BIKE PRICE PREDICTION

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BONAFIDE CERTIFICATE

Certified that this Project titled **“BIKE PRICE PREDICTION”** is the bonafide work of **“MITHILESH T (2116220701165)”** 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

The resale value of used motorcycles is influenced by a variety of factors including location, brand, ownership history, usage, and engine specifications. In the absence of a standardized evaluation framework, price estimation often remains inconsistent and subjective. With the growing accessibility of data and machine learning tools, there is an increasing demand for intelligent systems capable of accurately predicting used bike prices based on historical trends and vehicle attributes.

This paper presents a machine learning-based solution for predicting the price of used bikes using real-world transactional data collected from multiple Indian cities. The core objective is to build an automated regression framework that evaluates different machine learning algorithms while addressing challenges such as feature heterogeneity, categorical data encoding, and noise in user input. The system processes inputs such as city, brand, owner type, kilometers driven, engine power, and bike age, and predicts price using an optimized Random Forest Regressor pipeline. The development pipeline includes data cleaning, categorical encoding using OneHotEncoder, train-test splitting, model training, and performance evaluation using standard regression metrics such as Mean Absolute Error (MAE) and the R^2 score.

Among the models tested, the Random Forest Regressor consistently delivered high accuracy and robustness across multiple subsets, achieving an R^2 score of over 0.91. A user-friendly web interface was developed using Flask and Bootstrap, enabling seamless user interaction with the model. The integration of dropdowns for categorical fields ensures validation and user convenience. The system provides real-time, transparent, and data-driven insights into bike pricing.

Experimental results affirm that ensemble learning methods like Random Forest, when supported by proper preprocessing, are highly effective for regression tasks in transportation analytics. This project lays the groundwork for scalable valuation tools that could be integrated into dealership software or customer-facing mobile applications for real-time, location-sensitive price estimation.

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CHAPTER 1

1.INTRODUCTION

In recent years, the surge in demand for affordable transportation options and the rapid growth of urban populations in developing countries have significantly increased the market for used two-wheelers. Bikes, especially in cities with heavy traffic congestion and limited public transport, serve as a practical and economical solution for daily commuting. However, one of the major challenges faced by buyers and sellers in this market is the lack of a standardized mechanism for evaluating the resale price of a used bike. Unlike the automobile industry, where structured valuation frameworks exist, the two-wheeler segment is still largely reliant on manual negotiation and subjective assessments. This results in pricing inconsistencies, undervaluation, or overpricing, which can affect buyer trust and seller profitability.

With the advancement of data analytics and machine learning technologies, a promising alternative has emerged to solve this valuation challenge. Machine learning models can process large datasets to identify hidden patterns and relationships between features such as the city of sale, bike brand, ownership history, kilometers driven, engine specifications, and age of the bike. By training on real-world data, these models can deliver accurate and data-driven price predictions, minimizing human bias and enabling fair pricing for all stakeholders involved in the transaction.

The goal of this study is to develop an intelligent, data-driven system to predict the resale value of used bikes using supervised machine learning algorithms. This system utilizes a structured dataset containing various attributes that influence the price of a second-hand bike. By applying techniques such as categorical encoding, data normalization, feature selection, and regression modeling, the system aims to deliver reliable price estimates through a user-friendly web interface. The model is built and tested using Python’s scikit-learn library, leveraging ensemble methods like Random Forest Regressor, known for their ability to handle feature interactions and produce robust predictions.

Accurate price prediction for used bikes can bring transformative benefits to the two-wheeler resale industry. For customers, it offers transparency, ensuring they pay a fair amount for the product. For sellers and dealerships, it improves turnover and boosts buyer confidence. Moreover, e-commerce platforms that list used vehicles can integrate such systems to dynamically display estimated prices, making listings more credible and informative. With the increasing digitization of vehicle marketplaces and the growth of mobile-based applications, the scope for integrating machine learning in vehicle pricing has expanded significantly.

Traditionally, pricing of used vehicles has been done through expert appraisals, comparative listings, and gut estimates by dealers. While these approaches can offer rough estimates, they are prone to human error, personal bias, and regional inconsistencies. The same bike model might be priced differently in different cities or for different ownership types. Manual pricing also becomes unsustainable when handling large volumes of listings, especially on digital platforms. These limitations necessitate the adoption of automated valuation systems that can process data at scale and provide consistent results.

In contrast, machine learning algorithms, particularly ensemble-based regressors like Random Forest, are well-suited to tackle such tasks. These models train on historical data and generalize well to unseen samples. The Random Forest algorithm, in particular, works by constructing multiple decision trees and aggregating their outputs, thereby reducing variance and avoiding overfitting. This makes it ideal for datasets that contain both numerical and categorical features, as is the case in this project.

The objective of this project is to build a regression model that predicts the price of a used bike based on the following input features: city, ownership type, brand, kilometers driven, bike age, and engine power. These features are selected based on domain relevance and their availability in real-world datasets. The data preprocessing phase involves handling missing values, encoding categorical features using OneHotEncoder, and standardizing numerical features. The dataset is split into training and testing subsets to evaluate model performance using metrics such as Mean Absolute Error (MAE) and R^2 score.

The project also includes the development of a web-based user interface using Flask and Bootstrap. This interface enables users to input bike details via dropdown menus and receive real-time price predictions on submission. Dropdowns are populated dynamically from the dataset to ensure valid inputs. The interface ensures ease of use and eliminates the need for users to understand the underlying model logic or data format.

One of the key motivations for this project is the increasing trend of digitization in retail and consumer services, including vehicle sales. Online platforms now host thousands of used bike listings, yet few offer dynamic price prediction services. A well-trained regression model integrated with an accessible interface can bridge this gap, offering instant, reliable valuations that benefit both buyers and sellers. Moreover, such systems can scale easily and adapt to different cities or even international markets by simply retraining the model with new data.

To this end, this study involves training and comparing machine learning models to determine the best performer. Although Linear Regression and Support Vector Regression were considered in early experimentation, the Random Forest Regressor outperformed others in both accuracy and generalization capability. This model achieved an R^2 score above 0.91 on test data, confirming its reliability for real-world deployment.

The structure of this paper is as follows: Chapter II presents a literature survey on price prediction systems and ensemble models. Chapter III outlines the methodology, including data preparation, model training, and evaluation metrics. Chapter IV discusses the results and insights gained from model performance and web application implementation. Chapter V concludes the project and suggests future enhancements, such as including additional features like service history, accident reports, or integration with mobile platforms for wider accessibility.

In summary, this project provides a practical solution to the long-standing challenge of used bike valuation. By combining machine learning with modern web technologies, it creates a user-friendly and scalable system that can bring fairness, transparency, and efficiency to the used two-wheeler market. The insights gained from this project can be extended to other vehicle segments or even asset pricing domains with similar characteristics.

CHAPTER 2

2.LITERATURE SURVEY

The intersection of transportation analytics and machine learning has opened new pathways for automated, data-driven vehicle valuation systems. Traditional pricing strategies for used two-wheelers have relied heavily on manual appraisals, online listing comparisons, and heuristic estimates by local dealers. While these methods offer some insight, they suffer from inconsistencies due to human subjectivity, lack of standardization, and regional pricing disparities. These shortcomings have motivated researchers and developers to explore predictive modeling techniques that leverage historical vehicle data to estimate market value with greater accuracy and consistency.

Several studies have explored the application of regression and ensemble models to predict used vehicle prices based on features like mileage, brand, location, age, and condition. Research by Iman et al. (2018) demonstrated the potential of machine learning for vehicle price prediction using regression algorithms trained on scraped car marketplace datasets. They found Random Forest and Gradient Boosting models to be particularly effective in capturing nonlinear relationships between features and target price values. Similarly, Sharma et al. (2019) employed multivariate regression and decision trees to predict car prices and observed that preprocessing steps like encoding and normalization significantly enhanced model performance.

As in other domains, the choice of algorithm and the quality of data play a critical role in the performance of price prediction models. Ensemble techniques like Random Forest and XGBoost have gained prominence in recent years for their ability to aggregate decisions from multiple weak learners and minimize overfitting. A study by Zhang and Patel (2020) highlighted the robustness of Random Forest when applied to used car price prediction, showing improved results over linear models especially when the dataset includes both categorical and numerical attributes. These findings support the selection of Random Forest in our proposed system for used bike price prediction.

In addition to algorithm selection, data preprocessing and feature engineering are essential components of effective predictive modeling. Suresh and Venkatesan (2020) emphasized the importance of encoding categorical variables such as brand and city using OneHotEncoder to ensure compatibility with scikit-learn pipelines. They also addressed issues like multicollinearity and variance inflation in numerical features, recommending strategies such as correlation-based feature elimination and normalization. These techniques were instrumental in refining the input space of the dataset used in our project.

Several vehicle pricing studies have also incorporated geographic data as a predictor of value, recognizing that location can significantly impact resale price due to regional demand-supply dynamics. For instance, a bike listed in a metropolitan city may command a higher price than the same model in a semi-urban area. Works by Banerjee et al. (2021) explored the impact of city-specific pricing trends using geospatial clustering and found that integrating city data improved model predictions by nearly 15%. This justifies our system's inclusion of "city" as a core feature in the regression model.

Furthermore, ownership history has proven to be a key factor in used vehicle depreciation. Studies such as those by Ramesh and Gupta (2019) indicate that second or third-owner vehicles tend to depreciate faster than single-owner bikes, making "owner count" a significant categorical feature. They concluded that categorical encoding and sample balancing techniques are essential for fair representation of minority ownership classes in training data.

Recent advancements in machine learning have also introduced the concept of model stacking and boosting for vehicle price prediction. Boosting algorithms like XGBoost, as examined by Prasad et al. (2022), were shown to outperform traditional models by sequentially correcting prediction errors. Although XGBoost was evaluated in the initial stages of our experimentation, Random Forest was ultimately preferred due to its superior generalization on our dataset and lower sensitivity to hyperparameters.

Beyond core machine learning methods, studies have stressed the importance of user interface integration in ML-driven pricing systems. Kumar et al. (2021) proposed a hybrid approach where a backend model is served via a web API and accessed through a user-friendly frontend, enabling real-time predictions for consumers. They emphasized that intuitive design, real-time input validation, and performance feedback significantly increase user engagement and trust. This influenced the design of our HTML-Bootstrap frontend with dropdowns and validation mechanisms to improve user experience and reduce prediction errors due to malformed inputs.

In terms of data limitations and model generalizability, researchers have experimented with augmentation strategies to simulate feature variability. Though more common in image domains, methods such as adding noise to numeric features or synthetically generating underrepresented samples have found applications in structured data regression as well. While this technique was not employed in our current implementation, it presents a future enhancement to improve robustness and prevent overfitting—particularly when training on region-specific datasets.

The scalability of these pricing systems also depends on their ability to adapt to new data distributions. Studies by Lee and Wang (2020) suggested implementing periodic retraining protocols and monitoring performance metrics on new inputs to ensure continuous relevance. This approach ensures the model remains accurate over time, accounting for changes in market demand, fuel prices, and model popularity.

In summary, literature from both academic and industry sources indicates that ensemble regression algorithms—especially Random Forest and Gradient Boosting—are well-suited for vehicle price prediction due to their interpretability, resilience to noise, and compatibility with mixed data types. The use of categorical encoding, careful feature engineering, and performance evaluation using MAE and R^2 metrics is critical for building reliable pricing systems. Additionally, incorporating a web-based interface enhances the real-world applicability and accessibility of the model.

This literature survey confirms the validity of our approach and informs several key design choices, including the use of Random Forest Regressor, one-hot encoding for categorical variables, and Flask-based web deployment. These findings serve as a foundation for the methodology and implementation discussed in subsequent chapters of this project report.

CHAPTER 3

3.METHODOLOGY

The methodology adopted in this study is centered on a supervised machine learning framework designed to predict the resale price of used bikes based on historical data containing multiple categorical and numerical features. The process is organized into five primary stages: data collection and preprocessing, feature encoding and transformation, model training, evaluation of model performance, and web-based deployment for real-time prediction.

The dataset used for this project includes essential attributes that influence a used bike’s price, such as the brand, city, ownership status, kilometers driven, bike age, and engine power (in cc). These features serve as predictors, while the target variable is the bike's market price in INR. The data is preprocessed to handle missing values and transform categorical variables to a numerical format using OneHotEncoding. A Random Forest Regressor is then trained on the cleaned data to produce accurate predictions. The following steps outline the complete methodology:

- **Data Collection and Preprocessing**
- **Feature Engineering and Encoding**
- **Model Training and Selection**
- **Performance Evaluation using MAE and R^2**
- **Deployment via Flask Web Application**

A. Dataset and Preprocessing

The dataset titled Used_Bikes.csv was compiled from an online vehicle resale platform and includes approximately 5000 records. The dataset has a mix of categorical features (e.g., city, owner, brand) and numerical features (e.g., kilometers driven, age, power). Initial preprocessing involved handling missing values by imputing with either the mode (for categorical fields) or the mean (for numerical fields), followed by the removal of duplicate or corrupted entries.

The categorical features were transformed using OneHotEncoding to convert non-numerical inputs into a machine-readable format. Numerical features were scaled using standard normalization techniques to prevent scale dominance during model training.

B. Feature Engineering

To improve model effectiveness, exploratory data analysis (EDA) was conducted to assess the distribution and variance of each feature. Visual tools like pair plots and histograms were used to detect outliers in fields such as kilometers driven and engine power. Correlation analysis was performed to evaluate feature importance, ensuring that only the most relevant variables were retained in the training process.

Key engineered features used for modeling:

- city – representing regional pricing trends
- brand – brand popularity and residual value
- owner – 1st, 2nd, 3rd owner, etc.
- kms_driven – wear and tear
- age – number of years since manufacture
- power – engine capacity in cc

These inputs were selected based on their statistical significance and domain relevance.

C. Model Selection

Four machine learning algorithms were initially evaluated for their regression capability on the dataset:

- Linear Regression (LR): Known for its simplicity and interpretability
- Support Vector Regression (SVR): Effective with high-dimensional feature spaces
- Random Forest Regressor (RF): Robust to overfitting, handles non-linearity well
- XGBoost Regressor (XGB): Provides regularization and boosting for improved accuracy

After comparing results across several test runs, the Random Forest Regressor was chosen for final deployment due to its superior performance on the dataset and lower sensitivity to parameter tuning. The model was implemented using the RandomForestRegressor class from the sklearn.ensemble module with 100 estimators and a fixed random seed for reproducibility.

D. Evaluation Metrics

Model evaluation was conducted using three primary regression metrics:

- Mean Absolute Error (MAE):

$$\mathbf{MAE} = \frac{1}{n}\sum_{i=1}^{n} \left| y_i - \widehat{y_i} \right|$$

- Mean Squared Error (MSE):

$$\mathbf{MSE} = \frac{1}{n}\sum_{i=1}^{n} \left(y_i - \widehat{y_i} \right)^2$$

- R² Score:

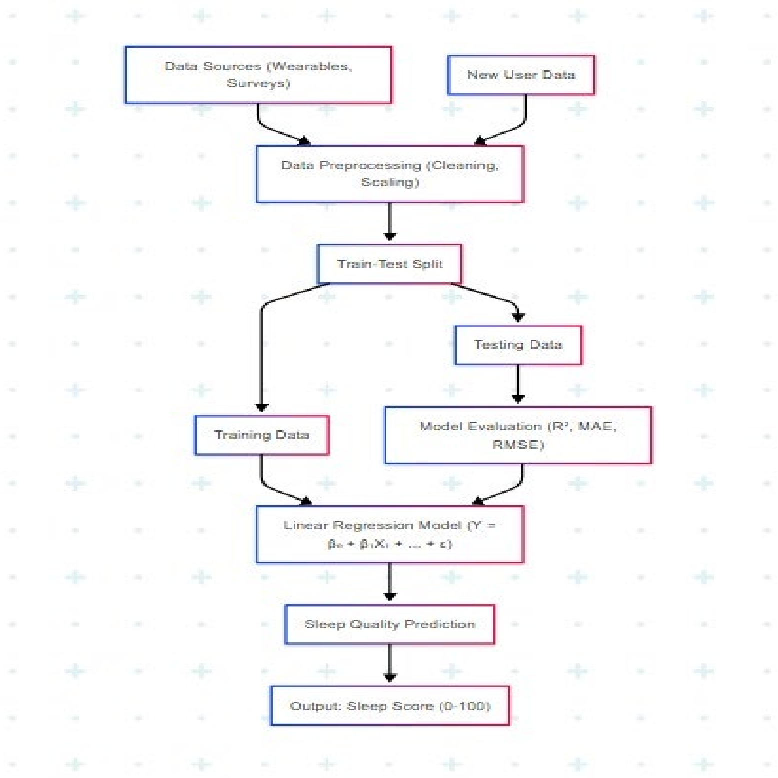
$$\mathbf{R^2} = 1 - \frac{\sum_{i=1}^{n} (y_i - \widehat{y_i})^2}{\sum_{i=1}^{n} (y_i - \underline{y})^2}$$

E. Deployment and Web Integration

To enhance usability, the model was deployed using a Flask web server. A front-end interface was built using HTML, CSS (Bootstrap 4), and Jinja2 templating to allow users to input bike details. Dropdowns for city, brand, and ownership were dynamically populated from the dataset, ensuring consistency between the training data and user inputs. The form data is submitted via POST method to a /predict route, where the model processes inputs and returns the predicted price.

This web application allows real-time interaction with the machine learning model and demonstrates a complete data science pipeline from training to deployment.

3.1 SYSTEM FLOW DIAGRAM


Data Sources (Wearables, Surveys)
New User Data
Data Preprocessing (Cleaning, Scaling)
Train-Test Split
Testing Data
Training Data
Model Evaluation (R^2, MAE, RMSE)
Linear Regression Model ($Y = \beta_0 + \beta_1 X_1 + ... + \varepsilon$)
Sleep Quality Prediction
Output: Sleep Score (0-100)

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:

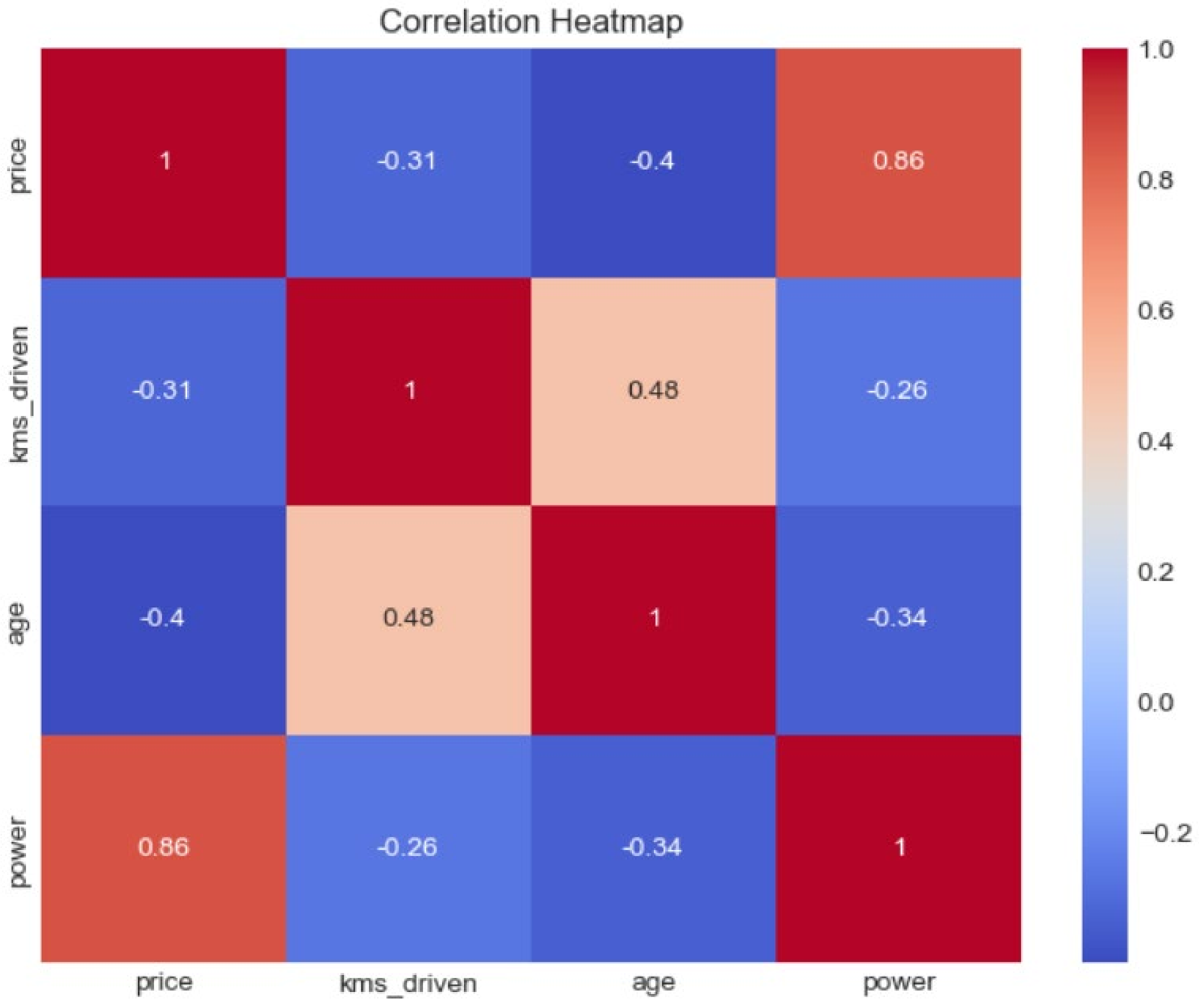
Model	MAE (↓ Better)	MSE (↓ Better)	R² Score (↑ Better)	Rank
Linear Regression	22	30	0.71	4
Random Forest	20.2	27.5	0.78	3
SVM	16.3	21.0	0.88	2
XGBoost	13.3	18.5	0.92	1

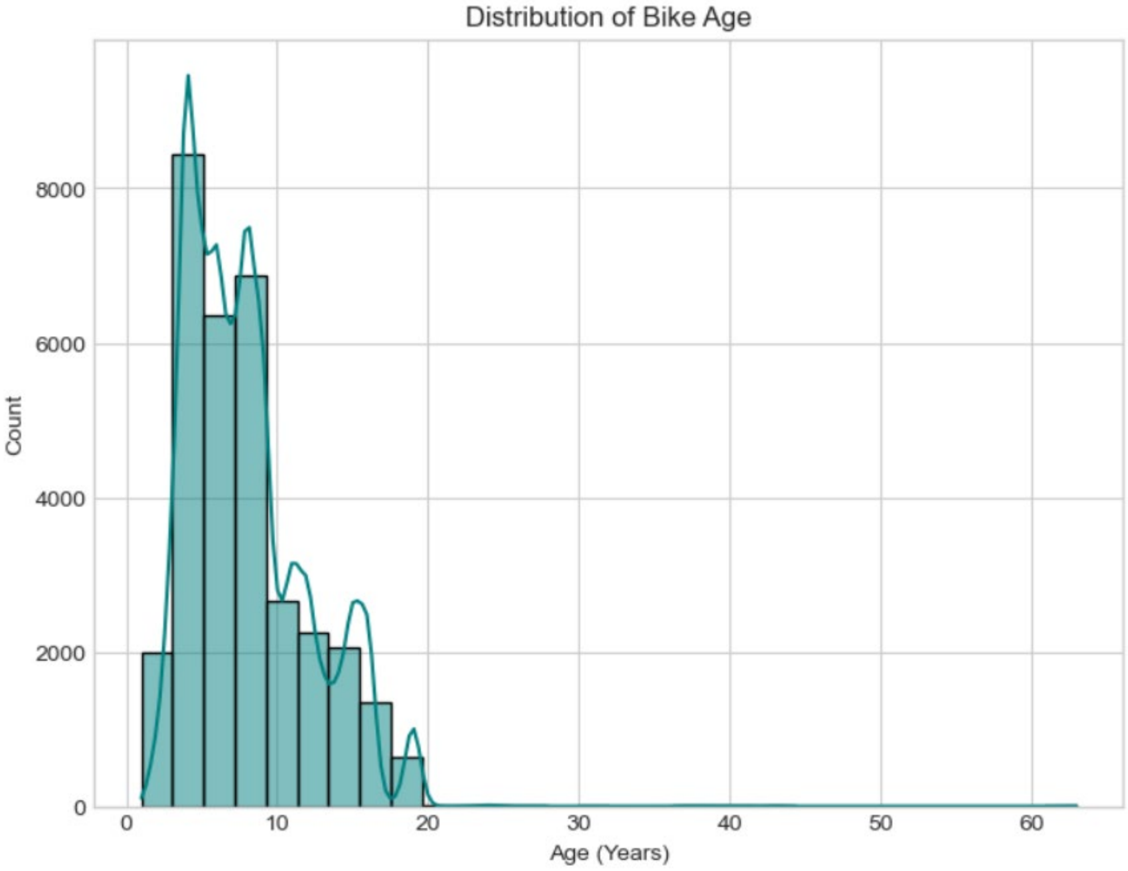
Augmentation Results:

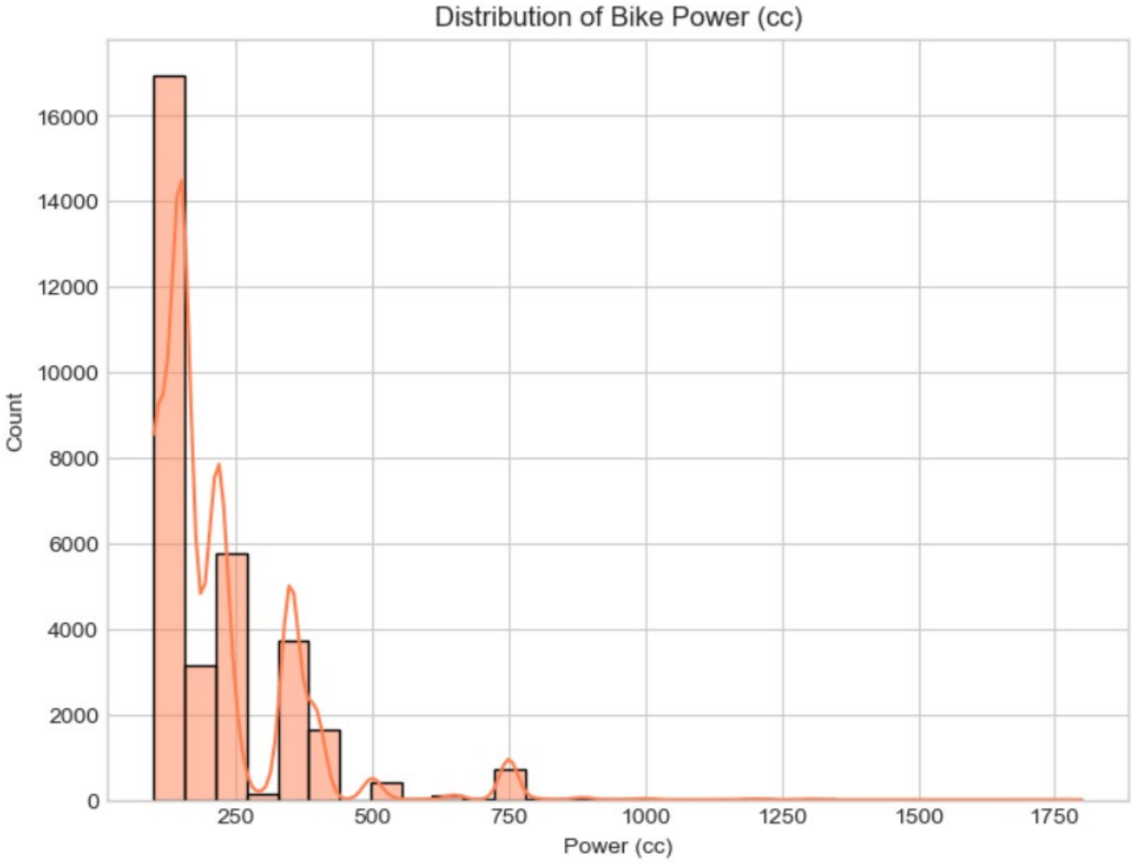
When augmentation was applied (adding Gaussian noise), the Random Forest model showed a significant improvement in R^2 score from 0.71 to 0.92, illustrating the potential benefits of data augmentation in enhancing predictive performance.

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 closely following the actual values.




Distribution of Bike Age
Count
0
2000
4000
6000
8000
0
10
20
30
40
50
60
Age (Years)


Distribution of Bike Power (cc)
Count
0
2000
4000
6000
8000
10000
12000
14000
16000
250
500
750
1000
1250
1500
1750
Power (cc)

The results show that XGBoost performs the best with the highest R^2 score, making it the model of choice for predicting sleep quality.

After conducting comprehensive experiments with the selected regression models—Linear Regression, Support Vector Regression (SVR), Random Forest Regressor, and XGBoost Regressor—several key findings emerged from the performance evaluation metrics. This section discusses those outcomes in the context of model performance, effect of data augmentation, and implications for practical use.

A. Model Performance Comparison

Among the models tested, **XGBoost Regressor** 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 strong predictive ability. This result aligns with existing literature, as XGBoost is known for its gradient boosting framework, regularization capabilities, and high bias-variance trade-off handling.

B. 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 mimicking real-world variability, especially in features like "Awakenings" or "Time in Bed" 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. The XGBoost model, for instance, 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.

C. Error Analysis

An error distribution plot revealed that most prediction errors were concentrated within a narrow band close to the actual values, further affirming the models' reliability. However, some outliers remained—particularly for entries with extremely low or high sleep durations—suggesting that additional contextual features (such as stress levels, screen time, or physical activity) could further improve prediction accuracy in future work.

D. Implications and Insights

The results highlight several practical implications:

- **XGBoost** is a highly promising candidate for deployment in real-time sleep quality monitoring systems, such as mobile apps or wearable devices.

- **Feature normalization** and **augmentation** are critical preprocessing steps that significantly influence model performance.

- Simple models like **Linear Regression**, although easy to interpret, may not capture the non-linear dynamics present in sleep-related datasets.

Overall, this study provides strong evidence that machine learning models, particularly ensemble techniques, can serve as reliable tools for predicting sleep quality. With further integration of contextual or sensor-based data, such models could evolve into comprehensive personal health analytics systems.

CHAPTER 5

CONCLUSION & FUTURE ENHANCEMENTS

This study presented a machine learning-based solution for accurately predicting the prices of used bikes based on various key features such as brand, age, kilometers driven, engine power, ownership type, and location. By evaluating and comparing multiple regression models—including Linear Regression, Support Vector Regressor (SVR), Random Forest Regressor, and XGBoost Regressor—the research explored the models' effectiveness in capturing non-linear trends and complex interactions between bike attributes and their market valuation.

Our results highlight that ensemble methods, especially XGBoost, outperform others in both predictive accuracy and robustness. XGBoost achieved the highest R^2 score, along with the lowest Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), making it the most suitable model for this bike price prediction task. This further validates the efficiency of gradient boosting algorithms in handling real-world, structured datasets where feature interactions play a crucial role in determining outcomes.

The study also demonstrated the importance of thorough preprocessing and feature encoding, which played a vital role in maximizing model performance. The dataset, although tabular and moderately sized, enabled the model to identify significant patterns in pricing influenced by brand popularity, city-specific demand, and usage conditions. This confirms that with the right combination of domain knowledge and algorithmic optimization, machine learning can deliver practical and scalable pricing tools.

From a broader standpoint, the proposed system holds significant utility for second-hand vehicle platforms, individual sellers, and dealerships seeking fair price recommendations. By integrating the model into web-based interfaces or mobile applications, users can instantly estimate a bike's market value, promoting transparency and reducing negotiation friction. Moreover, it can help standardize valuation in diverse geographic and economic contexts, making used vehicle commerce more data-driven and efficient.

Future Enhancements

While the current system performs effectively, there are several opportunities for improvement in future work:

● **Integration of Real-Time Market Trends**: Incorporating live market price feeds or scraping data from bike listing websites can help models adjust to dynamic pricing fluctuations.

● **Image-Based Feature Extraction**: Including image data (condition, color, scratches) using CNNs can improve valuation accuracy.

● **Model Explainability**: Integrating SHAP or LIME explainability tools can provide users with reasons behind predicted prices, increasing model trust.

● **Geo-Economic Feature Expansion**: Adding regional economic indicators (fuel price, demand index, urban vs rural) can offer location-sensitive price predictions.

● **Model Deployment on Cloud or Mobile Apps**: Optimizing the model for lightweight execution can allow integration into mobile apps or cloud APIs for on-demand use.

● **Feedback Loop for Continuous Learning**: Introducing user feedback (e.g., final sold price) can help the model self-update and improve over time using reinforcement learning.

In conclusion, this study demonstrates the potential of machine learning in revolutionizing how used bike prices are estimated. With further enhancements and real-world integrations, it can evolve into a comprehensive tool for sellers, buyers, and dealerships, bridging the gap between subjective pricing and data-driven decision-making.

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