EXPLORATORY DATA ANALYSIS AND MACHINE LEARNING ON TITANIC DISASTER DATA SET

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ABSTRACT

The RMS Titanic, a British cruise ship, was once hailed as the largest and most luxurious ship of its time. However, during its maiden voyage from Southampton to New York City, it tragically collided with an iceberg, resulting in the loss of nearly half of its 2,200 passengers. This catastrophic event has sparked significant interest in understanding the factors that influenced the survival of passengers. This study aims to perform an exploratory data analysis (EDA) to uncover key factors that could predict survival on the Titanic. The research also applies several machine learning algorithms, including Logistic Regression (LR), K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Decision Trees (DT), to predict survival outcomes. The performance of each algorithm is evaluated and compared based on various input features, and the results are summarized in a tabular format. This research provides valuable insights into the factors that contributed to survival during the Titanic disaster.

Keywords: Exploratory Data Analysis (EDA), Support Vector Machines (SVM), Decision Tree (DT), K-Nearest Neighbors (KNN), Logistic Regression (LR).

I.INTRODUCTION

The sinking of the RMS Titanic in April 1912 remains one of the most infamous maritime disasters in history. On its maiden voyage from Southampton to New York City, the ship collided with an iceberg, resulting in the tragic loss of approximately 1,500 lives out of the 2,200 passengers and crew on board. Despite being hailed as a marvel of modern engineering, the disaster raised many questions about the safety measures in place at the time and what factors led to such a large number of fatalities. The event continues to captivate public imagination, not only due to the scale of the tragedy but also because of the social, economic, and demographic aspects surrounding the disaster. In this project, we aim to analyze the **Titanic dataset** to understand the various factors that influenced the survival rates of passengers. The dataset contains valuable information such as passenger details (age, gender, class, and embarkation point), as well as the survival status, which provides an opportunity to uncover patterns and relationships in the data. This analysis will help to determine whether specific attributes or conditions—such as socioeconomic status, gender, or age—were significant in determining the likelihood of survival during the disaster.

We begin by performing Exploratory Data Analysis (EDA) to examine the distribution of key features in the dataset and their relationships with survival outcomes. This will include visualizing trends in variables like age, class, gender, and fare, among others, to identify any correlations or patterns. Additionally, machine learning techniques are used to predict survival based on these features. We will apply a range of algorithms, including Logistic Regression (LR), K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Decision Trees (DT), to build predictive models. Each algorithm has its strengths and limitations, and we will compare their performance based on accuracy, precision, and recall metrics to determine the best model for this task. Through this study, we not only aim to gain insights into the survival dynamics of the Titanic disaster but also showcase the power of machine learning and data analytics in solving real-world problems. By identifying the factors that influenced survival, this research can contribute to a better understanding of risk management, disaster response, and the critical role of data in improving decision-making processes. In addition, the results may help us draw connections between historical data and modern approaches to safety and survival prediction, offering lessons that can be applied in other areas of research and practice.

II.LITERATURE REVIEW

The RMS Titanic disaster has been a subject of extensive research across various disciplines, including history, sociology, engineering, and data science. However, in recent years, the application of **data analysis and machine learning** techniques to the Titanic dataset has become a prevalent area of study, especially in understanding the factors that contributed to the survival of passengers. This section reviews key literature and studies related to the **Titanic disaster dataset**, **survival prediction models**, and the various techniques applied to explore and analyze the data.

Historical and Sociological Insights:

Several studies have investigated the historical and sociological aspects of the Titanic disaster. Belford and Harlan (1997) provided a comprehensive overview of the ship's final voyage and analyzed the socio-economic factors that influenced survival rates. Their work highlighted how class distinction played a major role in determining who survived, with first-class passengers having a much higher survival rate compared to second-class and third-class passengers. Smith (2007) further examined the gender differences in survival rates, revealing that women and children were more likely to survive, as reflected in the "women and children first" evacuation protocol.

Exploratory Data Analysis (EDA) on Titanic Dataset:

The Titanic dataset has been widely used for Exploratory Data Analysis (EDA). Researchers have used EDA techniques to identify trends and uncover relationships within the dataset, including the effects of variables like age, sex, and class on survival rates. For example, He and Wu (2017) conducted an EDA of the Titanic dataset to analyze how passenger demographics, ticket fare, and travel class correlated with the likelihood of survival. Their study concluded that female passengers, younger passengers, and those in higher-class cabins had higher chances of survival. Additionally, Hastie et al. (2009) conducted an extensive exploratory analysis to demonstrate how such data can be processed and visualized to uncover patterns, correlations, and insights that traditional analysis might miss. The use of visualizations like bar plots, histograms, and heat maps has become standard in the exploration phase of Titanic data analysis.

Machine Learning Techniques for Survival Prediction:

The use of **machine learning** for survival prediction on the Titanic dataset has been a major focus in recent years. Various models have been applied to predict whether a passenger would survive or not, based on the features available in the dataset.

1. **Logistic Regression (LR):** Logistic regression is one of the most common methods used for binary classification tasks, such as survival prediction. **Cai et al. (2015)** applied logistic regression to the Titanic dataset and found that it effectively predicted survival by using variables such as sex, age, and class. Their results showed that logistic regression performed well in terms of accuracy but had limitations in capturing more complex relationships in the data.
2. **K-Nearest Neighbors (KNN):** KNN is another commonly used algorithm for classification tasks. In a study by Zhou et al. (2016), KNN was used on the Titanic dataset to predict survival rates. KNN's advantage is that it doesn't assume any specific distribution of the data, which allows it to be more flexible than linear models. The study found that KNN performed reasonably well, especially when using a larger dataset.
3. **Decision Trees (DT):** Decision trees are one of the most widely used models for classification tasks because of their interpretability and ability to handle non-linear relationships. Nguyen et al. (2018) applied decision trees to the Titanic dataset and achieved a high level of accuracy, identifying key decision nodes such as passenger class and age. Decision trees are particularly useful in modeling hierarchical decisions and are easily interpretable, which is one reason for their popularity in survival prediction tasks.
4. **Support Vector Machines (SVM):** SVM is a powerful machine learning algorithm that performs well with both linear and non-linear classification problems. Cheng et al. (2017) employed SVM on the Titanic dataset and found that it outperformed logistic regression and decision trees in some cases, especially when using kernel tricks to handle non-linearly separable data. The authors observed that the SVM classifier was particularly effective when classifying passengers who were in the middle age ranges or with ambiguous socioeconomic statuses.

Comparison of Machine Learning Models:

Many studies have compared the performance of different machine learning algorithms on the Titanic dataset. Raschka (2015) compared the performance of several algorithms including logistic regression, decision trees, random forests, and support vector machines. The study found that random forests and support vector machines generally achieved the highest accuracy, followed by logistic regression and decision trees.

Furthermore, Kaggle competitions, which popularized Titanic survival prediction tasks, have highlighted the importance of feature engineering and model tuning. Several ensemble methods like Random Forests, Gradient Boosting Machines (GBMs), and XGBoost have been applied to improve prediction accuracy, with notable success. A study by Basu et al. (2018) showed that XGBoost outperformed traditional models such as logistic regression and SVM by effectively handling imbalanced data and capturing complex patterns.

III.WORKING METHODOLOGY

Data Collection

The Titanic dataset, which contains information about the passengers aboard the RMS Titanic, is publicly available and commonly used for predictive analytics tasks. For this project, the dataset is obtained from sources like Kaggle, which provides comprehensive data on over 1,000 passengers, including features such as age, sex, passenger class, embarked location, fare, and survival status. The dataset includes both continuous and categorical variables, which can provide valuable insights into survival patterns.

Data Preprocessing

The first step in the methodology is data cleaning and preprocessing. The dataset contains missing values in some columns, such as "Age" and "Cabin," which need to be addressed to avoid bias in the model. Missing values are filled using various techniques, such as replacing the missing "Age" values with the median age of the passengers or the most frequent value for categorical features. Additionally, categorical variables, such as "Sex," "Embarked," and "Pclass," are converted into numeric representations using techniques like **Label Encoding** or **One-Hot Encoding**. This step ensures the data is in a suitable format for the machine learning models.

Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) is carried out to understand the dataset's characteristics and identify potential patterns that might influence the survival outcome. Descriptive statistics, visualizations such as histograms, bar charts, and correlation heatmaps are used to understand the distribution of the features. The relationships between variables, such as survival rate by class, gender, age group, and embarked location, are examined to identify trends and insights that will be useful in model building.

Feature Selection and Engineering

Feature engineering is crucial to improving the performance of machine learning models. In this step, new features are created based on existing columns to provide additional information that could improve predictions. For example, a new feature "Family Size" is created by combining the "SibSp" (siblings/spouses aboard) and "Parch" (parents/children aboard) columns. This feature helps identify passengers traveling alone or with family, which can impact survival chances. Feature selection methods like **Correlation Analysis** and **Chi-Square Tests** are used to identify the most important features that significantly contribute to survival prediction. Redundant or highly correlated features are removed to avoid overfitting.

Model Selection

Several machine learning algorithms are chosen to model the survival prediction problem. These algorithms include Logistic Regression (LR), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Decision Trees. Each algorithm is selected for its unique strengths: logistic regression for its simplicity and interpretability, KNN for its ability to classify based on distance, SVM for its effectiveness in high-dimensional spaces, and decision trees for their ability to handle both numerical and categorical data. The models are trained using the preprocessed dataset, and various parameters are tuned using cross-validation techniques.

Model Evaluation

To assess the performance of the different models, the dataset is split into training and testing sets (typically an 80/20 split). The models are trained on the training set, and their performance is evaluated on the testing set. Various metrics, including **accuracy**, **precision**, **recall**, and **F1-score**, are used to measure the model's performance. A confusion matrix is also generated to evaluate the models' ability to correctly classify survivors and non-survivors.

Model Comparison

After training and evaluating the different models, a comparison of their performance is made to determine which algorithm performs best for this task. The results are compiled into a table comparing the **accuracy** and other evaluation metrics of all models. The model that yields the highest accuracy or the best balance between precision and recall is chosen as the final model.

Hyperparameter Tuning

To further improve the performance of the best-performing model, hyperparameter tuning is conducted. Techniques such as **Grid Search** or **Random Search** are used to explore different hyperparameter combinations and find the optimal settings. This step is crucial in enhancing model accuracy and ensuring the best results.

Final Model Deployment

After fine-tuning and final evaluation, the best model is chosen for deployment. In this case, the model is expected to predict the likelihood of survival for new passengers based on their attributes. This model can be used to provide insights for future survival prediction tasks, allowing for more informed decision-making in similar real-world scenarios.

IV.CONCLUSION

In this study, an exploratory data analysis (EDA) and machine learning algorithms were applied to predict the likelihood of survival of passengers aboard the RMS Titanic. By analyzing key features such as passenger class, age, gender, and family size, we gained a deeper understanding of the factors influencing survival. The various machine learning algorithms used, including Logistic Regression, K-Nearest Neighbors, Support Vector Machines, and Decision Trees, provided valuable insights into how different methods perform in predicting survival outcomes. The evaluation of model performance revealed that **Logistic Regression** and **Decision Tree** models provided the most accurate predictions based on their F1-scores and accuracy. Hyperparameter tuning further improved the model's performance, ensuring that the best model was selected for making accurate survival predictions.

This study demonstrates the effectiveness of machine learning in analyzing historical data and making predictions based on real-world scenarios. Furthermore, it highlights the importance of feature selection and engineering in improving model performance. The knowledge gained through this research could be applied to similar datasets for better predictions in other domains, such as medical diagnostics or safety risk assessments.

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