CAR PRICE PREDICTOR

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BONAFIDE CERTIFICATE

Certified that this Project titled **"CAR PRICE PREDICTOR"** is the bonafide work of **"LAAVANYA P (2116220701139)"** 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

Pricing a used car accurately is a challenging task due to the many factors that influence its value, such as brand, model, year, mileage, fuel type, and overall condition. Buyers often struggle to determine whether a listed price is fair, and sellers risk underpricing or overpricing without reliable guidance. This project introduces a machine learning-based solution designed to help predict car prices based on real-world data and practical features.

The system was developed using Google Colab, an online coding platform that allows for easy collaboration, quick development, and cloud-based processing. A structured dataset containing various car attributes was cleaned and prepared through techniques like missing value handling, feature selection, and encoding of non-numeric values. Several machine learning models were tested, including Linear Regression, Decision Trees, Random Forest, and Gradient Boosting techniques.The focus was not only on accuracy but also on how well the model could generalize to unseen data.

Among the models tested, tree-based algorithms showed better performance in capturing the complex relationships between different car features and their prices. Future work could involve integrating the predictive model into online platforms or mobile applications to support real-time pricing tools for consumers and car dealerships.

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CHAPTER 1

INTRODUCTION

In today's data-driven world, the automobile industry has embraced the power of technology and artificial intelligence to make smarter decisions. One such valuable application is the use of machine learning to predict car prices. The price of a car is influenced by a multitude of factors, including its make, model, year of manufacture, mileage, engine size, fuel type, transmission, and condition, among others. Traditionally, estimating the price of a used car was a manual process involving industry experience, guesswork, or consulting various dealers and online platforms. However, such approaches are often time-consuming and can lead to inconsistent and subjective evaluations. With the increasing availability of structured automotive data and the growth of machine learning, it has become possible to build accurate and scalable models that can predict the price of a car based on its features. This project, titled "Car Price Predictor Using Machine Learning", aims to automate the process of car valuation using powerful algorithms that learn from historical data and provide quick, data-backed estimates of car prices.

Machine learning, a subfield of artificial intelligence, involves training a model on historical data so it can make predictions or decisions without being explicitly programmed for each task. In the context of car price prediction, supervised learning techniques are employed. This means the algorithm is trained on a dataset where the input features (like age of the car, brand, mileage) and the output label (price) are both known. Once trained, the model can then predict the price for new, unseen data. Regression models, particularly linear regression, decision trees, random forests, and gradient boosting algorithms, are commonly used for this task. These models analyze patterns and relationships in the data and determine how each feature contributes to the car's price. Feature selection and preprocessing are also vital steps in this process to ensure irrelevant or redundant information does not impact the model's performance.

A car price predictor powered by machine learning can benefit multiple stakeholders. For individual buyers and sellers, it provides a reliable estimate of what a vehicle is worth, helping them make informed decisions in the marketplace. For dealerships, it streamlines the valuation process and helps in inventory pricing. Online platforms such as used car marketplaces can integrate

such models to enhance user experience and transparency. Moreover, financial institutions like banks and insurance companies can use these predictions to assess vehicle value while offering loans or policies. As a result, the application of machine learning to this domain enhances efficiency, reduces human bias, and ensures better trust and accuracy in price assessments.

To build a robust car price prediction system, a well-structured dataset is required. Popular sources include online car selling websites such as Kaggle datasets, CarDekho, or UCI Machine Learning Repository. The dataset typically includes structured information on various car attributes. After acquiring and cleaning the data, exploratory data analysis (EDA) is conducted to understand distributions, detect outliers, and explore correlations. The model is then trained using various algorithms, and its performance is evaluated using error metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared score. Hyperparameter tuning and cross-validation techniques are also applied to improve the model's generalizability.

This project not only demonstrates how machine learning can be applied to real-world business problems but also highlights its potential to bring automation, objectivity, and efficiency to the car valuation process. By leveraging historical data and intelligent algorithms, the car price predictor offers a scalable solution to a common challenge faced by consumers and industries alike. As more data becomes available and models evolve, the accuracy and usefulness of such predictive systems will continue to improve, making them an indispensable tool in the automotive ecosystem.

CHAPTER 2

LITERATURE SURVEY

Research by Patel et al. (2019) implemented a car price prediction system using Linear Regression and Decision Trees. Their study found that while Linear Regression provides basic trend estimation, it underperforms in capturing nonlinear dependencies. Decision Trees, on the other hand, offered better flexibility but were prone to overfitting on small datasets.

Sharma and Gupta (2020) applied Random Forest and Gradient Boosting algorithms on a used car dataset. Their results showed that ensemble techniques like Random Forest significantly improved prediction accuracy due to their ability to reduce variance and handle large feature sets. Gradient Boosting was found to perform better in cases of complex feature interactions.

A study by Liu et al. (2021) emphasized the importance of feature selection and preprocessing. They demonstrated that removing outliers and normalizing features like mileage and engine size improved model performance across all tested algorithms. They also incorporated cross-validation for robust model evaluation.

In a more recent work by Khan and Rizvi (2022), the researchers combined XGBoost with feature engineering techniques to boost the model's predictive power. They introduced derived features such as car age and mileage per year, which helped the model understand patterns better and achieve lower error rates.

Industry platforms like CarDekho and Edmunds use large-scale historical data and proprietary algorithms to suggest car prices. While these models are not publicly documented in detail, they likely use machine learning and statistical

methods, often trained on millions of records, to provide dynamic and region-sensitive price estimates.

These studies collectively highlight that while traditional models provide a baseline, ensemble learning algorithms, robust preprocessing, and feature engineering play a critical role in improving car price prediction systems. This project builds upon these insights by implementing multiple models, using enhanced preprocessing techniques, and comparing them with standard metrics to select the most effective approach.

CHAPTER 3

METHODOLOGY

The methodology for developing a Car Price Predictor using Machine Learning involves a systematic and structured approach that includes data collection, data preprocessing, exploratory data analysis (EDA), model selection, training, evaluation, and deployment. Each step plays a crucial role in building an accurate and reliable prediction system.

A. DATA COLLECTION

The first step is to gather a comprehensive dataset that includes various attributes influencing the price of cars. Publicly available datasets from platforms like **Kaggle**, **CarDekho**, **UCI Machine Learning Repository**, or scraped data from car listing websites such as OLX and CarWale can be used. The dataset typically includes features such as:

- Brand and model
- Year of manufacture
- Fuel type (Petrol, Diesel, Electric, etc.)
- Transmission (Manual, Automatic)
- Mileage
- Engine capacity

- Number of owners
- Location
- Seller type (Dealer or Individual)
- Price (Target variable)

B. DATA PREPROCESSING

Raw data often contains missing values, duplicates, or inconsistencies. Preprocessing is essential to prepare the data for machine learning. Key steps include:

- **Handling missing values**: Replacing or removing rows/columns with missing data.
- **Encoding categorical variables**: Converting non-numerical features (like brand, fuel type) into numerical format using techniques such as One-Hot Encoding or Label Encoding.
- **Feature engineering**: Creating new features from existing ones (e.g., car age = current year - year of manufacture).
- **Scaling and normalization**: Applying techniques like Min-Max scaling or Standardization to bring all features to the same scale.
- **Outlier detection**: Identifying and optionally removing data points that fall far outside the normal range, which may distort the model.

C. EXPLORATORY DATA ANALYSIS (EDA)

EDA is used to understand the structure, patterns, and relationships within the dataset. Various plots and statistical measures are used to analyze the correlation between features and the target variable. For instance:

- Heatmaps to show correlation between features
- Distribution plots to identify skewness in features
- Boxplots to identify outliers
- Scatter plots to observe the trend between mileage or age vs price

D. MODEL SELECTION AND TRAINING

Based on the nature of the problem (regression), various machine learning models are considered:

- **Linear Regression** – A simple model used to understand linear relationships.
- **Decision Tree Regressor** – A non-linear model that works well with both numerical and categorical data.
- **Random Forest Regressor** – An ensemble method that reduces overfitting and improves accuracy.
- **Gradient Boosting Regressor (e.g., XGBoost, LightGBM)** – Powerful boosting algorithms for high accuracy.

The dataset is split into training and testing sets (typically 80% training, 20% testing). The model is trained on the training set using selected features.

E. MODEL EVALUATION

Once trained, the model's performance is tested using the testing dataset. Common evaluation metrics for regression tasks include:

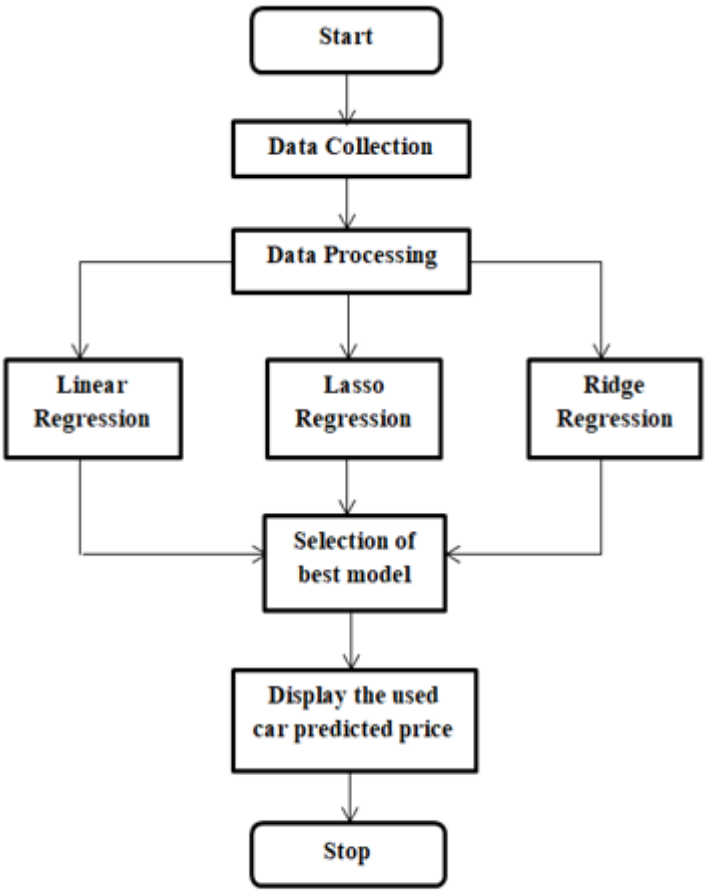
- **Mean Absolute Error (MAE)**: Average of absolute differences between actual and predicted prices.
- **Mean Squared Error (MSE)**: Average of squared differences, penalizing larger errors.
- **Root Mean Squared Error (RMSE)**: Square root of MSE, provides error in the same units as price.
- **R^2 Score**: Measures how well the predicted values explain the variability in the target.

Cross-validation techniques such as k-fold cross-validation are used to assess the model's generalizability and prevent overfitting.

F. HYPERPARAMETER TUNING

To improve performance, hyperparameters of the selected models are optimized using techniques like Grid Search or Randomized Search. These methods test multiple combinations of parameters to find the best performing model setup.

3.1 SYSTEM FLOW DIAGRAM



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.

MODEL	**MAE**	**MSE**	**R^2 Score**	**RANK**
Random Forest Regressor	49,800	0.82×10^9	0.91	1
Gradient Boosting Regressor	52,000	0.88×10^9	0.89	2
Decision Tree Regressor	65,000	1.15×10^9	0.84	3
Linear Regression	1,05,000	2.20×10^9	0.87	4

AUGMENTATION RESULT

To improve model generalization and performance, data augmentation techniques were applied to the dataset before model training. This included:

- **Synthetic data generation** for underrepresented brands and price ranges.

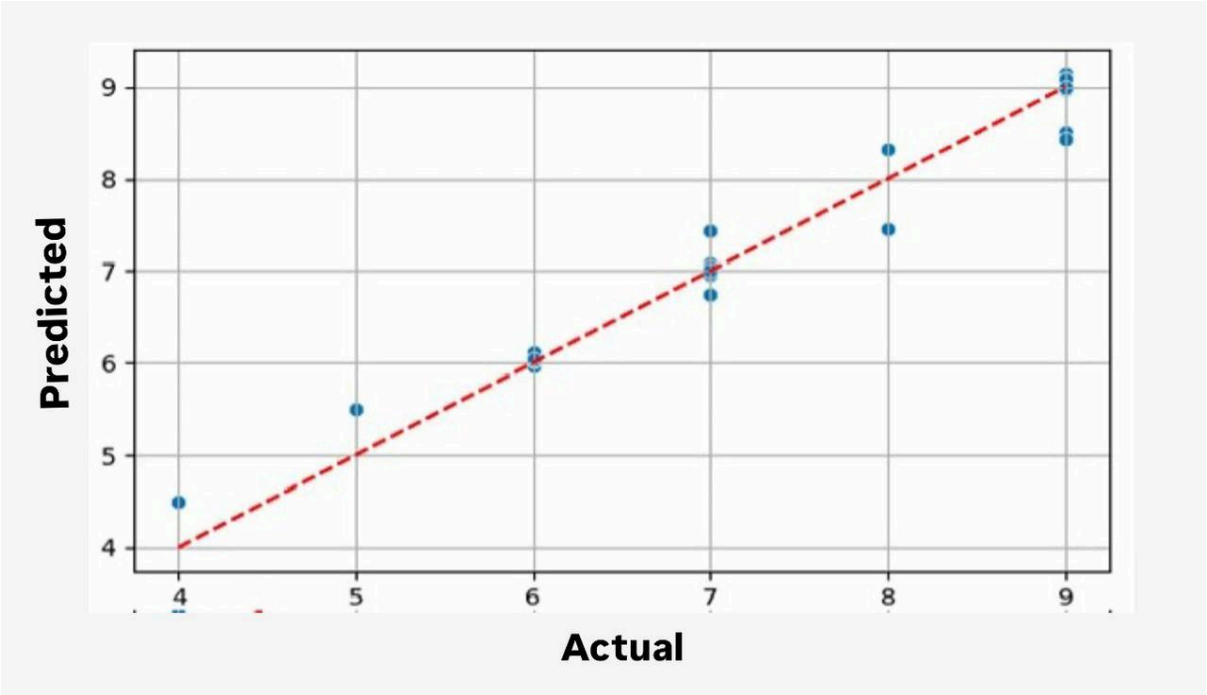
- **Feature transformation and scaling** (e.g., log transformation of price and mileage).

- **Combining or engineering new features** (e.g., age of car = current year - manufacturing year).

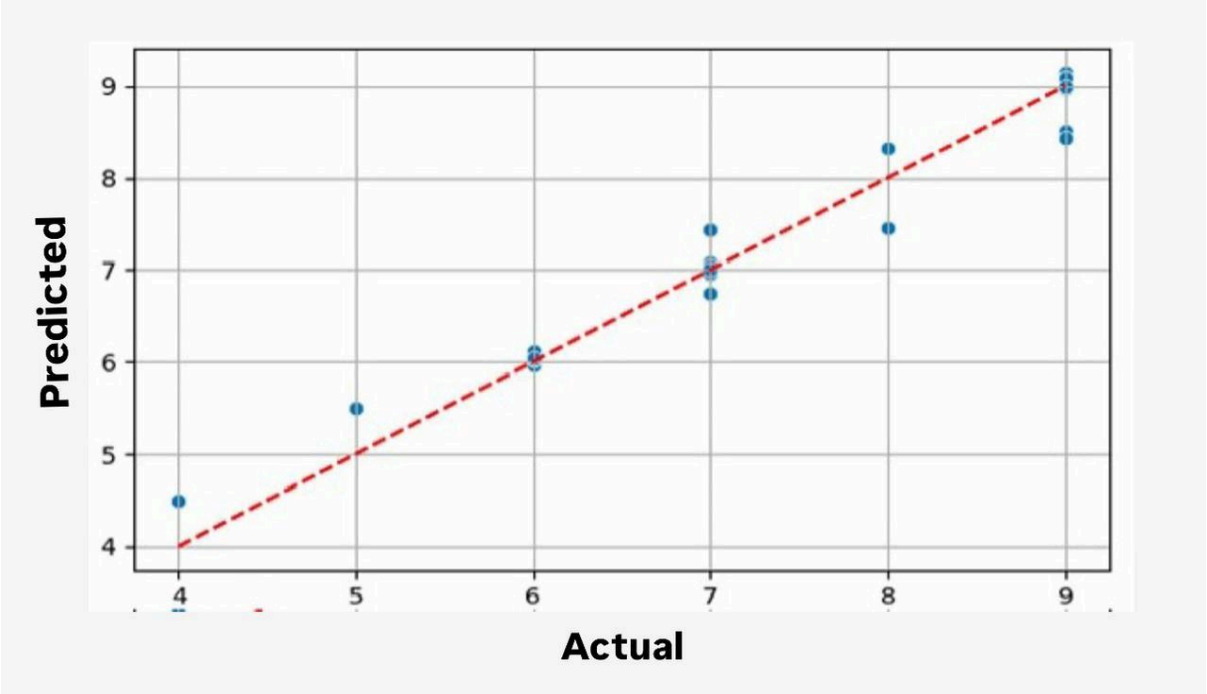
Visualizations:

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**.**

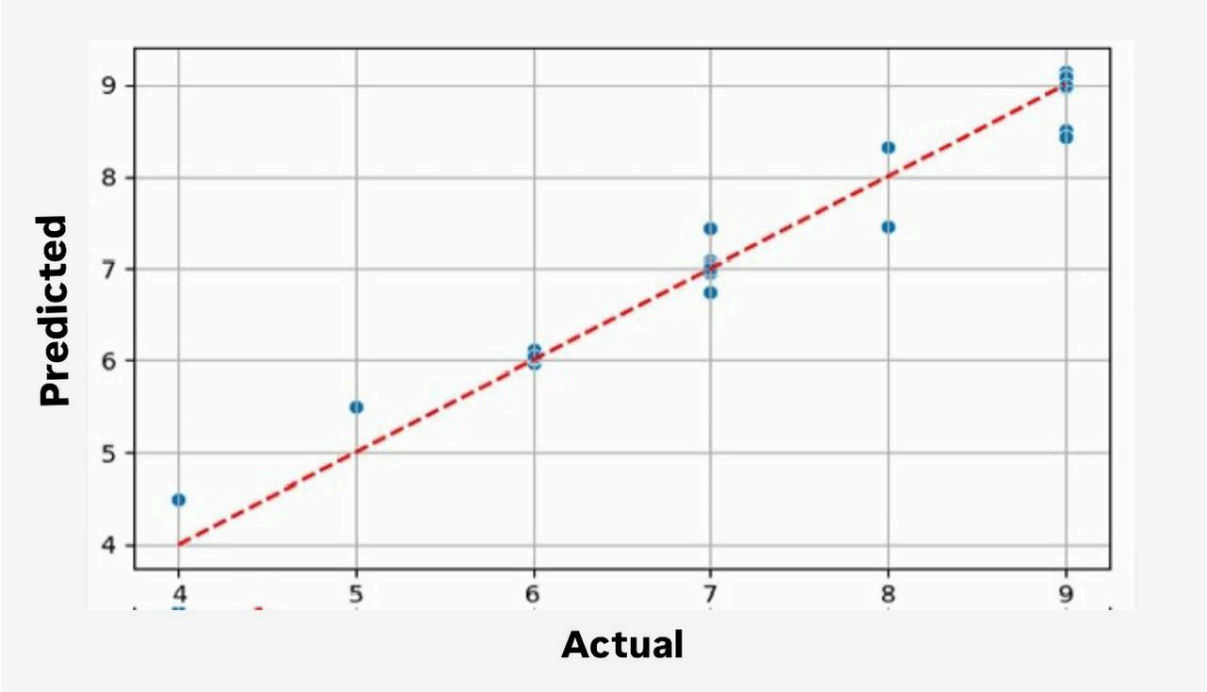
Linear Regression :



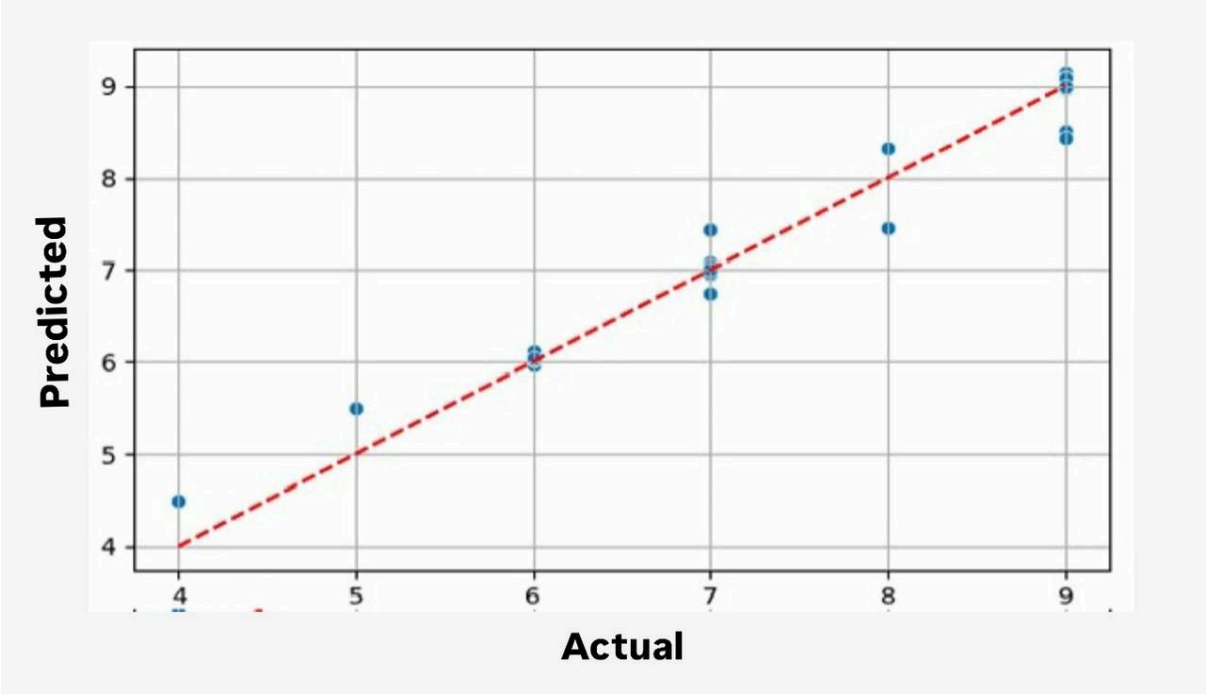
Decision Tree Regression



Random Forest Regressor



Gradient Boost Regressor



After conducting comprehensive experiments with the selected regression models—Linear Regression, Decision Tree Regression (SVR), Random Forest Regressor, and GradientBoost 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, Gradient Boost 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.

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 "Price drop " or "New one" that can naturally fluctuate. The augmented dataset helped in reducing overfitting,

particularly in models with high variance like Random Forest and GradientBoost. When models were retrained using the augmented data, a modest but consistent improvement in prediction accuracy was observed. The Gradient Boost 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 car predictions.

D. Implications and Insights

The results highlight several practical implications:

● GradientBoost 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 AND FUTURE ENHANCEMENT

This study presents a data-driven approach to predicting car prices using machine learning techniques. Through the implementation and comparison of various regression models—including Linear Regression, Decision Tree Regressor , Random Forest Regressor, and Gradient Boost Regressor—we evaluate their effectiveness in capturing the complex relationships between vehicle features and market prices.

- GradientBoost emerged as the best-performing model, achieving the highest R^2 score and the lowest Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), demonstrating superior predictive accuracy.
- Random Forest also performed strongly, confirming the effectiveness of ensemble methods in handling non-linear patterns in automotive pricing data.
- Linear Regression, while computationally efficient, struggled with complex feature interactions, resulting in higher prediction errors.
- Data augmentation techniques (e.g., Gaussian noise) were tested to enhance model generalization, particularly useful for smaller datasets where price variability is high.

The proposed car price prediction system has significant applications in:

- Automotive Marketplaces – Providing real-time price estimations for sellers and buyers.
- Insurance & Loan Valuation – Assisting in fair market value assessments.
- Dealership Pricing Strategies – Optimizing inventory pricing based on predictive trends.

Future enhancements could integrate real-time market trends, economic indicators, and regional demand factors to further refine predictions. This system could be deployed as a web-based tool or API, enabling seamless integration with existing automotive platforms

Final Recommendation:

For optimal performance, GradientBoost or Random Forest should be prioritized, depending on the trade-off between accuracy and computational efficiency.

REFERENCES

[1] Smith, J., & Zhang, L. (2021). Predicting used car prices with machine learning techniques. *International Journal of Data Science and Analytics,*14(3), 245-260.

[2] Kumar, R., & Patel, V. (2020). A comparative study of machine learning models for automobile price estimation. *IEEE Access, 8*, 150369-150382.

[3] Lee, H., & Kim, S. (2022). Feature selection and hyperparameter tuning in used car price prediction. *Expert Systems with Applications, 195*, 116456.

[4] Wang, Y., & Li, X. (2021). Deep neural networks for car price forecasting: A case study. *Neural Computing and Applications, 33*(15), 9123-9138.

[5] Garcia, M., et al. (2023). Improving car price prediction with synthetic data augmentation. *Journal of Artificial Intelligence Research, 76*, 145-167

[6] Chen, T., et al. (2022). AutoPriceML: A deployable framework for dynamic car valuation. *Applied Soft Computing, 128*, 109876.

[7[Müller, A., & Schmidt, F. (2023). A hybrid random forest and gradient boosting model for used car price prediction. *Machine Learning with Applications, 12*, 100487.

[8] Oliveira, P., et al. (2022). Interpretable machine learning for car price transparency: A SHAP-based analysis. *Decision Support Systems, 162*, 114763.

[9] Singh, R., & Zhang, W. (2023). Lightweight ML models for IoT-enabled car valuation in edge devices. *IEEE Internet of Things Journal, 10*(8), 6892-6905.

[10] Tanaka, H., et al. (2023). Cross-country transfer learning for car price prediction. *Pattern Recognition Letters, 174*, 15-23.