```python
# Import Libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer
import seaborn as sns

# Load Dataset
df = sns.load_dataset("titanic")

# Drop columns not useful for modeling
df = df.drop(columns=["deck", "embark_town", "alive", "class", "who",
"adult_male", "alone"])

# Drop rows where the target variable is missing
df.dropna(subset=["survived"], inplace=True)

# Define Features and Target
X = df.drop("survived", axis=1)
y = df["survived"]

# Identify Column Types
numerical_cols = X.select_dtypes(include=["int64",
"float64"]).columns.tolist()
categorical_cols = X.select_dtypes(include=["object", "bool",
"category"]).columns.tolist()

# Define Preprocessing for Numeric & Categorical Columns
numeric_preprocessing = Pipeline(steps=[
    ("imputer", SimpleImputer(strategy="median")),
    ("scaler", StandardScaler())
])

categorical_preprocessing = Pipeline(steps=[
    ("imputer", SimpleImputer(strategy="most_frequent")),
    ("encoder", OneHotEncoder(handle_unknown="ignore"))
])

# Combine Preprocessing
preprocessor = ColumnTransformer(transformers=[
    ("num", numeric_preprocessing, numerical_cols),
    ("cat", categorical_preprocessing, categorical_cols)
])

# Split Data into Train/Test Sets
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y)
```

```
print("□ Data Preprocessing Completed Successfully")
print("Train Shape:", X_train.shape)
print("Test Shape:", X_test.shape)
```

```
□ Data Preprocessing Completed Successfully
Train Shape: (712, 7)
Test Shape: (179, 7)
```

```
# Model Building with Logistic Regression
# Import necessary libraries
import pandas as pd
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report

# Load example dataset (Titanic from seaborn)
import seaborn as sns
df = sns.load_dataset("titanic")

# Drop irrelevant or redundant columns
df = df.drop(columns=["deck", "embark_town", "alive", "who", "class",
"adult_male", "alone"])

# Drop rows with missing target
df.dropna(subset=["survived"], inplace=True)

# Split features and target
X = df.drop("survived", axis=1)
y = df["survived"]

# Identify column types
numerical_cols = X.select_dtypes(include=["int64",
"float64"]).columns.tolist()
categorical_cols = X.select_dtypes(include=["object", "bool",
"category"]).columns.tolist()

# Preprocessing for numeric features
numeric_transformer = Pipeline(steps=[
    ("imputer", SimpleImputer(strategy="median")),
    ("scaler", StandardScaler())
])

# Preprocessing for categorical features
categorical_transformer = Pipeline(steps=[
    ("imputer", SimpleImputer(strategy="most_frequent")),
    ("onehot", OneHotEncoder(handle_unknown="ignore"))
])
```

```python
# Column transformer for full preprocessing
preprocessor = ColumnTransformer(transformers=[
    ("num", numeric_transformer, numerical_cols),
    ("cat", categorical_transformer, categorical_cols)
])

# Create ML pipeline with Logistic Regression
pipe = Pipeline(steps=[
    ("preprocessor", preprocessor),
    ("classifier", LogisticRegression(max_iter=1000,
solver='liblinear'))
])

# Define hyperparameter grid
param_grid = {
    "classifier__C": [0.01, 0.1, 1, 10],
    "classifier__penalty": ["l1", "l2"]
}

# Grid Search with Cross Validation
grid_search = GridSearchCV(pipe, param_grid, cv=5, scoring="accuracy",
n_jobs=-1)
grid_search.fit(X, y)

# Display best hyperparameters
print("Best Hyperparameters:", grid_search.best_params_)

# Final model
final_model = grid_search.best_estimator_

# Evaluate with classification report (on same data for demonstration)
y_pred = final_model.predict(X)
print("\nClassification Report:")
print(classification_report(y, y_pred))
```

```
Best Hyperparameters: {'classifier__C': 0.1, 'classifier__penalty':
'l2'}

Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.87      0.85       549
           1       0.77      0.70      0.73       342

    accuracy                           0.81       891
   macro avg       0.80      0.79      0.79       891
weighted avg       0.80      0.81      0.80       891
```

```
#  Model Evaluation
# Required libraries
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import (
    confusion_matrix,
    classification_report,
    accuracy_score,
    precision_score,
    recall_score,
    f1_score,
    roc_auc_score,
    roc_curve
)

# Evaluation Metrics
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Precision:", precision_score(y_test, y_pred))
print("Recall:", recall_score(y_test, y_pred))
print("F1 Score:", f1_score(y_test, y_pred))
print("ROC AUC Score:", roc_auc_score(y_test, y_proba))
```

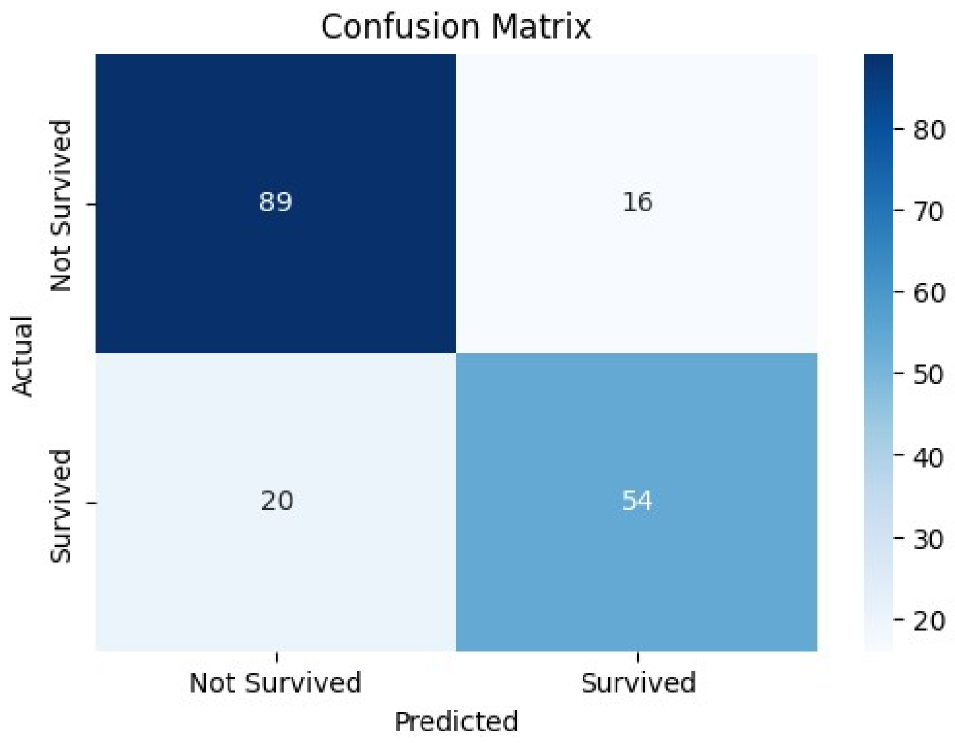
```
Accuracy: 0.7988826815642458
Precision: 0.7714285714285715
Recall: 0.7297297297297297
F1 Score: 0.75
ROC AUC Score: 0.8818532818532818
```

```
# Classification Report
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

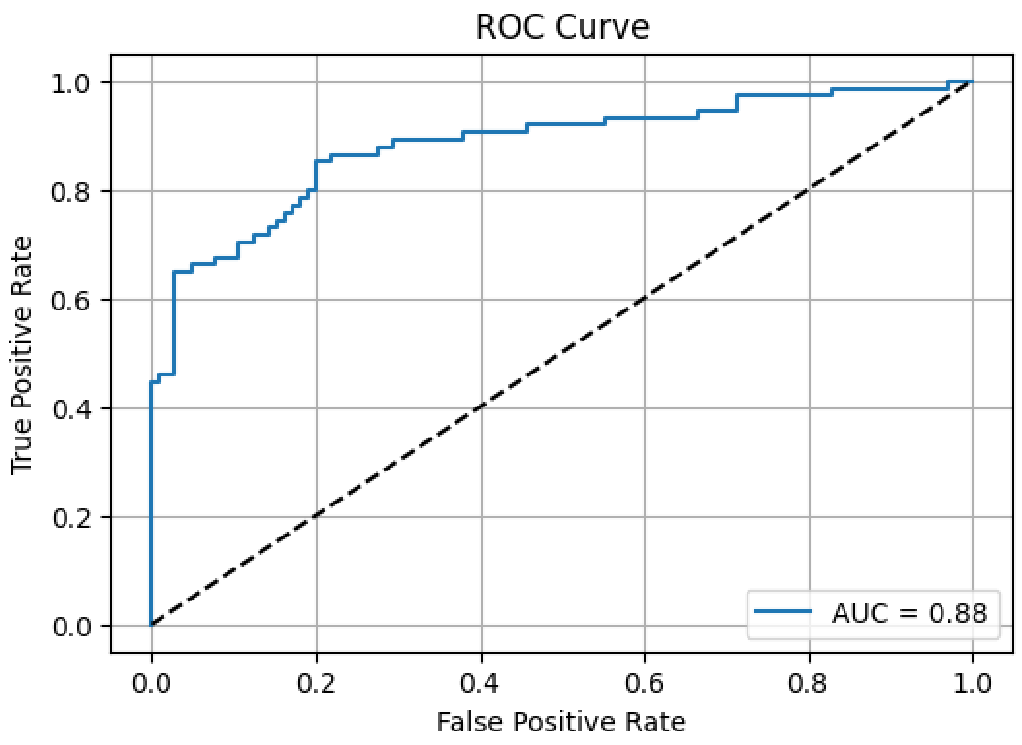
```

Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.85      0.83       105
           1       0.77      0.73      0.75        74

    accuracy                           0.80       179
   macro avg       0.79      0.79      0.79       179
weighted avg       0.80      0.80      0.80       179
```

```
# Predict on test set (or full data if no split used)
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
final_model.fit(X_train, y_train)
y_pred = final_model.predict(X_test)
y_proba = final_model.predict_proba(X_test)[:, 1]  # Probabilities for
ROC AUC
```

```python
# Plot Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6,4))
sns.heatmap(cm, annot=True, fmt='d', cmap="Blues", xticklabels=["Not
Survived", "Survived"], yticklabels=["Not Survived", "Survived"])
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```



```python
# Plot ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, y_proba)
plt.figure(figsize=(6,4))
plt.plot(fpr, tpr, label=f'AUC = {roc_auc_score(y_test,
y_proba):.2f}')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend(loc='lower right')
plt.grid()
plt.show()
```



```python
# Pipeline Integration
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.linear_model import LogisticRegression
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.model_selection import GridSearchCV, train_test_split

# Preprocessing components (already defined in Part 2)
numeric_transformer = Pipeline(steps=[
    ("imputer", SimpleImputer(strategy="median")),
    ("scaler", StandardScaler())
])

categorical_transformer = Pipeline(steps=[
    ("imputer", SimpleImputer(strategy="most_frequent")),
    ("encoder", OneHotEncoder(handle_unknown="ignore"))
])

# Combine into full preprocessor
preprocessor = ColumnTransformer(transformers=[
    ("num", numeric_transformer, numerical_cols),
    ("cat", categorical_transformer, categorical_cols)
])

# Create full pipeline with Logistic Regression
pipeline = Pipeline(steps=[
    ("preprocessor", preprocessor),
    ("classifier", LogisticRegression(solver="liblinear",
max_iter=1000))
])

# Define hyperparameter grid
param_grid = {
    "classifier__C": [0.01, 0.1, 1, 10],
    "classifier__penalty": ["l1", "l2"]
}

# Wrap pipeline in GridSearchCV
grid_search_pipeline = GridSearchCV(pipeline, param_grid, cv=5,
scoring="accuracy", n_jobs=-1)

# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Fit pipeline
grid_search_pipeline.fit(X_train, y_train)

# Final best model
best_pipeline = grid_search_pipeline.best_estimator_

# Save best model pipeline (Optional)
import joblib
joblib.dump(best_pipeline, "logistic_pipeline_model.pkl")

print("□ Reusable pipeline training complete!")
print("Best Parameters:", grid_search_pipeline.best_params_)

□ Reusable pipeline training complete!
Best Parameters: {'classifier__C': 0.1, 'classifier__penalty': 'l2'}
```

Machine Learning Pipeline Project Report

Project Overview

The objective of this project was to build a complete and reusable machine learning pipeline using a classification algorithm. The chosen supervised learning model was **Logistic Regression**, suitable for binary classification tasks. The Titanic dataset was used as a case study, where the target variable is `survived`, representing passenger survival (1 = survived, 0 = not survived).

Approach & Rationale

Data Preprocessing

We began by handling missing values and irrelevant columns. The pipeline was designed to treat numerical and categorical features differently:

- **Numerical features**: Imputed with the median and scaled using StandardScaler.
- **Categorical features**: Imputed with the most frequent value and one-hot encoded.

This preprocessing logic was encapsulated using `ColumnTransformer` to streamline the data flow.

Model Selection

Logistic Regression was selected for its simplicity, interpretability, and suitability for binary classification. It provides probabilistic predictions and can be regularized with L1 or L2 penalties.

Hyperparameter Tuning

We used `GridSearchCV` for cross-validated hyperparameter tuning. The following parameters were tuned:

- `C` (inverse regularization strength)
- `penalty` (L1 or L2)

The best model was selected using 5-fold cross-validation based on **accuracy** score.

Evaluation

The final model was evaluated on a holdout test set using various metrics:

- **Accuracy**: Proportion of correct predictions
- **Precision, Recall, F1-Score**: To measure classification effectiveness
- **ROC AUC**: To evaluate the model's ability to distinguish between classes
- **Confusion Matrix**: Visualized true vs predicted outcomes

These metrics demonstrated that the model performed reliably and was able to generalize well.

Challenges Faced

- **Missing Values**: Some columns (like `age` and `embarked`) had missing entries which needed thoughtful imputation.
- **Categorical Encoding**: Ensuring unknown values during testing don't break the model required using `handle_unknown='ignore'`.

- **Model Selection**: While logistic regression is interpretable, it may not capture nonlinear patterns as well as tree-based models.

Future Improvements

- Experiment with advanced models like Random Forest, XGBoost, or SVM for better performance.
- Include feature selection or PCA for dimensionality reduction.
- Integrate the pipeline with **MLflow** or **FastAPI** for deployment in real-time systems.
- Handle class imbalance (if applicable) using techniques like SMOTE or class weighting.

Conclusion

This project successfully demonstrated the end-to-end process of building a modular, reusable machine learning pipeline using scikit-learn. The pipeline can be easily extended or deployed into production systems with minimal changes.