iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** XII **Month of publication:** December 2025

DOI: https://doi.org/10.22214/ijraset.2025.76630

An AI-Enabled Platform for Crop Diversification Using AI

Prasad S R[1], Ayush D Rao[2], Chiranth S G[3], Yashwanth K [4], Yashwanth T[5]
[1]*Assistant Professor, Dept. of CSE, Shri Dharmasthala Manjunatheshwara Institute of Technology, Ujire-574240, Affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India*
[2, 3, 4, 5] *Students, Dept. of Computer Science and Engineering, Shri Dharmasthala Manjunatheshwara Institute of Technology, Ujire-574240, Affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India*

Abstract: Agriculture remains central to food security and rural livelihoods but faces mounting challenges from climate change, declining soil fertility, resource scarcity, pest and disease outbreaks, and fluctuating market dynamics. Traditional monoculture practices, though economically consistent in the short term, contribute to long-term ecological degradation through nutrient depletion, biodiversity loss, and increased climatic vulnerability. Crop diversification has emerged as a sustainable alternative, enhancing soil health, reducing pest pressure, and improving resilience and profitability. However, traditional decision-making in diversification—largely reliant on experiential knowledge and seasonal intuition—has become inadequate in a data-driven agricultural landscape. This project leverages Artificial Intelligence (AI) through OpenAI technology and the OpenAI API to transform crop diversification strategies by analyzing extensive datasets encompassing soil parameters, yield patterns, sustainability metrics, and real-time market trends. The system delivers location-specific, multi-criteria crop recommendations that optimize both environmental and economic outcomes. Unlike hardware-intensive precision agriculture systems, this framework is entirely software-driven, ensuring scalability, cost-efficiency, and accessibility for small and marginal farmers. A key innovation is AgriBot, an AI-powered conversational assistant enabling farmers to interact in natural language and receive intelligent, data-driven insights on crop selection, soil management, and weather-based planning. AgriBot's predictive analytics and market intelligence components forecast yield potential, assess profitability, and evaluate long-term sustainability. By integrating AI-driven analytics with conversational intelligence, the system democratizes agricultural decision-making, enhances adaptive capacity to climate variability, and promotes sustainable intensification. Ultimately, the proposed framework exemplifies how OpenAI-enabled digital agriculture can advance resilience, ecological balance, and inclusive technological empowerment in modern farming.
Keywords: Crop Diversification; Artificial Intelligence (AI); OpenAI API; Agricultural Decision Support System (ADSS); Predictive Analytics; AgriBot (AI Chatbot); Soil and Yield Analysis; Market Intelligence; Sustainable and Climate-Resilient Agriculture.

I. INTRODUCTION

Agriculture remains the cornerstone of global food security and rural livelihoods; however, it now faces unprecedented challenges driven by climate change, resource depletion, pest and disease outbreaks, and fluctuating market conditions. Traditional monoculture practices where the same crop is cultivated continuously on the same land offer short-term economic benefits but result in long-term degradation through nutrient depletion, loss of soil biodiversity, pest resistance, and heightened vulnerability to climatic variability. In contrast, crop diversification, defined as the cultivation of multiple crops either simultaneously or in rotation, has emerged as a volatility demand more precise, data-driven decision support. Recent advances in Artificial Intelligence (AI) offer promising solutions to these challenges by enabling the analysis of large-scale agricultural datasets to generate actionable insights. AI systems can integrate data on soil health, climatic parameters, historical yield patterns, and market prices to deliver accurate, location-specific crop recommendations. This data-centric approach enhances decision-making precision, thereby improving productivity, sustainability, and profitability. Although precision agriculture has successfully utilized technologies such as drones, IoT sensors, and satellite imagery to optimize farm management, these methods often require costly infrastructure and advanced technical skills, making them inaccessible to small and marginal farmers. There exists a significant research gap in the development of affordable, software-driven AI systems that can facilitate crop diversification without reliance on expensive hardware. The present study addresses this gap by developing an AI-powered decision-support system that integrates environmental, agronomic, and economic parameters to optimize crop diversification strategies.

The system leverages OpenAI technology and the OpenAI API to analyze agricultural datasets, predict yield per acre, and recommend sustainable crop combinations tailored to specific agro-climatic conditions and prevailing market dynamics.

A key component of this system is *AgriBot*, an AI-based conversational assistant designed to democratize access to agricultural intelligence. Through natural language interaction, AgriBot enables farmers to obtain personalized recommendations on crop selection, soil management, and weather-based planning. This integration of predictive analytics, market intelligence, and conversational AI enhances accessibility for farmers with limited digital literacy, providing them with real-time, context-aware support. The overall framework not only bridges the gap between traditional farming practices and digital agriculture but also empowers farmers to make informed, adaptive, and sustainable decisions that improve resilience and income stability.

II. RELATED WORK

Crop diversification is a critical strategy for sustainable agriculture, enabling farmers to mitigate risks associated with monoculture, climate variability, and resource depletion. The integration of Artificial Intelligence (AI) and Machine Learning (ML) has transformed this domain by enabling data-driven insights from soil, climate, and market datasets. Recent studies demonstrate that AI-driven decision-support frameworks can optimize crop selection, enhance soil fertility, and improve yield predictability. The following section presents a detailed review of key research works focusing on AI-enabled crop diversification, spanning remote sensing, predictive modeling, reinforcement learning, and deep learning methodologies.

Sishodia et al. (2020) [1] integrated remote sensing with machine learning models to evaluate the effects of crop diversification on soil productivity. By combining multi-temporal satellite imagery with ground-based data, they developed predictive frameworks to assess vegetation indices, soil moisture, and biomass dynamics. Their results indicated that diversified cropping improved nutrient cycling, soil organic content, and long-term ecological resilience.

Saleem et al. (2021) [2] proposed AI-driven digital agriculture platforms offering personalized diversification strategies for smallholder farmers. The systems employed ML algorithms to analyze soil characteristics, climatic forecasts, yield histories, and market prices. The platform produced adaptive, profitability-oriented crop recommendations, enhancing decision-making efficiency and sustainability under variable climatic and economic conditions.

Ali et al. (2021) [3] focused on AI-based climate resilience through ensemble and decision tree models analyzing historical yield and climate data. Their approach provided agroecological zone–specific diversification strategies that mitigated adverse impacts from drought, floods, and temperature extremes. The findings demonstrated the role of AI in strengthening adaptive capacity within diversified cropping systems.

Sharma et al. (2021) [4] utilized neural networks to predict plant disease risks and validated diversification as a preventive mechanism. The models integrated soil nutrient profiles, crop types, and disease incidence data to forecast outbreaks. Their work emphasized that diversified cropping systems lower disease susceptibility and improve agroecosystem stability through intelligent disease prediction.

Khosravi et al. (2021) [5] developed an AI-based agroecological zoning framework employing Random Forest and Support Vector Machine classifiers. The system integrated soil, temperature, precipitation, and vegetation data to categorize land into suitability zones. Their model provided precision in regional diversification planning, enhancing spatial accuracy for multi-crop recommendations and resource optimization.

Sarker et al. (2022) [6] demonstrated the role of AI in precision agriculture for promoting dynamic crop diversification. Their approach merged sensor networks, satellite data, and ML algorithms to monitor soil moisture, temperature, and weather in real time. The system enabled adaptive crop rotation strategies and improved site-specific resource management under changing environmental conditions.

Mohammadi et al. (2022) [7] applied reinforcement learning models to optimize land use for ecological sustainability. The framework continuously learned from soil, irrigation, and topographic data to identify optimal crop rotation sequences. Results indicated improvements in water efficiency, reduced fertilizer dependency, and enhanced biodiversity through intelligent, adaptive diversification strategies.

Paliwal et al. (2022) [8] analyzed intercropping and mixed cropping systems using regression and decision tree algorithms. By combining soil fertility metrics, historical yields, and market data, the model recommended economically viable crop combinations. Their findings revealed that AI-enabled intercropping improves resource efficiency, minimizes market risks, and ensures ecological stability.

Ramesh et al. (2022) [9] focused on the economic dimension of diversification using Support Vector Machines and time-series forecasting. The models analyzed historical price volatility, market demand, and production costs to guide profitability-oriented crop diversification. The AI-driven system provided market-aligned recommendations that maximized income stability for smallholder farmers.

Gupta et al. (2023) [10] provided a comprehensive overview of AI-driven crop rotation frameworks. Their work demonstrated that ML algorithms effectively sequence crops to enhance yield stability, soil fertility, and pest suppression. The study emphasized biodiversity preservation as a key outcome of AI-optimized rotation planning in sustainable agriculture systems.

Jaworski et al. (2023) [11] examined crop diversification as an ecological pest management approach. Their analysis revealed that diverse cropping systems disrupt pest life cycles and enhance populations of beneficial insects. Through simulation models, they demonstrated that AI can support biodiversity-driven pest control strategies, reducing chemical pesticide dependence.

Smart Farming Using AI: A Review (2023) [12] discussed the integration of ML and Deep Learning (DL) in precision agriculture applications. By analyzing soil properties, climatic variables, and pest datasets, AI systems were shown to support dynamic diversification planning. The review concluded that intelligent models significantly enhance sustainability, yield prediction accuracy, and resilience to environmental stresses.

Pramanik et al. (2023) [13] developed an adaptive AI-based agro-advisory system that merges historical agricultural data with real-time monitoring. Utilizing feedback learning mechanisms, the system provided region-specific diversification recommendations. Continuous refinement from farmer interactions improved prediction accuracy and fostered adaptive decision-making in heterogeneous agroecological contexts.

Qayyum et al. (2023) [14] employed ML algorithms including Random Forests, Decision Trees, and SVMs to optimize crop rotations. Their models predicted soil nutrient depletion, pest dynamics, and irrigation needs, generating optimal rotation plans. The approach enhanced resource efficiency and sustainability while reducing environmental footprint through data-driven crop selection.

Nguyen et al. (2023) [15] compared traditional ML models with advanced DL architectures such as CNNs and LSTMs for yield prediction. Their findings confirmed DL models' superiority in processing high-dimensional datasets involving soil, climate, and crop parameters. The approach improved regional yield forecasting accuracy, supporting diversification tailored to agroclimatic variability. Ghosal et al. (2024) [16] reviewed ML and DL techniques in yield prediction and diversification modeling. They highlighted the integration of heterogeneous datasets encompassing climate, soil, and management practices. The study demonstrated that multimodal data fusion enhances prediction reliability and supports climate-resilient diversification planning.

Santantonio et al. (2024) [17] explored AI applications in plant breeding for diversified cropping systems. Using ML and DL models to analyze genomic and phenotypic datasets, their research accelerated the identification of climate-resilient crop varieties. The study established that AI-driven breeding supports genetic diversity essential for adaptive crop diversification.

Hossen et al. (2025) [18] examined transfer learning for addressing data scarcity in agricultural AI. They demonstrated that fine-tuning pre-trained models with limited local datasets improves accuracy in region-specific diversification planning. This method enables cost-effective deployment of AI systems for smallholder farmers, ensuring scalability and inclusivity in sustainable agriculture.

III. PROBLEM STATEMENT

Crop diversification plays a vital role in achieving sustainable agriculture by enhancing soil fertility, stabilizing farmer income, mitigating pest and disease outbreaks, and improving resilience to climate variability. However, traditional decision-making methods based on farmers' experience or historical practices—fail to account for dynamic factors such as changing climate patterns, soil degradation, market fluctuations, and water availability. Although digital agriculture has enabled access to vast datasets from remote sensing, IoT sensors, and agricultural databases, transforming this multidimensional data into actionable insights remains a challenge. Existing systems are often static and lack predictive adaptability. Artificial Intelligence (AI) offers the capability to analyze complex interactions among soil, climate, and yield parameters for optimal crop planning, yet current AI applications are fragmented and limited in scalability and interpretability. Therefore, there is an urgent need for an integrated, AI-driven, real-time decision-support system to deliver adaptive, region-specific crop diversification recommendations.

IV. PROPOSED VEHICLE REVIEW SYSTEM

The proposed AI-driven architecture for crop diversification is designed as a multi-layered framework that integrates data acquisition, predictive analytics, and intelligent decision support. It begins with the collection and preprocessing of diverse agricultural datasets, followed by machine learning–based modeling and optimization to identify sustainable crop combinations. Finally, the integration of OpenAI-powered Agri Bot, a user-centric dashboard, and continuous monitoring ensures accessible, secure, and adaptive decision-making for farmers.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue XII Dec 2025- Available at www.ijraset.com

1) Data Sources Layer: This foundational layer aggregates heterogeneous agricultural datasets, including soil health parameters, meteorological data, crop yield history, and real-time market information. Integration of remote sensing datasets such as Sentinel or Landsat further enhances spatial and temporal understanding of soil and crop dynamics. By combining environmental and economic factors, this layer establishes a holistic dataset for AI-driven analysis.
2) Data Ingestion and Preprocessing: Data ingestion mechanisms, through APIs and automated connectors, collect and consolidate information into a unified repository. Preprocessing operations such as data cleaning, normalization, outlier handling, and imputation ensure data consistency and reliability. Subsequent feature engineering extracts meaningful indicators including rainfall variability, soil fertility indices, and commodity price trends. This stage transforms unstructured raw data into an analytical dataset suitable for machine learning workflows.
3) Machine Learning and Predictive Modeling: This layer constitutes the analytical core of the system. Supervised learning models are trained to predict yield outcomes, assess economic profitability, and simulate various crop diversification scenarios. Algorithms such as Random Forest, Gradient Boosting, or Neural Networks can be utilized to learn complex correlations between biophysical and market variables. The validated models enable the system to recommend optimal crop combinations that balance productivity, profitability, and sustainability
4) Optimization and Model Serving: The optimization engine incorporates multi-objective criteria—including soil health preservation, input efficiency, and profitability—to generate adaptive crop plans. Trained models are containerized and deployed through APIs, enabling real-time inference and scenario-based simulations. This architecture ensures scalability, interoperability, and continuous availability of predictive services without retraining on local devices.
5) OpenAI Integration and Agri Bot: Leveraging the OpenAI API, an intelligent conversational interface, termed Agri Bot, facilitates human–AI interaction in natural language. Farmers can query the system regarding crop selection, soil treatment, irrigation scheduling, or climate risks. The Agri Bot interprets contextual queries and delivers AI-generated insights in an accessible form, thereby democratizing advanced decision-support tools for non-technical users.
6) User Interface and Decision Support: A web or mobile-based decision-support dashboard visualizes predicted yields, profitability indices, and sustainability scores. It allows users to compare diversification strategies, assess trade-offs, and plan cultivation cycles through interactive modules. The interface integrates alerts, weather advisories, and recommendation updates, enabling data-driven agricultural decision-making.
7) Monitoring, Feedback, and Security: Continuous monitoring mechanisms evaluate model performance, data drift, and system latency. Farmer feedback loops support model retraining to accommodate evolving environmental and market dynamics. The architecture incorporates robust data privacy, encryption, and governance protocols, ensuring ethical and secure handling of agricultural data. This feedback-oriented design promotes system adaptability and long-term trust among stakeholders.

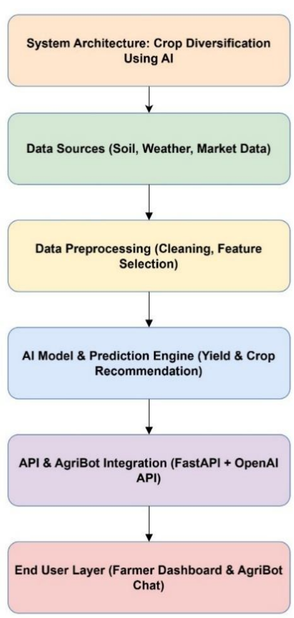


Figure 1: Architecture Design

V. OBJECTIVES

1) Promoting Sustainable Agriculture through AI Integration: The primary objective is to leverage Artificial Intelligence (AI) to foster sustainable agricultural practices by encouraging biodiversity and reducing dependence on monoculture. This approach aims to maintain soil fertility, enhance ecosystem balance, and ensure long-term food security through adaptive and intelligent crop diversification.
2) Data-Driven Decision-Making using AI and Machine Learning: This objective focuses on analyzing complex environmental and agronomic datasets using AI and machine learning (ML) algorithms. By interpreting soil, climate, and yield data, the system provides farmers with actionable insights to make informed and data-supported decisions for crop selection and management.
3) Optimization of Resource Utilization in Diversified Cropping Systems: AI-based models are developed to optimize the allocation and utilization of agricultural resources such as water, fertilizers, and land. The objective is to enhance environmental variables. A data sufficiency validation step ensures that the dataset is adequate in both volume and representativeness before model training.
4) AI Model Training and Validation: Machine learning algorithms are trained on the processed data to predict crop yields, assess profitability, and generate optimized diversification strategies. Techniques such as regression, classification, and ensemble learning are employed to capture complex dependencies among soil, weather, and economic parameters. The trained models are evaluated using performance metrics (e.g., RMSE, MAE, R^2), and iterative retraining is performed if accuracy thresholds are not met.
5) Optimization and Recommendation Generation: An optimization engine integrates multi-objective criteria such as soil health improvement, water use efficiency, and profitability to identify the best crop diversification strategies for specific regions. The validated models generate location-based recommendations that promote both environmental sustainability and economic stability

VI. METHODOLOGY AND SYSTEM FLOWCHART

The proposed methodology for *Crop Diversification Using Artificial Intelligence (AI)* follows a structured, data-centric framework aimed at optimizing agricultural decision-making through predictive modeling, real-time analytics, and intelligent recommendation systems. The approach systematically progresses through several interlinked stages, each contributing to transforming raw agricultural data into actionable insights for sustainable and profitable crop diversification.

1) Step 1: Problem Identification: The process begins with identifying the core agricultural challenges such as declining soil fertility, climatic fluctuations, pest infestation risks, and the economic vulnerability of monoculture practices. Recognizing these issues establishes the foundation for implementing an AI-driven framework that promotes sustainable and adaptive crop diversification strategies.
2) Step 2: Data Collection: This stage involves gathering heterogeneous agricultural datasets from multiple reliable sources, including soil health reports, meteorological records, market trend databases, and historical crop yield data. Optional integration of remote sensing data (e.g., Sentinel or Landsat imagery) enhances spatial resolution for soil and crop assessment. The collected datasets form the foundation for all subsequent analytical processes.
3) Step 3: Data Preprocessing and Validation: Collected data is subjected to preprocessing operations such as data cleaning, normalization, and missing value handling to ensure quality and consistency. Feature extraction and selection are performed to identify the most relevant agronomic and environmental variables. A data sufficiency validation step ensures that the dataset is adequate in both volume and representativeness before model training.
4) Step 4: AI Model Training and Validation: Machine learning algorithms are trained on the processed data to predict crop yields, assess profitability, and generate optimized diversification strategies. Techniques such as regression, classification, and ensemble learning are employed to capture complex dependencies among soil, weather, and economic parameters. The trained models are evaluated using performance metrics (e.g., RMSE, MAE, R^2), and iterative retraining is performed if accuracy thresholds are not met.
5) Step 5: Optimization and Recommendation Generation: An optimization engine integrates multi-objective criteria such as soil health improvement, water use efficiency, and profitability to identify the best crop diversification strategies for specific regions. The validated models generate location-based recommendations that promote both environmental sustainability and economic stability.

6) Step 6: Integration of Agri Bot and Decision Support System: The optimized models are deployed within a digital decision-support ecosystem comprising two main components:
a) Agri Bot – an AI-powered conversational interface built using the OpenAI API, which enables natural language interaction with farmers. It allows users to query crop choices, soil management practices, and weather-related advisories.
b) Decision-Support Dashboard – a web or mobile interface that visualizes key metrics such as predicted yields, profitability scores, and sustainability indices, assisting farmers in comparing alternative cropping plans and making informed decisions.
7) Step 7: Continuous Learning, Feedback, and Security: The system incorporates a feedback mechanism where user interactions, real-time environmental updates, and market fluctuations are continuously fed back into the AI models for retraining and adaptive learning. Strong data privacy and authentication protocols are implemented to ensure secure handling of all agricultural and user information, thereby maintaining trust and system integrity.

A. *Flowchart of the Proposed Methodology*

The overall system workflow is illustrated in Figure 2, which provides a graphical representation of the sequential process—from problem identification to AI-driven decision support.

The flowchart demonstrates how data flows through various stages, including collection, preprocessing, modeling, validation, optimization, and recommendation delivery, before finally reaching the end users through interactive interfaces. Feedback loops and validation nodes are embedded within the architecture to ensure continuous improvement, data reliability, and predictive accuracy.

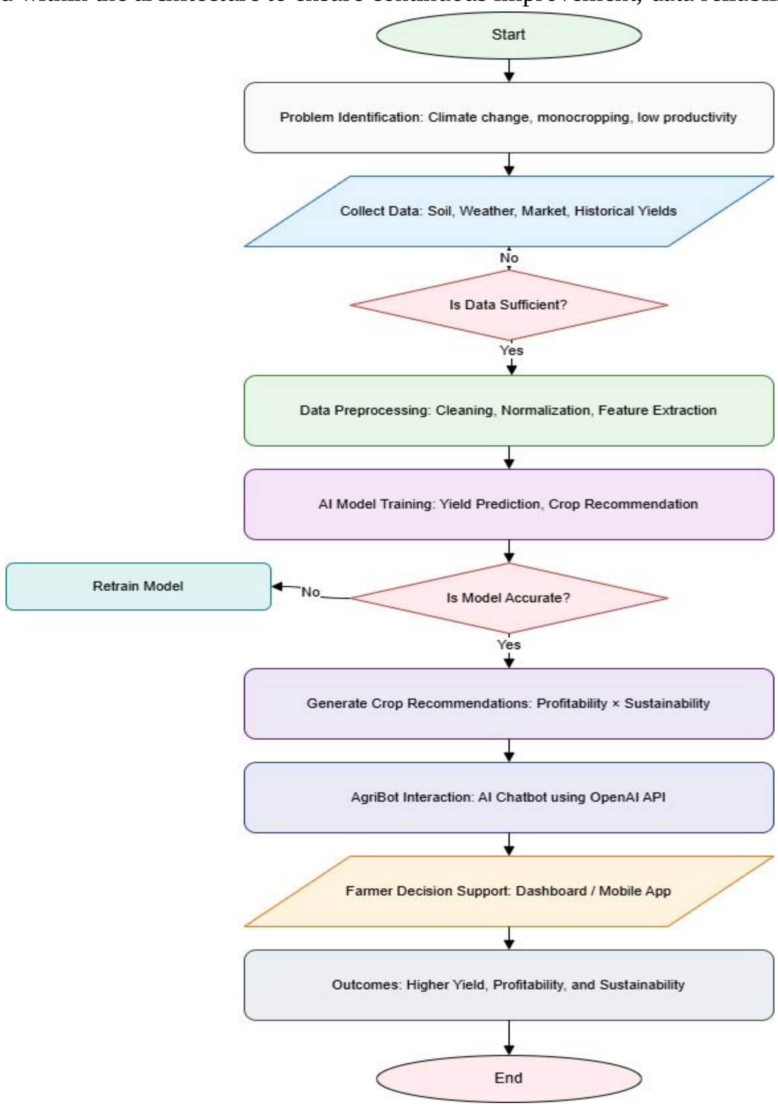


Figure 2: Flowchart

VII. SNAPSHOTS

Figure 3: Home Page of the Vehicle Review System

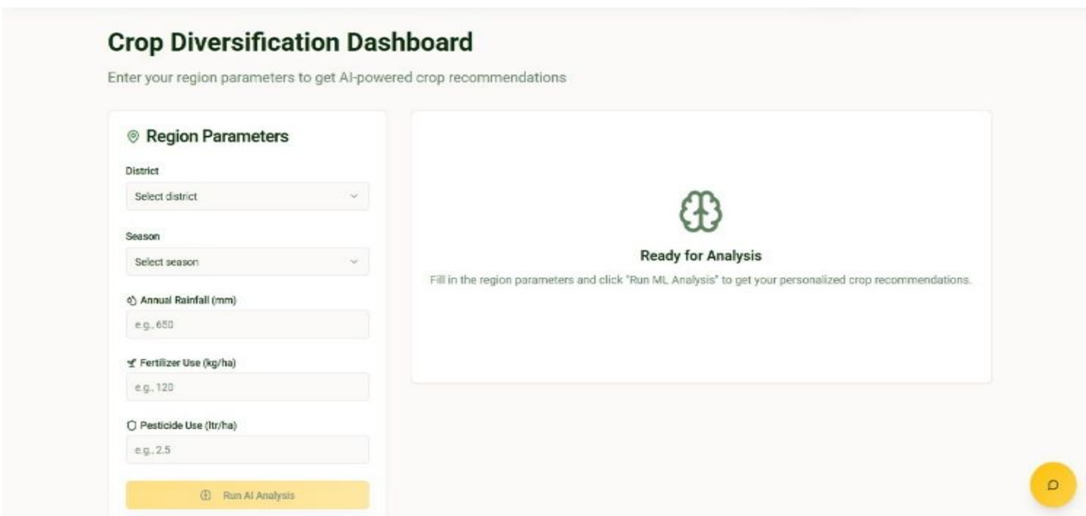


Figure 4: About Page of the Vehicle Review System

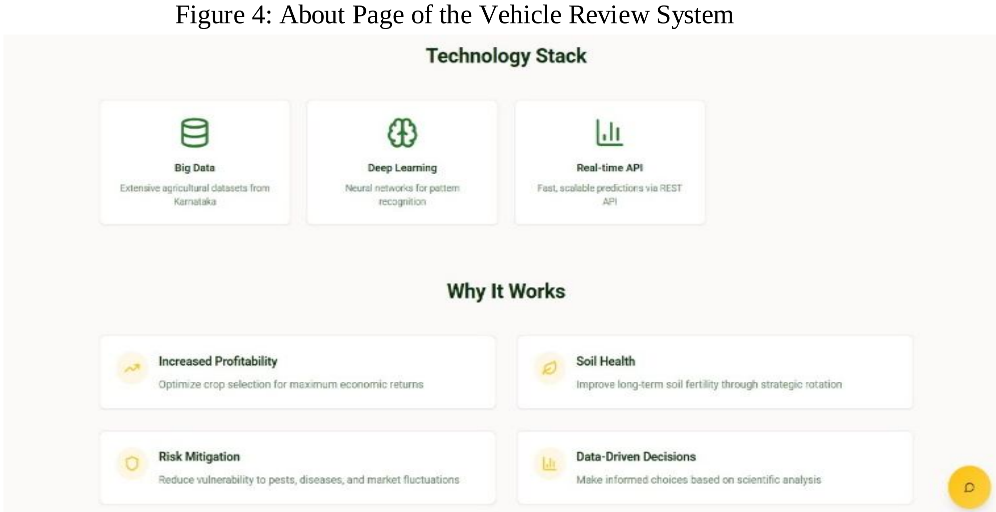


Figure 5: Feature Page of the Vehicle Review System

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue XII Dec 2025- Available at www.ijraset.com

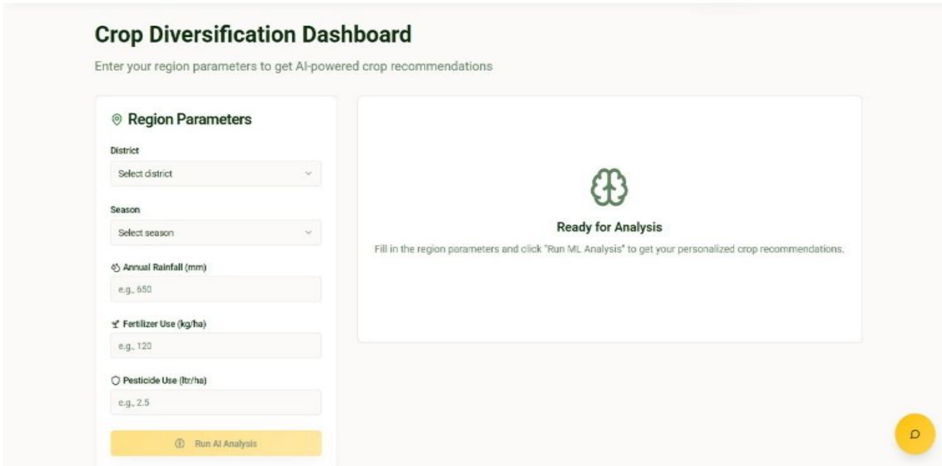


Figure 6: Comparison Page of the Vehicle Review System

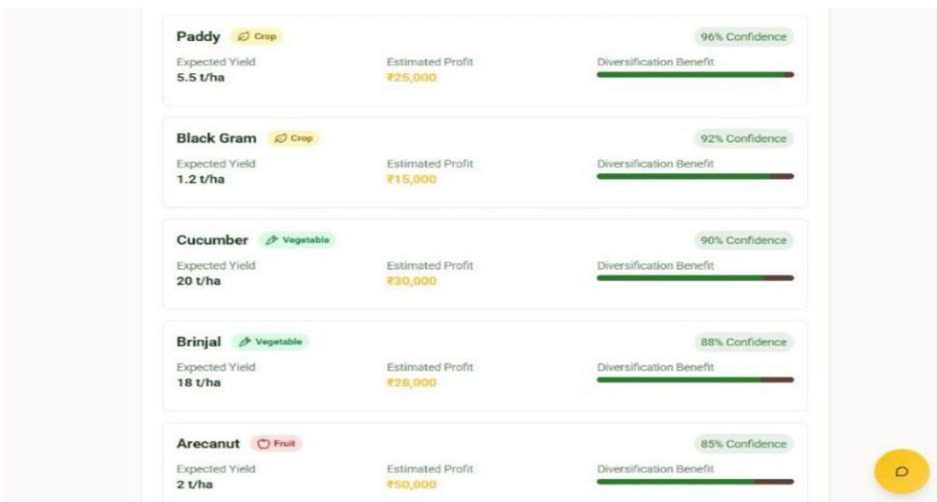


Figure 7: Contact Page of the Vehicle Review System

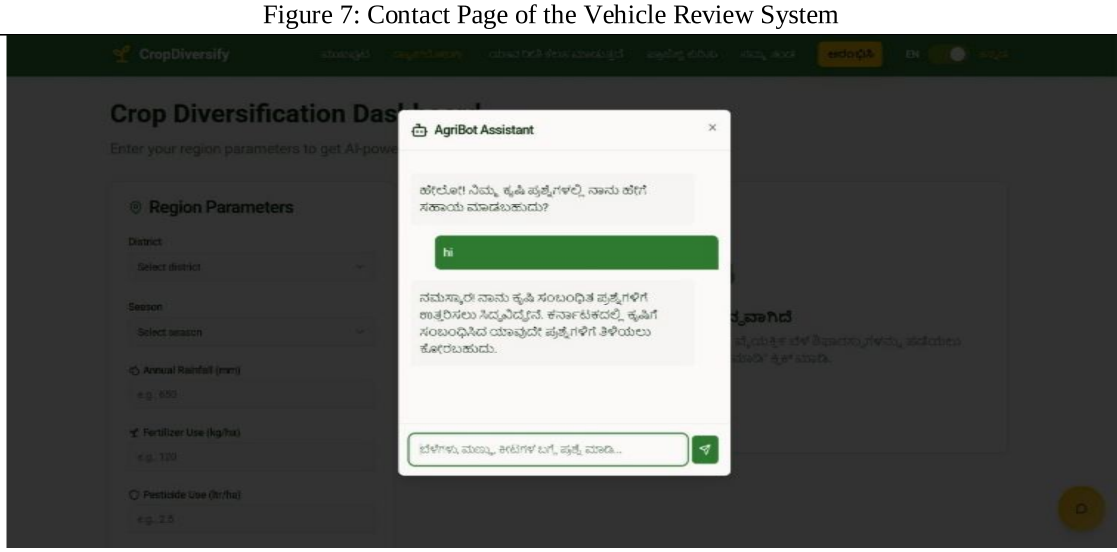


Figure 8: Chatbot Page of the Vehicle Review System

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

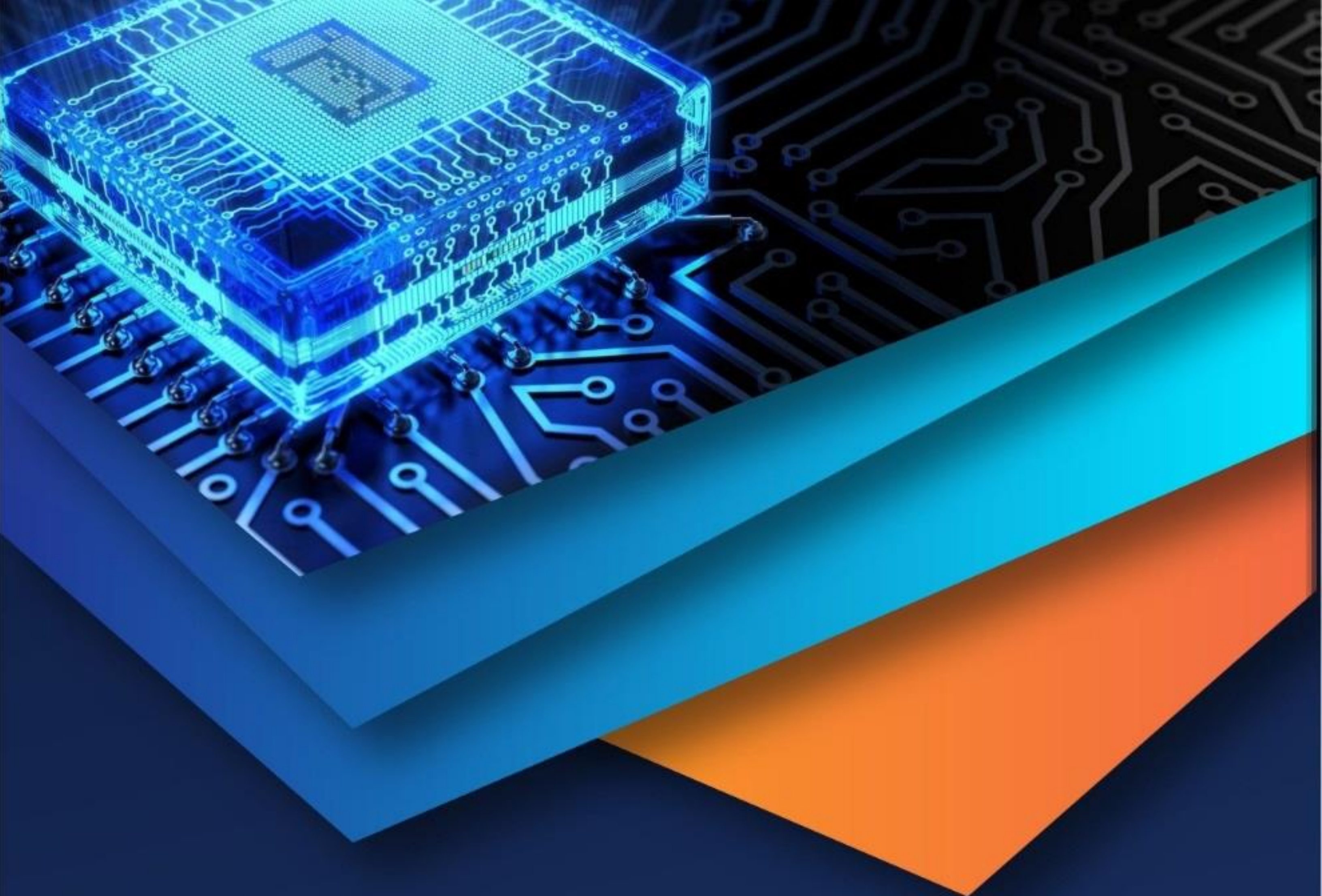
The Car and Bike Comparison System provide an efficient and user-friendly platform for comparing two vehicles based on various parameters such as price, specifications, features, and performance. It helps users make informed decisions by presenting detailed and organized information in one place. The 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.

X. ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to the project guide and faculty members of the Department of Computer Science and Engineering for their continuous guidance, valuable suggestions, and encouragement throughout the development of this project. We are thankful to our institution for providing the necessary infrastructure and resources required to complete this work successfully. We also extend our appreciation to our friends and teammates for their cooperation and support. Finally, we express our heartfelt thanks to our family members for their constant motivation and support, which played a vital role in the successful completion of the Vehicle Review System project.

REFERENCES

[1] Kumar and R. Sharma, “Sentiment analysis of automobile reviews using machine learning techniques,” Int. J. Computer Applications, vol. 174, no. 12, pp. 15–20, 2022.
[2] P. Sharma and S. Roy, “A hybrid recommendation system for vehicle selection using collaborative filtering,” Int. J. Eng. Res. Technol., vol. 10, no. 6, pp. 245–250, 2021.
[3] K. Patel, M. Shah, and R. Mehta, “Text mining and feature extraction for vehicle review analysis,” J. Intelligent Systems, vol. 31, no. 2, pp. 310–320, 2022.
[4] A. Yadav and P. Sinha, “User behaviour modelling for personalized recommendation in review systems,” Int. J. Advanced Computer Science and Applications, vol. 12, no. 4, pp. 198–205, 2021.
[5] N. Bhatt and M. Zaveri, “Fake review detection using support vector machines,” IEEE Access, vol. 8, pp. 121345–121354, 2020
[6] R. Iyer and S. Rao, “Cross-lingual sentiment analysis for multilingual vehicle reviews using BERT,” in Proc. IEEE Int. Conf. Data Science, 2022, pp. 112–118.
[7] A. Nair and J. Thomas, “Aspect-based sentiment analysis using Bi-LSTM with attention mechanism,” Expert Systems with Applications, vol. 210, pp. 118–129, 2024.
[8] S. Basu, A. Banerjee, and P. Ghosh, “Sentiment-based brand ranking in the automobile domain,” Int. J. Market Research, vol. 61, no. 3, pp. 285–296, 2019.
[9] S. Rao, M. Kulkarni, and A. Patil, “Transformer-based sentiment classification for online reviews,” IEEE Trans. Artificial Intelligence, vol. 3, no. 2, pp. 134–142, 2022.
[10] R. Pandey, S. Mishra, and A. Verma, “Graph-based spam review detection in online marketplaces,” ACM Trans. Information Systems, vol. 40, no. 3, pp. 1–22, 2022.
[11] J. Thomas, R. Mathew, and S. Joseph, “Vehicle review analysis using VADER sentiment analyzer,” in Proc. Int. Conf. Computing and Communication Systems, 2020, pp. 89–94
[12] Y. Zhang, L. Wang, and H. Chen, “Aspect-based sentiment analysis of SUV reviews,” J. Computational Linguistics, vol. 46, no. 4, pp. 721–734, 2020.
[13] J. Thomas and S. Rao, “Feature-level opinion mining for automobile review analysis,” Int. J. Information Technology, vol. 14, no. 1, pp. 55–62, 2022.
[14] S. Wang and C. D. Manning, “Latent Dirichlet allocation for topic modeling,” in Proc. ACL Conf., 2012, pp. 627–635.
[15] R. Feldman, “Techniques and applications for opinion mining,” Communications of the ACM, vol. 56, no. 4, pp. 82–89, 2013.
[16] L. Chen, Y. Liu, and Z. Li, “Sentiment analysis of car reviews using transformer-based deep learning,” Applied Sciences, vol. 11, no. 9, pp. 4021–4032,2021.
[17] S. Gaur, P. Khandelwal, and A. Jain, “Short text sentiment classification using naïve Bayes,” Int. J. Computer Science Trends and Technology, vol. 7, no. 2, pp. 45–50, 2019.
[18] R. Pandey and A. Gupta, “An ensemble machine learning model for review prediction,” J. Big Data Analytics, vol. 6, no. 1, pp. 1–12, 2023.
[19] A. Nair, S. Kumar, and J. Thomas, “Multimodal sentiment analysis using text and image data,” in Proc. IEEE Int. Conf. Multimedia Computing, 2024, pp. 201–206.



10.22214/IJRASET

INDEX COPERNICUS 45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY