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An AI-Enabled Platform for Authentic Vehicle Review Analysis and Intelligent Comparison

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Abstract: The rapid growth of the automotive industry and user-generated content has changed how consumers evaluate vehicles, but existing review platforms are often fragmented and unreliable. This paper proposes a Vehicle Review System, a centralized and intelligent platform that collects, analyses, and presents authentic vehicle reviews. The system uses AI, Machine Learning, and NLP to perform sentiment analysis and feature-based opinion mining on user feedback. Vehicles are evaluated using key factors such as mileage, comfort, safety, maintenance cost, and fuel efficiency, converting subjective opinions into quantitative insights. A Decision Tree model supports vehicle comparison, ranking, and recommendations, while review verification mechanisms filter spam and biased inputs. Developed with modern web technologies, the system is scalable, responsive, and user-friendly. The proposed framework enhances transparency, supports informed decision-making for consumers, and helps manufacturers understand market trends and product performance.
Keywords: Vehicle Review System; Artificial Intelligence; Machine Learning; Sentiment Analysis; Recommendation System.

I. INTRODUCTION

In the modern digital era, the automobile industry has undergone rapid growth with frequent launches of new models, advanced technologies, and rising consumer expectations. Vehicles play a vital role in daily life for personal transportation, logistics, and leisure activities. However, the increasing complexity of vehicle specifications, pricing, and features makes it difficult for consumers to select the most suitable option that balances performance, reliability, and cost. Traditionally, buyers relied on word-of-mouth, sales representatives, or scattered online reviews to make decisions. These methods often lack objectivity, consistency, and transparency, resulting in biased or incomplete information. Although digital review platforms have emerged to address this issue, many existing systems suffer from fake or promotional reviews, inconsistent rating mechanisms, and poorly structured data, reducing their credibility and usefulness for effective vehicle comparison. Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) offer effective solutions to these challenges. By analysing user-generated reviews, AI-driven systems can extract sentiments, identify feature-based opinions, and convert unstructured feedback into meaningful insights. Techniques such as sentiment analysis, decision tree classification, and data visualization enable intelligent vehicle evaluation, comparison, and recommendation.

The proposed Vehicle Review System integrates review verification, spam detection, and a user-friendly web interface to ensure authenticity and scalability. By transforming subjective opinions into data-driven intelligence, the system enhances transparency, supports informed decision-making, and improves trust within the automotive marketplace.

II. RELATED WORK

The integration of Artificial Intelligence (AI) and Machine Learning (ML) has revolutionized how vehicle reviews and consumer feedback are analysed. Traditional review systems lacked structure, credibility, and analytical depth, but AI-driven models now enable automated sentiment analysis, fake review detection, and intelligent recommendations. This section presents concise summaries of key research studies that demonstrate advancements in AI-based Vehicle Review Systems (VRS).

Kumar and Sharma (2022) [1] employed NLP and sentiment classification techniques to analyse automobile reviews. Their model used supervised ML algorithms such as SVM and Naïve Bayes to classify user opinions as positive, negative, or neutral. The approach improved accuracy in opinion mining and automated large-scale review processing. The system enhanced review transparency and user trust.

Sharma and Roy (2021) [2] developed a hybrid recommendation model using collaborative filtering techniques. Their approach analysed user behaviour and preferences to suggest vehicles matching personalized needs. It combined user-based and item-based recommendations for better engagement. The model achieved high accuracy in preference prediction and improved user satisfaction.
Patel et al. (2022) [3] utilized text mining and feature extraction to identify key attributes in user reviews. By applying NLP, the system summarized frequent topics like fuel efficiency, maintenance, and comfort. This method improved structured data representation from unstructured text. It provided better comparison and visualization of vehicle performance parameters.
Yadav and Sinha (2021) [4] focused on user behaviour modelling to improve engagement in vehicle review platforms. Their framework analysed review frequency, time spent, and rating patterns for personalized recommendations. By using adaptive feedback loops, the model enhanced user satisfaction. The study showed dynamic user profiling improves recommendation relevance.
Bhatt and Zaveri (2020) [5] introduced an SVM-based fake review detection model for online vehicle platforms. It used linguistic and behavioural features to identify spam or biased content. The classifier achieved over 90% precision and recall rates. Their work significantly improved review authenticity and platform credibility.
Iyer and Rao (2022) [6] proposed a cross-lingual sentiment analysis system for multilingual vehicle reviews. The model integrated neural translation with sentiment classification using BERT. It supported multiple languages including English and Hindi with high accuracy. Their approach improved inclusivity and broadened global accessibility for diverse users.
Nair and Thomas (2024) [7] applied Bi-LSTM with attention mechanisms for aspect-based sentiment analysis. Their model extracted opinions on specific features such as comfort, mileage, and braking. It achieved higher interpretability and contextual accuracy. This approach provided fine-grained insights into consumer satisfaction across vehicle components.
Basu et al. (2019) [8] developed a sentiment-based brand ranking system for automobile manufacturers. Using aggregated review scores, it ranked brands based on customer satisfaction and trust. The system offered insights into brand perception and market trends. This approach supported data-driven marketing and product improvement strategies.
Rao et al. (2022) [9] implemented transformer-based models like BERT for deep contextual sentiment classification. Their approach outperformed traditional ML models in accuracy and precision. Attention visualization helped interpret key sentiment indicators. This research enhanced transparency in automated review analysis.
Pandey et al. (2022) [10] proposed a graph-based model for spam review detection in automotive marketplaces. It analysed user–product relationships to detect coordinated fake reviews. The network analysis identified anomalies in reviewer behaviour. Their system ensured fair visibility for genuine reviews and improved consumer trust.
Thomas et al. (2020) [11] used the VADER sentiment analyser for aggregating user opinions in vehicle e-commerce. The model computed compound sentiment scores from text reviews. It efficiently summarized user feedback and ranked vehicles accordingly. This method improved decision-making through quick sentiment visualization.
Zhang et al. (2020) [12] implemented aspect-based sentiment analysis to evaluate SUV reviews. Their model extracted and classified sentiments for attributes like safety, design, and performance. The results highlighted user concerns with specific features. This approach enabled multi-criteria comparison for informed vehicle selection.
Thomas and Rao (2022) [13] enhanced feature-based opinion mining using syntactic parsing and sentiment scoring. Their system analysed component-level sentiments such as suspension and infotainment. It improved precision in review interpretation. The framework allowed detailed performance comparison between vehicle models.
Wang and Manning (2012) [14] utilized Latent Dirichlet Allocation (LDA) for thematic categorization of automotive reviews. Their probabilistic topic model grouped reviews into key themes like fuel economy and safety. The system improved organization of unstructured data. It supported better summarization for large-scale review datasets.
Feldman (2013) [15] reviewed opinion mining frameworks for sentiment analysis applications. The study compared lexicon-based and ML-based methods, emphasizing coverage versus interpretability. It outlined challenges in contextual understanding of vehicle reviews. The framework guided future AI-based sentiment system designs.
Chen et al. (2021) [16] introduced transformer-based deep learning for sentiment analysis of car reviews. Using BERT fine-tuning, their model achieved superior accuracy in emotion classification. Attention mechanisms provided explainability in predictions. Their work contributed to transparent AI applications in automotive analytics.
Gaur et al. (2019) [17] applied the Naïve Bayes algorithm for short-text vehicle sentiment classification. Their lightweight model achieved over 85% accuracy for concise reviews. It proved efficient for real-time review monitoring. The approach demonstrated ML's potential in low-resource sentiment analysis tasks.

Pandey and Gupta (2023) [18] developed an ensemble model combining Decision Trees and Neural Networks for review prediction. Their hybrid framework analysed correlations among ratings, text, and features. It achieved improved prediction reliability and reduced bias. The model offered enhanced scalability for large review datasets.

Nair et al. (2024) [19] explored multimodal fusion by integrating textual and visual data from vehicle images and reviews. The system used deep CNNs alongside text embeddings to improve review credibility. It provided holistic performance evaluation. Their model bridged data from multiple modalities for comprehensive analysis.

Jindal and Liu (2008) [20] pioneered fake review detection using logistic regression and syntactic similarity. Their work identified duplicate and misleading reviews in online systems. It laid the foundation for modern spam detection models. This early study remains fundamental in ensuring review integrity.

III. PROBLEM STATEMENT

In today's competitive automotive market, consumers face challenges in choosing suitable vehicles due to the abundance of options and the lack of reliable review systems. Existing platforms are often cluttered with fake, biased, or unverified reviews that compromise the credibility of information.

Moreover, most systems present unstructured data without intelligent tools for analysis or comparison, making it difficult for users to evaluate vehicles based on factors such as performance, fuel efficiency, comfort, and maintenance cost. The absence of Artificial Intelligence (AI) and Natural Language Processing (NLP)–based mechanisms further limits the ability to extract meaningful insights from large volumes of user feedback. Therefore, there is a pressing need for an AI-driven Vehicle Review System that can authenticate reviews, analyse sentiments, and provide structured, data-driven recommendations to enhance transparency and support informed consumer decision-making.

IV. PROPOSED VEHICLE REVIEW SYSTEM

Figure 1, shows the proposed AI-driven architecture for the Vehicle Review System, structured as a multi-layered framework integrating data acquisition, intelligent analytics, and automated decision support.

It begins with the systematic collection and preprocessing of vehicle-related datasets and user-generated reviews, ensuring data quality and consistency. The processed data is then analysed using Machine Learning (ML) and Natural Language Processing (NLP) models to extract sentiments, identify fake or biased feedback, and evaluate vehicle performance based on parameters such as mileage, comfort, safety, and maintenance cost.

The system employs Decision Tree and classification algorithms for predictive evaluation, enabling users to compare vehicles and receive data-driven recommendations. A user-centric dashboard and interactive interface provide real-time insights, visualization, and feedback summaries, while AI-driven moderation ensures content authenticity. This intelligent, scalable, and secure architecture aims to enhance transparency, build user trust, and support informed decision-making for both consumers and automobile manufacturers.

A. Data Sources Layer

This foundational layer aggregates vehicle-related datasets from heterogeneous sources such as manufacturer databases, user reviews, performance metrics, and pricing data. It may also include API integrations for real-time data like fuel efficiency.

B. Data Ingestion and Preprocessing

The ingestion mechanisms collect and unify vehicle data through APIs, web forms, and automated scrapers. Preprocessing operations—such as cleaning inconsistent entries, handling missing specifications, and normalizing numerical data—ensure reliability and consistency.

Feature engineering extracts essential indicators such as horsepower-to-weight ratio, price-to-performance index, and customer sentiment scores, preparing structured data for AI processing.

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Figure 1: System Architecture Diagram of the Vehicle Review System

C. AI Model Integration and Predictive Analysis

At the analytical core, the system integrates the Gemini AI Model (Google API) to analyse and compare vehicles. The AI interprets key specifications and qualitative features, generating detailed, context-aware vehicle reviews or comparisons. This layer may utilize natural language generation techniques to produce human-readable summaries highlighting pros.

D. Backend Logic Layer (Fast API Server)

This layer, powered by Fast API, handles the backend orchestration. It receives form data from the user interface, validates inputs, communicates with the Gemini AI API, and manages responses. It also coordinates data flow between different components, ensuring efficient asynchronous processing and smooth integration of AI-driven insights into the system's workflow.

E. Markdown to HTML Rendering Layer

Since the AI output is generated in Markdown format, this layer converts Markdown text into well-structured HTML content. Using Jinja2 templates, it ensures that the rendered pages maintain readability and design consistency across various devices. This transformation bridges raw AI output and the polished frontend presentation.

F. Presentation and User Interface Layer

The frontend interface serves as the interactive gateway for users, allowing them to input vehicle data, trigger comparisons, and view results. Built using HTML, CSS, and JavaScript, the interface displays structured vehicle comparisons, ratings, and summarized reviews in a clear and visually appealing manner. The design emphasizes usability, responsiveness, and accessibility across devices.

G. Monitoring, Feedback, and Security Layer

This layer oversees continuous monitoring of system performance, API latency, and AI output quality. User feedback loops help refine AI prompts and improve comparison accuracy over time. Additionally, data security and privacy mechanisms—such as encryption, API key management, and secure HTTPS communication—ensure ethical and safe handling of user and vehicle data, fostering trust and reliability in the system.

V. OBJECTIVES

1) To provide are liable and structured platform for vehicle reviews: The system aims to collect authentic user feedback and expert insights in a standardized format. This ensures that potential buyers can access credible information when comparing different vehicle models.
2) To detect and eliminate fake or biased reviews using AI-based filtering: By integrating natural language processing and sentiment analysis, the platform identifies and removes misleading or promotional reviews. This enhances the overall trustworthiness and quality of the review ecosystem.
3) To enable intelligent vehicle comparison and personalized recommendations: The system uses AI algorithms to analyse performance metrics, fuel efficiency, comfort, and maintenance costs. It then generates data-driven recommendations tailored to individual user preferences.
4) To enhance user engagement through an interactive and responsive interface: A user-friendly dashboard allows customers to post reviews, rate vehicles, and explore side-by-side comparisons. This promotes active participation and community-based decision-making.
5) To ensure data security, transparency, and continuous improvement: Robust authentication, encryption, and monitoring mechanisms safeguard user information. Regular feedback loops help retrain models, maintaining the accuracy and adaptability of the system over time.

VI. METHODOLOGY AND SYSTEM FLOWCHART

The proposed methodology for the Vehicle Review System follows a structured, AI-driven framework aimed at enhancing transparency, accuracy, and user engagement in automotive reviews. The approach systematically progresses through multiple stages, transforming raw vehicle data and user feedback into intelligent, comparative insights that assist consumers in making informed purchase decisions.

1) Step 1: Problem Identification: The process begins with identifying the key issues in existing vehicle review platforms—such as the presence of fake reviews, lack of structured comparisons, and limited personalization. Recognizing these challenges establishes the foundation for designing a reliable and intelligent vehicle review system that combines data analytics, AI-driven sentiment evaluation, and real-time performance comparison.
2) Step 2: Data Collection: This stage involves gathering datasets from various sources, including automotive databases (e.g., Kaggle), manufacturer APIs, and verified user-generated reviews. The collected data encompasses vehicle attributes such as mileage, price, engine type, performance ratings, and customer feedback. These datasets form the foundation for building robust analytical and AI models.
3) Step 3: Data Preprocessing and Validation :Collected data is pre-processed to ensure consistency, accuracy, and completeness. Steps such as data cleaning, handling missing values, and standardizing units (e.g., converting power to bhp, mileage to km/l) are performed. Natural Language Processing (NLP) techniques are applied to filter irrelevant textual content and extract meaningful sentiments from user reviews, ensuring high-quality input for the AI model.
4) Step 4: AI Model Training and Validation: AI and machine learning algorithms are trained to classify and analyse reviews based on multiple parameters, including performance, comfort, and maintenance. Models such as Decision Tree, Random Forest, or Support Vector Machine (SVM) are applied to identify relationships between quantitative attributes and qualitative feedback. Evaluation metrics such as accuracy, precision, and F1-score are used to validate the predictive performance of the models.
5) Step 5: Review Generation and Optimization: An AI-powered engine, integrated with Google's Gemini API, generates comparative summaries and structured vehicle insights. The optimization component ensures that generated reviews are unbiased, contextually accurate, and user-relevant. It dynamically updates the analysis based on new reviews or specifications, thereby maintaining up-to-date and adaptive content for all vehicle categories.
6) Step 6: System Integration and User Interface Development: The trained models and optimized logic are deployed within the system's Fast API-based backend architecture. The web interface, built using HTML, CSS, and Jinja2 templates, provides users with an interactive environment to input vehicle details, view AI-generated comparisons, and explore insights. The system supports side-by-side analysis, visual ratings, and graphical comparisons of specifications and performance.
7) Step 7: Integration of Vehicle Review Chatbot Bot: An AI-powered conversational interface built using the Gemini AI API, designed to enable natural language interaction with users. It allows individuals to query vehicle specifications, compare different models, and obtain AI-generated reviews or summaries in real time.

8) Step 8: Continuous Feedback, Monitoring, and Security: The system integrates continuous feedback loops that collect user responses, update model predictions, and retrain AI models as necessary. Monitoring tools ensure the accuracy of sentiment detection and maintain API performance. Strong security measures—such as authentication, encryption, and input validation—are enforced to safeguard user data and preserve the integrity of the system.

A. Flowchart of the Proposed Methodology

The overall workflow of the Vehicle Review System is illustrated in Figure 2, which presents a graphical overview of the sequential process—from problem identification to AI-driven decision support. It outlines the structured progression of data collection, preprocessing, model training, validation, and result generation within the system. The flowchart depicts how data flows through each phase, beginning with dataset acquisition and cleaning, followed by AI-based and comparison generation using the Gemini model. Processed outputs are optimized and converted into structured reviews, which are displayed through a user-friendly web interface. Integrated feedback mechanisms ensure continuous system enhancement, while security layers maintain data reliability and ethical use. This methodology ensures transparency, adaptability, and accurate decision support for users

Flowchart

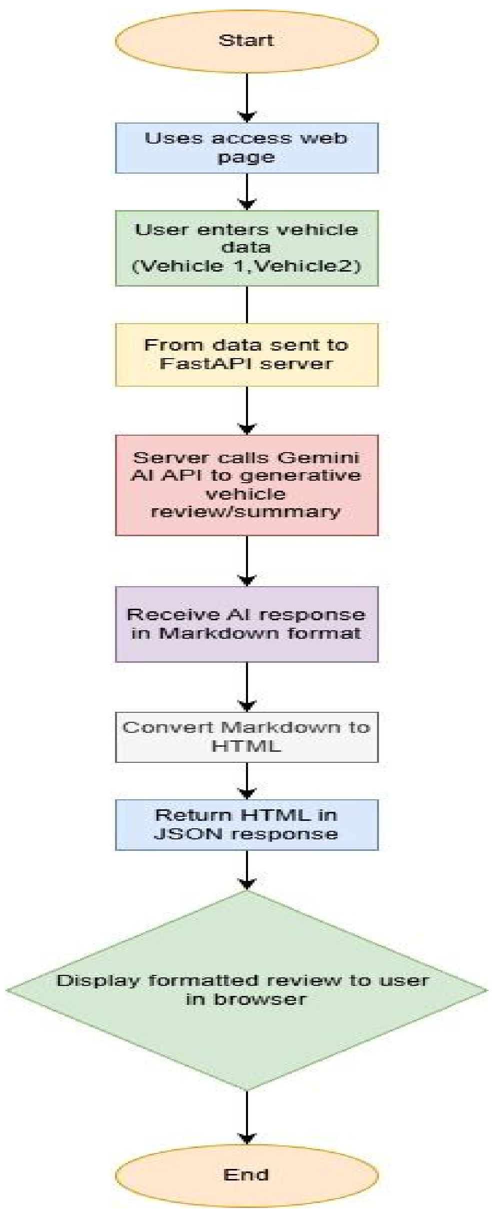

Figure 2: Flowchart

VII. SNAPSHOTS

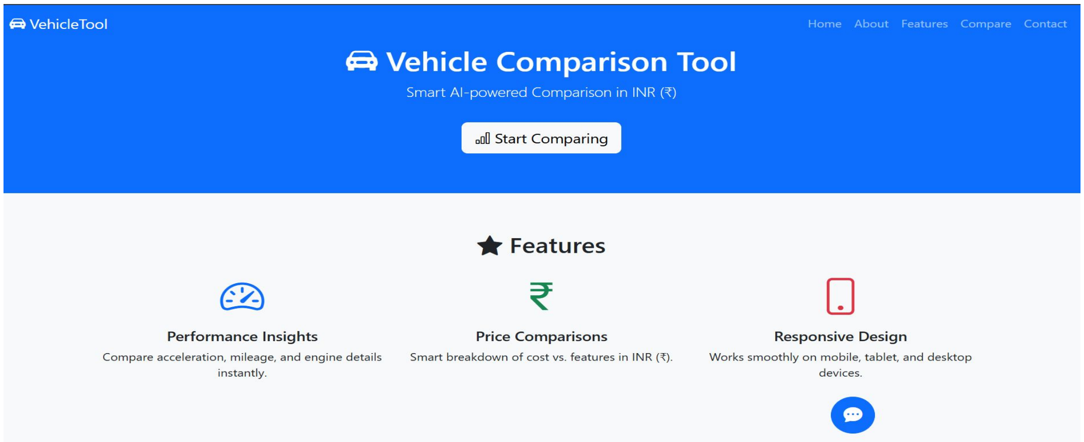

Figure 3: Home Page of the Vehicle Review System

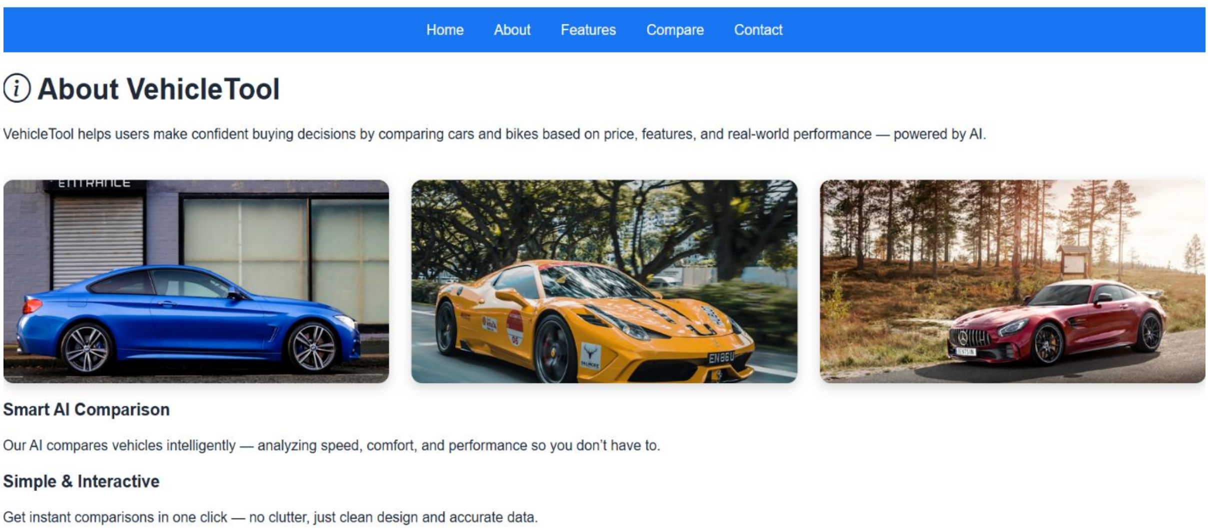

Figure 4: About Page of the Vehicle Review System

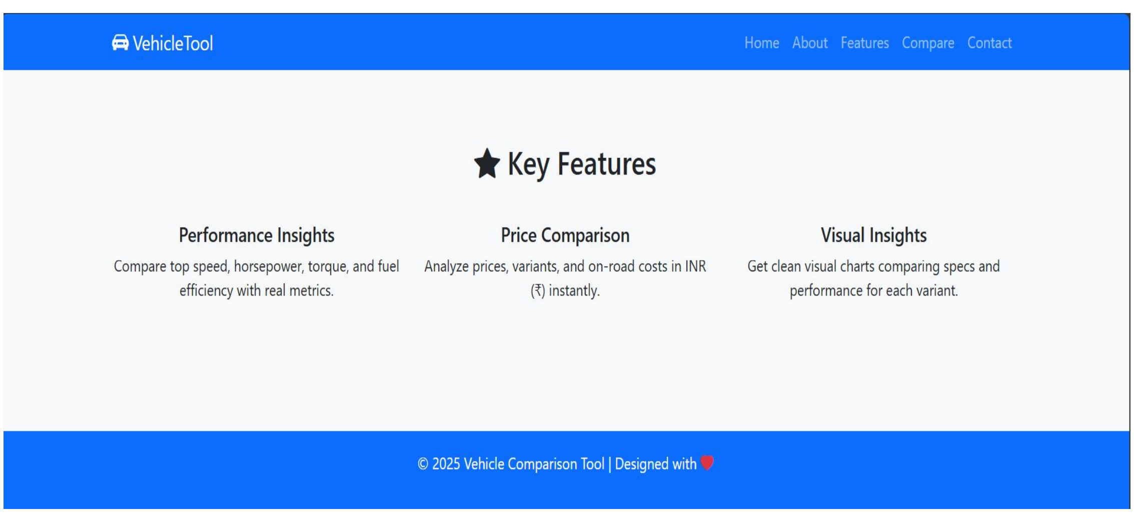

Figure 5: Feature Page of the Vehicle Review System

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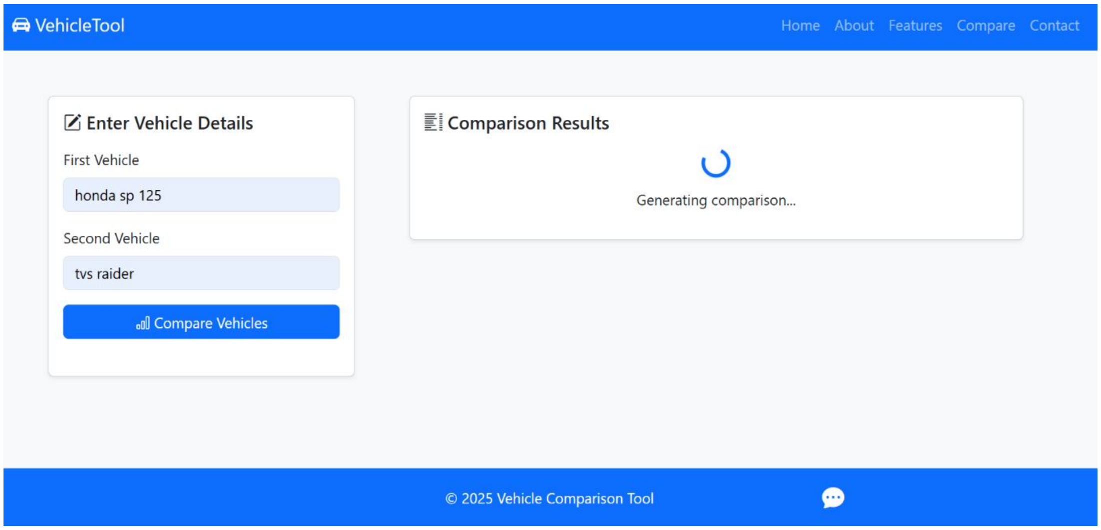

Figure 6: Comparison Page of the Vehicle Review System

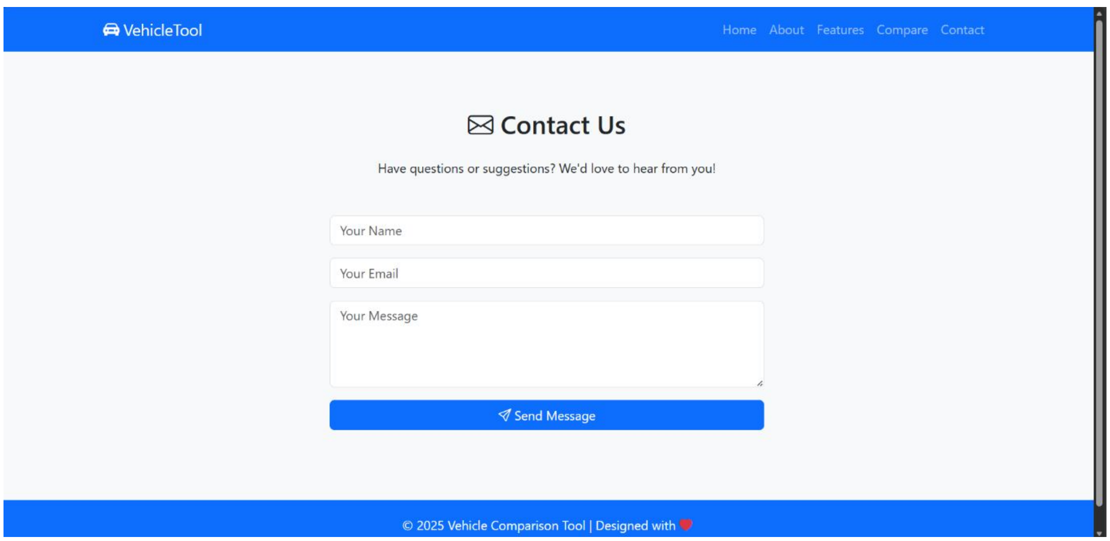

Figure 7: Contact Page of the Vehicle Review System

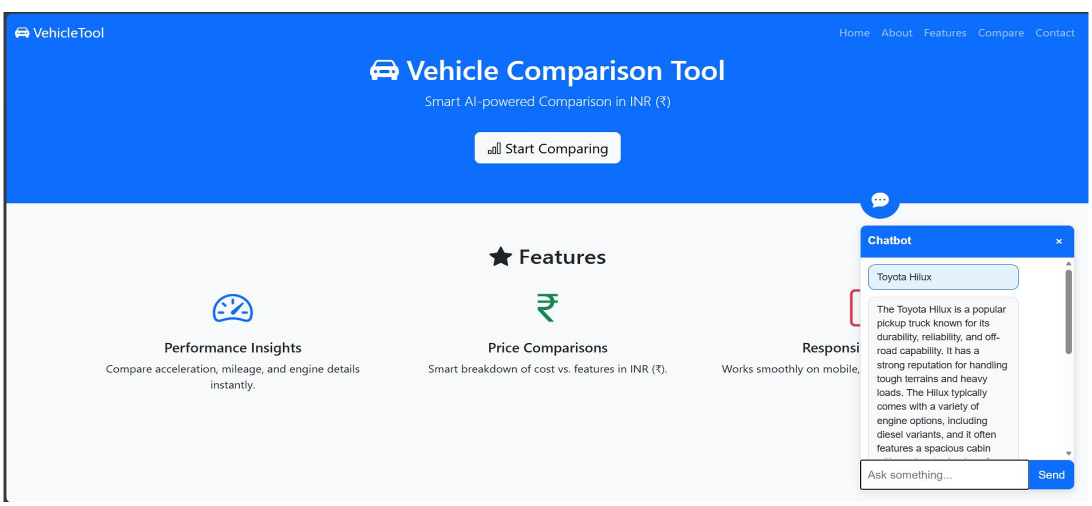

Figure 8: Chatbot Page of the Vehicle Review System

VIII. FUTURE SCOPE

The future scope of the Car and Bike Comparison System includes integrating real-time data from automobile APIs to provide the latest prices and specifications. Artificial intelligence can be implemented to recommend the best vehicles based on user preferences like budget and performance. The system can be enhanced with user reviews, ratings, and interactive visual comparisons. A mobile application version can improve accessibility and usability. Integration with dealers can allow features like test-drive bookings and insurance options. Future improvements may also include electric vehicle support and eco-friendly performance metrics.

IX. CONCLUSIONS

The Car and Bike Comparison System provide an efficient and user-friendly platform for comparing two vehicles based on various parameters such as price, specifications, features, and performance. It helps users make informed decisions by presenting detailed and organized information in one place. The system simplifies the comparison process, saving time and effort for potential buyers. It can be used by individuals, automobile enthusiasts, and dealers to analyse vehicle differences effectively. Overall, the project successfully demonstrates how technology can enhance the vehicle selection process and improve user experience.

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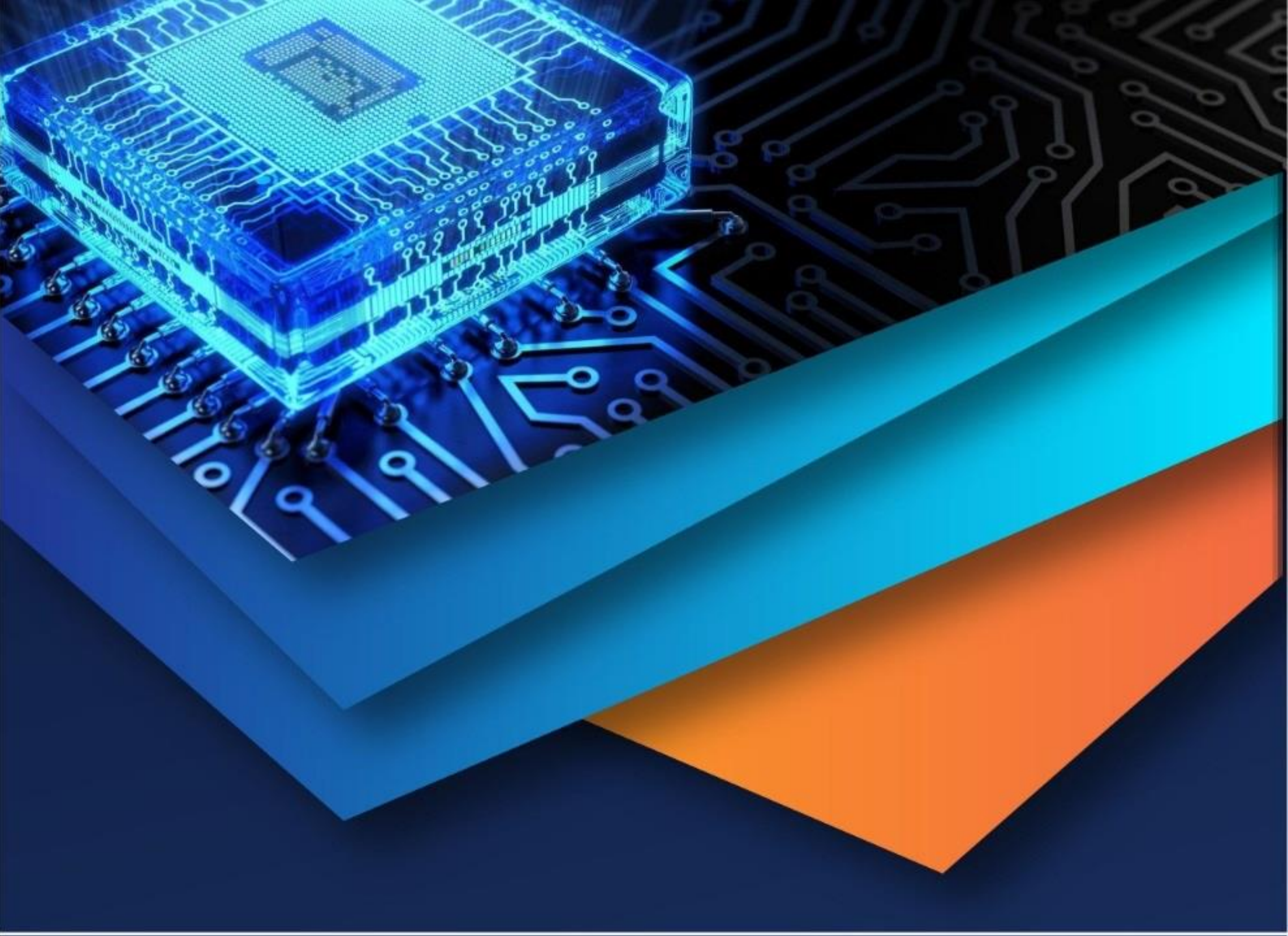

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