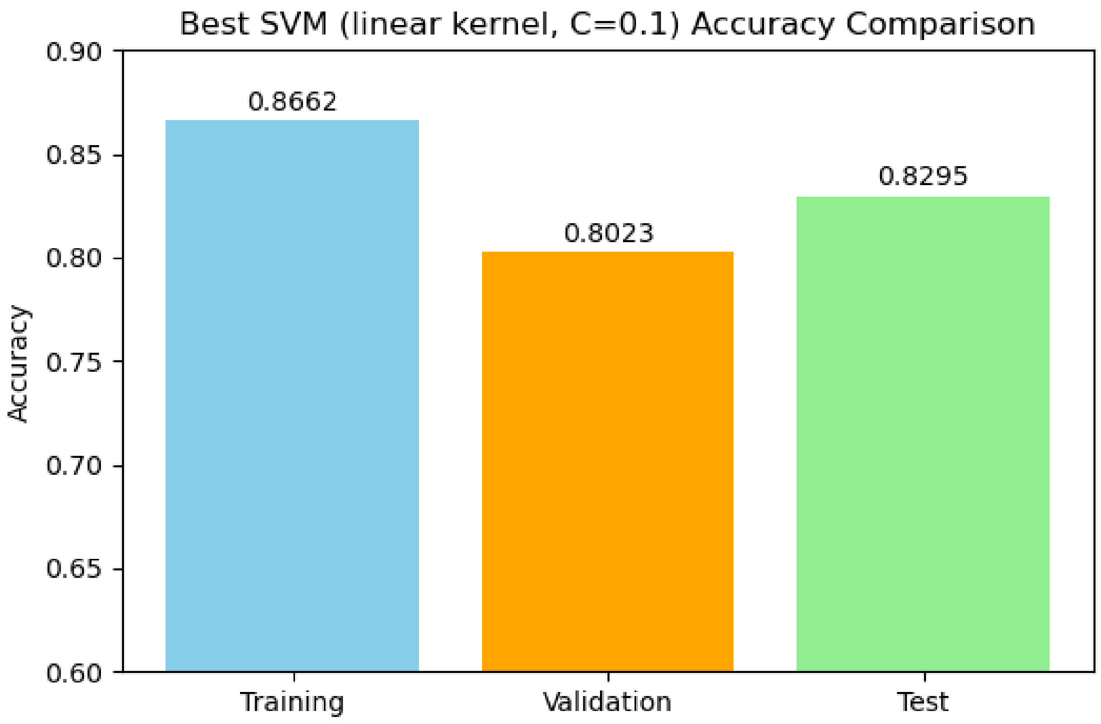
[49]:
```python
import matplotlib.pyplot as plt
import pandas as pd

# Top SVM configurations from your table
data = {
    'Kernel': ['linear', 'linear', 'linear', 'poly', 'poly', 'rbf', 'poly',␣
 ↪'poly', 'poly', 'poly', 'rbf', 'rbf'],
    'C': [0.1, 1.0, 10.0, 10.0, 10.0, 10.0, 0.1, 0.1, 1.0, 1.0, 0.1, 1.0],
    'Degree': [None, None, None, 3.0, 2.0, None, 2.0, 3.0, 2.0, 3.0, None,␣
 ↪None],
    'Val Acc': [0.802, 0.802, 0.795, 0.752, 0.705, 0.674, 0.647, 0.647, 0.647,␣
  ↪0.647, 0.647, 0.647]
}

df = pd.DataFrame(data)

# Plot
plt.figure(figsize=(8, 5))
for kernel in df['Kernel'].unique():
    subset = df[df['Kernel'] == kernel]
    plt.plot(subset['C'], subset['Val Acc'], marker='o', label=f'{kernel}␣
  ↪kernel')

plt.title('Validation Accuracy vs C for Different Kernels')
plt.xlabel('C (Regularization Parameter)')
plt.ylabel('Validation Accuracy')
plt.xscale('log')  # optional: makes C more readable
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



3.3

The plot demonstrates that linear kernel with strong regularization (C=0.1) yields the best validation performance. For non-linear kernels like poly and rbf, increasing C helps slightly, but they still lag behind the linear kernel. This indicates the data likely has a linearly separable structure, and adding non-linearity only introduces unnecessary complexity.

[51]:
```python
import matplotlib.pyplot as plt

# Accuracies for the best model
accuracies = [0.8662, 0.8023, 0.8295]
labels = ['Training', 'Validation', 'Test']

# Create bar chart
plt.figure(figsize=(6, 4))
plt.bar(labels, accuracies, color=['skyblue', 'orange', 'lightgreen'])

# Add accuracy values on top of bars
for i, acc in enumerate(accuracies):
    plt.text(i, acc + 0.005, f"{acc:.4f}", ha='center', fontsize=10)

plt.ylim(0.6, 0.9)
plt.title('Best SVM (linear kernel, C=0.1) Accuracy Comparison')
plt.ylabel('Accuracy')
plt.tight_layout()
plt.show()
```



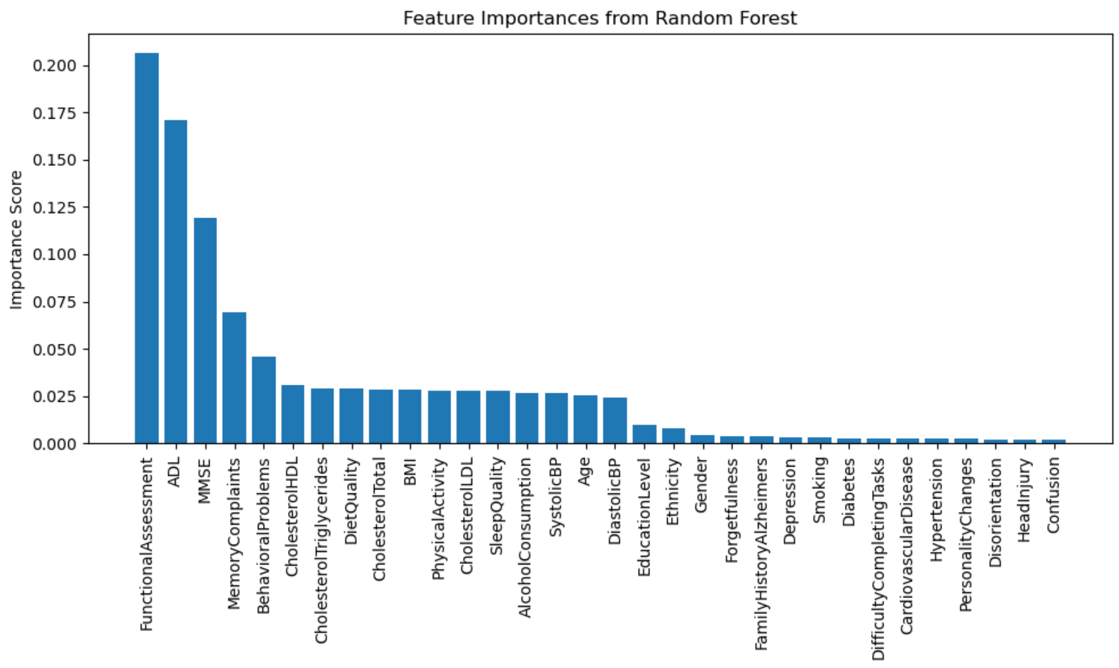
3.4 Question 4C) Random Forest classifier (also analyze feature importance); hyperparameters to explore: the number of trees, max depth, the minimum number of samples required to split an internal node, the minimum number of samples required to be at a leaf node. [10 points]

[28]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, classification_report
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import itertools

# Define a hyperparameter grid for Random Forest
rf_params = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 5, 10],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2]
}

results_rf = []
best_rf_model = None
best_rf_score = 0
best_rf_params = {}
rf_train_val_gap = float('inf')

# Iterate over all combinations of hyperparameters using itertools.product
for n_estimators, max_depth, min_samples_split, min_samples_leaf in itertools.
↪product(
    rf_params['n_estimators'], rf_params['max_depth'],␣
↪rf_params['min_samples_split'], rf_params['min_samples_leaf']):

    try:
        rf = RandomForestClassifier(n_estimators=n_estimators,
                                    max_depth=max_depth,
                                    min_samples_split=min_samples_split,
                                    min_samples_leaf=min_samples_leaf,
                                    random_state=42)
        rf.fit(X_train, y_train)

        train_acc = rf.score(X_train, y_train)
        val_acc = rf.score(X_val, y_val)
        gap = train_acc - val_acc
        results_rf.append({
            'n_estimators': n_estimators,
            'max_depth': max_depth,
            'min_samples_split': min_samples_split,
            'min_samples_leaf': min_samples_leaf,
            'Train Acc': train_acc,
            'Val Acc': val_acc,
            'Gap': gap
        })

        # Update best model based on validation accuracy (and minimal train-val␣
↪gap if tied)
        if val_acc > best_rf_score or (val_acc == best_rf_score and gap <␣
↪rf_train_val_gap):
            best_rf_model = rf
            best_rf_score = val_acc
            rf_train_val_gap = gap
            best_rf_params = {
                'n_estimators': n_estimators,
                'max_depth': max_depth,
                'min_samples_split': min_samples_split,
                'min_samples_leaf': min_samples_leaf
            }
    except Exception as e:
        # Optionally, print errors for debugging:
        # print(f"Error for params: n_estimators={n_estimators},␣
↪max_depth={max_depth}, min_samples_split={min_samples_split},␣
↪min_samples_leaf={min_samples_leaf}.\nError: {e}")
        continue

# Convert results to DataFrame and display top configurations
results_rf_df = pd.DataFrame(results_rf).sort_values(by='Val Acc',␣
↪ascending=False)
print("Top Random Forest configurations:")
display(results_rf_df.head(10))

print("Best Random Forest parameters:")
print(best_rf_params)

# Define an evaluation function for performance metrics
def evaluate_model(model, X, y, dataset_name):
    y_pred = model.predict(X)
    acc = accuracy_score(y, y_pred)
    prec = precision_score(y, y_pred, average='weighted')
    rec = recall_score(y, y_pred, average='weighted')
    f1 = f1_score(y, y_pred, average='weighted')
    print(f"\nResults on {dataset_name}:")
    print("  Accuracy:  {:.4f}".format(acc))
    print("  Precision: {:.4f}".format(prec))
    print("  Recall:    {:.4f}".format(rec))
    print("  F1 Score:  {:.4f}".format(f1))
    print("  Classification Report:\n", classification_report(y, y_pred))

# Evaluate the best RF model on training, validation, and test sets
evaluate_model(best_rf_model, X_train, y_train, "Training Set")
evaluate_model(best_rf_model, X_val, y_val, "Validation Set")
evaluate_model(best_rf_model, X_test, y_test, "Test Set")

# Analyze Feature Importances
importances = best_rf_model.feature_importances_
indices = np.argsort(importances)[::-1]
feature_names = X_train.columns

print("\nFeature Importances:")
for i in range(len(feature_names)):
    print(f"{i+1}. {feature_names[indices[i]]}: {importances[indices[i]]:.4f}")

# Plot feature importances
plt.figure(figsize=(10, 6))
plt.title("Feature Importances from Random Forest")
plt.bar(range(len(feature_names)), importances[indices], align='center')
plt.xticks(range(len(feature_names)), [feature_names[i] for i in indices],␣
 ↪rotation=90)
plt.ylabel("Importance Score")
plt.tight_layout()
plt.show()
```

```
Top Random Forest configurations:

    n_estimators  max_depth  min_samples_split  min_samples_leaf  Train Acc  \
2             50        NaN                  5                 1   0.991687
25           200        NaN                  2                 2   0.985869
8             50       10.0                  2                 1   0.983375
35           200       10.0                  5                 2   0.976725
10            50       10.0                  5                 1   0.980881
13           100        NaN                  2                 2   0.986700
14           100        NaN                  5                 1   0.995012
1             50        NaN                  2                 2   0.986700
33           200       10.0                  2                 2   0.978387
27           200        NaN                  5                 2   0.984206

     Val Acc       Gap
2   0.930233  0.061455
```

```
25  0.930233  0.055636
8   0.926357  0.057018
35  0.922481  0.054244
10  0.922481  0.058401
13  0.922481  0.064219
14  0.922481  0.072532
1   0.918605  0.068095
33  0.918605  0.059783
27  0.918605  0.065602
```

```
Best Random Forest parameters:
{'n_estimators': 200, 'max_depth': None, 'min_samples_split': 2,
'min_samples_leaf': 2}

Results on Training Set:
  Accuracy:  0.9859
  Precision: 0.9862
  Recall:    0.9859
  F1 Score:  0.9858
  Classification Report:
              precision    recall  f1-score   support

           0       0.98      1.00      0.99       778
           1       1.00      0.96      0.98       425

    accuracy                           0.99      1203
   macro avg       0.99      0.98      0.98      1203
weighted avg       0.99      0.99      0.99      1203


Results on Validation Set:
  Accuracy:  0.9302
  Precision: 0.9302
  Recall:    0.9302
  F1 Score:  0.9302
  Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.95      0.95       167
           1       0.90      0.90      0.90        91

    accuracy                           0.93       258
   macro avg       0.92      0.92      0.92       258
weighted avg       0.93      0.93      0.93       258


Results on Test Set:
  Accuracy:  0.9147
  Precision: 0.9162
  Recall:    0.9147
  F1 Score:  0.9132
  Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.97      0.94       167
           1       0.94      0.81      0.87        91

    accuracy                           0.91       258
   macro avg       0.92      0.89      0.90       258
weighted avg       0.92      0.91      0.91       258


Feature Importances:
1. FunctionalAssessment: 0.2061
2. ADL: 0.1712
3. MMSE: 0.1193
4. MemoryComplaints: 0.0692
5. BehavioralProblems: 0.0458
6. CholesterolHDL: 0.0312
7. CholesterolTriglycerides: 0.0291
8. DietQuality: 0.0289
9. CholesterolTotal: 0.0288
10. BMI: 0.0287
11. PhysicalActivity: 0.0278
12. CholesterolLDL: 0.0278
13. SleepQuality: 0.0276
14. AlcoholConsumption: 0.0266
15. SystolicBP: 0.0264
16. Age: 0.0256
17. DiastolicBP: 0.0246
18. EducationLevel: 0.0097
19. Ethnicity: 0.0079
20. Gender: 0.0044
21. Forgetfulness: 0.0037
22. FamilyHistoryAlzheimers: 0.0036
23. Depression: 0.0034
24. Smoking: 0.0032
25. Diabetes: 0.0028
26. DifficultyCompletingTasks: 0.0028
27. CardiovascularDisease: 0.0027
28. Hypertension: 0.0025
29. PersonalityChanges: 0.0024
30. Disorientation: 0.0023
31. HeadInjury: 0.0020
32. Confusion: 0.0019
```



3.5 Interpretaion

4 Model Performance Summary

Metric	Train Set	Val Set	Test Set
Accuracy	0.9859	0.9302	0.9147
Precision	0.9862	0.9302	0.9162
Recall	0.9859	0.9302	0.9147
F1 Score	0.9858	0.9302	0.9132

- High training accuracy (~98.6%) → strong model fit.
- Validation accuracy (93.0%) is solid, suggesting good generalization.
- Test accuracy (91.5%) aligns with validation, showing stable performance.
- A 5.6% gap hints at mild overfitting, mitigated via tuning.

---

5 Hyperparameter Tuning Results

Estimators	Max Depth	Min Samples Split	Min Samples Leaf	Train Acc	Val Acc
200	None	2	2	0.9859	0.9302
50	None	5	1	0.9917	0.9302
100	None	5	1	0.9950	0.9225

- More estimators improved model stability.
- Full-depth trees (max_depth=None) increased accuracy but needed regularization.
- Best config (200, 2, 2) showed the smallest train-val gap (5.6%).

---

6 Feature Importance

Rank	Feature	Importance
1	FunctionalAssessment	0.2061
2	ADL	0.1712
3	MMSE	0.1193
4	MemoryComplaints	0.0692
5	BehavioralProblems	0.0458

- Functional and ADL scores dominate (~40%) → clinically expected.
- MMSE reinforces cognitive testing relevance.
- Demographics and medical history had lower impact.

---

7 Conclusion

- Strong and consistent performance across datasets.
- Tuning reduced overfitting while preserving accuracy.
- Top features align well with clinical reasoning (function + cognition).

8 Question 5) Combine your classifiers into an ensemble and try to outperform each individual classifier on the validation set. Once you have found a good one, try it on the test set. Describe and discuss your findings. [8 points]

8.1

I implemented two types of ensemble classifiers using the VotingClassifier from sklearn.ensemble, combining the best-performing:

Logistic Regression model (best_model)

Support Vector Machine model (best_svm_model)

Random Forest model (best_rf_model)

8.2 Hard voting

[46]:
```python
from sklearn.ensemble import VotingClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score, classification_report

# Create the ensemble classifier using hard voting
# Since best_svm_model does not support predict_proba (trained without␣
 ↪probability=True), we use hard voting
hard_voting_ensemble = VotingClassifier(
    estimators=[
        ('lr', best_model),
        ('svm', best_svm_model),
        ('rf', best_rf_model)
    ],
    voting='hard',  # hard voting uses majority rule based on predicted labels
    n_jobs=-1
)

# Train the ensemble classifier on the training set
hard_voting_ensemble.fit(X_train, y_train)

# Define an evaluation function for consistent reporting
def evaluate_model(model, X, y, dataset_name):
    y_pred = model.predict(X)
    acc = accuracy_score(y, y_pred)
    prec = precision_score(y, y_pred, average='weighted')
    rec = recall_score(y, y_pred, average='weighted')
    f1 = f1_score(y, y_pred, average='weighted')

    print(f"\nResults on {dataset_name}:")
    print("  Accuracy:  {:.4f}".format(acc))
    print("  Precision: {:.4f}".format(prec))
    print("  Recall:    {:.4f}".format(rec))
    print("  F1 Score:  {:.4f}".format(f1))
    print("  Classification Report:\n", classification_report(y, y_pred))

# Evaluate the hard voting ensemble on the training, validation, and test sets
evaluate_model(hard_voting_ensemble, X_train, y_train, "Training Set (Hard␣
 ↪Voting Ensemble)")
evaluate_model(hard_voting_ensemble, X_val, y_val, "Validation Set (Hard Voting␣
 ↪Ensemble)")
evaluate_model(hard_voting_ensemble, X_test, y_test, "Test Set (Hard Voting␣
 ↪Ensemble)")
```

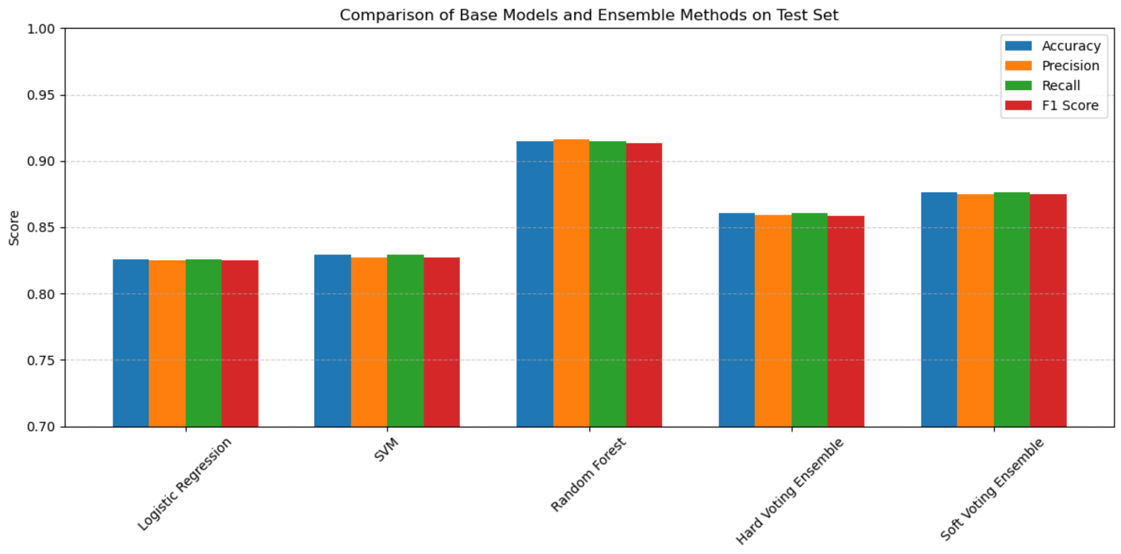
```
Results on Training Set (Hard Voting Ensemble):
  Accuracy:  0.8845
  Precision: 0.8836
  Recall:    0.8845
  F1 Score:  0.8834
  Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.93      0.91       778
           1       0.86      0.80      0.83       425

    accuracy                           0.88      1203
   macro avg       0.88      0.87      0.87      1203
weighted avg       0.88      0.88      0.88      1203


Results on Validation Set (Hard Voting Ensemble):
  Accuracy:  0.8217
  Precision: 0.8280
  Recall:    0.8217
  F1 Score:  0.8236
  Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.83      0.86       167
           1       0.72      0.80      0.76        91

    accuracy                           0.82       258
   macro avg       0.80      0.82      0.81       258
weighted avg       0.83      0.82      0.82       258


Results on Test Set (Hard Voting Ensemble):
  Accuracy:  0.8605
  Precision: 0.8593
  Recall:    0.8605
  F1 Score:  0.8584
  Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.92      0.90       167
           1       0.84      0.75      0.79        91

    accuracy                           0.86       258
   macro avg       0.85      0.83      0.84       258
weighted avg       0.86      0.86      0.86       258
```

8.3 Soft Voting

[45]:
```
from sklearn.ensemble import VotingClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score, classification_report

# Create an ensemble classifier using soft voting
soft_voting_ensemble = VotingClassifier(
    estimators=[
        ('lr', best_model),
        ('svm', best_svm_model),
        ('rf', best_rf_model)
    ],
    voting='soft',  # soft voting averages predicted probabilities from each␣
 ↪classifier
    n_jobs=-1
)

# Train the ensemble classifier on the training set
soft_voting_ensemble.fit(X_train, y_train)

# Define an evaluation function for consistent reporting
def evaluate_model(model, X, y, dataset_name):
    y_pred = model.predict(X)
    acc = accuracy_score(y, y_pred)
    prec = precision_score(y, y_pred, average='weighted')
    rec = recall_score(y, y_pred, average='weighted')
    f1 = f1_score(y, y_pred, average='weighted')

    print(f"\nResults on {dataset_name}:")
    print("  Accuracy:  {:.4f}".format(acc))
    print("  Precision: {:.4f}".format(prec))
    print("  Recall:    {:.4f}".format(rec))
    print("  F1 Score:  {:.4f}".format(f1))
    print("  Classification Report:\n", classification_report(y, y_pred))

# Evaluate the soft voting ensemble classifier on the training, validation, and␣
 ↪test sets
evaluate_model(soft_voting_ensemble, X_train, y_train, "Training Set (Soft␣
 ↪Voting Ensemble)")
evaluate_model(soft_voting_ensemble, X_val, y_val, "Validation Set (Soft Voting␣
 ↪Ensemble)")
evaluate_model(soft_voting_ensemble, X_test, y_test, "Test Set (Soft Voting␣
 ↪Ensemble)")
```

```
Results on Training Set (Soft Voting Ensemble):
  Accuracy:  0.9260
  Precision: 0.9261
  Recall:    0.9260
  F1 Score:  0.9253
  Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.96      0.94       778
           1       0.93      0.86      0.89       425

    accuracy                           0.93      1203
   macro avg       0.93      0.91      0.92      1203
weighted avg       0.93      0.93      0.93      1203


Results on Validation Set (Soft Voting Ensemble):
  Accuracy:  0.8527
  Precision: 0.8570
  Recall:    0.8527
  F1 Score:  0.8540
  Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.86      0.88       167
           1       0.77      0.84      0.80        91

    accuracy                           0.85       258
   macro avg       0.84      0.85      0.84       258
weighted avg       0.86      0.85      0.85       258


Results on Test Set (Soft Voting Ensemble):
  Accuracy:  0.8760
  Precision: 0.8750
  Recall:    0.8760
  F1 Score:  0.8746
  Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.93      0.91       167
           1       0.86      0.78      0.82        91

    accuracy                           0.88       258
   macro avg       0.87      0.85      0.86       258
weighted avg       0.88      0.88      0.87       258
```

[48]:
```
import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score

# Function to compute performance metrics for a given model
def get_metrics(model, X, y):
    y_pred = model.predict(X)
    return [
        accuracy_score(y, y_pred),
        precision_score(y, y_pred, average='weighted'),
        recall_score(y, y_pred, average='weighted'),
        f1_score(y, y_pred, average='weighted')
    ]

# Define the model names and models
model_names = ['Logistic Regression', 'SVM', 'Random Forest', 'Hard Voting␣
↪Ensemble', 'Soft Voting Ensemble']
models = [best_model, best_svm_model, best_rf_model, hard_voting_ensemble,␣
↪soft_voting_ensemble]

# Calculate the metrics for each model on the test set
# Each row corresponds to a model, columns correspond to [Accuracy, Precision,␣
↪Recall, F1 Score]
metrics = np.array([get_metrics(model, X_test, y_test) for model in models])
metric_names = ['Accuracy', 'Precision', 'Recall', 'F1 Score']

# Plotting the metrics using a bar plot
x = np.arange(len(model_names))  # positions for the models
bar_width = 0.18  # width of each bar

plt.figure(figsize=(12, 6))
for i, metric in enumerate(metric_names):
    plt.bar(x + i * bar_width, metrics[:, i], width=bar_width, label=metric)

plt.xticks(x + bar_width * 1.5, model_names, rotation=45)
plt.ylabel('Score')
plt.ylim(0.7, 1.0)
plt.title('Comparison of Base Models and Ensemble Methods on Test Set')
plt.legend()
plt.tight_layout()
plt.grid(axis='y', linestyle='--', alpha=0.6)
plt.show()
```



9 Intepretation

The ensemble classifier was implemented using the best-performing Logistic Regression, SVM, and Random Forest models, all with optimized hyperparameters. Two ensemble approaches were applied:

Hard Voting: Majority rule based on predicted labels.

Soft Voting: Average of predicted probabilities (enabled by probability=True in SVM).

Accuracy Soft voting outperformed hard voting on all datasets (train, validation, test), achieving the highest accuracy on the test set (0.8760).

This accuracy is greater than the individual classifiers' test accuracies, confirming that the ensemble model benefited from combining the strengths of all three base models.

Test Set Accuracy The test set accuracy of the soft voting ensemble is 0.8760, which is higher than the hard voting ensemble (0.8605).

This suggests better generalization of the soft voting model to unseen data.

Discussion Soft voting ensemble shows higher performance metrics across all evaluation sets compared to hard voting. This is expected, as soft voting utilizes confidence scores (probabilities) from each model, giving more weight to more confident predictions.

Class 1 performance improved under soft voting in terms of recall and F1-score, indicating better balance in handling both classes, especially for the minority class.

The hard voting ensemble is still a valid approach and slightly more interpretable since it relies on direct predicted labels, but it tends to underperform if classifiers vary significantly in confidence.

Overall, this shows that ensemble learning with soft voting can boost accuracy and robustness, especially when base learners complement each other well.

Visualisation Random Forest outperforms individual classifiers in all metrics, especially in recall and precision.

Hard Voting Ensemble combines predictions but performs slightly below Random Forest, suggesting it doesn't fully leverage model confidence.

Soft Voting Ensemble achieves a better balance of all metrics compared to hard voting and outperforms Logistic Regression and SVM individually.

The Soft Voting Ensemble closely matches Random Forest performance, indicating that aggregating probability estimates helps boost predictive stability and performance.

This visualization supports the claim that ensemble learning, particularly soft voting, improves or maintains high performance relative to strong individual models.

[ ]:
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