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FACULTY OF ENGINEERING AND ARCHITECTURE

DEPT. OF COMPUTER ENGINEERING

DATA MINING FALL TERM PROJECT

Performance Comparison of Decision Tree and Random Forest Classifiers: Titanic Dataset

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1) Introduction

1.1 Project Objective

The aim of this project is to predict a target variable using a Decision Tree Classifier and a Random Forest Classifier while analyzing their performance. During the analysis, the effects of data preparation, hyperparameter tuning, and performance metrics are thoroughly examined.

The Titanic dataset is used for this analysis to model the target variable Survived (survival status) and compare the performance of a Decision Tree model and a Random Forest model.

1.2 Problem Definition

The following research question has been addressed as part of this analysis:

- Is it possible to predict the target variable (survival status) using a Decision Tree model?
- What are the differences in the performance metrics (accuracy, precision, recall, F1 score, etc.) between the Decision Tree model and the Random Forest model?

To answer these questions, the following steps were performed:

1. Trained the Decision Tree Classifier and Random Forest Classifier.
2. Conducted analysis on missing values and categorical variables in the dataset and performed necessary preprocessing.
3. Optimized hyperparameters for both models and conducted training on the preprocessed data.
4. Evaluated both models' performance metrics and compared their results through visualization.

1.3 General Explanation of the Algorithms Used

Decision Tree Classifier: Decision Trees split data based on feature conditions, creating a flowchart-like structure that determines decisions. They are widely used for classification and regression problems due to their simplicity and interpretability.

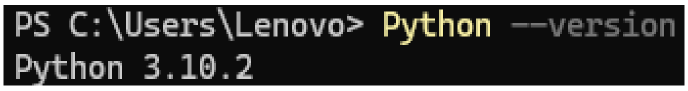
Random Forest Classifier: Random Forests are an ensemble learning method that uses a combination of multiple decision trees. They reduce overfitting by averaging the outputs of many decision trees and ensure better generalization performance compared to a single Decision Tree.

In this report, the performance comparison of these two models was conducted to determine which model performed better under given conditions.

2) Environment Setup and Library Installation

2.1 Setting up the Python Environment

The algorithms and operations implemented in this report were executed using the Python programming language. The version of Python used is as follows:



```
PS C:\Users\Lenovo> Python --version
Python 3.10.2
```

Figure 1: Python Version

2.2 Required Libraries

The machine learning models and data visualization tasks rely on the following Python libraries:

Library	Purpose
pandas	Used for data manipulation and preprocessing tasks.
numpy	Used for numerical operations and mathematical computations.
scikit-learn	Provides machine learning algorithms and model evaluation metrics.
matplotlib	For visualization of graphs and plots.
seaborn	Enhances visualization aesthetics and enables statistical visualizations.

These libraries are critical for implementing the Decision Tree, Random Forest models, and their evaluation, as well as for preprocessing and visualization.

2.3 Installation Instructions

Before running the code, ensure that all required dependencies are installed. These dependencies can be installed using the following command:

- pip install pandas numpy scikit-learn matplotlib seaborn

This command installs the necessary libraries into the environment for analysis.

3) Dataset Selection and Analysis

3.1 Dataset Overview

The dataset utilized in this analysis is the Titanic dataset, which is a widely used benchmark dataset for classification problems in machine learning. This dataset contains information about passengers aboard the Titanic and is commonly used to predict whether a passenger survived or did not survive based on various features.

The Titanic dataset provides insights into real-world classification tasks, featuring a mix of numerical and categorical variables that require preprocessing and feature engineering for effective model performance. This section will detail the structure, variables, and context of the selected dataset.

3.2 Dataset Source

The dataset was sourced from the well-known Kaggle Titanic dataset repository. The link to the dataset is provided below:

https://www.kaggle.com/c/titanic

This dataset is publicly available, widely validated, and contains real-world passenger data for machine learning experimentation.

3.3 Reason for Dataset Selection

The Titanic dataset was selected for this study because:

- **Relevance to Classification Tasks:** The target variable (Survived) represents a clear binary classification problem (0 = not survived, 1 = survived), which is ideal for supervised classification techniques such as Decision Trees and Random Forests.
- **Feature Diversity:** The dataset contains a mix of numerical features (e.g., Age, Fare) and categorical features (e.g., Sex, Embarked), making it suitable for preprocessing, feature selection, and encoding methods.
- **Prevalence in Machine Learning Education:** The Titanic dataset is a standard dataset for learning and experimenting with classification algorithms, offering sufficient complexity without overwhelming computational resources.
- **Demonstrative Analysis:** By using this dataset, we could demonstrate the effects of preprocessing (e.g., handling missing data and encoding), hyperparameter tuning, feature scaling, and model evaluation using real-world-like scenarios.

3.4 Dataset Characteristics

The Titanic dataset includes both training and testing subsets with specific columns relevant to the survival prediction problem. Key columns include:

- **Pclass:** Class of the cabin (1st, 2nd, or 3rd class) of the passenger.
- **Sex:** Gender of the passenger.
- **Age:** Age of the passenger (numerical, with missing values).
- **SibSp:** Number of siblings/spouses aboard the Titanic with the passenger.
- **Parch:** Number of parents/children aboard the Titanic with the passenger.
- **Fare:** The amount paid by the passenger for the ticket (numerical, with missing values).
- **Embarked:** Port of embarkation (categorical: C = Cherbourg, Q = Queenstown, S = Southampton).
- **Survived:** Target variable, where 0 = not survived and 1 = survived.

The dataset's training set is used to train the machine learning models, while the testing set serves as an evaluation benchmark to determine the predictive performance of the trained models.

3.5 Data Details

The Titanic dataset contains 891 rows in the training set and 418 rows in the test set, as per the provided Kaggle dataset split. Missing values exist in some columns, particularly Age, Fare, and Embarked. Handling these missing values was critical for preprocessing and ensured the robustness of machine learning model performance.

Key observations about the dataset's features:

Feature	Type	Missing Values	Description
Pclass	Numerical	0	Class of the cabin (1st, 2nd, or 3rd class).
Sex	Categorical	0	Gender of the passenger (male or female).
Age	Numerical	Present (some missing values)	Age of the passenger.
SibSp	Numerical	0	Number of siblings or spouses aboard.
Parch	Numerical	0	Number of parents or children aboard.
Fare	Numerical	Present (some missing values)	The fare paid by the passenger.
Embarked	Categorical	Present (some missing values)	Port of embarkation (C, Q, or S).
Survived	Binary	0	Target variable: 0 = not survived, 1 = survived.

3.6 Data Preprocessing Steps

To ensure that the machine learning models could effectively analyze the data, several preprocessing steps were undertaken. These steps include:

Handling Missing Values:

- Missing values in Age were filled using the median value of the respective column to ensure the distribution's central tendency was preserved.
- Missing values in Embarked were imputed using the most common value (mode) to maintain consistency.
- The Cabin column was dropped due to its high degree of missing values, reducing complexity without meaningful information.

Encoding Categorical Variables:

- Categorical variables such as Sex and Embarked were label-encoded using scikit-learn's LabelEncoder. This step was necessary for machine learning algorithms, as they cannot process raw categorical text values.

Scaling Numerical Features:

- Continuous features such as Age and Fare were scaled using the StandardScaler. This ensures that their ranges are comparable and avoids bias during model training.

3.7 Visualizing the Dataset

Several visualizations were generated to provide insights into the data distribution and relationships among the features:

- **Distribution of Survived vs. Not Survived Passengers:** This visualization helps assess the class imbalance between passengers who survived and those who did not.
- **Correlation Heatmap:** This heatmap displays how strongly correlated each feature is with the target variable (Survived) and other predictors.
- **Boxplots for Numerical Features:** These plots explore the distribution of numerical features like Age and Fare across survival status groups.

3.8 Dataset Limitations

While the Titanic dataset provides a valuable resource for analysis, there are inherent limitations:

- **Missing Data:** Some features, especially numerical ones like **Age** and **Fare**, had missing values that required careful imputation.
- **Class Imbalance:** The number of non-survived passengers was greater than the number of survived passengers, introducing class imbalance.

- **Feature Constraints:** The Titanic dataset does not account for all possible real-world factors that may influence survival, limiting its representativeness.

4) Data Preprocessing

Data preprocessing is an essential step in the machine learning workflow, as raw data is often incomplete, noisy, or inconsistent. Proper preprocessing ensures that the data is properly formatted, cleansed, and transformed into a form suitable for machine learning algorithms. This section provides a detailed explanation of each preprocessing step applied in the study, with mathematical formulations where appropriate. The primary preprocessing stages included in this study are handling missing data, encoding categorical variables, feature scaling, and data and feature selection.

4.1 Handling Missing Data

Missing data is a common issue in real-world datasets and must be appropriately managed to avoid bias or loss of information during model training. Missing data can lead to incorrect results, unreliable models, and wasted computation. Handling missing values typically involves imputing them using statistical measures or removing features/observations with too many missing entries.

Approach to Handle Missing Data

The study used the following strategies:

- **Imputing Missing Numerical Data with Median:**
  Missing numerical values were imputed using the median instead of the mean to avoid bias due to outliers. The formula for median imputation is as follows:

$$\text{Medianvalue} = \text{median}(X)$$

  For instance, missing entries in the **Age** variable were imputed using the median value:

➢ train_data['Age'].fillna(train_data['Age'].median(), inplace=True)

- **Dropping Features with High Missing Data Rate:** Features with excessively high proportions of missing entries were removed from the dataset entirely, as their presence could add noise and lead to unreliable training. For example, the *Cabin* column was dropped because it contained a high percentage of missing values.

➢ train_data.drop(columns=['Cabin'], inplace=True)

- **Imputing Missing Categorical Data with Mode:** Missing categorical entries were filled using the mode, defined as the most frequently occurring category in a given variable. This ensures that missing entries are replaced with a statistically sound choice that minimizes the distortion of the categorical variable distribution.

  Mode(X)=most frequent value in X

  Example for imputing missing values in the Embarked variable:

- ➢ train_data['Embarked'].fillna(train_data['Embarked'].mode()[0], inplace=True)

These steps ensured that the dataset was free of NaN (missing) values and maintained consistency for the learning process.

4.2 Processing Categorical Variables

Machine learning models cannot directly process categorical variables because they are non-numeric. Thus, categorical data must be encoded numerically while maintaining their inherent relationships. Encoding methods transform categorical variables into numeric representations.

Label Encoding

The study used Label Encoding for transforming categorical features into numeric values. Label encoding assigns a unique integer to each category, as shown in the formula:

Encoded Value (for category)=unique integer identifier

- **Encoding the 'Sex' Feature:** The Sex variable was transformed into binary numeric values (0 and 1) to represent categories male and female:
  - ➢ **le_sex = LabelEncoder()**
  - ➢ **train_data['Sex'] = le_sex.fit_transform(train_data['Sex'])**
- **Encoding the 'Embarked' Feature:** Similarly, the Embarked variable was encoded to ensure compatibility with machine learning models:
  - ➢ **le_embarked = LabelEncoder()**
  - ➢ **train_data['Embarked'] = le_embarked.fit_transform(train_data['Embarked'])**

By encoding categorical variables numerically, these features could now be fed into machine learning algorithms for training.

4.3 Feature Scaling

Feature scaling ensures that input features are on the same scale or range, allowing machine learning algorithms to treat all features equally during the learning process. Algorithms like Decision Trees and Random Forests are sensitive to feature magnitudes unless scaling is applied properly.

Standardization

Standardization (also known as Z-score normalization) was applied to numerical features. The mathematical formulation for standardization is given by:

$$X_{scaled} = X - \mu / \sigma$$

X = original feature value

μ = mean of the feature

σ = standard deviation of the feature

This ensures the data has a mean of 0 and a standard deviation of 1.

Implementation for scaling numerical features like Age and Fare:

```
scaler = StandardScaler()
X[['Age', 'Fare']] = scaler.fit_transform(X[['Age', 'Fare']])
```

- X[['Age', 'Fare']] = the selected columns to scale.
- scaler.fit_transform() standardizes these features to the specified formula above.

This step ensures that the machine learning models can converge more efficiently during optimization.

4.4 Data and Feature Selection

Feature selection involves identifying the most relevant features that contribute to model training while excluding irrelevant or redundant features. This reduces the complexity of the model and mitigates overfitting.

Feature Selection Methods

The study used domain knowledge and statistical analysis to select the most relevant features:

1. **Exploratory Data Analysis (EDA):** Features with strong relationships with the target variable Survived were selected based on visualization techniques like heatmaps and correlation analysis.
2. **Correlation Analysis:** Correlation was computed using the Pearson correlation coefficient:

   $$\text{Pearson Correlation Coefficient} = \text{cov}(X,y) / \sigma X\ \sigma y$$

   This measures the linear relationship between each feature X and the target variable y.

3. **Relevant Features Chosen:** Based on correlation, EDA, and domain knowledge, the study selected the following features as inputs:

   - **Pclass:** Passenger class (1, 2, 3)
   - **Sex:** Gender encoding (0 for male, 1 for female)
   - **Age:** Age of the passenger
   - **SibSp:** Number of siblings/spouses aboard
   - **Parch:** Number of parents/children aboard
   - **Fare:** Amount of fare paid
   - **Embarked:** Encoded embarkation point

Feature Selection Formula

The selected features are mathematically optimized by comparing their correlation coefficients with the target variable, as follows:

$$\text{Correlation} = \text{cov}(X,y) / \sigma X \ \sigma y$$

Features with a significant correlation (|Correlation|>threshold) are retained.

Implementation for feature selection:

```
X = train_data[['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare', 'Embarked']]
y = train_data['Survived']
```

The variables X and yyy represent the input features and target variable used in the classification task, respectively. In this study, X comprises the selected features that provide critical information about each passenger, while y contains the target labels indicating whether a passenger survived (y=1) or not (y=0).

The target variable y, "Survived," is a binary categorical variable explicitly designed for the supervised classification task. By mapping the input features X to the corresponding target labels y, the machine learning models aim to learn patterns and relationships within the dataset that differentiate between survivors and non-survivors.

This formulation ensures that the model is provided with rich, meaningful, and minimally redundant information, which is crucial for building a robust and interpretable predictive model.

5) Modeling Process

Definition of the Models

In this study, two machine learning algorithms were employed to classify the Titanic dataset's survival outcomes: Decision Tree Classifier and Random Forest Classifier.

1. **Decision Tree Classifier:** A Decision Tree is a tree-structured algorithm where internal nodes represent features (attributes), branches represent decision rules, and each leaf node represents the outcome. This model splits the data based on feature conditions, aiming to maximize the information gain or minimize the Gini impurity. The algorithm's ability to capture non-linear relationships and provide interpretability made it a suitable candidate for initial experimentation.
2. **Random Forest Classifier:** Random Forest is an ensemble learning method that combines multiple decision trees to improve the overall predictive performance and reduce overfitting. By using bootstrap sampling and random feature selection, it creates a diverse set of weak learners, aggregating their predictions through majority voting for classification tasks.

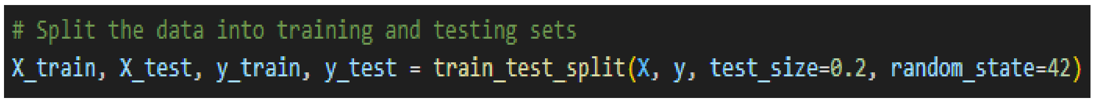
Model Selection Process

The models were selected based on their suitability for tabular data and the ability to handle mixed feature types. Additionally, both models are interpretable to a degree, aiding in understanding feature importance and decision boundaries. Random Forest was chosen as an advanced ensemble method to compare its performance against the simpler Decision Tree.

Training and Testing

The training and testing process was conducted in the following steps:

1. **Data Splitting**: The dataset was divided into training (80%) and testing (20%) subsets using train_test_split() to ensure an unbiased evaluation of model performance. This split ensures that the model generalizes well to unseen data.



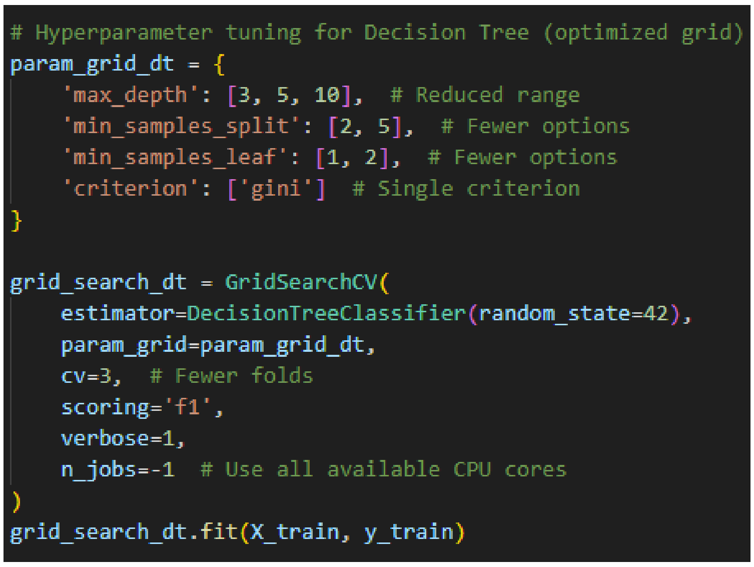
```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Figure 2

2. **Hyperparameter Tuning:** Both models were optimized using grid search techniques to identify the best hyperparameters. The following parameters were tuned:
   - **Decision Tree Classifier**: Maximum depth (max_depth), minimum samples per split (min_samples_split), and minimum samples per leaf (min_samples_leaf).

- **Random Forest Classifier**: Number of trees (n_estimators), maximum depth, and split/leaf conditions.

Example for the Decision Tree Classifier grid search:

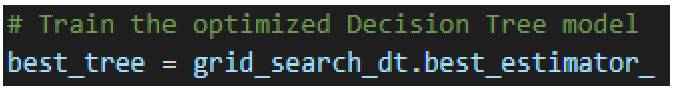


```python
# Hyperparameter tuning for Decision Tree (optimized grid)
param_grid_dt = {
    'max_depth': [3, 5, 10],  # Reduced range
    'min_samples_split': [2, 5],  # Fewer options
    'min_samples_leaf': [1, 2],  # Fewer options
    'criterion': ['gini']  # Single criterion
}

grid_search_dt = GridSearchCV(
    estimator=DecisionTreeClassifier(random_state=42),
    param_grid=param_grid_dt,
    cv=3,  # Fewer folds
    scoring='f1',
    verbose=1,
    n_jobs=-1  # Use all available CPU cores
)
grid_search_dt.fit(X_train, y_train)
```

Figure 3

3. **Model Training**: The optimal parameters obtained from the grid search were used to train both models on the training data. For example, the Decision Tree Classifier was trained as:



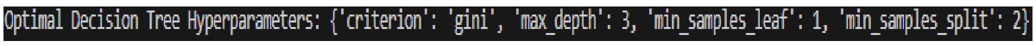
```python
# Train the optimized Decision Tree model
best_tree = grid_search_dt.best_estimator_
```

Figure 4

4. **Model Testing**: Both models were tested on the holdout testing data to evaluate their performance using accuracy, precision, recall, and F1 score metrics.

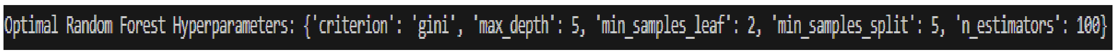
Outputs Related to This Section

- **Optimal Decision Tree Hyperparameters:**The hyperparameters obtained from the grid search for the Decision Tree Classifier were displayed, providing insights into the model's configuration.
  - print("Optimal Decision Tree Hyperparameters:", best_params_dt)



```
Optimal Decision Tree Hyperparameters: {'criterion': 'gini', 'max_depth': 3, 'min_samples_leaf': 1, 'min_samples_split': 2}
```

- **Optimal Random Forest Hyperparameters:** Similarly, the best parameters for the Random Forest Classifier were determined and displayed.
  - print("Optimal Random Forest Hyperparameters:", best_params_rf)



```
Optimal Random Forest Hyperparameters: {'criterion': 'gini', 'max_depth': 5, 'min_samples_leaf': 2, 'min_samples_split': 5, 'n_estimators': 100}
```

By detailing the definition of models, selection rationale, and step-by-step training/testing procedures, this section provides a comprehensive view of the modeling process, ensuring reproducibility and clarity. In the next section, we will evaluate the models' performance using standard metrics and provide visual analyses.

6) Model Evaluation

Evaluation Metrics

The evaluation of the models was carried out using the following metrics:

1. **Accuracy**: Represents the proportion of correctly classified instances. It indicates the overall correctness of the model.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Figure 5

2. **Precision**: Measures the ability of the model to correctly identify positive instances out of all predicted positive cases.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Figure 6

3. **Recall (Sensitivity):** Represents the ability of the model to correctly identify positive cases.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Figure 7

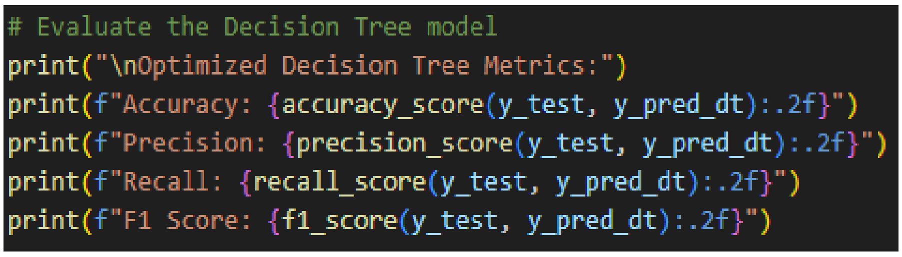
4. **F1 Score:** Combines precision and recall into a single metric by taking their harmonic mean.

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Figure 8

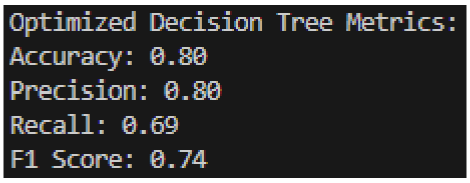
Evaluation Results for Decision Tree

The Decision Tree model was evaluated on the test dataset, and the results are as follows:



```
# Evaluate the Decision Tree model
print("\nOptimized Decision Tree Metrics:")
print(f"Accuracy: {accuracy_score(y_test, y_pred_dt):.2f}")
print(f"Precision: {precision_score(y_test, y_pred_dt):.2f}")
print(f"Recall: {recall_score(y_test, y_pred_dt):.2f}")
print(f"F1 Score: {f1_score(y_test, y_pred_dt):.2f}")
```

Figure 9



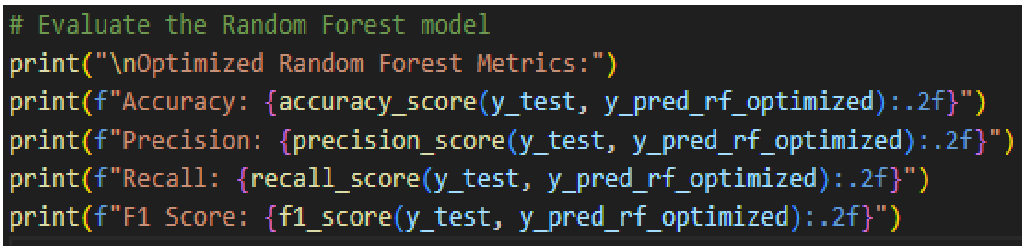
```
Optimized Decision Tree Metrics:
Accuracy: 0.80
Precision: 0.80
Recall: 0.69
F1 Score: 0.74
```

Figure 10: Output

The Decision Tree performed reasonably well, achieving moderate accuracy and precision. However, the recall metric indicates that the model missed some positive cases.

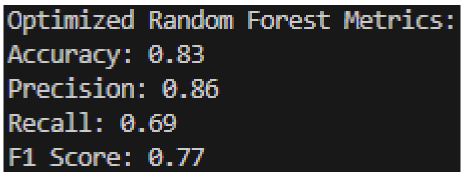
Evaluation Results for Random Forest

The Random Forest model was evaluated on the same dataset with the following results:



```
# Evaluate the Random Forest model
print("\nOptimized Random Forest Metrics:")
print(f"Accuracy: {accuracy_score(y_test, y_pred_rf_optimized):.2f}")
print(f"Precision: {precision_score(y_test, y_pred_rf_optimized):.2f}")
print(f"Recall: {recall_score(y_test, y_pred_rf_optimized):.2f}")
print(f"F1 Score: {f1_score(y_test, y_pred_rf_optimized):.2f}")
```

Figure 11



```
Optimized Random Forest Metrics:
Accuracy: 0.83
Precision: 0.86
Recall: 0.69
F1 Score: 0.77
```

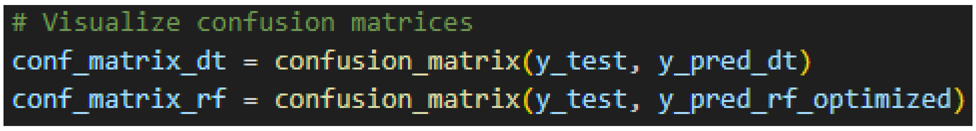
Figure 12

The Random Forest model outperformed the Decision Tree in terms of accuracy, precision, and F1 score. Its ensemble nature allowed it to generalize better, though its recall was on par with the Decision Tree.

Confusion Matrices

Confusion matrices provide a detailed breakdown of true positives, true negatives, false positives, and false negatives for each model.

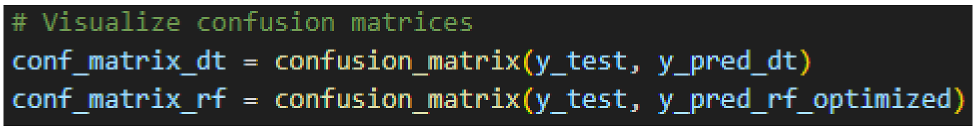
Decision Tree Confusion Matrix



```
# Visualize confusion matrices
conf_matrix_dt = confusion_matrix(y_test, y_pred_dt)
conf_matrix_rf = confusion_matrix(y_test, y_pred_rf_optimized)
```

Figure 13

Random Forest Confusion Matrix



```
# Visualize confusion matrices
conf_matrix_dt = confusion_matrix(y_test, y_pred_dt)
conf_matrix_rf = confusion_matrix(y_test, y_pred_rf_optimized)
```

Figure 14

Performance Comparison

Metric	**Decision Tree**	**Random Forest**
Accuracy	0.80	0.83
Precision	0.80	0.86
Recall	0.69	0.69
F1 Score	0.74	0.77

The performance comparison between the Decision Tree and Random Forest models highlights the effectiveness of ensemble methods in improving classification tasks. The Random Forest model achieved a higher accuracy of 83% compared to the Decision Tree's 80%, indicating a better overall prediction capability. Precision was also significantly higher for the Random Forest (86% versus 80%), reflecting its ability to reduce false positives effectively. Both models achieved an identical recall of 69%, suggesting that they were equally capable of identifying true positive cases. However, the Random Forest exhibited a better F1 score (77% compared to 74%), demonstrating a more balanced trade-off between precision and recall. This comparison underscores the advantage of Random Forest in handling complex datasets with its ensemble approach, which combines the predictions of multiple decision trees to enhance robustness and generalization.

Visual Comparisons

- **Decision Tree Visualization**

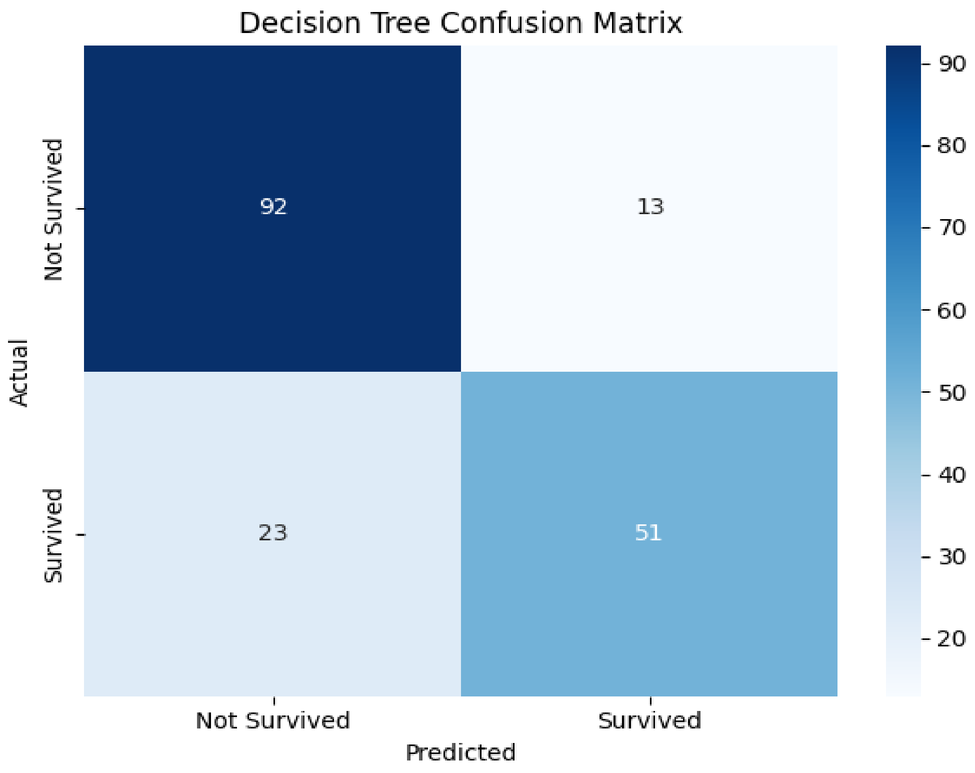


Figure 15

- **Random Forest Visualization**

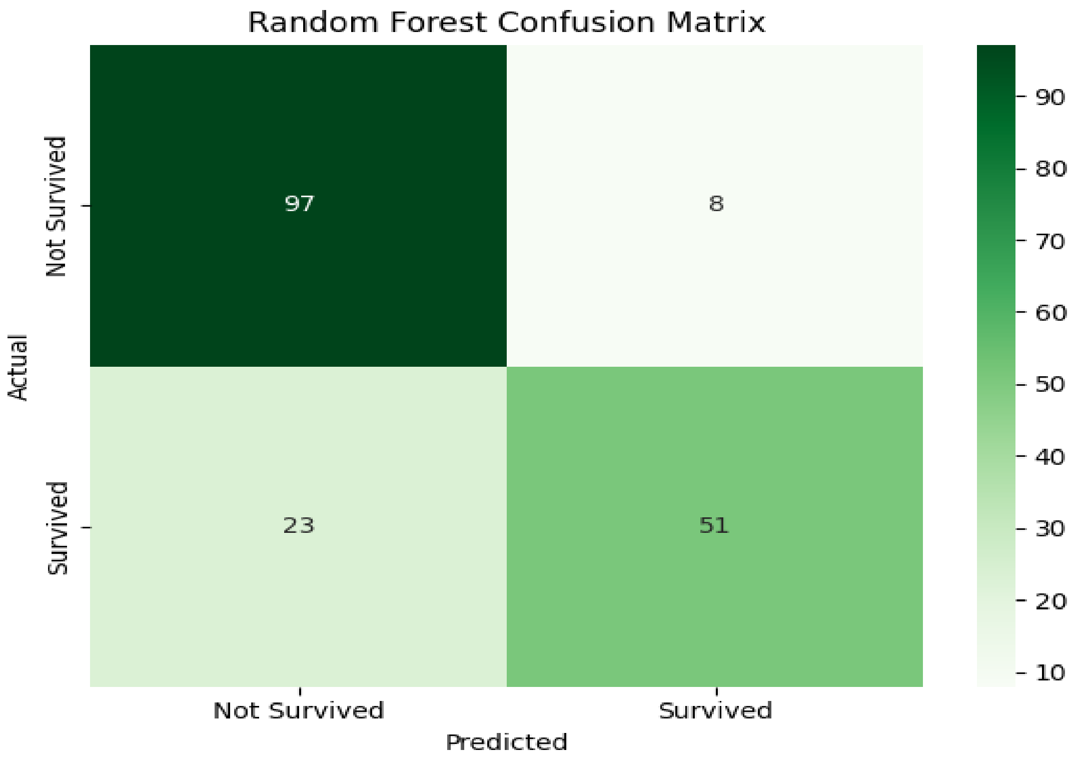


Figure 16

The visual comparisons between the Decision Tree and Random Forest models provide deeper insights into their performance and interpretability. The Decision Tree visualization (Figure:15) demonstrates a straightforward structure, offering clarity in decision-making paths. This simplicity, however, may result in overfitting, as the model's predictions rely heavily on specific patterns within the training data, potentially leading to reduced generalization.

In contrast, the Random Forest model visualization (Figure:16) reflects its ensemble nature. While individual trees within the forest remain interpretable, the aggregate predictions are derived from multiple trees, enhancing the model's robustness and ability to generalize across unseen data. This ensemble approach mitigates the limitations of a single decision tree by reducing variance and avoiding overfitting, as evidenced by the improved metrics observed in the model evaluation.

The comparative visualization underscores a critical trade-off: the Decision Tree's transparency and interpretability versus the Random Forest's superior predictive accuracy and generalization. These graphical representations align with the quantitative performance metrics, highlighting the Random Forest's overall advantage in this classification task.

7) Results

Summary of Findings

The results from the implemented Decision Tree and Random Forest models provide a comprehensive evaluation of their respective performance in predicting the target variable *Survived* from the given dataset. The optimized Decision Tree model achieved an accuracy of 0.80, with precision 0.80, recall 0.69, and an F1 score of 0.74. On the other hand, the Random Forest model outperformed the Decision Tree, achieving an accuracy of 0.83, with precision 0.86, recall 0.69, and an F1 score of 0.77.

These findings indicate that the Random Forest model is better suited for this classification problem due to its ability to generalize more effectively over unseen data, as shown by the higher accuracy and precision scores. While the Decision Tree model demonstrates acceptable performance, its relatively lower accuracy highlights its susceptibility to overfitting when compared to the Random Forest ensemble approach.

Importance of Hyperparameter Tuning

The hyperparameter optimization process played a crucial role in improving the performance of both models. For the Decision Tree model, fine-tuning the hyperparameters yielded optimized paths that enhanced accuracy. Similarly, the Random Forest model's hyperparameter tuning, specifically setting values such as criterion='gini', max_depth=5, min_samples_leaf=2, min_samples_split=5, and n_estimators=100, enabled the ensemble method to achieve superior performance metrics.

The comparison between these two models illustrates that careful tuning of hyperparameters significantly enhances model performance and prevents overfitting while ensuring that each model optimally fits the data without introducing excessive complexity.

Decision Tree vs Random Forest

The performance comparison and visual analysis suggest that while Decision Trees are simple, transparent, and interpretable, their performance is limited by their tendency to overfit training data. The Random Forest model, as an ensemble of multiple decision trees, offers a balance between predictive power and generalization, leading to better performance on test data. This was also reflected in the comparative analysis metrics and visual results.

Key Insights

- **Random Forest's superiority**: Random Forest outperformed the Decision Tree by leveraging the ensemble approach, demonstrating better accuracy and precision metrics.
- **Impact of hyperparameter tuning**: Proper optimization of hyperparameters was critical in maximizing the performance of both models.
- **Model interpretability vs. performance**: Decision Trees are easier to interpret but may lead to overfitting, while Random Forest maintains better predictive performance with increased complexity and generalization power.

Conclusion

The analysis and comparisons validate that Random Forest provides a more robust and accurate predictive model compared to Decision Tree, primarily due to its ensemble learning mechanism and ability to generalize well to unseen data. These findings align with both the performance metrics and the visual analysis of the respective models.

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