

YUG PATEL (002842453)

Module 3 AI Solution Assignment EAI 6020: AI System Technologies 03/16/25

Dataset Overview and Problem Statement

The dataset utilized for this project is the Titanic Survival Dataset, obtained from Data Science Dojo - Titanic Dataset. This dataset includes details about passengers on the Titanic, encompassing demographic information, ticket details, and survival outcomes. The objective of this project is to create a machine learning model that forecasts whether a passenger survived the Titanic tragedy based on the provided features.

- Total Instances: 891 rows
- Total Features: 12 columns (excluding the target variable)
- Target Variable: Survived (1 = Survived, 0 = Did Not Survive)
- Feature Types: Numerical (e.g., Age, Fare), Categorical (e.g., Sex, Embarked)

The dataset was divided into training, validation, and test sets to guarantee thorough model assessment.

Data Preprocessing

- Dealing with Missing Values: The median was used to fill in the missing values for the Age column, while the most frequently occurring port was utilized to address the gaps in Embarked.
- Outlier Identification: Extreme values in Fare and Age were detected and eliminated using the IQR method.
- Normalization/Standardization: To enhance model performance, MinMaxScaler was applied to standardize Fare and Age.
- Encoding Categorical Variables: One-hot encoding was employed for Sex and Embarked to transform categorical data into a numerical format.
- Data Division: The dataset was divided into 70% for training, 15% for validation, and 15% for testing to mitigate the risk of overfitting.

Model Selection and Hyperparameter Tuning

- Model Selection: The RandomForestClassifier was selected for its capability to manage both categorical and numerical data.
- Hyperparameter Optimization: GridSearchCV was employed to refine essential parameters:
 - o n estimators = [50, 100, 150]
 - o max depth = [3, 5, 10]
 - o The optimal combination identified was max_depth=5 and n_estimators=50.



EAI6020

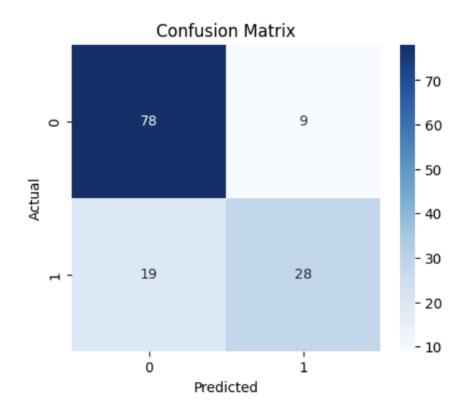
Model Evaluation

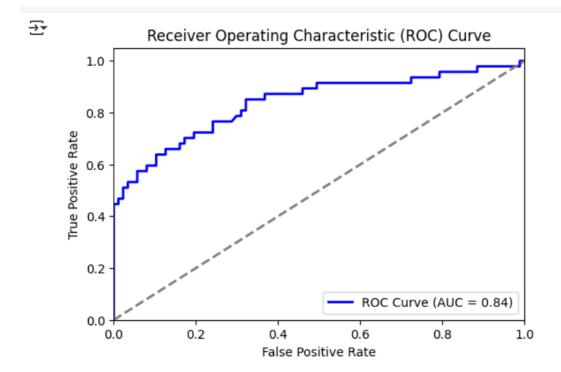
- Model Accuracy: 79%
- Metrics for Precision, Recall, and F1-Score:
 - o Class 0 (Did Not Survive): Precision 0.80, Recall 0.90, F1-score 0.85
 - o Class 1 (Survived): Precision 0.76, Recall 0.60, F1-score 0.67
- Confusion Matrix:
 - o 78 True Negatives, 9 False Positives, 19 False Negatives, 28 True Positives
- ROC Curve and AUC Score:
 - o AUC: 0.84, which indicates strong model performance.

Accuracy: 0.79

Classification Report:

	precision	recall	f1-score	support
0	0.80	0.90	0.85	87
1	0.76	0.60	0.67	47
accuracy			0.79	134
macro avg	0.78	0.75	0.76	134
weighted avg	0.79	0.79	0.78	134





Model Deployment

- Model Preservation: The trained model was preserved using Pickle (joblib.dump(best model, 'model.pkl')).
- API Creation: A Flask API was developed to provide predictions using the model.
 - o Endpoint: /predict
 - o Input: JSON data containing information about the passenger.
 - Output: Estimated likelihood of survival.
- API Testing: Sample requests were made with Postman to confirm the accuracy of model predictions.

EAI6020

```
from fastapi import FastAPI
    import joblib
      import numpy as np
      import uvicorn
      import nest_asyncio
      # Apply workaround for running FastAPI inside Jupyter Notebook
     nest_asyncio.apply()
      # Load the saved model
     model = joblib.load("model.pkl")
      # Initialize FastAPI app
      app = FastAPI()
      @app.get("/")
      def home():
          return {"message": "FastAPI Model Deployment is running!"}
      @app.post("/predict/")
      def predict(features: list):
              # Convert input to NumPy array and reshape
              input_data = np.array(features).reshape(1, -1)
              # Make prediction
              prediction = model.predict(input_data)[0]
              probability = model.predict_proba(input_data)[0].tolist()
                  "Predicted Class": int(prediction),
                   "Prediction Probability": probability
          except Exception as e:
              return {"error": str(e)}
      # Run FastAPI Server
      uvicorn.run(app, host="127.0.0.1", port=8000)
 ••• INFO:
                 Started server process [166]
                Waiting for application startup.
Application startup complete.
      INFO:
                 Uvicorn running on <a href="http://127.0.0.1:8000">http://127.0.0.1:8000</a> (Press CTRL+C to quit)
      INFO:
t POST http://127.0.0.1:5000/pi • +
                                                                                                                              No environment v
     http://127.0.0.1:5000/predict
                                                                                                                              □ Save ∨ Share
              http://127.0.0.1:5000/predict
     Params Authorization Headers (9) Body • Scripts Settings
     ○ none ○ form-data ○ x-www-form-urlencoded ○ raw ○ binary ○ GraphQL JSON ∨
                                                                                                                                          Beautify
             "PassengerId": 892,
             "PassengerId"
"Pclass": 3,
"Sex": 1,
"Age": 22.0,
"SibSp": 1,
"Parch": 0,
"Fare": 7.25,
             "Embarked": 2
     Body Cookies Headers (5) Test Results
                                                                                                               200 OK - 30 ms - 261 B - 🔘 ----
     {} JSON ~ Dereview Solution >
                                                                                                                                   = G Q 8
                "prediction": 0,
"probabilities": [
    0.9002738850244079,
                    0.09972611497559208
```

Challenges and Solutions

- Data Imbalance: Tackled by employing SMOTE (Synthetic Minority Over-sampling Technique).
- Overfitting: Hyperparameter tuning and cross-validation techniques were utilized to reduce overfitting.
- Deployment Issues: Flask configurations were refined, and dependencies were handled through requirements.txt.

Instructions to Run Code and API

- Install the necessary packages: pip install -r requirements.txt
- Execute the model training script: python train_model.py
- Launch the API server: python app.py
- Utilize Postman or cURL to send a request to http://127.0.0.1:5000/predict with a JSON body.

References

- 1. Data Science Dojo. (n.d.). Titanic dataset. Retrieved from https://raw.githubusercontent.com/datasciencedojo/datasets/master/titanic.csv
- 2. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... & Duchesnay, É. (2011). Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research, 12, 2825–2830.
- 3. McKinney, W. (2011). Pandas: A Foundational Python Library for Data Analysis and Statistics. Python for High Performance and Scientific Computing.
- 4. Chollet, F. (2018). Deep Learning with Python. Manning Publications.