International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper

A Data-Centric Model for Analyzing Driving Efficiency of Electric Buses Around Stops

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Abstract: Eco-driving practices are essential for minimizing energy usage and emissions in electric public transportation systems. Traditional evaluation methods predominantly depend on human criteria or constrained statistical indicators, which inadequately represent intricate driving behaviors in proximity to bus stops. This study examines the ecological driving performance of electric buses during stop entry and exit situations through data-driven analysis. Natural driving datasets were developed for both stages, encompassing operational, kinematic, and behavioral attributes captured from electric buses during standard service intervals. Data preprocessing entailed the elimination of missing values and duplicates, succeeded by feature engineering via Pearson correlation analysis with associated p-values, multicollinearity mitigation through variance inflation factor evaluation, and stepwise forward regression for the selection of representative variables. Various machine-learning classifiers, such as Random Forest, Gradient Boosting, and LightGBM, were employed, with optimized pipelines featuring recursive feature reduction and Min–Max scaling. Advanced ensemble and boosting models, including XGBoost and a Voting Classifier, were also created. Performance was assessed utilizing accuracy, precision, recall, F1-score, and ROC–AUC metrics. Experimental results indicate that XGBoost attains the highest overall performance, achieving an accuracy of 89.0% and a ROC–AUC of 0.944, surpassing all baseline models across both datasets, but the Voting Classifier exhibits enhanced discrimination capabilities. Additionally, explainability was achieved with LIME and SHAP, while a Flask-based framework was utilized to facilitate real-time prediction and visualization. The suggested framework enhances the accuracy of eco-driving assessments and facilitates interpretable decision-making for intelligent bus operation systems.

***"Index Terms:** Energy consumption, Driver behavior, Vehicles, Biological system modeling, Predictive models, Mathematical models, Motors, Machine learning, Roads, Radio frequency".*

1. INTRODUCTION

The swift electrification of public transportation has established electric buses as a crucial element of sustainable urban mobility, owing to their capacity to diminish greenhouse gas emissions, noise pollution, and reliance on fossil fuels [1]. In addition to technological progress in battery systems and powertrains, operational elements like driving behavior have become essential factors influencing real-world energy efficiency [2]. Urban bus operations present intricate challenges for drivers due to frequent stops, congested traffic, and diverse road conditions, especially during station entry and exit phases [3]. These phases entail recurrent acceleration, deceleration, and low-velocity maneuvers, rendering them disproportionately impactful on total energy consumption and vehicle performance [4].

While previous studies have thoroughly examined eco-driving principles and energy management in electric vehicles, a significant portion of the current literature has focused on vehicle-centric approaches or comprehensive trip-level evaluations [5]. Such methodologies frequently neglect the detailed behavioral traits of drivers in particular high-stakes operational contexts, especially at bus stops [6]. The lack of specific evaluation frameworks for these stages hinders the systematic quantification of ecological driving levels and the differentiation between energy-efficient and inefficient driving patterns [7]. Thus, a gap persists in comprehending how driver behavior during station ingress and egress directly influences energy variability and how this behavior may be objectively assessed within a cohesive framework [8].

This project aims to establish an eco-driving level evaluation model specifically designed for electric buses at stops. The main aim is to examine the correlation between driver behavior and energy consumption during station entry and exit, and to create a systematic evaluation framework that reflects the influence of behavior on energy efficiency [9]. The study aims to deliver a more precise and behavior-focused evaluation of ecological driving performance by highlighting driver–vehicle–road interactions during these crucial phases, thus facilitating the identification of energy-efficient driving traits without depending on particular control methods or computational processes.

This innovation is significant for its potential to improve energy efficiency and operational sustainability in electric bus systems. An effective evaluation model for eco-driving behavior can enhance driver training, facilitate performance feedback systems, and aid in developing ecologically sustainable operating plans for public transport operators [10]. The proposed framework provides practical value within the context of intelligent transportation systems and sustainable mobility by integrating behavioral analysis with energy efficiency, thereby assisting cities in minimizing operational costs and environmental impact while ensuring safe and reliable public transit services.

2. LITERATURE REVIEW

Prior research has extensively recognized the impact of driving behavior on energy consumption and emissions in electric and hybrid vehicles. Vignati et al. established that aggressive driving behaviors markedly elevate energy consumption and CO_2 emissions, underscoring the significance of behavioral elements in conjunction with vehicle technology [11]. Zhang et al. developed a driving style categorization model for bus stop scenarios, demonstrating that the phases of entering and departing stops display unique energy consumption patterns in contrast to cruising operations [12]. Zhang et al. examined real-world electric bus data and established that acceleration intensity, braking behavior, and speed fluctuation significantly influence energy variability [13]. Although these studies yield significant empirical insights, they primarily focus on classification or correlation analysis and give minimal support for a thorough evaluation of eco-driving levels.

Preliminary fundamental research investigated the factors between driving behavior and energy use. Huang et al. measured the influence of various driving behaviors on electric vehicle energy consumption, thereby building a theoretical foundation for behavior-oriented energy analysis [14]. Younes et al. examined many contributing elements, such as speed profiles and driver inputs, demonstrating the intricate relationship between human behavior and vehicle efficiency [15]. Meseguer et al. presented a mobile platform for the characterization of driving behaviors and fuel consumption, illustrating the viability of extensive behavioral data collecting [16]. Notwithstanding their methodological advantages, these studies predominantly focus on general driving circumstances and conventional vehicles, providing insufficient specificity for electric buses and critical operational stages such station entry and leave.

Recent studies have increasingly focused on the formal assessment of eco-driving competencies. Zavalko employed an energy-based methodology to evaluate eco-driving competencies and the efficacy of training for truck operators, demonstrating that systematic assessment can facilitate behavioral enhancement [17]. Liu et al. devised and validated an eco-driving evaluation model, establishing a systematic framework for analyzing ecological driving performance [18]. Nevertheless, these methodologies primarily emphasize overall driving performance across excursions, neglecting the examination of specific micro-scenarios. The distinctive behavioral traits and energy ramifications of low-speed, stop-related operations in electric buses are inadequately addressed.

Supplementary research has concentrated on estimating energy consumption and doing system-level analysis. Zhang and Yao provided methodologies for assessing electric vehicle energy consumption in real driving settings, enhancing the precision of energy assessment models [19]. Lajunen performed an extensive energy and cost-benefit analysis of hybrid and electric urban buses, highlighting the operational benefits of electrified public transportation [20]. Although these studies improve comprehension of energy utilization at the systemic level, they offer less information into the assessment of driver behavior. This project seeks to create an eco-driving level evaluation framework for electric buses during station entry and exit, addressing behavioral analysis and energy efficiency in critical operational contexts.

3. MATERIALS AND METHODS

The proposed approach intends to assess eco-driving levels of electric buses during stop entrance and exit maneuvers through supervised machine learning applied to naturalistic driving data obtained from actual electric bus operations. The dataset includes

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ISSN: 3070-0515 www.zesterapublications.com Original Research Paper

kinematic, operational, and behavioral characteristics that define stop-related maneuvers. A systematic procedure is implemented, in which data quality assurance and partitioning are conducted generically, succeeded by statistically informed feature optimization. Pearson correlation analysis with significance testing, variance inflation factor analysis, and Recursive Feature Elimination are utilized collectively to discover a relevant and non-redundant subset of features. Advanced ensemble learning models, such as Random Forest, Gradient Boosting, LightGBM, XGBoost, and a Voting Classifier, are constructed to improve resilience and generalization. Model-agnostic explainability with LIME and SHAP enhances interpretability, while a Flask-based deployment framework facilitates real-time user engagement. The system provides dependable, transparent, and scalable eco-driving evaluations for advanced electric bus applications.

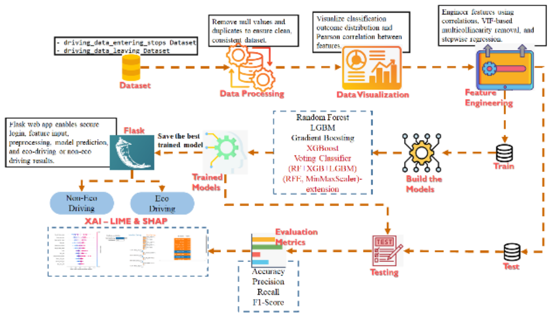

Fig.1 Proposed Architecture

The suggested system architecture amalgamates real-world driving datasets with a systematic machine learning workflow. The method encompasses data preprocessing, visualization, and feature engineering, succeeded by the training of ensemble classification models. Model evaluation guarantees performance dependability, while deployment through Flask and XAI tools facilitates interpretable, real-time measurement of eco-driving levels.

a) Dataset Collection:

This study employs the driving_data_entering_stops dataset sourced from a publicly accessible research library dedicated to eco-driving analysis. The dataset consists of 271 samples with 29 normalized features that encompass speed profiles, acceleration, deceleration, jerk, braking behavior, and temporal driving characteristics. Each occurrence is categorized into two groups denoting eco-driving and non-eco-driving behaviors, exhibiting a fairly equal class distribution. The dataset's comprehensive kinematic attributes and balanced labels render it ideal for training and assessing machine learning models aimed at predicting eco-driving behavior during bus stop entry procedures.

	Maximum_speed	Minimum_speed	Average_speed	Std_speed	Mean_nonzero_speed	Std_nonzero_speed	Max_brake_pedal	Min_brake_pedal	Avg_brake_pedal	Std_brake_pedal	...	Std_neg_acc	Max_jerk	Min_jerk	Avg_abs_jerk
0	0.316183	0.740276	0.868887	-1.394123	1.064180	-0.629878	-0.254723	-1.632775	-0.849689	-1.390675	...	0.737280	-0.422747	-0.460192	0.061495
1	-1.628355	-0.414130	1.142579	-0.575629	1.723715	1.075331	-0.811054	0.430636	-1.152236	0.701722	...	0.813566	-1.034398	-0.478039	1.189018
2	1.727586	-0.579845	2.758635	0.575507	-0.590587	0.695565	0.442258	1.121306	0.909728	1.202290	...	-0.790249	0.421140	0.193077	-0.598618
3	0.101851	0.876853	0.874750	0.543660	0.739403	0.845151	0.886660	0.527754	0.922205	0.495744	...	1.790583	-0.059027	0.770512	1.099708
4	-0.986882	0.538491	0.898507	1.739884	1.452667	-1.802557	-0.118663	-0.299504	-0.911231	-1.490169	...	-0.023336	-0.389153	0.704573	-0.230260

5 rows × 29 columns

Fig.2 Driving Data Entering

This study utilizes the driving_data_leaving dataset sourced from a publicly accessible research resource dedicated to the examination of eco-driving behavior. The collection comprises 271 samples characterized by 29 standardized parameters, encompassing speed statistics, acceleration and deceleration patterns, jerk measurements, pedal utilization, and temporal driving proportions. Each sample is categorized into eco-driving and non-eco-driving classes, exhibiting a fairly balanced distribution. The dataset's extensive kinematic representation and balanced classes render it ideal for dependable machine learning evaluation of eco-driving behavior in bus stop departure scenarios.

	Maximum_speed	Minimum_speed	Average_speed	Std_speed	Mean_nonzero_speed	Std_nonzero_speed	Max_acc_pedal	Min_acc_pedal	Avg_acc_pedal	Std_acc_pedal	...	Std_neg_acc	Max_jerk	Min_jerk	Avg_abs_jerk
0	0.316183	0.740276	0.868887	-1.394123	1.064180	-0.629878	-0.254723	-1.632775	-0.849689	-1.390675	...	0.737280	-0.422747	-0.460192	0.061495
1	-1.628355	-0.414130	1.142579	-0.575629	1.723715	1.075331	-0.811054	0.430636	-1.152236	0.701722	...	0.813566	-1.034398	-0.478039	1.189018
2	1.727586	-0.579845	2.758635	0.575507	-0.590587	0.695565	0.442258	1.121306	0.909728	1.202290	...	-0.790249	0.421140	0.193077	-0.598618
3	0.101851	0.876853	0.874750	0.543660	0.739403	0.845151	0.886660	0.527754	0.922205	0.495744	...	1.790583	-0.059027	0.770512	1.099708
4	-0.986882	0.538491	0.898507	1.739884	1.452667	-1.802557	-0.118663	-0.299504	-0.911231	-1.490169	...	-0.023336	-0.389153	0.704573	-0.230260

5 rows × 29 columns

Fig.3 Driving Data leaving

b) Pre-Processing:

The preprocessing phase guarantees data integrity, feature significance, and statistical validity via cleaning, analysis, and selection processes, establishing a dependable basis for precise and generalizable eco-driving behavior prediction models.

Data Cleaning and Integrity Verification: This stage guarantees the dataset's quality and dependability by scrutinizing absent and redundant records. The study verified the lack of null values and duplicate entries, demonstrating strong dataset integrity. Eliminating inconsistencies mitigates biased learning, diminishes noise, and enhances model generalization. Index reinitialization guarantees accurate data alignment for ensuing operations. This stage is essential for ensuring consistency and preventing distorted statistical correlations, thereby building a reliable basis for precise feature analysis and predictive modeling.

Categorical Attribute Verification: The dataset was analyzed to ascertain the existence of categorical variables necessitating encoding or modification. The study indicated that all features were numerical, hence obviating the necessity for categorical preprocessing. This streamlines the modeling pipeline and mitigates superfluous transformations that may result in redundancy or information loss. Ensuring uniform numeric data facilitates effective correlation analysis and regression-based feature selection, allowing for the direct use of statistical methods while maintaining the original semantic significance of driving behavior indicators.

Class Distribution Analysis: An analysis of class distribution was performed to assess the balance of labels between eco-driving and non-eco-driving occurrences. The dataset displayed a roughly same quantity of samples in both classes, hence reducing classification bias. Equitable class representation is crucial for impartial model training, averting the predominance of one class over another. This equilibrium improves forecast accuracy, stabilizes assessment metrics, and minimizes the necessity for resampling methods, therefore maintaining the dataset's inherent structure and authentic driving behavior patterns.

Data Visualization: Visualization was employed to depict class-wise sample distribution and to facilitate an intuitive comprehension of dataset composition. Graphical representation aids in detecting potential imbalances, verifying dataset preparedness, and effectively conveying data attributes. These visual insights facilitate the early identification of distorted distributions and enhance transparency in data processing. This approach enhances interpretability and offers a visual confirmation of dataset appropriateness for supervised classification tasks in predicting eco-driving behavior.

Correlation Analysis for Feature Relevance: A Pearson correlation analysis was conducted to assess the strength and direction of the correlations between individual driving features and the target variable. This step determines the features that substantially impact the classification of driving behavior. Comprehending feature significance aids in diminishing dimensionality, discarding ineffective predictors, and enhancing model interpretability. Correlation-based analysis guarantees that selected features provide significant information, thus improving learning efficiency and minimizing processing demands while preserving prediction accuracy.

Statistical Significance-Based Feature Filtering: Feature selection was enhanced using statistical significance testing by concurrently evaluating correlation strength and probability values. Features surpassing established correlation thresholds and demonstrating substantial statistical significance were omitted to prevent repetition. This stage mitigates the risk of overfitting and guarantees the retention of only informative, non-dominant variables. Integrating statistical rigor enhances model robustness and guarantees that the chosen feature subset generalizes efficiently to novel data while maintaining critical driving behavior patterns.

Feature Selection: A forward stepwise selection method was utilized to systematically find traits that significantly enhance explanatory power. This approach systematically assesses attributes according to their aggregate impact on predictive accuracy. It guarantees an ideal equilibrium between model simplicity and efficacy. Stepwise selection diminishes dimensionality, augments interpretability, and precludes the incorporation of extraneous variables, resulting in efficient learning and enhanced stability in regression-based prediction models.

Multicollinearity Removal Using Variance Analysis: Variance-based analysis was utilized to find highly correlated predictors in order to mitigate multicollinearity among selected features. Features surpassing acceptable variance levels were eliminated to guarantee model stability. Mitigating multicollinearity averts exaggerated coefficient estimates and improves numerical reliability. This phase enhances interpretability and guarantees that each maintained feature provides distinct information, resulting in more robust and generalizable predictive models.

c) Training and Testing:

The finalized dataset was partitioned into training and testing subsets to objectively assess model

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performance. Isolating unseen data guarantees an impartial evaluation of generalization ability. This measure mitigates information leakage and facilitates rigorous confirmation of forecast accuracy. A fixed split ratio ensures consistency across experiments, facilitating valid model comparisons and guaranteeing that learnt patterns represent genuine eco-driving behavior instead of just recollection of training data.

d) Algorithms:

Random Forest: Random Forest is an ensemble classification technique that consolidates predictions from numerous decision trees to improve accuracy and resilience. By employing random sampling of features and examples, it mitigates overfitting, captures intricate feature interactions, and provides consistent generalization across varied operating conditions.

$$Gini = 1 - \sum_{i=1}^{C} (Pi)^2 \quad (1)$$

Light Gradient Boosting Machine (LGBM): Light Gradient Boosting Machine is a gradient boosting system that incrementally constructs decision trees to minimize classification errors. The leaf-wise growth technique and quick learning procedure facilitate robust prediction performance, scalability, and adept modeling of nonlinear interactions in intricate data.

Gradient Boosting: Gradient Boosting is an iterative ensemble method that amalgamates weak learners to reduce prediction errors via continuous enhancement. By concentrating on residual errors at each phase, it enhances accuracy, diminishes bias, and attains dependable generalization in high-dimensional feature spaces.

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x) \quad (2)$$

XGBoost: XGBoost is an enhanced gradient boosting algorithm that improves predicting accuracy via regularized tree ensembles. Its effective learning technique, parallel processing ability, and overfitting regulation mechanisms provide strong performance and flexibility under diverse operational settings.

$$\hat{y}_i = \sigma\left(\sum_{k=1}^{K} f_k(x_i)\right), f_k \in F \quad (3)$$

Voting Classifier (RF, XGB, LGBM): The vote Classifier amalgamates various ensemble models by consolidating their predictions by majority vote. This cooperative approach harmonizes the strengths of separate models, mitigates volatility, and enhances classification stability, resulting in consistent and dependable outputs for intricate decision-making tasks.

$$\hat{y} = argmax_c\left(\sum_{i=1}^{n} II\ (\hat{y}_i = c)\right) \quad (4)$$

e) Integration of XAI and Flask Framework:

To improve the interpretability and transparency of eco-driving prediction models, Explainable Artificial Intelligence (XAI) approaches, such as LIME and SHAP, were incorporated. LIME was employed to produce localized explanations for specific predictions, emphasizing the impact of each attribute on the classification result. SHAP offered both global and local interpretability by measuring feature significance across many instances, facilitating the depiction of how driving characteristics affect eco-driving level predictions. This integration enables users and researchers to comprehend model behavior, validate decision logic, and discern the most significant factors influencing energy-efficient or non-eco-driving behavior.

The taught machine learning models were implemented via a Flask-based web framework to offer an interactive user experience. Users may enter real-time or previous driving data and obtain immediate estimates of eco-driving levels, along with explanations given by explainable artificial intelligence (XAI). The seamless integration of model deployment and interpretability guarantees accessibility, usefulness, and transparency, facilitating informed decision-making and practical adoption of energy-efficient driving evaluation tools for electric bus operations.

4. EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test refers to its capacity to correctly distinguish between patient and healthy cases. To assess the accuracy of a test, one must compute the ratio of true positives and true negatives across all assessed cases. This can be expressed mathematically as:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} (5)$$

Precision: Precision assesses the proportion of accurately classified cases among those identified as positive. Consequently, the formula for calculating precision is expressed as:

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$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} (6)$$

Recall: Recall is a metric in machine learning that assesses a model's capacity to recognize all pertinent instances of a specific class. It is the ratio of accurately predicted positive observations to the total actual positives, offering insights into a model's efficacy in identifying occurrences of a specific class.

$$Recall = \frac{\text{TP}}{\text{TP } + \text{ FN}} (7)$$

F1-Score: The F1 score is a metric for evaluating the accuracy of a machine learning model. It amalgamates the precision and recall metrics of a model. The accuracy metric quantifies the frequency of true predictions generated by a model throughout the entire dataset.

$$F1\ Score = 2 * \frac{Recall \text{ X } Precision}{Recall + Precision} * 100 (8)$$

AUC-ROC Curve: The AUC-ROC Curve is a metric for evaluating classification performance across different threshold levels. ROC plots the True Positive Rate versus the False Positive Rate. The AUC measures the model's overall capacity to differentiate across classes, with a higher AUC signifying superior model performance.

$$AUC = \sum_{i=1}^{n-1} (FPR_{i+1} - FPR_i) \cdot \frac{TPR_{i+1} + TPR_i}{2} \quad (9)$$

Table.1 Performance Evaluation Table – Dataset 1

ML Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random Forest	0.829	0.829	0.829	0.829	0.915
LGBM	0.476	0.226	0.476	0.307	0.500
Gradient Boosting	0.854	0.855	0.854	0.854	0.925
XGBoost	**0.890**	**0.893**	**0.890**	**0.890**	**0.944**
Voting Classifier	0.854	0.855	0.854	0.854	0.951

Table 1 compares machine learning models based on Accuracy, Precision, Recall, F1-Score, and ROC-AUC. XGBoost exhibits superior performance with the greatest metrics, whilst LGBM demonstrates the lowest overall efficacy.

Table.2 Performance Evaluation Table – Dataset 2

ML Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random Forest	0.829	0.833	0.829	0.829	0.950
LightGBM (LGBM)	0.476	0.226	0.476	0.307	0.500
Gradient Boosting	0.841	0.844	0.841	0.842	0.949
XGBoost	**0.890**	**0.893**	**0.890**	**0.890**	**0.944**
Voting Classifier	0.878	0.882	0.878	0.878	0.951

Table 2 assesses machine learning models based on Accuracy, Precision, Recall, F1-Score, and ROC-AUC. XGBoost demonstrates superior overall performance, whereas LGBM exhibits the worse results across all metrics.

Fig.4 Comparison Graph – Dataset 1

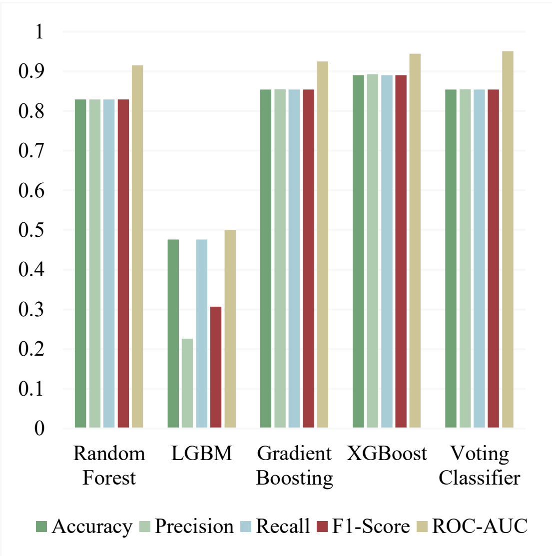

Figure 4 presents a comparative graph illustrating Accuracy, Precision, Recall, F1-Score, and ROC-AUC for five machine learning models. XGBoost

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consistently excels in the majority of measurements, whereas LGBM has inferior performance across all evaluation criteria.

Fig.5 Comparison Graph – Dataset 2

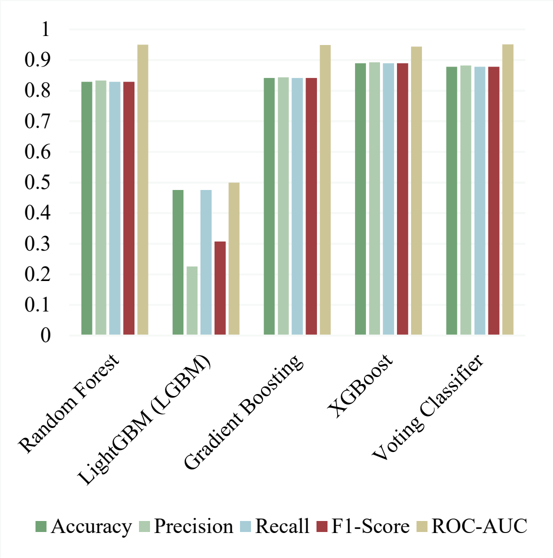

Figure 5 presents a comparative graph depicting Accuracy, Precision, Recall, F1-Score, and ROC-AUC for five machine learning models. XGBoost demonstrates superior performance overall, whereas LightGBM consistently exhibits inferior results across all criteria.

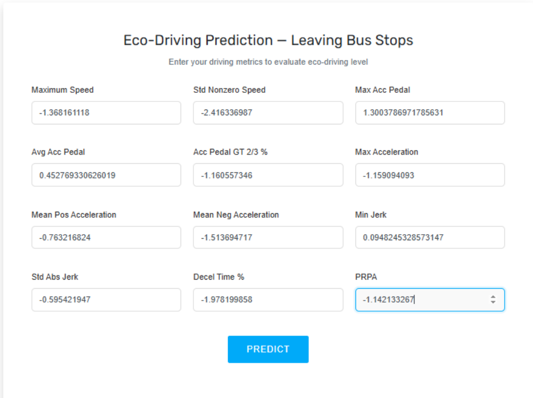

Fig.6 Enter the input Data

Figure 6 illustrates the input interface that enables users to input eco-driving parameters about speed, acceleration, braking, and jerk to forecast eco-driving behavior when departing from bus stops.

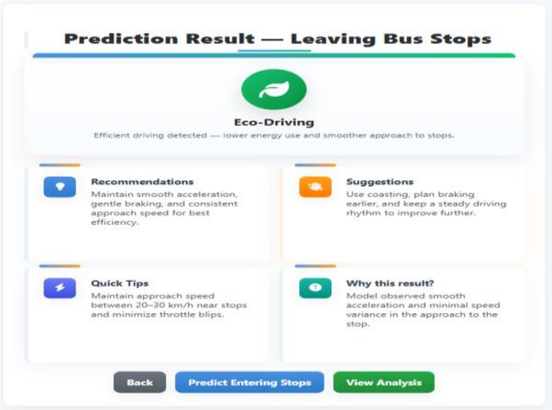

Fig.7 Predicted Result

Figure 7 displays the output screen identifying the projected outcome as Eco-Driving, signifying economical driving behavior characterized by reduced energy usage and smoother acceleration upon departing from bus stops.

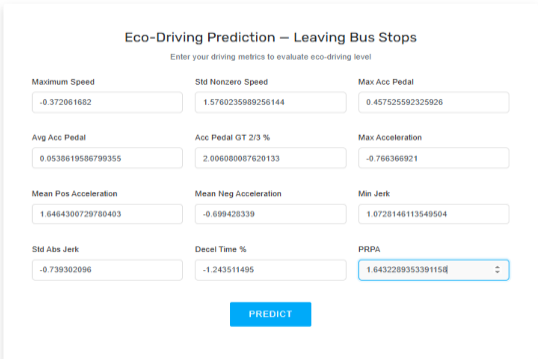

Fig.8 Enter the input Data

Figure 8 displays the input panel that takes information relating to speed, acceleration, jerk, braking, and pedal usage for eco-driving predictions during departures from bus stops.

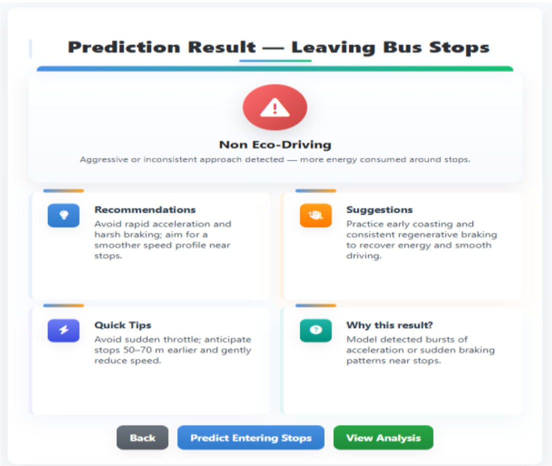

Fig.9 Predicted Result

Figure 9 illustrates the outcome of Non Eco-Driving forecast, signifying aggressive or erratic driving behavior accompanied with increased energy usage when departing from bus stops.

5. CONCLUSION

In conclusion, the main aim of this system was to accurately assess the eco-driving behavior of electric buses during stop entry and exit scenarios to promote energy-efficient and sustainable public transportation operations. This was accomplished by utilizing natural driving datasets that include operational, kinematic, and behavioral characteristics gathered from actual electric bus services. A systematic approach was employed that combined statistical feature analysis methods, including correlation evaluation and multicollinearity management, with machine learning classifiers such as Random Forest, Gradient Boosting, and LightGBM to predict intricate driving behaviors. Advanced ensemble learning was integrated as an upgrade via boosting and voting procedures, facilitating enhanced discrimination and robustness. The experimental assessment of standard performance criteria validated the system's efficacy, with the XGBoost model attaining a peak accuracy of 89.0%, exhibiting enhanced predictive performance relative to baseline models across both datasets. Furthermore, explainability was enhanced by including model-agnostic interpretation methods, while practical application was facilitated by a streamlined deployment framework for real-time prediction. The developed system delivers a dependable, interpretable, and automated solution for evaluating eco-driving levels, providing essential decision support for the intelligent management of electric buses and aiding in the reduction of energy consumption and promotion of environmentally sustainable transportation practices.

Future improvements may concentrate on integrating larger and more varied datasets encompassing varying routes, traffic situations, and driving behaviors to better model robustness and generalization. Incorporating real-time car sensor data along with external variables such as traffic density, road grade, and weather conditions can enhance the precision of eco-driving assessments. Advanced deep learning architectures and online learning processes can be investigated to dynamically adapt to changing driving patterns. Furthermore, implementing the technology into digital transportation platforms facilitates ongoing monitoring and driver feedback, hence promoting proactive energy management and sustainable electric bus operations on a large scale.

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