# Libraries Used

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import time
import warnings
from sklearn.model_selection import train_test_split, GridSearchCV,
cross_val_score
from sklearn.preprocessing import MinMaxScaler, StandardScaler,
LabelEncoder
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, confusion_matrix, classification_report
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier, plot_tree

warnings.filterwarnings('ignore', category=FutureWarning)
warnings.filterwarnings('ignore', category=DeprecationWarning)
```

# (I) Data Preprocessing

```
df=pd.read_csv('Titanic-Dataset.csv')

df

      PassengerId  Survived  Pclass  \
0               1         0       3
1               2         1       1
2               3         1       3
3               4         1       1
4               5         0       3
...           ...       ...     ...
1304         1305         0       3
1305         1306         1       1
1306         1307         0       3
1307         1308         0       3
1308         1309         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
...                                                 ...     ...   ...
...
1304                              Spector, Mr. Woolf    male   NaN
0
1305                     Oliva y Ocana, Dona. Fermina  female  39.0
0
1306                     Saether, Mr. Simon Sivertsen    male  38.5
0
1307                              Ware, Mr. Frederick    male   NaN
0
1308                         Peter, Master. Michael J    male   NaN
1

      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
...     ...                 ...       ...   ...      ...
1304      0           A.5. 3236    8.0500   NaN        S
1305      0            PC 17758  108.9000  C105        C
1306      0  SOTON/O.Q. 3101262    7.2500   NaN        S
1307      0              359309    8.0500   NaN        S
1308      1                2668   22.3583   NaN        C

[1309 rows x 12 columns]
```

```python
print("Dataset Overview:")
print(df.info())
```

```
Dataset Overview:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1309 entries, 0 to 1308
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  1309 non-null   int64  
 1   Survived     1309 non-null   int64  
 2   Pclass       1309 non-null   int64  
 3   Name         1309 non-null   object 
 4   Sex          1309 non-null   object 
 5   Age          1046 non-null   float64
 6   SibSp        1309 non-null   int64  
 7   Parch        1309 non-null   int64  
 8   Ticket       1309 non-null   object 
```

```
 9   Fare         1308 non-null   float64
 10  Cabin        295 non-null    object
 11  Embarked     1307 non-null   object
dtypes: float64(2), int64(5), object(5)
memory usage: 122.8+ KB
None
```

```
# Count null values
null_values = df.isnull().sum()
print("Number of null values:", null_values)

# Count duplicated rows
duplicate_rows = df.duplicated().sum()
print("Number of duplicated rows:", duplicate_rows)
```

```
Number of null values: PassengerId       0
Survived          0
Pclass            0
Name              0
Sex               0
Age             263
SibSp             0
Parch             0
Ticket            0
Fare              1
Cabin          1014
Embarked          2
dtype: int64
Number of duplicated rows: 0
```

```
df['Age'] = df['Age'].fillna(df['Age'].median())
df['Fare'] = df['Fare'].fillna(df['Fare'].median())
df['Embarked'] = df['Embarked'].fillna(df['Embarked'].mode()[0])

df.drop(['PassengerId','Name','Ticket','Cabin'], axis=1,inplace=True)

df.rename(columns={"Pclass":'Passenger_Class','Sex':'Gender','SibSp':
'Siblings_Aboard', 'Parch': 'Family_Aboard'}, inplace=True)

gender_mapping={'male':0,'female':1}
embarked_mapping={'S':0,'C':1,'Q':2}

df['Gender']=df['Gender'].map(gender_mapping)
df['Embarked']=df['Embarked'].map(embarked_mapping)

print("Descriptive Statistics:")
print(df.describe())
```

```
Descriptive Statistics:
          Survived  Passenger_Class       Gender          Age  \
count  1309.000000      1309.000000  1309.000000  1309.000000
```

```
mean      0.377387         2.294882     0.355997    29.503186
std       0.484918         0.837836     0.478997    12.905241
min       0.000000         1.000000     0.000000     0.170000
25%       0.000000         2.000000     0.000000    22.000000
50%       0.000000         3.000000     0.000000    28.000000
75%       1.000000         3.000000     1.000000    35.000000
max       1.000000         3.000000     1.000000    80.000000

       Siblings_Aboard  Family_Aboard         Fare     Embarked
count      1309.000000    1309.000000  1309.000000  1309.000000
mean          0.498854       0.385027    33.281086     0.394194
std           1.041658       0.865560    51.741500     0.653499
min           0.000000       0.000000     0.000000     0.000000
25%           0.000000       0.000000     7.895800     0.000000
50%           0.000000       0.000000    14.454200     0.000000
75%           1.000000       0.000000    31.275000     1.000000
max           8.000000       9.000000   512.329200     2.000000
```

```
df
```

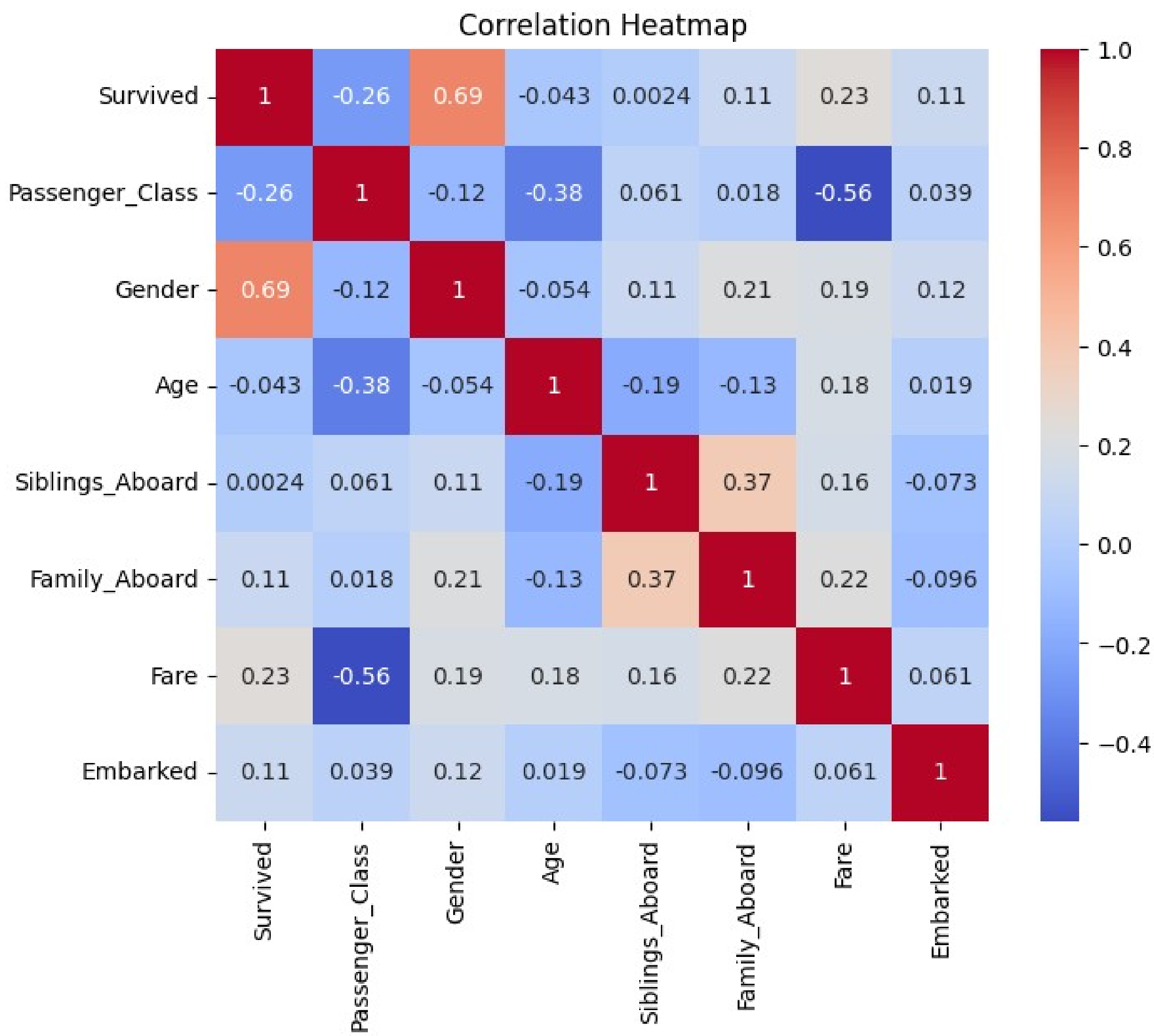
```
      Survived  Passenger_Class  Gender   Age  Siblings_Aboard
Family_Aboard  \
0            0                3       0  22.0                1
0
1            1                1       1  38.0                1
0
2            1                3       1  26.0                0
0
3            1                1       1  35.0                1
0
4            0                3       0  35.0                0
0
...        ...              ...     ...   ...              ...
...
1304         0                3       0  28.0                0
0
1305         1                1       1  39.0                0
0
1306         0                3       0  38.5                0
0
1307         0                3       0  28.0                0
0
1308         0                3       0  28.0                1
1

          Fare  Embarked
0       7.2500         0
1      71.2833         1
2       7.9250         0
3      53.1000         0
```

```
4       8.0500         0
...        ...       ...
1304    8.0500         0
1305  108.9000         1
1306    7.2500         0
1307    8.0500         0
1308   22.3583         1

[1309 rows x 8 columns]
```

```
X = df.drop(columns=['Survived'])
y = df['Survived']
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

standard_scaler=StandardScaler()
minmax_scaler=MinMaxScaler()

X_train_standard,
X_test_standard=standard_scaler.fit_transform(X_train),standard_scaler
.fit_transform(X_test)
X_train_minmax,
X_test_minmax=minmax_scaler.fit_transform(X_train),minmax_scaler.fit_t
ransform(X_test)

# Initialize lists to store accuracy and runtime
model_names = []
training_accuracies = []
testing_accuracies = []
runtimes = []
```

## (II) Data Exploration

```
correlation_matrix = df.corr()

plt.figure(figsize=(8,6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
cbar=True, square=True)
plt.title('Correlation Heatmap')
plt.show()
```




# Possible Explanations for Correlation Between Survival and Other Attributes

## Passenger Class (Moderate Negative Correlation)

- Passengers in higher classes (1st class, represented by the lowest numerical value) were more likely to survive compared to those in lower classes (2nd or 3rd class).
- Likely due to better access to lifeboats and assistance during evacuation.

---

## Gender (Strong Positive Correlation)

- Females (encoded as 1) had a higher likelihood of survival compared to males (encoded as 0).

- Aligns with the historical account of the Titanic's evacuation policy, where women and children were given priority for lifeboats.

## Age (Weak Negative Correlation)

- Younger passengers were marginally more likely to survive than older ones.
- This might reflect children receiving priority for lifeboat access.
- The effect is weak, possibly due to the low number of children on board.

---

## Siblings Aboard (Weak Negative Correlation)

- Having more siblings aboard slightly reduced the likelihood of survival.
- Likely due to the challenge of coordinating survival among multiple family members during the chaos.
- The effect is very minor.

---

## Family Aboard (Weak Positive Correlation)

- Having parents or children aboard slightly increased the likelihood of survival.
- Family members may have helped each other during evacuation.
- The effect is not strong.

---

## Fare (Positive Correlation)

- Passengers who paid higher fares were more likely to survive.
- Higher fares were typically associated with higher passenger classes, which had better access to lifeboats and crew assistance.

---

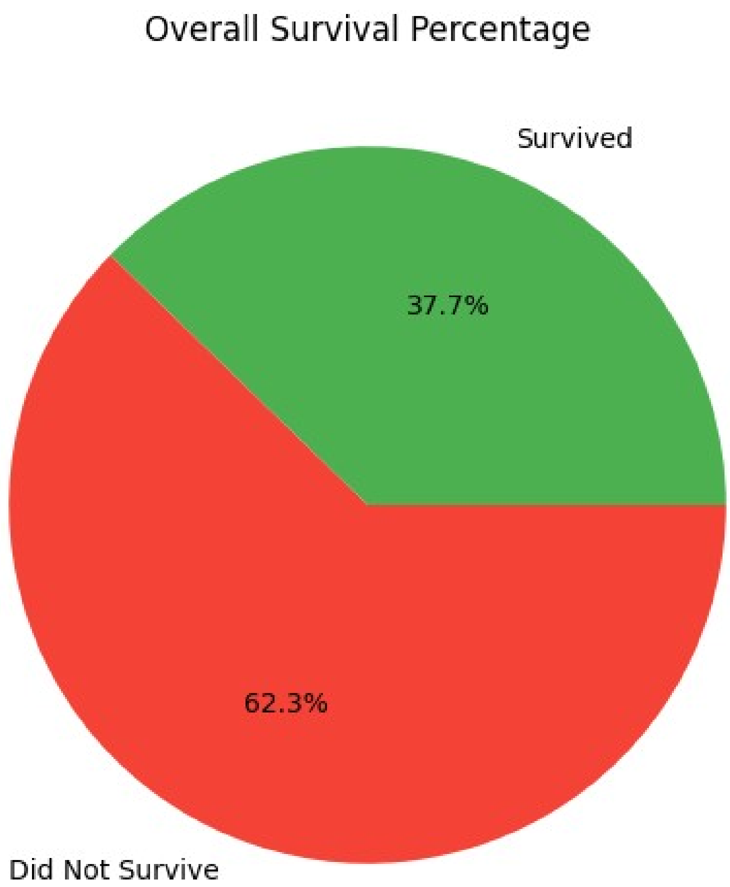
## Embarked (Weak Positive Correlation)

- Passengers who embarked at Cherbourg (encoded as 1) and Queenstown (encoded as 2) were slightly more likely to survive than those who embarked at Southampton (encoded as 0).

- This may reflect demographic differences or disparities in ticket type, class, or access to lifeboats among passengers from different ports.

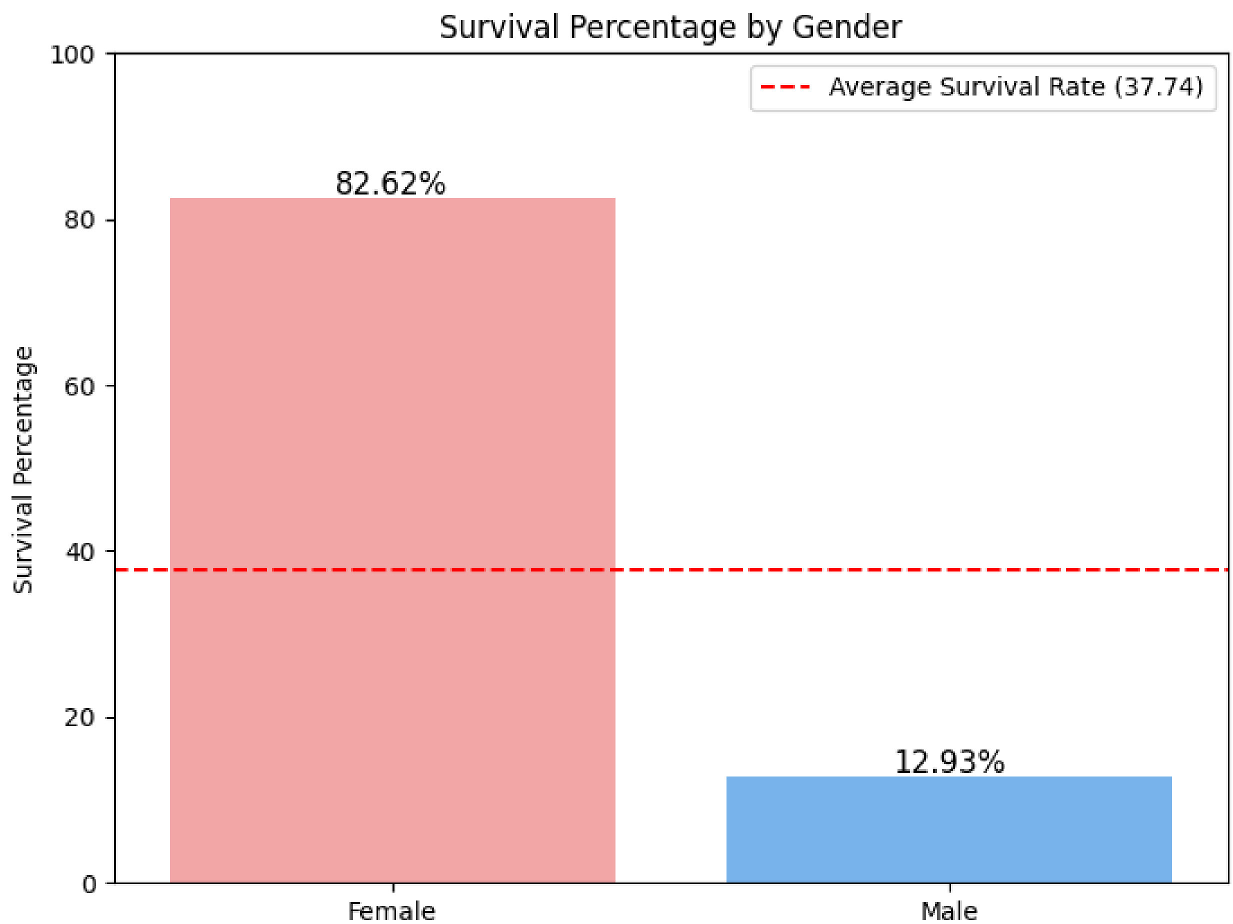
Visualizations to support the previous claims

```
# Visualization 3: Pie Chart for Overall Survival
survival_labels = ['Survived', 'Did Not Survive']
survival_counts = [df[df['Survived'] == 1].shape[0], df[df['Survived']
== 0].shape[0]]
survival_percentage=round(df[df['Survived'] ==
1].shape[0]/df.shape[0]*100,2)

plt.figure(figsize=(8, 6))
plt.pie(survival_counts, labels=survival_labels, autopct='%1.1f%%',
colors=['#4caf50', '#f44336'])
plt.title('Overall Survival Percentage')
plt.show()
```



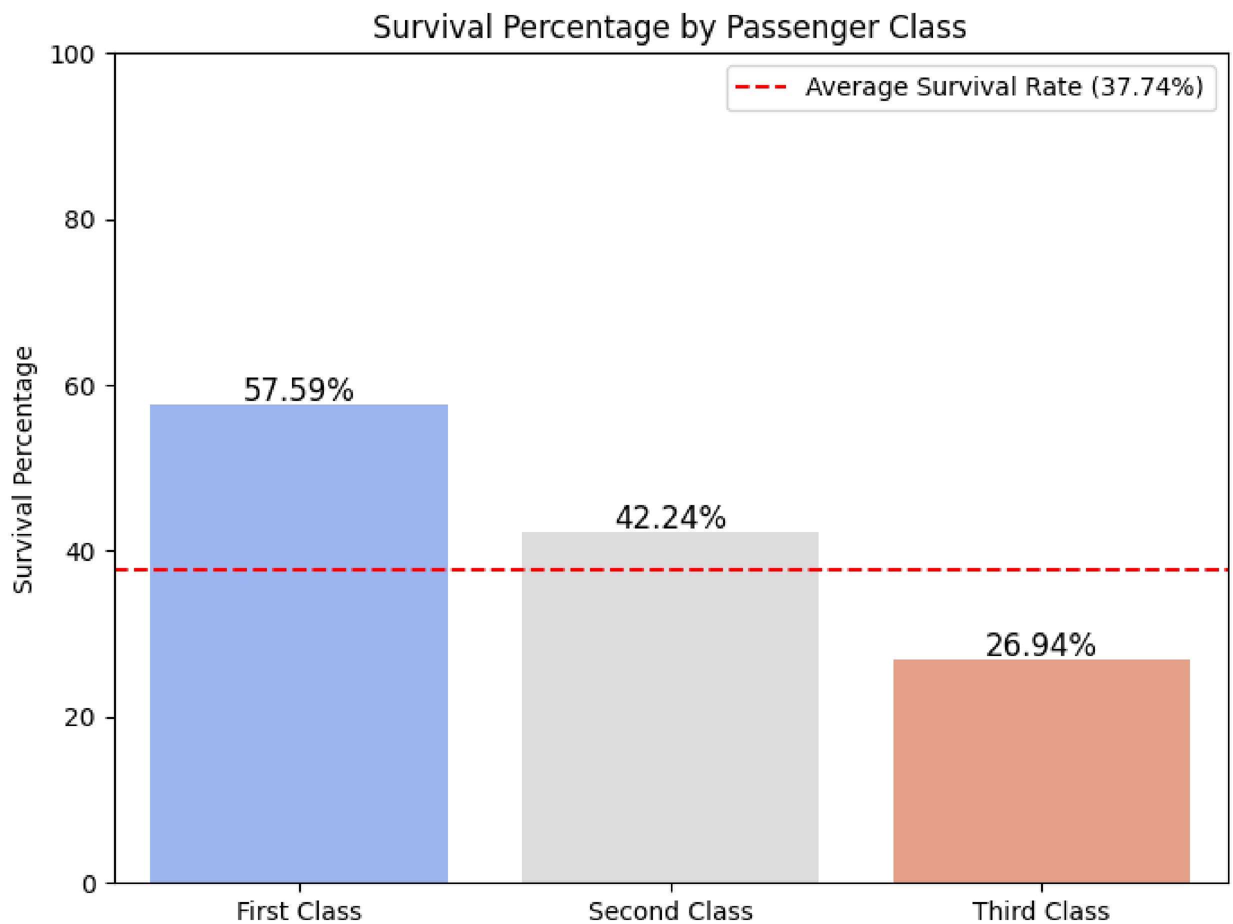
Calculate the overall survival percentage as a baseline control metric. This will serve as a reference point to compare survival rates across subsets of the dataset.

```
# Calculate variables for gender survival analysis
female_survivors = df[(df['Gender'] == 1) & (df['Survived'] ==
1)].shape[0]
male_survivors = df[(df['Gender'] == 0) & (df['Survived'] ==
1)].shape[0]

total_females = df[df['Gender'] == 1].shape[0]
total_males = df[df['Gender'] == 0].shape[0]

# Visualization 1: Survival by Gender
gender_labels = ['Female', 'Male']
gender_survival_rates = [
    (female_survivors / total_females) * 100 if total_females > 0 else
0,
    (male_survivors / total_males) * 100 if total_males > 0 else 0
]

# Plot the barplot
plt.figure(figsize=(8, 6))
ax = sns.barplot(x=gender_labels, y=gender_survival_rates,
palette=['#ff9999', '#66b3ff'])
plt.title('Survival Percentage by Gender')
plt.ylabel('Survival Percentage')
plt.ylim(0, 100)

# Add horizontal line at y=survival_percentage
plt.axhline(y=survival_percentage, color='r', linestyle='--',
label=f'Average Survival Rate ({survival_percentage})')

# Show the legend
plt.legend()

# Add the value labels on top of each bar
for p in ax.patches:
    ax.annotate(f'{p.get_height():.2f}%',
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center',
                fontsize=12, color='black',
                xytext=(0, 5), textcoords='offset points')

# Show the plot
plt.show()
```



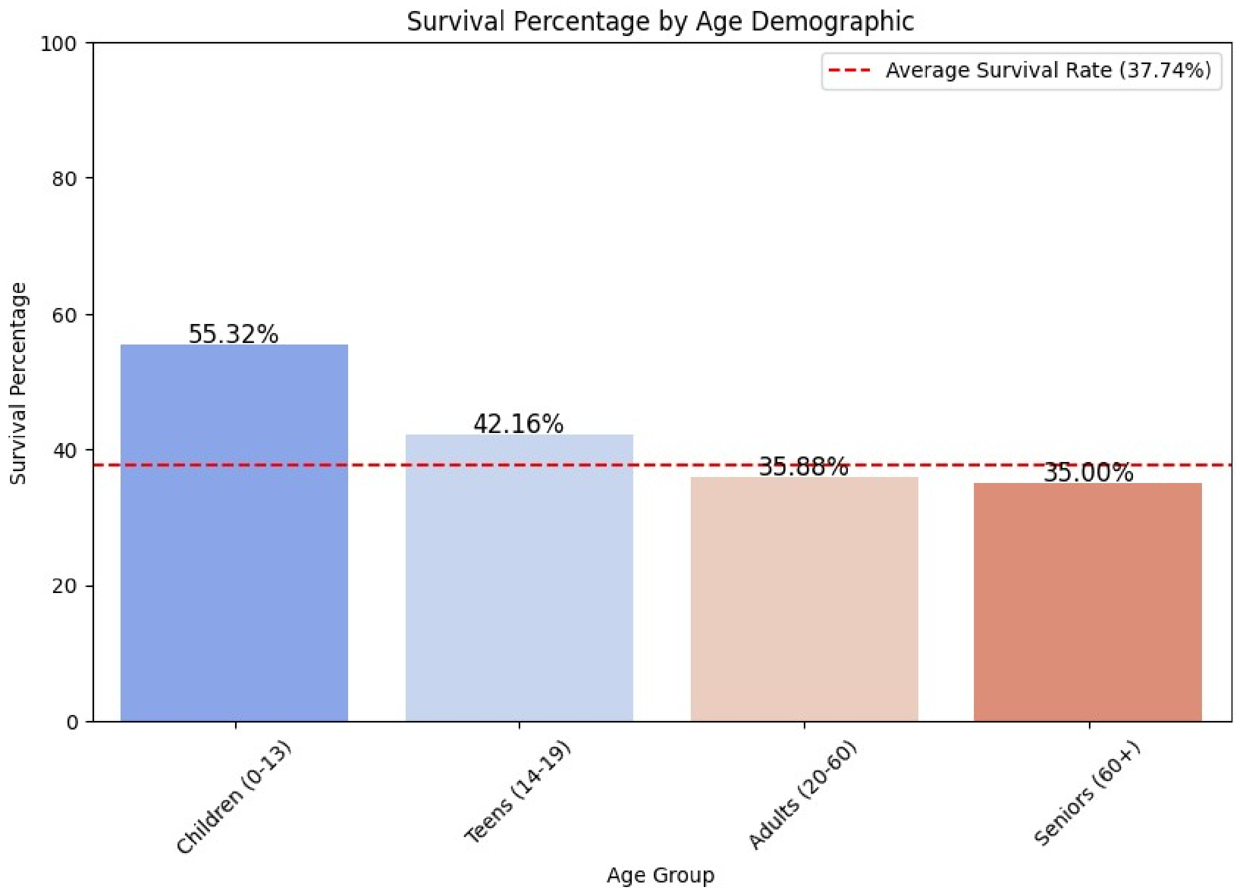

```
# Calculate variables for passenger class survival analysis
first_class_survivors = df[(df['Passenger_Class'] == 1) &
(df['Survived'] == 1)].shape[0]
second_class_survivors = df[(df['Passenger_Class'] == 2) &
(df['Survived'] == 1)].shape[0]
third_class_survivors = df[(df['Passenger_Class'] == 3) &
(df['Survived'] == 1)].shape[0]

total_first_class = df[df['Passenger_Class'] == 1].shape[0]
total_second_class = df[df['Passenger_Class'] == 2].shape[0]
total_third_class = df[df['Passenger_Class'] == 3].shape[0]

# Visualization 2: Survival by Passenger Class
class_labels = ['First Class', 'Second Class', 'Third Class']
class_survival_rates = [
    (first_class_survivors / total_first_class) * 100 if
total_first_class > 0 else 0,
    (second_class_survivors / total_second_class) * 100 if
total_second_class > 0 else 0,
    (third_class_survivors / total_third_class) * 100 if
total_third_class > 0 else 0
```

```
]

plt.figure(figsize=(8, 6))
ax = sns.barplot(x=class_labels, y=class_survival_rates,
palette='coolwarm')
plt.title('Survival Percentage by Passenger Class')
plt.ylabel('Survival Percentage')
plt.ylim(0, 100)

# Add horizontal line at y=survival_percentage
plt.axhline(y=survival_percentage, color='r', linestyle='--',
label=f'Average Survival Rate ({survival_percentage}%)')

# Show the legend
plt.legend()

# Add the value labels on top of each bar
for p in ax.patches:
    ax.annotate(f'{p.get_height():.2f}%',
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center',
                fontsize=12, color='black',
                xytext=(0, 5), textcoords='offset points')

# Show the plot
plt.show()
```




```
# Define age demographics
age_bins = [0, 13, 19, 60, 100]  # Children, Teens, Adults, Seniors
age_labels = ['Children (0-13)', 'Teens (14-19)', 'Adults (20-60)',
'Seniors (60+)']

# Add an age group column to the DataFrame
age_df = df.copy()
age_df['Age_Group'] = pd.cut(age_df['Age'], bins=age_bins,
labels=age_labels, right=False)

# Calculate survival percentages by age group
age_group_survivors = age_df[age_df['Survived'] ==
1].groupby('Age_Group').size()
age_group_totals = age_df.groupby('Age_Group').size()
age_group_survival_rates = (age_group_survivors / age_group_totals) *
100

# Visualization: Survival by Age Demographic
plt.figure(figsize=(10, 6))
ax = sns.barplot(x=age_group_survival_rates.index,
y=age_group_survival_rates, palette='coolwarm')
```

```python
plt.title('Survival Percentage by Age Demographic')
plt.xlabel('Age Group')
plt.ylabel('Survival Percentage')
plt.ylim(0, 100)
plt.xticks(rotation=45)

# Add horizontal line at y=survival_percentage
plt.axhline(y=survival_percentage, color='r', linestyle='--',
label=f'Average Survival Rate ({survival_percentage}%)')

# Show the legend
plt.legend()

# Add the value labels on top of each bar
for p in ax.patches:
    ax.annotate(f'{p.get_height():.2f}%',
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center',
                fontsize=12, color='black',
                xytext=(0, 5), textcoords='offset points')

# Show the plot
plt.show()
```

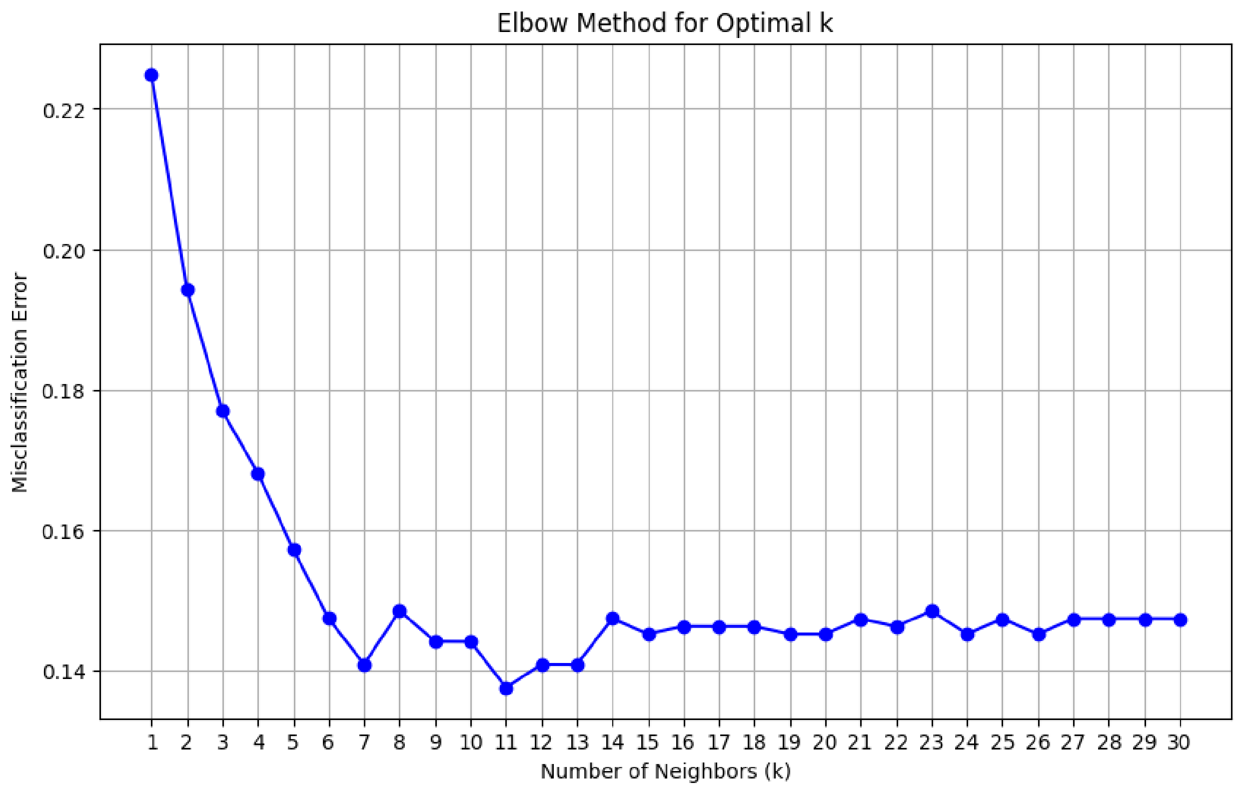



# (III) K-Nearest Neighbors (KNN)

```
print("Running K-Nearest Neighbors (KNN)...")

# Step 4: Find the optimal k using the Elbow Method
k_values = range(1, 31)  # Testing k from 1 to 30
cv_scores = []  # Store cross-validation scores

for k in k_values:
    knn = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn, X_train_standard, y_train, cv=10,
scoring="accuracy")  # 10-fold cross-validation
    cv_scores.append(scores.mean())

# Calculate the misclassification error for each k
error_rates = [1 - score for score in cv_scores]

# Step 5: Plot the Elbow Curve
plt.figure(figsize=(10, 6))
plt.plot(k_values, error_rates, marker='o', linestyle='-', color='b')
plt.title("Elbow Method for Optimal k")
plt.xlabel("Number of Neighbors (k)")
plt.ylabel("Misclassification Error")
```

```
plt.xticks(k_values)
plt.grid()
plt.show()

# Step 6: Select the best k (minimum error) and train the final model
optimal_k = k_values[np.argmin(error_rates)]
print(f"The optimal number of neighbors is k = {optimal_k}")
```

```
Running K-Nearest Neighbors (KNN)...
```




```
The optimal number of neighbors is k = 11
```

## K-Nearest Neighbors (KNN) with the Elbow Method

1. **Determine Optimal ( k )**:
   - Test ( k ) values ranging from 1 to 30.
   - Perform 10-fold cross-validation for each ( k ).
   - Calculate the average cross-validation score for accuracy.
   - Calculate the missclassification score.
2. **Train the Final Model**:
   - Select the ( k ) with the minimum missclassification score and use it to train the final KNN model.

```
distance_metrics = ['euclidean', 'manhattan',
'minkowski','cityblock','cosine','l1','l2','nan_euclidean']
```

```
for metric in distance_metrics:
    knn = KNeighborsClassifier(n_neighbors=optimal_k, metric=metric)
    knn.fit(X_train_standard, y_train)
    y_pred = knn.predict(X_test_standard)

    print(f"\nMetric: {metric}")
    print(f"Accuracy: {accuracy_score(y_test, y_pred)*100:.2f}%")
```

```
Metric: euclidean
Accuracy: 87.53%

Metric: manhattan
Accuracy: 88.80%

Metric: minkowski
Accuracy: 87.53%

Metric: cityblock
Accuracy: 88.80%

Metric: cosine
Accuracy: 87.53%

Metric: l1
Accuracy: 88.80%

Metric: l2
Accuracy: 87.53%

Metric: nan_euclidean
Accuracy: 87.53%
```

## Evaluating Distance Metrics for KNN

Various distance metrics were tested to assess their impact on KNN accuracy:

- **Best Performance:** Manhattan (and equivalents like Cityblock, L1) achieved the highest accuracy (88.80%).
- **Slightly Lower Accuracy**: Metrics like Euclidean, Minkowski, and Cosine scored 87.53%.
- **Key Insight**: The dataset aligns better with grid-like Manhattan calculations than straight-line (Euclidean) or angle-based (Cosine) measures.

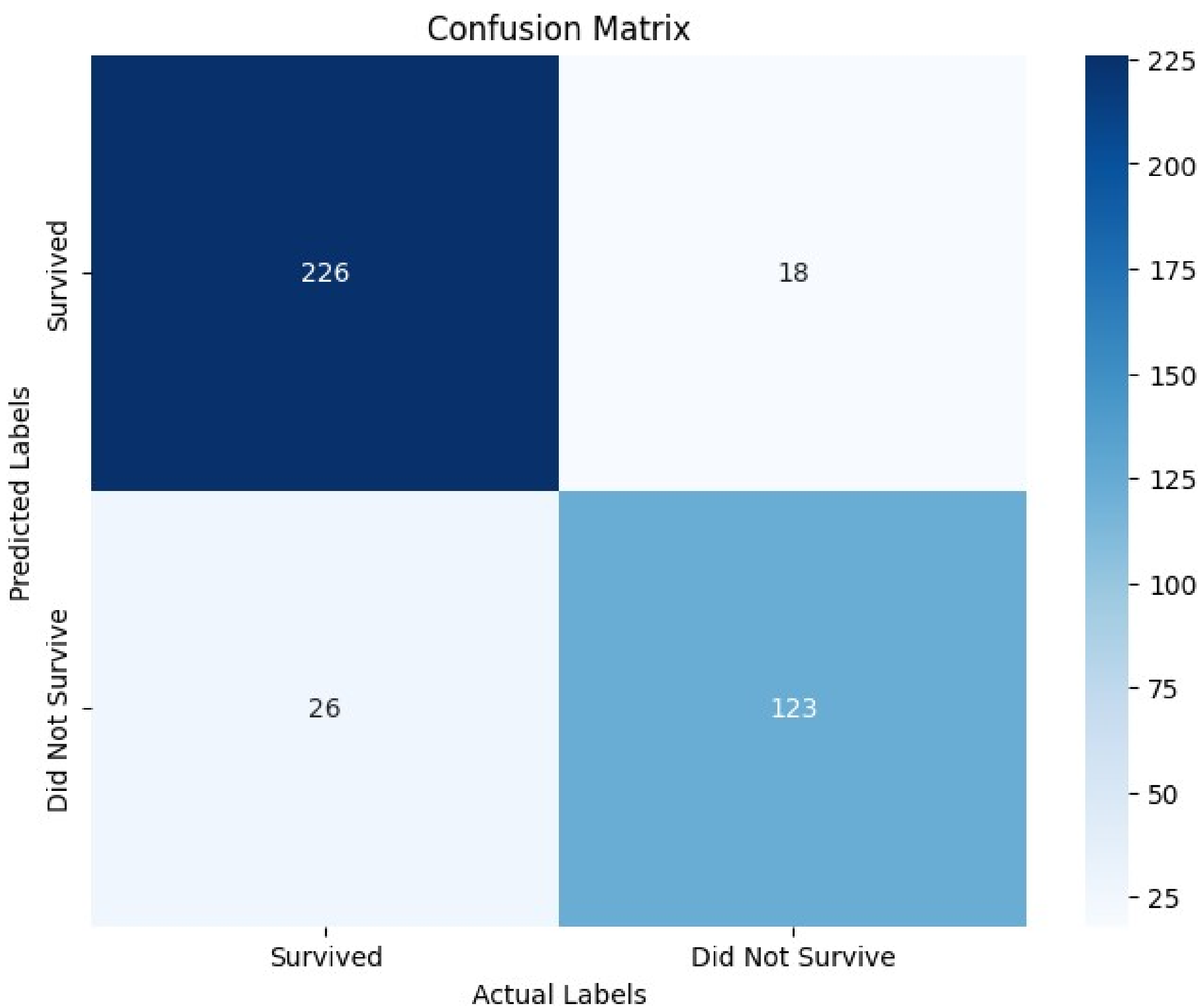
**Conclusion**: Manhattan-based metrics are more effective for this dataset, highlighting the importance of tailoring distance metrics to data characteristics.

```
start_time = time.time()
# Define the KNN model
k = optimal_k  # Number of neighbors (you can change this)
knn = KNeighborsClassifier(n_neighbors=k,metric='manhattan')
```

```
# Train the model
knn.fit(X_train_standard, y_train)

# Make predictions
train_predictions = knn.predict(X_train_standard)
test_predictions = knn.predict(X_test_standard)

# Calculate accuracies
training_accuracy = accuracy_score(y_train, train_predictions)*100
testing_accuracy = accuracy_score(y_test, test_predictions)*100

# Print results
print(f"Training Accuracy: {training_accuracy:.2f}%")
print(f"Testing Accuracy: {testing_accuracy:.2f}%")

knn_report=classification_report(y_test, test_predictions,
output_dict=True)
print(classification_report(y_test, test_predictions))

knn_train_time = time.time() - start_time
model_names.append("KNN")
training_accuracies.append(training_accuracy)
testing_accuracies.append(testing_accuracy)
runtimes.append(knn_train_time)
```

```
Training Accuracy: 86.24%
Testing Accuracy: 88.80%
              precision    recall  f1-score   support

           0       0.90      0.93      0.91       244
           1       0.87      0.83      0.85       149

    accuracy                           0.89       393
   macro avg       0.88      0.88      0.88       393
weighted avg       0.89      0.89      0.89       393
```

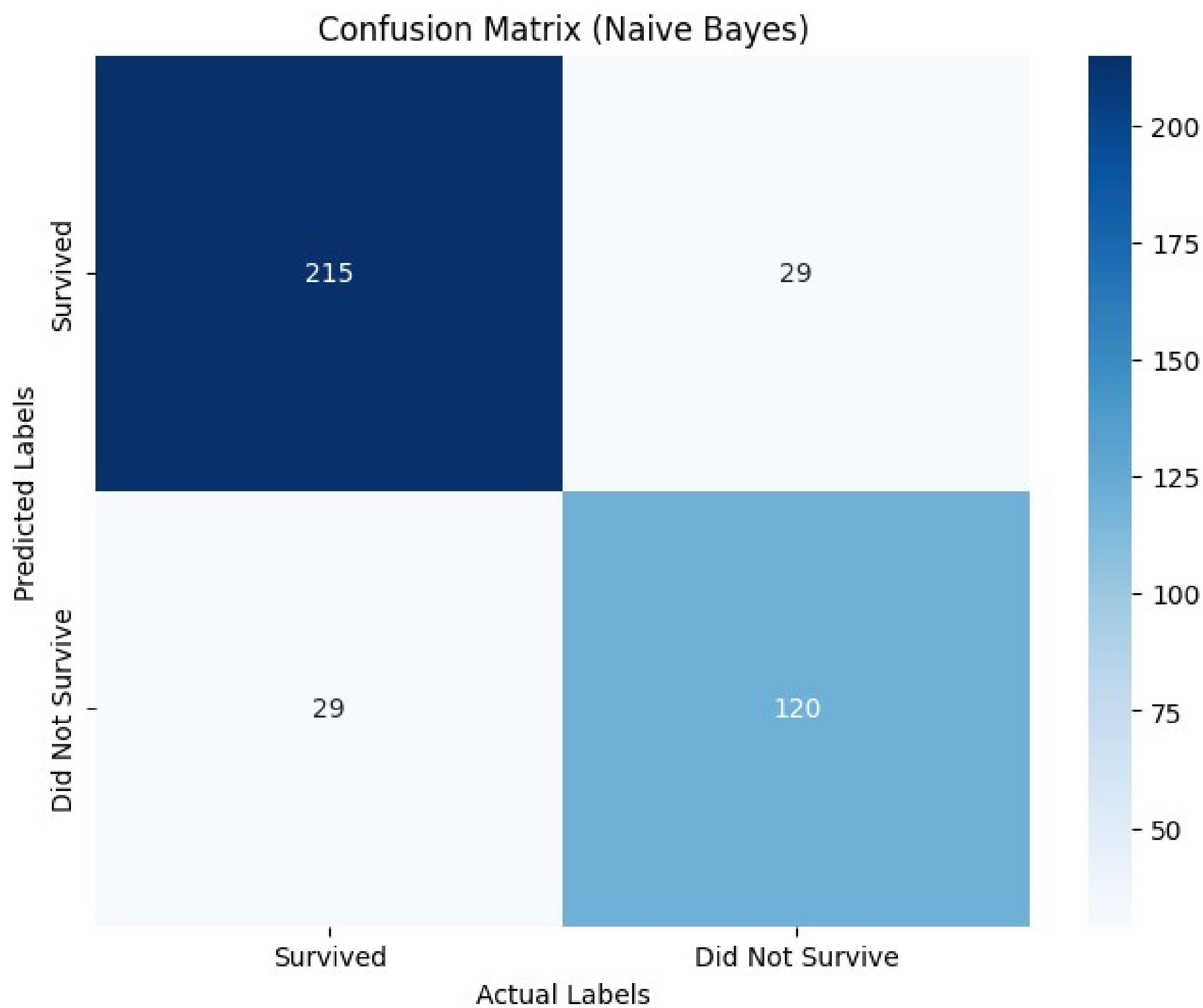
```
# Optional: Define class names
class_names = ['Survived', 'Did Not Survive']

# Plot using Seaborn heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(confusion_matrix(y_test, test_predictions), annot=True,
fmt='d', cmap='Blues', xticklabels=class_names,
yticklabels=class_names)
plt.title('Confusion Matrix')
plt.xlabel('Actual Labels')
plt.ylabel('Predicted Labels')
plt.show()
```




# (IV) Naive Bayes

```
start_time = time.time()
# Initialize Naive Bayes model
nb = GaussianNB()

# Fit the model
nb.fit(X_train_standard, y_train)

# Predict on the test data
y_pred_nb = nb.predict(X_test_standard)

# Calculate training time
nb_train_time = time.time() - start_time

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred_nb)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
```

```
xticklabels=class_names, yticklabels=class_names)
plt.title("Confusion Matrix (Naive Bayes)")
plt.xlabel("Actual Labels")
plt.ylabel("Predicted Labels")
plt.show()
```




## Confusion Matrix - Naive Bayes Classifier

The confusion matrix below summarizes the performance of the Naive Bayes classifier in predicting survival outcomes.

### Key Insights:

1. **True Positives (Top-Left, 215):**
   The model correctly predicted 215 individuals who survived.

2. **False Negatives (Bottom-Left, 29):**
   29 individuals who survived were incorrectly predicted as "Not Survived."

3. **False Positives (Top-Right, 29):**
   29 individuals who did not survive were incorrectly predicted as "Survived."

4. **True Negatives (Bottom-Right, 120):**
   The model correctly predicted 120 individuals who did not survive.

## Model Evaluation:

The model seems to perform well with balanced predictions for both survival and non-survival cases. False positives and false negatives are symmetric (29 each), suggesting the model does not favor one class heavily over the other. Additionally, the number of true predictions (True Positives: 215, True Negatives: 120) is significantly higher than the number of false predictions (False Positives: 29, False Negatives: 29), indicating the model's overall reliability in making accurate predictions.

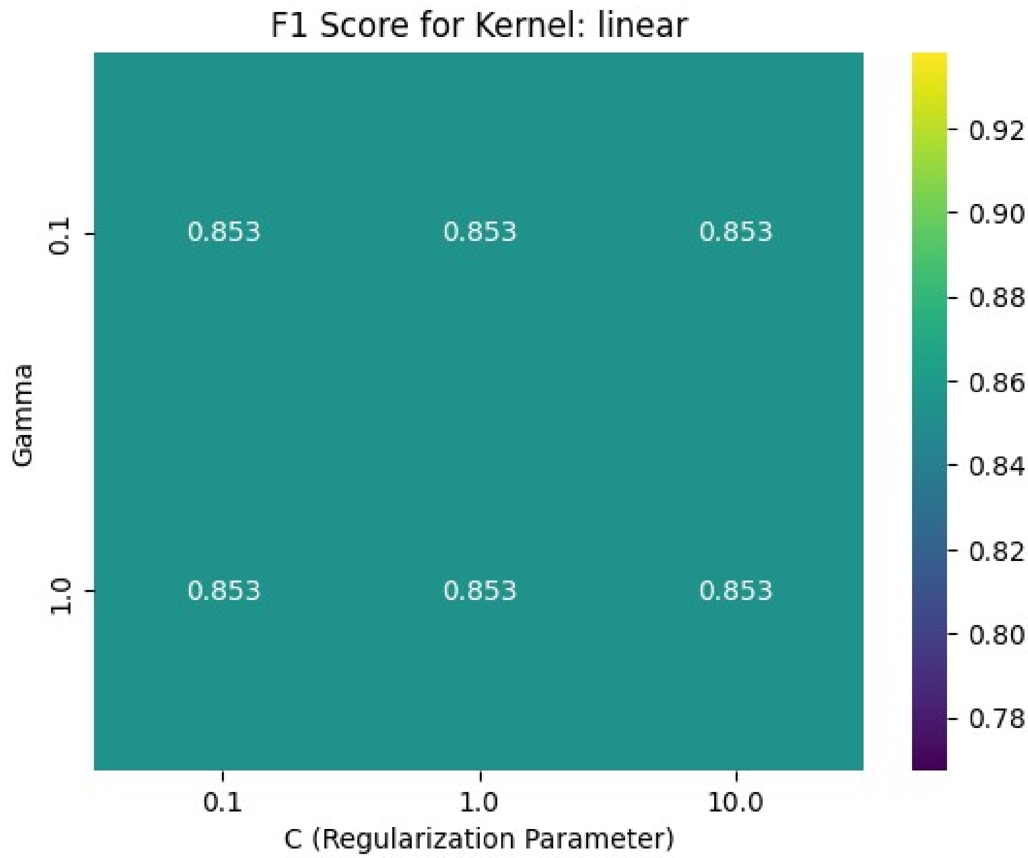
```
# Predict on training data
y_train_pred=nb.predict(X_train_standard)

# Calculate training accuracy
nb_training_accuracy = accuracy_score(y_train, y_train_pred)*100

print(f"Training Accuracy: {nb_training_accuracy:.2f}%")

# Calculate test accuracy
nb_test_accuracy = accuracy_score(y_test, y_pred_nb)*100

print(f"Test Accuracy: {nb_test_accuracy:.2f}%")

# Performance Metric
print("Naive Bayes Performance:")
nb_report=classification_report(y_test, y_pred_nb,output_dict=True)
print(classification_report(y_test, y_pred_nb))

model_names.append("Naive Bayes")
training_accuracies.append(nb_training_accuracy)
testing_accuracies.append(nb_test_accuracy)
runtimes.append(nb_train_time)

Training Accuracy: 84.50%
Test Accuracy: 85.24%
Naive Bayes Performance:
              precision    recall  f1-score   support

           0       0.88      0.88      0.88       244
           1       0.81      0.81      0.81       149

    accuracy                           0.85       393
   macro avg       0.84      0.84      0.84       393
weighted avg       0.85      0.85      0.85       393
```

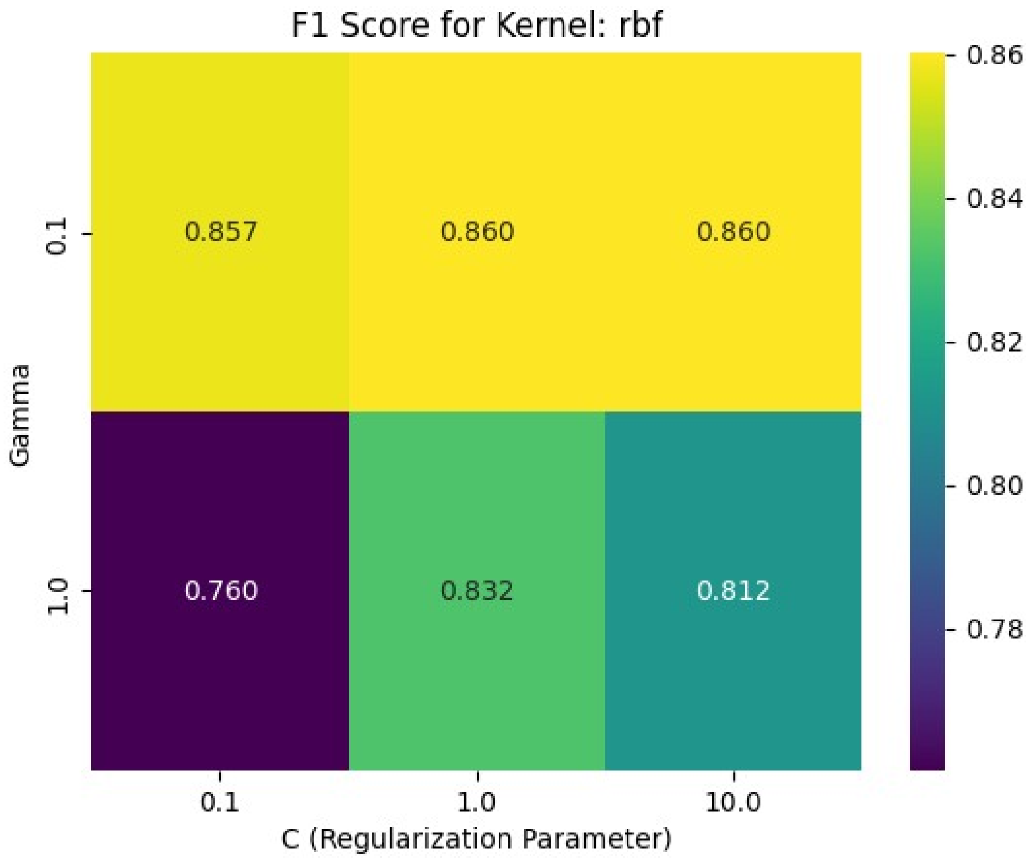
## (V) Support Vector Machine (SVM)

```
start_time = time.time()

# Experiment with different kernel functions and regularization
parameters
kernel_options = ['linear', 'rbf']
C_values = [0.1, 1, 10]
gamma_values = [0.1, 1]

svm_params = {
    'kernel': kernel_options,
    'C': C_values,
    'gamma': gamma_values
}

svm = SVC()

grid_search_svm = GridSearchCV(svm, svm_params, cv=3,
scoring='f1_weighted')
grid_search_svm.fit(X_train_standard, y_train)

best_svm = grid_search_svm.best_estimator_
print("Best SVM Parameters:", grid_search_svm.best_params_)
y_pred_svm = best_svm.predict(X_test_standard)

svm_train_time = time.time() - start_time
```

```
Best SVM Parameters: {'C': 10, 'gamma': 0.1, 'kernel': 'rbf'}
```

```
# Extract results from GridSearchCV
results = pd.DataFrame(grid_search_svm.cv_results_)
# Heatmap for F1-Score across C and gamma for each kernel type
for kernel in kernel_options:
    kernel_results = results[results['param_kernel'] == kernel]
    pivot_table = kernel_results.pivot_table(
        index='param_gamma',
        columns='param_C',
        values='mean_test_score'
    )
    sns.heatmap(pivot_table, annot=True, fmt=".3f", cmap="viridis")
    plt.title(f"F1 Score for Kernel: {kernel}")
    plt.xlabel("C (Regularization Parameter)")
    plt.ylabel("Gamma")
    plt.show()
```


F1 Score for Kernel: linear
Gamma
0.1
1.0
0.853
0.853
0.853
0.853
0.853
0.853
0.1
1.0
10.0
C (Regularization Parameter)
0.92
0.90
0.88
0.86
0.84
0.82
0.80
0.78




## Heatmap for F1-Score Across C and Gamma for Each Kernel Type

The following heatmaps visualize the F1-Score for each kernel type, varying with the regularization parameter `C` and the kernel coefficient `gamma`. These heatmaps were generated using the results from GridSearchCV applied to an SVM classifier.

Each heatmap shows the F1-Score as a function of the `C` and `gamma` parameters for the specified kernel type.

- **C**: The regularization parameter, controlling the trade-off between achieving a low error on the training data and minimizing the model complexity.
- **Gamma**: The kernel coefficient, influencing the decision boundary's flexibility.
- **Color Gradient**: Represents the F1 score, with brighter colors indicating better performanc

# Why are All F1 Scores Equal for the Linear Kernel?

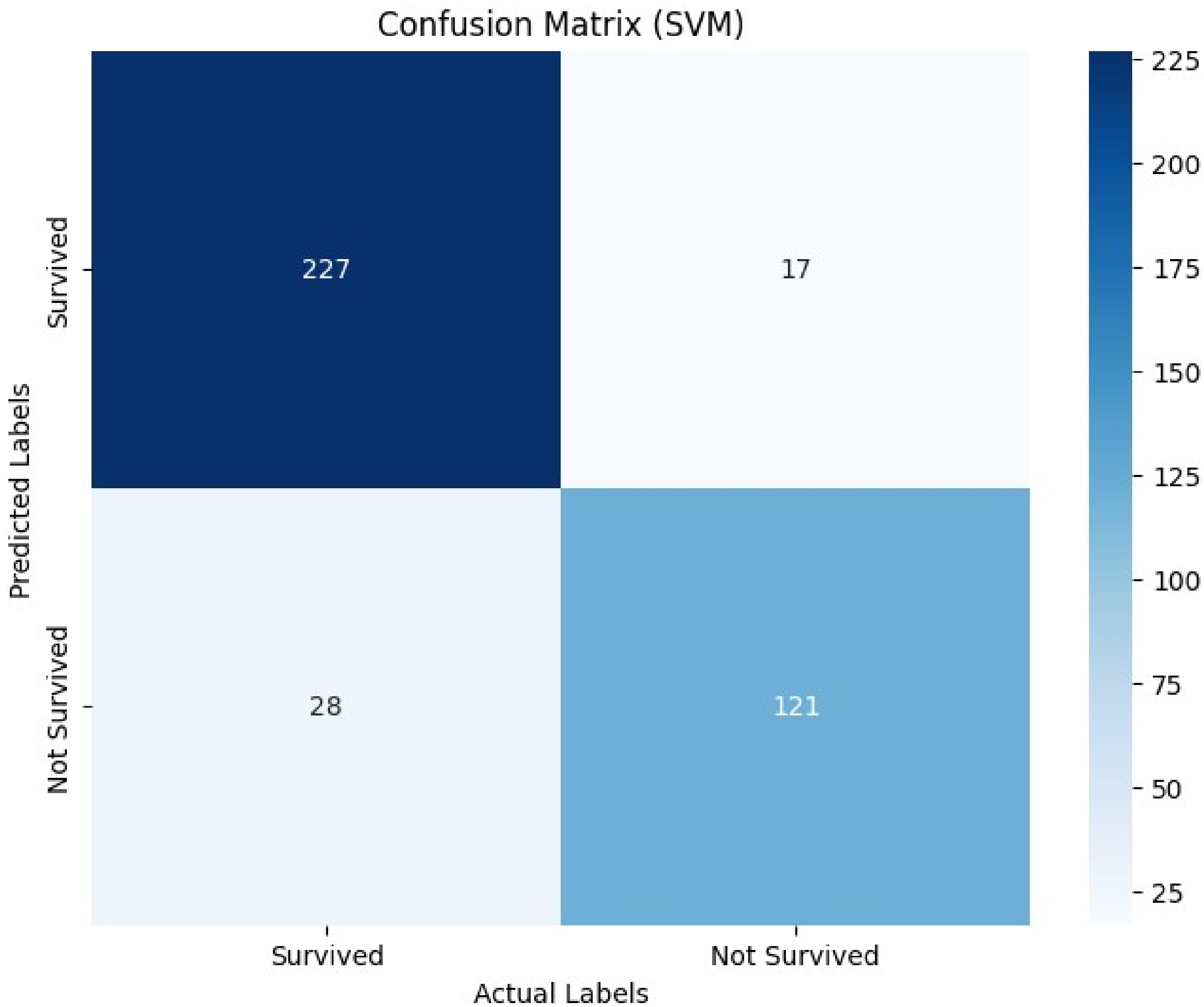
## Key Reasons:

1. **Gamma is Ignored**:

- The `linear` kernel does not use the `gamma` parameter, which explains why varying `gamma` has no effect.

2. **Minimal Impact of `C`**:
    - The regularization parameter `C` has little to no influence in this case, likely because the dataset is linearly separable or nearly so after preprocessing.
3. **Dataset Characteristics**:
    - The linear kernel already achieves optimal performance, making the F1 score constant across all combinations of `C` and `gamma`.

```python
# Calculate the confusion matrix
cm = confusion_matrix(y_test, y_pred_svm)
class_names = ['Survived', 'Not Survived']


# Plot the confusion matrix as a heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
xticklabels=class_names, yticklabels=class_names)
plt.title("Confusion Matrix (SVM)")
plt.xlabel("Actual Labels")
plt.ylabel("Predicted Labels")
plt.show()
```




# Confusion Matrix for SVM Model

The confusion matrix provides insights into the performance of the SVM model, highlighting the number of correctly and incorrectly classified samples.

## Matrix Overview:

- **True Positives (Top-Left, 227):**
  The model correctly predicted individuals who survived.

- **True Negatives (Bottom-Right, 121):**
  The model correctly identified individuals who did not survive.

- **False Positives (Top-Right, 17):**
  The model incorrectly predicted that individuals survived when they did not.

- **False Negatives (Bottom-Left, 28):**
  The model incorrectly predicted that individuals did not survive when they actually did.

## Model Evaluation:

The model performs well, indicating it is effective in predicting survival on the Titanic dataset. However, the model has slightly more False Negatives compared to False Positives, meaning it tends to miss some "Survived" cases.

**Conclusion**:

- The model demonstrates strong performance, with true predictions significantly outweighing false predictions, reflecting its effectiveness on the Titanic dataset.

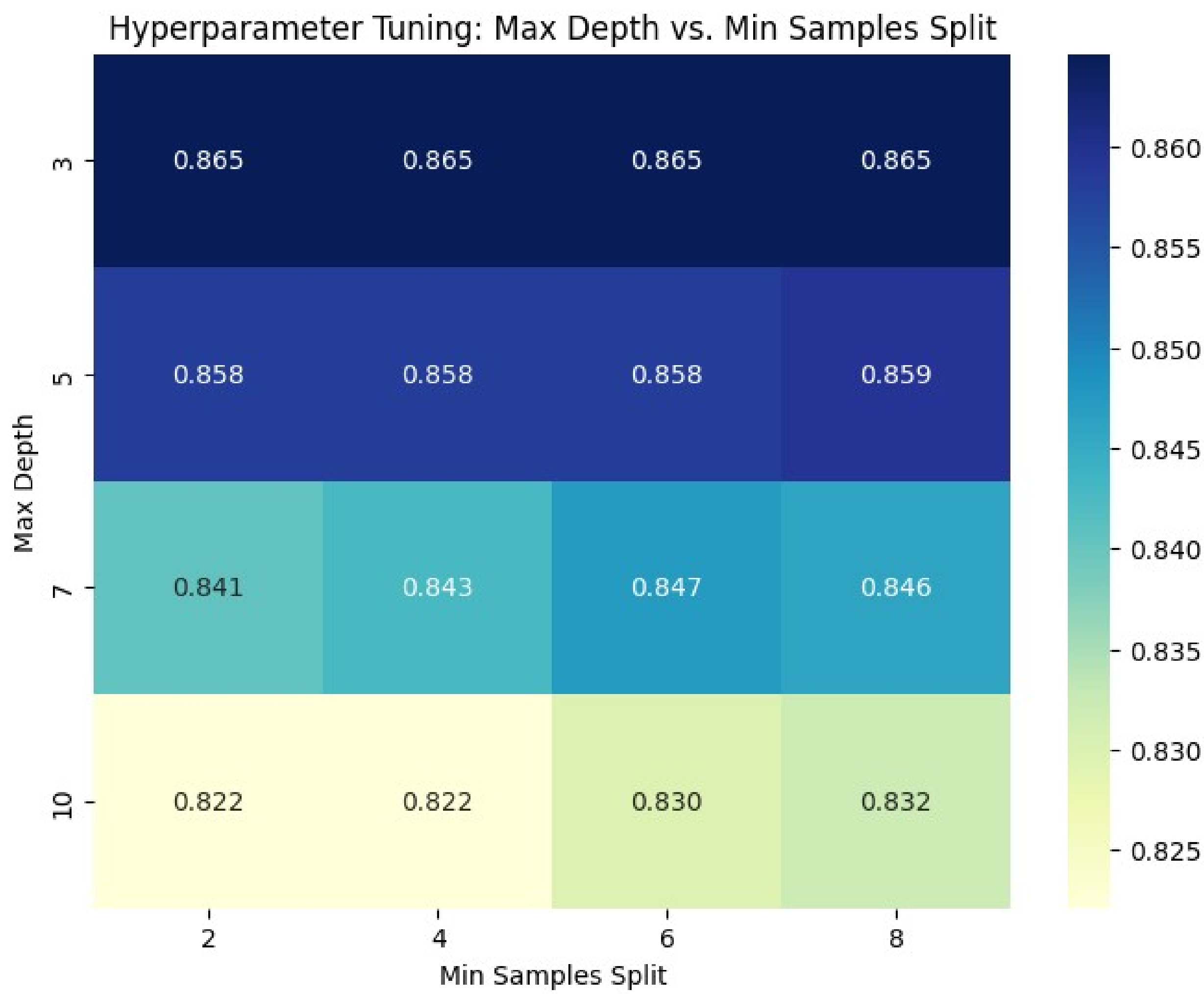
```
# Predict on training data
y_train_pred = best_svm.predict(X_train_standard)

# Calculate training accuracy
svm_training_accuracy = accuracy_score(y_train, y_train_pred)*100

print(f"Training Accuracy: {svm_training_accuracy:.2f}%")

# Calculate test accuracy
svm_test_accuracy = accuracy_score(y_test, y_pred_svm)*100

print(f"Test Accuracy: {svm_test_accuracy:.2f}%")

print("SVM Performance:")
svm_report=classification_report(y_test, y_pred_svm,output_dict=True)
print(classification_report(y_test, y_pred_svm))

model_names.append("SVM")
training_accuracies.append(svm_training_accuracy)
testing_accuracies.append(svm_test_accuracy)
runtimes.append(svm_train_time)
```

```
Training Accuracy: 87.66%
Test Accuracy: 88.55%
SVM Performance:
              precision    recall  f1-score   support

           0       0.89      0.93      0.91       244
           1       0.88      0.81      0.84       149

    accuracy                           0.89       393
   macro avg       0.88      0.87      0.88       393
weighted avg       0.89      0.89      0.88       393
```

# (VI) Decision Tree

```
# Define the parameter grid
param_grid = {
    'max_depth': [3, 5, 7, 10],
```

```
    'min_samples_split': [2, 4, 6, 8]
}

# Perform GridSearchCV
grid_search =
GridSearchCV(estimator=DecisionTreeClassifier(random_state=42),
                           param_grid=param_grid,
                           scoring='accuracy', cv=5)
grid_search.fit(X_train_minmax, y_train)

# Get the results into a DataFrame
results = pd.DataFrame(grid_search.cv_results_)

# Pivot the results for visualization
heatmap_data = results.pivot(index='param_max_depth',
columns='param_min_samples_split', values='mean_test_score')

# Plot heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(heatmap_data, annot=True, cmap='YlGnBu', fmt='.3f')
plt.title('Hyperparameter Tuning: Max Depth vs. Min Samples Split')
plt.xlabel('Min Samples Split')
plt.ylabel('Max Depth')
plt.show()
```




## Hyperparameter Tuning: Max Depth vs. Min Samples Split

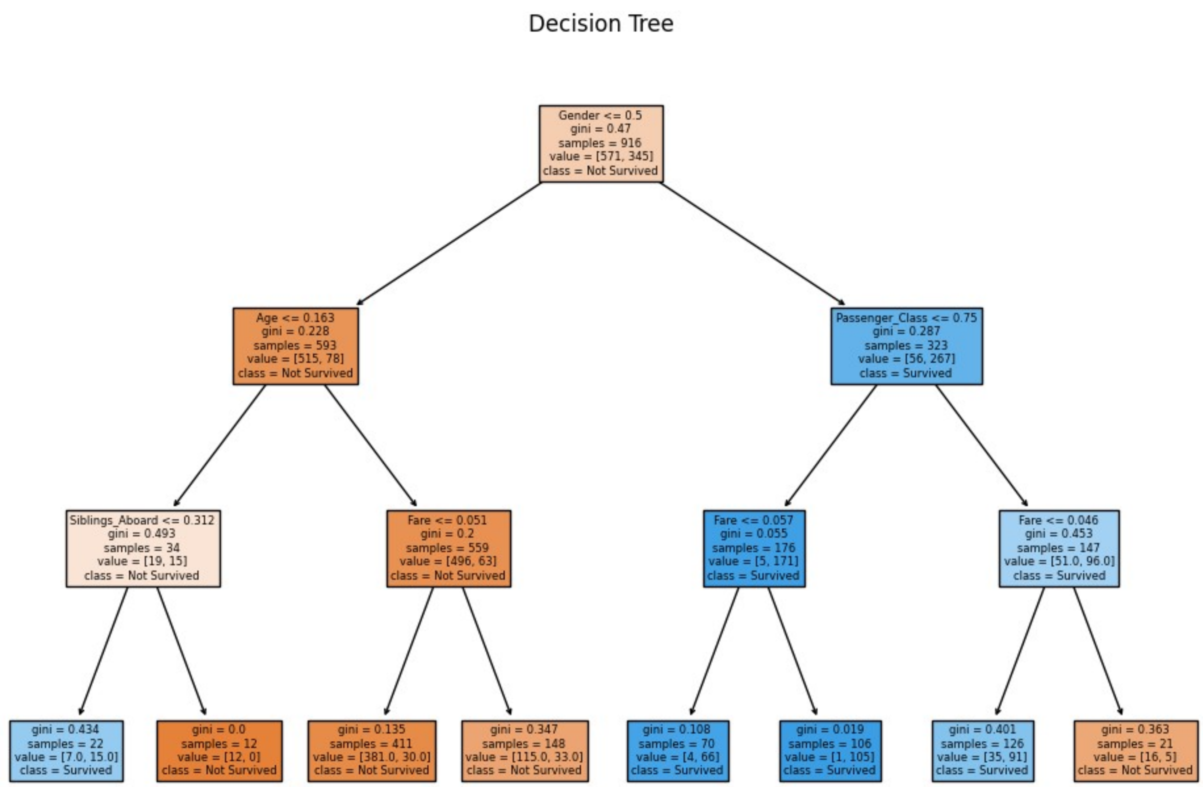
## Observations

1. **Max Depth**:
   - A smaller `max_depth` (e.g., 3) resulted in the highest accuracy (0.865) across all `min_samples_split` values.
   - Increasing `max_depth` reduced accuracy, especially with lower `min_samples_split`.
2. **Min Samples Split**:
   - The impact of `min_samples_split` was minimal at smaller `max_depth` values.
   - At higher `max_depth` values, increasing `min_samples_split` slightly improved performance.
3. **Overall Trends**:
   - Shallow trees with fewer splits tend to generalize better, as seen in this result.
   - The combination of `max_depth=3` and any value of `min_samples_split` achieved the optimal balance.

## Conclusion

- **Max Depth** is the most influential hyperparameter for this dataset.

```
start_time = time.time()

# Define the Decision Tree model
decision_tree = DecisionTreeClassifier(
    max_depth=3,                # Limit the depth of the tree
    min_samples_split=4,        # Minimum samples needed to split a
node
    min_samples_leaf=2,         # Minimum samples in a leaf node
    max_leaf_nodes=10,          # Maximum number of leaf nodes
    random_state=42
)

# Train the model
decision_tree.fit(X_train_minmax, y_train)

# Make predictions
train_predictions = decision_tree.predict(X_train_minmax)
test_predictions = decision_tree.predict(X_test_minmax)
tree_train_time = time.time() - start_time

# Visualize the tree
plt.figure(figsize=(12, 8))
plot_tree(decision_tree, feature_names=X.columns,class_names=['Not
Survived', 'Survived'], filled=True)
plt.title("Decision Tree")
plt.show()
```




- **DecisionTreeClassifier**: A supervised learning algorithm used for classification tasks.

## Observations

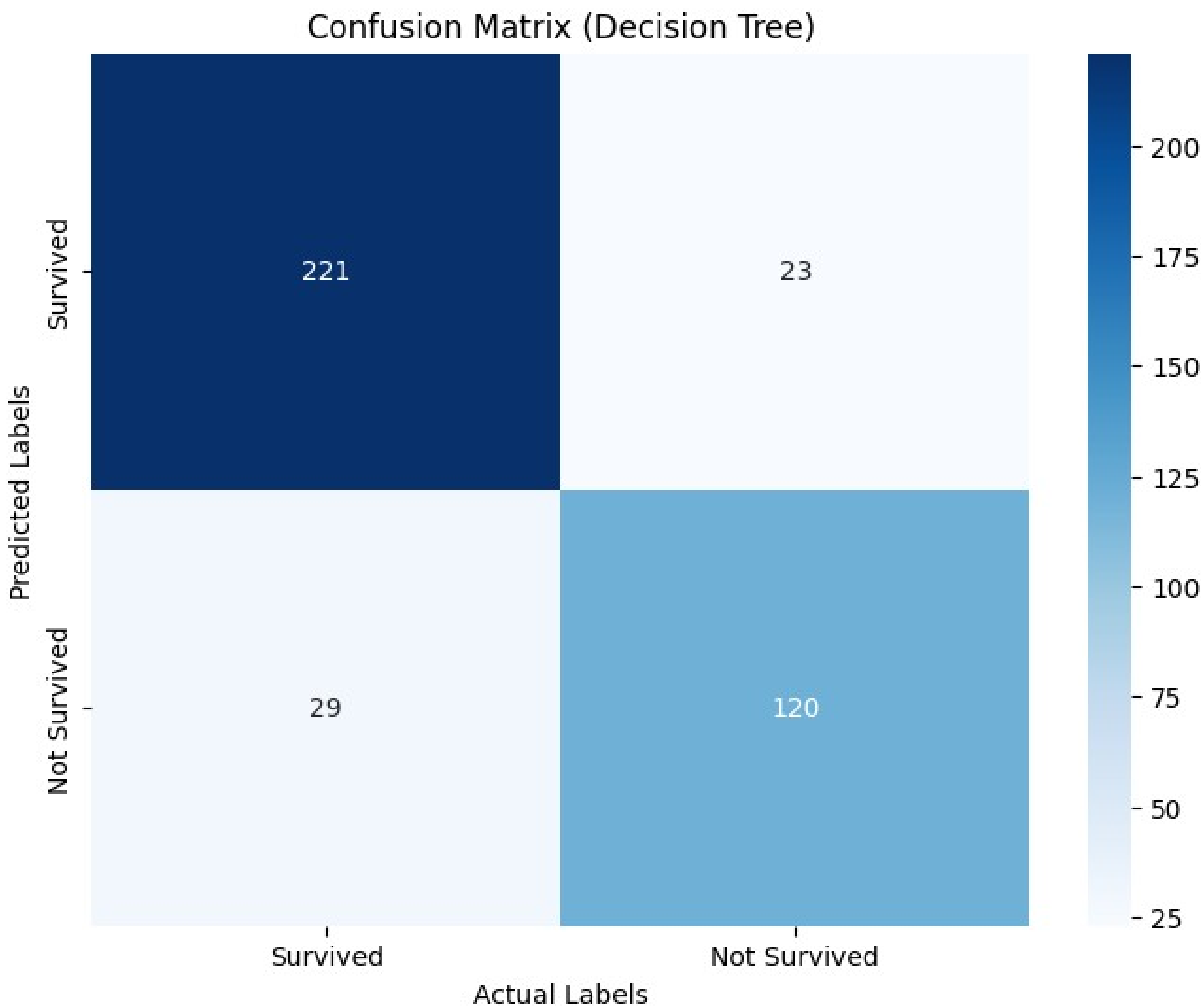
1. **Gender Influence**:
   - Female passengers (right subtree) had a higher survival rate.
   - Male passengers (left subtree) had a lower survival rate.
2. **Age and Fare**:
   - For females, **higher fares** and **Passenger Class** improved survival probability.
   - Among males, **younger ages** and **lower fares** improved survival probability.
3. **Pure Nodes**:
   - Some nodes (Gini = 0.0, 0.019) indicate near-perfect classification, where all samples belong to one class.

## Conclusion

- **Gender** is the most critical predictor of survival.
- **Fare, Age**, and **Passenger Class** are significant secondary predictors..

```
# Calculate the confusion matrix
cm = confusion_matrix(y_test, test_predictions)

# Plot the confusion matrix as a heatmap
plt.figure(figsize=(8, 6))
```

```
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
xticklabels=class_names, yticklabels=class_names)
plt.title("Confusion Matrix (Decision Tree)")
plt.xlabel("Actual Labels")
plt.ylabel("Predicted Labels")
plt.show()
```




**The confusion matrix illustrates how good of a choice the decision model has been, so far, for the survivors' prediction, with the true positives/negatives dominating the matrix.**

```
# Calculate accuracies
tree_training_accuracy = accuracy_score(y_train,
train_predictions)*100
tree_testing_accuracy = accuracy_score(y_test, test_predictions)*100

# Print results
print(f"Training Accuracy: {tree_training_accuracy:.2f}%")
print(f"Testing Accuracy: {tree_testing_accuracy:.2f}%")
```

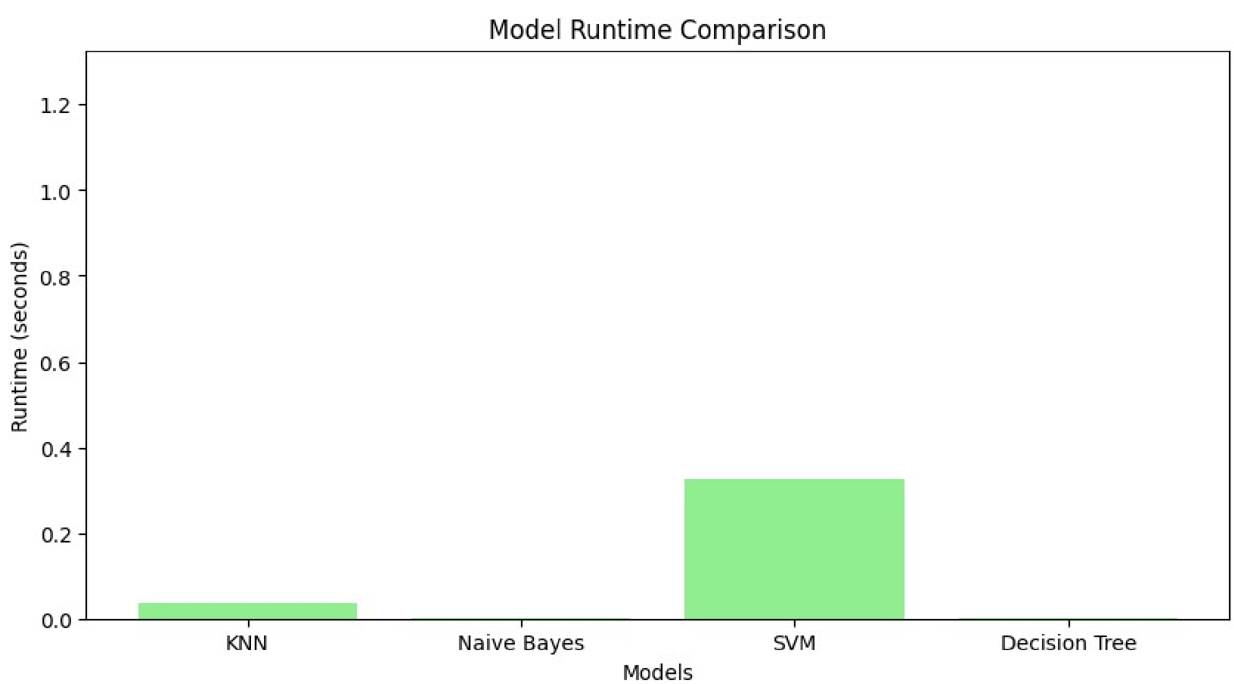
```
tree_report=classification_report(y_test,
test_predictions,output_dict=True)
print(classification_report(y_test, test_predictions))

model_names.append("Decision Tree")
training_accuracies.append(tree_training_accuracy)
testing_accuracies.append(tree_testing_accuracy)
runtimes.append(tree_train_time)
```

```
Training Accuracy: 87.45%
Testing Accuracy: 86.77%
              precision    recall  f1-score   support

           0       0.88      0.91      0.89       244
           1       0.84      0.81      0.82       149

    accuracy                           0.87       393
   macro avg       0.86      0.86      0.86       393
weighted avg       0.87      0.87      0.87       393
```

# (VII) Results Comparison

```
results = {
    'Algorithm': model_names,
    'Training Accuracy': training_accuracies,
    'Testing Accuracy': testing_accuracies,
    'Runtime (seconds)': runtimes,
    'Class 0 Precision': [
        knn_report['0']['precision'],
        nb_report['0']['precision'],
        svm_report['0']['precision'],
        tree_report['0']['precision']
    ],
    'Class 1 Precision': [
        knn_report['1']['precision'],
        nb_report['1']['precision'],
        svm_report['1']['precision'],
        tree_report['1']['precision']
    ],
    'Class 0 Recall': [
        knn_report['0']['recall'],
        nb_report['0']['recall'],
        svm_report['0']['recall'],
        tree_report['0']['recall']
    ],
    'Class 1 Recall': [
        knn_report['1']['recall'],
```

```
        nb_report['1']['recall'],
        svm_report['1']['recall'],
        tree_report['1']['recall']
    ],
    'Class 0 F1-Score': [
        knn_report['0']['f1-score'],
        nb_report['0']['f1-score'],
        svm_report['0']['f1-score'],
        tree_report['0']['f1-score']
    ],
    'Class 1 F1-Score': [
        knn_report['1']['f1-score'],
        nb_report['1']['f1-score'],
        svm_report['1']['f1-score'],
        tree_report['1']['f1-score']
    ]
}

# Convert to DataFrame
results_df = pd.DataFrame(results)

# Visualization for Runtime
plt.figure(figsize=(10, 5))
plt.bar(model_names, runtimes, color='lightgreen')
plt.xlabel('Models')
plt.ylabel('Runtime (seconds)')
plt.title('Model Runtime Comparison')
plt.ylim(0, max(runtimes) + 1)
plt.show()
```



## Conclusion

In evaluating the four machine learning algorithms for predicting Titanic survivors, their execution time was compared to assess computational efficiency.

---

## Summary of Findings

- **KNN**: Had the average runtime out of the four.
- **Naive Bayes** and **Decision Tree**: Had an almost zero runtime, performing the computations with very hgih speed.

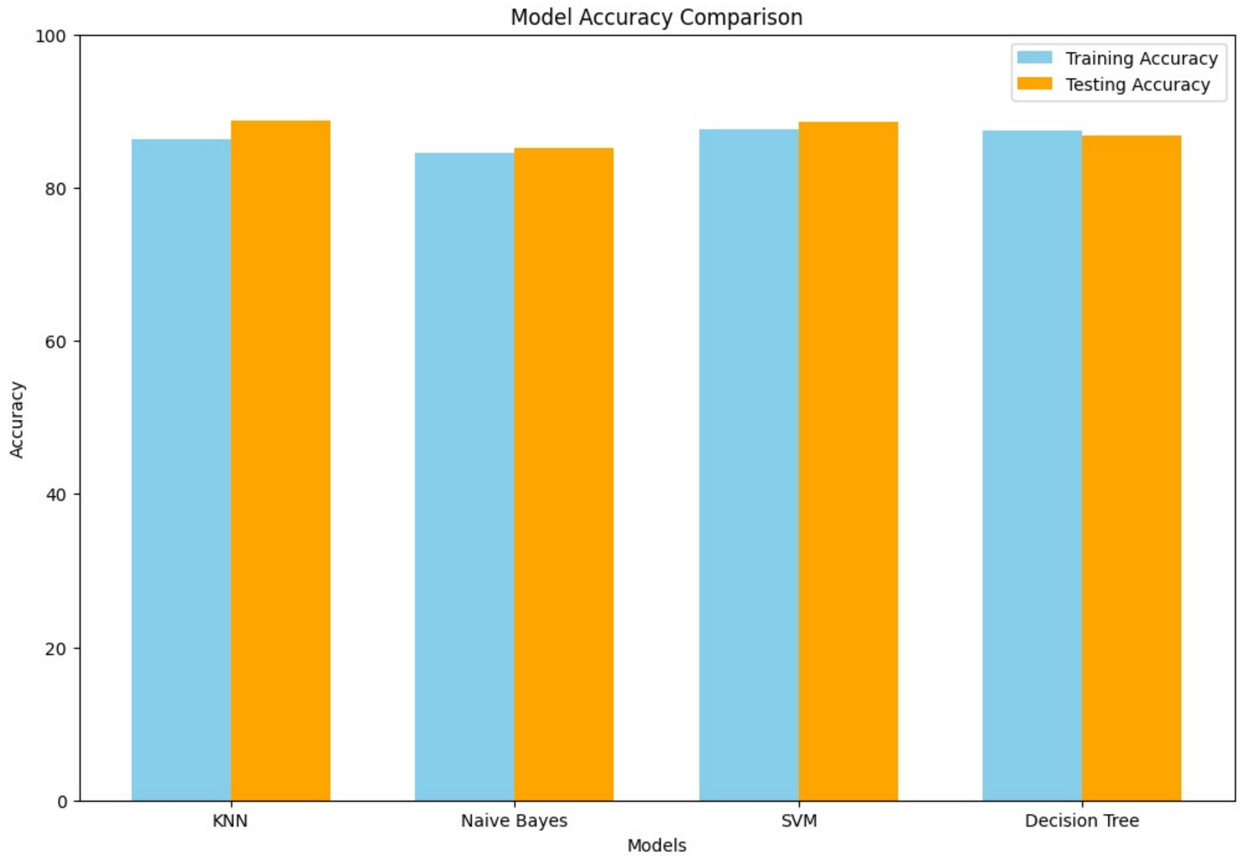
- **SVM**: Had the highest runtime, indicating that it is the most computationally intensive model.

## Final Recommendation

**SVM** offers strong performance but its high runtime may limit use for large datasets or real-time applications.

For faster execution, **Naive Bayes, Decision Tree, and KNN** are recommended for their efficiency. If runtime is not a concern, **SVM** is a strong choice for its balanced performance across all metrics.

```
# Visualization for Accuracy
plt.figure(figsize=(12, 8))
x = np.arange(len(model_names))
bar_width = 0.35

plt.bar(x - bar_width / 2, training_accuracies, width=bar_width,
label='Training Accuracy', color='skyblue')
plt.bar(x + bar_width / 2, testing_accuracies, width=bar_width,
label='Testing Accuracy', color='orange')

plt.xlabel('Models')
plt.ylabel('Accuracy')
plt.title('Model Accuracy Comparison')
plt.xticks(x, model_names)
plt.ylim(0, 100)
plt.legend()
plt.show()
```




## Conclusion

The image shows a comparison of the training accuracy and testing accuracy for four different machine learning models: KNN, Naive Bayes, SVM, and Decision Tree.

In predicting Titanic survivors, the four machine learning algorithms were evaluated based on the following performance metrics:

## Summary of Findings

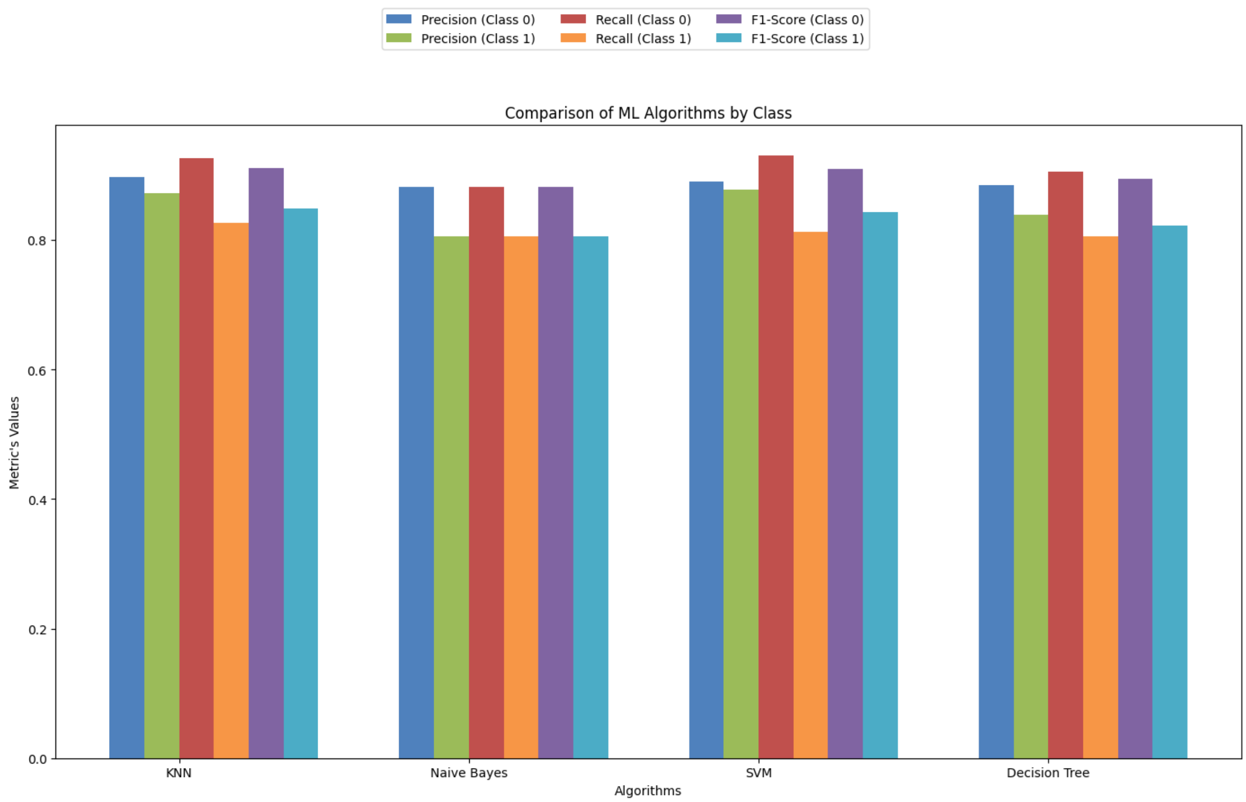
- **KNN**: The testing accuracy is slightly higher than the training accuracy, indicating apparent but small level of underfitting.
- **Naive Bayes**: The lowest training and testing accuracy.
- **SVM**: The highest training and testing accuracy.
- **Decision Tree**: The training accuracy is slightly higher than the testing accuracy, indicating apparent but small level of overfitting.

### Final Recommendation

- Ordering the models based on the smallest gaps between training and testing accuracy (The smaller the gap, the better the generalization of data):

1. **Naive Bayes**
2. **Decision Tree**
3. **SVM**
4. **KNN**

```
# Visualization
fig, ax1 = plt.subplots(figsize=(14, 8))

bar_width = 0.12
index = np.arange(len(results_df['Algorithm']))  # Default index for each algorithm

# Plot bars for Class 0 and Class 1 Precision
ax1.bar(index - 1.5 * bar_width, results_df['Class 0 Precision'], bar_width, label='Precision (Class 0)', color='#4F81BD')
ax1.bar(index - 0.5 * bar_width, results_df['Class 1 Precision'], bar_width, label='Precision (Class 1)', color='#9BBB59')

# Plot bars for Class 0 and Class 1 Recall
ax1.bar(index + 0.5 * bar_width, results_df['Class 0 Recall'], bar_width, label='Recall (Class 0)', color='#C0504D')
ax1.bar(index + 1.5 * bar_width, results_df['Class 1 Recall'], bar_width, label='Recall (Class 1)', color='#F79646')

# Plot bars for Class 0 and Class 1 F1-Score
ax1.bar(index + 2.5 * bar_width, results_df['Class 0 F1-Score'], bar_width, label='F1-Score (Class 0)', color='#8064A2')
ax1.bar(index + 3.5 * bar_width, results_df['Class 1 F1-Score'], bar_width, label='F1-Score (Class 1)', color='#4BACC6')

# Set labels, title, and ticks
ax1.set_xlabel('Algorithms')
ax1.set_ylabel("Metric's Values")
ax1.set_title('Comparison of ML Algorithms by Class')
ax1.set_xticks(index)
ax1.set_xticklabels(results_df['Algorithm'])

# Add legends
fig.legend(loc="lower center", bbox_to_anchor=(0.5, 1.05), ncol=3)

# Show plot
plt.tight_layout()
plt.show()
```




## Conclusion

In predicting Titanic survivors, the four machine learning algorithms were evaluated based on the following performance metrics:

1. **Precision**

2. **Recall**

3. **F1 Score**

### Summary of Findings

- **KNN**: Had the best performance for recall and f1-score on both survivors and non-survivors.

- **Naive Bayes**: Had relatively lower performance compared to its counterparts.

- **SVM** and **Decision Tree**: Had a strong and balanced performance across all metrics.

### Final Recommendation

- While an algorithm (Naive Bayes) showed lower performance than the rest,
- still the four algorithms are on the higher spectrum of the scale and all shared consistently high performance across all metric values
- **Thus, the four models recommended for Titanic survival prediction, with slight reservations regarding the Naive Bayes algorithm.**