Tree Based and Boosting MLAlgorithms

September 25, 2024

1 Tree Based and Boosting MLAlgorithms

1.1 Objective : To predict the survival status of passengers based on other features.

1.2 Task 1

Import the required libraries:

Import Pandas and alias it as pd.

Import NumPy and alias it as np.

Import Scikit-learn and alias it as sklearn.

[71]:
```
import pandas as pd
import numpy as np
import sklearn
from sklearn.linear_model import LogisticRegression
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.feature_selection import RFE
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import classification_report
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.tree import DecisionTreeClassifier
from imblearn.over_sampling import RandomOverSampler, SMOTE
from imblearn.under_sampling import RandomUnderSampler, EditedNearestNeighbours
import pickle
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import RFECV
from sklearn.model_selection import cross_val_score
import matplotlib.pyplot as plt
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import AdaBoostClassifier
import xgboost as xgb
from sklearn.ensemble import StackingClassifier
from sklearn.svm import SVC
```

Load the Titanic dataset: Load the 'titanic.csv' file using the Pandas library and assign it to a variable named 'data'.

[72]:
```
df = pd.read_excel('/kaggle/input/train-xlsx-62-56-kb/train.xlsx')
df.head()
```

[72]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

[73]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

[74]:
```
df.isnull().sum()
```

[74]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

[ ]:
```

```

1.3 Task 2

Load the Titanic dataset:

Load the 'titanic.csv' file using the Pandas library and assign it to a variable named 'data'.

[75]:
```
data = pd.read_excel('/kaggle/input/train-xlsx-62-56-kb/train.xlsx')
data.head()
```

[75]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

[ ]:

```

```

1.4 Task 3

Data preprocessing:

Handle missing values by imputing the mean agefor the 'Age' column and the most frequent valuefor the 'Embarked' column.

Check out for the Outliers and If present, treat them by using the concept of Winsorization.

Drop the 'Cabin' column from the dataset.Convert categorical variables (e.g., 'Sex','Embarked') into numerical variables usingappropriate techniques (e.g., one-hot encoding,label encoding).

Split the dataset into features (X) and target (y) variables.

[76]:

```
# Handle missing values by imputing the mean age for the 'Age' column and the␣
↪most frequent value for the 'Embarked' column.
df['Age'] = df['Age'].fillna(df['Age'].mean())
df['Embarked'] = df['Embarked'].fillna(df['Embarked'].mode()[0])
```

[77]:

```
# Check out for the Outliers and If present, treat them by using the concept of␣
↪Winsorization.

for col in df[['Age','Fare']].columns:
    first_quartile = df[col].quantile(0.25)
    third_quartile = df[col].quantile(0.75)
    iqr = third_quartile - first_quartile
    lower_bound = first_quartile - 1.5 * iqr
    upper_bound = third_quartile + 1.5 * iqr
    # Applying Winsorization
    df[col] = df[col].apply(lambda value: lower_bound if value < lower_bound␣
↪else upper_bound if value > upper_bound else value)
```

[78]:

```
#Drop the 'Cabin' column from the dataset.
df = df.drop(columns=['Cabin'])
df.head()
```

[78]:

```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
```

```
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Embarked
0      0         A/5 21171   7.2500        S
1      0          PC 17599  65.6344        C
2      0  STON/O2. 3101282   7.9250        S
3      0            113803  53.1000        S
4      0            373450   8.0500        S
```

[79]:

```
from sklearn.preprocessing import OneHotEncoder
# Convert categorical variables (e.g., 'Sex','Embarked') into numerical␣
↪variables using appropriate techniques (e.g., one-hot encoding,label␣
↪encoding).
saved_encoders = {}
encoder = OneHotEncoder(sparse_output=False, drop='first')
encoder.fit(df[['Sex','Embarked']])
saved_encoders[col] = encoder
encoded_df = pd.DataFrame(encoder.transform(df[['Sex','Embarked']]), columns =␣
↪encoder.get_feature_names_out(['Sex', 'Embarked']))
df = pd.concat([df,encoded_df],axis=1)
df.head()
```

[79]:

```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Embarked  Sex_male  Embarked_Q  Embarked_S
0      0         A/5 21171   7.2500        S       1.0         0.0         1.0
1      0          PC 17599  65.6344        C       0.0         0.0         0.0
2      0  STON/O2. 3101282   7.9250        S       0.0         0.0         1.0
3      0            113803  53.1000        S       0.0         0.0         1.0
4      0            373450   8.0500        S       1.0         0.0         1.0
```

[80]:

```
#Split the dataset into features (X) and target (y) variables.
```

```
X =␣
↪df[['Pclass','Age','SibSp','Parch','Fare','Sex_male','Embarked_Q','Embarked_S']]
y = df['Survived']
```

1.5 Tasks 4:

Classification models: Build a logistic regression model to predict the survival status ('Survived') of passengers based on other features.

Build a decision tree model to classify the passengers as survivors or non-survivors using the Gini Index or Information Gain as the splitting criterion.

Build a random forest model by aggregating multiple decision trees and compare its performance with the single decision tree model.

Build an ensemble model using bagging (e.g., BaggingClassifier) and compare its performance with the single decision tree model.

Build an ensemble model using boosting algorithms such as Adaptive Boosting (AdaBoost)and Gradient Boosting and compare their performance with the single decision tree model.

Compare the performance of all the classification models using appropriate evaluation metrics (e.g.,accuracy, precision, recall, F1-score).

Model evaluation:

Split the dataset into training and testing sets using appropriate techniques (e.g., train test split,cross-validation).

Train and evaluate the regression and classification models on the testing set using appropriate evaluation metrics.

Tasks: Perform hyperparameter tuning (if applicable) to improve the performance of the models.

Final model selection: Select the best performing regression and classification models based on the evaluation metrics.

Discuss the strengths and weaknesses of the selected models

1.6 Logistic regression model

1.6.1 feature selection

[81]:
```
# Fit logistic regression model
logreg = LogisticRegression(max_iter=200)
logreg.fit(X, y)

# Print the coefficients
coefficients = pd.DataFrame({"Feature": X.columns, "Coefficient": np.abs(logreg.
↪coef_[0])})
coefficients = coefficients.sort_values(by="Coefficient", ascending=False)
print(coefficients)
```

```
      Feature  Coefficient
5    Sex_male     2.625422
0      Pclass     0.870599
2       SibSp     0.407019
7  Embarked_S     0.336911
3       Parch     0.140933
1         Age     0.042779
6  Embarked_Q     0.030377
4        Fare     0.016235
```

[82]:

```
# Logistic Regression model
logreg = LogisticRegression(max_iter=200)

# Initialize RFE with the logistic regression model
rfe = RFE(logreg, n_features_to_select=1)

# Fit RFE
rfe.fit(X, y)

# Rank the features
feature_ranking = pd.DataFrame({"Feature": X.columns, "Ranking": rfe.ranking_})
feature_ranking = feature_ranking.sort_values(by="Ranking")
print(feature_ranking)
```

```
      Feature  Ranking
5    Sex_male        1
0      Pclass        2
7  Embarked_S        3
2       SibSp        4
3       Parch        5
1         Age        6
6  Embarked_Q        7
4        Fare        8
```

[83]:

```
### removing removing Fare, Embarked_Q, and possibly Age, as they show the␣
↪least importance in both the coefficient and RFE rankings.

X_logistic = df[['Pclass', 'Sex_male', 'SibSp', 'Parch', 'Embarked_S']]
y_logistic = y

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_logistic, y_logistic,␣
↪test_size=0.20, random_state=42, stratify=y_logistic)
```

[84]:

```
#Oversampling

#Before Oversampling
print('Before Oversampling:', y_train.value_counts())
```

```
# Applying oversampling SMOTE
over_sampler = SMOTE(sampling_strategy=0.
 ↪75,random_state=42,k_neighbors=3,n_jobs=None)
X_train, y_train = over_sampler.fit_resample(X_train, y_train)

print('\n')

#After Oversampling
print('After Oversampling:', y_train.value_counts())
```

```
Before Oversampling: Survived
0    439
1    273
Name: count, dtype: int64


After Oversampling: Survived
0    439
1    329
Name: count, dtype: int64
```

[85]:
```
# #Undersampling

# #Before Undersampling
# print('Before Undersampling:', y_train.value_counts())

# # Applying undersampling EditedNearestNeighbours
# enn = EditedNearestNeighbours(n_neighbors=3, kind_sel='all', n_jobs=-1)
# X_train, y_train = enn.fit_resample(X_train, y_train)

# print('\n')

# #After Undersampling
# print('After Undersampling:', y_train.value_counts())
```

[86]:
```
# Define the model
logreg = LogisticRegression()

# Define the adjusted parameter grid to avoid warnings
param_grid_adjusted = [
    {
        'penalty': ['l1', 'l2'],
        'C': [0.1, 1, 10, 100],
        'solver': ['liblinear'],  # 'liblinear' supports 'l1' and 'l2' only
        'max_iter': [100, 200, 300],
        'class_weight': [None, 'balanced']
```

```python
    },
    {
        'penalty': ['l2'],
        'C': [0.1, 1, 10, 100],
        'solver': ['lbfgs'],  # 'lbfgs' only supports 'l2'
        'max_iter': [100, 200, 300],
        'class_weight': [None, 'balanced']
    },
    {
        'penalty': ['elasticnet'],  # Only elasticnet uses l1_ratio
        'C': [0.1, 1, 10, 100],
        'solver': ['saga'],  # 'saga' supports 'l1', 'l2', and 'elasticnet'
        'max_iter': [100, 200, 300, 1000],
        'class_weight': [None, 'balanced'],
        'l1_ratio': [0, 0.5, 1]  # Only relevant for 'elasticnet'
    }
]

# Perform grid search with the refined parameter grid
grid_search = GridSearchCV(
    estimator=logreg,
    param_grid=param_grid_adjusted,
    cv=5,  # 5-fold cross-validation
    scoring='recall',
    n_jobs=-1,  # Use all available cores
    verbose=1
)

# Fit grid search
grid_search.fit(X_train, y_train)

print("Best Parameters:", grid_search.best_params_)

best_model_logistic = grid_search.best_estimator_

# Predict on the training set
y_train_pred = best_model_logistic.predict(X_train)

# Predict on the test set
y_test_pred = best_model_logistic.predict(X_test)

# Generate the classification reports
print("Training Classification Report:")
print(classification_report(y_train, y_train_pred))

print("Testing Classification Report:")
print(classification_report(y_test, y_test_pred))
```

```
Fitting 5 folds for each of 168 candidates, totalling 840 fits
Best Parameters: {'C': 0.1, 'class_weight': 'balanced', 'max_iter': 100,
'penalty': 'l2', 'solver': 'lbfgs'}
Training Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.74      0.78       439
           1       0.69      0.79      0.74       329

    accuracy                           0.76       768
   macro avg       0.76      0.76      0.76       768
weighted avg       0.77      0.76      0.76       768

Testing Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.76      0.80       110
           1       0.68      0.78      0.72        69

    accuracy                           0.77       179
   macro avg       0.76      0.77      0.76       179
weighted avg       0.78      0.77      0.77       179
```

[ ]:

1.7 Decision Tree Model

1.7.1 Feature Importance

[87]:

```python
# Train the model
decision_tree = DecisionTreeClassifier(criterion='gini', random_state=42)

decision_tree.fit(X, y)

# Feature importances
feature_importances = decision_tree.feature_importances_

# DataFrame for better readability
importance_df = pd.DataFrame({
    'Feature': X.columns,
    'Importance': feature_importances
}).sort_values(by='Importance', ascending=False)

print(importance_df)
```

```
      Feature  Importance
5    Sex_male    0.310364
```

```
1         Age    0.239450
4        Fare    0.231425
0      Pclass    0.118360
2       SibSp    0.047997
3       Parch    0.034013
7  Embarked_S    0.014695
6  Embarked_Q    0.003696
```

[88]:

```
# RFE with Decision Tree
rfe = RFE(estimator=decision_tree, n_features_to_select=4)
rfe.fit(X, y)

# Feature ranking
rfe_ranking = pd.DataFrame({
    'Feature': X.columns,
    'Ranking': rfe.ranking_
}).sort_values(by='Ranking')

print(rfe_ranking)
```

```
      Feature  Ranking
0      Pclass        1
1         Age        1
4        Fare        1
5    Sex_male        1
2       SibSp        2
3       Parch        3
7  Embarked_S        4
6  Embarked_Q        5
```

[89]:

```
# Using use Sex_male, Age, Fare, and Pclass as for the model based on both␣
↪feature importance and RFE ranking.

X_decision = df[['Sex_male', 'Age', 'Fare', 'Pclass']]
y_decision = y

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_decision, y_decision,␣
↪test_size=0.20, random_state=42, stratify=y_decision)
```

[90]:

```
#Oversampling

#Before Oversampling
print('Before Oversampling:', y_train.value_counts())

# Applying oversampling SMOTE
over_sampler = SMOTE(sampling_strategy=0.
↪75,random_state=42,k_neighbors=3,n_jobs=None)
```

```
X_train, y_train = over_sampler.fit_resample(X_train, y_train)

print('\n')

#After Oversampling
print('After Oversampling:', y_train.value_counts())
```

```
Before Oversampling: Survived
0    439
1    273
Name: count, dtype: int64


After Oversampling: Survived
0    439
1    329
Name: count, dtype: int64
```

[91]:
```
# #Undersampling

# #Before Undersampling
# print('Before Undersampling:', y_train.value_counts())

# # Applying undersampling EditedNearestNeighbours
# enn = EditedNearestNeighbours(n_neighbors=3, kind_sel='all', n_jobs=-1)
# X_train, y_train = enn.fit_resample(X_train, y_train)

# print('\n')

# #After Undersampling
# print('After Undersampling:', y_train.value_counts())
```

[92]:
```
# Model Training

model = DecisionTreeClassifier(random_state = 42)

# Parameter Grid
param_grid = [{
    'criterion': ['gini', 'entropy'],
    'splitter': ['best'],
    'max_depth': [5, 7, 10, 20],
    'min_samples_split': [10, 15],
    'min_samples_leaf': [4, 6],
    'max_leaf_nodes': [10, 20],
    'min_impurity_decrease': [0.01, 0.05],
    'class_weight': ['balanced'],
    'ccp_alpha': [0.01, 0.1]
}]
```

```python
# GridSearchCV
grid_search = GridSearchCV(
    estimator=model,
    param_grid=param_grid,
    scoring = 'recall',
    n_jobs=-1,
    cv = 10,
    verbose=1)

# Fit the model
grid_search.fit(X_train, y_train)

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

best_model_decision = grid_search.best_estimator_

# Predict on training set
y_train_pred = best_model_decision.predict(X_train)

# Predict ontest set
y_test_pred = best_model_decision.predict(X_test)

# classification reports
print("Training Classification Report:")
print(classification_report(y_train, y_train_pred))

print("Testing Classification Report:")
print(classification_report(y_test, y_test_pred))

# Save model using pickle
with open('model_decision.pkl', 'wb') as f:
    pickle.dump(best_model_decision, f)
```

```
Fitting 10 folds for each of 256 candidates, totalling 2560 fits
Best Parameters: {'ccp_alpha': 0.01, 'class_weight': 'balanced', 'criterion':
'entropy', 'max_depth': 5, 'max_leaf_nodes': 10, 'min_impurity_decrease': 0.01,
'min_samples_leaf': 4, 'min_samples_split': 10, 'splitter': 'best'}
Training Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.89      0.85       439
           1       0.83      0.74      0.79       329

    accuracy                           0.83       768
   macro avg       0.83      0.82      0.82       768
weighted avg       0.83      0.83      0.83       768
```

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

           0       0.80      0.88      0.84       110
           1       0.78      0.65      0.71        69

    accuracy                           0.79       179
   macro avg       0.79      0.77      0.77       179
weighted avg       0.79      0.79      0.79       179
```

[93]:

```python
# Adjusting the decision threshold to improve the model performance

# Predicted probabilities for class 1
y_train_proba = best_model_decision.predict_proba(X_train)[:, 1]
y_test_proba = best_model_decision.predict_proba(X_test)[:, 1]

# Custom threshold (using 0.3 instead of 0.5)
threshold = 0.3

# Apply the threshold to make predictions
y_train_pred_threshold = (y_train_proba >= threshold).astype(int)
y_test_pred_threshold = (y_test_proba >= threshold).astype(int)

# New Predictions
print("Training Classification Report with threshold adjustment:")
print(classification_report(y_train, y_train_pred_threshold))

print("Testing Classification Report with threshold adjustment:")
print(classification_report(y_test, y_test_pred_threshold))
```

```
Training Classification Report with threshold adjustment:
              precision    recall  f1-score   support

           0       0.89      0.76      0.82       439
           1       0.73      0.87      0.79       329

    accuracy                           0.80       768
   macro avg       0.81      0.81      0.80       768
weighted avg       0.82      0.80      0.81       768

Testing Classification Report with threshold adjustment:
              precision    recall  f1-score   support

           0       0.84      0.68      0.75       110
           1       0.61      0.80      0.69        69
```

```
    accuracy                           0.73       179
   macro avg       0.73      0.74      0.72       179
weighted avg       0.75      0.73      0.73       179
```

[ ]:

1.8 Random Forest model

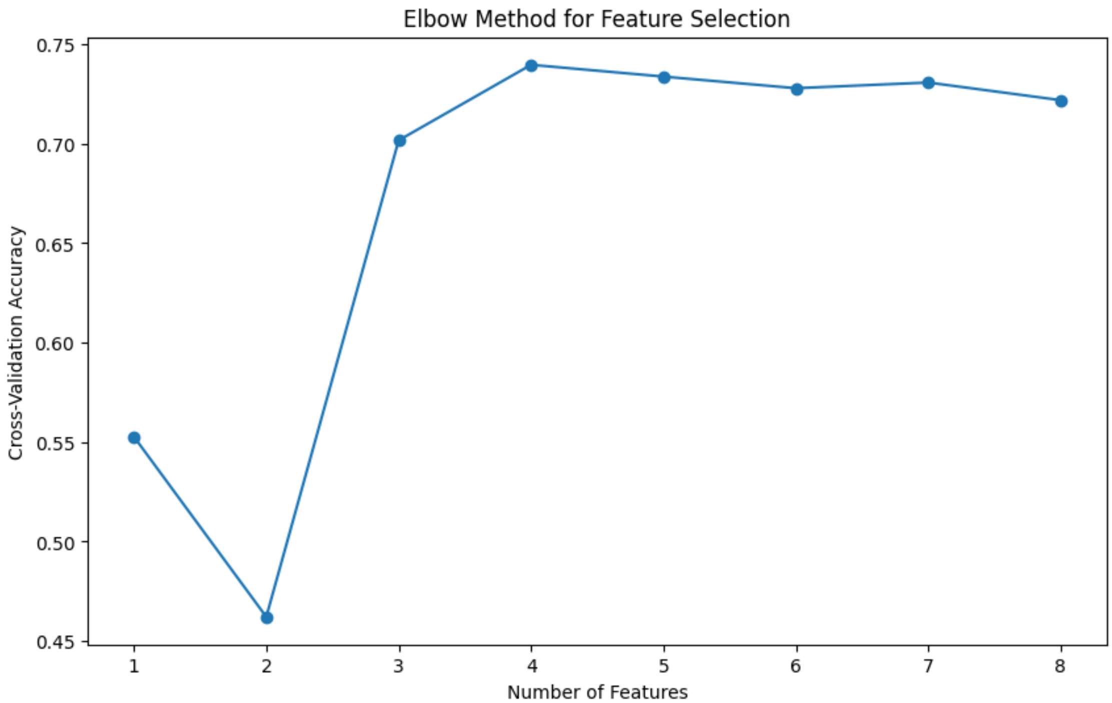
Feature Importance

[94]:
```
# Initialize the classifier
random_forest = RandomForestClassifier(random_state=42)

# Mean cross-validation scores
scores = []

# Loop through various numbers of selected features
for i in range(1, X.shape[1] + 1):
    rfe = RFE(estimator=random_forest, n_features_to_select=i)
    rfe.fit(X, y)
    scoring='recall'
    # Perform cross-validation
    score = np.mean(cross_val_score(rfe, X, y, cv=5, scoring=scoring))
    scores.append(score)

# Plot the elbow curve
plt.figure(figsize=(10, 6))
plt.plot(range(1, X.shape[1] + 1), scores, marker='o')
plt.title("Elbow Method for Feature Selection")
plt.xlabel("Number of Features")
plt.ylabel("Cross-Validation Accuracy")
plt.show()
```



[95]:
```
#Using RECURSIVE FEATURE ELEMINATION WITH CROSS-VALIDATION(RFECV)
rfecv = RFECV(estimator=random_forest, step=1, cv=5, scoring='f1')
rfecv.fit(X,y)

# Number of features chosen
print("Optimal number of features:", rfecv.n_features_)

pd.DataFrame({'Feature': X.columns, 'Ranking': rfecv.ranking_}).
 ↪sort_values(by='Ranking')
```

```
Optimal number of features: 5
```

[95]:

	Feature	Ranking
0	Pclass	1
1	Age	1
2	SibSp	1
4	Fare	1
5	Sex_male	1
3	Parch	2
7	Embarked_S	3
6	Embarked_Q	4

[96]:
```
# Using use Sex_male, Age, Fare, and Pclass as for the model based on both␣
 ↪feature importance and RFE ranking.
```

```
X_random = df[['Pclass', 'Age', 'SibSp', 'Fare', 'Sex_male']]
y_random  = y

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_random , y_random ,␣
↪test_size=0.20, random_state=42, stratify=y_random)
```

[97]:
```
#Oversampling

#Before Oversampling
print('Before Oversampling:', y_train.value_counts())

# Applying oversampling SMOTE
over_sampler = SMOTE(sampling_strategy=0.
↪75,random_state=42,k_neighbors=3,n_jobs=None)
X_train, y_train = over_sampler.fit_resample(X_train, y_train)

print('\n')

#After Oversampling
print('After Oversampling:', y_train.value_counts())
```

```
Before Oversampling: Survived
0    439
1    273
Name: count, dtype: int64


After Oversampling: Survived
0    439
1    329
Name: count, dtype: int64
```

[98]:
```
model = RandomForestClassifier(random_state=42)

param_distributions = {
    'n_estimators': [100, 200, 500],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 10, 20],
    'min_samples_leaf': [1, 2, 5],
    'max_features': ["sqrt", "log2", None],
    'bootstrap': [True, False],
    'criterion': ['gini', 'entropy'],
    'class_weight': [None, 'balanced']
}
```

```python
random_seach = RandomizedSearchCV(
    estimator=model,
    param_distributions=param_distributions,
    n_iter=10,
    scoring='recall',
    n_jobs=-1,
    cv=5,
    verbose=1,
    random_state=42)

random_seach.fit(X_random,y_random)

print("Best Parameters:", random_seach.best_params_)

best_model_random = random_seach.best_estimator_


# Predict on the training set
y_train_pred = best_model_random.predict(X_train)

# Predict on the test set
y_test_pred = best_model_random.predict(X_test)

# Generate the classification reports
print("Training Classification Report:")
print(classification_report(y_train, y_train_pred))

print("Testing Classification Report:")
print(classification_report(y_test, y_test_pred))
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
Best Parameters: {'n_estimators': 100, 'min_samples_split': 20,
'min_samples_leaf': 2, 'max_features': 'log2', 'max_depth': 10, 'criterion':
'entropy', 'class_weight': 'balanced', 'bootstrap': True}
Training Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.91      0.89       439
           1       0.87      0.84      0.85       329

    accuracy                           0.88       768
   macro avg       0.88      0.87      0.87       768
weighted avg       0.88      0.88      0.88       768

Testing Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.86      0.87       110
```

```
           1       0.79      0.81      0.80        69

    accuracy                           0.84       179
   macro avg       0.83      0.84      0.84       179
weighted avg       0.84      0.84      0.84       179
```

[ ]:

```

```

1.9 BaggingClassifier

Feature importance

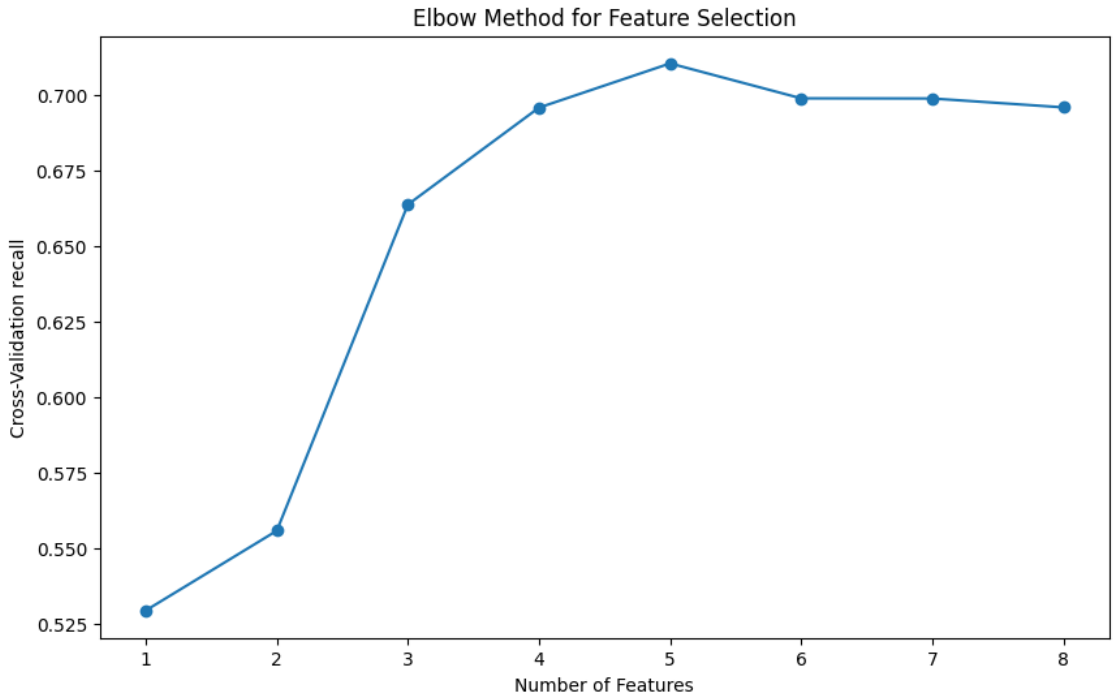
[99]:

```
#Calculating optimal number of features i

scores = []

for i in range(1,X.shape[1]+1):
    rfe = RFE(estimator=DecisionTreeClassifier(random_state =␣
 ↪42),n_features_to_select=i)
    rfe.fit(X,y)
    scoring='recall'
    # Perform cross-validation
    score = np.mean(cross_val_score(rfe, X, y, cv=5, scoring=scoring))
    scores.append(score)

# Plot the elbow curve
plt.figure(figsize=(10, 6))
plt.plot(range(1, X.shape[1] + 1), scores, marker='o')
plt.title("Elbow Method for Feature Selection")
plt.xlabel("Number of Features")
plt.ylabel(f"Cross-Validation {scoring}")
plt.show()
```



[100]:
```
#Using RECURSIVE FEATURE ELEMINATION WITH CROSS-VALIDATION(RFECV)
rfecv = RFECV(estimator=DecisionTreeClassifier(random_state = 42), step=1,␣
 ↪cv=5, scoring='recall')
rfecv.fit(X,y)

# Number of features chosen
print("Optimal number of features:", rfecv.n_features_)

pd.DataFrame({'Feature': X.columns, 'Ranking': rfecv.ranking_}).
 ↪sort_values(by='Ranking')
```

```
Optimal number of features: 5
```

[100]:

	Feature	Ranking
0	Pclass	1
1	Age	1
2	SibSp	1
4	Fare	1
5	Sex_male	1
3	Parch	2
7	Embarked_S	3
6	Embarked_Q	4

[101]:
```
# Using use Sex_male, Age, Fare, and Pclass as for the model based on both␣
↪feature importance and RFE ranking.

X_bagging = df[['Pclass', 'Age', 'SibSp', 'Fare', 'Sex_male']]
y_bagging   = y

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_random , y_random ,␣
↪test_size=0.20, random_state=42, stratify=y_random)
```

[102]:
```
#Oversampling

#Before Oversampling
print('Before Oversampling:', y_train.value_counts())

# Applying oversampling SMOTE
over_sampler = SMOTE(sampling_strategy=0.
↪75,random_state=42,k_neighbors=3,n_jobs=None)
X_train, y_train = over_sampler.fit_resample(X_train, y_train)

print('\n')

#After Oversampling
print('After Oversampling:', y_train.value_counts())
```

```
Before Oversampling: Survived
0    439
1    273
Name: count, dtype: int64


After Oversampling: Survived
0    439
1    329
Name: count, dtype: int64
```

[103]:
```
# Define the base model
bagging_classifier = BaggingClassifier(estimator=DecisionTreeClassifier(),␣
↪random_state=42)

# Define the hyperparameter grid
param_distributions = {
    'n_estimators': [10, 50, 100, 200],
    'estimator__max_depth': [None, 10, 20, 30],  # Note the change here as well
    'max_samples': [0.5, 0.7, 1.0],
    'max_features': [0.5, 0.7, 1.0],
    'bootstrap': [True, False],
```

```
    'bootstrap_features': [True, False]
}

# Perform RandomizedSearchCV
random_search = RandomizedSearchCV(estimator=bagging_classifier,␣
 ↪param_distributions=param_distributions, n_iter=10, cv=5, random_state=42)
random_search.fit(X_train, y_train)

# Print the best parameters
print("Best Parameters:", random_search.best_params_)

best_model_bagging = random_search.best_estimator_

# Predict on the training set
y_train_pred = best_model_bagging.predict(X_train)

# Predict on the test set
y_test_pred = best_model_bagging.predict(X_test)

# Generate the classification reports
print("Training Classification Report:")
print(classification_report(y_train, y_train_pred))

print("Testing Classification Report:")
print(classification_report(y_test, y_test_pred))
```

```
Best Parameters: {'n_estimators': 100, 'max_samples': 0.7, 'max_features': 1.0,
'estimator__max_depth': 10, 'bootstrap_features': False, 'bootstrap': False}
Training Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.99      0.96       439
           1       0.99      0.89      0.94       329

    accuracy                           0.95       768
   macro avg       0.96      0.94      0.95       768
weighted avg       0.95      0.95      0.95       768

Testing Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.88      0.85       110
           1       0.79      0.71      0.75        69

    accuracy                           0.82       179
   macro avg       0.81      0.80      0.80       179
weighted avg       0.81      0.82      0.81       179
```

```
[ ]:
```

1.10 Adaptive Boosting (AdaBoost)

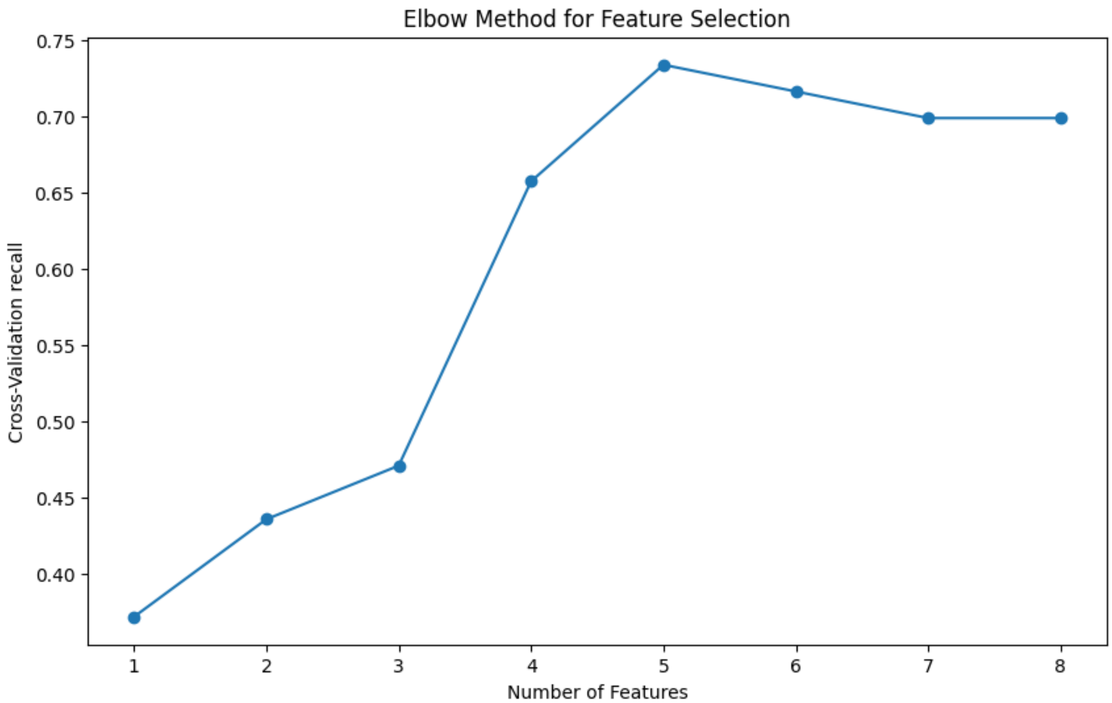
Feature Importance

```
[104]: scores = []
selected_features_list = {}

for i in range(1,X.shape[1]+1):
    rfe = RFE(estimator=AdaBoostClassifier(random_state=42),n_features_to_select=i, step=1)
    rfe.fit(X,y)
    scoring='recall'
    score = np.mean(cross_val_score(rfe, X, y, scoring=scoring, cv=5))
    scores.append(score)

    # Save the names of selected features
    selected_features_list[i] = X.columns[rfe.support_].tolist()  # Extracting the selected features based on boolean mask

# Plot the elbow curve
plt.figure(figsize=(10, 6))
plt.plot(range(1, X.shape[1] + 1), scores, marker='o')
plt.title("Elbow Method for Feature Selection")
plt.xlabel("Number of Features")
plt.ylabel(f"Cross-Validation {scoring}")
plt.show()
selected_features_list
```




```
[104]: {1: ['Fare'],
 2: ['Age', 'Fare'],
 3: ['Age', 'SibSp', 'Fare'],
 4: ['Pclass', 'Age', 'SibSp', 'Fare'],
 5: ['Pclass', 'Age', 'SibSp', 'Fare', 'Sex_male'],
 6: ['Pclass', 'Age', 'SibSp', 'Parch', 'Fare', 'Sex_male'],
 7: ['Pclass', 'Age', 'SibSp', 'Parch', 'Fare', 'Sex_male', 'Embarked_S'],
 8: ['Pclass',
  'Age',
  'SibSp',
  'Parch',
  'Fare',
  'Sex_male',
  'Embarked_Q',
  'Embarked_S']}
```

```
[105]: rfecv = RFECV(estimator=AdaBoostClassifier(random_state = 42), step=1, cv=5,␣
  ↪scoring='recall')
rfecv.fit(X,y)
# Number of features chosen
print("Optimal number of features:", rfecv.n_features_)

pd.DataFrame({'Feature': X.columns, 'Ranking': rfecv.ranking_}).
  ↪sort_values(by='Ranking')
```

```
Optimal number of features: 5
```

[105]:

```
     Feature  Ranking
0     Pclass        1
1        Age        1
2      SibSp        1
4       Fare        1
5   Sex_male        1
3      Parch        2
7 Embarked_S        3
6 Embarked_Q        4
```

[106]:

```
X_adaboost = X[['Pclass','Age','SibSp','Fare','Sex_male']]
y_adaboost = y

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_decision, y_decision,␣
 ↪test_size=0.20, random_state=42, stratify=y_decision)
```

[107]:

```
#Oversampling

#Before Oversampling
print('Before Oversampling:', y_train.value_counts())

# Applying oversampling SMOTE
over_sampler = SMOTE(sampling_strategy=0.
 ↪75,random_state=42,k_neighbors=3,n_jobs=None)
X_train, y_train = over_sampler.fit_resample(X_train, y_train)

print('\n')

#After Oversampling
print('After Oversampling:', y_train.value_counts())
```

```
Before Oversampling: Survived
0    439
1    273
Name: count, dtype: int64


After Oversampling: Survived
0    439
1    329
Name: count, dtype: int64
```

[108]:

```
# Define the base model
adaboost = AdaBoostClassifier(estimator=DecisionTreeClassifier(),␣
 ↪random_state=42)
```

```python
# Hyperparameter grid with 'estimator__max_depth'
param_distributions = {
    'n_estimators': [50, 100, 200, 300, 500],
    'learning_rate': [0.01, 0.1, 0.5, 1.0],
    'estimator__max_depth': [1, 2, 3, 4, 5],
    'algorithm': ['SAMME', 'SAMME.R']
}

# Create a StratifiedKFold object
# stratified_kfold = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# RandomizedSearchCV
random_search = RandomizedSearchCV(estimator=adaboost,␣
 ↪param_distributions=param_distributions, n_iter=10, cv=10, random_state=42)
random_search.fit(X_train, y_train)

# Print the best parameters
print("Best Parameters:", random_search.best_params_)

# Get the best model
best_model_adaboost = random_search.best_estimator_

# Predict on the training set
y_train_pred = best_model_adaboost.predict(X_train)

# Predict on the test set
y_test_pred = best_model_adaboost.predict(X_test)

# classification reports
print("Training Classification Report:")
print(classification_report(y_train, y_train_pred))

print("Testing Classification Report:")
print(classification_report(y_test, y_test_pred))
```

```
Best Parameters: {'n_estimators': 500, 'learning_rate': 0.1,
'estimator__max_depth': 4, 'algorithm': 'SAMME'}
Training Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.90      0.89       439
           1       0.87      0.84      0.85       329

    accuracy                           0.88       768
   macro avg       0.87      0.87      0.87       768
weighted avg       0.87      0.88      0.87       768
```

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

           0       0.83      0.85      0.84       110
           1       0.76      0.72      0.74        69

    accuracy                           0.80       179
   macro avg       0.79      0.79      0.79       179
weighted avg       0.80      0.80      0.80       179
```

[ ]:

1.11 Gradient Boosting

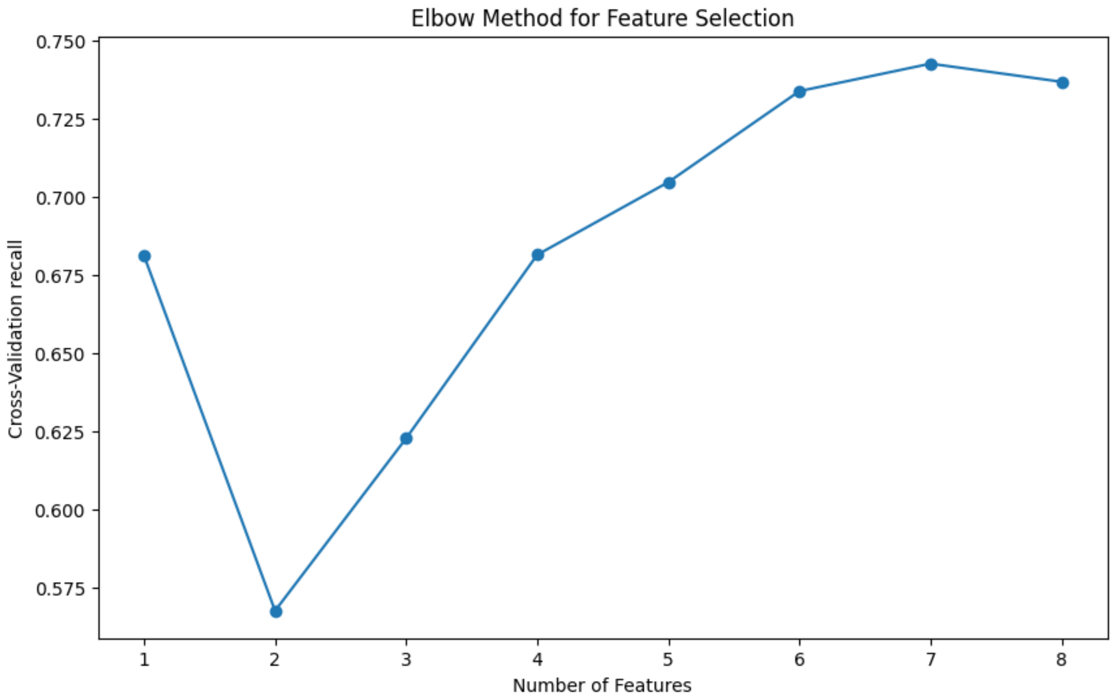
Feature Importance

[109]:
```python
#Calculating optimal number of features i

scores = []

for i in range(1,X.shape[1]+1):
    rfe = RFE(estimator= xgb.
 ↪XGBClassifier(random_state=42),n_features_to_select=i)
    rfe.fit(X,y)
    scoring='recall'
    # Perform cross-validation
    score = np.mean(cross_val_score(rfe, X, y, cv=5, scoring=scoring))
    scores.append(score)

# Plot the elbow curve
plt.figure(figsize=(10, 6))
plt.plot(range(1, X.shape[1] + 1), scores, marker='o')
plt.title("Elbow Method for Feature Selection")
plt.xlabel("Number of Features")
plt.ylabel(f"Cross-Validation {scoring}")
plt.show()
```



[110]:
```
#Using RECURSIVE FEATURE ELEMINATION WITH CROSS-VALIDATION(RFECV)
rfecv = RFECV(estimator=xgb.XGBClassifier(random_state=42), step=1, cv=5,␣
 ↪scoring='recall')
rfecv.fit(X,y)

# Number of features chosen
print("Optimal number of features:", rfecv.n_features_)

pd.DataFrame({'Feature': X.columns, 'Ranking': rfecv.ranking_}).
 ↪sort_values(by='Ranking')
```

```
Optimal number of features: 7
```

[110]:

	Feature	Ranking
0	Pclass	1
1	Age	1
2	SibSp	1
3	Parch	1
4	Fare	1
5	Sex_male	1
7	Embarked_S	1
6	Embarked_Q	2

[111]:
```
X_gradient = X[['Pclass','Age','SibSp','Fare','Parch','Fare','Sex_male']]
y_gradient = y

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_decision, y_decision,␣
↪test_size=0.20, random_state=42, stratify=y_decision)
```

[112]:
```
#Oversampling

#Before Oversampling
print('Before Oversampling:', y_train.value_counts())

# Applying oversampling SMOTE
over_sampler = SMOTE(sampling_strategy=0.
↪75,random_state=42,k_neighbors=3,n_jobs=None)
X_train, y_train = over_sampler.fit_resample(X_train, y_train)

print('\n')

#After Oversampling
print('After Oversampling:', y_train.value_counts())
```

```
Before Oversampling: Survived
0    439
1    273
Name: count, dtype: int64


After Oversampling: Survived
0    439
1    329
Name: count, dtype: int64
```

[113]:
```
# Hyperparameter grid for tuning
param_grid = {
    'n_estimators': [100, 200, 300, 500],
    'learning_rate': [0.01, 0.1, 0.2, 0.3],
    'max_depth': [3, 5, 7],
    'min_child_weight': [1, 3, 5],
    'subsample': [0.6, 0.8, 1.0],
    'colsample_bytree': [0.6, 0.8, 1.0],
    'gamma': [0, 0.1, 0.2],
    'reg_alpha': [0, 0.01, 0.1, 1.0],
    'reg_lambda': [0, 0.01, 0.1, 1.0]
}

# Perform RandomizedSearchCV for hyperparameter tuning
```

```python
random_search = RandomizedSearchCV(estimator=xgb.
 ↪XGBClassifier(random_state=42), param_distributions=param_grid, n_iter=10,␣
 ↪scoring='accuracy', cv=5, random_state=42, verbose=1, n_jobs=-1)
random_search.fit(X_train, y_train)

# Print the best parameters found by RandomizedSearchCV
print("Best Parameters:", random_search.best_params_)

# Get the best model
best_model_gradient = random_search.best_estimator_

# Predict on the training set
y_train_pred = best_model_gradient.predict(X_train)

# Predict on the test set
y_test_pred = best_model_gradient.predict(X_test)

# Classification report for training set
print("Training Classification Report:")
print(classification_report(y_train, y_train_pred))

# Classification report for testing set
print("Testing Classification Report:")
print(classification_report(y_test, y_test_pred))
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
Best Parameters: {'subsample': 0.6, 'reg_lambda': 0.01, 'reg_alpha': 0,
'n_estimators': 200, 'min_child_weight': 3, 'max_depth': 3, 'learning_rate':
0.1, 'gamma': 0.2, 'colsample_bytree': 0.6}
Training Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.92      0.90       439
           1       0.89      0.81      0.85       329

    accuracy                           0.88       768
   macro avg       0.88      0.87      0.87       768
weighted avg       0.88      0.88      0.88       768

Testing Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.91      0.87       110
           1       0.83      0.70      0.76        69

    accuracy                           0.83       179
   macro avg       0.83      0.80      0.81       179
weighted avg       0.83      0.83      0.82       179
```

[ ]:

1.12 SUPPORT VECTOR MACHINE(SVM)

Feature Selection

[114]:
```
# Using pretuned best models

param_grid = {
    'kernel': ['linear', 'poly', 'rbf', 'sigmoid']
}

# Instantiate the SVC
svc = SVC()

scoring = 'recall'

# Perform Grid Search with Cross-Validation (5-fold)
grid_search = GridSearchCV(svc, param_grid, cv=5, scoring=scoring, n_jobs=-1)
grid_search.fit(X, y)

# Best kernel and parameters
print("Best parameters found: ", grid_search.best_params_)
print(f"Best {scoring} score: ", grid_search.best_score_)
```

```
Best parameters found:  {'kernel': 'linear'}
Best recall score:  0.6811594202898551
```

[115]:
```
# # The linear kernel is the best, we can now use it with Recursive Feature
↪Elimination (RFE).

# scores = []
# selected_features_list = {}

# for i in range(1,X.shape[1]+1):
#     rfe = RFE(estimator=SVC(kernel='linear',
↪random_state=42),n_features_to_select=i, step=1)
#     rfe.fit(X,y)
#     scoring='recall'
#     score = np.mean(cross_val_score(rfe, X, y, scoring=scoring, cv=5))
#     scores.append(score)

#     # Save the names of selected features
#     selected_features_list[i] = X.columns[rfe.support_].tolist()  #
↪Extracting the selected features based on boolean mask

# # Plot the elbow curve
```

```
# plt.figure(figsize=(10, 6))
# plt.plot(range(1, X.shape[1] + 1), scores, marker='o')
# plt.title("Elbow Method for Feature Selection")
# plt.xlabel("Number of Features")
# plt.ylabel(f"Cross-Validation {scoring}")
# plt.show()
# selected_features_list
```

[116]:
```
# The linear kernel is the best, we can now use it with Recursive Feature␣
↪Elimination (RFE).

rfecv = RFECV(estimator=SVC(kernel='linear', random_state=42), step=1, cv=5,␣
↪scoring='recall')
rfecv.fit(X,y)
# Number of features chosen
print("Optimal number of features:", rfecv.n_features_)

pd.DataFrame({'Feature': X.columns, 'Ranking': rfecv.ranking_}).
↪sort_values(by='Ranking')
```

```
Optimal number of features: 1
```

[116]:

	Feature	Ranking
5	Sex_male	1
0	Pclass	2
2	SibSp	3
7	Embarked_S	4
3	Parch	5
4	Fare	6
1	Age	7
6	Embarked_Q	8

[117]:
```
#RFECV identified only 'Sex_male'

X_svm = X[['Sex_male']]
y_svm  = y

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_decision, y_decision,␣
↪test_size=0.20, random_state=42, stratify=y_decision)
```

[118]:
```
#Oversampling

#Before Oversampling
print('Before Oversampling:', y_train.value_counts())

# Applying oversampling SMOTE
```

```
over_sampler = SMOTE(sampling_strategy=0.
↪75,random_state=42,k_neighbors=3,n_jobs=None)
X_train, y_train = over_sampler.fit_resample(X_train, y_train)

print('\n')

#After Oversampling
print('After Oversampling:', y_train.value_counts())
```

```
Before Oversampling: Survived
0    439
1    273
Name: count, dtype: int64


After Oversampling: Survived
0    439
1    329
Name: count, dtype: int64
```

[119]:
```
# RandomizedSearchCV
param_grid = {
    'C': [0.1, 1, 10, 100],
    'gamma': [1, 0.1, 0.01, 0.001],
    'kernel': ['linear'],
    'degree': [2, 3, 4]
}

# Initialize SVC model
svc = SVC(random_state=42)

# RandomizedSearchCV for hyperparameter tuning
random_search = RandomizedSearchCV(estimator=svc,␣
↪param_distributions=param_grid,
                                   n_iter=10, cv=5, verbose=2, random_state=42,␣
↪n_jobs=-1, scoring='accuracy')

# Fit the model with the best hyperparameters
random_search.fit(X_train, y_train)

# Print the best parameters found by RandomizedSearchCV
print("Best Parameters:", random_search.best_params_)

# Get the best model
best_model_svc = random_search.best_estimator_

# Predict on the training set
```

```python
y_train_pred = best_model_svc.predict(X_train)

# Predict on the test set
y_test_pred = best_model_svc.predict(X_test)

# Classification report for training set
print("Training Classification Report:")
print(classification_report(y_train, y_train_pred))

# Classification report for testing set
print("Testing Classification Report:")
print(classification_report(y_test, y_test_pred))
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
Best Parameters: {'kernel': 'linear', 'gamma': 1, 'degree': 3, 'C': 100}
Training Classification Report:
              precision    recall  f1-score   support

           0       0.78      0.85      0.82       439
           1       0.78      0.68      0.73       329

    accuracy                           0.78       768
   macro avg       0.78      0.77      0.77       768
weighted avg       0.78      0.78      0.78       768

Testing Classification Report:
              precision    recall  f1-score   support

           0       0.80      0.85      0.82       110
           1       0.74      0.65      0.69        69

    accuracy                           0.78       179
   macro avg       0.77      0.75      0.76       179
weighted avg       0.77      0.78      0.77       179
```

[ ]:

```python

```

1.13 Ensemble Stacking

[120]:

```python
#Determining the best meta model's algorithm

# Base models
base_models = [
    ('logistic', best_model_logistic),
    ('decision_tree', best_model_decision),
    ('random_forest', best_model_random),
```

```
    ('bagging', best_model_bagging),
    ('adaboost', best_model_adaboost),
    ('gradient_boost', best_model_gradient),
]

# Meta-models to test
meta_models = {
    'LogisticRegression': LogisticRegression(random_state=42),
    'RandomForest': RandomForestClassifier(random_state=42),
    'SVC': SVC(kernel='linear', random_state=42),
    'XGBClassifier': xgb.XGBClassifier(random_state=42)
}

scoring ='recall'
# Loop through different meta-models
for name, meta_model in meta_models.items():
    stacking_model = StackingClassifier(estimators=base_models,␣
 ↪final_estimator=meta_model, cv=5)

    # Cross-validation
    cv_scores = cross_val_score(stacking_model, X_train, y_train, cv=5,␣
 ↪scoring=scoring)

    print(f"{name} Meta-Model - Mean CV {scoring}: {cv_scores.mean():.4f}")
```

```
LogisticRegression Meta-Model - Mean CV recall: 0.7694
RandomForest Meta-Model - Mean CV recall: 0.7418
SVC Meta-Model - Mean CV recall: 0.7541
XGBClassifier Meta-Model - Mean CV recall: 0.7419
```

[125]:
```
# Hyperparameter tuning for Logistic Regression as the meta-model
param_grid = {
    'final_estimator__C': [0.01, 0.1, 1, 10],
    'final_estimator__solver': ['liblinear', 'lbfgs']
}
stacking_model = StackingClassifier(estimators=base_models,␣
 ↪final_estimator=LogisticRegression(random_state=42), cv=5)

grid_search = GridSearchCV(estimator=stacking_model, param_grid=param_grid,␣
 ↪cv=5, scoring='recall')
grid_search.fit(X_train, y_train)

print("Best Parameters:", grid_search.best_params_)

# Get the best model
best_model_ensemblestacking = grid_search.best_estimator_
```

```
# Predict on the training set
y_train_pred = best_model_ensemblestacking.predict(X_train)

# Predict on the test set
y_test_pred = best_model_ensemblestacking.predict(X_test)

# Classification report for training set
print("Training Classification Report:")
print(classification_report(y_train, y_train_pred))

# Classification report for testing set
print("Testing Classification Report:")
print(classification_report(y_test, y_test_pred))
```

```
Best Parameters: {'final_estimator__C': 0.01, 'final_estimator__solver':
'liblinear'}
Training Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.91      0.91       439
           1       0.88      0.88      0.88       329

    accuracy                           0.90       768
   macro avg       0.89      0.89      0.89       768
weighted avg       0.90      0.90      0.90       768

Testing Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.82      0.83       110
           1       0.72      0.74      0.73        69

    accuracy                           0.79       179
   macro avg       0.78      0.78      0.78       179
weighted avg       0.79      0.79      0.79       179
```

[ ]:

```

```

1.14 Explaining the approach

1. Importing neccesary libraries
2. Loading the dataset
3. Data preprocessing: Handle missing values, Checking for the Outliers, checking for the outliers and treating them by using the concept of Winsorization, dropping irrelevant columns.
4. Converting categorical variables into numerical variables using one-hot encoding,label encoding
5. Splitting the dataset into features (X) and target (y) variables.

6. Using the following Algorithm to create model:-

(I) Building Logistic Regression model

a) Feature selection by determining coefficient
b) Feature selection using RFE(Recursive Feature Elemination)
c) removing removing Fare, Embarked_Q, and Age, as they show the least importance in both the coefficient and RFE rankings.
d) Applying oversampling using SMOTE due to class imbalance
e) Defining the adjusted parameter grid,perform grid search with the refined parameter grid, Fit grid search, generating the classification reports.

(II) Building Decision Tree Model

```
a) Calculating Feature importances decision_tree.feature_importances_
b) Calculating Feature ranking using RFE(Recursive Feature Elemination)
c) Using Sex_male, Age, Fare, and Pclass  for the model based on both feature importance and RI
d) Applying oversampling using SMOTE due to class imbalance
e) Performing GridSearchCV to hyper tune the parameters.
f) Perform grid_search.fit
g) Generating Classification report.
h) Saving the model using pickle.
i) Adjusting the decision threshold to improve the model performance.
```

(III) Building Random Forest Model

```
a) Performing feature selection using Elbow Method to determine the optimal number of features
b) Performing feature selection using RECURSIVE FEATURE ELEMINATION WITH CROSS-VALIDATION(RFECV
c)Using optimal number of features to Split the data into training and testing sets.
d)Performing oversampling SMOTE due to class imbalance
e)Performing RandomizedSearchCV to hypertune the parameters
f)Generating the classification reports for training and test set
```

(IV) BaggingClassifier

```
a) Performing feature selection using Elbow Method to determine the optimal number of features
b) Performing feature selection using RECURSIVE FEATURE ELEMINATION WITH CROSS-VALIDATION(RFECV
c) Using optimal number of features to Split the data into training and testing sets.
d)Performing oversampling SMOTE due to class imbalance
e)Performing RandomizedSearchCV to hypertune the parameters
f)Generating the classification reports for training and test set
```

(V)Adaptive Boosting (AdaBoost)

```
a)Performing feature selection using Elbow Method to determine the optimal number of features
b) Performing feature selection using RECURSIVE FEATURE ELEMINATION WITH CROSS-VALIDATION(RFECV
c)Performing oversampling SMOTE due to class imbalance
d)Performing RandomizedSearchCV to hypertune the parameters
e)Generating the classification reports for training and test set
```

(VI)Adaptive Boosting (AdaBoost)

```
a)Performing feature selection using Elbow Method to determine the optimal number of features
b)Performing feature selection using RECURSIVE FEATURE ELEMINATION WITH CROSS-VALIDATION(RFECV)
```

c)Performing oversampling SMOTE due to class imbalance
d)Performing RandomizedSearchCV to hypertune the parameters
e)Generating the classification reports for training and test set

(VII)SUPPORT VECTOR MACHINE(SVM)

a)Peforming GridSearchCV for SVC kernal selection
b)Performing feature selection using RECURSIVE FEATURE ELEMINATION WITH CROSS-VALIDATION(RFECV)
c)Performing oversampling SMOTE due to class imbalance
d)Performing RandomizedSearchCV to hypertune the parameters
e)Generating the classification reports for training and test set

(VIII)Ensemble Stacking

a)Determining the best meta model's algorithm through cross validation
b)Hyperparameter tuning for Logistic Regression as the meta-model
c)e)Generating the classification reports for training and test set

1.15 Logistic Regression:

Strengths

Interpretability
Efficient and Fast
Well-suited for Linearly Separable Data
Handles Binary Classification Well
Probabilistic Output
Works Well with Categorical Data

Weaknesses

Linear Decision Boundary
Poor Performance with Non-linear Data
Sensitive to Multicollinearity
Requires Feature Engineering
Not Suitable for High-dimensional Data
No Built-in Feature Selection
Assumes Independence of Features
Logistic regression can struggle with imbalanced datasets

1.16 Decision Tree

Strengths

Decision trees are easy to understand and interpret.
Decision trees don't require the input features to be scaled
Decision trees can capture non-linear relationships between features and the target variable
They provide a ranking of feature importance, helping to understand which features contribute t
Decision trees can handle both categorical and numerical data effectively
Since splits in the tree are based on feature values, decision trees are relatively robust to o
Non-parametric Model : Decision trees do not make assumptions about the distribution of the dat

Weaknesses

```
Decision trees are prone to overfitting
Decision trees can be quite unstable because small changes in the data can lead to completely d
Decision trees can become biased towards classes that are more frequent in the data
If the dataset is small or has little variation, decision trees may not capture meaningful patt
The predictions of decision trees are not smooth or continuous, as they rely on discrete splits
In datasets with many features, decision trees may struggle,
```

1.17 Random Forest

Strengths

```
highly resistant to overfitting compared to a single decision tree.
resilient to outliers because each decision tree is trained on a subset of the data,
ranking of feature importance, which can be very useful in understanding which features are the
Random Forest does not assume any underlying distribution in the data, making it suitable for d
Random Forest tends to perform well with large datasets and high-dimensional data, especially i
Through its bootstrapping method (bagging) and averaging predictions from different trees, Rand
Random Forest can handle both classification and regression tasks and is capable of working wel
```

Weaknesses

```
  One of the primary drawbacks of Random Forest is the lack of interpretability.
  Random Forest requires considerable computational power and memory due to the need to build a
  Tendency to Overfit with Noisy Data
  Less Effective for Small Datasets
  It may give biased results when dealing with high cardinality categorical features or when th
  the prediction phase can be slow compared to simpler models.
  Tuning hyperparameters such as the number of trees, maximum depth, and number of features to
```

1.18 Bagging Classifier

Strengths

```
Bagging (Bootstrap Aggregating) reduces the variance of individual models by training multiple
Bagging allows for parallel model training since each base model is trained independently on di
By aggregating the results of multiple base models, Bagging Classifier generally achieves bette
Bagging works well when the dataset contains noisy data or outliers
Models like decision trees are prone to high variance, but bagging can greatly improve their pe
```

Weaknesses

```
For models with low variance, such as logistic regression or support vector machines, bagging m
Make the overall model hard to interpret.
the training process can be computationally expensive, especially for large datasets or when ea
Bagging is not well-suited for small datasets because the base models are trained on bootstrapp
While bagging reduces overfitting by averaging, it may lead to underfitting in some cases, espe
Complexity in Hyperparameter Tuning
```

1.19 Adaptive Boosting

strenghs

AdaBoost is designed to combine multiple weak learners (often decision trees with one level, kn
AdaBoost can work with many types of base models.
AdaBoost is relatively resistant to overfitting when used with simple base learners like decisi
AdaBoost can provide feature importance measures based on how frequently and how early in the p
AdaBoost typically requires fewer hyperparameter adjustments compared to other ensemble methods

Weaknesses

Because AdaBoost gives more weight to misclassified examples at each iteration, noisy data and
Requires High-quality Base Learners
Slow Convergence with Large Datasets
Difficulty with High-dimensional Data

1.20 SUPPORT VECTOR MACHINE(SVM)

strenghs

SVM is highly effective when the number of features (dimensions) is large relative to the numbe
SVM uses a regularization parameter (C) to prevent overfitting.
kernel trick, SVM can handle non-linearly separable data by transforming it into a higher-dime
SVM can effectively model complex decision boundaries, especially when combined with non-linea
SVM is robust to outliers because it focuses on the support vectors, which are the data points
SVM allows the use of custom kernels, making it adaptable to different types of data

Weaknesses

Computationally Expensive for Large Datasets
Sensitive to Parameter Tuning
Limited Interpretability
Not Ideal for Imbalanced Data
No Probabilistic Interpretation
Kernel Choice Can Be Challenging

1.21 Ensemble Stacking

strenghs

Stacking leverages the strengths of different algorithms by combining their predictions. This a
Different models capture different aspects of the data
This flexibility allows you to choose models that perform best for your specific problem.
Stacking is especially useful in complex datasets with non-linear relationships and high-dimens
By relying on the combined predictions of multiple models, stacking reduces the risk of overfit
The meta-model (or level-1 model) can be tuned separately to adjust the way it combines the bas

Weaknesses

Stacking involves multiple models, and as the number of base learners increases, so does the co
Since you are training several models, stacking can be computationally expensive, especially wi
While stacking is meant to reduce overfitting by combining models, if the base models are highl
There's a risk of data leakage if the meta-model has access to the true target labels during tr
Stacking models are typically harder to interpret than individual models.

```
Tuning a stacking ensemble is more complex than tuning a single model
The effectiveness of stacking depends on the choice of the meta-model.
```