AutoValuator: Car Price Prediction Model

A Minor Project Synopsis Submitted to Rajiv Gandhi Proudyogiki Vishwavidyalaya

Towards Partial Fulfillment for the Award of Bachelor of Technology in Computer Science and Engineering

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1. Introduction

AutoValuator is a smart and easy-to-use website that helps users predict the price of a car based on its details like brand, model, year, fuel type, kilometres driven, and more. Many people face confusion when buying or selling a car because they don't know its correct market value. Our project solves this problem using machine learning. By entering basic information about the car, users can get an estimated price within seconds. This saves time, removes guesswork, and helps users make better decisions. AutoValuator aims to make car buying and selling easier, faster, and more trustworthy for everyone.

2. Objective

- Build a smart platform that can predict the price of a car based on user input.
- Help users know the estimated market value of used cars easily.
- Use machine learning to make accurate and quick predictions.
- Allow users to input car details like brand, model, year, fuel type, and kilometers driven.
- Make car buying and selling decisions easier and more informed.

3. Scope

This project focuses on building a web-based platform where users can easily check the estimated price of a car by entering basic details. It is designed for anyone who wants to buy or sell a used car and needs to know its fair market value. In its initial version, AutoValuator will focus on predicting prices using important features like brand, model, year, fuel type, and kilometres driven. It will not include features like car loan estimation or insurance suggestions for now. The platform requires an internet connection and works best on modern web browsers. In the future, more features like comparison between multiple cars, saving search history, and user accounts can be added to improve the overall experience.

4. Study Of Existing System

This survey explores various research studies on second-hand car price prediction using machine learning techniques. Each study utilizes different models, datasets, and preprocessing techniques to improve accuracy. The following sections summarize five key research papers relevant to the AutoValuator project.

1. **Second-hand car price prediction based on Multiple Linear Regression and Random Forest**

- **Author**: Jiaying Gao
- **ML Techniques Used**: Multiple Linear Regression (MLR), Random Forest (RF)
- **Dataset**: Kaggle: Old Car Dataset (Updated by Milan Vaddoriya).
- **Overview**

  This study compares the performance of Multiple Linear Regression and Random Forest models for predicting second-hand car prices. The dataset used was preprocessed by handling missing values, removing outliers, and selecting relevant features. The study found that while MLR provided basic insights, it struggled with non-linearity in data, making it less effective for real-world applications. In contrast, Random Forest performed significantly better as it could handle complex relationships between variables, leading to more accurate predictions. The research highlights the importance of feature selection and choosing the right model to improve prediction accuracy.

2. **Predicting the price of used cars using machine learning-based regression models**

- **Authors**: G. SelvaKumar, S. Sruthi, M. Surya, A. Tamilselvi, R. Kavya
- **ML Techniques Used**: Linear Regression, Decision Tree, Random Forest, XGBoost
- **Dataset**: Cardekho Used Car dataset from Kaggle
- **Overview**

  This research examines multiple regression models for second-hand car price prediction. The study uses various preprocessing techniques such as data cleaning, feature selection, and outlier removal. Decision Tree and Random Forest showed better performance than Linear Regression, but XGBoost emerged as the most accurate model due to its ability to handle non-linear relationships. The research emphasizes the importance of choosing the right regression model, with XGBoost being the most effective due to its boosting mechanism that reduces errors.

3. Vehicle Price Prediction System using Machine Learning Techniques

- **Authors**: Kafeel Noor, Shahbaz Jan
- **ML Techniques Used**: Multiple Linear Regression
- **Dataset**: Data collected from pakweheels.com (Pakistan's largest used car website)
- **Overview**

  This study focuses on predicting car prices using Multiple Linear Regression. The dataset was scraped from PakWheels.com and underwent preprocessing to remove duplicate records and missing values. The model achieved 98% accuracy, showing that MLR can work effectively when the dataset is well-structured. However, the study was conducted on Pakistani market data, which may limit its applicability to other regions. The research underlines that while MLR can yield high accuracy, it may not generalize well across different datasets and vehicle markets.

4. Prediction of Used Car Prices Using Machine Learning Techniques Based on Vehicle Characteristics and Details

- **Authors**: Enis Gegic, Becir Isakovic, Dino Keco, Darko Kreso, Dijana Asceric
- **ML Techniques Used**: Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Network (ANN)
- **Dataset**: Scraped from https://autopijac.rs/ (Bosnian car marketplace)
- **Overview**

  This paper evaluates different machine learning techniques for car price prediction, comparing SVM, Random Forest, and Artificial Neural Networks. The dataset was scraped from an online marketplace and underwent preprocessing to remove inconsistencies. Random Forest emerged as the best-performing model due to its ability to handle high-dimensional data and complex relationships. ANN showed promising results but required substantial computational power. The study suggests that Random Forest is a reliable choice for real-world applications, while ANN can be explored for further advancements.

5. Used Cars Price Prediction using Supervised Learning Techniques

- **Authors**: V Pattabiraman, M Ganesh
- **ML Techniques Used**: Linear Regression, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest (RF)
- **Dataset**: Kaggle dataset sourced from Craigslist ("Used Cars Price Prediction")
- **Overview**

  This study investigates the effectiveness of different supervised learning models for predicting used car prices. Data preprocessing steps included handling missing values, scaling features, and feature selection. Among the tested models, Random Forest provided the highest accuracy making it suitable for real-world application.

K-Nearest Neighbors (KNN) performed well but required extensive fine-tuning for optimal results. SVM was effective but computationally expensive. The research highlights that Random Forest remains the best-performing model, while KNN and SVM serve as alternative approaches with potential for optimization.

5. Project Description

Flowchart:

The flow of information in the project can be illustrated as follows:

1. **User Input**: The user enters car details like brand, model, manufacturing year, fuel type, transmission type, kilometres driven, etc.
2. **Data Preprocessing**: The input data is cleaned and converted into a format that the machine learning model can understand.
3. **Prediction Model**: A trained machine learning model (such as Linear Regression or Random Forest) processes the data.
4. **Price Prediction**: The model calculates and returns an estimated price of the car.
5. **Result Display**: The predicted car price is shown on the screen in a simple and understandable way.
6. **Optional Feedback**: Users may give feedback to improve prediction accuracy in future versions.

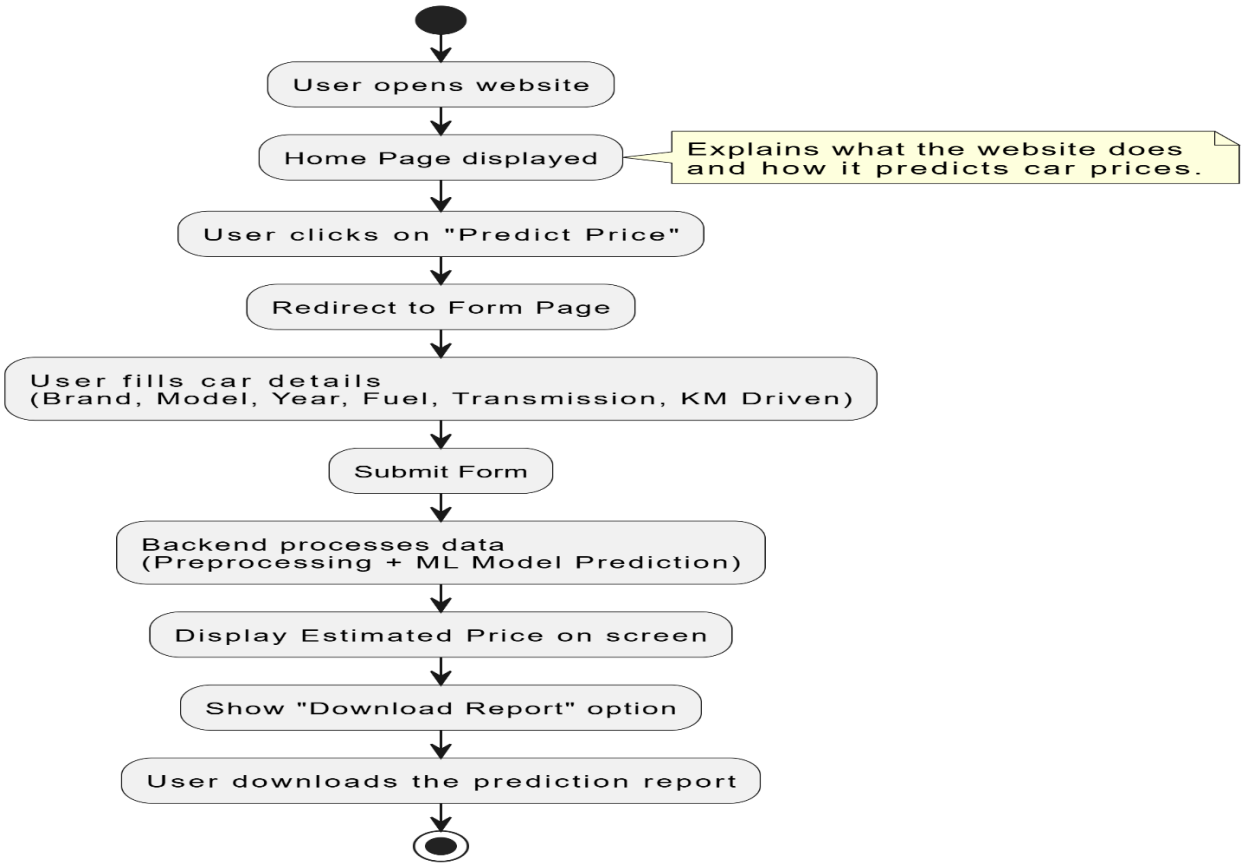


Figure: Flow Chart of System

ER Diagram:
The ER (Entity-Relationship) diagram defines the core structure and interactions between various entities in the **AutoValuator – Car Price Prediction System**. It highlights how data flows between users, cars, evaluation tools, and the generated price reports. Below is a brief description of each entity and its role in the system:

1. User:
This entity represents the registered individuals who use the AutoValuator platform to predict their car's resale value.
Attributes:
- userID (unique identifier)
- name
- password

Each user owns one or more cars and can request price predictions through the evaluation tool. Users can also view the reports generated for their vehicles.

2. Car:
This entity contains the detailed specifications of the car owned by a user. These specifications are used by the evaluation tool to estimate the car’s value.
Attributes:
- carID (unique identifier)
- brand
- model
- year
- fuelType
- transmissionMedium

Each car is linked to a user and is evaluated using the prediction tool.

3. Admin:
The Admin manages the platform and is responsible for approving users and overseeing the evaluation tools.
Attributes:
- username
- password

The admin approves new users and manages the tools used for evaluating the car data.

4. Evaluation Tool:
This entity represents the model or logic used to evaluate car details and predict their resale value.
Attributes:
- toolID (unique identifier)
- toolName
- version

It is managed by the Admin and is responsible for generating a price report based on the car's attributes.

5. Price Report:
This entity stores the final output of the evaluation – the estimated price of the car.
Attributes:

- reportID (unique identifier)
- estimatedPrice

Each report is linked to one car and is generated by the evaluation tool. Users can view this report to understand the value of their car.

Relationships:

- **Admin** approves **Users** and manages the **Evaluation Tool**.
- **Users** own one or more **Cars**.
- **Cars** are evaluated using the **Evaluation Tool**.
- The **Evaluation Tool** generates a **Price Report**.
- **Users** can view the generated **Price Report**.

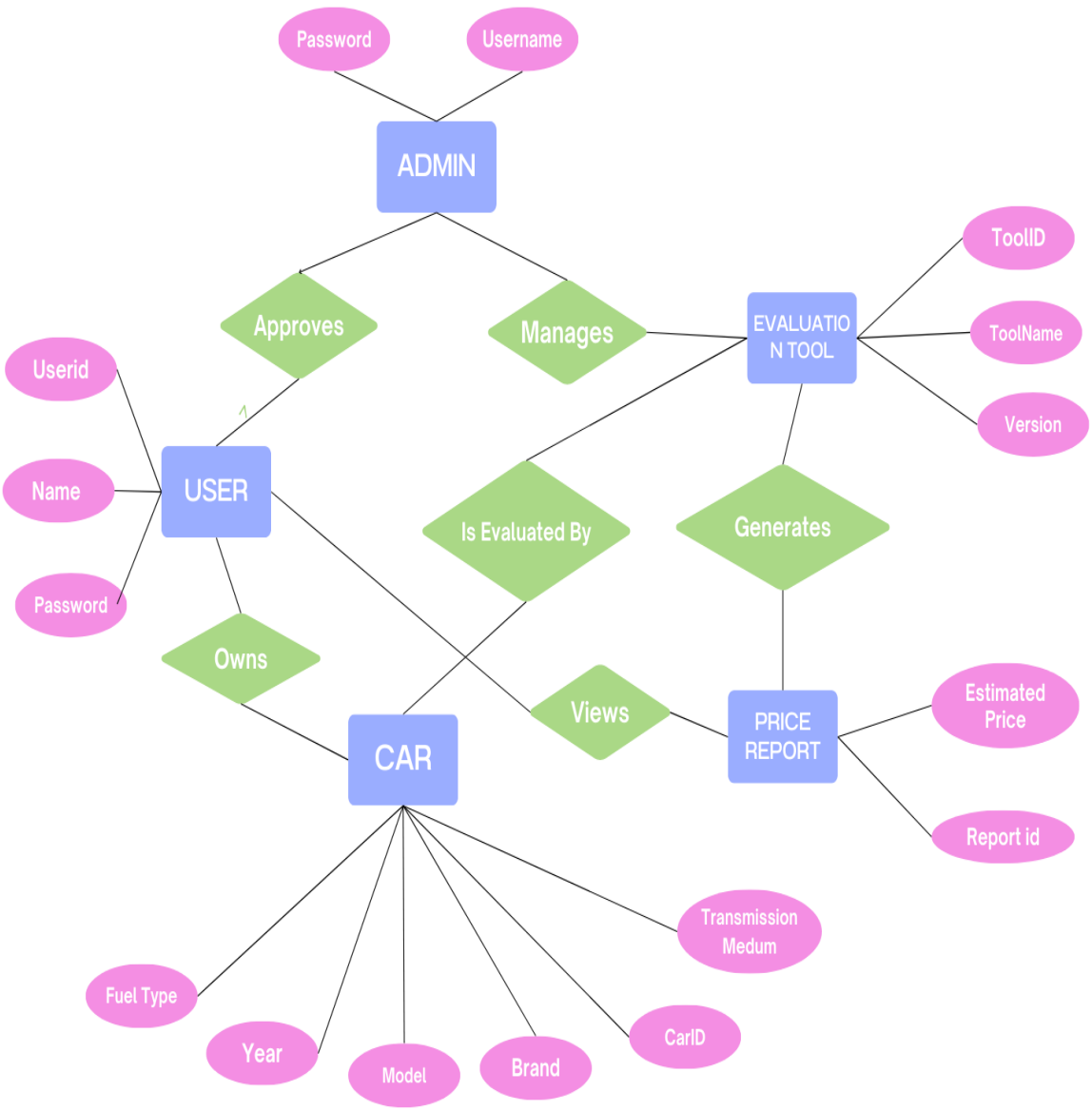


Figure: ER Diagram

6. Methodology

The methodology adopted in this project for predicting the price of used cars involves the following key steps:

1. Data Collection

The dataset used in this project was imported from Kaggle using the KaggleHub API. It contains various features of used cars like brand, model, manufacturing year, kilometers driven, fuel type, transmission, engine capacity, mileage, number of seats, and the target variable: selling price.

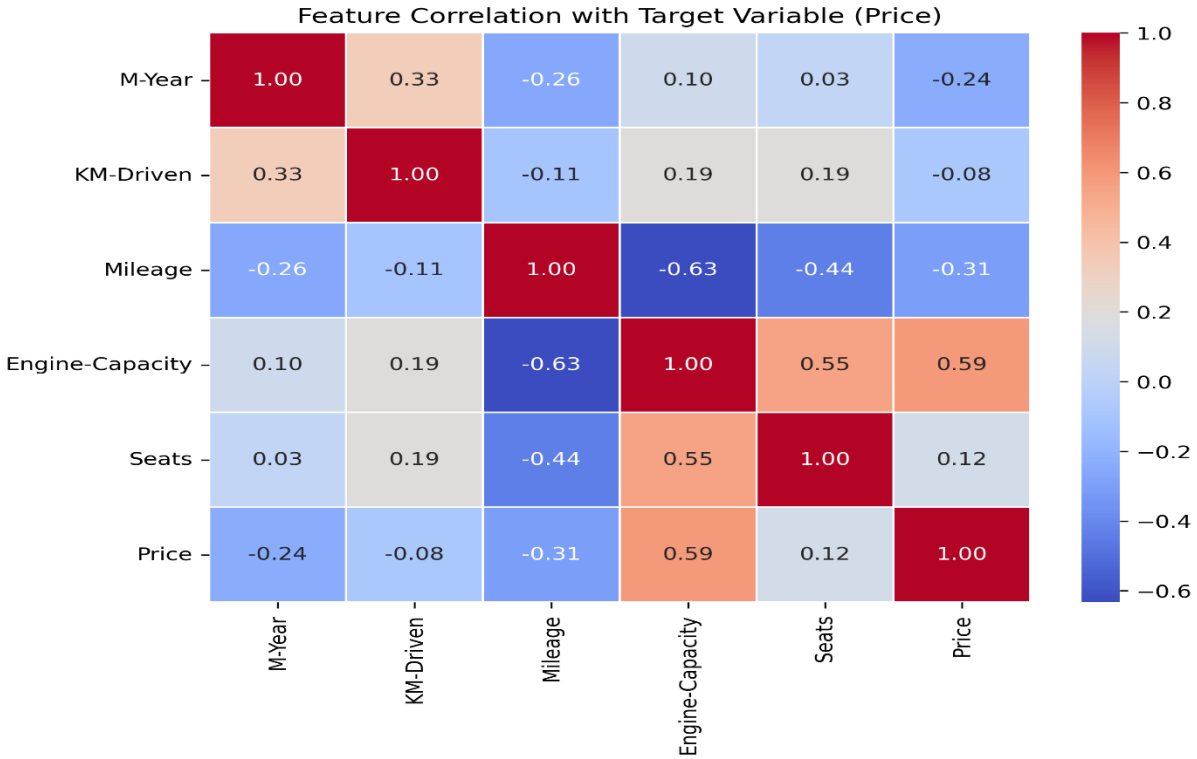
2. Data Preprocessing

Several preprocessing techniques were applied to clean and prepare the data for training:

- Unnecessary columns such as max_power, car_name, seller_type, and Unnamed: 0 were dropped.
- Column names were renamed for better readability.
- The Engine-Capacity values were converted from cc to liters.
- Missing or incorrect values (e.g., cars with 0 seats) were fixed by replacing them with appropriate values.
- Duplicate entries were removed to avoid data redundancy.
- One-hot encoding was applied to categorical features like brand, fuel type, and transmission to convert them into numeric format.

3. Feature Selection

To determine which features were most important in predicting the car price, an ExtraTreesRegressor model was used. This model provided feature importance scores, and a bar chart was plotted to visualize the top influencing features.



4. Data Splitting

The dataset was split into training (80%) and testing (20%) sets using the train_test_split function from scikit-learn. This ensures that the model is evaluated on unseen data to check its real performance.

5. Model Building

Multiple machine learning regression algorithms were considered, including:

- Linear Regression
- Support Vector Regression (SVR)
- Decision Tree Regressor
- Extra Trees Regressor
- Random Forest Regressor (Final choice)

After testing different models, the Random Forest Regressor was selected due to its better performance in terms of accuracy and lower error values.

6. Model Evaluation

The model was evaluated using the following metrics:

- Mean Squared Error (MSE)
- R-squared (R^2) Score

These metrics were used to assess how well the model predicted car prices on the test data. A higher R^2 score indicates better performance.

7. Visualization

Important features influencing the price were visualized using bar graphs. This helped in understanding which attributes (like mileage, engine capacity, etc.) have more impact on the final price.

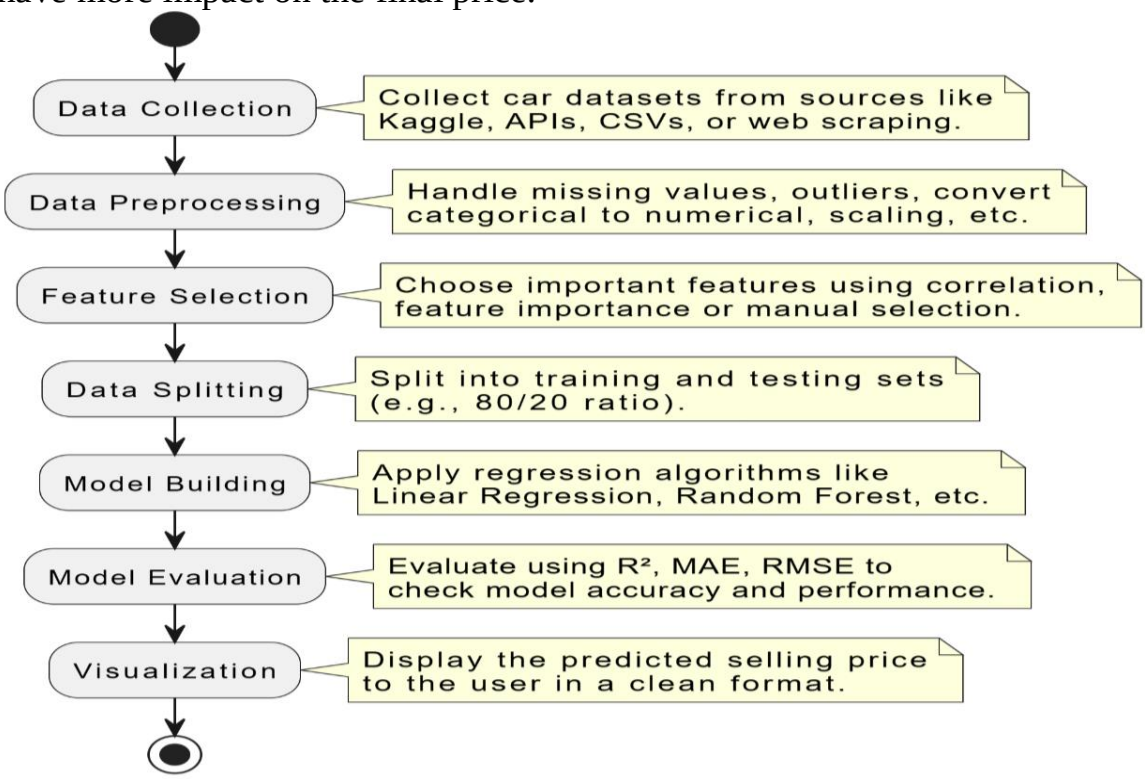


Figure: Methodology

PHASES	TIMELINE	TASK COMPLETED
Requirements Gathering	Week 1	Identified dataset, defined evaluation objectives, and functional specifications
Data Collection	Week 2	Collected structured form data or sample entries for training
Data Preprocessing	Week 3	Cleaned, normalized data, handled missing values, and feature selection
Model Selection & Design	Week 4	Chose appropriate ML algorithm (e.g., Linear Regression, Random Forest, etc.)
Model Training	Week 5	Trained model using historical data and tuned hyperparameters
Model Evaluation	Week 6	Evaluated accuracy using metrics like MAE, RMSE, and cross-validation
Integration & Development	Week 7-8	Integrated model with frontend/backend, created user form and dashboard interface
Testing	Week 9	Performed end-to-end system testing and ML model prediction testing
Deployment	Week 10	Deployed system on cloud/local server
Maintenance	Week 11	Collected feedback, improved performance, and updated model periodically.

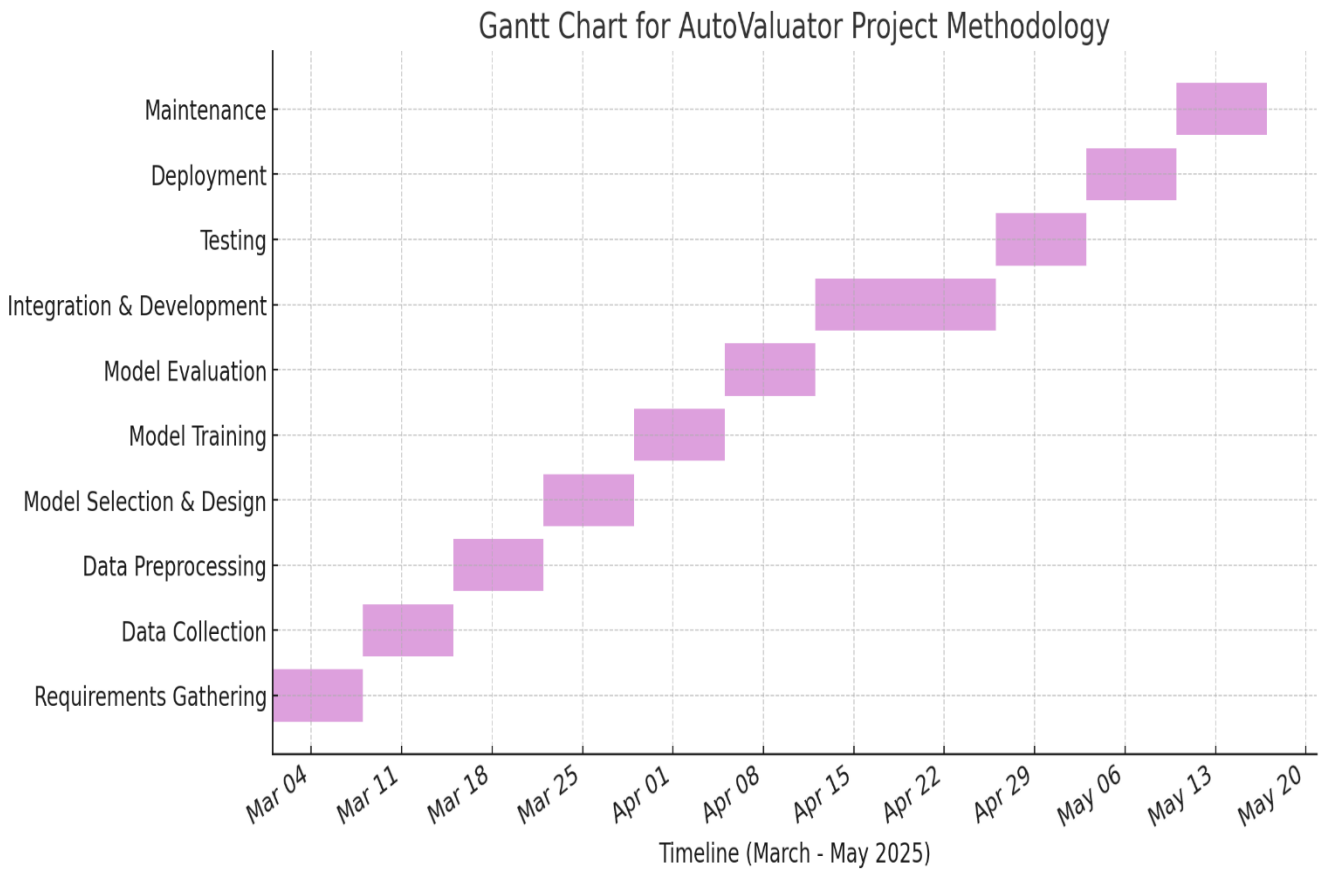


Figure: Gantt Chart

7. Features

Here are the main features that make your project stand out:

1. **Form-Based Car Data Entry:** Users can enter car details such as brand, model, year, fuel type, transmission, and kilometers driven through a simple and intuitive form.
2. **ML-Based Price Prediction:** The system uses trained Machine Learning models like Linear Regression or Random Forest to predict the estimated resale value of the car accurately.
3. **Instant Report Generation:** After submitting the car details, users receive a detailed evaluation report including estimated price, model info, and confidence range.
4. **Data-Driven Decision Support:** The platform helps users make informed decisions by evaluating current market trends, historical data, and similar car listings.

5. **Simple & User-Friendly Interface:** Designed with a clean and intuitive layout, users can smoothly navigate through the evaluation process without any technical hassle.

8. System Architecture

The system architecture of this project is made up of two main parts that work together to provide accurate car price predictions:

1. **Frontend (User Interface):**

- **What it does:**
  This is what users see and interact with. It allows them to enter car details such as brand, model, year, fuel type, transmission, and kilometres driven through a clean and simple form.

- **How it works:**
  Built using **React.js, CSS and JavaScript** the frontend collects user input and sends it to the backend for processing. It also displays the predicted selling price received from the backend.

2. **Backend (Processing Engine):**

- **What it does:**
  This part takes the user input, runs it through a trained **Machine Learning model**, and returns the estimated price of the car.

- **How it works:**
  Developed using **Python**, the backend receives car details, loads the trained ML model (like Decision Regression or Random Forest), performs the prediction, and sends the result back to the frontend.

How They Work Together:

1. **User Input:**
   The user submits car details via the frontend form.

2. **Backend Prediction:**
   The backend processes this input using the ML model and calculates the car's estimated selling price.

3. **Response:**
   The frontend displays the predicted price instantly to the user in a report format.

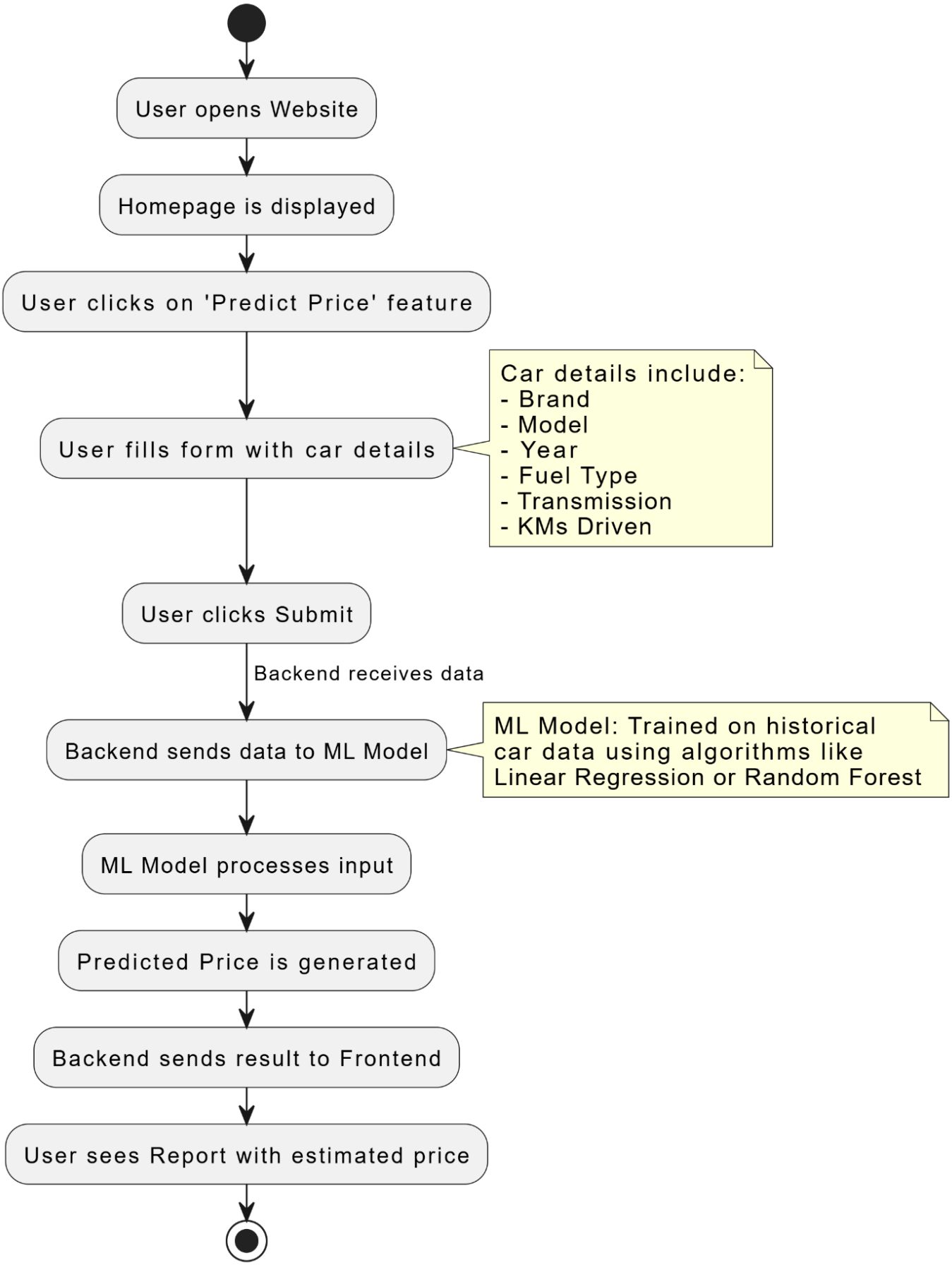


Figure: System Architecture

9. User Interface (UI)

The User Interface (UI) of the AutoValuator platform is designed to be intuitive and beginner-friendly, ensuring users can easily predict their car's price without any confusion or complexity.

1. **Homepage**:
   - The homepage welcomes users with a clean, minimal layout.
   - A prominent **"Estimate Now"** button is placed at the center to grab attention and guide users directly to the main feature.
   - A simple top navigation bar allows users to navigate easily across the platform if needed.

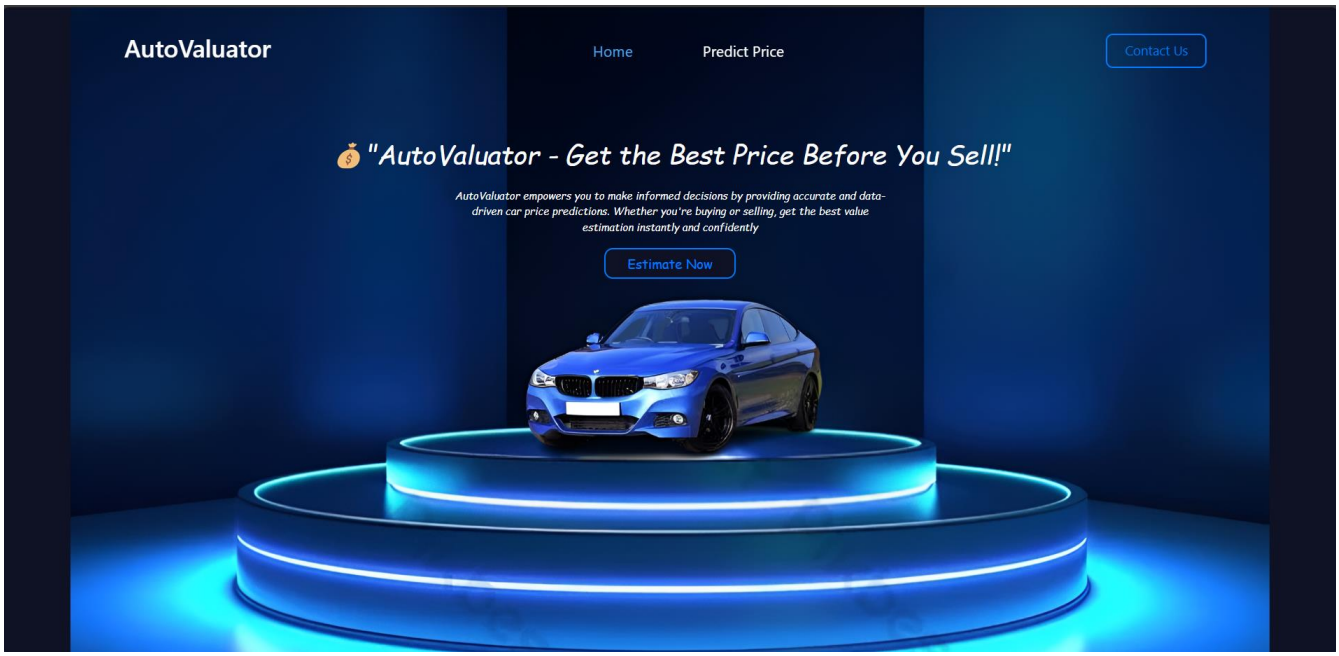
2. **Predict Price** :
   - This page includes a form-based interface where users can fill in essential car details like:
     - Brand, Model, Year
     - Fuel Type, Transmission
     - KMs Driven, Ownership
   - Each field has a dropdown or input box with hints, making it easier even for non-technical users.
   - A "Get Estimated Price" button is shown at the bottom to submit the form.

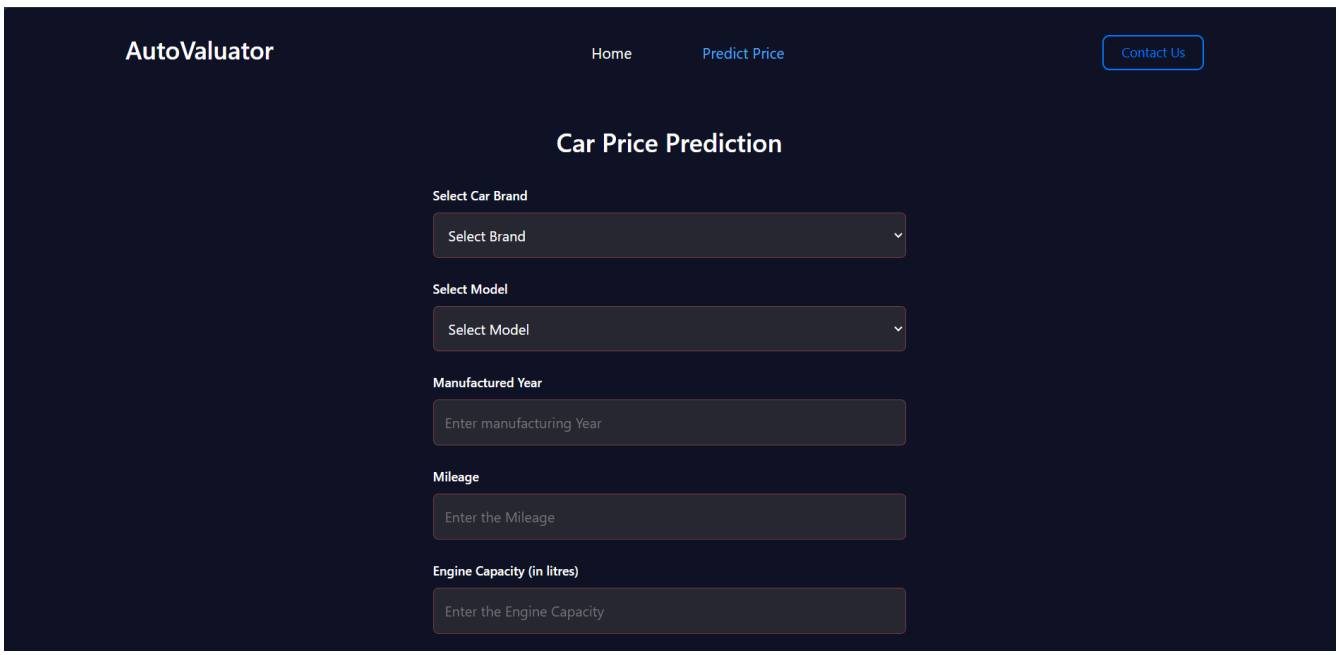
3. **Report Page (After Prediction):**
   - Once the price is predicted using the ML model, users are taken to a new page showing the estimated car price.
   - A neat, card-style layout displays:
     - User's input summary
     - Predicted price
   - A "Download Your Report" button allows users to save a PDF version of their car valuation.

4. Mobile-Friendly Design:

- The entire platform is responsive and works seamlessly on mobile devices.
- Buttons, forms, and text auto-adjust for smaller screens, ensuring a smooth experience on the go.
- All actions like form filling, prediction, and downloading reports can be done from a phone without hassle.

This simple, clean design makes sure users can find what they need without feeling overwhelmed. Every step is straightforward to ensure a smooth experience!


AutoValuator
Home
Predict Price
Contact Us
"AutoValuator - Get the Best Price Before You Sell!"
AutoValuator empowers you to make informed decisions by providing accurate and data-driven car price predictions. Whether you're buying or selling, get the best value estimation instantly and confidently
Estimate Now


AutoValuator
Home
Predict Price
Contact Us
Car Price Prediction
Select Car Brand
Select Brand
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Manufactured Year
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Mileage
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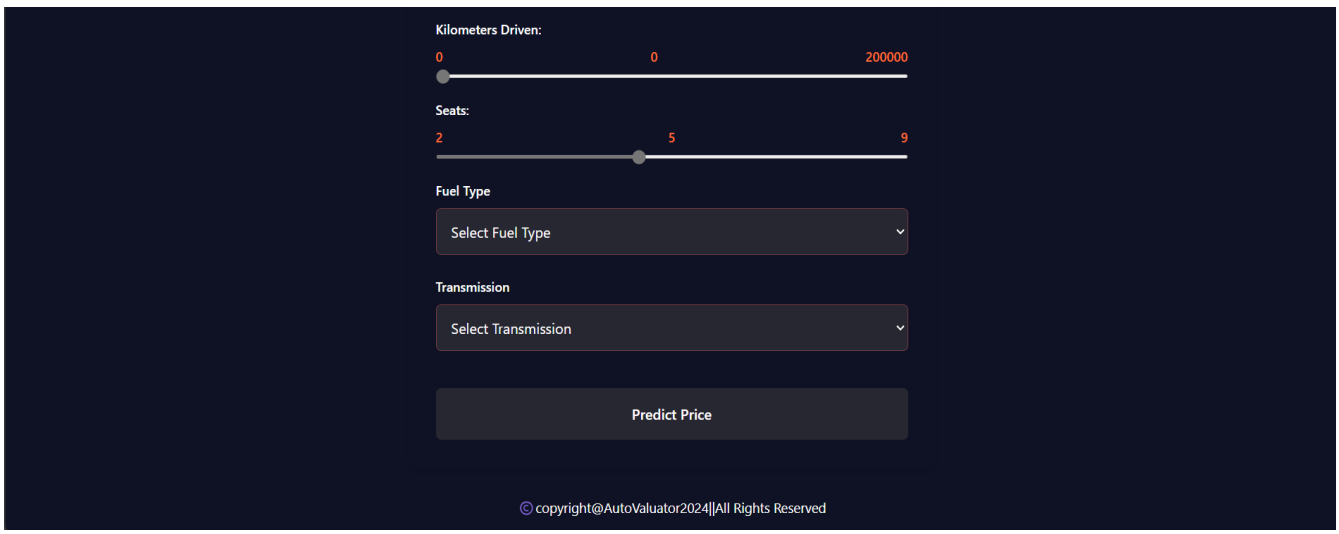
Engine Capacity (in litres)
Enter the Engine Capacity


Kilometers Driven:
0
0
200000
Seats:
2
5
9
Fuel Type
Select Fuel Type
Transmission
Select Transmission
Predict Price
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10. Technology Stack

Here's a simple breakdown of the technologies we'll use to build the project:

1. **Frontend (User Interface)**:

   - **React.js:** Used to create a dynamic and responsive user interface with component-based architecture.
   - **CSS:** For styling and designing a clean, modern, and visually appealing layout.
   - **JavaScript:** To handle interactivity, form validation, and dynamic UI behavior.

2. **Backend (Processing & Logic)**:

   - **Python:** Acts as the main backend processing language, managing logic and connecting the ML model with the frontend.
   - **Machine Learning Libraries:** Used to train, evaluate, and deploy the ML model for car price prediction.

     These are the list of libraries used in our project:

     - numpy
     - pandas
     - os
     - matplotlib.pyplot
     - sklearn.ensemble
     - sklearn.linear_model
     - sklearn.svm
     - sklearn.tree
     - sklearn.model_selection
     - sklearn.metrics
     - kagglehub
     - pickle

This tech stack ensures the platform runs smoothly, processes files quickly, and securely handles user data.

11. Testing Plan

To ensure that the AutoValuator platform performs accurately and smoothly for users, we'll follow a structured testing approach. Here's the plan:

1. **Unit Testing:**
   - **What it is:** We will test individual components of the project separately — such as the form input fields, price prediction logic, and the ML model.
   - **Why it's important:** This helps us identify any issues in small units before integrating them into the complete system.

2. **Integration Testing:**
   - **What it is:** We'll check how different parts of the system work together — for example, whether user inputs from the frontend are correctly sent to the backend and whether the predicted price is properly shown on the frontend.
   - **Why it's important:** Ensures seamless communication between UI and backend, and validates proper flow.

3. **User Testing:**
   - **What it is:** Real users will test the platform by entering car details and predicting prices to see if the UI is intuitive and the results are understandable.
   - **Why it's important:** Users give feedback from a practical perspective, helping to improve usability and fix hidden issues.

4. **Performance Testing:**
   - **What it is:** We'll test the platform's speed and responsiveness when multiple users use it simultaneously or when complex data is entered.
   - **Why it's important:** Ensures the platform performs well under load and provides results in real-time without delays.

5. **Security Testing:**
   - **What it is:** We'll test for secure data handling — especially ensuring that the user inputs are protected from common threats like injection attacks or data breaches.
   - **Why it's important:** Builds trust by ensuring that the website is safe and secure for public use.

6. **Bug Fixing and Retesting:**

- **What it is:** After discovering any bugs, we'll fix them and retest the full workflow — from user input to report download — to make sure everything works correctly.
- **Why it's important:** Fixes don't cause new issues, and the overall system remains stable.

12. Expected Outcome

1. **Smart Price Prediction Tool**
   • The project delivers a reliable and intelligent platform for users to predict the resale price of their cars using machine learning.
   • It provides instant, data-driven predictions based on various car attributes like model, year, fuel type, etc.

2. **Streamlined User Experience**
   • Users can easily input car details and get accurate price predictions within seconds.
   • Eliminates the need for manual price research or dealer dependence.

3. **Improved Decision-Making**
   • Helps users make informed decisions when selling their cars by offering fair market estimates.
   • Builds user confidence by providing a downloadable prediction report.

4. **User-Friendly Web Interface**
   • Built with React, CSS, and JavaScript, the UI is clean, modern, and easy to use for all age groups.
   • Supports both desktop and mobile viewing for accessibility on-the-go.

5. **Fast & Efficient Backend**
   • Powered by Python and a trained ML model, the backend handles predictions smoothly and responds quickly.
   • Ensures real-time output without delay, even with complex input data.

6. **Report Download Feature**
   • Users get a detailed car value report after prediction, which can be downloaded and shared.
   • Adds a professional touch and increases trust in the result.

7. **Data Privacy Focused**
    - No unnecessary data storage; user inputs are only used for real-time prediction.
    - Keeps user data secure and private throughout the session.

13. Resources And Limitation

To build the AutoValuator – Car Price Predictor, basic hardware like a laptop or PC is required for development and testing. Software tools include Visual Studio Code for coding, React, CSS, and JavaScript for frontend design, and Python with libraries like pandas and scikit-learn for backend and ML. Hosting platforms like Netlify and PythonAnywhere are used for deployment, and browsers/mobile devices for UI testing.

However, the project has some limitations. The prediction accuracy depends on the dataset used, and it doesn't support real-time market data. Rare or unique car models may produce less accurate results. Also, features like location-based pricing or image-based evaluation are not included in this version. Minor compatibility issues may occur on older devices or browsers.

14. Conclusion

In conclusion, this project aims to provide a simple and effective solution for users to predict accurate car prices based on key inputs like brand, model, fuel type, and more. With a clean, user-friendly interface and machine learning on the backend, the platform ensures that users can easily get an estimated price for their vehicle in just a few steps.

While there are some limitations, such as dependency on existing data and lack of real-time market updates, these can be improved with future enhancements. Overall, AutoValuator helps users make informed decisions, making the car-selling process faster, smarter, and more convenient.

15. Reference

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