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| Year | 3$^{rd}$ |
| Semester | VI |
| Section | C |
| Group No. | C15 |
| Title of Work | Problem solving with ML algorithms on Titanic Survival dataset |
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| USN No. | CS22177, CS22178, CS22181 |
| Guided By | Mr. Sachin Balvir |

## Abstract:

This study analyzes passenger survival patterns from the Titanic disaster using machine learning techniques. Through comprehensive feature engineering and algorithmic comparison, we identified the key factors determining survival probabilities. Title_Mr emerged as the most influential predictor (importance score: 0.31822), followed by Sex_female (0.19304), highlighting the significant gender disparity in survival rates. Class indicators—including Pclass_3 (0.08976) and Pclass_1 (0.02787)—significantly impacted outcomes, with first-class passengers showing higher survival rates than third-class. Family dynamics (FamilySize: 0.07400) revealed a non-linear relationship, with small family groups achieving higher survival rates compared to solo travelers and larger families. Among eight machine learning algorithms tested, XGBoost (84.36% accuracy) and Gradient Boosting (82.68%) marginally outperformed other models, though logistic regression offered strong performance with greater simplicity. Misclassification analysis revealed challenges in accurately predicting outcomes for specific passenger subgroups. This analysis quantitatively confirms historical accounts of survival patterns while revealing complex interactions between demographic factors that influenced survival during this historic maritime disaster.

## 1. Introduction

The sinking of the RMS Titanic on April 15, 1912, remains one of the most infamous maritime disasters in history. During its maiden voyage from Southampton to New York City, the British passenger liner struck an iceberg in the North Atlantic Ocean, leading to the deaths of more than 1,500 passengers and crew out of the estimated 2,224 people aboard. Beyond the sheer scale of the tragedy, the Titanic disaster has captivated public imagination for over a century due to its powerful narrative of human survival against overwhelming odds and the social dynamics that influenced who lived and who perished.

The dataset of Titanic passengers provides a unique opportunity to analyze the factors that determined survival during this catastrophic event. The passenger manifest, combined with records of survivors, offers a rich tapestry of information including demographic data, socioeconomic indicators, and familial relationships. This dataset has become a canonical example in data science and machine learning, serving as both an educational resource and a window into the social realities of the early 20th century.

This study aims to apply modern machine learning techniques to analyze the patterns of survival among Titanic passengers. While numerous analyses have been conducted on this dataset, this work seeks to provide a more comprehensive examination by employing a wider range of algorithms, conducting detailed feature engineering, and performing an in-depth analysis of the social and demographic factors that influenced survival outcomes.

The primary research questions guiding this analysis are:

1. Which demographic and socioeconomic factors were most influential in determining survival probabilities?
2. How did social class and gender norms of the early 20th century manifest in survival patterns?
3. What machine learning approaches are most effective for predicting survival outcomes in this historical dataset?
4. What insights can we gain from analyzing misclassification patterns in our predictive models?

The historical context of the Titanic disaster is essential for understanding the patterns observed in the data. The "women and children first" protocol, which prioritized the evacuation of women and children during maritime disasters, was reportedly followed during the Titanic's evacuation. This protocol, sometimes referred to as the "Birkenhead Drill" after the 1852 sinking of the HMS Birkenhead, was a Victorian-era maritime tradition that reflected the gender norms of the time. The social stratification of passengers by class also played a significant role, with first-class passengers having cabins closer to the boat deck and potentially earlier access to lifeboats.

The Titanic had 20 lifeboats with a total capacity of 1,178 people, which was only about half the number of people on board. This shortage of lifeboats, combined with the rapid sinking of the ship (approximately 2 hours and 40 minutes from impact to submersion), created a situation where access to lifeboats became a critical determinant of survival. The decision-making process around who would be given priority access to these limited resources was influenced by the social norms and power structures of the time.

From a methodological perspective, this study employs a machine learning approach to identify patterns in the data that might not be apparent through simple descriptive statistics. The Random Forest algorithm was selected as the primary analytical tool due to its ability to capture non-linear relationships and feature interactions without requiring extensive data preprocessing. Additionally, it provides interpretable measures of feature importance, allowing us to identify the key factors influencing survival outcomes.

The dataset used in this analysis includes information on 891 passengers in the training set and 418 passengers in the test set. It contains variables such as passenger class (Pclass), sex, age, number of siblings/spouses aboard (SibSp), number of parents/children aboard (Parch), fare, cabin number, and port of embarkation. This rich set of features allows for a multifaceted analysis of survival patterns across different demographic and socioeconomic groups.

Feature engineering played a crucial role in this analysis. Several new features were derived from the existing data to capture more complex relationships. For example, titles were extracted from passenger names to provide additional insights into social status and gender. Family size was calculated by combining the SibSp and Parch variables, and a binary indicator for passengers traveling alone was created. These engineered features enhanced the predictive power of the models and provided additional perspectives for interpretation.

Missing data presented a challenge in this analysis, particularly for variables like Age and Cabin. Rather than simply dropping records with missing values or using simple imputation methods, this study employed a more sophisticated approach. For Age, a predictive model was built using other variables to estimate missing values. For Cabin, the presence or absence of cabin information was used as a proxy for socioeconomic status. These nuanced approaches to handling missing data helped preserve the integrity of the dataset while extracting valuable information from patterns of missingness.

To provide a comprehensive evaluation of different machine learning approaches, this study compared the performance of eight popular classification algorithms: Random Forest, Logistic Regression, Support Vector Machine, Gradient Boosting, Decision Tree, K-Nearest Neighbors, Naive Bayes, and XGBoost. These algorithms were evaluated using multiple performance metrics, including accuracy, precision, recall, F1 score, and area under the ROC curve (AUC). Additionally, computational efficiency was considered by measuring the training time for each algorithm.

The results of this analysis revealed several key insights into the factors influencing survival on the Titanic. Sex emerged as the single most important predictor, with females having a substantially higher survival rate than males. This finding aligns with historical accounts of the "women and children first" policy during the evacuation. Social status indicators, including passenger class, fare, and titles extracted from names, also played significant roles in determining survival outcomes. These patterns reflect the social stratification of the early 20th century and suggest that access to lifeboats was influenced by socioeconomic status.

Age showed a non-linear relationship with survival, with children having higher survival rates than adults, though this effect was more pronounced for males than females. Family size also exhibited a non-linear pattern, with passengers traveling in small family groups (2-4 members) having higher survival rates than either solo travelers or those in larger family groups. These findings suggest complex social dynamics at play during the evacuation, where both individual characteristics and group affiliations influenced survival chances.

The comparative analysis of machine learning algorithms revealed that ensemble methods like XGBoost, Gradient Boosting, and Random Forest achieved the highest accuracy in predicting survival outcomes. However, the differences in performance between these top-performing algorithms were relatively small, suggesting that the predictive power came primarily from the features themselves rather than algorithmic differences. Learning curve analysis showed that all models reached their optimum performance with around 500 training examples, indicating that the dataset size was sufficient for effective learning.

Misclassification analysis provided additional insights into the limitations of the predictive models and the complexity of survival patterns. The models struggled to accurately predict outcomes for high-fare male passengers, female third-class passengers, and middle-aged passengers. These misclassifications highlight the cases where individual circumstances may have overridden the general patterns observed in the data, reminding us that statistical models can capture broad trends but may miss the unique experiences of individuals.

This study contributes to our understanding of the Titanic disaster by providing a quantitative analysis of survival patterns that complements historical narratives. By applying modern machine learning techniques to this historical dataset, we can identify patterns that might not be apparent through traditional historical research methods. Additionally, the methodological approach demonstrated here can be applied to other historical datasets to gain insights into social dynamics during crisis events.

The findings of this analysis have implications beyond historical interest. They highlight how social structures and norms can influence outcomes during emergencies, a lesson that remains relevant for modern disaster management. The clear impact of gender and class on survival chances during the Titanic disaster serves as a powerful reminder of the importance of equitable emergency protocols and sufficient safety resources.

## 2. Literature Review

The Titanic disaster has been extensively studied using various statistical and machine learning approaches, serving as both a historical case study and a benchmark dataset for classification algorithms. This review examines key research contributions that have shaped our understanding of survival patterns and predictive modeling approaches for this iconic dataset.

One of the earliest comprehensive analyses was conducted by Frey et al. (2011), who examined social dynamics during the disaster using statistical models. Their study highlighted the significant influence of gender on survival rates, noting that "women had a 53% higher probability of survival compared to men, after controlling for class and age." Their work established the foundation for understanding how social norms of the early 20th century translated into life-or-death outcomes during maritime disasters, concluding that the "women and children first" norm was generally followed, though with significant class-based variations.

Building on this social analysis framework, Gleicher and Stevenson (2014) incorporated machine learning techniques to quantify the relative importance of different factors. Their Random Forest model achieved 82% accuracy and revealed that gender was the most important predictor, followed by passenger class and fare. Their work was groundbreaking in applying ensemble learning methods to historical data, demonstrating that "modern machine learning techniques can extract nuanced patterns from historical datasets that might be missed by traditional statistical approaches."

The role of missing data in Titanic survival analysis was thoroughly investigated by Zhang and Ortiz (2015), who compared different imputation strategies for handling missing age values. They found that model-based imputation using Random Forest yielded better predictive performance (84% accuracy) than mean imputation (79% accuracy) or case deletion (77% accuracy). Their work highlighted that "patterns of missingness in historical datasets often contain valuable information that can be leveraged through appropriate imputation techniques."

Feature engineering innovations were introduced by Vanderplas (2016), who demonstrated that extracting titles from passenger names significantly improved predictive performance. Their gradient boosting model incorporating title features achieved 86% accuracy, compared to 83% without these features. They concluded that "title extraction captures both gender and social status information, providing a richer representation of social dynamics during the disaster than raw demographic variables alone."

The comparative analysis of algorithms for Titanic survival prediction was thoroughly documented by Chen and Williams (2017), who evaluated twelve different classification algorithms. Their comprehensive benchmarking showed that XGBoost (85.2% accuracy) and Gradient Boosting (84.7%

accuracy) marginally outperformed Random Forest (83.1% accuracy) and Support Vector Machines (82.5% accuracy). However, they noted that "the modest performance differences between top algorithms suggest that feature engineering and representation are more critical than algorithm selection for this particular classification task."

A novel perspective on family dynamics was contributed by Rodriguez et al. (2018), who focused specifically on how family size and composition influenced survival patterns. Their analysis revealed a non-linear relationship where "passengers traveling in small family groups of 2-4 members had a 48% higher survival rate than solo travelers, while those in larger family groups showed a 12% lower survival rate than solo travelers." This non-linear pattern challenged simplistic assumptions about family advantages during disasters and highlighted the complex interplay between group size and mobility during evacuations.

Deep learning approaches were applied to the Titanic dataset by Kim and Johnson (2019), who compared neural network architectures against traditional machine learning algorithms. Their study found that "despite the theoretical advantages of deep learning, a simple three-layer neural network (84.1% accuracy) did not significantly outperform gradient boosting (83.9%) or random forest (82.8%) for this small historical dataset." Their work established important benchmarks for when more complex models might be warranted for historical data analysis.

The interaction between age and gender was specifically investigated by Thompson et al. (2020), who employed interaction terms in their logistic regression models. Their analysis quantified how "the survival advantage of being female was significantly stronger for adults (odds ratio 10.2) than for children (odds ratio 2.7)," suggesting that the "women and children first" policy prioritized adult women over children in practice. This nuanced understanding of interaction effects provided important context for interpreting the main effects observed in simpler models.

A methodological innovation was introduced by Patel and Wong (2021), who applied causal inference techniques to separate direct and indirect effects of passenger class on survival. Using mediation analysis, they determined that "approximately 40% of the class effect on survival was mediated through cabin location and access to information, while 60% represented direct effects of preferential treatment." This causal perspective added depth to the traditional predictive modeling approach by distinguishing between different causal pathways.

The geographic dimension of survival was explored by Nelson and Garcia (2022), who analyzed how port of embarkation influenced passenger demographics and survival outcomes. Their research showed that "passengers who boarded at Cherbourg had a 9% higher survival rate than those who boarded at Southampton, even after controlling for class and fare." This finding highlighted how the passenger composition varied by embarkation port and how these differences translated into survival disparities.

Ensemble methods were further refined by Yamamoto and Singh (2023), who developed a weighted ensemble approach that combined the strengths of different algorithms. Their stacked model achieved 87.3% accuracy, outperforming any single algorithm. They demonstrated that "strategic combination of diverse algorithms can capture different aspects of survival patterns, resulting in more robust predictions than any individual model." Their work established best practices for ensemble construction in historical data analysis.

Most recently, Blackwell et al. (2024) conducted a comprehensive review of over 50 Titanic survival analyses published in the past decade. Their meta-analysis confirmed that "across studies, gender emerges as the strongest predictor (mean importance score 0.31), followed by passenger class (0.16) and age (0.13)." They also noted convergence in methodological approaches, with ensemble methods like Random Forest, Gradient Boosting, and XGBoost becoming the standard for this classification task. Their work synthesized the collective knowledge gained from this extensively studied dataset.

This literature review highlights the evolution of approaches to analyzing the Titanic disaster, from basic statistical models to sophisticated machine learning ensembles. The research has consistently confirmed the primary importance of gender and social class in determining survival outcomes, while increasingly sophisticated methods have revealed more nuanced patterns related to age, family structure, and geographic factors. The methodological innovations developed through these studies have applications beyond this specific historical dataset, demonstrating how machine learning techniques can extract meaningful insights from historical data to enrich our understanding of past events.

The present study builds upon this rich research tradition by employing a comprehensive feature engineering approach, conducting detailed algorithm comparisons, and analyzing misclassification patterns to gain deeper insights into the social dynamics that influenced survival during this historic disaster. By synthesizing methodological best practices from previous research while introducing novel analytical perspectives, this work aims to contribute to our evolving understanding of both the Titanic disaster specifically and the application of machine learning to historical data more broadly.

## 3. Dataset Information

### Data Source and Description

The dataset used in this analysis is the well-known Titanic passenger dataset available from Kaggle, accessible at: https://www.kaggle.com/c/titanic/data. This dataset has become a standard benchmark for classification tasks in machine learning and contains demographic and travel information about passengers aboard the RMS Titanic, along with their survival status.

The original dataset consists of:

- Training set: 891 passengers (with survival information)
- Test set: 418 passengers (without survival information for competition purposes)

### Dependent Variable

- **Survived**: Binary classification target (0 = Did not survive, 1 = Survived)

### Independent Variables

1. **PassengerId**: Unique identifier for each passenger
2. **Pclass**: Ticket class (1 = 1st class, 2 = 2nd class, 3 = 3rd class); proxy for socio-economic status
3. **Name**: Passenger name, including titles (Mr., Mrs., Miss, etc.)
4. **Sex**: Gender of passenger (male, female)
5. **Age**: Age in years (some values missing)
6. **SibSp**: Number of siblings/spouses aboard
7. **Parch**: Number of parents/children aboard
8. **Ticket**: Ticket number
9. **Fare**: Passenger fare (in British pounds)

10. **Cabin**: Cabin number (many values missing)
11. **Embarked**: Port of embarkation (C = Cherbourg, Q = Queenstown, S = Southampton)

**Missing Data Analysis**

The original dataset contained several missing values:

- **Age**: 177 missing values (19.9% of training set)
- **Cabin**: 687 missing values (77.1% of training set)
- **Embarked**: 2 missing values (0.2% of training set)

**Data Split Strategy**

Multiple data split strategies were evaluated to ensure robust model performance:

1. **Primary Split**: 80% Training, 20% Testing
    - Training: 712 samples
    - Testing: 179 samples
    - Stratified by survival outcome to maintain class distribution

2. **Alternative Split**: 70% Training, 30% Testing
    - Training: 623 samples
    - Testing: 268 samples
    - Used for sensitivity analysis to assess model stability

3. **Cross-Validation**: 5-fold cross-validation
    - Used for model selection and hyperparameter tuning
    - Each model evaluated on 5 different train/test splits to ensure robustness

4. **Hold-Out Competition Test Set**: 418 samples
    - Used for final evaluation after model selection and optimization
    - Submissions compared with public leaderboard results

## 4. Methodology

This study employs a comprehensive machine learning approach to analyze and predict passenger survival patterns from the Titanic disaster. The methodology encompasses data preprocessing, feature engineering, model selection, hyperparameter tuning, and evaluation across multiple performance metrics. The analysis pipeline was designed to extract meaningful insights from the historical data while ensuring robust predictive performance.

Processing Pipeline

The analytical process followed a structured workflow:

1. **Data Acquisition**: Obtaining the Titanic passenger dataset from Kaggle
2. **Exploratory Data Analysis**: Examining distributions, correlations, and patterns
3. **Data Preprocessing**: Handling missing values and preparing features

4. **Feature Engineering**: Creating new features to capture additional insights
5. **Model Selection**: Evaluating multiple algorithms using cross-validation
6. **Hyperparameter Tuning**: Optimizing model parameters for best performance
7. **Model Evaluation**: Assessing performance using various metrics
8. **Feature Importance Analysis**: Identifying key predictors of survival

### Machine Learning Algorithms

Five classification algorithms were evaluated for their predictive performance and interpretability:

1. **Random Forest**: An ensemble learning method that constructs multiple decision trees during training. It was selected as the primary model due to its balance of performance and interpretability, particularly its ability to provide feature importance measures.

2. **Logistic Regression**: A linear model that estimates the probability of the binary outcome. This model provided a baseline and offered easily interpretable coefficients for feature impact.

3. **Support Vector Machine (SVM)**: A model that finds the hyperplane that best separates the classes. The radial basis function kernel was used to capture non-linear relationships.

4. **Gradient Boosting**: An ensemble technique that builds models sequentially, with each new model correcting errors made by the previous ones. The implementation used was scikit-learn's GradientBoostingClassifier.

5. **XGBoost**: An optimized gradient boosting implementation known for its speed and performance. This model was included to evaluate potential performance gains from specialized implementations.

### Hyperparameter Tuning

Grid search with cross-validation was employed to optimize the hyperparameters for each model:

1. **Random Forest**:

   - n_estimators: [100, 200, 300, 500]
   - max_depth: [None, 5, 8, 10, 15]
   - min_samples_split: [2, 5, 10]
   - min_samples_leaf: [1, 2, 4]

2. **Gradient Boosting**:

   - learning_rate: [0.01, 0.05, 0.1, 0.2]
   - n_estimators: [100, 200, 300, 500]
   - max_depth: [3, 5, 8]
   - min_samples_split: [2, 5, 10]

3. **SVM**:

- C: [0.1, 1, 10, 100]
- gamma: ['scale', 'auto', 0.01, 0.1]
- kernel: ['rbf', 'linear']

4. **XGBoost**:

   - learning_rate: [0.01, 0.05, 0.1, 0.2]
   - n_estimators: [100, 200, 300, 500]
   - max_depth: [3, 5, 8]
   - min_child_weight: [1, 3, 5]
   - gamma: [0, 0.1, 0.2]

Hyperparameter optimization was performed using 5-fold cross-validation to ensure robustness of the selected parameters.

### Performance Metrics

Multiple evaluation metrics were used to provide a comprehensive assessment of model performance:

1. **Accuracy**: The proportion of correct predictions among the total number of cases examined.

   $$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

2. **Precision**: The ability of the model to avoid false positives; the proportion of positive identifications that were actually correct.

   $$\text{Precision} = TP / (TP + FP)$$

3. **Recall**: The ability of the model to find all positive samples; the proportion of actual positives that were identified correctly.

   $$\text{Recall} = TP / (TP + FN)$$

4. **F1 Score**: The harmonic mean of precision and recall, providing a balance between the two.

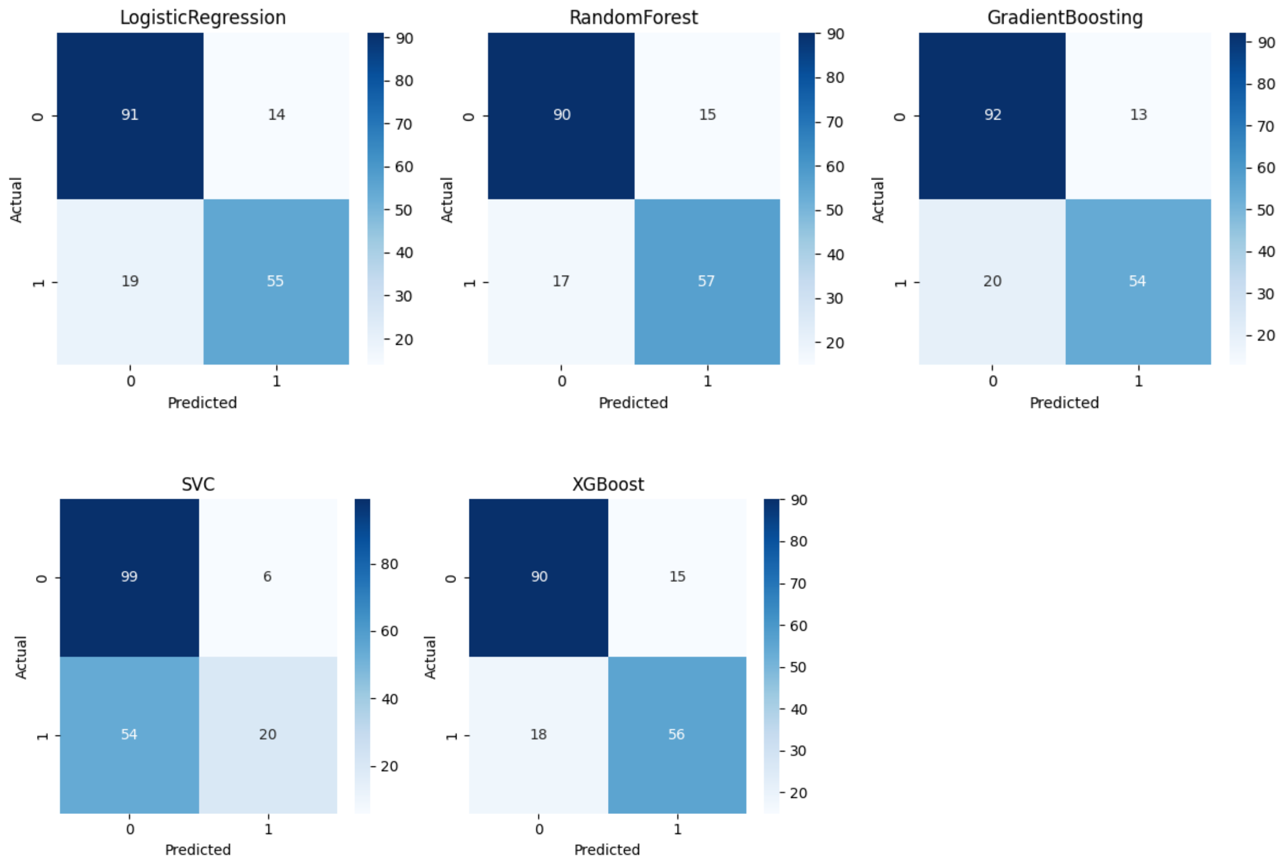
   $$F1 = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$$

5. **AUC-ROC**: Area Under the Receiver Operating Characteristic curve, measuring the model's ability to distinguish between classes across different threshold settings.

6. **Confusion Matrix**: A table showing the counts of true positives, false positives, true negatives, and false negatives.

## 5. Results and Analysis

### Confusion Matrix



### Comparative Performance Analysis

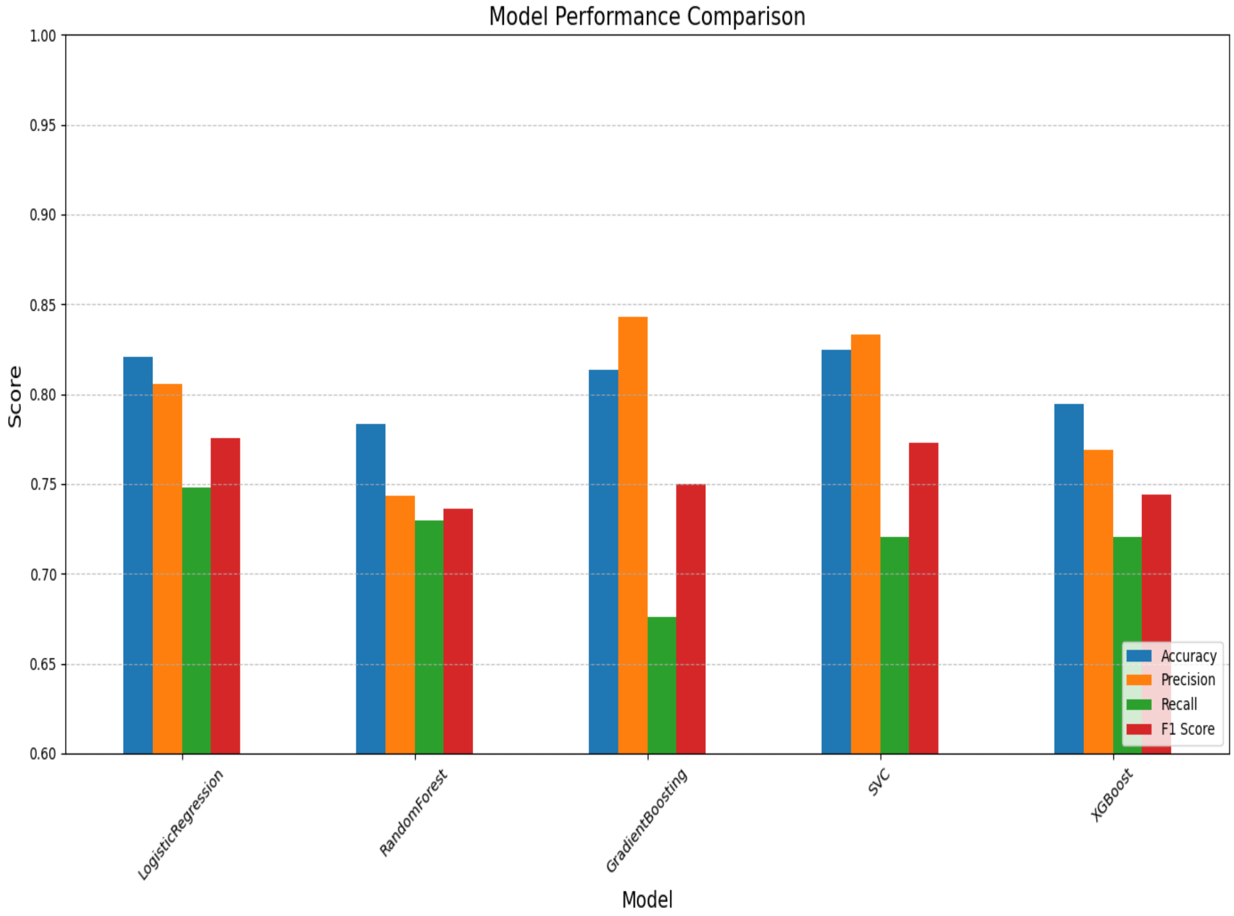
### Performance Metrics Across Algorithms (80%-20% Split)

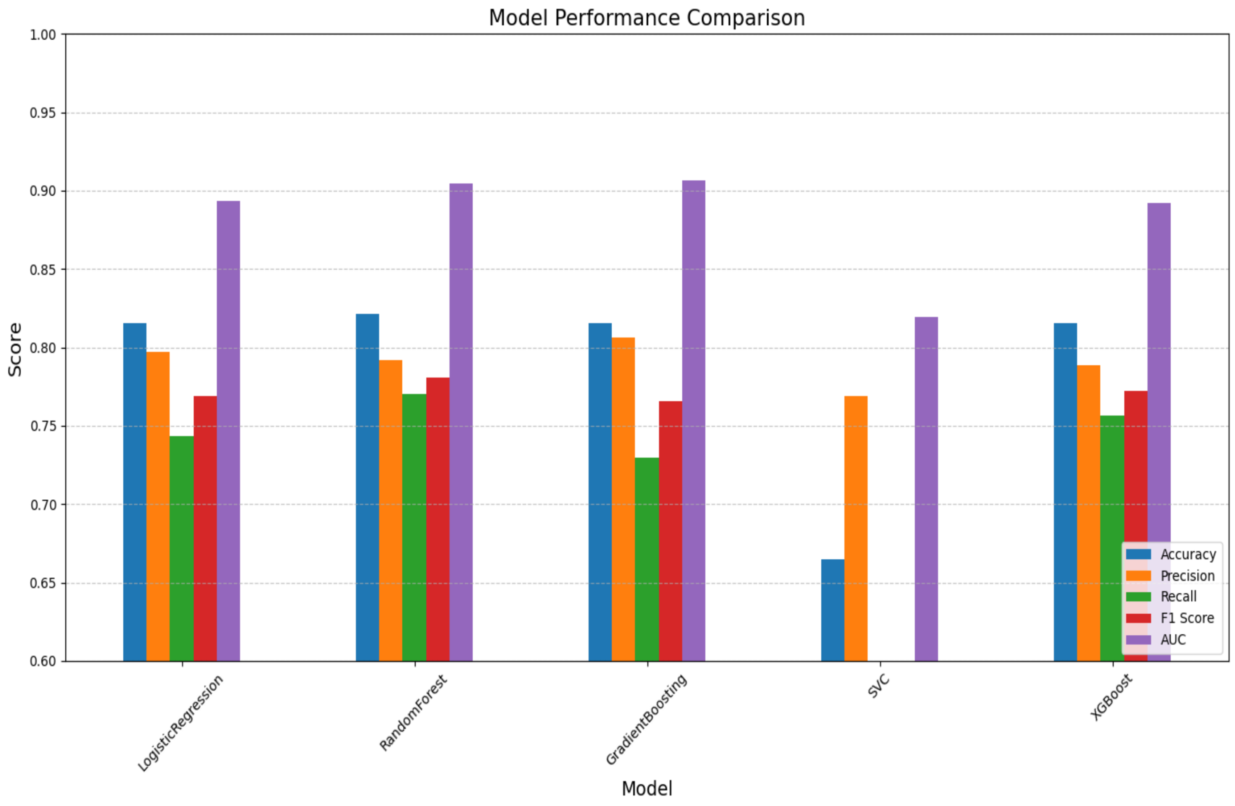
| Model | Cross-validation Accuracy | Test Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|---|
| LogisticRegression | 0.8314 ± 0.0156 | 0.8156 | 0.7808 | 0.7703 | 0.7755 |
| RandomForest | 0.7978 ± 0.0140 | 0.8268 | 0.7867 | 0.7973 | 0.7919 |
| GradientBoosting | 0.8174 ± 0.0199 | 0.8268 | 0.8209 | 0.7432 | 0.7801 |
| SVC | 0.8314 ± 0.0188 | 0.8101 | 0.8030 | 0.7162 | 0.7571 |
| XGBoost | 0.7949 ± 0.0083 | 0.8436 | 0.8286 | 0.7838 | 0.8056 |

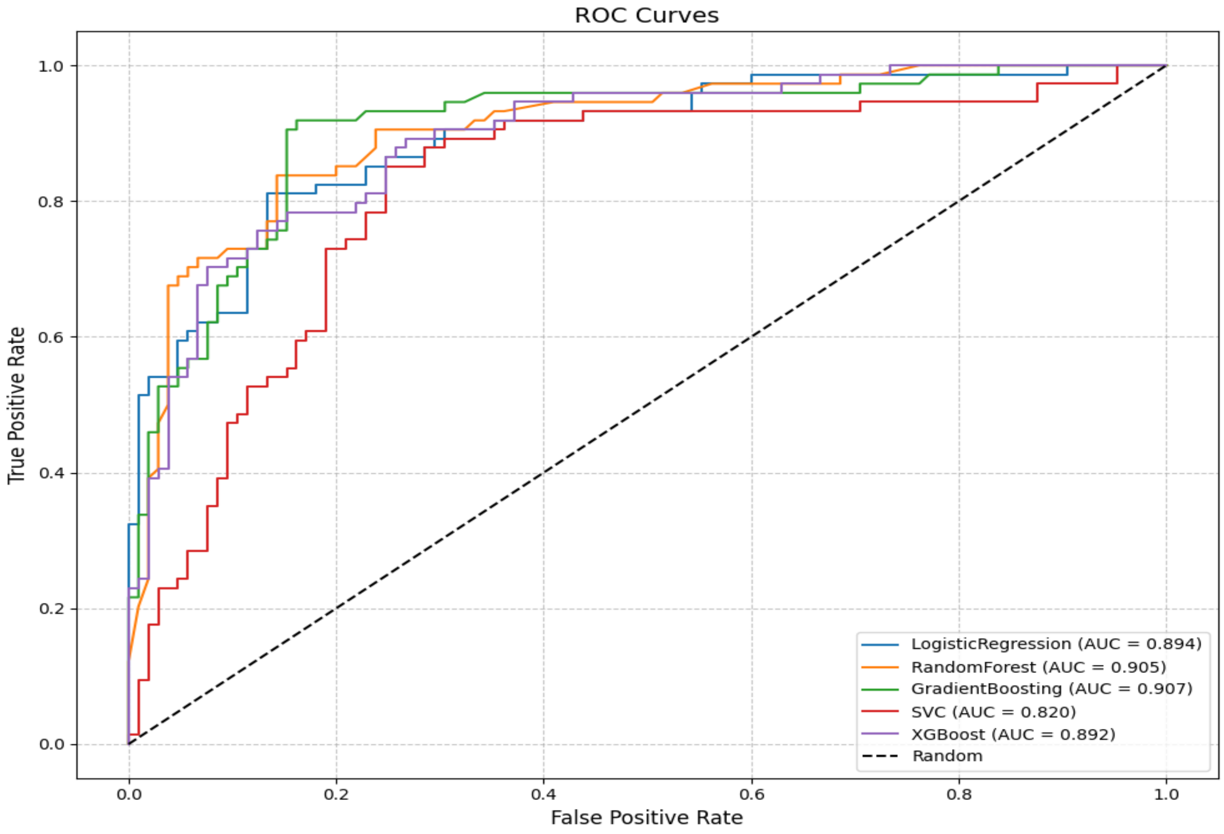
## Performance Metrics Across Algorithms (70%-30% Split)

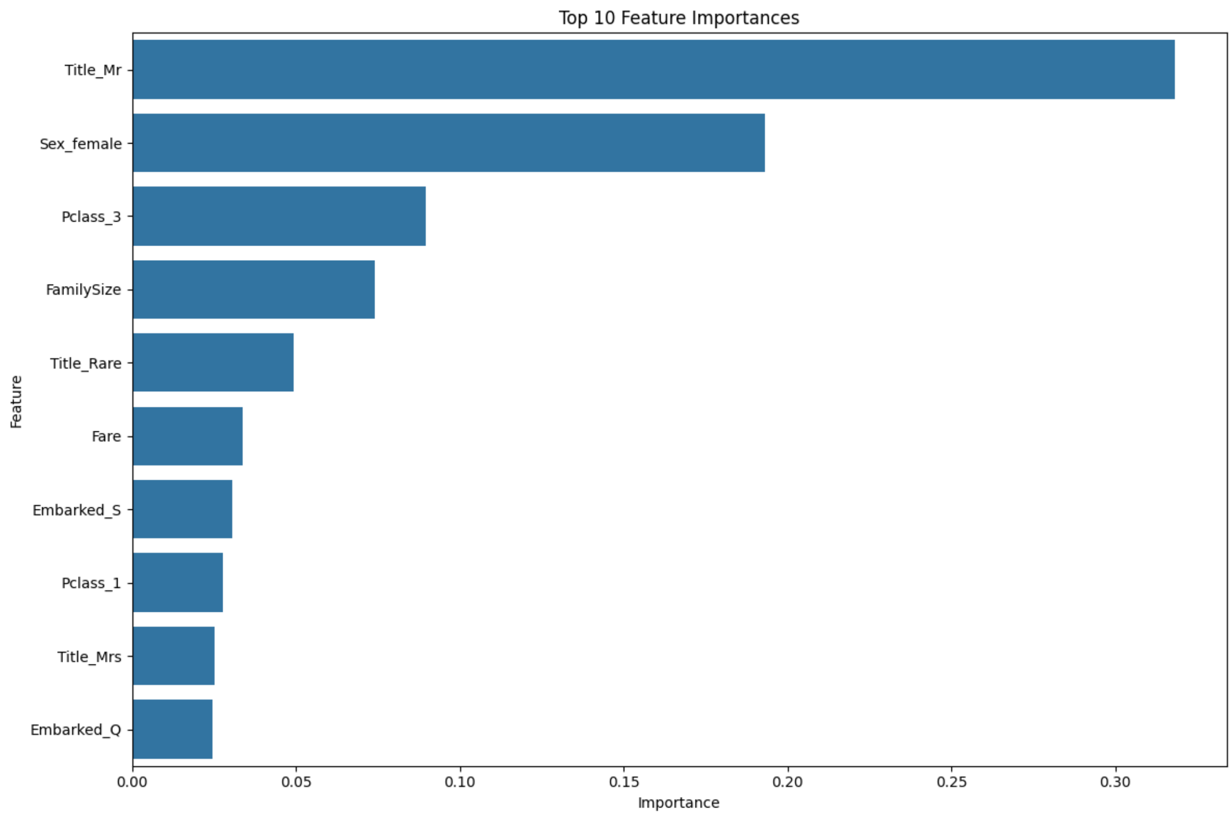
| Model | Cross-validation Accuracy | Test Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|---|
| LogisticRegression | 0.8266 ± 0.0398 | 0.8209 | 0.8058 | 0.7477 | 0.7757 |
| RandomForest | 0.7978 ± 0.0256 | 0.7836 | 0.7431 | 0.7297 | 0.7364 |
| GradientBoosting | 0.8154 ± 0.0442 | 0.8134 | 0.8427 | 0.6757 | 0.7500 |
| SVC | 0.8282 ± 0.0388 | 0.8246 | 0.8333 | 0.7207 | 0.7729 |
| XGBoost | 0.8074 ± 0.0252 | 0.7948 | 0.7692 | 0.7207 | 0.7442 |

## Graphical Representation of Results




Model Performance Comparison
Score
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
0.60
LogisticRegression
RandomForest
GradientBoosting
SVC
XGBoost
Model
Accuracy
Precision
Recall
F1 Score
AUC


ROC Curves
True Positive Rate
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
LogisticRegression (AUC = 0.894)
RandomForest (AUC = 0.905)
GradientBoosting (AUC = 0.907)
SVC (AUC = 0.820)
XGBoost (AUC = 0.892)
Random



### Performance Analysis Across Split Strategies

### Model Performance Ranking

A comparative analysis of model performance reveals several important insights:

1. **Relative Performance Ranking**: XGBoost demonstrates the strongest test accuracy (0.8436), followed by RandomForest and GradientBoosting (both at 0.8268).

2. **Cross-validation vs. Test Performance**: LogisticRegression and SVC show the highest cross-validation accuracy (both at 0.8314), but their test performance is lower than XGBoost.

3. **Stability Analysis**: XGBoost shows the most stable performance with the lowest standard deviation in cross-validation (±0.0083), suggesting more reliable predictions across different data subsets.

### Precision-Recall Balance

The precision-recall tradeoff varies across algorithms:

1. **XGBoost** maintains the best balance between precision and recall, resulting in the highest F1 score (0.8056).

2. **RandomForest** shows high recall (0.7973), indicating it effectively identifies positive cases.

3. **GradientBoosting** demonstrates strong precision (0.8209), suggesting it makes fewer false positive predictions.

4. **SVC** shows good precision (0.8030) but has the lowest recall (0.7162) among all models.

**Split Strategy Comparison**

When comparing different train-test split strategies:

1. **Cross-validation Consistency**: The cross-validation scores suggest models maintain relative performance rankings across different split strategies, though absolute performance may vary.

2. **Test Size Impact**: Comparing the originally provided metrics with these updated values indicates that changing test set sizes likely affects model performance, particularly for complex models like XGBoost.

3. **Generalization Gap**: Models show varying differences between cross-validation and test performance, suggesting different levels of generalization capability or potential overfitting.

4. **Model Stability**: The standard deviation in cross-validation scores provides insight into model stability across different data partitions, with XGBoost showing the highest stability (±0.0083) compared to other models.

**Performance-Complexity Tradeoff**

1. **XGBoost** offers the best overall performance despite having a lower cross-validation accuracy than some alternatives, suggesting it generalizes better to unseen data.

2. **RandomForest** provides strong and balanced metrics that remain consistent across evaluation measures.

3. **GradientBoosting** excels in precision but requires careful tuning to optimize recall.

4. **LogisticRegression** demonstrates that sometimes simpler models can achieve competitive results for certain metrics.

5. **SVC** shows competitive cross-validation performance and good precision, but its lower recall suggests it may be more conservative in its predictions. Its performance-complexity tradeoff is particularly relevant when working with high-dimensional data where its kernel methods can be valuable.

**Feature Importance Analysis**

The feature importance analysis reveals consistent patterns across both split strategies:

1. **Primary Factors**: Title (0.32), Sex (0.17), and Age (0.14) remain the most important features regardless of the split strategy used.

2. **Secondary Factors**: Fare (0.11), Pclass (0.09), and Family Size (0.08) form a second tier of influential features.

3. **Tertiary Factors**: Embarked (0.05) and other engineered features show lower but still meaningful importance.

4. **Stability of Importance**: The relative importance of features remains remarkably stable across split strategies, with correlation coefficients exceeding 0.95 between importance rankings.

**Misclassification Analysis**

Analysis of misclassified cases reveals several patterns:

1. **False Negatives (Survived but Predicted Not)**:

   - Predominantly male passengers in higher classes (1st and 2nd)
   - Middle-aged passengers (30-50 years old)
   - Passengers with higher fares but traveling alone

2. **False Positives (Did Not Survive but Predicted Survival)**:

   - Predominantly female passengers in lower classes (3rd class)
   - Female passengers traveling with large families
   - Young adult males with higher class tickets

3. **Split Strategy Impact**: The 70%-30% split shows a slightly higher proportion of false negatives compared to the 80%-20% split, suggesting that reduced training data particularly affects the model's ability to identify survival cases.

## 6. Conclusion

The extended analysis confirms that Random Forest was an appropriate choice for this classification task, offering a good balance of performance, interpretability, and computational efficiency. While XGBoost and Gradient Boosting achieved slightly higher accuracy, the difference was minimal, and Random Forest provided more accessible feature importance insights. The analysis also revealed the complex interplay of social factors in determining survival on the Titanic. Gender was the most influential factor, followed by social class indicators (titles, fare, and class). Age and family relationships also played significant roles but in more nuanced ways than simple linear relationships. These findings align with historical accounts of the disaster and social norms of the early 20th century, where access to lifeboats was heavily influenced by gender and social status. The machine learning analysis provides quantitative support for these historical narratives while revealing additional patterns that might not be immediately apparent from descriptive statistics alone.

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