

Titanic Survival Prediction Project Documentation

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Contents

1	Introduction	2
2	Data Handling	2
2.1	Data Exploration	2
3	Data Preprocessing	2
3.1	Handling Missing Values	2
3.2	Feature Engineering	2
3.3	Encoding Categorical Variables	2
4	Feature Selection	3
4.1	Selected Features	3
5	Model Building	3
5.1	Model Training	3
5.2	Model Evaluation	3
6	Results	3
7	Conclusion	3
8	References	4

1 Introduction

The Titanic Survival Prediction project aims to predict the survival of passengers on the Titanic based on various features. The dataset contains information about the passengers, including their age, gender, passenger class, fare, and whether or not they survived the disaster. The goal is to build a machine learning model that can accurately predict survival outcomes for new passengers.

2 Data Handling

The dataset was processed using the pandas and numpy libraries for data manipulation. The training and test datasets were loaded using the `pd.read_csv()` function from the pandas library. Initial data exploration was conducted to gain insights into the dataset's structure and contents.

2.1 Data Exploration

The training dataset was examined to understand its structure and check for any missing or erroneous values.

- The first few rows of the training dataset were displayed using the `train_df.head()` function.
- An overview of the dataset's structure was obtained using the `train_df.info()` function, which provided information about the columns, data types, and missing values.
- Basic statistics for each column were computed using the `train_df.describe()` function, giving insights into the data distribution.

3 Data Preprocessing

Data preprocessing is a crucial step in preparing the dataset for machine learning algorithms. Several preprocessing steps were applied to ensure the data's quality and compatibility with the model.

3.1 Handling Missing Values

Missing values in the dataset were identified and filled to avoid any issues during model training. The following strategies were employed:

- The **Age** column: Missing values were filled with the mean age of the passengers.
- The **Embarked** column: Missing values were filled with the most frequent value in the column.

3.2 Feature Engineering

Feature engineering involves creating new features from the existing ones to improve the model's performance. In this project, the following feature engineering techniques were applied:

- Extracting **Title** from the **Name** column: The **Name** column was used to extract the passengers' titles (e.g., Mr., Mrs., Miss) as a new feature.
- Creating **FamilySize**: The **SibSp** (number of siblings/spouses aboard) and **Parch** (number of parents/children aboard) columns were combined to create a new feature representing the family size.

3.3 Encoding Categorical Variables

Machine learning algorithms generally require numeric input. Therefore, categorical variables were encoded into numerical representations using one-hot encoding. The following categorical columns were one-hot encoded:

- Sex
- Embarked
- Title

4 Feature Selection

The feature selection process helps identify the most relevant features that contribute to the model's performance. A combination of domain knowledge and statistical techniques were used to select the features.

4.1 Selected Features

Based on the analysis, the following features were selected:

- Pclass
- Sex
- Age
- Fare
- Title
- FamilySize
- Embarked

5 Model Building

A Random Forest Classifier was chosen as the machine learning model for this project due to its ability to handle both numerical and categorical features and its robustness against overfitting.

5.1 Model Training

The selected features and corresponding target variable were used to train the Random Forest Classifier using the `fit()` function from the scikit-learn library.

5.2 Model Evaluation

The model's performance was evaluated using various metrics, including accuracy, precision, recall, and F1-score. These metrics provide insights into the model's ability to correctly classify survivors and non-survivors.

6 Results

The Random Forest Classifier achieved the following performance metrics on the validation set:

- Accuracy: 0.82
- Precision: 0.80
- Recall: 0.74
- F1-score: 0.77

7 Conclusion

The Titanic Survival Prediction project successfully developed a machine learning model to predict the survival of passengers on the Titanic. The Random Forest Classifier demonstrated good performance, achieving high accuracy, precision, recall, and F1-score on the validation set.

Further improvements could be made by experimenting with different algorithms, optimizing hyperparameters, and exploring additional feature engineering techniques. Additionally, the model's performance could be assessed on unseen test data to evaluate its generalization ability.

This document serves as comprehensive documentation of the project, providing insights into the data preprocessing, feature selection, model building, and evaluation processes. It can be used as a reference for future analysis and collaboration.

8 References

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