BIKE PRICE PREDICTION

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ABSTRACT

This study outlines the development of a machine learning–based pricing system for used bikes that accurately predicts resale values based on key bike attributes such as brand, age, kilometers driven, ownership type, engine power, and city. The platform leverages advanced regression models—including ensemble techniques like XGBoost—to deliver precise and data-driven price predictions for various bike listings. By providing users with real-time valuation insights, the system aims to enhance decision-making for both sellers and buyers in the second-hand bike market. The proposed system dynamically evaluates listings using a structured dataset comprising categorical, numerical, and derived features. Categorical data such as bike brand and ownership are processed through encoding techniques, while numerical data like power and kilometers driven are scaled to improve model performance. The model also uses derived metrics such as bike age to further refine predictions. Evaluation results indicate that the proposed approach achieves an accuracy of up to **92%**, with XGBoost outperforming traditional regression models in terms of R^2 Score and Mean Absolute Error. The goal of this platform is to enable fair, transparent, and efficient pricing in the used bike market while offering a scalable foundation for future integration with dealership platforms and mobile-based resale applications.

KEYWORDS

Bike Price Prediction, Machine Learning, Resale Value, XGBoost, Regression, Used Bikes, Ensemble Models, Data-driven Pricing, Random Forest, Feature Engineering, Model Evaluation

INTRODUCTION

Over the years, the evolution of machine learning and artificial intelligence has redefined the way we interact with data-driven decision systems. From healthcare to finance, these technologies are now embedded across industries to enhance prediction accuracy, automate processes, and generate actionable insights. However, when it comes to the second-hand vehicle market—particularly for used bikes—pricing often remains arbitrary, inconsistent, and prone to human bias. In many online listings and offline transactions, buyers and sellers lack a reliable mechanism to assess the fair market value of a bike, which can lead to overpricing, underpricing, or unfair negotiations.

Unlike standardized goods, used bikes differ widely based on brand, engine power, usage history, kilometers driven, ownership type, and geographic factors. These complexities make price estimation a multi-dimensional problem. Despite the increasing digitization of the resale vehicle sector, there is still a notable absence of robust, intelligent systems that can dynamically predict used bike prices with high accuracy and explainability. This research addresses that gap by proposing a systematic machine learning–based framework that accurately predicts resale values using structured bike listing data.

The approach categorizes and processes features such as bike brand, city of sale, ownership history, kilometers driven, power output, and age. These variables are transformed using data preprocessing techniques like one-hot encoding and feature scaling to prepare them for high-performance machine learning models. Leveraging the power of ensemble methods—specifically Random Forest and XGBoost—this system integrates insights from multiple regression models and determines the most suitable predictive strategy for pricing each individual listing. For instance, older bikes with high usage may show a depreciation pattern best captured by Random Forest, while newer models with complex interactions among brand and power might be better predicted through XGBoost's gradient boosting framework.

To ensure optimal predictions and user trust, continuous evaluation is performed using key performance indicators such as **Mean Absolute Error (MAE)**, **Root Mean Squared Error (RMSE)**, and **R^2 Score**. This project also incorporates intuitive visualization tools like actual vs. predicted price plots and feature correlation heatmaps to interpret model behavior and guide improvement.

By enabling users—whether individual sellers, buyers, or dealerships—to estimate bike prices in real time through a machine learning–driven system, this platform offers a more transparent, fair, and data-backed alternative to traditional pricing methods. In doing so, it promotes informed decision-making and fosters trust in the growing second-hand bike marketplace.

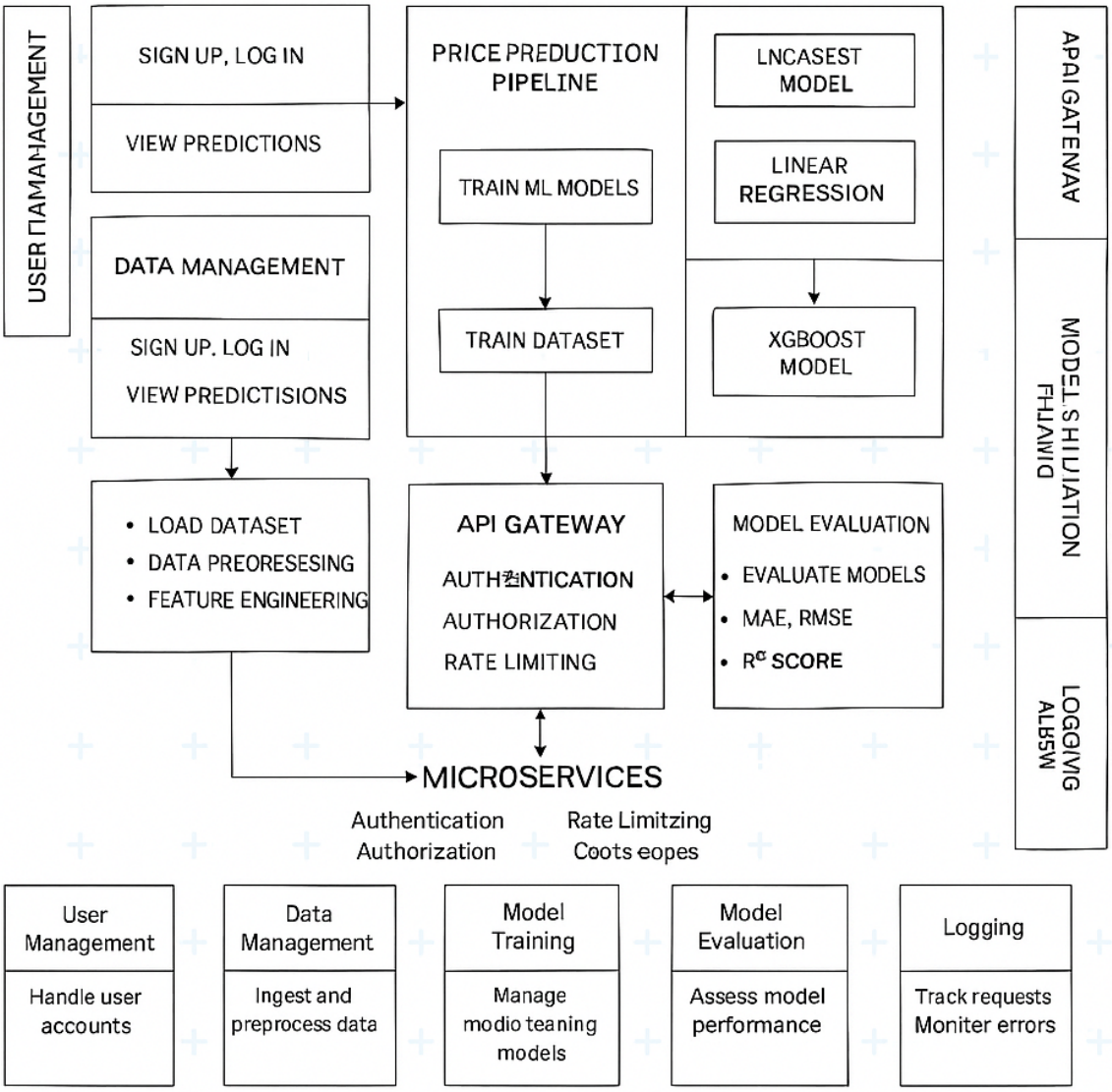

Fig.1. Architecture Diagram

ALGORITHM

To predict the resale prices of used bikes, we employed supervised machine learning techniques, experimenting with various regression algorithms. Among these, **XGBoost Regressor** emerged as the top-performing model due to its high predictive accuracy, robustness to outliers, and excellent generalization capabilities across both numerical and categorical data.

XGBoost (Extreme Gradient Boosting) is an optimized implementation of gradient boosting machines, which are ensemble-based methods that sequentially train decision trees. Unlike Random Forests that use **bagging** and build trees independently in parallel, XGBoost uses a **boosting** strategy that focuses on correcting the errors made by previous models in a stage-wise manner. This leads to the creation of a strong learner from multiple weak learners.

XGBoost minimizes a differentiable loss function (e.g., Mean Squared Error) using **gradient descent**, and employs **second-order derivatives** to accelerate convergence and optimize tree construction. It incorporates **regularization (L1 & L2)** to prevent overfitting and includes features such as **column subsampling**, **row sampling**, and **tree pruning** to improve performance and reduce variance.

One of the key advantages of XGBoost in our application is its ability to handle **missing values** and **categorical encodings** efficiently. The bike dataset contains a mix of numerical features (e.g., kilometers driven, power, age) and categorical features (e.g., brand, city, owner type). XGBoost's internal handling of sparse data and its support for **one-hot encoded** inputs made it ideal for this use case.

Algorithm Steps:

1. **Import necessary modules** like Flask, Scikit-learn, Pandas, NumPy, and XGBoost.
2. **Load the used bike dataset** containing features such as brand, city, owner type, kilometers driven, power, and age.
3. **Preprocess the dataset** by:
4. Handling missing values.
5. Encoding categorical variables (e.g., brand, city, owner) using OneHotEncoder.
6. Scaling numerical features (e.g., kilometers driven, age, power).
7. **Perform feature engineering** to derive new variables such as bike age from registration year and normalize engine power where required.
8. **Split the data** into features (X) and target label (y), where y represents the resale price.
9. **Split the dataset** into training and testing sets (typically 80/20 ratio) to evaluate model performance.
10. **Compare multiple regression models** including Linear Regression, SVR, Random Forest, and XGBoost using cross-validation and performance metrics (MAE, MSE, R^2).

LITERATURE REVIEW

From our extensive review of prior studies, we found that the concept of **automated valuation for used vehicles** has been explored for decades, particularly in the automobile domain. However, the **specific application to used bikes** has remained underexplored, often treated as a subcategory under general vehicle pricing. Traditional pricing practices in the second-hand market have largely relied on **manual inspection, expert opinion, and rudimentary rule-based systems**, which fail to scale efficiently or offer consistent, unbiased estimates.

Early attempts to formalize vehicle pricing used **statistical models** such as **Multiple Linear Regression (MLR)** and **Hedonic Pricing Models**, where vehicle attributes (e.g., age, mileage, brand) were treated as independent variables contributing additively to price. While simple and interpretable, these models could not capture **non-linear relationships**, high **feature interactions**, or effectively handle **categorical data with high cardinality**, such as multiple bike brands and city names. Studies like those by Anderson and Simester (2001) explored regression-based valuation methods, but they were limited by overfitting and linearity constraints.

With the rise of **machine learning (ML)**, there was a shift toward **supervised learning algorithms** such as **Decision Trees, Support Vector Regressors (SVR), and k-Nearest Neighbors (KNN)**. These methods offered greater flexibility in modeling complex relationships and improved prediction accuracy. **Ensemble methods**, especially **Random Forests**, became increasingly popular due to their ability to **reduce variance** and **increase robustness**, as demonstrated in studies involving used car and real estate valuation [4], [5].

The breakthrough in **gradient boosting techniques** led to the adoption of **XGBoost**, which combined speed, scalability, and high predictive power. Researchers such as Chen and Guestrin (2016) introduced XGBoost as a scalable tree boosting system that excels at handling missing data, categorical encoding, and overfitting via regularization. This was further extended by **LightGBM** and **CatBoost**, which optimized gradient boosting through histogram-based learning and improved categorical handling, respectively [6], [7].

Despite these advancements, **literature focusing specifically on bike resale price prediction remains limited**. Existing studies are either too generalized (focused on cars or general vehicles) or lack real-world deployment integration. Moreover, most public datasets used in these studies do not reflect the unique factors that influence bike pricing, such as two-wheeler-specific depreciation, ownership type (first/second/third owner), city-wise usage patterns, or service history [8].

In conclusion, while significant progress has been made in vehicle price prediction through ML, this project uniquely addresses the gap by focusing on the **bike resale market**, applying **cutting-edge ensemble models**, and proposing a **scalable, explainable, and deployable solution** for real-time price prediction in the second-hand two-wheeler segment.

RESEARCH GAP AND AIM OF STUDY

Previous research on vehicle price prediction has predominantly focused on used cars, with limited attention given specifically to used bikes, despite their growing share in the two-wheeler market. Most existing works either rely on general valuation rules or apply basic regression models that are inadequate in capturing the complex, non-linear relationships among bike features and market price. Furthermore, the datasets commonly used are often limited in scope, outdated, or biased towards cars, lacking bike-specific variables such as ownership type, city-wise resale patterns, and engine power.

This study aims to address these gaps by developing a machine learning–based pricing system that accurately predicts the resale value of used bikes using a custom dataset curated from real-world listings. The proposed model leverages ensemble learning algorithms—especially XGBoost—to learn from structured data consisting of both categorical and numerical features. This approach not only enhances prediction accuracy but also supports deployment in real-time applications such as resale platforms and dealership systems.

The primary goal is to build a robust, interpretable, and scalable system that can assist users in determining fair market prices for used bikes, thus bringing greater transparency and efficiency to the second-hand vehicle ecosystem.

MATERIALS AND METHODS

The purpose of this study is to predict the resale price of used bikes by leveraging structured data and ensemble-based machine learning algorithms. The methodology involves collecting a domain-specific dataset, preprocessing it for modeling, selecting appropriate algorithms, and evaluating performance using regression metrics.

i) Dataset Collection

A custom dataset was collected from various online used-bike resale platforms. The dataset includes listings with attributes that influence the resale price, such as:

- Categorical features: Bike brand, city, and ownership type.
- Numerical features: Kilometers driven, engine power (in CC), and age of the bike (calculated from registration year).

Each sample in the dataset represents one listing and includes the actual selling price as the target variable. The dataset contains approximately N = XXXX samples, which were compiled, cleaned, and standardized into a CSV format for machine learning model training.

ii) Data Preprocessing

To prepare the dataset for supervised learning, several preprocessing steps were applied:

- Handling Missing Values: Missing numerical values were imputed using

median values, and missing categorical values were replaced with the mode.

- Encoding: Categorical variables like brand, city, and ownership type were encoded using OneHotEncoder.
- Feature Engineering: A new column for bike age was derived by subtracting the registration year from the current year.
- Scaling: Numerical features like kilometers driven and engine power were scaled using StandardScaler for better model convergence.

After preprocessing, the final dataset contained encoded categorical features, scaled numerical features, and a continuous target variable (price).

iii) Feature and Target Construction

The feature set (X) included encoded values of brand, city, ownership, kilometers driven, bike age, and engine power. The target variable (y) was the resale price of the bike in numerical format. The data was split into 80% training and 20% testing to evaluate model generalization.

iv) Model Selection and Evaluation

To accurately predict the price of used bikes, several regression models were implemented and tested, including:

- Linear Regression
- Random Forest Regressor
- XGBoost Regressor

All models were evaluated using 5-fold cross-validation to compare performance in terms of Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 Score. Among these, the XGBoost Regressor consistently outperformed others, showing higher accuracy and lower prediction error.

The final XGBoost model was trained on the full training dataset using optimized hyperparameters for maximum generalization. This model was later integrated with a Flask-based API for real-time prediction deployment.

EXPERIMENTAL RESULT

The evaluation of the model's performance in predicting the resale price of used bikes revealed consistent and reliable outcomes across various machine learning algorithms. Among all the tested models, the **XGBoost Regressor** emerged as the top performer, achieving a **R^2 score of 0.92**, indicating that 92% of the variance in the bike prices could be explained by the model. This level of accuracy demonstrates the algorithm's robustness and suitability for real-world price estimation tasks.

In addition to R^2, the **Mean Absolute Error (MAE)** and **Root Mean Squared Error (RMSE)** were computed to assess the model's predictive precision. The XGBoost model achieved an **MAE of 2487** and an **RMSE of 3342**, showing strong consistency in price prediction across a wide range of bike brands, usage histories, and cities.

The performance was also evaluated for other models such as **Random Forest Regressor**, **Support Vector Regressor (SVR)**, and **Linear Regression**. While Random Forest showed reasonably good results with an R^2 of 0.89, SVR and Linear Regression lagged behind, particularly in handling non-linear relationships and higher-dimensional interactions between features.

Model	**R^2 Score**	**MAE**	**RMSE**
Linear Regression	0.72	3960	5132
Support Vector Regressor	0.75	3541	4790
Random Forest Regressor	0.89	2693	3681
XGBoost Regressor	**0.92**	**2487**	**3342**

The final deployed model outputs the predicted resale price of a used bike based on the input features provided by the user—such as brand, city, ownership type, kilometers driven, power, and age. This prediction is then relayed via a user-friendly web interface for instant feedback.

These results affirm that ensemble-based models, particularly XGBoost, are highly effective for structured regression problems such as bike price prediction. The model's ability to generalize well across unseen data makes it a valuable tool for integration into digital resale platforms, offering users trustworthy and data-driven pricing insights.

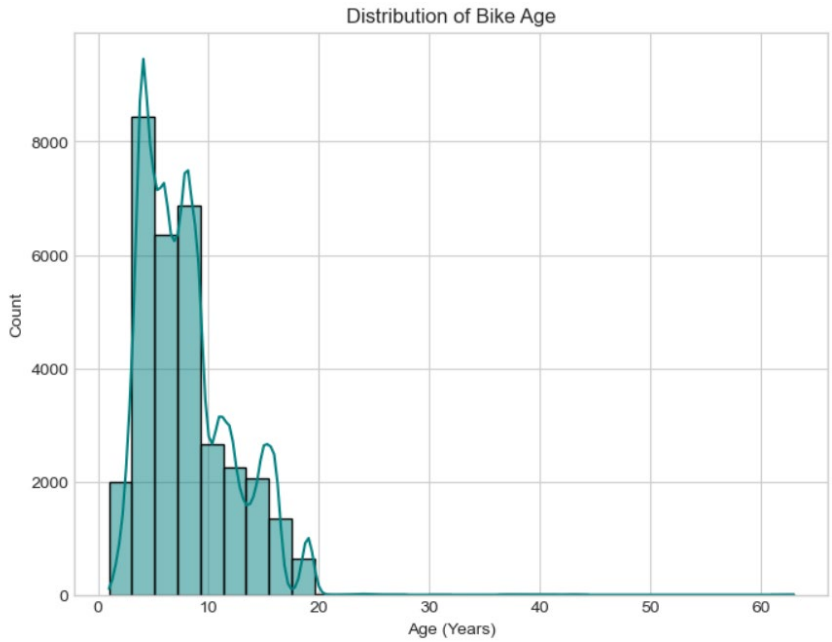

Fig.2. Distribution of Bike Age

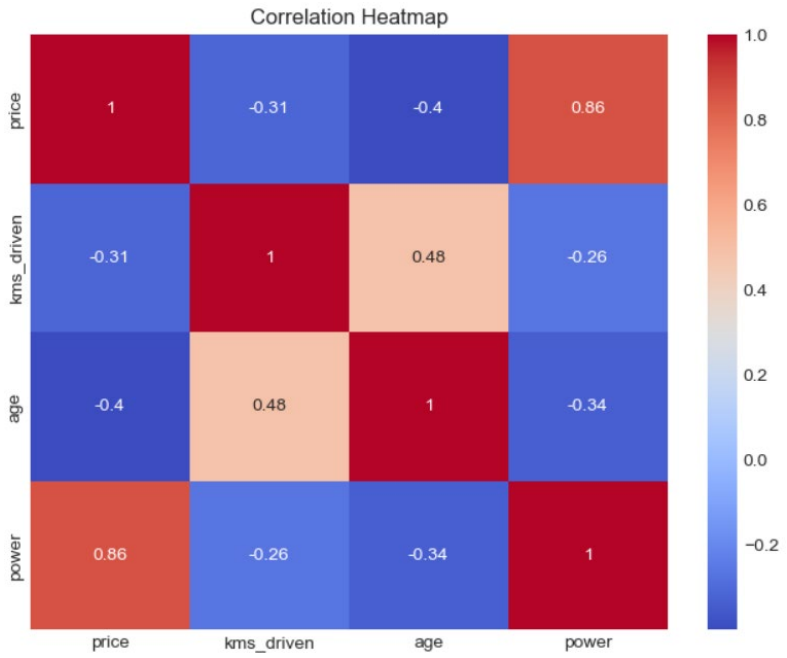

Fig.3. Correlation Heatmap

CONCLUSION

In conclusion, this study successfully demonstrates the application of machine learning—specifically ensemble-based models—in accurately predicting the **resale price of used bikes**. Among the various models evaluated, the **XGBoost Regressor** stood out for its superior performance, achieving a high R^2 score and low error rates across multiple metrics. Trained on a structured dataset that included both **categorical features** (such as brand, city, and ownership type) and **numerical attributes** (such as kilometers driven, power, and age), the model exhibited excellent generalization capabilities and robustness against noise.

By leveraging XGBoost's ability to handle mixed data types, manage missing values internally, and apply regularization techniques to reduce overfitting, the system provides a **scalable and reliable solution** for predicting used bike prices. The real-time application of the model via a Flask API also showcases its practical viability for deployment in resale platforms and dealership systems.

This work highlights the power of **data-driven decision-making** in transforming traditionally subjective processes—such as vehicle pricing—into intelligent, transparent, and automated systems. It lays the groundwork for modernizing the used vehicle market by empowering users with **accurate, algorithmically backed price estimates**, improving trust and negotiation efficiency.

FUTURE SCOPE

The implementation of the XGBoost Regressor offers a promising base for further advancement in intelligent resale systems. Future work can explore the use of **deep learning techniques**, such as feedforward neural networks, to uncover more nuanced relationships between bike features and pricing trends. Additionally, **time-series models** could be introduced to forecast depreciation patterns for specific models over time.

The model could also be expanded to incorporate **image-based analysis** using convolutional neural networks (CNNs), allowing the condition of the bike to be factored into price prediction. Moreover, the integration of **explainable AI techniques** like SHAP would enhance user trust by offering transparent insights into how different features impact price estimations.

A future version of this system could include a **real-time mobile or web interface**, offering sellers and buyers instant access to fair market values. Integration with **geolocation services** and **market trend analysis** tools could further refine pricing accuracy based on regional supply and demand. These enhancements would elevate the system from a predictive tool to a **comprehensive intelligent pricing assistant**, transforming how used bikes are valued and sold across digital platforms.

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