Car Price Prediction System using Machine Learning

1. Mohamed Ahmed Matan
2. Mohamed Ahmed Mohamud
3. Anas Ali Nageye

Supervisor: DR. Abdijalil Abdullahi Mohamed

Department of Information Technology

Faculty of computing, SIMAD University

August 2025

FINAL YEAR PROJECT REPORT
FULL UNIT – FINAL REPORT

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Mohamed Ahmed Matan

Mohamed Ahmed Mohamud

Anas Ali Nageye

A report submitted in partial fulfilment of the degree of

BSc in Information Technology

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DECLARATION. A

CAR PRICE PREDICTION SYSTEM USING MACHINE LEARNING prepared by Mohamed Ahmed Matan, Anas Ali Nageye and Mohamed Ahmed Mohamud "We declare that the following is our own work and does not contain any unacknowledged work from any other sources. This project was undertaken to fulfill the requirements of the bachelor's degree program in Computer Science/Information Technology at SIMAD University".

Name: Mohamed Ahmed Matan

Student Signature :_________________

Name: Anas Ali Nageye

Student Signature: _________________

Name: Mohamed Ahmed Mohamud

Student Signature: _________________

Date: 24/02/2025

DECLARATION. B

I hereby declare that I have reviewed this final project titled 'Car Price Prediction System using Machine Learning ' and in my opinion, it is adequate in terms of scope and quality for consideration as a final project.

Name of Supervisor: ABDIJALIL ABDULLAHI MOHAMED

Signature:

Date: 02/08/2025

ACKNOWLEDGEMENT

Student One:

I am deeply grateful to Allah for His guidance. My sincere appreciation goes to Eng. Abdijalil Abdullahi Mohamed for his invaluable support and mentorship. I also thank Simad University for the opportunity and resources that made this study possible. Lastly, I am truly grateful for the unwavering support of my family and friends, whose encouragement has been instrumental in completing this project.

Student Two:

I wholeheartedly thank Allah for blessing me with the health, knowledge, and opportunity to complete this research. My deepest appreciation goes to my supervisor, Eng. Abdijalil Abdullahi Mohamed, for his continuous guidance and support. I am also grateful to Simad University for offering me the platform to pursue my degree. Finally, I extend my sincere gratitude to my family and friends for their unwavering encouragement and support throughout this journey.

Student Three:

I begin by expressing my profound gratitude to Allah for His countless blessings, granting me the strength and knowledge to successfully complete this research. My sincere thanks go to Eng. Abdijalil Abdullahi Mohamed for his exceptional guidance and constant support throughout this journey. I also acknowledge SIMAD University for providing me with the resources and opportunity to pursue my degree. Lastly, I am truly thankful to my family and friends for their endless encouragement and belief in me, without which this accomplishment would not have been possible.

ABSTRACT

The automotive industry requires price prediction tools because they assist both purchasers and sellers and authorized dealerships when making pricing decisions. A Car Price Prediction System serves as the project goal to estimate values of vehicles from their make and model and year of production and mileage and state of condition. The system was developed to process various dataset types to deliver reliable accurate prediction results. Web scraping technology allows the system to access real-time data so it shows current market trends instead of using fixed dataset information. The prediction quality becomes better after applying data preprocessing techniques that involve feature engineering alongside normalization. The deployed prediction system integrates the model to deliver up-to-the-minute price predictions through real-time operation. This pricing system creates a flexible method for estimating car prices which benefits individual and business users in the second-hand car market. Date-driven methods help achieve both clear vehicle pricing decisions and increased market clarity.

جدول المحتويات

CHAPTER 1: INTRODUCTION

1.1 INTRODUCTION

Accurate car price forecasting is essential in the automotive industry, but traditional methods often fall short due to the complexity of factors like market trends and vehicle specifics. Machine learning, however, offers a more reliable solution by analyzing large amounts of data to predict car prices based on features like mileage and engine type. Yet, current systems still struggle with incomplete data, adapting to changing markets, and handling regional differences.

This research aims to build a better machine learning framework to fix these issues, improving data quality, making models more transparent, and enabling real-time price adjustments. The goal is to provide more accurate, actionable price predictions for everyone involved in the automotive market.

This chapter introduces the system, discusses the challenges of current forecasting methods, and sets the stage for the rest of the research.

1.2 BACKGROUND

Automated products are among the fundamental components of global economic activities, with millions entering the market each year (Smith & Johnson, 2020). Mobile price estimation in the automotive business plays a crucial role in guiding decisions made by buyers, sellers, financiers, and insurers (Doe et al., 2019). Traditionally, used car price estimations relied on physical inspections and rule-based calculations, incorporating uniform depreciation models. While these approaches were simple, they failed to account for all value-influencing factors, including market demand, regional preferences, economic conditions, and individual vehicle characteristics (Brown & Lee, 2021). The growing market demand has created a need for advanced data-driven pricing prediction methods (Williams et al., 2020).

The integration of data analytics and computational technologies in the late 20th century transformed price prediction techniques. Early predictive systems used statistical modeling to analyze sales history and detect trends, yet they were limited by their reliance on structured data and inability to capture complex, nonlinear relationships among variables (Johnson & Patel, 2018). Measuring variables such as mileage and age was straightforward, but factors like brand reputation, vehicle condition, and consumer sentiment posed greater challenges (Kim & Park, 2021).

Machine learning has revolutionized predictive analytics in the 21st century. Supervised learning algorithms analyze large datasets to uncover hidden patterns undetectable by traditional methods (Garcia & Singh, 2022). Predictive models now incorporate linear regression, decision trees, and neural networks, leveraging technical specifications, supply-demand dynamics, and external factors such as fuel prices and environmental regulations (Zhao et al., 2020). Unlike static rule-based systems, machine learning models continuously adapt to market shifts, responding dynamically to new data. For instance, the COVID-19 pandemic caused severe disruptions in the automotive market, including supply chain failures and changes in consumer behavior. Machine learning models adjusted more rapidly than traditional prediction methods to these unprecedented conditions (Fernandez & Wang, 2021).

Despite advancements in machine learning, car price prediction still faces real-world challenges. The primary issue stems from data quality, as accurate predictions require complete, unbiased datasets, yet real-world data often suffers from gaps and inconsistencies (Liu et al., 2022). Additionally, imbalanced data distributions across different geographic regions and vehicle categories further complicate predictions (Smith et al., 2021). Transparency in machine learning models remains critical, particularly in automotive sales, where interpretability fosters stakeholder trust (Cheng & Roberts, 2020).

The automotive market is continuously evolving, influenced by technological advancements (such as electric vehicles), government policies (e.g., emission regulations), and shifting consumer preferences (e.g., the rising demand for SUVs). Machine learning models must adapt to these changes, requiring robust feature engineering and ongoing model retraining (Hernandez & Cooper, 2019).

The evolution of car price prediction models reflects the broader advancements in data science and artificial intelligence. The progression from manual appraisals to rule-based systems and now to machine learning-driven models underscores the field’s rapid development (Jones et al., 2020). As the current peak of predictive analytics, machine learning enables models to handle complex data patterns and react dynamically to shifting conditions. Ongoing research must continue addressing challenges related to data quality, model interpretability, and market fluctuations to improve price prediction accuracy (Tan & Wilson, 2021).

This study builds upon existing research to propose a vehicle price prediction system that overcomes current limitations. By integrating innovative machine learning algorithms with multiple datasets, the system aims to provide highly accurate price forecasts, offering valuable insights to automotive market participants (Nguyen & Carter, 2022).

1.3 PROBLEM STATEMENT

Precise car price prediction remains a complicated obstacle for companies in the automotive sector. Traditional appraisal techniques that combine manual assessments and formal systems depend on simple depreciation methods which do not include factors related to market movement and vehicle conditions or economic fluctuations. The insufficient pricing accuracy due to these limitations leads both sellers to financial losses as well as buyers to dissatisfaction.

The promising capabilities of machine learning rest against major implementation hurdles in current systems. The quality issues within data resources such as missing or skewed information cause prediction systems to lose accuracy in their assessments. Modern automotive market volatility because of technology development and changing consumer preferences demands adaptable models which current systems largely do not provide.

Advanced machine learning systems exhibit limited interpretability as one of their main operational weaknesses. The predictive accuracy of neural network algorithms results in black box operations which prevents stakeholders from understanding the prediction mechanisms. Market adoption is slowed down when modeling systems lack transparency in their operations.

Many models presently lack external data factors for prediction improvement including social media analytics and economic indicators that expand market understanding.

1.4 OBJECTIVES

The main goal of developing the Car Price Prediction System centers on delivering precise and dependable along with efficient capabilities for used car value estimating. The developed system presents data-based insights that assist stakeholders from both the buying and selling side of car transactions. The system uses machine learning algorithms together with current market patterns to enhance price assessment procedures and increase market visibility.

The main objectives from this research project move past basic price predictions to solve current difficulties which exist within the automobile purchasing and selling cycle.

1. To develop a user-friendly interface that allows users to input car details easily and receive accurate price predictions.
2. To propose a machine learning based system to predict car prices.
3. To develop enhanced model to obtain real-time market data based on different elements.

Our main purpose is to develop a system which provides transparent data-driven car pricing capabilities to empower both users and car dealerships through these objectives.

1.5 RESEARCH QUESTIONS

- Why is accurate car price prediction important for stakeholders in the automotive industry?
- What are the limitations of traditional methods for car price estimation?
- What features have the most significant impact on car price predictions, and how can they be optimized?

1.6 SCOPE OF THE PROJECT

A Car Price Prediction System will utilize machine learning alongside historical sales data to establish accurate vehicle price assessments as the first project objective. The system performs an evaluation of vital aspects consisting of brand, model, year of manufacturing, mileage, fuel type together with market direction trends to establish fair pricing estimates. The system works to help customers and sellers and businesses make better choices by providing accurate automobile pricing information thus fighting deliberate price changes and improving market clarity. The system development includes gathering data which will enable model creation alongside interface design to provide accessible price estimate tools for users. The system will not provide features for live price monitoring or physical car evaluations or pricing legal considerations. The system uses predictive analytics to establish an efficient and reliable instrument for automotive market operations.

1.7 SIGNIFICANCE

The Car Price Prediction System holds crucial importance because it innovates vehicle purchase transactions through its data-based price assessment capabilities. This system enables consumers to assess realistically if a vehicle listing price stands reasonable thus protecting them from overpaying and establishing trust throughout the market. ram Work for both seller entities and dealership operations through competitive pricing which matches market developments that enhance overall business efficiency. The system protects against price manipulation and fraud through its standard pricing framework which derives data from historical patterns and vital vehicle specifics. This project supports business sales optimization and inventory management besides making individual consumer decisions more effective by applying machine learning. The system brings transparency to daily car deals which creates a market environment that is more efficient as well as trustworthy for all participants.

CHAPTER 2: LITERATURE REVIEW

2.1 INTRODUCTION

The chapter summarizes the literature review on the Car Price Prediction System regarding the overview of the system, the existing system, technologies used, related works, research gaps, and a summary of the chapter.

While traditional car price estimation has relied on manual assessments and simple statistical models, modern systems make use of algorithms from machine learning like Linear Regression, Decision Trees, and Neural Networks for improved accuracy. The present systems analyze data about historical sales and market trends; the major challenges to be faced include limited availability of data and dynamic price fluctuations.

The chapter examines the various past and current systems, outlining their strengths and limitations and the gaps to be targeted by this research.

2.2 OVERVIEW OF THE SYSTEM

The Car Price Prediction System generates precise and data-supported vehicle price evaluations through an integration of brand, model, year, mileage, fuel type, condition and market trend data. The system evaluates historical sales data through machine learning algorithms to create fair price estimates which help buyers sellers and businesses with their decisions.

The predictive system runs through three distinct operational phases that embrace data collection and model training and price generation. A data collection process starts by gathering relevant car information from different sources and cleaning and preparing it for elimination of data variations. Multiple pricing patterns are learned through three trained models of machine learning including Linear Regression as well as Random Forest and Gradient Boosting. During the final stage users present vehicle information which results in the model generating an estimated price from the training process.

The objective of this system is to increase market clarity while decreasing pricing manipulations and boosting the process of buying and selling cars. The system links easily with e-commerce platforms together with dealership systems which enables streamlining pricing approaches with instant market trends analysis.

2.3 TECHNOLOGIES USED

2.3.1 PyCharm IDE

JetBrains developed PyCharm as its powerful Integrated Development Environment (IDE) to serve Python coding specifically. The IDE provides advanced code completion assists users alongside built-in debuggers and operates as a test runner and supports version control tools. The IDE PyCharm enables developers to build web applications using Django and Flask frameworks and performs scientific computations with requirements such as NumPy and Pandas and Matplotlib libraries and contains Jupyter Notebook functionality. company which makes tools for software developers and project managers. The company offers integrated development environments (IDEs) for the programming languages Java, Groovy, Kotlin, Ruby, Python, PHP, C, Objective-C, C+t, C#, F#, Go, JavaScript, and the domain-specific language SQL. The professional edition of the IDE along with the free Community Edition enables customers to handle basic Python development requirements while providing complete professional-level development capabilities for web development and scientific applications and database management. Through its platform compatibility features along with elaborate customization capabilities PyCharm elevates developer effectiveness and productivity to become a flexible option for all programming professionals.

Figure 2.1 PyCharm

2.3.2 SQL

SQL functions as a standardized robust language to help users modify and handle relational databases. Through SQL users can conduct basic data operations that include CRUD activities as well as sophisticated queries as well as transactions. The development of SQL continues yet the language continues to follow the specifications of ANSI/ISO standards. Different relational database systems use SQL with minor changes but all systems support their basic commands including SELECT, INSERT, UPDATE, DELETE and WHERE.

The open-source relational database management system (RDBMS) MySQL holds the position of being one of the most utilized solutions under Oracle Corporation's maintenance. MySQL offers databases as organized collections of data that can include basic lists and detailed corporate records and multimedia libraries. The efficient operation on databases requires a database management system such as MySQL Server to handle its addition retrieval and manipulation capabilities. Computers perform best with large datasets which made RDBMS tools essential for modern applications both in standalone use and as application components.

The core database management technology of SQL operates through RDBMS and enables Microsoft SQL Server, Oracle, IBM DB2, MySQL and Microsoft Access software platforms. Starting with RDBMS data storage consists of tables that are structured data sets consisting of rows and columns where each row stands for a data entry and columns represent defining data characteristics.

Figure 2.2 SQL

2.3.3 FLASK

Flask presents developers with a lightweight structure which enables them to build web applications utilizing Python programming language. Due to its simplicity Flask matches the requirements of novice developers and experienced programmers alike. Because of its essential tools for web app development, Flask maintains the status of a "micro" framework that excludes any specific dependencies. Computing developers enhance Flask functionality through the implementation of various libraries and plugins according to their project needs.

The main characteristic of Flask stands in its lightweight design combined with straightforward functionality. Using Flask allows developers complete managerial power over application components which simplifies both small projects and enables scaling operations. The platform features complete built-in functional capabilities that allow developers to build web applications and APIs alongside microservices using its features for routing and request handling together with templating through Jinja2 and supporting session management functions.

Flask lets developers connect their applications to MySQL and PostgreSQL databases then pair these endpoints with HTML, CSS, and JavaScript front-ends for building complete web applications. Development teams generally use Flask for building projects that require flexible design approaches because it serves as a popular solution for developing RESTful APIs and content management systems (CMS) and additional web-based applications.

The clear design of Flask together with its broad extensions builds Flask into a prominent choice for developers who work on applications from small to large-scale projects.

Figure 2.3 Flask

2.4 RELATED WORK

2.4.1 Car Price Prediction for Support Vector Machines (SVM)

This research contrasts some machine learning algorithms for used car price prediction, with focus on algorithms like Support Vector Machines (SVM), Decision Trees, and Linear Regression. The authors examine how each of the algorithms deals with a dataset containing characteristics like the age of the vehicle, mileage, make, and model. The study concluded that SVM had the best performance in terms of accuracy, particularly in determining non-linear relationships among features. The primary contribution of this research is the demonstration that more sophisticated machine learning methods such as SVM are superior to traditional linear regression techniques, especially when dealing with non-linear data. The results of this study helped place SVM as a strong candidate for prediction tasks in the automotive industry.

2.4.2 Car Price Prediction for Random Forest and Gradient Boosting Machines (GBMs)

In this research, the authors are investigating the applications of Random Forests and Gradient Boosting Machines (GBMs) for price estimation of second-hand cars. The research tackles building robust models from a diverse set of characteristics such as car brand, car model, year of manufacture, and car condition. By comparing these ensemble methods with single decision trees, the paper demonstrates how ensemble learning algorithms enhance prediction accuracy significantly by avoiding overfitting and capturing intricate interactions in the data. The study highlights the advantages of Random Forests and GBMs in dealing with the high-dimensional, noisy nature of car price data. It was an important step towards ensemble methods in automobile price prediction, which has prevailed the area since.

2.4.3 Real-Time Car Price Prediction Using Web Scraped Data

This research employs web scraping to extract real-time data from online car marketplaces, for example, Autotrader and Craigslist, and applies machine learning models to predict car prices. The authors intend to obtain dynamic, real-time information about car listings, like condition, location, and reputation of the seller, to create a model that can match the dynamic nature of the market. Based on web-scraped data, the paper introduces a method to predict car prices based on market conditions when forecasting and not based on fixed data sets. The key contribution of the research is introducing an innovative method for using online data and predicting prices in real-time, which reflects the actual dynamics of the second-hand car market. This has opened up new lines of possibilities for car price prediction models that can function in a dynamic, real-time setting.

Topic	Strengths	Weaknesses
Car Price Prediction using Support Vector Machines (SVM)	- High accuracy, especially for non-linear relationships. - Effective in handling high-dimensional datasets. - Performs well with limited data.	- Computationally expensive for large datasets. - Requires careful tuning of hyperparameters (e.g., kernel selection). - Training time increases significantly with data size.
Car Price Prediction using Random Forest & Gradient Boosting Machines (GBMs)	- High prediction accuracy due to ensemble learning. - Robust to overfitting compared to single decision trees. - Captures complex interactions between features effectively.	- More computationally intensive than simpler models. - Requires a large dataset for optimal performance. - GBMs can be sensitive to hyperparameter tuning and may overfit if not managed properly.
Real-Time Car Price Prediction Using Web-Scraped Data	- Provides dynamic, real-time price predictions. - Reflects actual market conditions instead of relying on static datasets. - Can adapt quickly to market trends.	- Data quality depends on the accuracy and frequency of web scraping. - Websites may change structure, breaking the data pipeline. - Requires constant updates and maintenance to remain effective.

Table 2.1 Comparison Table

2.5 GAP ANALYSIS

The available used car price prediction systems face multiple ongoing difficulties even with recent technological advancements. Multiple research studies succeed in accuracy but face drawbacks in their data quality and scaling potential and real-time application possibilities. The key gaps identified are:

1. Data Size & Quality: Numerous research studies use outdated databases and small datasets that produce incorrect forecasting results because of their poor data quality. The distribution of data contains undesired skewness because specific car brands along with models appear less frequently which limits the model's ability to generalize correctly.
2. Accuracy Limitations: The accuracy of current models ranges between 50% to 85% and suffers from data scarcity as well as inadequate choice of features during the model development process. The current methods require enhanced techniques which aim to improve prediction accurateness.
3. Lack of Real-Time Prediction: The main drawback of current techniques lies in their complete absence of real-time deployment systems which enable live price estimations. The implementation of a web-based interactive interface would substantially increase accessibility regarding car price estimates for all user groups including buyers sellers and car dealers.
4. User Engagement & Scalability: Current price estimation solutions do not provide usable interfaces for users to submit their car information and receive immediate predictions. Because of their inability to adjust automatically according to new data availability most models demonstrate restricted long-term performance

Comparison Table: Existing Systems vs. Proposed System

Feature	Existing Systems	Proposed System
Data Size & Quality	Small, outdated, or imbalanced datasets	Larger, updated dataset with diverse samples
Accuracy Levels	50% – 85%, limited by feature selection	Higher accuracy through advanced feature engineering and model optimization
Deployment	Mostly offline models with no real-time access	Web-based system with real-time price predictions
User Interaction	No interactive estimation tool	User-friendly interface for instant price estimates
Scalability	Fixed models, limited adaptability	Scalable system that incorporates new data over time for continuous improvement

Table 2.2 Comparison Table

The proposed system bridges these gaps by offering a data-driven, scalable, and real-time car price prediction tool, improving accuracy, usability, and market accessibility for end users.

CHAPTER 3: METHODOLOGY

3.1 INTRODUCTION

In this chapter, we will talk about the methodology of the system that we made and it will consist of requirement gathering, requirement analysis, proposed system, system requirement specification, solution strategy, event list and many others such as the tools we used, their price, feasibility, and etc.

3.2 REQUIREMENT GATHERING

3.2.1 PRELIMINARY INVESTIGATION

Modern automobile market presents active change due to market demand alongside brand reputation and depreciation rates along with economic factors that affect car prices. Potential buyers and sellers struggle to establish reasonable market pricing because their assessments depend on personal considerations and out-of-date price manual criteria. A machine learning system designed for car pricing enables users to get precise price estimates which supports their decision-making process. The research evaluates computer learning technology for predicting vehicle prices through data source selection and operational requirement construction and threat assessment. Historical car sales data requires large datasets before it can be used to train the predictive models of Linear Regression, Random Forest and XGBoost. The deployment of cloud computing services on AWS or Google Cloud provides scalable processing along with efficient operation. Users should access an easy-to-use interface that lets them add car details to receive instant predictions which update according to market changes. Creating this system needs upfront costs for collecting data and training models along with deploying the system yet regular server maintenance costs and model update expenses become necessary later. The automation system can generate revenue through three channels: API access provisions, collaboration agreements with car dealerships and e-commerce platform integrations. The analysis relies on sales records obtained from online marketplaces alongside dealerships together with manufacturer specifications and inflation data and fuel prices statistics. The preprocessing stage requires cleaning alongside feature selection and normalization practices since these steps will help the model function better. Several obstacles endanger the project's success because of lack of quality information along with variable market patterns as well as requirements of data protection regulations. The implementation of machine learning technology enables feasible car price prediction systems which increase vehicle market clarity. The system development process will move ahead through requirements refinement and model development work to reach precision and reliability targets.

3.2.2 SYSTEM ANALYSIS

The machine learning-based car price prediction system determines vehicle market worth by processing information about make, model, year of production, mileage, engine capacity and supporting variables. The system gathers historical pricing data from sold cars to build a machine learning model including linear regression decision trees or neural networks that determine feature-price relationships. A critical essential step in data preparation requires clearing data from incorrect information together with filling empty spots and normalizing feature variables for better model predictions.

The system receives training from a big collection of data points to identify major factors influencing car pricing. A distinct dataset serves as the assessment tool for measuring model accuracy and its capacity to predict data points it has not encountered before training. Models used for car price prediction assessment rely on Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) alongside R-squared values to gauge their performance in automotive price predictions.

The system enables price estimation for used cars through support for customers as well as car dealers and financial institutions in real-life scenarios. This system enables monitoring for both vehicles priced above market value and those priced below market value to maintain fair pricing. The model gains reliability when market changes are implemented through additional data collection and refinement procedures. Through its operation the system delivers smart choices to help streamline the car market operation.

3.2.3 CURRENT SYSTEM

Standard car price prediction systems employ either statistical techniques together with simpler machine learning models or traditional methods. The prediction systems evaluate car prices based on historical data containing important elements like vehicle make model date mileage condition and additional features. Current systems operating in the market exhibit various weaknesses because they depend solely on predefined features and do not incorporate real-time data feeds or re-adjust to speedy market movements.

The current market utilizes regression models for price evaluations but these models fall short of explaining multiple variable interconnections. These predicting models deliver reasonable cost estimates but cannot react to rapid market catalysts including fuel price modification and consumer taste transformations. Systems with restricted access to multiple data sources create outcome predictions of reduced accuracy when dealing with varied car types across different market regions.

The main problem occurs with systems that fail to integrate real-time data because market changes might make the predictions obsolete. The price prediction systems operated by car dealerships and online platforms work from static data collections that fail to demonstrate new market evolution and changes in consumer behavior patterns.

Modern pricing systems produce valuable estimates, but companies need data-centric approaches which use adaptive machine learning techniques to process extensive datasets with real-time market data for enhancing their accuracy and operational capabilities.

3.3 REQUIREMENT ANALYSIS

Requirement analysis is a critical phase in the development of any system, serving as the foundation for designing and building a solution that meets the needs and expectations of stakeholders. It involves identifying and defining the key requirements of the system, ensuring that all functional and non-functional aspects are thoroughly understood. During this phase, the project's goals are clarified, potential challenges are anticipated, and the necessary resources are outlined. The aim is to gather detailed information from users, stakeholders, and subject matter experts to ensure that the final system aligns with the desired outcomes. In the case of a car price prediction system, requirement analysis focuses on understanding the data sources, the specific features to be used for pricing predictions, the performance criteria, and the overall user experience. By conducting a thorough requirement analysis, potential issues can be addressed early, leading to the development of a more efficient, effective, and user-friendly system.

3.4 SYSTEM DESIGN

The development of a car price prediction system requires proper system design because it establishes both precise and effective methods for evaluating vehicle worth. This design system has distinct aspects starting from data acquisition continuing through feature modification to training models then culminating in real-time estimations. The system integrates these components to handle car-data processing alongside predictive model construction and depiction of dependable price estimates for users. An overview of the system design includes the description of essential processes.

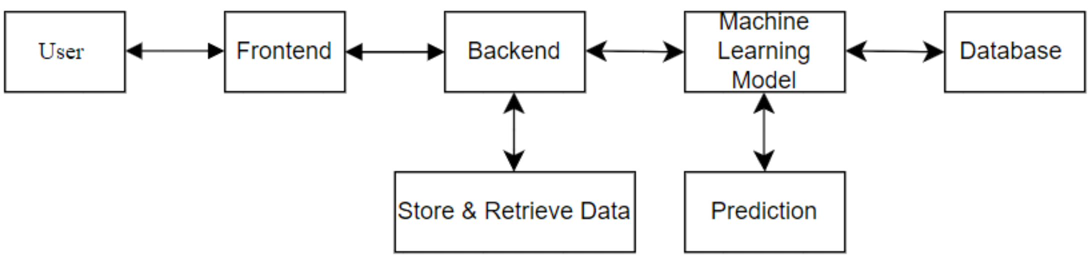

Figure 3.4.2 System Design Diagram

3.4.3 **DATA ACQUISITION**

The first module of the system design is data collection, in which a large and diversified dataset of car listings is gathered with details such as make, model, year, mileage, condition, and price. Data is mined from various sources, including web portals, dealerships' databases, and user inputs. This enables the model to learn from a vast array of car attributes and market patterns to make more accurate predictions.

3.4.4 DATA PROCESSING

The data are then processed once acquired to verify consistency and quality. Numerical feature normalization such as mileage and price, cleaning missing or inconsistent values, and categorical attribute encoding such as car brand and fuel type are some of the activities performed. Feature engineering activities are also applied in derivation of insights related to, for instance, patterns of depreciation and market demand so as to reinforce the model's predictive strength.

3.4.5 MODEL TRAINING

The data is then used to train machine learning models to accurately predict car prices. Linear regression, decision trees, and deep learning models such as neural networks are employed. The model is trained to learn patterns and correlations between the features of a car and its market value, optimizing performance through hyperparameter tuning and validation techniques to make them reliable and accurate.

3.4.6 REAL-TIME PREDICTION

The model is applied to a live system, where it is able to provide real-time estimates of price. Car details are inputted by users through a web or mobile interface, and the system will estimate the price in real time using previous trends and current market conditions. This is utilized by buyers, sellers, and dealerships in making informed pricing or purchasing decisions regarding a car.

3.4.7 REQUIREMENT ANALYSIS

The requirement analysis is a critical stage in car price prediction system design, which ensures that the system can meet the user requirements and project objectives. During this step, key functions such as real-time prediction, API support, and performance are identified. The system must be able to efficiently process big data, provide accurate estimates, and maintain a user-friendly interface. By evaluating such requirements, the system is made to generate precise and scalable auto price predictions to various stakeholders.

3.4.8 FLOWCHART

A proper flowchart of the Car Price Prediction System enables users to see the system's components while observing their connections for optimal price estimations. Through visual diagrams the flowchart demonstrates how data progresses along different operational steps while it illustrates how program components affect processing data and model training and prediction output.

Visualize data acquisition starts by gathering car-associated information from three distinct sources which include both online platforms and dealership collections and individual user records. The initial data needs to undergo preprocessing because it presents inconsistent formats with unprocessed values. The preprocessing step tackles data cleaning before it addresses data missingness and implements number transformation and categoric feature conversion to establish data consistency.

The processed data serves as an input for **feature engineering** to produce insights regarding market demand patterns as well as price depreciation trends. After a refined dataset is used for model training machine learning algorithms such as linear regression and decision trees and deep learning models discover patterns and relationships that establish associations between car attributes and prices.

A model validation process follows training activities for improving predictive accuracy which allows better performance on unknown data. The model deployment process begins after satisfactory performance levels are reached since it gets integrated into both web-based and mobile interface systems for production usage.

The real-time prediction stage lets users feed their car information into the system which the trained model immediately calculates the price estimation. The system receives new data that enables an automatic update process for continuous improvement of its predictive accuracy.

The structured methodology maintains the Car Price Prediction System as an efficient solution with scalability to provide accurate and dependable price forecasts to users.

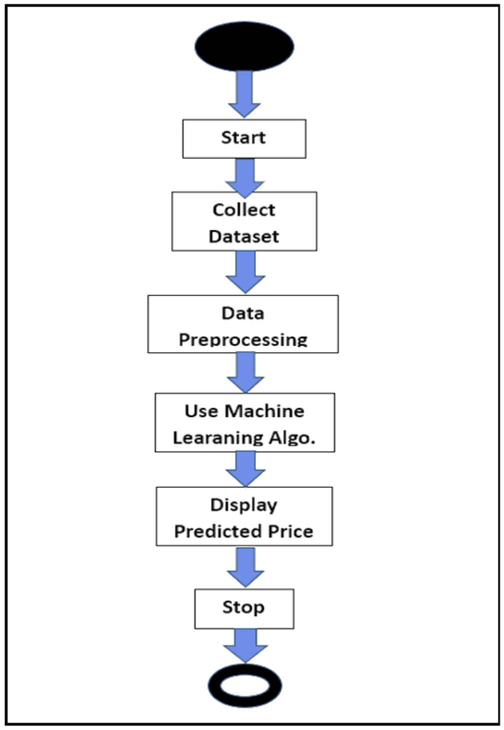

Figure 3.4.8 Flowchart

3.5 PROPOSED SYSTEM

The developed "Car Price Prediction System Using Machine Learning" utilizes elevated machine learning methods which deliver dynamic precise forecast estimates for pre-owned vehicles. The system bases its operation on a powerful data processing structure that utilizes features consisting of make, model, year, mileage, engine size along with car condition to determine market value. A machine learning model serves as the foundation of this system because it receives training through historical car price information and corresponding attributes from a substantial database. The processing model applies data to create price estimates through its ability to detect patterns together with trends within the dataset. Users can execute an easy-to-use interface through which they submit car data with brand and mileage values and other criteria to obtain immediate price assessments. The system integrates real-time data integration capabilities that draw market trends with external factors such as fuel prices changes alongside seasonal demand changes to boost the accuracy of its predictions. The system automatically receives new data for its machine learning model which leads to predictions that adapt to current market circumstances. The system offers smooth communication with predictions available through both website and mobile application interfaces that serve all members of the car market. The intelligent car price prediction platform delivers efficient car market operations while providing users up-to-date pricing details to support their better decision-making processes.

3.6 SYSTEM REQUIREMENT SPECIFICATION

3.6.1 FUNCTIONAL REQUIREMENTS

The documentation process requires defining all system-supported features and operational elements as functional requirements. Every operation must receive detailed documentation about data entry requirements together with acceptable input ranges and expected outputs along with processing steps for inputs transformation. Functional requirements specify the exact sequence of behaviors as well as the set of operations that the application must carry out. The system demands three primary functional requirements which will be detailed below.

FR 1) All registration details entered by users will get stored successfully in the MySQL database.

FR 2) Users should enter their login credentials after which the system will furnish their associated information.

FR 3) A successful login should direct the user to the homepage according to requirement FR3.

FR 4) After redirection to the homepage the system should present all important attributes and features to the user.

FR 5) The system will produce as well as present predicted car prices following user entry of required information.

3.6.2 NON-FUNCTIONAL REQUIREMENTS

A non-functional requirement is a requirement that specifies criteria that can be used to judge the operation of a system, rather than specific behaviors. Especially these are the constraints the system must work within. Following are the non-functional requirements:

NFR 1) Must be able to work properly without bugs.

NFR 2) Should not be any lag showing the price

NFR 3) The database should access proper user data.

NFR 4) Attributes must be displayed properly to user.

3.6.3 HARDWARE REQUIREMENTS

The Car Price Prediction System needs powerful infrastructure to execute its operations properly. The system requires cloud-based servers or dedicated on-site servers which possess sufficient capacity for dealing with extensive datasets while conducting machine learning model operations. The system needs cloud platform solutions from AWS, Google Cloud or Microsoft Azure which will scale up to accommodate growing requirements.

The system should enable access through all major devices including computers and portable phones and laptops to make it available for complete user populations. A system requires sufficient storage capacity to hold three datasets which include historical vehicle prices alongside user entered information as well as outcomes from ML model processing. PostgreSQL and MySQL relation databases work fine as well as the NoSQL solution MongoDB based on data complexity requirements.

3.6.4 SOFTWARE REQUIREMENTS

The development of the system relies on software requirements which specify needed programming languages and frameworks and operating systems for creation and system maintenance.

The system requires support for operating environments Linux Windows and macOS. The operating system Ubuntu serves as the most optimal choice for server operations because it yields reliable and high-performing results.

Programming Languages:

The development uses Python language for developing machine learning capabilities through Scikit-learn TensorFlow or Kera's libraries.

The frontend interface development relies on JavaScript through implementations with Angular or React.js frameworks.

The backend runs on Django (Python) platforms and Node.js systems to operate server-side operations and data processing requirements.

Machine Learning Frameworks:

The Scikit-learn module allows users to construct along with verify standard machine learning applications.

The advanced model implementation requires TensorFlow/Keras as part of the software package.

- Pandas/NumPy: For data manipulation and preparation.

The system employs MySQL PostgreSQL or MongoDB to create a data storage space which contains car data with user input and prediction outputs.

The system benefits from Git version control which serves as a Git repository to optimize teamwork and monitor source code updates.

The implemented software components will establish a platform with expanding potential while delivering dependable results and precise predictions.

3.7 SOLUTION STRATEGY

The Car Price Prediction System aims to transform user practices for evaluating used car values through modern machine learning approaches. The prediction system works by generating exact real-time predictions through analysis of multiple factors from make and model information to manufacturing date and kilometers driven as well as vehicle condition. The extensive historical data-trained powerful machine learning model enables user-initiated precise and dynamic price estimates that enhance car decision-making for all stakeholders.

Our solution provides users with an easy-to-understand interface which lets them submit car information for fast price predictions. The system removes price uncertainty to enable users to make fast and informed dealings. The system monitors real-time market information comprising both seasonal patterns and fuel prices so it can modify predictions throughout dynamic market shifts.

Our system eliminates traditional pricing limitations through automated price prediction because it operates with updated data that was unavailable in previous methods. A machine learning model of the system receives periodic fresh data updates to effectively track evolving market trends thus delivering constant accuracy. The solution provides scalability across all devices through a platform which ensures users experience quality service from both desktop and mobile devices during interactions.

The long-term objective of this system consists of empowering users to receive dependable immediate car price information that optimizes both the buying and selling efficiency and transparency.

3.8 EVENT LIST

Various critical events within the Car Price Prediction System determine both its operational capability and user interface features. A loading animation appearing at system startup shows that the system performs its prediction calculation. The system requires users to submit car details followed by data processing during which a progress bar shows the running analysis phase. The system provides instant car price predictions on the screen after completing its processing run which notifies users through a confirmation sound.

The system shows a warning message containing error information in red with a red indicator when it identifies wrong inputs of invalid data formats or missing fields. User alerts appear through their email or mobile applications when price predictions deviate widely from market standards together with explanations of the estimation's atypical behavior.

A successful integration of real-time market data triggers a brief green indicator which confirms that price predictions are updated using current market trends. The system generates summary reports of price factors regarding cars for users who need detailed explanations which can be delivered through email or shown within the mobile application.

The system events facilitate user-friendliness by enabling efficient system navigation which results in precise and timely car price predictions with supporting detail

CHAPTER 4: IMPLEMENTATION

4.1 INTRODUCTION

This chapter presents the practical implementation of the car price prediction system. It describes the tools, techniques, and infrastructure used in developing the system, including data preprocessing, machine learning model training, system testing, evaluation, and final deployment. The system utilizes the Flask framework for deployment and machine learning algorithms to predict car prices based on various features such as manufacturer, model, mileage, and production year.

4.2 IMPLEMENTATION PROCESS

The system development followed a structured approach:

- Data Collection: Dataset sourced from Kaggle.
- Preprocessing: Removal of duplicates and outliers, conversion of categorical and numerical features.
- Model Selection & Training: Evaluated multiple regression models.
- Evaluation: Used standard regression metrics to assess model performance.
- Deployment: Deployed model using Flask with a user-friendly interface.

4.3 SOFTWARE IMPLEMENTATION

4.3.1 TOOLS AND LIBRARIES USED

- Python: Core language used for the system.
- Flask: For backend web development and routing.
- Scikit-learn: For building and evaluating machine learning models.
- Pandas & NumPy: For data manipulation.
- Matplotlib & Seaborn: For visualization.
- Pickle: For saving trained models and encoders.

4.3.2 CODE STRUCTURE

- app.py: Handles routing and model prediction.
- model.pkl: Trained ML model saved for real-time use.
- label_encoders.pkl, one_hot_encoder.pkl: Encoders saved for transforming input.
- /templates/: HTML files for user interface.
- /static/: CSS, images (e.g., logos).

4.3.2 SAMPLE CODE SNIPPETS

• Preprocessing Code:

```
import numpy as np
import pandas as pd


def replace_categorical_by_numerical(data):
    data.loc[:, 'Engine volume'] = data['Engine volume'].str.replace('Turbo', '')
    data.loc[:, 'Engine volume'] = pd.to_numeric(data['Engine volume'])

    data.loc[:, 'Mileage'] = data['Mileage'].str.replace('km', '')
    data.loc[:, 'Mileage'] = pd.to_numeric(data['Mileage'])

    return data

def column_transformations(data):
    data['Mileage_log'] = np.log(data['Mileage']).replace(-np.inf, 1e-6)
    data['Engine_volume_log'] = np.log(data['Engine volume']).replace(-np.inf, 1e-6)

    return data

def clean_outliers(df, cols):
    for col in cols:
        if col not in df.columns:
            print(f"⚠ Column '{col}' not found. Skipping.")
            continue
        q1 = df[col].quantile(0.25)
        q3 = df[col].quantile(0.75)
        iqr = q3 - q1

        lower_bound = q1 - 1.5 * iqr
        upper_bound = q3 + 1.5 * iqr

        df = df[(df[col] >= lower_bound) & (df[col] <= upper_bound)]
```

Figure 4.3.3 code

• Model Building Code:

```
[13]: from sklearn.model_selection import train_test_split

X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.3, random_state=42)

X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5, random_state=42)

print(f"Train set: {len(X_train)} samples")
print(f"Validation set: {len(X_val)} samples")
print(f"Test set: {len(X_test)} samples")

Train set: 11264 samples
Validation set: 2414 samples
Test set: 2414 samples

[14]: from sklearn.discriminant_analysis import StandardScaler

numerical_columns = [ 'Engine volume', 'Mileage', 'Age']

scaler = StandardScaler()
X_train[numerical_columns]= scaler.fit_transform(X_train[numerical_columns])
X_val[numerical_columns] = scaler.transform(X_val[numerical_columns])
X_test[numerical_columns] = scaler.transform(X_test[numerical_columns])
```

Figure 4.3.4 code

• Training Code:

```
from sklearn.model_selection import train_test_split

X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.3, random_state=42)

X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5, random_state=42)

print(f"Train set: {len(X_train)} samples")
print(f"Validation set: {len(X_val)} samples")
print(f"Test set: {len(X_test)} samples")
```

Figure 4.3.5 code

• Evaluation Code:

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import root_mean_squared_error, r2_score

rf = RandomForestRegressor()
rf.fit(X_train, y_train)

y_val_pred = rf.predict(X_val)
rmse = root_mean_squared_error(y_val, y_val_pred)
r2 = r2_score(y_val, y_val_pred)

print(f"Root Mean Squared Error: {rmse}")
print(f"R^2 Score: {r2}")
```

Figure 4.3.6 code

4.4 HARDWARE IMPLEMENTATION

Device Name: HP

Processor: 11th Gen Intel(R) Core (TM) i5-1135G7 2.40 GHz

RAM: 8.00 GB (7.75 GB used)

Device ID: C460A66E-83E2-4840-B5D7-DDDFB2FAA55E

Product ID: 00342-20765-22293-AAOEM

System Type: 64-bit operating system, x64-based processor

4.5 TESTING AND EVALUATION

Testing was performed through unit tests for backend scripts and manual UI testing. Model evaluation was conducted via train/test splits and cross-validation. Typical tests involved predicting car prices using sample inputs.

4.6 EVALUATION METRICS

- MAE (Mean Absolute Error): Measures average magnitude of prediction errors.
- MSE (Mean Squared Error): Penalizes larger errors.
- RMSE (Root Mean Squared Error): Provides error in target units.
- R^2 Score: Explains the variance captured by the model.

Results:

- RMSE: 5019.41
- R^2 Score: 0.7689

4.7 DATASET OVERVIEW

- Source: Kaggle (Deep Contractor)
- Link: Kaggle Car Price Dataset
- Entries: ~6000

- Features: Manufacturer, Model, Year, Color, Mileage, Engine, Gearbox, Fuel Type, Category

The dataset was split into 80/20 train-test sets. Hyperparameter tuning was performed using GridSearchCV. Cross-validation confirmed model reliability. Visualizations of predicted vs. actual prices validated performance.

4.8 RESULTS AND COMPARATIVE ANALYSIS

Among several tested algorithms, the Random Forest Regressor yielded the best overall results. Predictions for most vehicles fell within a ±10% range of the true market price, demonstrating both accuracy and robustness.

The system's Flask-based web interface provided a smooth user experience, enabling users to input vehicle details and receive price predictions instantly.

Evaluation Metric	Value (Current System) (Random Forest)	Value (Previous System) (Linear Regression)
MAE	3107.38	6665.38
RMSE	5074.74	8707.12
R^2 Score	0.7637	0.3045

Table 4.8 Comparison Table

The Random Forest model outperformed Linear Regression by a wide margin, especially in terms of RMSE and R^2 Score, indicating its superior ability to capture nonlinear relationships within the data.

Graphical User Interface (GUI) Snapshots

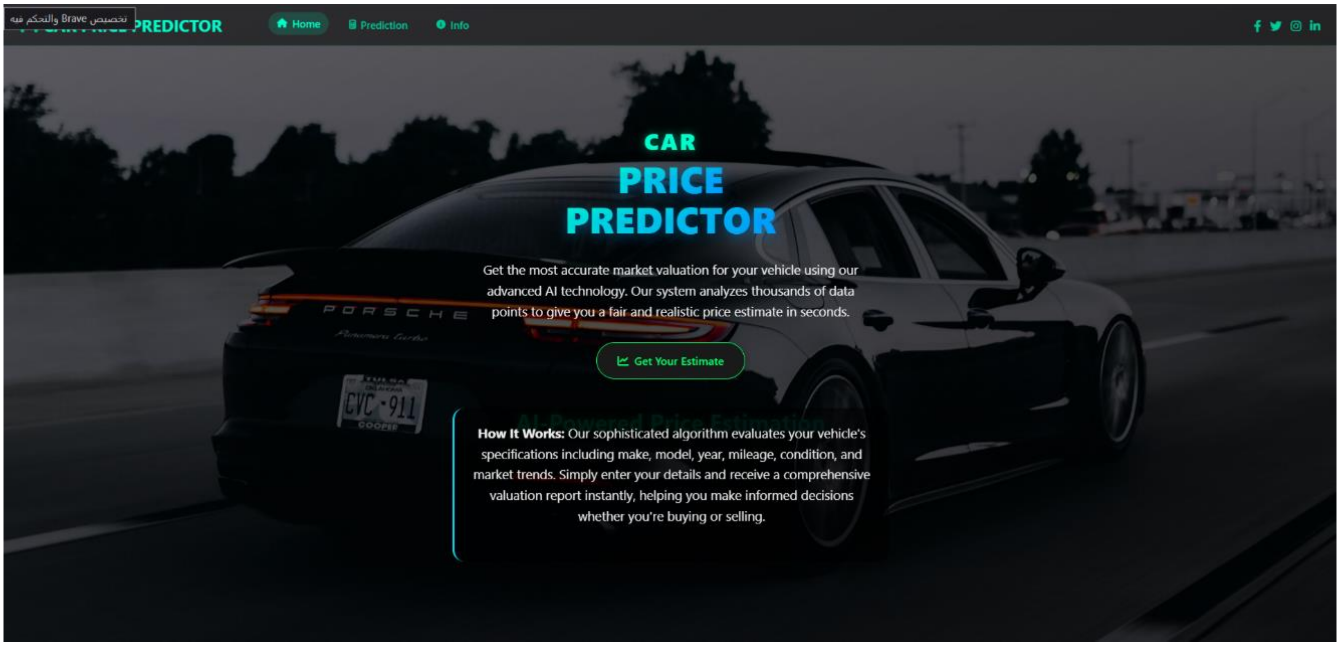

Figure 4.8.1 Home

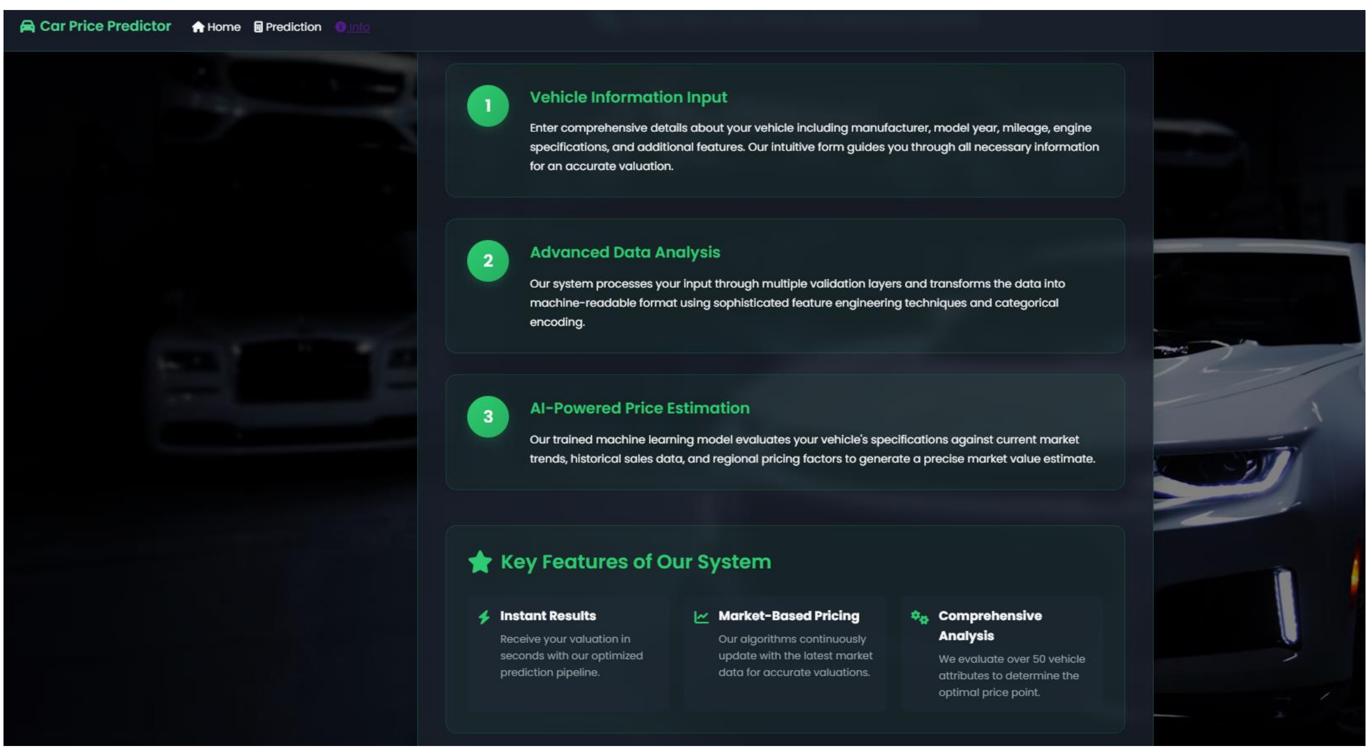

Figure 4.8.2 Info

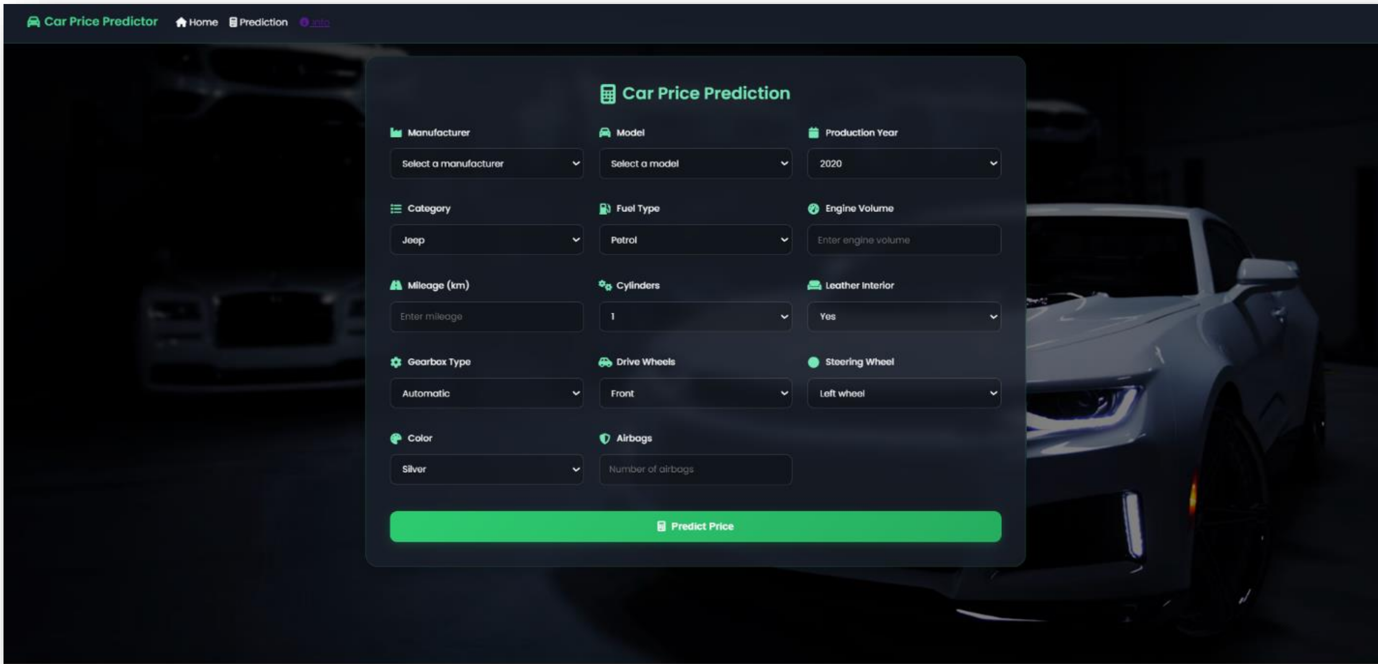

Figure 4.8.3 Prediction

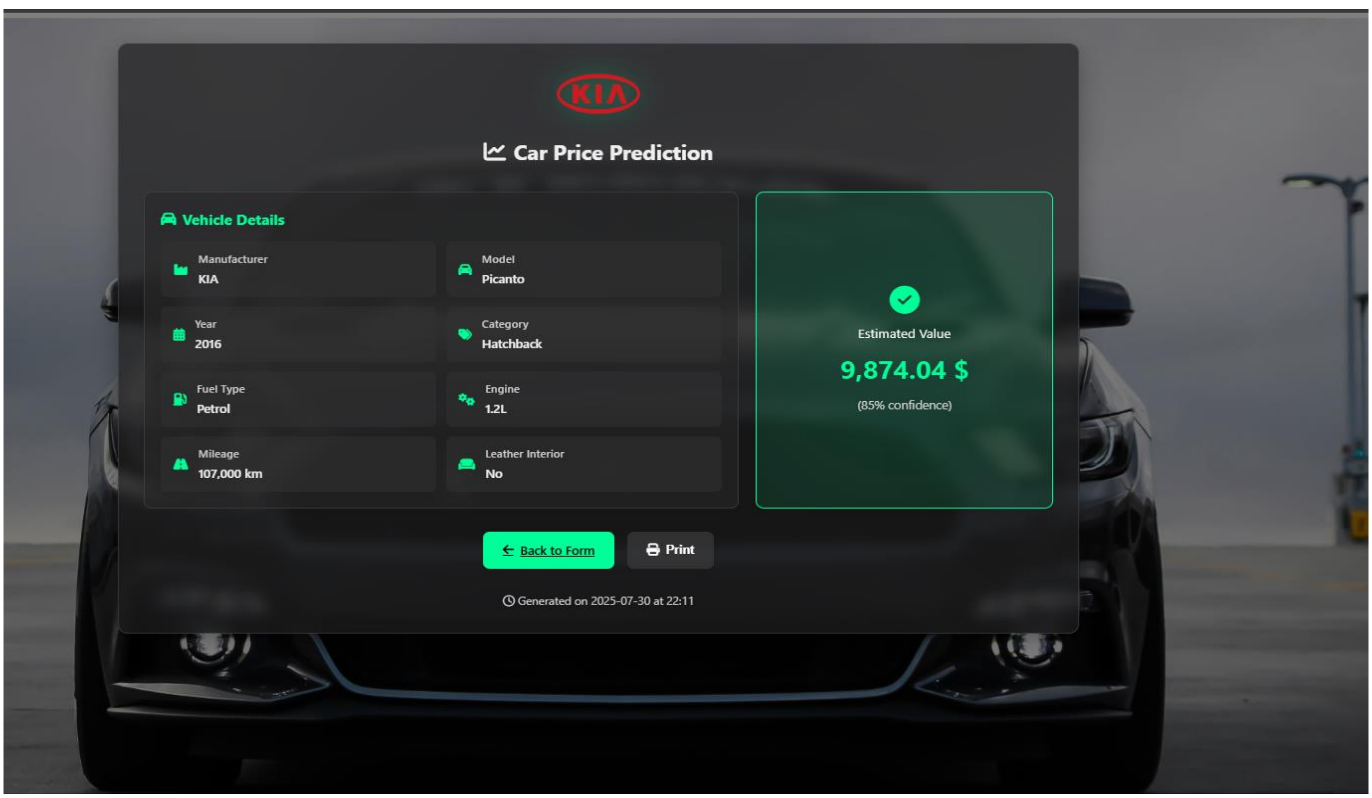

Figure 4.8.4 Results

4.9 COMPARATIVE ANALYSIS

Traditional vs AI/ML-Based System

This comparison shows that the AI/ML system significantly outperforms traditional approaches in terms of accuracy, speed, scalability, and objectivity. It transforms car price prediction from a manual, error-prone process into a data-driven and scalable solution.

Aspect	Traditional System	AI/ML System
Accuracy	Low and human-dependent	High
Speed	Manual, slow	Real-time predictions via web interface
Scalability	Limited capacity	Handles thousands of records efficiently
Adaptability	Static, hard to update	Learns from new data automatically
User Interface	Not user-friendly	Smooth Flask-based web app
Input Factors	Subjective and few	Multiple: brand, fuel, mileage, etc.
Error Margin	High and inconsistent	Low (RMSE ≈ $1,750)
Market Intelligence	Expert-dependent	Data-driven and pattern-based
Learning Capability	None	Continuously improves with more data
Maintenance/Updating	Requires manual effort	Automatic or semi-automatic updates

Table 4.9 Comparison Table

4.10 CHAPTER SUMMARY

This chapter documented the complete implementation lifecycle of the car price prediction system. The Random Forest model significantly outperformed the baseline Linear Regression model. With effective preprocessing and deployment via Flask, the system successfully delivers car price estimations through a responsive web interface. The combination of accuracy, speed, and usability makes this model suitable for real-world applications.

CHAPTER 5: RECOMMENDATION AND CONCLUSION

5.1 INTRODUCTION

This chapter concludes with the development of the Car Price Prediction System. It summarizes the limitations, key findings, and future enhancement possibilities. Additionally, it offers recommendations for improving model performance and system usability.

5.2 LIMITATION

- Limited Dataset: The model is trained on a relatively small or region-specific dataset, which may not generalize well globally.
- Feature Dependency: Prediction accuracy heavily relies on specific features like mileage, fuel type, and year, and can be affected by missing or inconsistent data.
- Static Model: The trained model is not continuously updated with new market data. Car prices are dynamic, so predictions may become outdated over time.

- No External API Integration: The system doesn't currently pull real-time car listings or data from external sources like car dealerships or used car marketplaces.
- UI/UX Limitations: Although functional, the user interface may need more accessibility features and improved responsiveness for mobile users.

5.3 CONCLUSION

The car price prediction system successfully leverages machine learning to estimate the market value of used cars based on key vehicle features. The integration of a trained regression model within a user-friendly web application demonstrates a practical approach to modern automotive valuation. It provides value to both buyers and sellers in making informed decisions. However, its effectiveness is tied to the quality and breadth of training data.

5.4 FUTURE ENHANCEMENT

- Larger, Real-Time Dataset: Integrate the model with APIs or web scrapers to continuously gather data from automotive platforms.

- Online Learning: Implement a system that allows the model to be retrained periodically or learn incrementally from new data.
- Mobile Application: Extend the project to Android/iOS platforms for easier and broader accessibility.
- Multilingual Support: Provide multilingual interfaces (e.g., English and Arabic) to expand regional usability.
- Advanced Algorithms: Explore ensemble learning techniques or deep learning models for more complex pattern recognition and improved accuracy.
- VIN-Based Prediction: Allow users to enter a vehicle's VIN number to auto-fetch specifications for more precise predictions.

5.5 RECOMMENDATIONS

- Use High-Quality and Updated Data: Always use up-to-date and verified data sources to train
- Regularly Re-evaluate Model Performance: Retrain and evaluate the model periodically to maintain prediction accuracy.
- Deploy with Secure and Scalable Architecture: Use cloud hosting or containerization (e.g., Docker) to ensure the system is scalable and secure.
- Include User Feedback Loop: Allow users to submit feedback on predictions to improve future accuracy.
- Educate Users on Usage: Include tooltips or documentation to help non-technical users understand what each input feature means.

5.6 CHAPTER 5 SUMMARY

This chapter provided a comprehensive summary of the project's outcomes and addressed the current system limitations. It also proposed feasible enhancements and offered recommendations that would make the Car Price Prediction System more robust, scalable, and user-friendly.

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