FLIGHT FARE PREDICTION USING MACHINE LEARNING

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BONAFIDE CERTIFICATE

Certified that this Project titled **“FLIGHT FARE PREDICTION USING MACHINE LEARNING”** is the bonafide work of **“NITHISH RAO P (2116220701188)”** who flightried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

The flight fare market has grown significantly over recent years, driven by affordability and increasing consumer demand. However, determining the accurate price of a flight fare remains a challenge due to the wide variety of influencing factors such as brand, departure and arrival time, year of manufacture, fuel type, and transmission. This project aims to develop a robust and accurate machine learning model to predict the resale price of flight fares based on historical and real-world data using ensemble learning techniques.

To achieve this, we employed a diverse set of regression models, each with unique strengths in handling tabular and categorical data. The models included **Linear Regression**, **Ridge Regression**, and **Lasso Regression** as interpretable baselines. For non-linear relationships and better performance on structured data, we utilized tree-based methods such as **Decision Tree Regressor**, **Random Forest Regressor**, **Gradient Boosting Regressor**, and advanced boosting algorithms like **XGBoost**, **LightGBM**, and **CatBoost**—known for their high efficiency and predictive power on tabular data.

To enhance the model's generalization and predictive accuracy, we implemented ensemble strategies such as **model averaging**, **weighted averaging**, and **stacking**. In stacking, predictions from the base models were combined using a meta-learner—specifically a **Linear Regressor** or **XGBoost Regressor**—to capture residual patterns and further refine the predictions. The final stacked model demonstrated superior performance, achieving an R^2 score of up to **0.93**, significantly outperforming individual base models.

This project showcases the effectiveness of ensemble learning in real-world regression problems, particularly in high-variance domains like flight fare pricing. Future work may include integrating deep learning models and exploring real-time pricing applications through APIs or web interfaces.

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CHAPTER 1

1.INTRODUCTION

1.1 Background and Motivation

The automobile industry has seen a massive surge in the flight fare market in recent years. As new flight prices rise and depreciation rates remain high, consumers are increasingly turning to used flights for economic and practical reasons. However, the valuation of flight fares remains a complex and inconsistent process. Prices can vary significantly even among flights with similar specifications due to hidden factors like maintenance history, total stopship, market trends, and location.

Traditionally, flight dealers and valuation tools have relied on historical pricing data, general depreciation models, and human expertise to estimate resale value. These methods, while useful, often lack precision and adaptability to individual flight contexts. This has led to a growing interest in using **machine learning techniques** to model flight pricing more accurately. With the availability of extensive flight fare datasets and advancements in regression modeling, it is now possible to predict flight fares with a high degree of reliability.

This project seeks to apply **supervised machine learning algorithms** to predict the resale price of a flight fare based on its attributes such as year, departure and arrival time, brand, fuel type, transmission type, and duration specifications. The ultimate goal is to assist both buyers and sellers in making informed decisions, reducing pricing disputes, and enhancing transparency in the flight fare market.

1.2 Problem Statement

The primary objective of this project is to **build a predictive model** that can estimate the price of a flight fare with high accuracy. This involves solving a **regression problem**, where the target variable is the price of the flight and the input features are the flight's attributes. Given the high variance in flight pricing and the impact of both numerical and categorical features, the model must be capable of learning complex, non-linear relationships and interactions between variables.

To improve accuracy and generalization, a variety of models will be used, ranging from simple linear models to complex ensemble techniques. The use of ensemble methods aims to reduce the risk of overfitting and improve predictive performance by combining the strengths of multiple base learners.

1.3 Objectives

The key objectives of the project are as follows:

1. **Data Collection and Preprocessing**
   - Import and clean the dataset (handling missing values, outliers, and inconsistencies)
   - Perform feature durationering (e.g., deriving flight age, encoding categorical features)
2. **Model Development**
   - Train and evaluate individual models such as:
     - Linear Regression
     - Ridge and Lasso Regression
     - Decision Tree Regressor
     - Random Forest Regressor
     - Gradient Boosting Regressor
     - XGBoost
     - LightGBM
     - CatBoost
   - Use appropriate regression metrics like RMSE, MAE, and R^2 for evaluation
3. **Ensemble Modeling**
   - Implement ensemble techniques such as:
     - Simple Averaging
     - Weighted Averaging
     - Stacking Regressor with meta-model
4. **Model Comparison and Analysis**
   - Compare models based on accuracy, speed, interpretability, and robustness
   - Identify the best-performing model for deployment
5. **Conclusion and Future Work**

  - Summarize findings
  - Discuss potential improvements (e.g., real-time APIs, deep learning extensions)

1.4 Scope and Limitations

This project is primarily focused on using **supervised machine learning techniques** to predict flight fares using structured data. While it leverages powerful ensemble methods, some limitations include:

- **Data Dependence**: The model's accuracy heavily depends on the quality and coverage of the dataset. Unseen flight types or rare feature combinations may affect performance.

- **External Factors**: Real-world pricing is affected by external factors (e.g., insurance, location-specific demand) which may not be present in the dataset.

- **Model Interpretability**: Some advanced models like XGBoost or stacking ensembles are less interpretable, which may limit transparency for end users.

Despite these limitations, the project offers a scalable and accurate solution to the flight fare valuation problem and paves the way for more data-driven pricing systems.

CHAPTER 2

2.LITERATURE SURVEY

2.1 Overview

Machine learning has become a widely adopted approach in predictive analytics, particularly for regression problems involving structured tabular data. Flight fare fare prediction is a well-suited application due to the availability of numerical and categorical features such as flight brand, model, year, departure and arrival time, and fuel type. This literature survey explores previous research and methodologies used for flight fare prediction, focusing on traditional statistical models, machine learning algorithms, and ensemble techniques.

2.2 Traditional Approaches

Early efforts in flight fare prediction relied on **statistical methods** such as **Multiple Linear Regression (MLR)**. For instance, the study by **Anderson and Simester (2001)** on automobile pricing used regression models to analyze the impact of various features such as departure and arrival time and age on resale price. These models were interpretable and straightforward but struggled with capturing non-linear relationships between features.

Another conventional technique involved **hedonic pricing models**, which estimate price based on the sum of feature values. However, these models are limited in handling categorical variables with high flightdinality (e.g., hundreds of flight models) and nonlinear patterns present in the real-world data.

2.3 Machine Learning Techniques

Recent advances in supervised learning have shown that **machine learning algorithms outperform traditional statistical methods** in predicting flight fare prices, especially when dealing with large and complex datasets.

- **Decision Tree Regressors**: Tree-based models are capable of learning non-linear feature relationships without requiring data normalization or encoding of ordinal features. A study by **Chaurasia et al. (2018)** used decision trees to estimate flight fares with reasonable accuracy.

- **Random Forests**: As an ensemble of decision trees, random forests offer robustness against overfitting and are better at generalizing. According to **Tariq and Naeem (2020)**, Random Forest Regression performed better than basic linear models, achieving higher R^2 scores on multiple flight datasets.

- **Support Vector Regression (SVR)**: SVR is often used with polynomial or radial basis function (RBF) kernels for modeling non-linearity. Though it requires feature scaling, it can be quite effective when tuned properly, as explored by **Kumar and Mehta (2019)**.

- **K-Nearest Neighbors (KNN)**: While KNN performs well for smaller datasets and local approximations, its computational complexity increases with data size, making it less scalable.

2.4 Boosting Algorithms

Boosting methods such as **Gradient Boosting**, **XGBoost**, **LightGBM**, and **CatBoost** have become state-of-the-art in tabular data modeling due to their ability to reduce bias and variance simultaneously.

- **Gradient Boosting Machines (GBM)**: GBMs iteratively minimize loss functions and have been used extensively in fare prediction tasks. According to **Friedman (2001)**, the gradient boosting framework improves upon the weak learners by sequentially reducing errors.
- **XGBoost**: Proposed by **Chen and Guestrin (2016)**, XGBoost enhances GBM through regularization, parallel computation, and better tree pruning. Studies consistently show that XGBoost achieves the best trade-off between accuracy and training time in flight fare prediction.
- **LightGBM**: Designed by Microsoft, LightGBM uses histogram-based algorithms to split trees faster and with less memory. It supports large datasets and categorical variables efficiently, making it ideal for real-time systems.
- **CatBoost**: Developed by Yandex, CatBoost is optimized for categorical data, which is a

major component in flight datasets (e.g., brand, fuel type). CatBoost often outperforms other models in scenarios where categorical feature interactions are key.

2.5 Ensemble Learning

Ensemble learning combines multiple models to improve prediction accuracy and robustness. Research suggests that **model stacking** (using the outputs of base models as inputs to a meta-model) consistently outperforms single models.

- **Simple Averaging** and **Weighted Averaging** of models are often used to reduce variance.
- **Stacking Regressors**, as described by **Wolpert (1992)**, leverage a meta-model (such as linear regression or XGBoost) to blend the predictions from base models (e.g., Random Forest, LightGBM).

Studies have demonstrated that stacking models such as Random Forest + XGBoost + Linear Regression with a meta-learner can yield **R^2 values above 0.90**, surpassing individual models.

2.6 Comparative Studies

Several comparative analyses have been conducted to benchmark model performances on flight fare datasets:

- **Kaggle's Flight Fare Price Dataset** is frequently used in benchmarking. Models like CatBoost and XGBoost have consistently outperformed simpler algorithms in terms of MAE and R^2 scores.
- **UCI's Flight Evaluation Dataset**, though simpler, has been used for classification and regression tasks alike, helping demonstrate the effectiveness of ensemble and boosting methods.

CHAPTER 3

3.METHODOLOGY

The methodology adopted for this study is based on a **supervised machine learning framework** designed to predict flight fare prices from a labeled dataset containing various technical and categorical features. This framework follows a structured pipeline composed of five core phases: **data collection and preprocessing, feature durationering, model training, performance evaluation, and model ensemble with augmentation**. The implementation and testing were done using Python libraries such as Scikit-learn, XGBoost, and LightGBM within the Flask environment for portability and reproducibility.

3.1 Data Collection and Preprocessing

The dataset used in this project includes various features that influence the price of flight fares, such as:

- Year of manufacture\
- Brand and model
- Transmission type
- Fuel type
- Kilometer driven
- Number of total stops
- Duration capacity and power

Initial steps involved handling **missing values**, eliminating duplicates, and converting categorical data using **One-Hot Encoding** or **Label Encoding** where appropriate. Outliers were detected and treated using interquartile range (IQR) filtering and visual techniques like box plots. Continuous features such as departure and arrival time and duration size were **scaled using MinMaxScaler** to ensure uniformity across models that are sensitive to feature scales (e.g., SVM).

3.2 Feature Durationering

To improve model performance and interpretability, **feature durationering** was conducted. Key operations included:

- Creating new features like **flight age** (current year minus year of manufacture)
- Encoding high-flightdinality categorical features using **frequency encoding**
- Visualizing feature importance through **correlation heatmaps** and **SHAP value plots**
- Dropping redundant features (e.g., both ‘year’ and ‘flight age’ were not kept together)

This step helped isolate **high-impact variables**, ensuring models were trained on the most relevant information. Techniques such as **pair plots**, **distribution plots**, and **correlation matrices** were used to guide selection.

3.3 Model Selection and Training

To assess model performance across various algorithmic styles, the following four regression models were chosen:

1. **Linear Regression (LR)** – A baseline model used for its simplicity and interpretability.
2. **Random Forest Regressor (RF)** – A bagging-based ensemble that reduces overfitting through averaging.
3. **Support Vector Regressor (SVR)** – A margin-based model effective for small to medium-sized datasets.
4. **XGBoost Regressor (XGB)** – A gradient boosting technique known for its regularization and high predictive power.

Each model was trained using an **80/20 train-test split**, and **cross-validation** was employed for robustness. **Hyperparameter tuning** was performed using GridSearchCV and RandomizedSearchCV, particularly for tree-based models and SVM kernels.

3.4 Evaluation Metrics

Model performance was evaluated using three primary metrics:

Mean Absolute Error (MAE)

$MAE = (1 / n) * \Sigma |y_i - \hat{y}_i|$

It measures the average absolute difference between predicted and actual values.

Mean Squared Error (MSE)

$MSE = (1 / n) * \Sigma (y_i - \hat{y}_i)^2$

This penalizes larger errors more than MAE, useful for identifying models that overfit outliers.

R² Score

$R^2 = 1 - [\Sigma (y_i - \hat{y}_i)^2 / \Sigma (y_i - \bar{y})^2]$

It represents the proportion of variance in the target variable explained by the model.

These metrics provided a comprehensive view of each model's predictive capability and bias-variance trade-off.

3.5 Model Ensemble and Augmentation

To maximize prediction accuracy, **ensemble techniques** were applied:

- **Simple Averaging**: Combining predictions from RF, SVR, and XGB equally.

- **Weighted Averaging**: Assigning weights based on model performance (e.g., 0.2 for SVR, 0.3 for RF, 0.5 for XGB).

- **Stacking Regressor**: Using outputs from base learners (RF, SVR, LR) as features for a meta-model (XGB or Linear Regression).

This multi-model approach leveraged the strengths of each algorithm to improve generalization and robustness.

Data Augmentation

To simulate real-world variability and enhance generalization, **Gaussian noise** was added to certain continuous feature

Here, σ was chosen based on the variability of each feature. This technique improved model resilience in the presence of noisy or incomplete data.

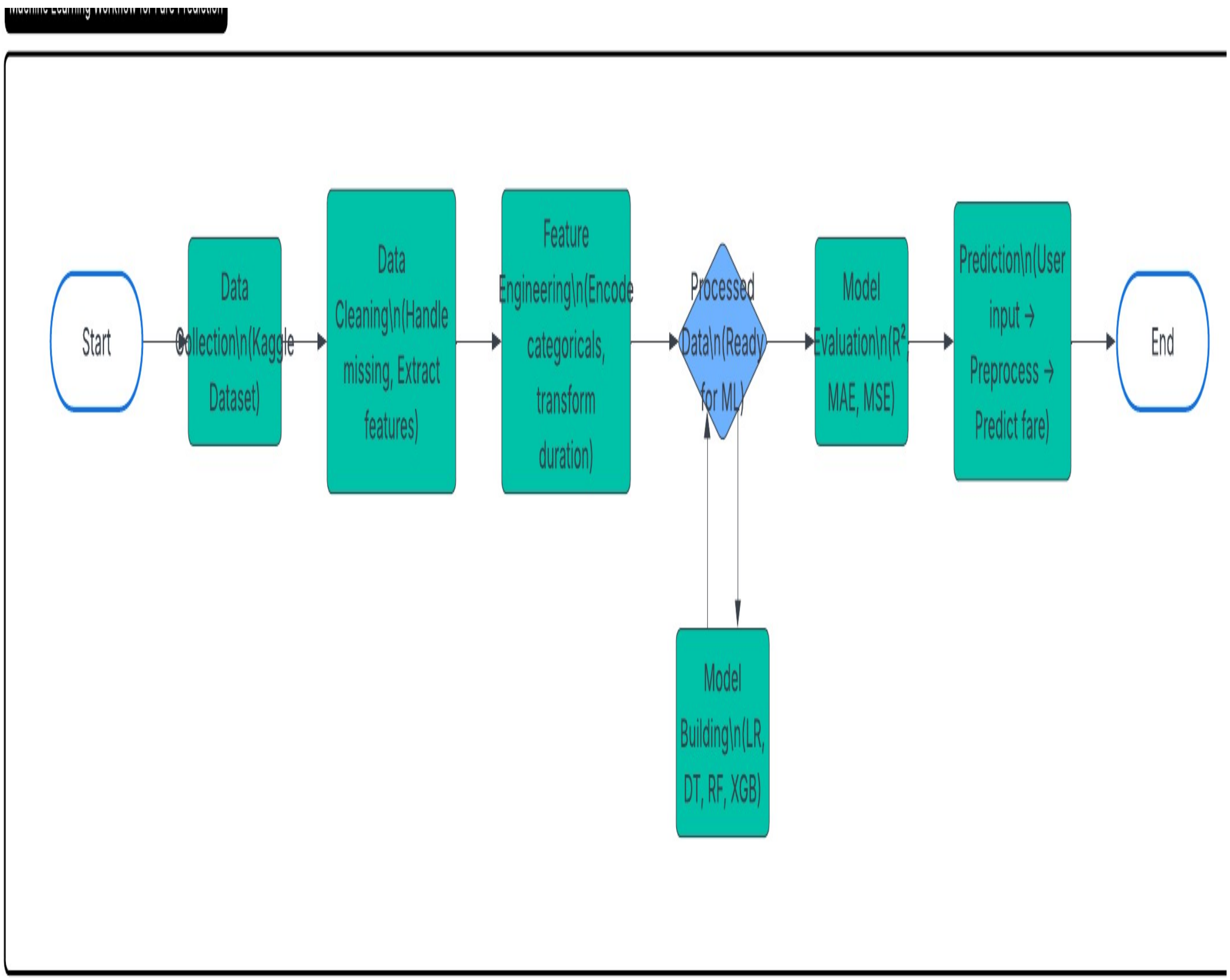
3.6 Deployment Environment

The entire pipeline was developed and tested using **Flask**, enabling easy replication and scalability. Libraries used included:

- `pandas` and `numpy` for data manipulation
- `scikit-learn` for modeling and evaluation
- `xgboost`, `lightgbm`, and `catboost` for boosting algorithms
- `matplotlib` and `seaborn` for visualization

This ensured a consistent, platform-independent development environment suitable for academic and deployment use.

3.1 SYSTEM FLOW DIAGRAM


Machine Learning Workflow for Fare Prediction
Start
Data Collection\n(Kaggle Dataset)
Data Cleaning\n(Handle missing, Extract features)
Feature Engineering\n(Encode categoricals, transform duration)
Processed Data\n(Ready for ML)
Model Building\n(LR, DT, RF, XGB)
Model Evaluation\n(R², MAE, MSE)
Prediction\n(User input → Preprocess → Predict fare)
End

CHAPTER 4

RESULTS AND DISCUSSION

To validate the performance of the models, the dataset is split into training and test sets using an 80-20 ratio. Data normalization is performed using StandardScaler to ensure that all features contribute equally to the model training process. Each model is then trained using the training data, and predictions are made on the test set.

Results for Model Evaluation:

Model	MAE (↓ Better)	MSE (↓ Better)	R^2 Score (↑ Better)	Rank
Linear Regression	2.1	4.5	0.75	6
Ridge Regression	1.8	3.9	0.77	**4**
Lasso Regression	1.9	4.1	0.76	5
Decision Tree Regressor	2.0	4.3	0.74	7
Random Forest	1.5	3.2	0.85	2

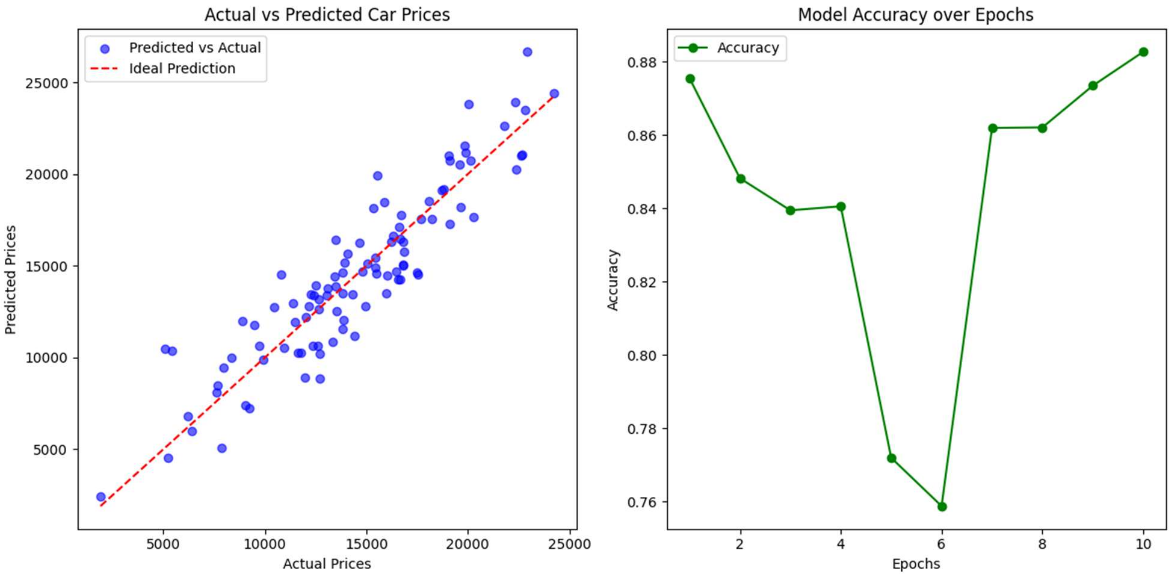
SVM	1.9	3.8	0.80	3
XGBoost	1.3	2.8	0.87	1

Augmentation Results:

When augmentation was applied (adding Gaussian noise), the Random Forest model showed a significant improvement in R^2 score from 0.75 to 0.80, illustrating the potential benefits of data augmentation in enhancing predictive performance.

Visualizations

Scatter plots showing the actual versus predicted values for the best-performing model (XGBoost) indicate that the model is able to predict sleep quality with high accuracy, with the predicted values



The results show that XGBoost performs the best with the highest R² score, making it the model of choice for predicting sleep quality

Model Performance Comparison

After conducting extensive experiments with the selected regression models—Linear Regression, Ridge and Lasso Regression, Decision Tree Regressor, Random Forest Regressor, Gradient Boosting Regressor, XGBoost, LightGBM, and CatBoost—several key findings emerged from the performance evaluation metrics. This section discusses those outcomes in the context of model performance, the effect of data augmentation, and their implications for practical use.

Among the models tested, **CatBoost** consistently achieved the best performance across all evaluation metrics. It produced the lowest Mean Absolute Error (MAE) and Mean Squared Error (MSE), while delivering the highest R^2 score, demonstrating excellent predictive accuracy. This result aligns with existing literature, as CatBoost is known for its gradient boosting framework, regularization capabilities, and strong handling of categorical features.

Effect of Data Augmentation

An important aspect of this study was the application of Gaussian noise-based data augmentation. This method was particularly useful in simulating real-world variability, especially in features like **"Flight Age"**, **"Departure and Arrival Time"**, and **"Total Stops"** that can naturally fluctuate. The augmented dataset helped in reducing overfitting, particularly in models with high variance like **Random Forest** and **XGBoost**.

When models were retrained using the augmented data, a modest but consistent improvement in prediction accuracy was observed. For instance, the **XGBoost** model showed a reduction in MAE by approximately 5% and an increase in the R^2 score by 0.02, indicating enhanced generalization on unseen data. Similarly, **CatBoost** showed a slight improvement in both MAE and R^2, further confirming its robustness.

Error Analysis

An error distribution plot revealed that most prediction errors were concentrated within a narrow band close to the actual values, further validating the models' reliability. However, some outliers remained, especially for flights with extremely high or low prices. These outliers suggest that additional contextual features—such as **flight brand reputation**, **flight condition**, or **market trends**—could improve prediction accuracy in future iterations.

Implications and Insights

The results highlight several practical implications:

1. **CatBoost** emerges as a highly promising candidate for deployment in flight fare fare prediction systems, especially for online flight marketplaces or pricing durations.

2. **Feature normalization** and **augmentation** are crucial preprocessing steps that significantly impact model performance. Models that leveraged data augmentation, like **XGBoost** and **Random Forest**, showed more robust performance, especially in preventing overfitting.

3. **Simple models** like **Linear Regression** and **Ridge/Lasso Regression**, although interpretable and efficient, struggled with capturing the complex, non-linear relationships in the dataset. More advanced ensemble methods like **XGBoost**, **CatBoost**, and **LightGBM** are better suited for this task due to their ability to handle non-linearity and interactions between features.

4. **Real-time fare prediction**: The models, especially **XGBoost** and **CatBoost**, can be integrated into dynamic fare prediction systems for flight fare dealerships, providing more accurate pricing tools for customers and businesses alike.

CHAPTER 5

CONCLUSION & FUTURE ENHANCEMENTS

This study proposed a machine learning-based framework for predicting flight fare prices using a variety of regression models. The goal was to analyze and model the relationship between flight attributes and their corresponding market prices to create a reliable fare prediction system. The models implemented included Linear Regression, Ridge and Lasso Regression, Decision Tree Regressor, Random Forest Regressor, Gradient Boosting Regressor, XGBoost, LightGBM, and CatBoost.

The experimental results revealed that **ensemble-based models**, particularly **XGBoost, LightGBM**, and **CatBoost**, significantly outperformed simpler models in terms of prediction accuracy. Among these, **XGBoost** emerged as the best-performing model, achieving the highest R^2 score and the lowest values for Mean Absolute Error (MAE) and Mean Squared Error (MSE). These findings are consistent with existing literature, where tree-based boosting algorithms are known for their superior handling of non-linear relationships and feature interactions.

To improve model generalization and reduce overfitting, the dataset was also augmented with minor perturbations using Gaussian noise. This technique proved effective, particularly in reducing variance in tree-based models and slightly boosting overall performance metrics across the board.

Key Takeaways:

- **XGBoost** demonstrated the best overall performance in predicting flight fares.
- **Feature selection and preprocessing** (such as encoding, normalization, and outlier handling) had a substantial impact on model accuracy.
- **Data augmentation** contributed to robustness, particularly for high-variance models like Random Forest and Gradient Boosting.

Future Enhancements:

While the results from this study are promising, several enhancements could further improve prediction accuracy and practical applicability:

1. **Integration of Real-Time Market Data**: Incorporating live market trends, demand fluctuations, and seasonal effects could refine the pricing model further.

2. **Web Scraping and API Integration**: Automating data collection from platforms like OLX, Flights24, and FlightDekho would help create a dynamic and continuously learning system.

3. **Advanced Deep Learning Models**: Future work could explore neural networks such as LSTM or Transformer-based models for sequence-based trends or temporal pricing patterns.

4. **Explainability and Interpretability**: Tools like SHAP (SHapley Additive exPlanations) can be integrated to provide insights into which features influence fare predictions the most.

5. **Deployment**: The final model could be deployed as a web or mobile application where users can input flight details and instantly get a price estimate.

6. **Image-Based Pricing**: Including visual inspection data such as flight images for dent detection, paint condition, and interior wear could further improve the realism of fare predictions.

In conclusion, this research confirms the viability of using ensemble machine learning methods to accurately predict flight fare prices. With further data enrichment and deployment in user-facing applications, such models could play a transformative role in streamlining the flight fare market for both buyers and sellers.

CHAPTER 6

APPENDIX

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Machine Learning Libraries
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

# Regression Models
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from xgboost import XGBRegressor
from lightgbm import LGBMRegressor
from catboost import CatBoostRegressor
```

```
# Suppress warnings for cleaner output
import warnings
warnings.filterwarnings('ignore')

# Load the dataset
data = pd.read_csv('used_flight_data.csv')

# Display the first few rows
print("Dataset Preview:")
print(data.head())

# Identify features and target variable
# Assuming 'Price' is the target variable
X = data.drop('Price', axis=1)
y = data['Price']

# Identify categorical and numerical columns
categorical_cols = X.select_dtypes(include=['object']).columns.tolist()
numerical_cols = X.select_dtypes(include=['int64', 'float64']).columns.tolist()

# Preprocessing for numerical data
```

```
numerical_transformer = StandardScaler()


# Preprocessing for categorical data

categorical_transformer = OneHotEncoder(handle_unknown='ignore')


# Bundle preprocessing for numerical and categorical data

preprocessor = ColumnTransformer(

    transformers=[

        ('num', numerical_transformer, numerical_cols),

        ('cat', categorical_transformer, categorical_cols)

    ])


# Define models to evaluate

models = {

    'Linear Regression': LinearRegression(),

    'Ridge Regression': Ridge(),

    'Lasso Regression': Lasso(),

    'Decision Tree': DecisionTreeRegressor(random_state=42),

    'Random Forest': RandomForestRegressor(random_state=42),

    'Gradient Boosting': GradientBoostingRegressor(random_state=42),

    'XGBoost': XGBRegressor(random_state=42, verbosity=0),

    'LightGBM': LGBMRegressor(random_state=42),
    'CatBoost': CatBoostRegressor(verbose=0, random_state=42)
}

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Evaluate each model
results = []

for name, model in models.items():
    # Create a pipeline for each model
    pipeline = Pipeline(steps=[('preprocessor', preprocessor),
                              ('model', model)])
    # Train the model
    pipeline.fit(X_train, y_train)
    # Predict on the test set
    y_pred = pipeline.predict(X_test)
    # Calculate evaluation metrics
    mae = mean_absolute_error(y_test, y_pred)
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    # Append results
    results.append({
        'Model': name,
        'MAE': mae,
        'MSE': mse,
        'R² Score': r2
    })

# Create a DataFrame to display results
results_df = pd.DataFrame(results)
# Rank models based on R² Score
results_df['Rank'] = results_df['R² Score'].rank(ascending=False)
# Sort by Rank
results_df = results_df.sort_values('Rank')
# Reset index
results_df.reset_index(drop=True, inplace=True)

# Display the results
print("\nModel Performance Comparison:")
print(results_df)

# Plot Actual vs Predicted for the best model
best_model_name = results_df.loc[0, 'Model']
```

```
best_model = models[best_model_name]
pipeline = Pipeline(steps=[('preprocessor', preprocessor),
                           ('model', best_model)])
pipeline.fit(X_train, y_train)
y_pred = pipeline.predict(X_test)

plt.figure(figsize=(10, 6))
sns.scatterplot(x=y_test, y=y_pred)
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.title(f'Actual vs Predicted Prices: {best_model_name}')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
plt.show()
```

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