Next-Generation Vehicle Performance Modeling Through Polynomial Interaction Learning Driven Interpretable Predictive Structures

Ch. Mounika[1]*, Mudunuri Akhil Varma[1], Jillapally Vinil Bharath[1], Kodulla Venu[1]

[1]Department of Computer Science and Engineering (DS), Kommuri Pratap Reddy Institute of Technology, Ghanpur, Ghatkesar, 501301, Telangana, India.

*Correspondence: Ch. Mounika

ABSTRACT

Vehicle performance evaluation and condition monitoring are essential for improving efficiency, safety, and maintenance planning in the automotive domain. Traditionally, these tasks were performed using manual inspection methods and basic statistical analysis, which required significant human effort, consumed time, and lacked scalability for handling large datasets. These conventional approaches also failed to provide accurate predictive insights and real-time decision support. The proposed system presents an intelligent web-based solution developed using the Django framework, integrating advanced Machine Learning (ML) techniques for automated vehicle analysis and prediction. The system supports both classification and regression tasks based on the Classification and Regression Trees (CART) methodology, including Vehicle Condition and Performance Optimization (classification), as well as Engine Performance and Fuel Efficiency (regression). Multiple ML algorithms such as Ridge, Huber, SLIM, and a novel PCN-FIGS (Polynomial Convolution Network with Fast Interpretable Greedy-Tree Sums) model are implemented. The PCN-FIGS model enhances feature representation through polynomial expansion and convolution-based smoothing, resulting in improved predictive performance. Experimental results demonstrate that the proposed model achieves high accuracy in classification tasks and strong R^2 scores in regression analysis. The system incorporates Exploratory Data Analysis (EDA), model comparison, and both single and batch prediction functionalities. Role-based access control enables corporate users to perform advanced analytics, while general users utilize prediction features. The research is completed by integrating data preprocessing, model training, evaluation, and deployment into a unified and user-friendly platform, providing a scalable and efficient solution for real-time vehicle performance prediction.

Keywords: Vehicle Performance Evaluation, Condition Monitoring, Automotive Analytics, Predictive Maintenance, Classification and Regression, Data Preprocessing, Exploratory Data Analysis, Web-Based System, Django Framework, Real-Time Prediction, Feature Engineering.

1. INTRODUCTION

Vehicle maintenance is an important part of owning a vehicle to ensure the safety, reliability and long life of the vehicle. But, the traditional methods for identifying maintenance needs rely on mileage coverage or a certain schedule; sometimes, they fail to identify the actual maintenance need, leading to either service early or late from the actual time. As shown in fig. 1 This may lead to spending more money and time. In 2023, the average spending on maintenance of a vehicle is USD 1475 yearly for 15,000 miles [1]. Regardless of this cost, unneeded maintenance can lead to financial burden, as over half of U.S. adults are unable to afford the maintenance cost of USD 1000 or more in case of emergency [2]. However, the traditional methods do not always align with the actual needs of the vehicle. Over the years, the cost of vehicle parts has increased, as shown in the Consumer Price Index (CPI). From 2014 to 2024, the CPI rose from 120.5 to 181.387, showing an 81.4% increase in cost since 1982 to 1984 as base years [3].

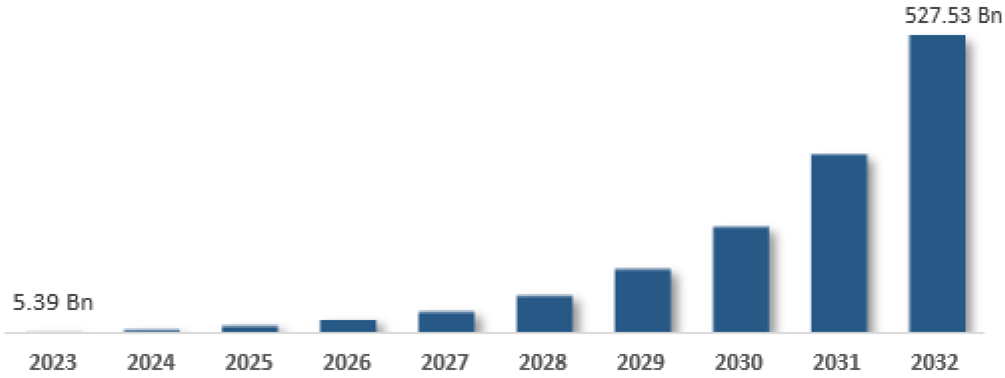

Fig. 1: Next-Generation Vehicle Performance.

Currently, the maintenance of a vehicle is often managed by routine checks like mileage coverage or the vehicle manufacturer's guidance. For example, routine maintenance is generally conducted between 5000 and 7500 miles, which includes services like oil change, tire rotations and other multiple inspections [4]. many vehicle owners carry out needless maintenance or ignore the main issue, which leads them to face big failures. Some studies have applied the machine learning models to predict vehicle maintenance, but they are limited to specific data points, model accuracy or complexity in implementation. They are using data from IOT devices, but sometimes it will be noisy and can lead the models to not perform well [5].

2. LITERATURE SURVEY

Anaissi et al. [6] proposed a network-level road condition detection system that utilizes two statistical features of vertical acceleration to detect pavement anomalies through SVM algorithms. Egaji et al. [7] extracted 42 features from the vehicle vibration data and applied several machine learning models to identify potholes. The results showed that the random forest (RF) model with hyperparameters adjusted by grid search achieved the highest recognition accuracy. Jang et al. [8] also used a neural network to detect the pavement condition and fused the trajectories of multiple vehicles to determine the abnormal location. These studies demonstrated that machine learning methods could provide a reliable solution for pavement condition detection. However, the performance of different machine learning methods in abnormal pavement detection based on vehicle vibration data still needs further exploration.

Celaya et al. [9] extracted a total of 42time domain features from vehicle three-axis acceleration and three-axis angular velocity data obtained by on-board accelerometers and gyroscopes for pavement speed bump detection. Hornyák et al. [10] focused on monitoring automotive engine health using an Adaboost-based AI model that analyzed real-world engine data such as temperature, pressure, and other operational parameters. The system detected early signs of potential problems by identifying patterns and anomalies that traditional methods might have missed. This approach enabled predictive maintenance, reduced downtime and costs, and enhanced engine safety. The solution was scalable and could be applied across various vehicle and engine types, promoting more efficient and proactive maintenance practices.

Behnamfar et al. [11] researched methods to enhance dynamic wireless charging (DWC) for electric vehicles by accurately determining vehicle positions to control transmitter coil activation. It proposed and examined multiple machine learning algorithms to accommodate variations in vehicle ground clearance and speed. After evaluating eight algorithms, the random forest algorithm was identified as the most effective, achieving the lowest error in predicting the vehicle's actual position and improving the overall efficiency of DWC systems. Zhan et al. [12] researched a mobile approach for pavement condition monitoring by employing low-cost sensors and machine-learning-based methodologies. It proposed an on-board unit (OBU) equipped with an inertial measurement unit (IMU) and GPS to collect vehicle posture data in real time. The study examined time and frequency domain features to identify key factors affecting abnormal pavement detection and developed six machine learning models to classify different pavement conditions. Furthermore, it analyzed the effect of vehicle speed on assessment accuracy and found that the random forest model considering speed achieved the best performance, offering a cost-effective solution for pavement maintenance.

Mahiyudin et al. [13] investigated predictive vehicle maintenance to minimize downtime and reduce costs by improving upon conventional mileage-based approaches. It introduced machine learning techniques to anticipate maintenance requirements using vehicle feature data. The study handled dataset imbalance by applying SMOTE to expand the dataset from 50,000 to 80,000 samples and evaluated several algorithms, including Random Forest, Decision Tree, Gradient Boosting, Naïve Bayes, and KNN. The Decision Tree model demonstrated the highest performance, achieving 99.97% accuracy on both balanced and imbalanced datasets, highlighting the effectiveness of machine learning for efficient and cost-saving maintenance planning. Yuan et al. [14] investigated vehicle emissions to support climate change mitigation by developing a comparative machine learning framework for predicting CO2 outputs from internal combustion engines (ICEs) and hybrid electric vehicles (HEVs). It incorporated both standard technical variables and acoustic factors rarely used in emission modeling. The research applied explainable machine learning techniques, such as accumulated local effects, to clarify how engine capacity, fuel consumption, and pollutant indicators influenced CO2 emissions under different driving conditions.

Doikin et al. [15] proposed a machine-learning-based energy optimization strategy for plug-in hybrid electric vehicles (PHEVs) that predicted upcoming journeys without relying on external data. It analyzed real-world data from 10 vehicles over 12 months and found that the RusBoosted ensemble classifier effectively learned trip patterns. Simulations showed up to 76% reduction in engine running time, with benefits for CO2 emissions, tailpipe output, and engine reliability.

3. PROPOSED SYSTEM

The proposed system is an intelligent, web-based platform for vehicle performance evaluation and condition monitoring using advanced ML techniques. It automates analysis, prediction, and reporting, overcoming the limitations of traditional manual methods. The workflow of the research follows as shown in Fig. 2.

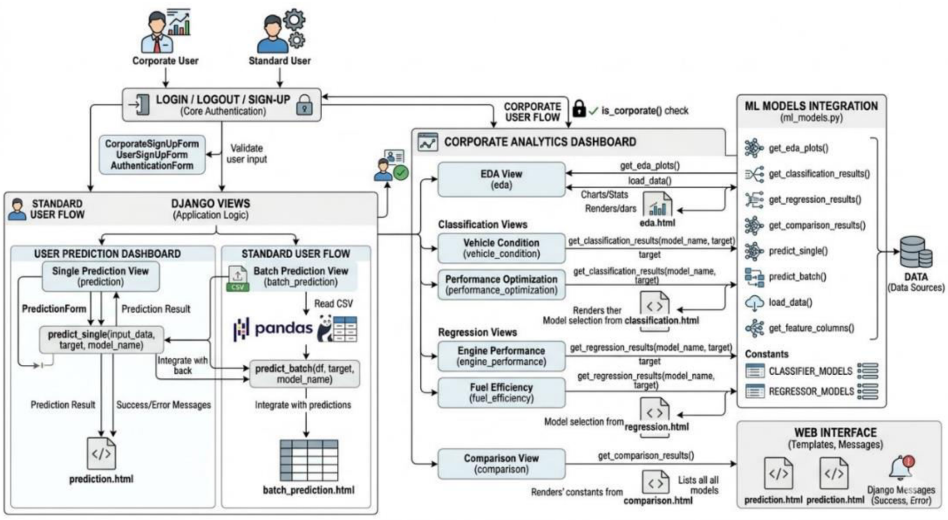

Fig. 2: Proposed system architecture.

Data Acquisition: Vehicle-related data is collected from multiple sources, including engine specifications, fuel efficiency records, vehicle condition metrics, and maintenance history. The dataset is cleaned and consolidated to remove inconsistencies, ensuring completeness. This structured data forms the foundation for accurate analysis and predictive modeling.

Data Preprocessing: The system preprocesses the collected data by encoding categorical variables and standardizing numeric features using techniques like Label Encoding and StandardScaler. Missing values are handled carefully to maintain data integrity. Preprocessing ensures that ML models can efficiently learn patterns from the dataset.

EDA: EDA is performed to visualize data trends, distributions, and correlations. Graphs such as bar charts, histograms, pie charts, and heatmaps provide insights into key features influencing vehicle performance. This step identifies critical attributes and potential anomalies in the dataset.

Model Selection and Training: Different ML algorithms are applied depending on the task. Classification targets like Vehicle Condition and Performance Optimization use Ridge, Huber, SLIM, and PCN-FIGS. Regression targets like Engine Performance and Fuel Efficiency also use Ridge, Huber, SLIM**,** and PCN-FIGS. The PCN-FIGS model improves feature representation through polynomial expansion and convolution-based smoothing, resulting in higher predictive performance.

Model Evaluation: Trained models are evaluated using classification metrics (Accuracy, Precision, Recall, F1-score) and regression metrics (MAE, MSE, RMSE, R^2). Visualizations such as confusion matrices, ROC curves, and scatter plots provide clear insights into model performance. This ensures that selected models are robust and reliable for real-world predictions.

Prediction Module: The system allows both single and batch predictions. Users can input vehicle details manually for real-time predictions or upload CSV files for batch processing. Trained models process the data and produce precise outputs for Vehicle Condition, Performance Optimization, Engine Performance, and Fuel Efficiency.

User Interface and Role-Based Access: Implemented using Django, the system provides role-based access. Corporate users can perform EDA, model comparison, and advanced analytics, while general users can access single and batch prediction modules. The user-friendly web interface ensures accessibility and ease of use.

Deployment and Integration: All components, including preprocessing, model training, evaluation, visualization, and prediction, are integrated into a single web platform. The system operates in real-time, scales to large datasets, and provides actionable insights for improving vehicle efficiency, safety, and predictive maintenance.

4. RESULTS ANALYSIS

The results of the proposed system demonstrate the effectiveness of integrating Machine Learning models with a web-based interface for real-time vehicle performance prediction and monitoring. The system successfully supports both classification and regression tasks, providing accurate insights into Vehicle Condition, Performance Optimization, Engine Performance, and Fuel Efficiency. The interface is designed for ease of use, offering functionalities such as dataset upload, single and batch predictions, EDA visualization, and role-based access for corporate and general users. The experimental outputs validate that the system handles large-scale vehicle datasets efficiently while providing actionable predictions and analytics.

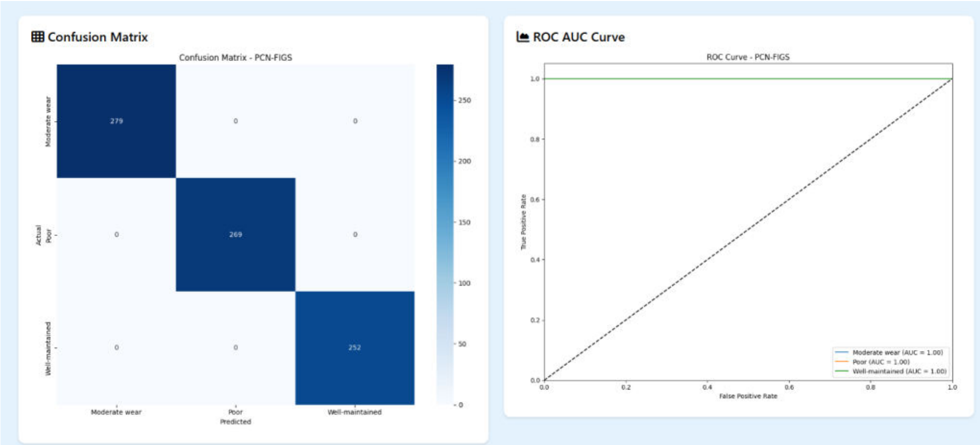

Fig. 3: Obtained confusion matrix and ROC curve of Vehicle Condition from PCN-FIGS.

Fig. 3 PCN-FIGS – The confusion matrix depicts the classification accuracy of the PCN-FIGS Classifier, while the ROC curve highlights its superior discrimination ability across vehicle condition classes. The model effectively captures complex feature interactions, improving overall prediction quality.

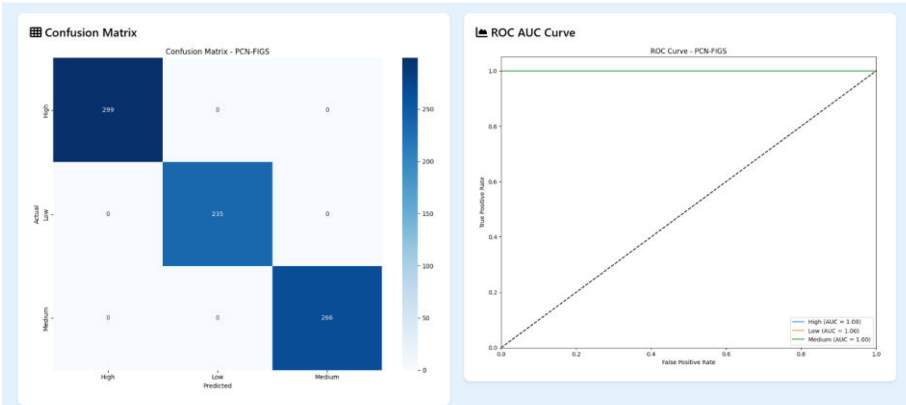

Fig. 4: Obtained confusion matrix and ROC curve of Performance Optimization from PCN-FIGS.

Fig. 4 PCN-FIGS – The confusion matrix depicts the classification results of the PCN-FIGS Classifier, highlighting minimal misclassifications. The ROC curve demonstrates superior class discrimination, leveraging feature interactions to improve performance prediction accuracy.

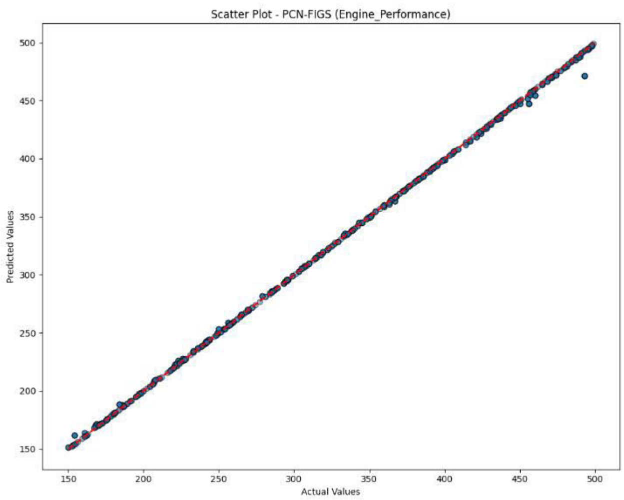

Fig. 5: Obtained scatter plot of Engine Performance from PCN-FIGS.

Fig. 5 PCN-FIGS – The scatter plot illustrates PCN-FIGS Regressor predictions. Points lie very close to the ideal line, highlighting superior regression performance due to enhanced feature representation and interaction modeling.

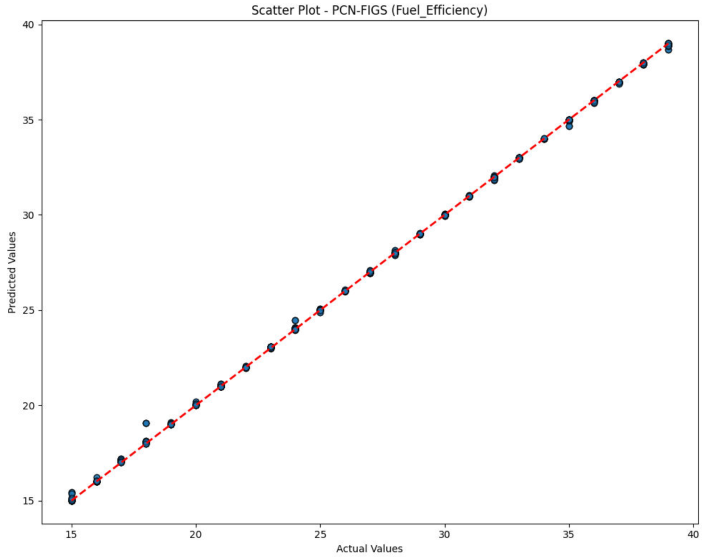

Fig. 6: Obtained scatter plot of Fuel Efficiency from PCN-FIGS.

Fig. 6 PCN-FIGS – The scatter plot represents PCN-FIGS Regressor predictions, showing points very close to the ideal line. This indicates high predictive accuracy, leveraging advanced feature representation and the combined PCN-FIGS architecture to minimize prediction errors.

Prediction Results

Condition	Battery_Range	Braking_Performance	Comfort_Rating	Emissions	Acceleration	Suspension_Performance	Tire_Condition	Driver_Experience	Scenario_Adaptability	Prediction
	NaN	170	6	150	6	6	Worn	Novice	6	Poor
	NaN	193	8	286	9	8	New	Novice	5	Poor
	NaN	110	9	272	6	8	Worn	Novice	2	Well-maintained
	NaN	191	8	268	5	5	New	Intermediate	7	Moderate wear
	NaN	109	9	178	7	8	Worn	Novice	3	Poor
	NaN	159	7	226	9	5	Flat	Expert	2	Poor
	NaN	188	6	261	5	8	Flat	Expert	5	Well-maintained
	NaN	150	9	260	5	8	Worn	Novice	3	Well-maintained
	NaN	146	8	225	9	6	New	Expert	3	Poor
	NaN	122	9	168	6	8	Flat	Novice	4	Poor
	NaN	121	9	177	7	8	Worn	Expert	6	Well-maintained
	NaN	176	8	295	5	9	Flat	Expert	2	Well-maintained

(a)

Prediction Results

Condition	Battery_Range	Braking_Performance	Comfort_Rating	Emissions	Acceleration	Suspension_Performance	Tire_Condition	Driver_Experience	Scenario_Adaptability	Prediction
	NaN	170	6	150	6	6	Worn	Novice	6	Medium
	NaN	193	8	286	9	8	New	Novice	5	Low
	NaN	110	9	272	6	8	Worn	Novice	2	Medium
	NaN	191	8	268	5	5	New	Intermediate	7	High
	NaN	109	9	178	7	8	Worn	Novice	3	High
	NaN	159	7	226	9	5	Flat	Expert	2	Medium
	NaN	188	6	261	5	8	Flat	Expert	5	Medium
	NaN	150	9	260	5	8	Worn	Novice	3	Medium
	NaN	146	8	225	9	6	New	Expert	3	Low
	NaN	122	9	168	6	8	Flat	Novice	4	Low
	NaN	121	9	177	7	8	Worn	Expert	6	Low
	NaN	176	8	295	5	9	Flat	Expert	2	Low
	NaN	156	8	170	6	9	New	Expert	6	High
	NaN	113	7	152	9	7	Flat	Intermediate	4	High

(b)

Prediction Results

Condition	Battery_Range	Braking_Performance	Comfort_Rating	Emissions	Acceleration	Suspension_Performance	Tire_Condition	Driver_Experience	Scenario_Adaptability	Prediction
	NaN	170	6	150	6	6	Worn	Novice	6	404.000
	NaN	193	8	286	9	8	New	Novice	5	266.845
	NaN	110	9	272	6	8	Worn	Novice	2	244.000
	NaN	191	8	268	5	5	New	Intermediate	7	373.000
	NaN	109	9	178	7	8	Worn	Novice	3	488.000
	NaN	159	7	226	9	5	Flat	Expert	2	158.000
	NaN	188	6	261	5	8	Flat	Expert	5	163.760
	NaN	150	9	260	5	8	Worn	Novice	3	241.000
	NaN	146	8	225	9	6	New	Expert	3	450.000
	NaN	122	9	168	6	8	Flat	Novice	4	361.015
	NaN	121	9	177	7	8	Worn	Expert	6	458.790
	NaN	176	8	295	5	9	Flat	Expert	2	307.715

(c)

Prediction Results

Condition	Battery_Range	Braking_Performance	Comfort_Rating	Emissions	Acceleration	Suspension_Performance	Tire_Condition	Driver_Experience	Scenario_Adaptability	Prediction
	NaN	170	6	150	6	6	Worn	Novice	6	35.000
	NaN	193	8	286	9	8	New	Novice	5	26.020
	NaN	110	9	272	6	8	Worn	Novice	2	15.000
	NaN	191	8	268	5	5	New	Intermediate	7	21.000
	NaN	109	9	178	7	8	Worn	Novice	3	29.000
	NaN	159	7	226	9	5	Flat	Expert	2	17.000
	NaN	188	6	261	5	8	Flat	Expert	5	32.065
	NaN	150	9	260	5	8	Worn	Novice	3	39.000
	NaN	146	8	225	9	6	New	Expert	3	16.000
	NaN	122	9	168	6	8	Flat	Novice	4	33.005
	NaN	121	9	177	7	8	Worn	Expert	6	36.935
	NaN	176	8	295	5	9	Flat	Expert	2	36.920
	NaN	156	8	170	6	9	New	Expert	6	22.995

(d)

Fig. 7: Predictions on Test Data. (a) Vehicle Condition, (b) Performance Optimization, (c) Engine Performance, (d) Fuel Efficiency.

Fig. 7 the prediction module of the system presents the outputs generated by the trained models on unseen test data. It allows users to visualize and analyze the effectiveness of each model across different target variables, providing a clear comparison of predicted versus actual values. The interface integrates both classification and regression results, supporting a comprehensive understanding of vehicle performance.

Fig. 7 (a) Vehicle Condition – Displays predicted vehicle conditions for test samples using Ridge, Huber, SLIM, and PCN-FIGS models. Users can compare predicted classes with actual conditions such as Poor, Moderate wear, and Well-maintained.

Fig. 7 (b) Performance Optimization – Shows predictions of performance optimization ratings (Low, Medium, High) for the test dataset, reflecting the models' ability to evaluate overall vehicle efficiency.

Fig. 7 (c) Engine Performance – Presents regression outputs for engine performance scores, enabling comparison between predicted and true sensor-based performance metrics. Scatter plots or tables highlight prediction accuracy across models.

Fig. 7 (d) Fuel Efficiency – Displays predicted fuel efficiency values for test vehicles. This allows assessment of each model's capability in estimating fuel economy accurately based on input features such as engine type, driving conditions, and vehicle attributes.

Table 1: Classification Metrics for Vehicle Condition

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Ridge	41.5	41.29	41.5	41.36
Huber	33.25	11.24	33.25	16.8
SLIM	34.88	12.16	34.88	18.04
PCN-FIGS	100.0	100.0	100.0	100.0

Table 1 presents the performance of different models in classifying vehicle conditions. Among the four models, Ridge achieved moderate accuracy of 41.5%, with precision and recall closely matching its accuracy, indicating balanced performance. Huber and SLIM showed lower overall classification capabilities, with Huber particularly underperforming in precision (11.24%). In contrast, PCN-FIGS achieved perfect scores across all metrics, demonstrating its superior ability to correctly classify vehicle conditions without errors. The results highlight a clear distinction between traditional regression-based models and the PCN-FIGS model. Overall, PCN-FIGS dominates in both reliability and predictive accuracy.

Table 2: Classification Metrics for Performance Optimization

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Ridge	38.88	39.5	38.88	38.84
Huber	29.5	46.01	29.5	13.6

SLIM	37.38	13.97	37.38	20.34
PCN-FIGS	100.0	100.0	100.0	100.0

Table 2 evaluates model effectiveness for performance optimization tasks. Ridge maintained moderate performance with 38.88% accuracy, while Huber and SLIM exhibited lower accuracy and inconsistent precision and recall values, reflecting instability in prediction. PCN-FIGS again achieved perfect scores across all metrics, emphasizing its robustness and superior classification capability. The gap between conventional models and PCN-FIGS suggests that advanced architectures capture complex patterns more effectively. These results indicate PCN-FIGS is highly suitable for performance optimization classification scenarios.

Table 3: Regression Metrics for Engine Performance

Model	MAE	MSE	RMSE	R^2-Score
Ridge	89.8615	10677.1383	103.3302	0.0031
Huber	89.8628	10718.9074	103.5322	-0.0008
SLIM	89.8230	10662.1524	103.2577	0.0045
PCN-FIGS	0.8771	5.6404	2.3749	0.9995

Table 3 compares the regression performance of models for predicting engine performance. Ridge, Huber, and SLIM produced very high MAE, MSE, and RMSE values, indicating substantial prediction errors, with R^2 values close to zero or slightly negative, showing poor explanatory power. In contrast, PCN-FIGS achieved near-zero MAE, minimal MSE, and a very low RMSE, along with an R^2 of 0.9995, indicating almost perfect prediction accuracy. The table demonstrates the superior ability of PCN-FIGS to model nonlinear relationships in engine performance. Traditional regression models failed to capture the complex dependencies inherent in the data.

Table 4: Regression Metrics for Fuel Efficiency

Model	MAE	MSE	RMSE	R^2-Score
Ridge	6.0555	51.1921	7.1549	-0.0164
Huber	6.0920	52.5722	7.2507	-0.0438
SLIM	6.1091	51.6152	7.1844	-0.0248
PCN-FIGS	0.0552	0.0169	0.1300	0.9997

Table 4 highlights the models' ability to predict fuel efficiency. Ridge, Huber, and SLIM yielded similar MAE and RMSE values around 6 and 7, respectively, with negative R^2 scores, reflecting inadequate predictive performance. PCN-FIGS again achieved near-perfect results, with extremely low MAE and RMSE and an R^2 of 0.9997, showing excellent agreement with actual fuel efficiency values. The table underscores the model's exceptional generalization and precision for regression tasks. It clearly illustrates that PCN-FIGS outperforms conventional regression techniques in capturing complex patterns in fuel efficiency data.

5. CONCLUSION

The proposed intelligent vehicle performance evaluation and condition monitoring system successfully integrates advanced ML techniques within a web-based Django framework. The system efficiently handles both classification and regression tasks, including Vehicle Condition, Performance Optimization, Engine Performance, and Fuel Efficiency. Experimental results demonstrate that the novel PCN-FIGS model significantly outperforms conventional algorithms like Ridge, Huber, and SLIM, achieving near-perfect accuracy in classification and R^2 values close to 1 in regression. The platform provides comprehensive functionalities such as EDA, model comparison, and both single and batch predictions. Role-based access control ensures secure and tailored analytics for corporate and general users. Overall, the system provides a scalable, reliable, and user-friendly solution for real-time vehicle performance prediction, reducing dependency on manual inspection and enabling data-driven decision-making.

REFERENCES

[1] Betterton, R. Average Cost of Car Maintenance: 2024 Estimates. Bankrate. Available online: https://www.bankrate.com/loans/auto-loans/average-car-maintenance-costs/ (accessed on 14 January 2025).

[2] Baluch, A.C.A. How Much Car Maintenance Costs in 2025. Available online: https://insurify.com/car-insurance/knowledge/car-maintenance-costs/ (accessed on 14 January 2025).

[3] Consumer Price Index for All Urban Consumers: Motor Vehicle Parts and Equipment in U.S. City Average (CUUR0000SETC) | FRED | St. Louis Fed. Available online: https://fred.stlouisfed.org/series/CUUR0000SETC (accessed on 14 January 2025).

[4] Your Driving Costs 2024: How Much Does It Really Cost to Own a New Car? Available online: https://newsroom.aaa.com/wp-content/uploads/2024/09/YDC_Fact-Sheet-FINAL-9.2024.pdf (accessed on 14 January 2025).

[5] Selvaraj, A.; Venkatachalam, D.; Sunder Singh, J.T. Advanced Telematics and Real-Time Data Analytics in the Automotive Industry: Leveraging Edge Computing for Predictive Vehicle Maintenance and Performance Optimization. J. Artif. Intell. Res. Appl. 2023, 3, 581–622.

[6] Anaissi, A.; Khoa, N.L.D.; Rakotoarivelo, T.; Alamdari, M.M.; Wang, Y. Smart Pothole Detection System Using Vehicle-Mounted Sensors and Machine Learning. J. Civ. Struct. Health Monit. 2019, 9, 91–102.

[7] Egaji, O.A.; Evans, G.; Griffiths, M.G.; Islas, G. Real-Time Machine Learning-Based Approach for Pothole Detection. Expert Syst. Appl. 2021, 184, 115562.

[8] Jang, J.; Yang, Y.; Smyth, A.W.; Cavalcanti, D.; Kumar, R. Framework of Data Acquisition and Integration for the Detection of Pavement Distress via Multiple Vehicles. J. Comput. Civ. Eng. 2017, 31, 04016052.

[9] Celaya-Padilla, J.M.; Galván-Tejada, C.E.; López-Monteagudo, F.E.; Alonso-González, O.; Moreno-Báez, A.; Martínez-Torteya, A.; Galván-Tejada, J.I.; Arceo-Olague, J.G.; Luna-García, H.; Gamboa-Rosales, H. Speed Bump Detection Using Accelerometric Features: A Genetic Algorithm Approach. Sensors 2018, 18, 443.

[10] Hornyák, O. Data-Driven Engine Health Monitoring with AI. *Eng. Proc.* 2024, *79*, 39. https://doi.org/10.3390/engproc2024079039.

[11] Behnamfar, M.; Stevenson, A.; Tariq, M.; Sarwat, A. Vehicle Position Detection Based on Machine Learning Algorithms in Dynamic Wireless Charging. *Sensors* 2024, *24*, 2346. https://doi.org/10.3390/s24072346.

[12] Zhan, Q.; Ding, Y.; Lei, T.; Yin, X.; Wei, L.; Liu, Y.; Luo, Q. Abnormal Pavement Condition Detection with Vehicle Posture Data Considering Speed Variations. *Sensors* 2024, *24*, 4555. https://doi.org/10.3390/s24144555.

[13] Mahiyudin, G.; Hussain, M.; Dewi, D.D. A Comprehensive Study on Predicting the Need for Vehicle Maintenance Using Machine Learning. *Eng. Proc.* 2025, *107*, 89. https://doi.org/10.3390/engproc2025107089.

[14] Yuan, D.; Tang, L.; Yang, X.; Xu, F.; Liu, K. Explainable Machine Learning Prediction of Vehicle CO_2 Emissions for Sustainable Energy and Transport. *Energies* 2025, *18*, 5408. https://doi.org/10.3390/en18205408.

[15] Doikin, A.; Korsunovs, A.; Campean, F.; García-Afonso, O.; Agostinelli, E. ML-Based Control Strategy for PHEV Under Predictive Vehicle Usage Behaviour. *Vehicles* 2025, *7*, 23. https://doi.org/10.3390/vehicles7010023.