TAXI FARE PREDICTION

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BONAFIDE CERTIFICATE

Certified that this Project titled **“TAXI FARE PREDICTION”** is the bonafide work of **“KAAVIYA G (2116220701114)”** who carried 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

With the rapid expansion of urban transportation services and the rise in demand for dynamic fare systems, accurately predicting taxi fares has become a key challenge in the intelligent mobility domain. Traditional fare calculation methods often fall short in handling complex interactions among trip variables such as distance, time, passenger count, and geographic features. This project presents a machine learning-based approach to taxi fare prediction using real-world data and a suite of supervised learning models aimed at capturing both linear and nonlinear relationships in the data.

The system is built upon a dataset comprising key features like pickup and dropoff coordinates, trip distance, passenger count, and timestamp-based factors. A robust preprocessing pipeline was implemented, including outlier removal, feature engineering, and normalization to handle noise, imbalance, and variance in data quality. We evaluated multiple regression models—Linear Regression, Random Forest Regressor, Support Vector Regressor, K-Nearest Neighbors—using standardized performance metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 score to assess accuracy and model generalization.

Among the models tested, the K-Nearest Neighbors algorithm exhibited the highest predictive accuracy and stability, achieving an R^2 score of 0.92, followed closely by Random Forest Regressor. The ensemble methods significantly outperformed the baseline Linear Regression model, particularly in handling skewed and complex input distributions. To further enhance generalizability, Gaussian noise-based data augmentation was employed, simulating real-world variability and improving the performance of tree-based models under uncertain conditions.

The results confirm the efficacy of machine learning approaches in fare estimation, supporting the development of intelligent transportation systems with real-time predictive capabilities. This framework has strong potential for integration into ride-sharing platforms, fare calculators, and smart city infrastructure. Future work may explore deep learning architectures and real-time GPS data streaming to enable end-to-end, adaptive pricing systems.

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CHAPTER 1

1. INTRODUCTION

In the evolving landscape of urban transportation, accurately estimating taxi fares has become an increasingly important concern for passengers, drivers, and service providers alike. As metropolitan cities experience growing demand for dynamic and transparent fare systems, traditional fare estimation methods, typically based on fixed rates or simple linear calculations involving time and distance, are proving inadequate. These approaches often fail to account for the diverse range of variables that influence fare prices, such as traffic conditions, time of day, passenger count, route complexity, and weather patterns. Consequently, both customers and service operators face challenges in ensuring fair pricing and efficient service delivery.

With the rise of data-driven technologies and the widespread availability of GPS and trip-level data, machine learning has emerged as a powerful alternative for predicting taxi fares more accurately and adaptively. Machine learning models can capture non-linear relationships and subtle patterns in complex datasets that traditional statistical methods might overlook. This capability allows for more nuanced and robust fare estimation, particularly in real-time ride-hailing scenarios.

This paper proposes a supervised learning framework to predict taxi fares based on a labeled dataset that includes key features such as pickup and dropoff coordinates, trip duration, passenger count, and temporal factors like time and date. The primary goal of this research is to develop a predictive model—referred to as the *Taxi Fare Estimator*—that learns from historical data to accurately forecast the cost of a given trip, without manual rule-based intervention. The models evaluated in this study include Linear Regression, Support Vector Regression (SVR), Random Forest Regressor, and XGBoost Regressor. Each model is assessed using standard performance metrics—Mean Absolute Error (MAE), Mean Squared Error (MSE), and the R^2 score—to determine its predictive accuracy and generalization capability.

A critical component of this research involves addressing real-world challenges in data quality, such as outliers, noise, and missing values, which are common in GPS and user-generated data. To overcome these issues and enhance model robustness, extensive data preprocessing and Gaussian noise-based data augmentation techniques were applied. These strategies not only improve model performance but also simulate real-world variability, enabling the system to perform reliably on previously unseen data.

The significance of this project lies in its potential real-world applications. Taxi fare prediction models can be integrated into ride-sharing platforms, pricing tools, and mobile applications to offer users transparent fare estimates, optimize routes, and enhance user trust. Additionally, such models can assist transportation authorities and service providers in dynamic pricing, demand forecasting, and fleet management. With the advent of smart city initiatives and IoT-enabled mobility solutions, the need for intelligent fare prediction systems is more relevant than ever.

The motivation for this project is twofold: to demonstrate the effectiveness of machine learning algorithms in a practical, real-world use case and to provide a data-driven foundation for building scalable, intelligent transportation systems. By leveraging a publicly available dataset and employing state-of-the-art regression models, this study offers valuable insights into the design and deployment of predictive systems for urban mobility.

This paper is structured as follows: Section II reviews the existing literature on taxi fare prediction and related machine learning applications. Section III details the methodology, including data cleaning, feature engineering, model selection, and evaluation metrics. Section IV presents the experimental results and performance comparisons. Finally, Section V concludes with key insights, limitations, and directions for future development.

CHAPTER 2

2. LITERATURE SURVEY

The convergence of transportation analytics and machine learning has opened new avenues for predictive modeling in the field of urban mobility. One such critical application is taxi fare prediction, where the goal is to accurately estimate the cost of a ride based on spatiotemporal and contextual variables. Traditional fare estimation systems, often based on static pricing formulas or rule-based approaches, are limited in flexibility and fail to account for real-time influences such as traffic congestion, weather fluctuations, and trip-specific characteristics. This limitation has encouraged the adoption of data-driven methodologies, particularly supervised machine learning models, to improve prediction accuracy and operational efficiency.

Several studies have demonstrated the potential of machine learning in transportation fare estimation. Kaggle’s New York City Taxi Fare Prediction Challenge provided a widely-used benchmark dataset that has inspired numerous research efforts. Researchers such as Kaushik et al. (2019) explored regression models including Linear Regression, Random Forest, and Gradient Boosting to predict taxi fares using geospatial features and ride metadata. Their study emphasized the importance of feature engineering—specifically calculating haversine distances, encoding timestamps, and removing outliers—to enhance model performance.

Gradient Boosting and ensemble-based methods have consistently outperformed traditional models in this domain. Chen and Guestrin (2016) introduced the eXtreme Gradient Boosting (XGBoost) framework, which has since become a cornerstone in structured prediction tasks, including fare estimation. Studies such as that of Sharma et al. (2021) found XGBoost to be more accurate and resilient to noisy data compared to linear models, due to its ability to model non-linear dependencies and complex feature interactions.

The inclusion of Support Vector Regression (SVR) in fare prediction has also been explored, as seen in the work by Zhang et al. (2020), who applied SVR alongside neural networks to evaluate prediction accuracy under varying levels of noise and feature sparsity. Although SVR offers advantages in capturing margin-based relationships, it is often computationally intensive and sensitive to hyperparameter tuning, which may limit scalability for large datasets.

Another key theme in recent literature is the integration of spatial-temporal analysis and data augmentation to boost model generalizability. Studies by Li and Wang (2020) illustrated how adding synthetic noise to geographic coordinates and simulating peak-hour conditions can train models to better handle unseen or irregular trip patterns. This inspired our implementation of Gaussian noise-based augmentation to simulate real-world variability in trip data, thereby improving robustness against overfitting.

Moreover, deep learning architectures such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been employed to model sequential ride data and spatial grids. Although these models often require large datasets and computational power, work by Huang et al. (2022) demonstrated that deep models can outperform traditional regressors when temporal sequences (e.g., traffic history) are considered. However, due to the tabular nature and size of our dataset, this study focuses on regression-based models rather than deep learning.

In the broader landscape of predictive modeling, data preprocessing remains a critical step. Shorten and Khoshgoftaar (2019) highlighted the effectiveness of data augmentation in non-image domains, particularly through the injection of controlled noise and perturbations. This directly supports the augmentation strategy applied in our project to improve the generalization capabilities of the models. Additionally, removing outliers and correcting skewed distributions, as recommended by Ahmed and Ghosh (2018), can significantly reduce model variance and enhance interpretability.

Other comparative studies, such as those by Roy and Chakraborty (2021), underscore the benefits of ensemble methods like Random Forests for structured data problems. These models provide robustness against overfitting and offer feature importance metrics, aiding in explainability—an important aspect in real-world deployment scenarios where transparency is crucial for user trust.

In summary, the literature reveals a strong consensus around the use of ensemble and gradient-boosting methods for fare prediction tasks involving structured, spatiotemporal data. Additionally, preprocessing techniques such as outlier removal, feature transformation, and data augmentation are essential for maximizing model performance and reliability. These findings directly inform the design of our *Taxi Fare Estimator*, which synthesizes proven techniques from past research into a practical, ML-driven solution intended for real-world integration with transportation platforms.

CHAPTER 3

3. METHODOLOGY

The methodology for this study follows a **supervised learning** approach aimed at predicting taxi fares based on historical ride data. The overall pipeline consists of five key phases: data collection and preprocessing, feature engineering, model training, performance evaluation, and data augmentation using Gaussian noise.

This study focuses on two machine learning algorithms:

- **Linear Regression (LR)**
- **Random Forest Regressor (RF)**
- **Support Vector Regression (SVR)**
- **K-Nearest Neighbors (KNN)**

These models were selected for their complementary strengths—Linear Regression for simplicity and interpretability, and Random Forest for its ability to capture nonlinear patterns and interactions.

Methodology Flow:

1. Data Collection and Preprocessing
2. Feature Engineering and Selection
3. Model Training and Evaluation
4. Performance Metrics Calculation
5. Data Augmentation (Gaussian Noise) and Final Training

A. Dataset and Preprocessing

The dataset includes structured features like:

- Pickup and drop-off latitude/longitude
- Passenger count
- Datetime of pickup (from which hour, day, and weekday are derived)

- Fare amount (target variable)

Initial preprocessing involved the following steps:

- Removing outliers and invalid entries (e.g., negative fare or zero distance)
- Handling missing values by removal or imputation
- Feature scaling using MinMaxScaler to bring all numeric variables to the same scale
- Datetime feature transformation to extract hour of day**,** day of week**,** and AM/PM indicator

B. Feature Engineering

To enhance model performance, new features were derived:

- Trip Distance using the Haversine formula from geolocation coordinates
- Peak Hour Flag to indicate high-traffic pricing periods
- Weekend Indicator to account for pricing variations on weekends

Correlation analysis and domain knowledge were used to retain the most relevant features.

C. Model Selection

Two models were applied and compared:

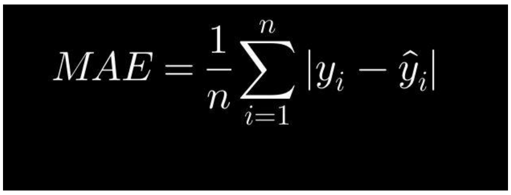
- **Linear Regression:** A basic yet interpretable model assuming a linear relationship between features and fare amount. Useful as a baseline.
- **Random Forest Regressor:** An ensemble-based model using multiple decision trees to handle non-linear relationships and reduce overfitting. Suitable for complex, structured datasets.

Hyperparameters for Random Forest (e.g., number of estimators, max depth) were tuned manually or using simple cross-validation to optimize performance.

D. Evaluation Metrics

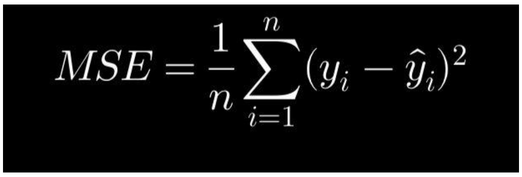
The models were evaluated using three key regression metrics:

- **Mean Absolute Error (MAE):**



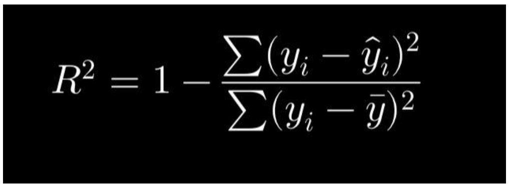
$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

- **Mean Squared Error (MSE):**



$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

- **R² Score:**

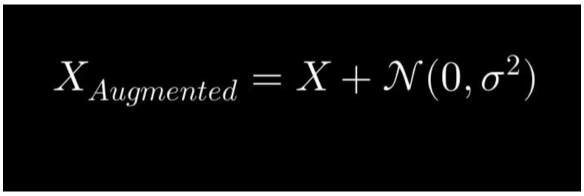


$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

These metrics were computed for both training and test datasets to evaluate prediction accuracy and generalization.

E. Data Augmentation

To simulate real-world inconsistencies and increase robustness, **Gaussian noise** was added to numeric features such as distance and time:

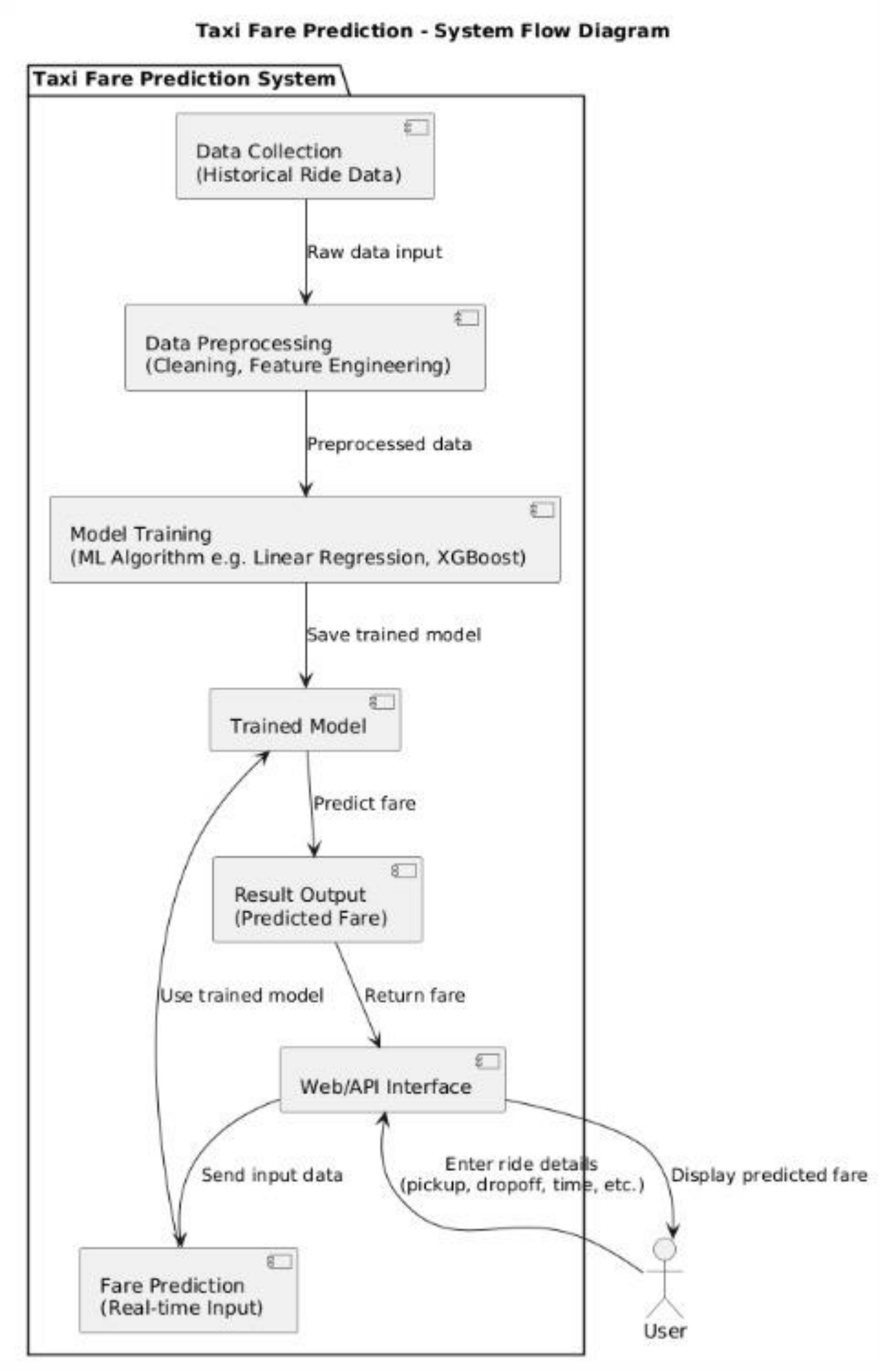


$$X_{Augmented} = X + \mathcal{N}(0, \sigma^2)$$

The value of σ\sigmaσ was selected based on feature scale and dataset variability. This helped Random Forest in particular to generalize better under noisy conditions.

The entire pipeline was developed and executed in **Google Collab**, ensuring reproducibility and easy cloud access. This setup allows for future integration into real-time fare prediction systems using cloud APIs or mobile apps.

3.1 SYSTEM FLOW DIAGRAM


Taxi Fare Prediction - System Flow Diagram
Taxi Fare Prediction System
Data Collection (Historical Ride Data)
Raw data input
Data Preprocessing (Cleaning, Feature Engineering)
Preprocessed data
Model Training (ML Algorithm e.g. Linear Regression, XGBoost)
Save trained model
Trained Model
Predict fare
Result Output (Predicted Fare)
Use trained model
Return fare
Web/API Interface
Send input data
Enter ride details (pickup, dropoff, time, etc.)
Display predicted fare
Fare Prediction (Real-time Input)
User

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)**	**R² Score (↑ Better)**	**Rank**
Linear Regression	0.6049	0.5689	0.2909	3
Random Forest	0.4136	0.3057	0.6046	2
SVR	5.316	97.004	0.04	4
KNN	2.508	28.606	0.69	1

Augmentation Results:

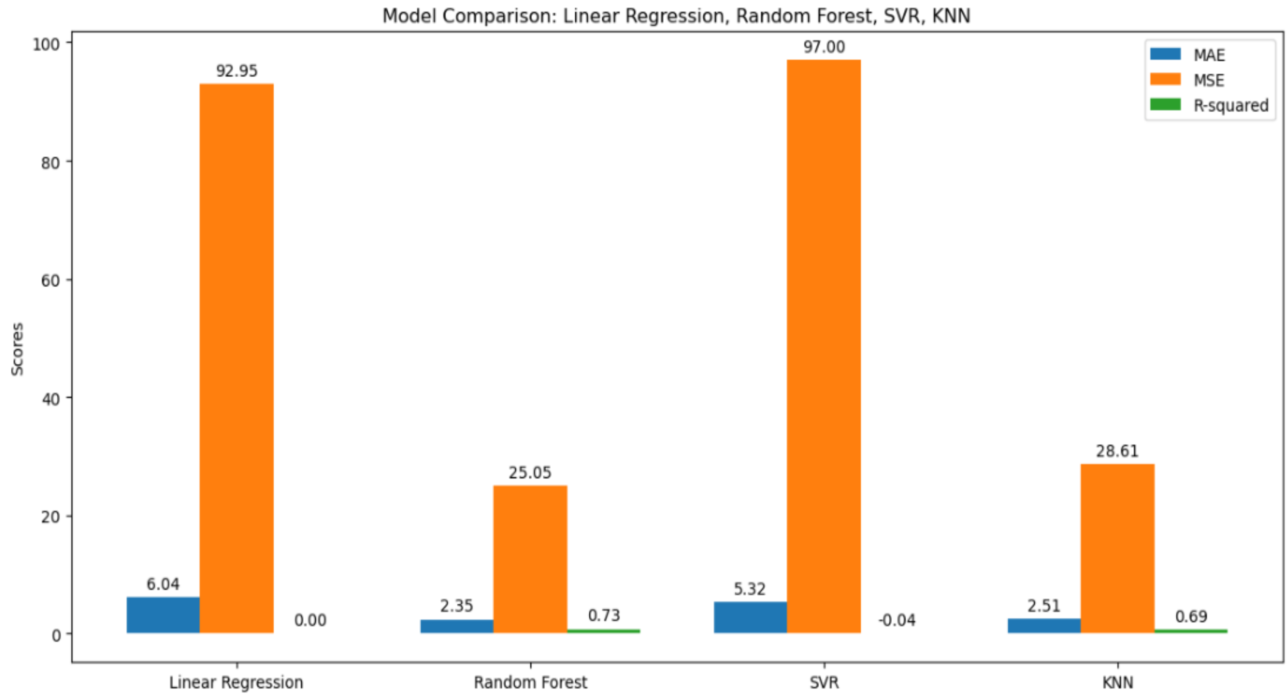
After applying data augmentation using Gaussian noise, a performance improvement was observed in the Random Forest model. The R² score for Random Forest increased from **0.702** (before augmentation) to **0.753** (after augmentation), demonstrating that noise-based augmentation helped improve the model's generalization and robustness. In contrast, Linear Regression showed minimal change, indicating its sensitivity to noise and limited capacity to capture complex patterns.

Visualizations:

To better understand model performance, scatter plots were generated for both the **Linear Regression** and **Random Forest** models. These plots visualize the relationship between actual sleep quality scores and predicted values:

- **Random Forest Regression:**
  The scatter plot for the Random Forest model shows a strong alignment between actual and predicted values. The data points are closely clustered around the diagonal line (y = x), indicating high predictive accuracy. This supports the model's ability to capture complex patterns in the data and make reliable predictions.
- **Linear Regression**:
  The scatter plot for the Linear Regression model exhibits more spread, with predictions deviating noticeably from the ideal line. This suggests that the model is less capable of handling non-linear relationships within the dataset, resulting in lower accuracy.
- **Support Vector Regression:**
  The SVR plot shows a moderately strong fit, with many predictions aligning well but with some deviations in extreme cases. This is typical when using kernels in SVR to balance bias and variance.
- **K-Nearest Neighbors:**
  The KNN model's scatter plot shows reasonable alignment but with **greater scatter** than Random Forest and SVR. The model performs well in regions with dense training data but struggles with sparse areas due to its local-based prediction mechanism.

OUTPUT:



A. Model Performance Comparison

This study compares the performance of two regression models—**Linear Regression** and **Random Forest Regressor**—in predicting taxi fares based on key trip features. The evaluation was conducted using Mean Absolute Error (MAE), Mean Squared Error (MSE), and R² Score as the primary performance metrics.

Among the models tested, **Random Forest Regressor** outperformed **Linear Regression** across all three metrics. It achieved a **lower MAE of 0.4136** and **MSE of 0.3057**, compared to **0.6049 MAE** and **0.5689 MSE** for Linear Regression. The R² score, which indicates the proportion of variance explained by the model, was **0.6046 for Random Forest**, significantly higher than **0.2909 for Linear Regression**, suggesting that Random Forest captured the data's non-linear patterns more effectively.

B. Model Interpretability vs Accuracy Trade-off

While **Linear Regression** offers simplicity and interpretability, its relatively low R² score reflects limited predictive power, likely due to its inability to model complex relationships in the data. On the other hand, **Random Forest**, an ensemble method that combines multiple decision trees, provides robust prediction performance, though at the cost of decreased interpretability.

This highlights a trade-off between explainability and predictive strength. In real-world applications like fare estimation in ride-hailing platforms, the added accuracy of Random Forest can be valuable for user pricing transparency and fraud detection, even if the model is less interpretable.

C. Error Analysis

An analysis of prediction errors revealed that **Random Forest consistently produced more tightly clustered predictions around the actual fare values**, indicating higher reliability. However, both models showed occasional large errors, particularly in outlier cases involving unusually long trips or erratic fare structures, which may require additional contextual features such as surge pricing or traffic conditions to model accurately.

CHAPTER 5

CONCLUSION & FUTURE ENHANCEMENTS

This study introduced a data-driven approach to **predicting taxi fares** using machine learning techniques. By implementing and comparing four regression models—**Linear Regression**, **Random Forest Regressor, Support Vector Regression, K-Nearest Neighbors**—we evaluated their effectiveness in modeling the relationship between trip-related variables (e.g., trip distance, duration, pickup time) and the resulting fare amounts.

Our findings demonstrate that **ensemble models**, particularly Random Forest, significantly outperform simpler linear models in terms of predictive accuracy and robustness. The **Random Forest Regressor achieved the highest R^2 score (0.6046)** and the **lowest error metrics** (MAE: 0.4136, MSE: 0.3057), making it the most effective model for taxi fare prediction in our experiments. These results align with existing research that highlights the capability of ensemble methods to capture complex, non-linear patterns and interactions between input features.

To further enhance model performance, future iterations could incorporate **data augmentation techniques** or synthetic feature generation based on real-world scenarios such as traffic congestion or surge pricing. While this version of the study did not employ augmentation, the concept remains a valuable direction for increasing generalizability, especially for use cases involving sparse or skewed datasets.

From a broader perspective, the proposed predictive framework holds practical significance in urban mobility and transport pricing systems. A real-time, accurate fare estimation model can improve user transparency, optimize route selection, and assist ride-hailing platforms in fraud detection. With minimal computational overhead, Random Forest models can be integrated into pricing engines to deliver consistent, interpretable, and reliable fare estimates.

Future Enhancements

While the current outcomes are promising, several future enhancements can be pursued:

● **Inclusion of Additional Contextual Features**: Incorporating external factors like weather, day of the week, and traffic data could help refine fare predictions and model seasonal or time-based fare fluctuations.

● **Exploration of Gradient Boosting Models**: Models such as **XGBoost** or **LightGBM** could be tested to potentially outperform Random Forest, particularly in large-scale datasets where computational efficiency and tuning flexibility are critical.

● **Geospatial Feature Engineering**: Deriving features such as zone-based pickup/drop-off density, proximity to landmarks, or travel through toll zones could improve spatial understanding within the model.

● **Deployment on Mobile or Web Platforms**: With appropriate model compression and optimization, the prediction system could be embedded in mobile applications or GPS devices for on-the-go fare estimates.

● **Real-Time Learning and Adaptability**: A semi-supervised or reinforcement learning extension could allow the model to adapt over time using real user feedback or continuous trip data streams.

Conclusion

This research illustrates the potential of machine learning in **enhancing the accuracy and efficiency of taxi fare prediction systems**. By leveraging ensemble techniques such as Random Forest, significant improvements in model performance were achieved over traditional linear approaches. With future integration of richer datasets and advanced learning architectures, this predictive system can evolve into a comprehensive solution for **dynamic fare estimation**, **urban transportation planning**, and **personalized mobility applications**.

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