```python
import random
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
```

i.Data Generation Based on given Code

```python
id_1 = 7721 #change to first student id
id_2 = 7818 #change to second student id
id_3 = 0000 #change to third student id "leave 0000 if team of 2"
random_seed = id_1+id_2+id_3
random.seed(random_seed)
data_path="Data.csv"#replace with data path
output_path="MyData.csv"#replace with output data path

all_data=pd.read_csv(data_path)
all_columns = all_data.columns.tolist()

target_column = 'smoking'

all_columns.remove(target_column)

selected_columns = random.sample(all_columns, 10)

print(selected_columns) #MUST BE PRINTED
selected_columns = np.append(selected_columns, target_column)
sample_df = all_data[selected_columns].copy()
sample_df.to_csv(output_path)   #From HERE YOU CAN SPLIT FOR
TRAIN ,VALID AND TEST
```

```
['hearing(left)', 'Cholesterol', 'ALT', 'eyesight(left)', 'waist(cm)',
'hearing(right)', 'dental caries', 'hemoglobin', 'weight(kg)', 'serum
creatinine']
```

ii.Data Check and normalization

```python
# Load the dataset
data = pd.read_csv("MyData.csv")

# Drop the first column by index
data = data.drop(data.columns[0], axis=1)

# save the updated dataset back to a CSV file
data.to_csv("MyData_updated.csv", index=False)

# Display the first few rows
print("First few rows of the dataset:")
```

```
display(data.head())

# Overview of the dataset
print("\nDataset Information:")
data.info()

print("\nStatistical Summary:")
display(data.describe())
```

```
First few rows of the dataset:

   hearing(left)  Cholesterol  ALT  eyesight(left)  waist(cm)
hearing(right)  \
0              1          172   25             0.5       81.0
1
1              2          194   23             0.6       89.0
2
2              1          178   31             0.4       81.0
1
3              1          180   27             1.5      105.0
1
4              1          155   13             1.5       80.5
1

   dental caries  hemoglobin  weight(kg)  serum creatinine  smoking
0              0        16.5          60               1.0        1
1              1        16.2          65               1.1        0
2              0        17.4          75               0.8        1
3              1        15.9          95               1.0        0
4              0        15.4          60               0.8        1


Dataset Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 159256 entries, 0 to 159255
Data columns (total 11 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   hearing(left)     159256 non-null  int64  
 1   Cholesterol       159256 non-null  int64  
 2   ALT               159256 non-null  int64  
 3   eyesight(left)    159256 non-null  float64
 4   waist(cm)         159256 non-null  float64
 5   hearing(right)    159256 non-null  int64  
 6   dental caries     159256 non-null  int64  
 7   hemoglobin        159256 non-null  float64
 8   weight(kg)        159256 non-null  int64  
 9   serum creatinine  159256 non-null  float64
 10  smoking           159256 non-null  int64  
```

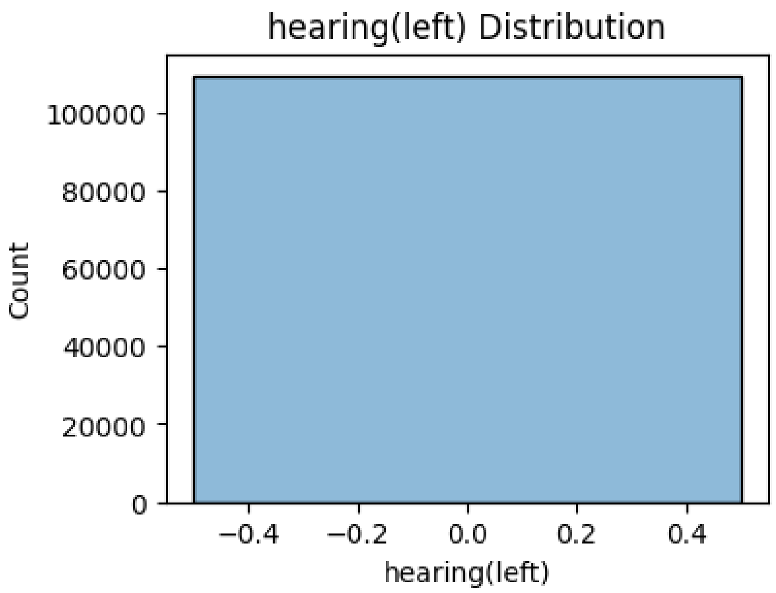
```
dtypes: float64(4), int64(7)
memory usage: 13.4 MB

Statistical Summary:

       hearing(left)    Cholesterol            ALT  eyesight(left)  \
count  159256.000000  159256.000000  159256.000000   159256.000000
mean        1.023974     195.796165      26.550296        1.005798
std         0.152969      28.396959      17.753070        0.402113
min         1.000000      77.000000       1.000000        0.100000
25%         1.000000     175.000000      16.000000        0.800000
50%         1.000000     196.000000      22.000000        1.000000
75%         1.000000     217.000000      32.000000        1.200000
max         2.000000     393.000000    2914.000000        9.900000

           waist(cm)  hearing(right)  dental caries     hemoglobin  \
count  159256.000000   159256.000000  159256.000000  159256.000000
mean       83.001990        1.023421       0.197996      14.796965
std         8.957937        0.151238       0.398490       1.431213
min        51.000000        1.000000       0.000000       4.900000
25%        77.000000        1.000000       0.000000      13.800000
50%        83.000000        1.000000       0.000000      15.000000
75%        89.000000        1.000000       0.000000      15.800000
max       127.000000        2.000000       1.000000      21.000000

          weight(kg)  serum creatinine        smoking
count  159256.000000     159256.000000  159256.000000
mean       67.143662          0.892764       0.437365
std        12.586198          0.179346       0.496063
min        30.000000          0.100000       0.000000
25%        60.000000          0.800000       0.000000
50%        65.000000          0.900000       0.000000
75%        75.000000          1.000000       1.000000
max       130.000000          9.900000       1.000000

# Check for missing values
missing_values = data.isnull().sum()
print("\nMissing Values in Each Column:")
print(missing_values[missing_values > 0])

#Handle missing values:
data.fillna(data.median(), inplace=True)

#remove outliers using
IQR!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!
Q1 = data.quantile(0.25)
Q3 = data.quantile(0.75)
IQR = Q3 - Q1
df = data[~((data < (Q1 - 1.5 * IQR)) | (data > (Q3 + 1.5 *
IQR))).any(axis=1)] ## remvoe outliers
```

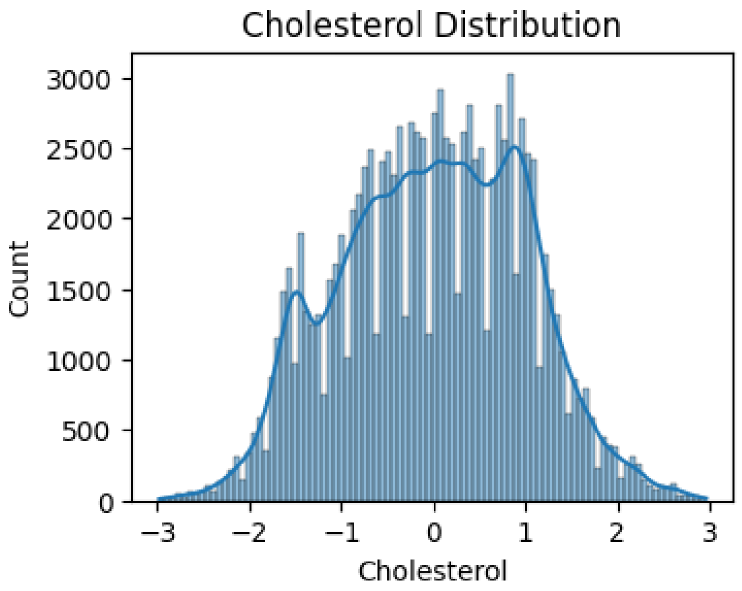
```
#scaling (Normalization)
scaler = StandardScaler()
df_scaled = pd.DataFrame(scaler.fit_transform(df), columns=df.columns)
```

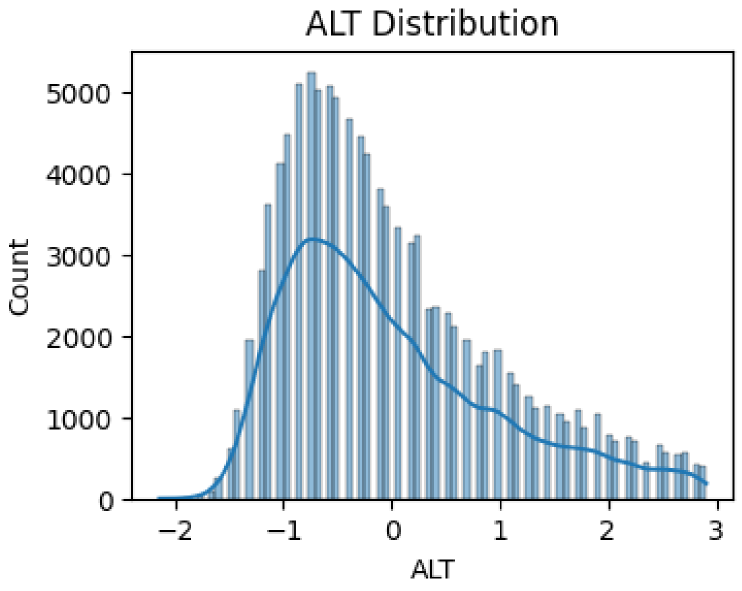
```
Missing Values in Each Column:
Series([], dtype: int64)
```

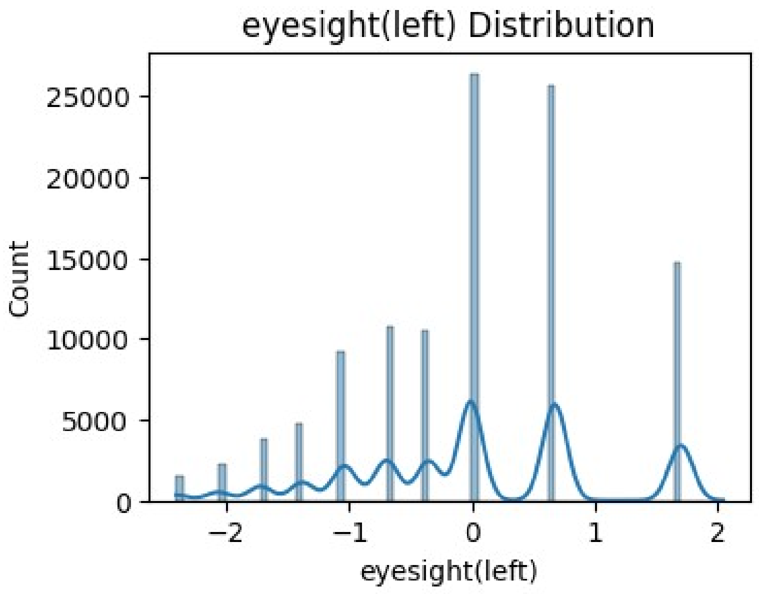
1.Data Analysis : Univariate

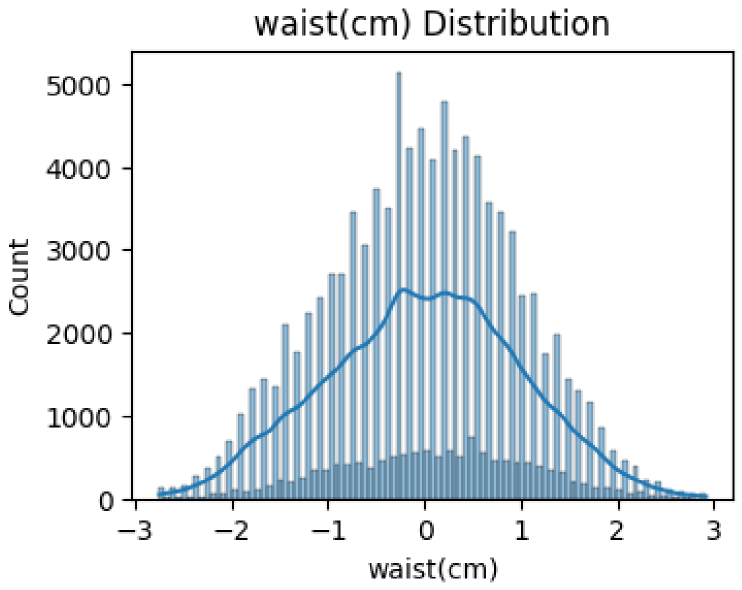
```
for column in df_scaled.columns:
    if column != 'smoking':
        plt.figure(figsize=(4,3))
        sns.histplot(df_scaled[column], kde=True)
        plt.title(f'{column} Distribution')
        plt.show()
```

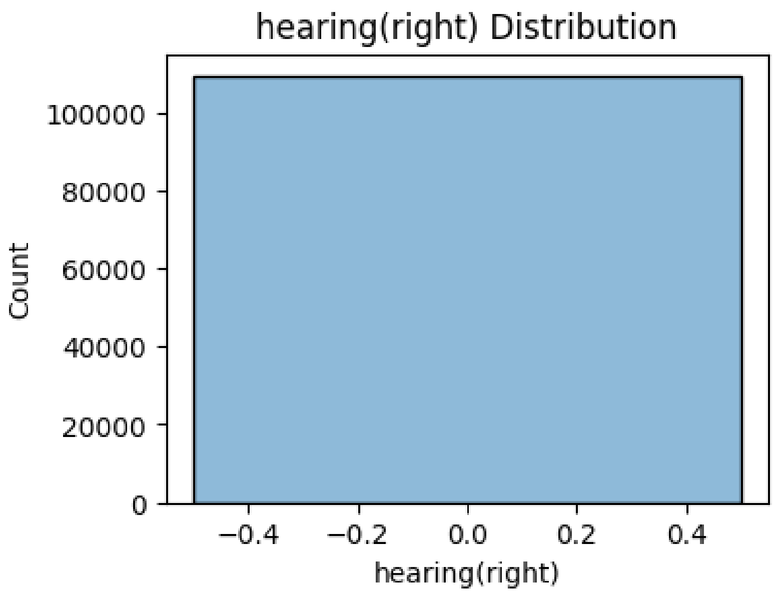


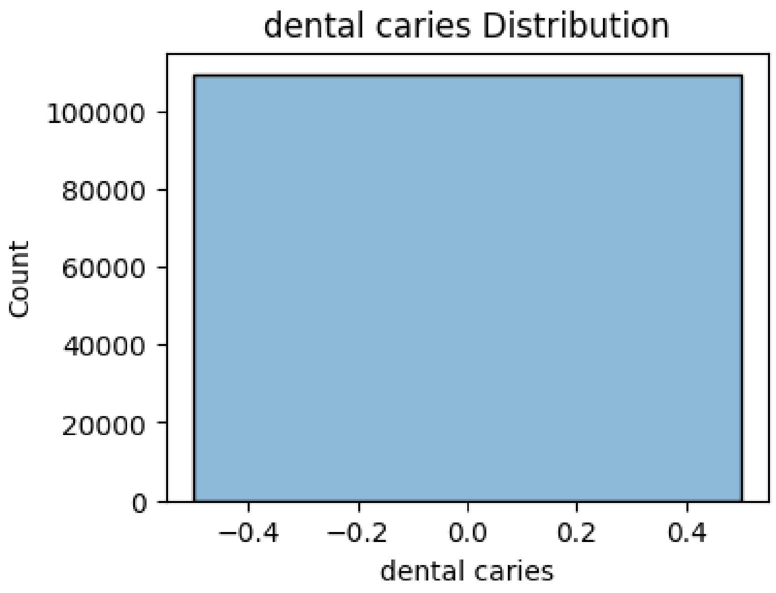

Cholesterol Distribution
Count
0
500
1000
1500
2000
2500
3000
−3
−2
−1
0
1
2
3
Cholesterol

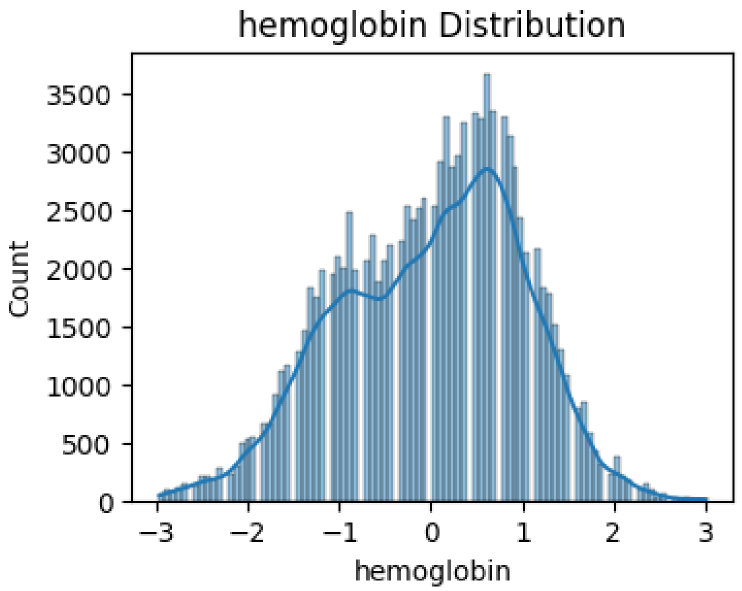

ALT Distribution
Count
0
1000
2000
3000
4000
5000
−2
−1
0
1
2
3
ALT

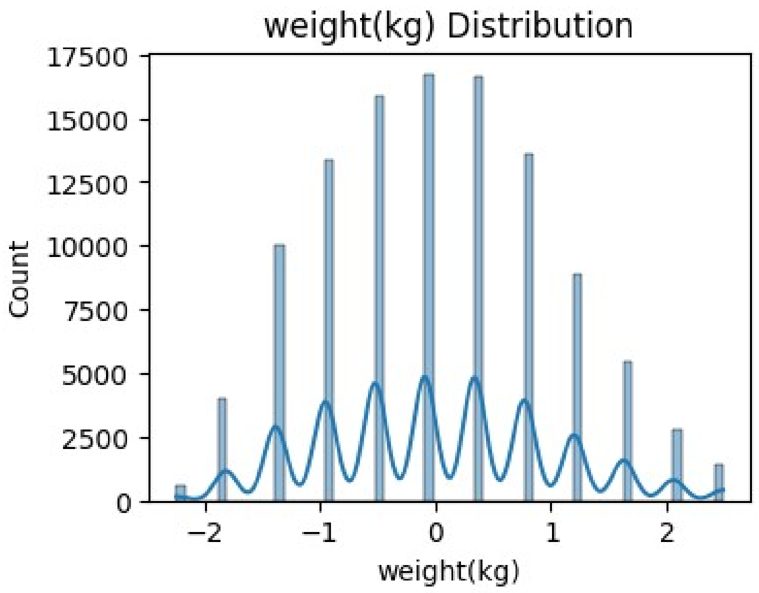

eyesight(left) Distribution
Count
eyesight(left)
0
5000
10000
15000
20000
25000
−2
−1
0
1
2

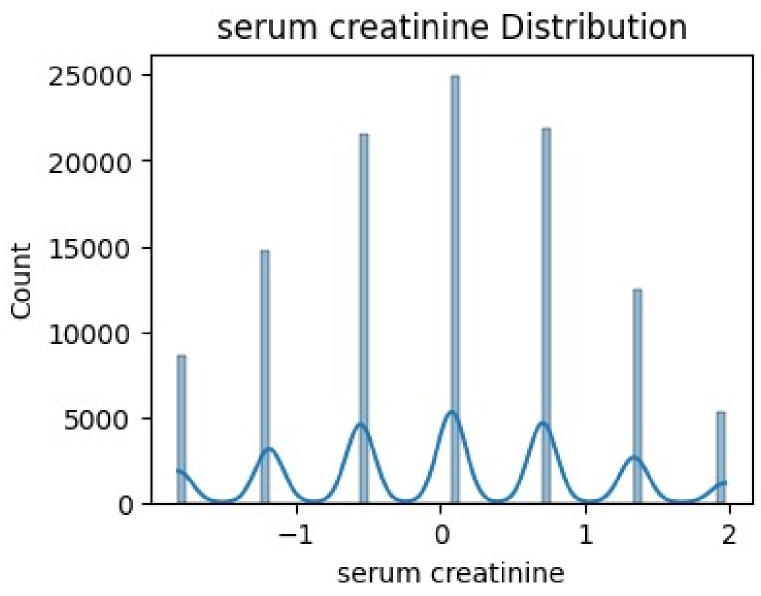

waist(cm) Distribution
Count
waist(cm)
0
1000
2000
3000
4000
5000
−3
−2
−1
0
1
2
3


hearing(right) Distribution
Count
100000
80000
60000
40000
20000
0
−0.4
−0.2
0.0
0.2
0.4
hearing(right)


dental caries Distribution
Count
100000
80000
60000
40000
20000
0
−0.4
−0.2
0.0
0.2
0.4
dental caries


hemoglobin Distribution
Count
hemoglobin
0
500
1000
1500
2000
2500
3000
3500
−3
−2
−1
0
1
2
3

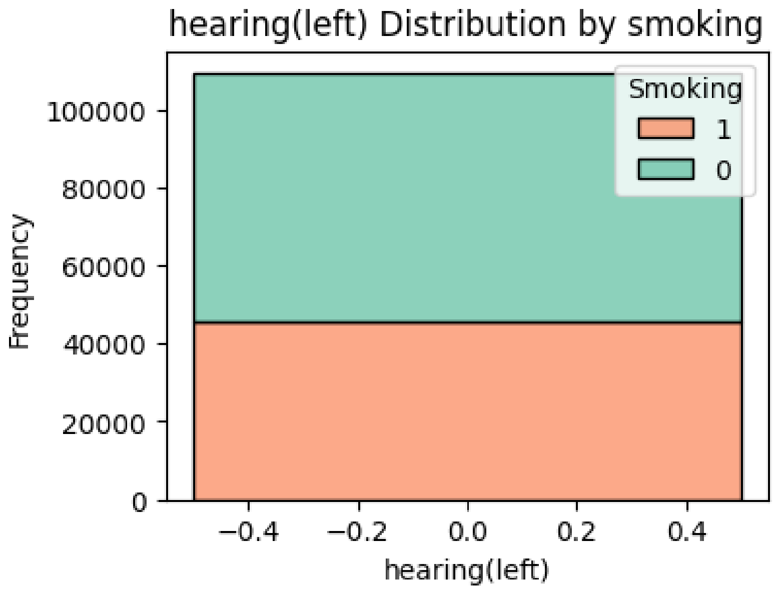

weight(kg) Distribution
Count
weight(kg)
0
2500
5000
7500
10000
12500
15000
17500
−2
−1
0
1
2

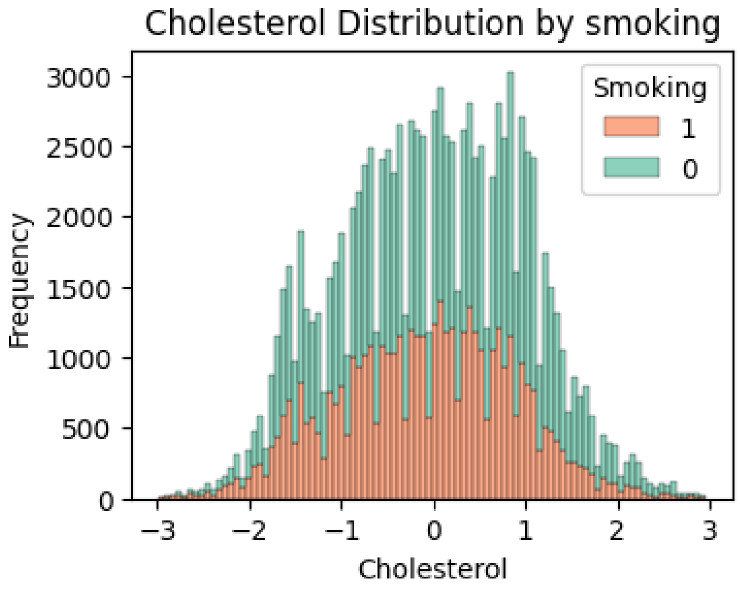


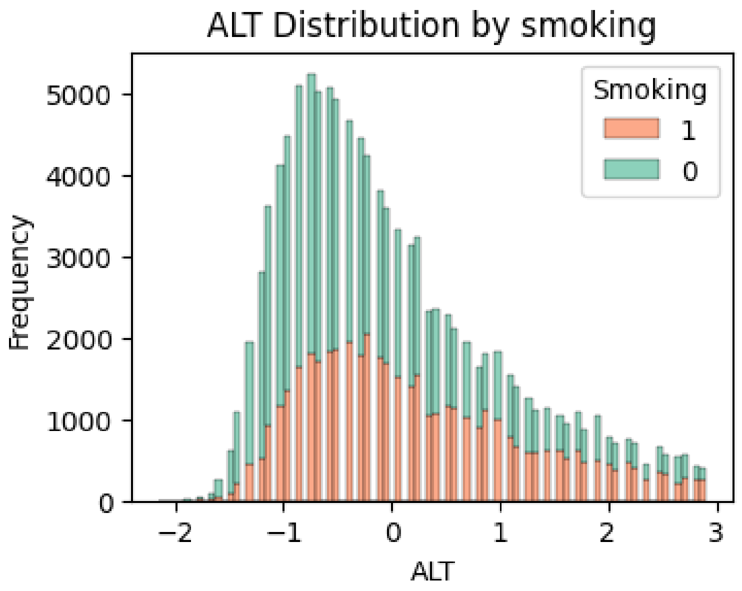
studying the data only without paying attention to the label is not very insightful. it only helps see if some feature is skewed.

next we study each feature with respect to the label.

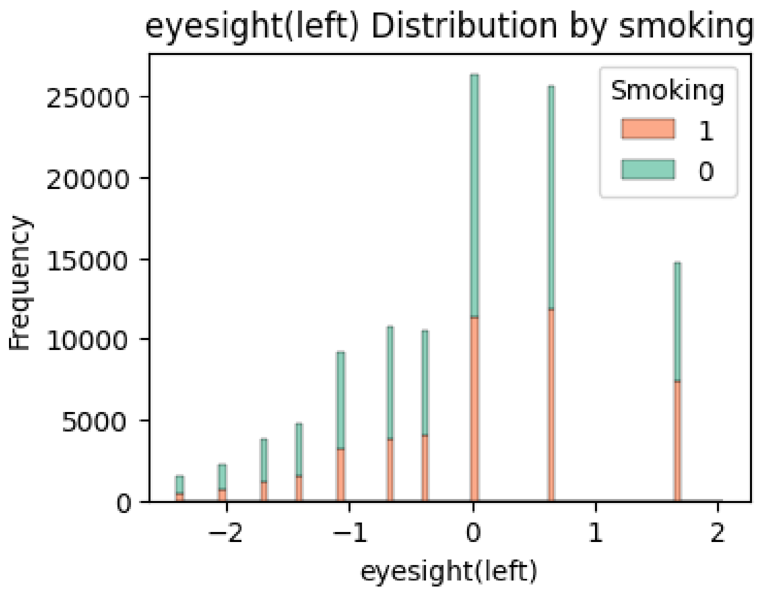
```
# Features and label
features = ['hearing(left)', 'Cholesterol', 'ALT', 'eyesight(left)',
'waist(cm)',
            'hearing(right)', 'dental caries', 'hemoglobin',
'weight(kg)', 'serum creatinine']
label = 'smoking'

# Iterate through each feature and plot histogram
for feature in features:
    plt.figure(figsize=(4, 3))
    sns.histplot(data=df_scaled, x=feature, hue=label,
multiple='stack', palette='Set2')
    plt.title(f'{feature} Distribution by {label}')
    plt.xlabel(feature)
    plt.ylabel('Frequency')
    plt.legend(title='Smoking', labels=df[label].unique())
    plt.show()

for feature in features:
    plt.figure(figsize=(6, 3))
    sns.boxplot( x= label, y= feature, data= df, palette="deep",
hue=label)
    plt.title(f'{feature} Distribution by {label}')
    plt.xlabel(label)
    plt.ylabel(feature)
    plt.xticks([0,1],['improbable to quit smoking', 'probable to quit
smoking'])
    plt.show()
```



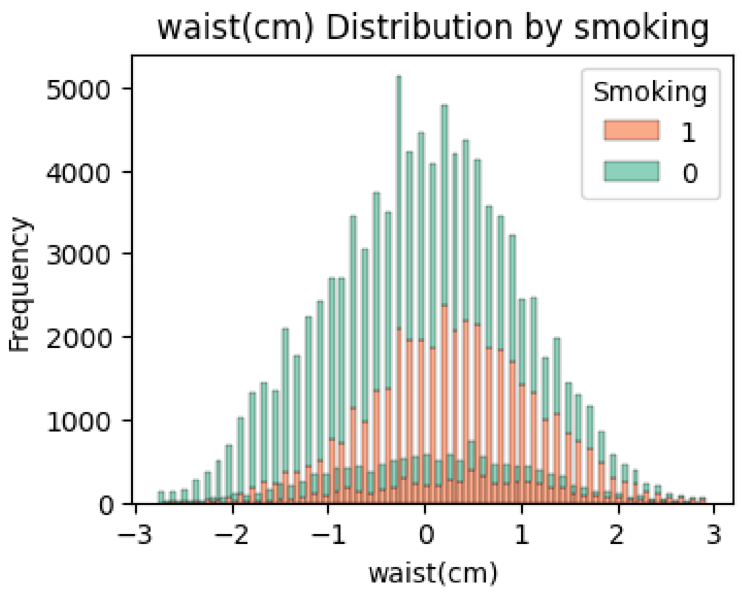


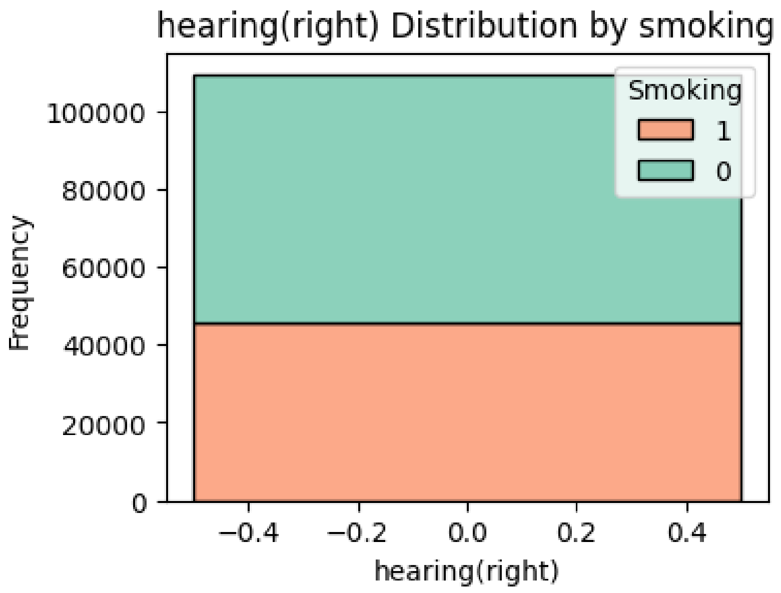


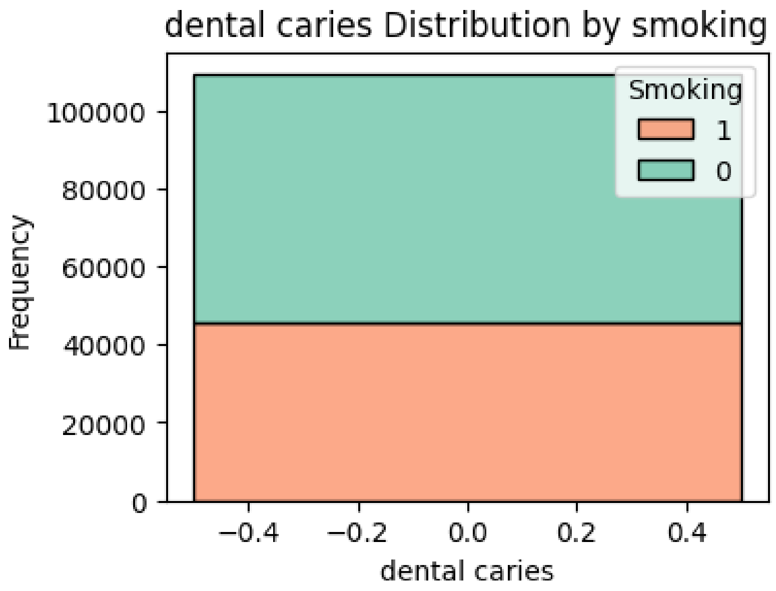
ALT Distribution by smoking
Smoking
1
0
Frequency
ALT

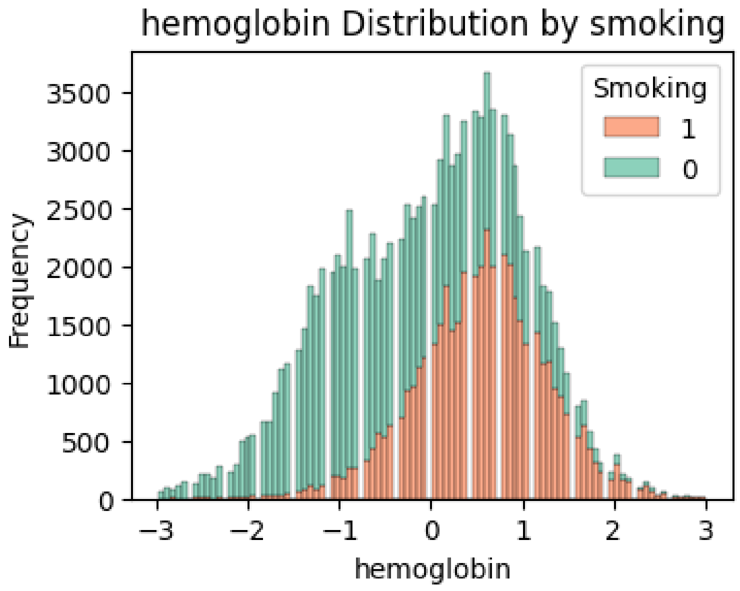


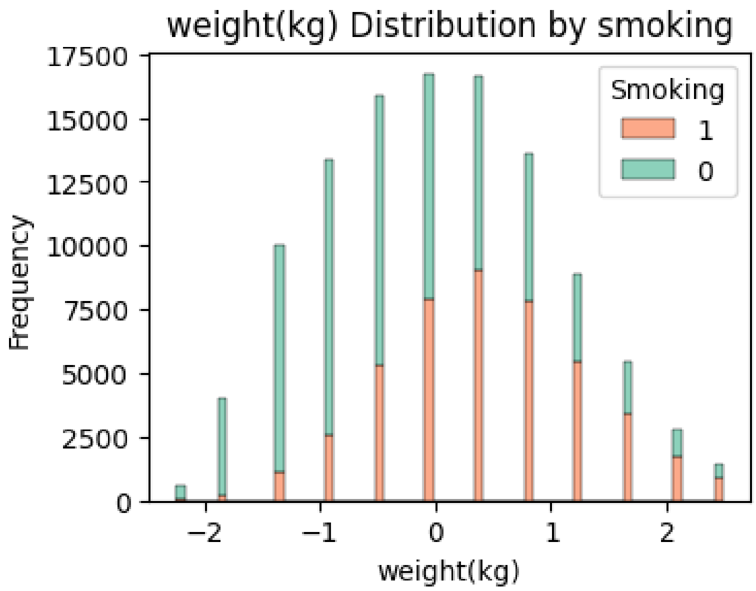
eyesight(left) Distribution by smoking
Smoking
1
0
Frequency
eyesight(left)

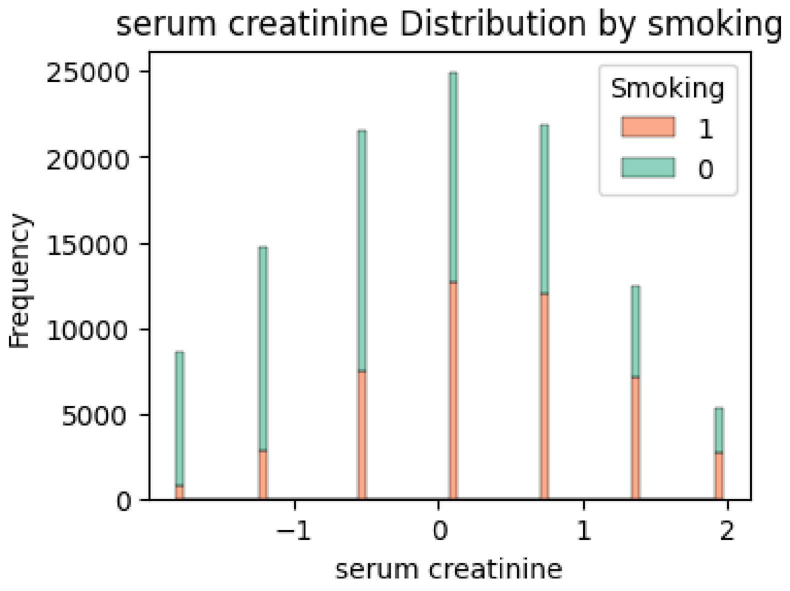

waist(cm) Distribution by smoking
Smoking
1
0
Frequency
5000
4000
3000
2000
1000
0
−3
−2
−1
0
1
2
3
waist(cm)

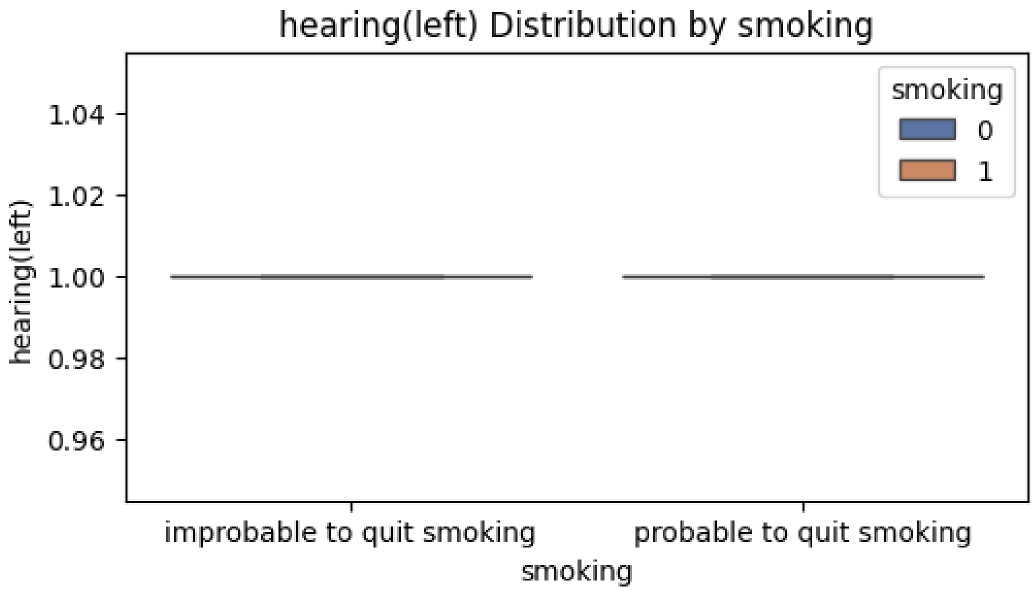

hearing(right) Distribution by smoking
Smoking
1
0
Frequency
100000
80000
60000
40000
20000
0
−0.4
−0.2
0.0
0.2
0.4
hearing(right)

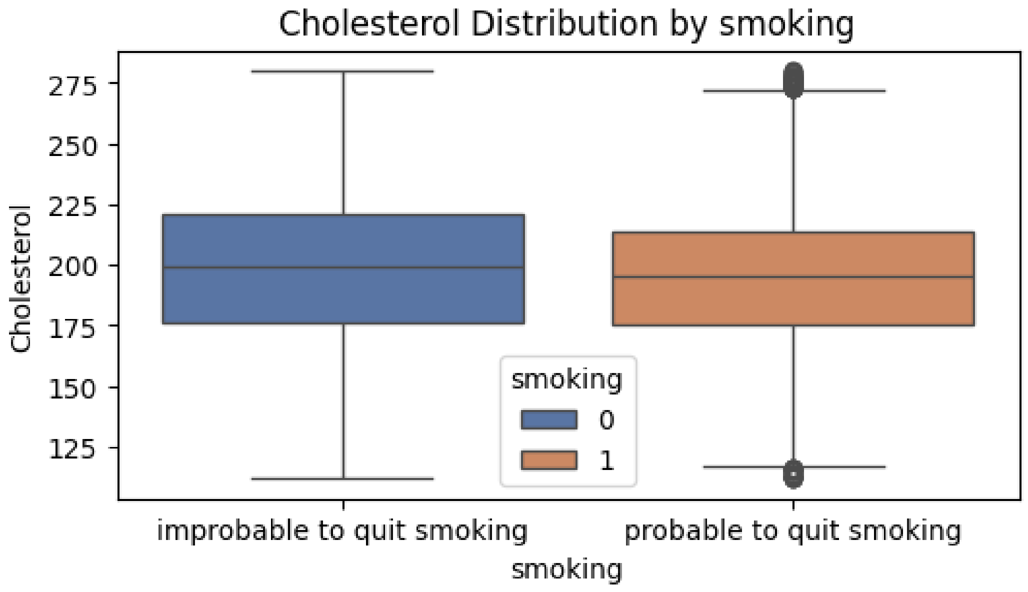

dental caries Distribution by smoking
Smoking
1
0
Frequency
dental caries
0
20000
40000
60000
80000
100000
−0.4
−0.2
0.0
0.2
0.4

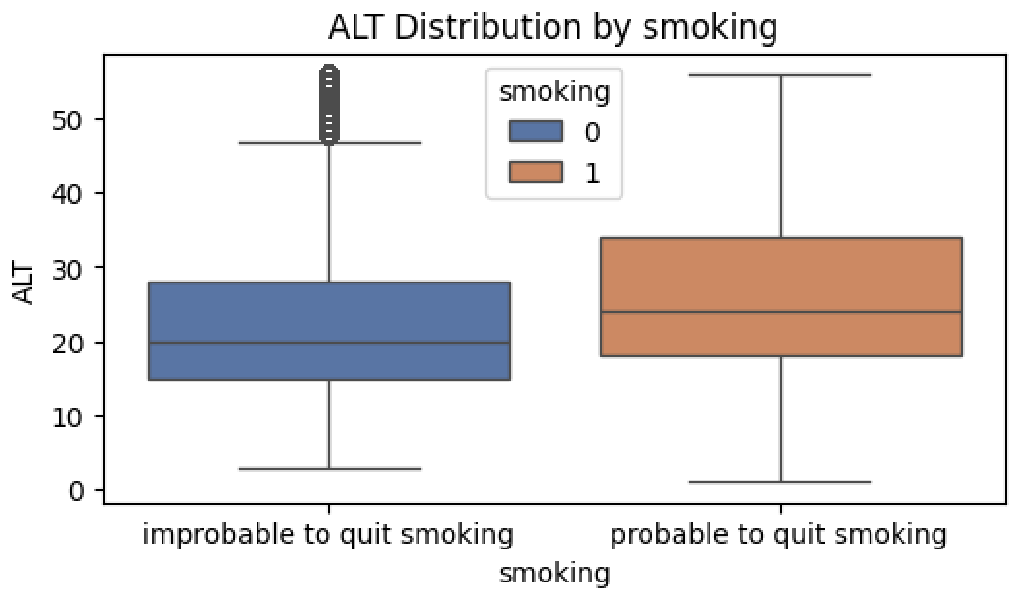

hemoglobin Distribution by smoking
Smoking
1
0
Frequency
hemoglobin
0
500
1000
1500
2000
2500
3000
3500
−3
−2
−1
0
1
2
3

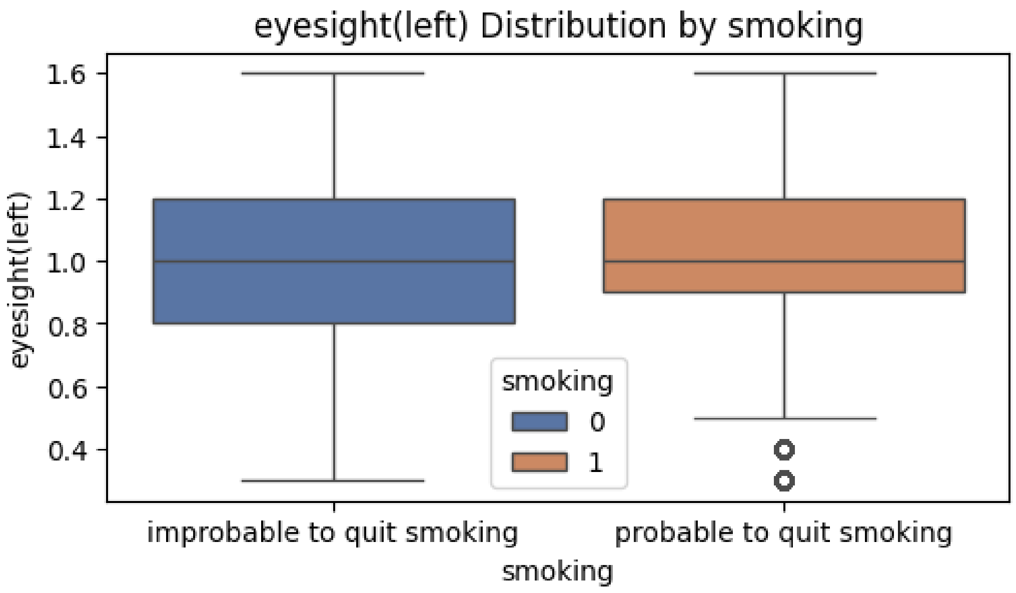

weight(kg) Distribution by smoking
Frequency
weight(kg)
Smoking
1
0
17500
15000
12500
10000
7500
5000
2500
0
−2
−1
0
1
2

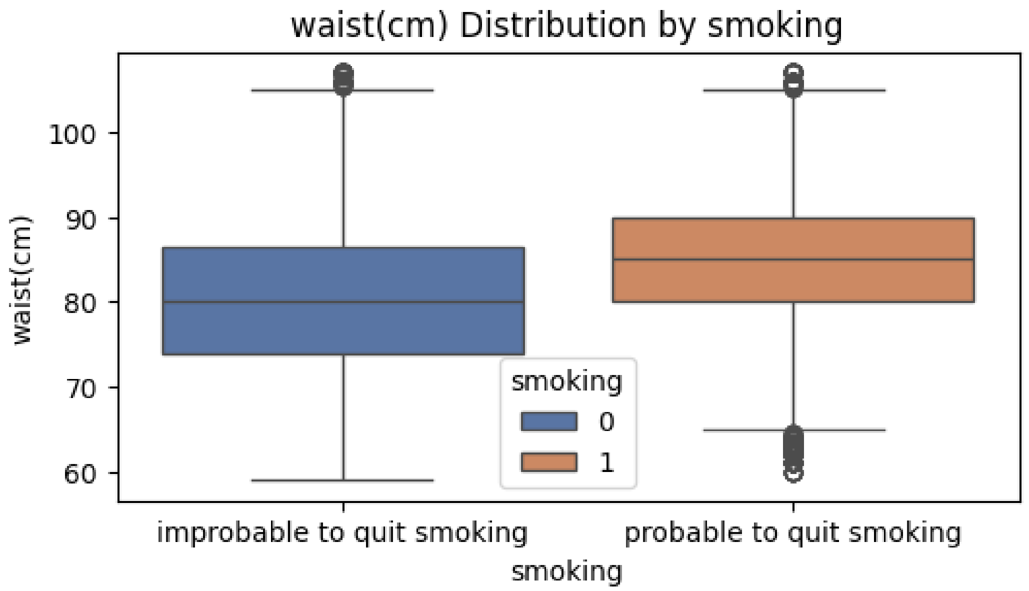

serum creatinine Distribution by smoking
Frequency
serum creatinine
Smoking
1
0
25000
20000
15000
10000
5000
0
−1
0
1
2

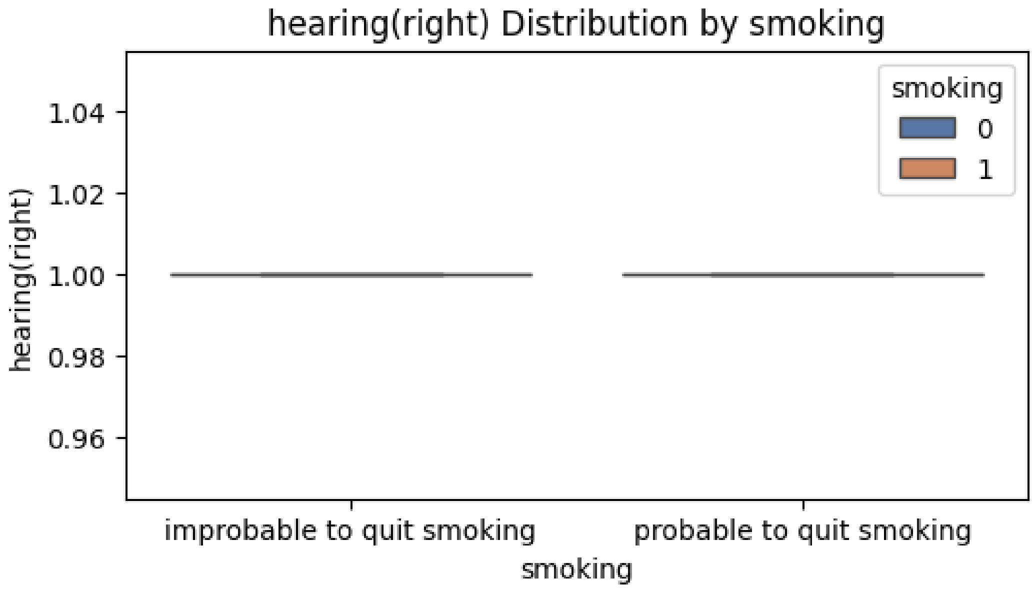

hearing(left) Distribution by smoking
hearing(left)
1.04
1.02
1.00
0.98
0.96
smoking
0
1
improbable to quit smoking
probable to quit smoking
smoking

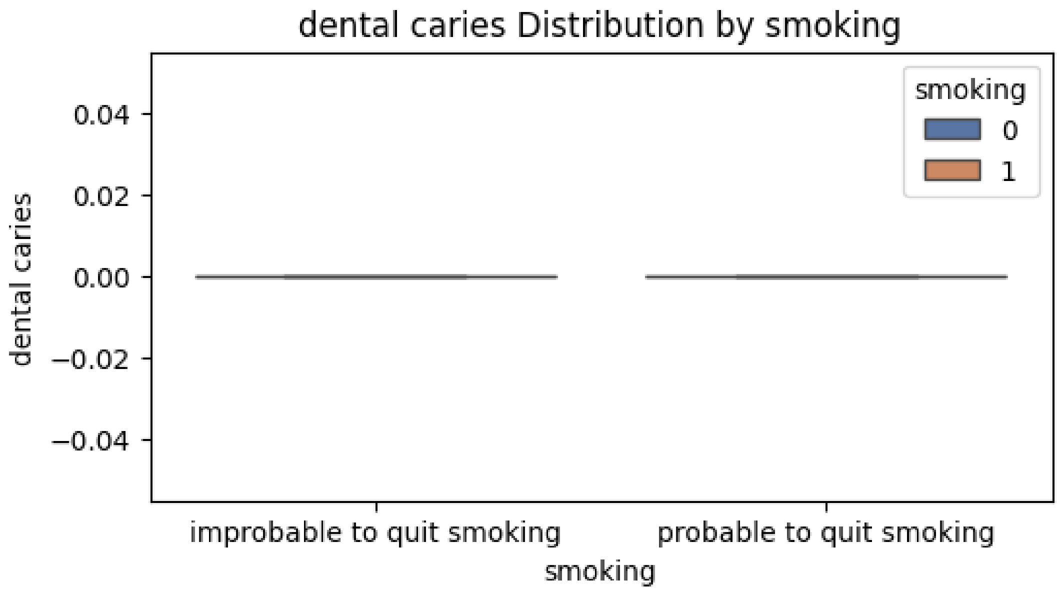

Cholesterol Distribution by smoking
Cholesterol
275
250
225
200
175
150
125
smoking
0
1
improbable to quit smoking
probable to quit smoking
smoking

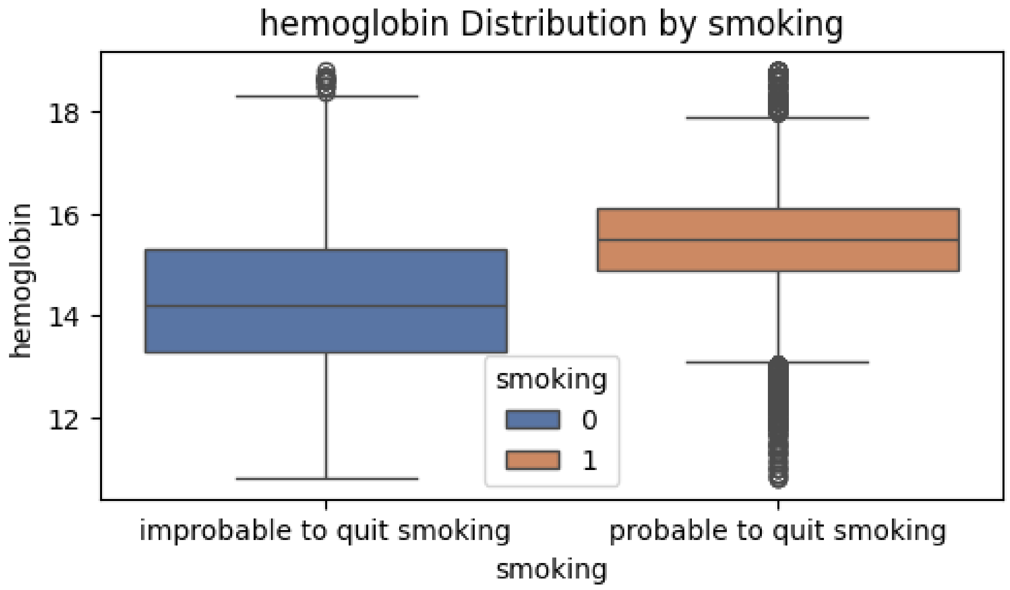

ALT Distribution by smoking
ALT
50
40
30
20
10
0
smoking
0
1
improbable to quit smoking
probable to quit smoking
smoking

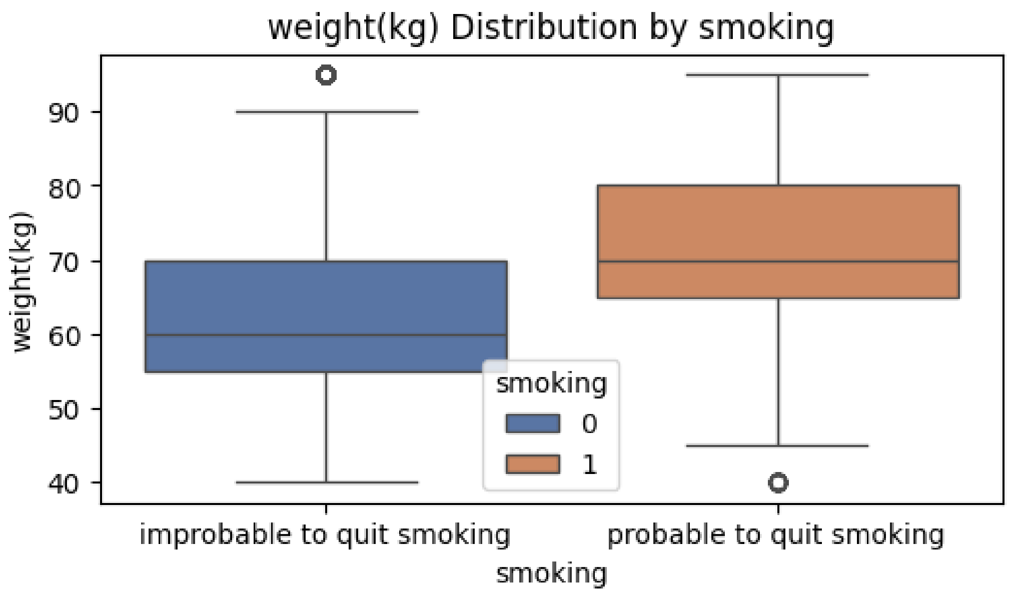

eyesight(left) Distribution by smoking
eyesight(left)
1.6
1.4
1.2
1.0
0.8
0.6
0.4
smoking
0
1
improbable to quit smoking
probable to quit smoking
smoking

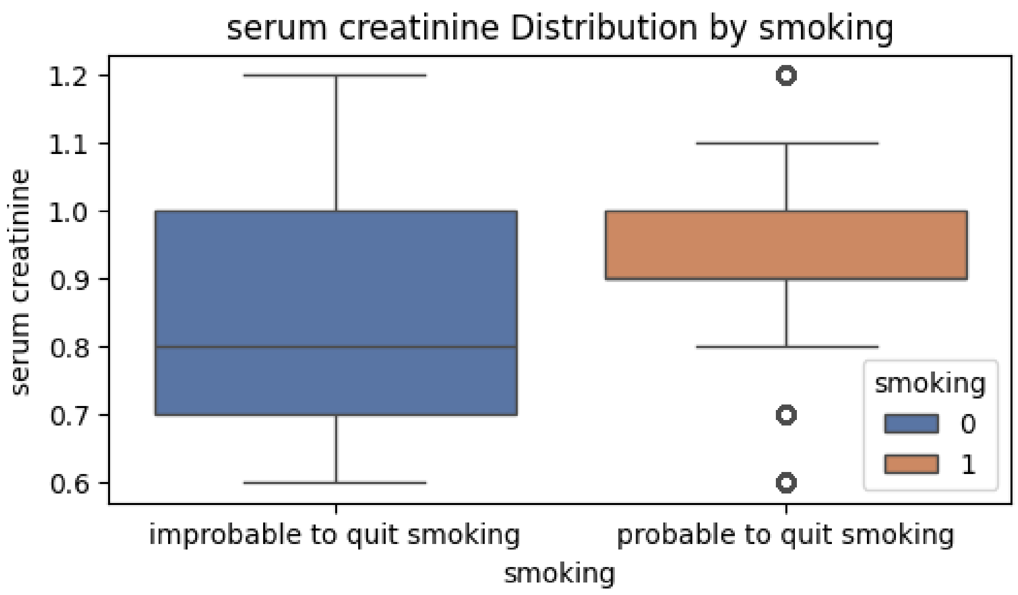

waist(cm) Distribution by smoking
waist(cm)
100
90
80
70
60
smoking
0
1
improbable to quit smoking
probable to quit smoking
smoking


hearing(right) Distribution by smoking
hearing(right)
1.04
1.02
1.00
0.98
0.96
smoking
0
1
improbable to quit smoking
probable to quit smoking
smoking


dental caries Distribution by smoking
smoking
0
1
dental caries
0.04
0.02
0.00
−0.02
−0.04
improbable to quit smoking
probable to quit smoking
smoking


hemoglobin Distribution by smoking
hemoglobin
18
16
14
12
smoking
0
1
improbable to quit smoking
probable to quit smoking
smoking





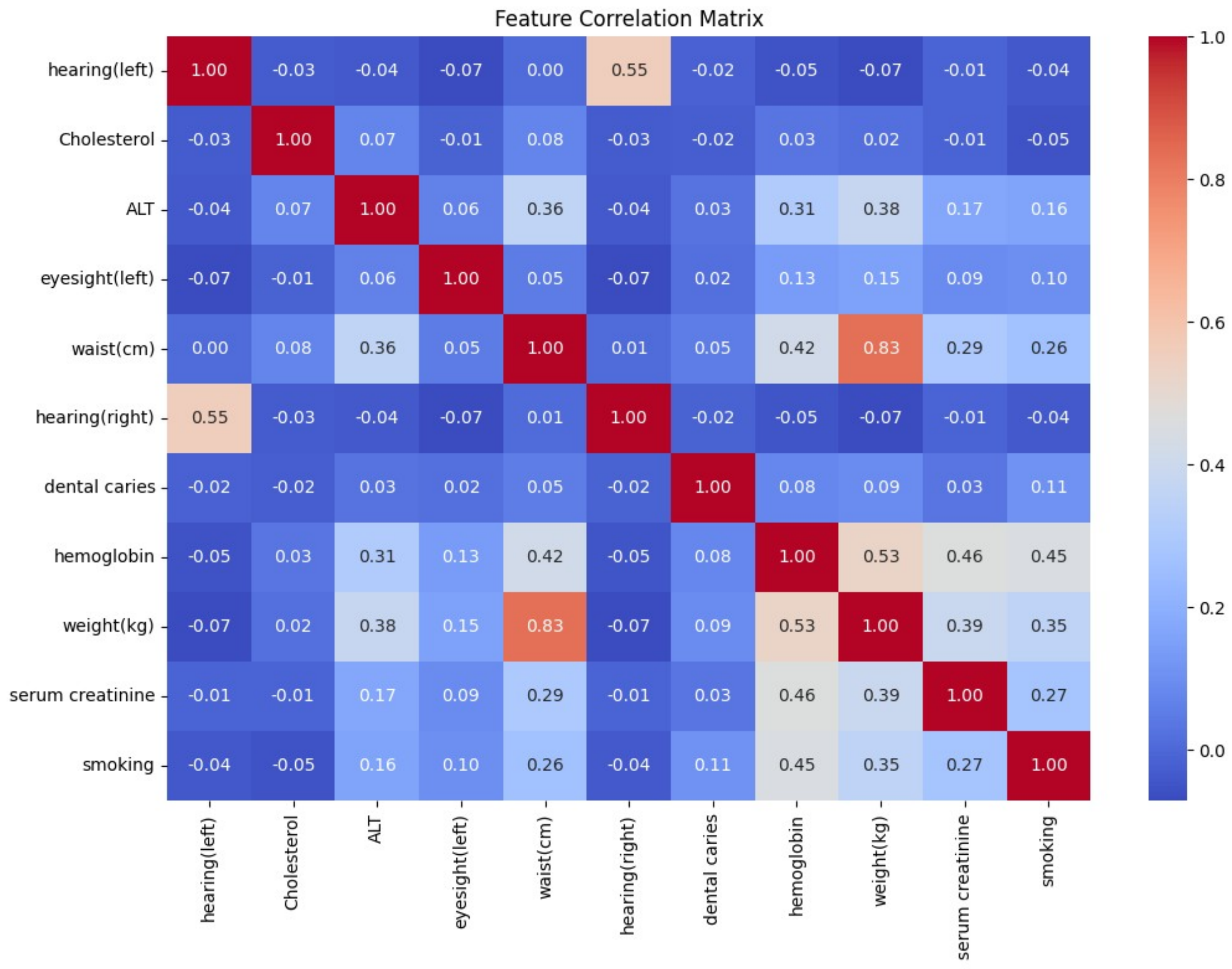
it becomes clear certain faetures are more indicative of a class label while others are not helpful.

helpful features: weight, serum creatinine, hemoglobin, waist, alt.

Data Analysis : Bivariate

```
# Heatmap for correlations
plt.figure(figsize=(12, 8))
correlation_matrix = data.corr()
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm",
fmt=".2f")
plt.title("Feature Correlation Matrix")
plt.show()
```

```
'''
[ 'ALT', 'waist(cm)',  'hemoglobin', 'weight(kg)', 'serum creatinine']

# Scatter plots for selected pairs
selected_pairs = [("nicotine_dependency", "daily_cigarettes"),
                  ("carbon_monoxide_levels", "age_of_initiation")]

for x, y in selected_pairs:
    plt.figure(figsize=(8, 6))
    sns.scatterplot(data=data, x=x, y=y, hue="smoking_status",
alpha=0.7)
    plt.title(f"{x} vs {y}")
    plt.xlabel(x)
    plt.ylabel(y)
    plt.show()
    '''
```

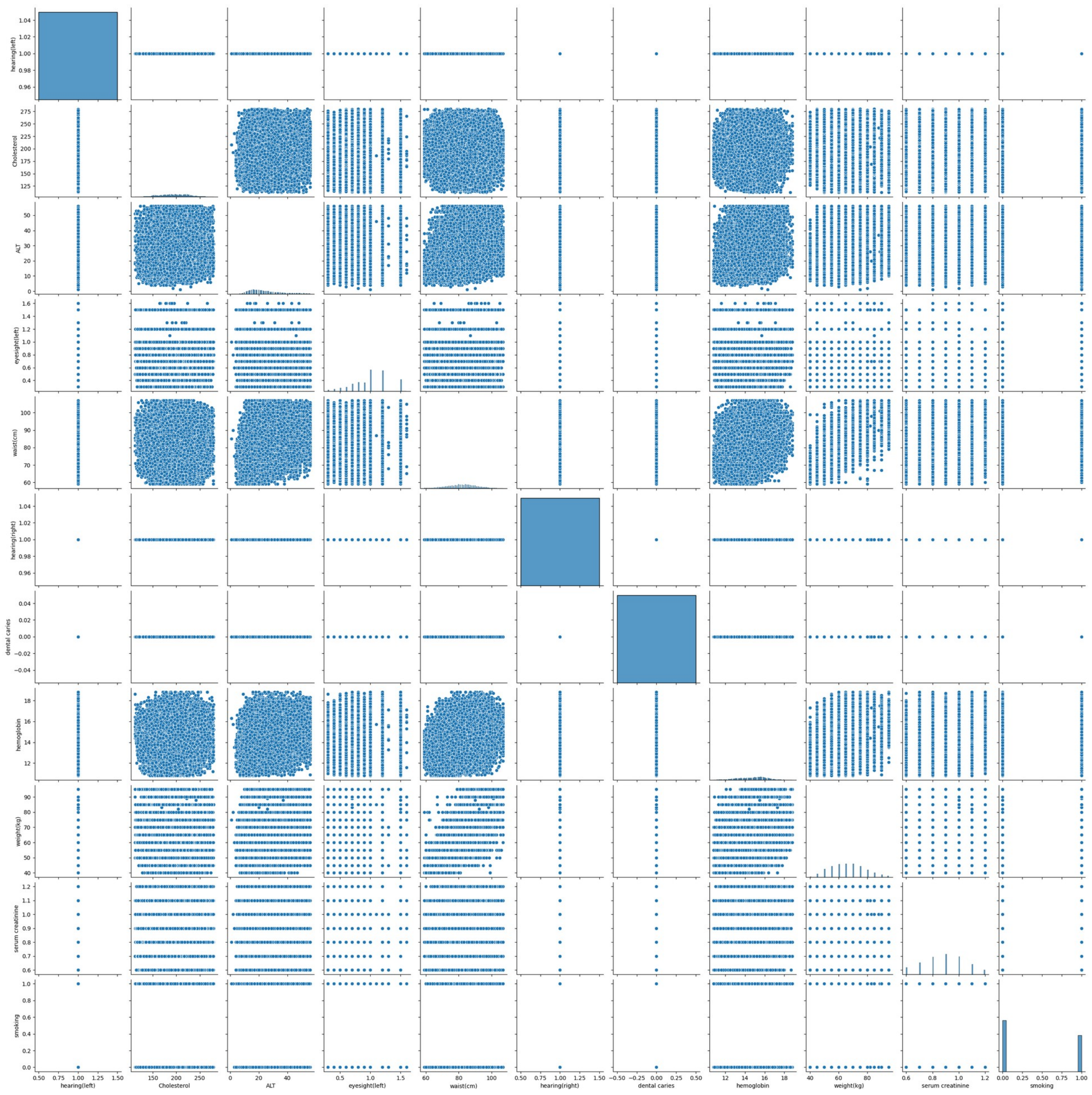


```
'\n[ \'ALT\', \'waist(cm)\',  \'hemoglobin\', \'weight(kg)\', \'serum
creatinine\']\n\n# Scatter plots for selected pairs\nselected_pairs =
[("nicotine_dependency", "daily_cigarettes"),\n
("carbon_monoxide_levels", "age_of_initiation")]\n\nfor x, y in
selected_pairs:\n    plt.figure(figsize=(8, 6))\n
sns.scatterplot(data=data, x=x, y=y, hue="smoking_status", alpha=0.7)\
n    plt.title(f"{x} vs {y}")\n    plt.xlabel(x)\n    plt.ylabel(y)\n
plt.show()\n    '
```

we note that some features have somewhat postive correlations with one another.

- positive correlations with smoking: [waist, hemoglobin, weight, serum creatinine]
- paris with postive correlations: (ALT,weight) (ALT,hemoglobin) (ALT,waist)
- (waist,serum creatinine) (waist,wieght) (waist,hemoglobin)
- (weight,serum creatinine) (weight,hemoglobin)

```
# Select numeric columns (or specific columns) from the DataFrame
numeric_columns = df.select_dtypes(include=['float64',
'int64']).columns

# Use the selected columns to create a pairplot
sns.pairplot(df[numeric_columns])  # Pass the DataFrame with numeric
columns
plt.show()
```



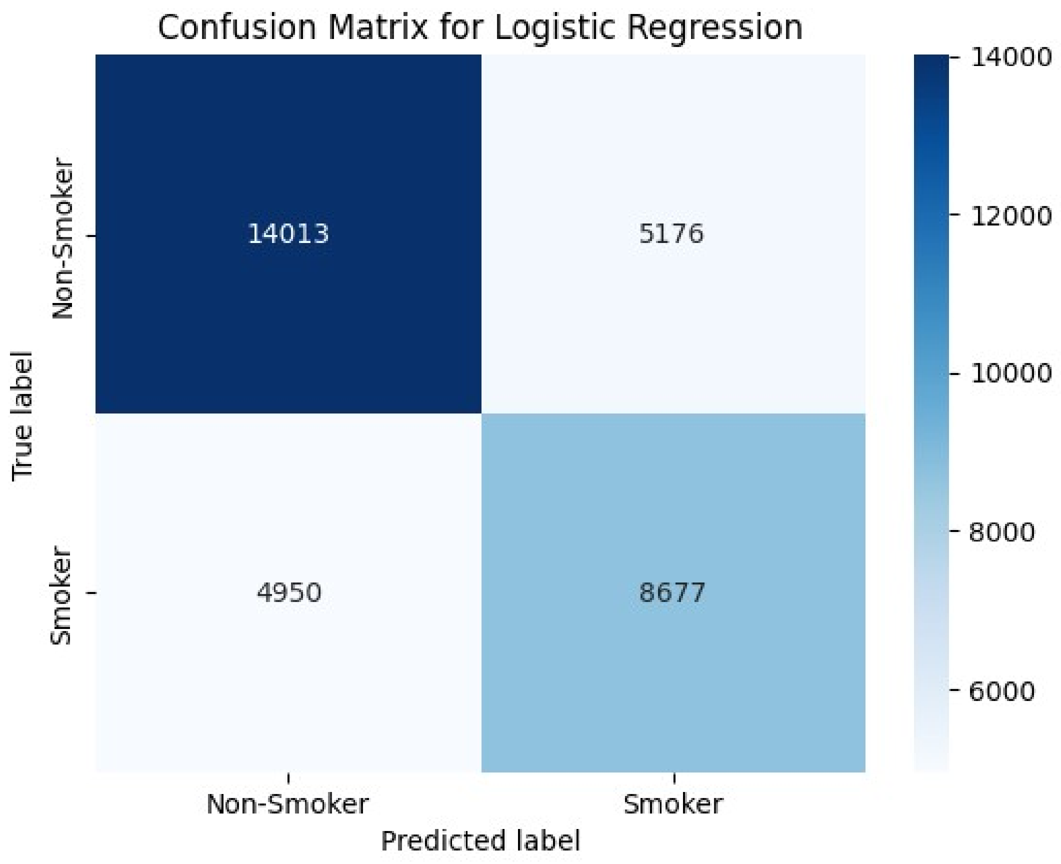
Data Analysis: multivariate

using linear regression since the label is binary

```
import pandas as pd
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns
```

```
features = ['hearing(left)', 'Cholesterol', 'ALT', 'eyesight(left)',
'waist(cm)',
            'hearing(right)', 'dental caries', 'hemoglobin',
'weight(kg)', 'serum creatinine']

# Split the data into training and testing sets
X = df_scaled[features]
y = df['smoking']
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42,stratify=y)

# Train a logistic regression model
log_reg = LogisticRegression()
log_reg.fit(X_train, y_train)

# Predict on the test set
y_pred = log_reg.predict(X_test)

# Evaluation metrics
print("Classification Report:")
print(classification_report(y_test, y_pred))

# Confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=['Non-Smoker', 'Smoker'], yticklabels=['Non-Smoker',
'Smoker'])
plt.title("Confusion Matrix for Logistic Regression")
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()
```

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

           0       0.74      0.73      0.73     19189
           1       0.63      0.64      0.63     13627

    accuracy                           0.69     32816
   macro avg       0.68      0.68      0.68     32816
weighted avg       0.69      0.69      0.69     32816
```



PCA

```
import pandas as pd
import numpy as np
from sklearn.decomposition import PCA

# Fit PCA (assuming PCA is already fitted with n_components=2 or
n_components=3)
pca = PCA(n_components=2)
pca_components = pca.fit_transform(df_scaled[features])

# Display the components and their loadings
component_df = pd.DataFrame(pca.components_, columns=features,
index=[f'PC{i+1}' for i in range(pca.n_components_)])
print("PCA Components (Loadings):")
print(component_df)

# To show the absolute contributions of features for each component
feature_contributions = component_df.abs()

# Show the features that contribute most to each principal component
for i in range(pca.n_components_):
    print(f"Top contributing features for PC{i+1}:")
    top_contributors =
feature_contributions.iloc[i].sort_values(ascending=False).head(3)  #
top 3 features
    print(top_contributors)
    print()

PCA Components (Loadings):
     hearing(left)  Cholesterol       ALT  eyesight(left)
waist(cm)  \
PC1            0.0     0.029048  0.365620        0.149751   0.480476

PC2            0.0     0.729967  0.230359       -0.530680   0.227157


     hearing(right)  dental caries  hemoglobin  weight(kg)  serum
creatinine
PC1   -0.000000e+00  -0.000000e+00    0.447076    0.525516
0.368987
PC2    5.551115e-17  -1.387779e-17   -0.146257    0.036629         -
0.241099
Top contributing features for PC1:
weight(kg)    0.525516
waist(cm)     0.480476
hemoglobin    0.447076
Name: PC1, dtype: float64

Top contributing features for PC2:
Cholesterol         0.729967
eyesight(left)      0.530680
serum creatinine    0.241099
Name: PC2, dtype: float64
```

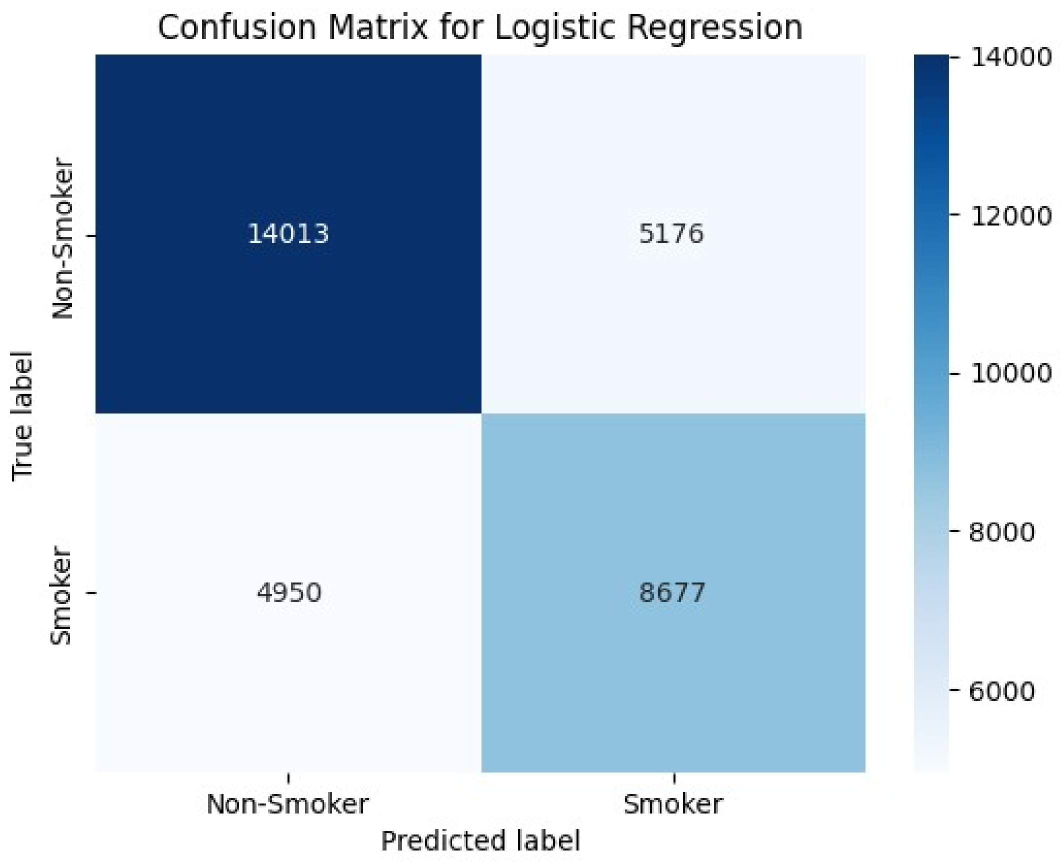
note that hearing left, hearing right , and dental carries contribute very little. we might drop them for dimensionality reduction.

now, we attempt to retrain the model using only seven features(excluding hearing left, hearing right , and dental carries)

```
features = ['Cholesterol', 'ALT', 'eyesight(left)', 'waist(cm)',
              'hemoglobin', 'weight(kg)', 'serum creatinine']

# Split the data into training and testing sets
X = df_scaled[features]
y = df['smoking']
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42,stratify=y)

# Train a logistic regression model
log_reg = LogisticRegression()
```

```python
log_reg.fit(X_train, y_train)

# Predict on the test set
y_pred = log_reg.predict(X_test)

# Evaluation metrics
print("Classification Report:")
print(classification_report(y_test, y_pred))

# Confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=['Non-Smoker', 'Smoker'], yticklabels=['Non-Smoker',
'Smoker'])
plt.title("Confusion Matrix for Logistic Regression")
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()
```

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

           0       0.74      0.73      0.73     19189
           1       0.63      0.64      0.63     13627

    accuracy                           0.69     32816
   macro avg       0.68      0.68      0.68     32816
weighted avg       0.69      0.69      0.69     32816
```

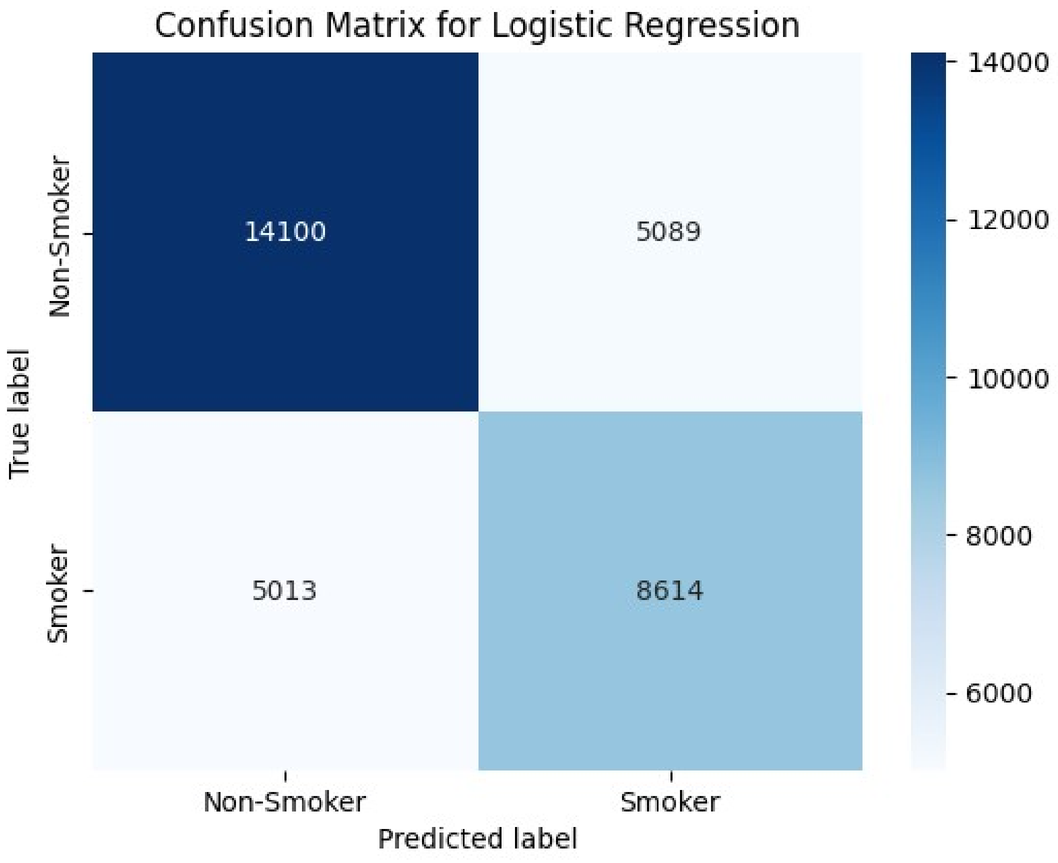


now, we attempt to retrain the model using only the fearures with high correlation to smoking.

```
features = [ 'waist(cm)',
              'hemoglobin', 'weight(kg)', 'serum creatinine']

# Split the data into training and testing sets
X = df_scaled[features]
y = df['smoking']
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42,stratify=y)

# Train a logistic regression model
log_reg = LogisticRegression()
log_reg.fit(X_train, y_train)

# Predict on the test set
y_pred = log_reg.predict(X_test)

# Evaluation metrics
print("Classification Report:")
print(classification_report(y_test, y_pred))

# Confusion matrix
```

```
conf_matrix = confusion_matrix(y_test, y_pred)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=['Non-Smoker', 'Smoker'], yticklabels=['Non-Smoker',
'Smoker'])
plt.title("Confusion Matrix for Logistic Regression")
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()
```

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

           0       0.74      0.73      0.74     19189
           1       0.63      0.63      0.63     13627

    accuracy                           0.69     32816
   macro avg       0.68      0.68      0.68     32816
weighted avg       0.69      0.69      0.69     32816
```



note that we have managed to refuce the dimensionality drastically while getting the consistent accuracy.

Bonus Experimental Feature Engineering

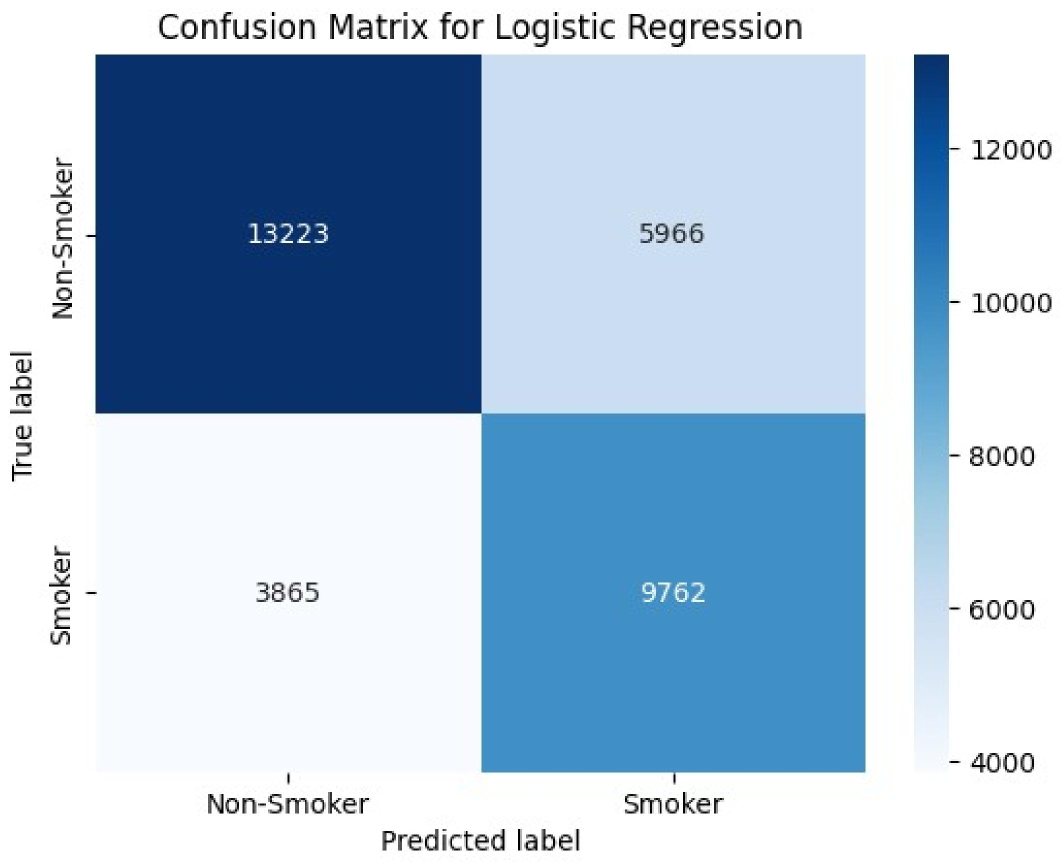
for the sake of experiment, we will engineer a feature which is the product of the four most correlated features with 'smoking'. we will call this feature E_feature.

- E_feautre= 'hemoglobin' * 'weight(kg)'

```
features = [ 'waist(cm)', 'hemoglobin', 'weight(kg)', 'serum
creatinine']

# Split the data into training and testing sets
X = df_scaled[features]
y = df['smoking']

# Convert X and y to numpy arrays for clarity
X_scaled = np.array(X)
y = np.array(y)

# Engineered feature: Multiply features across columns for each sample
E_feature = X_scaled[:, 1] * X_scaled[:, 2]

# Concatenate the engineered feature to the original features
E_X = np.column_stack((X_scaled, E_feature))  # Shape will now be
(109386, 5)

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(E_X, y,
test_size=0.3, random_state=42, stratify=y)

# Display the first few rows of the processed datasets
print("First few rows of the training set:")
print(X_train[:3])

print("\nFirst few rows of the test set:")
print(X_test[:3])

First few rows of the training set:
[[-0.03191435  1.21478193  0.33825249  0.71056785  0.41090301]
 [ 1.73705132  0.46776826  1.62816423  0.0807063   0.76160355]
 [ 0.79360296  0.16896279  1.19819365  1.3404294   0.20245014]]

First few rows of the test set:
[[ 0.79360296 -0.50334951  1.19819365  0.71056785 -0.60311019]
 [ 2.09084445  0.99067783  1.62816423  1.3404294   1.6129862 ]
 [ 1.26532714  1.36418466  0.76822307 -0.54915525  1.04799812]]

#Train a logistic regression model
log_reg = LogisticRegression()
log_reg.fit(X_train, y_train)

# Predict on the test set
```

```
y_pred = log_reg.predict(X_test)

# Evaluation metrics
print("Classification Report:")
print(classification_report(y_test, y_pred))

# Confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=['Non-Smoker', 'Smoker'], yticklabels=['Non-Smoker',
'Smoker'])
plt.title("Confusion Matrix for Logistic Regression")
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()
```

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

           0       0.77      0.69      0.73     19189
           1       0.62      0.72      0.67     13627

    accuracy                           0.70     32816
   macro avg       0.70      0.70      0.70     32816
weighted avg       0.71      0.70      0.70     32816
```



our new feautre resulted in a slightly increased accuracy

3.Ensembles

firstly we will use sickit learn premade ensembles for refrence and we will train using all 10 features.

```
all_feautres=['hearing(left)', 'Cholesterol', 'ALT', 'eyesight(left)',
'waist(cm)', 'hearing(right)', 'dental caries', 'hemoglobin',
'weight(kg)', 'serum creatinine']

# Split the data into training and testing sets
X = df_scaled[all_feautres]
y = df['smoking']

# Convert X and y to numpy arrays for clarity
X_scaled = np.array(X)
y = np.array(y)

# Split into train, validation, and test sets
X_train, X_temp, y_train, y_temp = train_test_split(X_scaled, y,
test_size=0.4, random_state=42, stratify=y)
X_valid, X_test, y_valid, y_test = train_test_split(X_temp, y_temp,
test_size=0.5, random_state=42, stratify=y_temp)

# Verify shapes
print("Training set size:", X_train.shape)
print("Validation set size:", X_valid.shape)
print("Test set size:", X_test.shape)
```

```
Training set size: (65631, 10)
Validation set size: (21877, 10)
Test set size: (21878, 10)
```

using sickintlearn

```
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# Create a BaggingClassifier with a DecisionTreeClassifier as the base
estimator
bagging = BaggingClassifier(
    DecisionTreeClassifier(),  # Base model
    n_estimators=300,                              # Number of estimators
    random_state=42                               # Reproducibility
)

# Fit the model to the training data
bagging.fit(X_train, y_train)

# Evaluate the model on the validation data
y_pred = bagging.predict(X_valid)
accuracy = accuracy_score(y_valid, y_pred)

print("Bagging Accuracy:", accuracy)
```

```
Bagging Accuracy: 0.6967134433342323
```

```
from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# Create an AdaBoostClassifier with a DecisionTreeClassifier as the
base estimator
boosting = AdaBoostClassifier(
   DecisionTreeClassifier(max_depth=1),  # Shallow decision tree as
base model
    n_estimators=300,                                     # Number of
estimators
    random_state=42                                       #
Reproducibility
)

# Fit the model to the training data
boosting.fit(X_train, y_train)

# Evaluate the model on the validation data
y_pred = boosting.predict(X_valid)
accuracy = accuracy_score(y_valid, y_pred)

print("Boosting Accuracy:", accuracy)
```

```
a:\pycharm\lib\site-packages\sklearn\ensemble\_weight_boosting.py:527:
FutureWarning: The SAMME.R algorithm (the default) is deprecated and
will be removed in 1.6. Use the SAMME algorithm to circumvent this
warning.
  warnings.warn(
```

```
Boosting Accuracy: 0.7051241029391598
```

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# Create a RandomForestClassifier
random_forest = RandomForestClassifier(
    n_estimators=300,        # Number of estimators
    random_state=42,          # Reproducibility
    n_jobs=-1                 # Use all cores for faster training
)

# Fit the model to the training data
random_forest.fit(X_train, y_train)

# Evaluate the model on the validation data
y_pred = random_forest.predict(X_valid)
accuracy = accuracy_score(y_valid, y_pred)

print("Random Forest Accuracy:", accuracy)
```

```
Random Forest Accuracy: 0.705215523152169
```

using custom ensembles

we are going to use selected faetures .

```
features = [ 'waist(cm)', 'hemoglobin', 'weight(kg)', 'serum
creatinine','eyesight(left)','Cholesterol']
```

```
# Split the data into training and testing sets
X = df_scaled[features]
y = df['smoking']

# Convert X and y to numpy arrays for clarity
X_scaled = np.array(X)
y = np.array(y)

# Split into train, validation, and test sets
X_train, X_temp, y_train, y_temp = train_test_split(X_scaled, y,
test_size=0.4, random_state=42, stratify=y)
X_valid, X_test, y_valid, y_test = train_test_split(X_temp, y_temp,
test_size=0.5, random_state=42, stratify=y_temp)

# Verify shapes
print("Training set size:", X_train.shape)
print("Validation set size:", X_valid.shape)
print("Test set size:", X_test.shape)


Training set size: (65631, 6)
Validation set size: (21877, 6)
Test set size: (21878, 6)
```

Bagging

```
import numpy as np
from sklearn.tree import DecisionTreeClassifier
from sklearn.base import clone
from sklearn.metrics import accuracy_score
from scipy.stats import mode
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier

class BaggingClassifier:
    def __init__(self, base_estimators=None, n_estimators=300,
random_state=None):
        """
        Bagging ensemble classifier.

        Parameters:
        - base_estimators: List of base models to use for bagging
(default: [DecisionTreeClassifier()]).
        - n_estimators: Number of estimators/models in the ensemble.
        - random_state: Random seed for reproducibility.
        """
        self.base_estimators = base_estimators or
[DecisionTreeClassifier()]
        self.n_estimators = n_estimators
        self.random_state = random_state
        self.models = []

    def fit(self, X, y):
        """
        Train the bagging classifier by fitting multiple base
estimators on bootstrapped samples.
        """
        np.random.seed(self.random_state)
        self.models = []
        n_estimators_per_model = self.n_estimators //
len(self.base_estimators)

        for base_estimator in self.base_estimators:
            for _ in range(n_estimators_per_model):
                # Create a bootstrap sample
                indices = np.random.choice(len(X), size=len(X),
replace=True)
                X_bootstrap = X[indices]
                y_bootstrap = y[indices]

                # Train a new base model on the bootstrap sample
                model = clone(base_estimator)
                model.fit(X_bootstrap, y_bootstrap)
                self.models.append(model)

    def predict(self, X):
        """
        Predict class labels for the input data by majority voting.
        """
        # Collect predictions from each model
        predictions = np.array([model.predict(X) for model in
self.models])

        # Perform majority voting
        majority_vote = mode(predictions, axis=0).mode.flatten()
        return majority_vote


# Define a list of diverse base classifiers
base_estimators = [
    DecisionTreeClassifier(),
    #LogisticRegression(),
    #KNeighborsClassifier(),
]

# Initialize and train the Bagging ensemble
bagging_model = BaggingClassifier(base_estimators=base_estimators,
n_estimators=300, random_state=42)
bagging_model.fit(X_train, y_train)
```

```
# Make predictions
majority_vote = bagging_model.predict(X_valid)
# Evaluate the model
accuracy = accuracy_score(y_valid, majority_vote)
print("Bagging Accuracy:", accuracy)
```

```
Bagging Accuracy: 0.6811262970242721
```

Boosting

```
import numpy as np
from sklearn.tree import DecisionTreeClassifier
from sklearn.base import clone
from sklearn.metrics import accuracy_score
from scipy.stats import mode
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier

class BoostClassifier:
    def __init__(self, base_estimators=None, n_estimators=100,
random_state=None):
        """
        AdaBoost ensemble classifier.

        Parameters:
        - base_estimators: List of base models to use for boosting.
        - n_estimators: Total number of models in the ensemble.
        - random_state: Random seed for reproducibility.
        """
        self.base_estimators = base_estimators or
[DecisionTreeClassifier(max_depth=1, random_state=random_state)]
        self.n_estimators = n_estimators
        self.random_state = random_state
        self.models = []
        self.alphas = []

    def fit(self, X, y):
        """
        Train the AdaBoost classifier using weighted training samples.
        """
        np.random.seed(self.random_state)
        n_samples = len(X)
        weights = np.ones(n_samples) / n_samples
        self.models = []
        self.alphas = []

        n_estimators_per_model = self.n_estimators //
len(self.base_estimators)
```

```
        for base_estimator in self.base_estimators:
            for _ in range(n_estimators_per_model):
                # Clone the base estimator
                model = clone(base_estimator)

                # Resample the dataset based on the weights manually
                indices = np.random.choice(n_samples, size=n_samples,
replace=True, p=weights)
                X_resampled, y_resampled = X[indices], y[indices]
                model.fit(X_resampled, y_resampled)

                # Predict on the full dataset
                y_pred = model.predict(X)

                # Calculate error and alpha
                incorrect = (y_pred != y)
                error = np.dot(weights, incorrect) / np.sum(weights)

                # Avoid division by zero or invalid alpha calculation
                if error >= 1.0:
                    continue
                alpha = 0.5 * np.log((1 - error) / error) if error > 0
else 1.0
                self.alphas.append(alpha)

                # Update weights
                weights *= np.exp(-alpha * y * y_pred)
                weights /= np.sum(weights)

                # Store the model
                self.models.append(model)

    def predict(self, X):
        """
        Predict class labels using weighted voting.
        """
        model_preds = np.array([model.predict(X) for model in
self.models])
        weighted_preds = np.zeros(model_preds.shape[1])

        for i in range(len(self.models)):
            weighted_preds += self.alphas[i] * model_preds[i]

        return np.sign(weighted_preds)



# Define diverse base classifiers
base_estimators = [
    DecisionTreeClassifier(max_depth=1, random_state=42),

]

# Train the AdaBoost ensemble
adaboost_model = BoostClassifier(base_estimators=base_estimators, 
n_estimators=100, random_state=42)
adaboost_model.fit(X_train, y_train)

# Make predictions
y_pred_adaboost = adaboost_model.predict(X_valid)
print("AdaBoost Accuracy:", accuracy_score(y_valid, y_pred_adaboost))
```

```
AdaBoost Accuracy: 0.6861086986332678
```

Random Forest

```
import numpy as np
from sklearn.tree import DecisionTreeClassifier
from sklearn.base import clone
from sklearn.metrics import accuracy_score
from sklearn.utils import resample

class RandomForest:
    def __init__(self, base_estimators=None, n_estimators=100, 
max_features='sqrt', random_state=None):
        """
        Random Forest classifier that can use multiple base 
estimators.

        Parameters:
        - base_estimators: List of base models to use for ensemble 
(e.g., [DecisionTree, LogisticRegression]).
        - n_estimators: Total number of models to train.
        - max_features: The number of features to use for each model. 
Options: 'sqrt', 'log2', or an integer.
        - random_state: Random seed for reproducibility.
        """
        self.base_estimators = base_estimators or 
[DecisionTreeClassifier(random_state=random_state)]
        self.n_estimators = n_estimators
        self.max_features = max_features
        self.random_state = random_state
        self.models = []

    def fit(self, X, y):
        """
        Train the RandomForest classifier using bootstrap sampling and 
feature selection.
        """
        np.random.seed(self.random_state)
        self.models = []

        n_samples, n_features = X.shape
        n_estimators_per_model = self.n_estimators //
len(self.base_estimators)

        for base_estimator in self.base_estimators:
            for _ in range(n_estimators_per_model):
                # Bootstrap sampling
                indices = np.random.choice(n_samples, size=n_samples,
replace=True)
                X_bootstrap = X[indices]
                y_bootstrap = y[indices]


                max_features = n_features

                features = np.random.choice(n_features,
size=max_features, replace=False)
                X_bootstrap = X_bootstrap[:, features]

                # Train a model on the bootstrap sample with a random
subset of features
                model = clone(base_estimator)
                model.fit(X_bootstrap, y_bootstrap)
                self.models.append((model, features))

    def predict(self, X):
        """
        Predict class labels using majority voting.
        """
        predictions = np.zeros((len(self.models), len(X)))
        for i, (model, features) in enumerate(self.models):
            X_subset = X[:, features]
            predictions[i, :] = model.predict(X_subset)

        # Majority vote (for classification)
        return np.round(np.mean(predictions, axis=0)).astype(int)


# Define multiple base classifiers
base_estimators = [
    DecisionTreeClassifier(max_depth=1, random_state=42),
    #LogisticRegression(max_iter=500, random_state=42),
    #KNeighborsClassifier(n_neighbors=3)
]

# Train the Random Forest ensemble
rf_model = RandomForest(base_estimators=base_estimators,
n_estimators=150, random_state=42)
rf_model.fit(X_train, y_train)

# Make predictions
y_pred_rf = rf_model.predict(X_valid)
print("Random Forest Accuracy:", accuracy_score(y_valid, y_pred_rf))

Random Forest Accuracy: 0.6973990949398912
```

we note that we acquired close values to the models using all 10 dimensions while only using 5 dimensions.

4. Parameter Tuning

```
param_grid = {
    'n_estimators': [ 50, 100, 150],
    'max_features': [2, 3, 5],
    'base_estimators': [
        [DecisionTreeClassifier(max_depth=1, random_state=42)],
        [DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)],
        [DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3),LogisticRegression(max_iter=500,
random_state=42)]
    ]
}


from itertools import product
from sklearn.metrics import accuracy_score
import numpy as np

def grid_search_random_forest(X_train, y_train, X_valid, y_valid,
param_grid):
    """
    Perform grid search on the custom RandomForest implementation.

    Parameters:
    - X_train, y_train: Training data
    - X_valid, y_valid: Validation data
    - param_grid: Dictionary containing lists of hyperparameter values

    Returns:
    - Best parameters and corresponding accuracy
    """
    param_names = list(param_grid.keys())
    param_values = list(param_grid.values())
    best_params = None
    best_score = 0
    # Iterate over all combinations of parameters
    for combination in product(*param_values):
        # Map the combination to parameter names
        params = dict(zip(param_names, combination))

        # Instantiate and train the Random Forest with these
parameters
        rf_model = RandomForest(
            base_estimators=params['base_estimators'],
            n_estimators=params['n_estimators'],
            max_features=params['max_features'],
            random_state=42
        )
        rf_model.fit(X_train, y_train)

        # Evaluate on the validation set
        y_pred = rf_model.predict(X_valid)
        accuracy = accuracy_score(y_valid, y_pred)
        print(f"Params: {params} -> Accuracy: {accuracy:.4f}")

        # Update the best score and parameters
        if accuracy > best_score:
            best_score = accuracy
            best_params = params

    return best_params, best_score

best_params, best_score = grid_search_random_forest(X_train, y_train,
X_valid, y_valid, param_grid)
print("Best Parameters:", best_params)
print("Best Validation Accuracy:", best_score)
```

```
Params: {'n_estimators': 50, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6902
Params: {'n_estimators': 50, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.6987
Params: {'n_estimators': 50, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.6941
Params: {'n_estimators': 50, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 50, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.7066
Params: {'n_estimators': 50, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.7037
Params: {'n_estimators': 50, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 50, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.7035
Params: {'n_estimators': 50, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.7016
Params: {'n_estimators': 100, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6941
Params: {'n_estimators': 100, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.7007
Params: {'n_estimators': 100, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.6918
Params: {'n_estimators': 100, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 100, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.7061
Params: {'n_estimators': 100, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.7045
Params: {'n_estimators': 100, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 100, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.7030
Params: {'n_estimators': 100, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.7024
Params: {'n_estimators': 150, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6974
Params: {'n_estimators': 150, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.7009
Params: {'n_estimators': 150, 'max_features': 2, 'base_estimators':
```

```
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.6891
Params: {'n_estimators': 150, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 150, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.7070
Params: {'n_estimators': 150, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.7039
Params: {'n_estimators': 150, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 150, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.7034
Params: {'n_estimators': 150, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.7028
Best Parameters: {'n_estimators': 150, 'max_features': 3,
'base_estimators': [DecisionTreeClassifier(max_depth=3,
random_state=42), KNeighborsClassifier(n_neighbors=3)]}
Best Validation Accuracy: 0.7069525071993418
```

now we retrain the model no the parameters which give the highest accuracy.

```
best_estimators = [
    DecisionTreeClassifier(max_depth=3, random_state=42),
    KNeighborsClassifier(n_neighbors=3)
]

X_combined = np.concatenate((X_train, X_valid), axis=0)
y_combined= np.concatenate((y_train,y_valid), axis=0)

    # Train the Random Forest ensemble
rf_model = RandomForest(base_estimators=best_estimators,
n_estimators=150, random_state=42,  max_features=3)
rf_model.fit(X_combined, y_combined)
```

validate on test set

```
# Make predictions
y_pred_rf = rf_model.predict(X_test)
print("Random Forest Accuracy:", accuracy_score(y_test, y_pred_rf))
```

```
Random Forest Accuracy: 0.7124051558643386
```

repeat for bagging and boosting

```
param_grid = {
    'n_estimators': [50, 100, 150],
    'max_features': [2, 3, 5],
    'base_estimators': [
        [DecisionTreeClassifier(max_depth=1, random_state=42)],
        [DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)],
        [DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]
    ]
}


from itertools import product
from sklearn.metrics import accuracy_score

def grid_search_ensemble(X_train, y_train, X_valid, y_valid,
param_grid, model_class):
    """
    Perform grid search on Bagging or Boosting classifiers.

    Parameters:
    - X_train, y_train: Training data
    - X_valid, y_valid: Validation data
    - param_grid: Dictionary containing lists of hyperparameter values
    - model_class: BaggingClassifier or BoostClassifier

    Returns:
    - Best parameters and corresponding accuracy
    """
    param_names = list(param_grid.keys())
    param_values = list(param_grid.values())
    best_params = None
    best_score = 0

    for combination in product(*param_values):
        params = dict(zip(param_names, combination))

        # Instantiate the model with these parameters
        model = model_class(
            base_estimators=params['base_estimators'],
            n_estimators=params['n_estimators']
        )
        model.fit(X_train, y_train)
        # Evaluate on the validation set
        y_pred = model.predict(X_valid)
        accuracy = accuracy_score(y_valid, y_pred)
        print(f"Params: {params} -> Accuracy: {accuracy:.4f}")

        if accuracy > best_score:
            best_score = accuracy
            best_params = params

    return best_params, best_score

bagging_best_params, bagging_best_score = grid_search_ensemble(
    X_train, y_train, X_valid, y_valid, param_grid, BaggingClassifier
)
print("Best Params (Bagging):", bagging_best_params)
print("Best Score (Bagging):", bagging_best_score)
```

```
Params: {'n_estimators': 50, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 50, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.7028
Params: {'n_estimators': 50, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.7014
Params: {'n_estimators': 50, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 50, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.7040
Params: {'n_estimators': 50, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.7027
Params: {'n_estimators': 50, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 50, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.7023
Params: {'n_estimators': 50, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.7026
Params: {'n_estimators': 100, 'max_features': 2, 'base_estimators':
```

```
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 100, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.7035
Params: {'n_estimators': 100, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.7030
Params: {'n_estimators': 100, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 100, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.7030
Params: {'n_estimators': 100, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.7028
Params: {'n_estimators': 100, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 100, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.7032
Params: {'n_estimators': 100, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.7032
Params: {'n_estimators': 150, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 150, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.7035
Params: {'n_estimators': 150, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.7019
Params: {'n_estimators': 150, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 150, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.7027
Params: {'n_estimators': 150, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.7017
```

```
Params: {'n_estimators': 150, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 150, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.7029
Params: {'n_estimators': 150, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.7025
Best Params (Bagging): {'n_estimators': 50, 'max_features': 3,
'base_estimators': [DecisionTreeClassifier(max_depth=3,
random_state=42), KNeighborsClassifier(n_neighbors=3)]}
Best Score (Bagging): 0.7040270603830507
```

```
# Define a list of diverse base classifiers
base_estimators = [
    DecisionTreeClassifier(max_depth=3, random_state=42),
   KNeighborsClassifier(),
]

# Initialize and train the Bagging ensemble
bagging_model = BaggingClassifier(base_estimators=base_estimators,
n_estimators=50, random_state=42)
bagging_model.fit(X_combined, y_combined)

# Make predictions
majority_vote = bagging_model.predict(X_test)
# Evaluate the model
accuracy = accuracy_score(y_test, majority_vote)
print("Bagging Accuracy:", accuracy)
```

```
Bagging Accuracy: 0.7094798427644209
```

```
boosting_best_params, boosting_best_score = grid_search_ensemble(
    X_train, y_train, X_valid, y_valid, param_grid, BoostClassifier
)
print("Best Params (Boosting):", boosting_best_params)
print("Best Score (Boosting):", boosting_best_score)
```

```
Params: {'n_estimators': 50, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 50, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.6622
Params: {'n_estimators': 50, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.6606
```

```
Params: {'n_estimators': 50, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 50, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.6599
Params: {'n_estimators': 50, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.6604
Params: {'n_estimators': 50, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 50, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.6608
Params: {'n_estimators': 50, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.6595
Params: {'n_estimators': 100, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 100, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.6595
Params: {'n_estimators': 100, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.6586
Params: {'n_estimators': 100, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 100, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.6591
Params: {'n_estimators': 100, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.6591
Params: {'n_estimators': 100, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6925
Params: {'n_estimators': 100, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.6590
Params: {'n_estimators': 100, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.6584
Params: {'n_estimators': 150, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 150, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.6602
Params: {'n_estimators': 150, 'max_features': 2, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.6587
Params: {'n_estimators': 150, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 150, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.6581
Params: {'n_estimators': 150, 'max_features': 3, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.6598
Params: {'n_estimators': 150, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=1, random_state=42)]} -> Accuracy:
0.6861
Params: {'n_estimators': 150, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3)]} -> Accuracy: 0.6582
Params: {'n_estimators': 150, 'max_features': 5, 'base_estimators':
[DecisionTreeClassifier(max_depth=3, random_state=42),
KNeighborsClassifier(n_neighbors=3), LogisticRegression(max_iter=500,
random_state=42)]} -> Accuracy: 0.6593
Best Params (Boosting): {'n_estimators': 100, 'max_features': 5,
'base_estimators': [DecisionTreeClassifier(max_depth=1,
random_state=42)]}
Best Score (Boosting): 0.6924624034374

# Define diverse base classifiers
base_estimators = [
    DecisionTreeClassifier(max_depth=1, random_state=42),

]

# Train the AdaBoost ensemble
adaboost_model = BoostClassifier(base_estimators=base_estimators,
n_estimators=100, random_state=42)
adaboost_model.fit(X_combined, y_combined)

# Make predictions
y_pred_adaboost = adaboost_model.predict(X_test)
print("AdaBoost Accuracy:", accuracy_score(y_test, y_pred_adaboost))
```

```
AdaBoost Accuracy: 0.6892768991681141
```