Eco-Driving Level Evaluation Model for Electric Buses Entering and Leaving Stops

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Abstract— Sustainable driving is a crucial driver to optimise energy use and emissions in electric public transport. But the current evaluation approaches mostly depend on human assessment or poor statistical parameters which do not adequately reflect complex driving activities around bus stops. The purpose of this effort is to evaluate an electric bus' ecological driving level during stop entry and exit via data-driven intelligence. We developed natural driving datasets for both phases with operational, kinematic and behavioral parameters of electric buses during their normal service time. In this study, the preprocessing of the data included removal of missing data, duplicate data, feature engineering from the Pearson correlation analysis with a p-value, multicollinearity removal via variance inflation factor assessment, and stepwise forward regression for selecting representative variables of the data. Several machine-learning classifiers such as RF, Gradient Boosting and LightGBM were introduced and improved pipelines such as recursive feature elimination and Min-Max scaling were utilized. We also developed sophisticated combination/boosting models such as XGBoost and Voting Classifier. The accuracy, precision, recall, F1-score and ROC–AUC were used to assess the performance of the performance. Performance of Experimental models that were tested on both datasets, shows that XGBoost surpassed all the baseline models with an accuracy of 89.0% and ROC–AUC of 0.944 while Voting Classifier excelled in terms of discrimination potential. Furthermore, we implemented explainability through LIME and SHAP, and the real-time prediction and visualization have been achieved by a flask-based framework. The proposed framework improves the accuracy of eco-driving evaluation and facilitates the intelligently interpretable decision making for intelligent bus operation system.

Keywords: Energy consumption, Driver behavior, Vehicles, Biological system modeling, Predictive models, Mathematical models, Motors, ML, Roads, Radio frequency.”

1. INTRODUCTION

With the fast growth of public transportation electrification, electric buses have emerged as a vital measure to reduce fossil fuel consumption and lower greenhouse gas emissions, noise pollution, and fossil fuel consumption in urban regions. However, operational influences, particularly driving behavior, are significant in the energy efficiency in real world applications as well as advances in battery development and powertrain technologies.In addition to developments in battery and powertrain technologies, operational considerations, primarily driving behavior, have an important contribution to make to real world energy efficiency [2]. Electric buses are used in difficult situations in the metropolitan area, such as kinds of traffic jams, traffic congestion and different road problems [3]. Of these, the repetitive acceleration, deceleration and low speed manoeuvres at the entry and exit of each station are especially important as they are a significant factor for total energy consumption and vehicle performance [4].

Eco-driving strategies and energy management of EVs have been well studied, but most existing research is either at the vehicle level or trip level [5]. These approaches usually ignore micro-driving behaviors and driving styles for high impact operational situations, especially when approaching a bus stop [6]. When deciding whether to enter or exit the station, there is no standardized way to measure the level of ecological driving and differentiate efficient from inefficient practices vigorously adopted by people [7]. Thus, the knowledge of the role of driver behaviours in these stages on the energy variability and how they may be objectively evaluated in a common framework are still missing [8].

To overcome this gap, the present work introduces an evaluation methodology of eco-driving level at the stops for electric buses. It reviews the effects of driving behavior and energy consumption on station entry and exit and introduces a formal framework which captures the effect of driving behaviors on efficiency [9]. In this study, by analysing the interactions between the driver, the vehicle and the road system in these critical phases, an assessment of ecological driving performance is made without concentrating on the specific driving measures.

This work contributes positively to the energy consumption and operation sustainability improvement in electric bus systems. The proposed model can be useful for training of drivers, feedback and operational strategies to make the transport system more polluting and economical, and finally, to offer safe and reliable public transport services [10].

2. Related Work

The relationship of driving behavior to energy consumption and emissions in EVs has been well documented in prior studies. Vignati et al. demonstrated that aggressive driving is a major factor affecting energy consumption and CO_2 emissions, highlighting the importance of behavioural aspects apart from vehicle technology [11]. Zhang et al. constructed a driving style classification algorithm for the bus stop entering and exiting scenario based on the bus stop situations, and demonstrated that bus stop situations consist of two phases (entering and exiting bus stops), which have different energy consumption patterns than they do during cruising operations [12]. Likewise, Zhang et al. analysed the real-world energy consumption information of electric buses and came out with the conclusion that the intensity of accelerating, braking operation, and speed fluctuation are the major sources of energy [13]. Though these studies provide valuable empirical knowledge, they are mostly limited to classification or correlation analysis and only limited support of a comprehensive assessment of eco-driving levels.

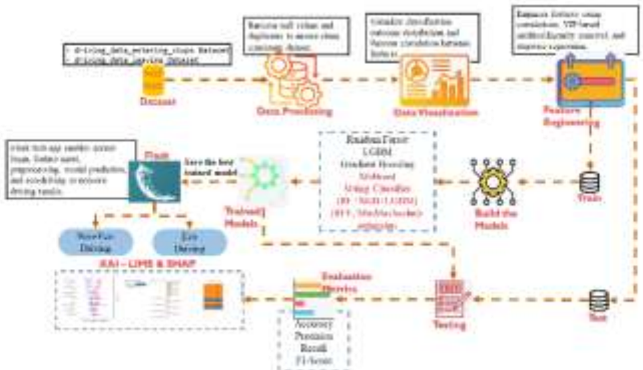
Through more detailed basic research, the impact of driving behavior on energy consumption was investigated. Huang et al. gave a theoretical framework for behavior-oriented energy analysis and evaluated the impact of various driving methods on energy consumption of EVs [14]. The work done by Younes et al. investigated numerous other scenarios related to human behaviour and vehicle efficiency including speed profiles and driver inputs; highlighting the complexity of the relationship between these two [15]. Meseguer et al. [16] designed a mobile platform for driving behavior and fuel consumption characterization and demonstrated its ability to gather huge quantities of behavioral data. Although these studies offer methodological benefits, they seem to be primarily applicable to generic driving scenarios and conventional vehicles, rather than specific situations and impacts for electric buses and critical operations like on-board station access and disembarkation.

Recently, some efforts have been devoted to a systematic evaluation of an eco-driving skill. Structured evaluation has been proved-effective in the improvement of behavior, as Zavalko [17] showed by assessing and testing the degree of eco-driving skill and training effectiveness of the truck drivers using an energy-based approach. Liu et al. [18] built and tested the eco-driving assessment model and gave a systematical framework for eco-driving assessment. They measure overall driving performance over journeys, however, rather than single key micro-scenarios. Therefore, it remains unclear how special behavioral patterns and energy effects are in electric buses when driving at reduced speed or at a standstill.

Complementary studies have been made for estimation of energy consumption, and for a whole system analysis. Zhang and Yao gave solutions to the estimation of energy consumption of electric vehicles in real driving conditions, which made the energy assessment models more accurate [19]. Lajunen [20] made a thorough study on Energy and Cost–Benefit of Hybrid and Electric city buses with special emphasis on operational benefits of electrified public transport. These works elucidate the knowledge of the energy use at a system level, but give limited insight into driver behaviour evaluation. In response to these limitations, the present work aims at developing an eco-driving level evaluation framework for electric buses for high impact operating scenarios such as station entry/exit, between behavioral analysis and energy efficiency evaluation.

3. Materials And Methods

In this paper, we introduce a system to evaluate the "Eco-driving" levels of electric buses within the stop entrance and exit operations, by leveraging supervised machine learning algorithms on naturalistic driving data gathered from electric bus deployments in the real world. The data provides kinematic, operating and behavioral attributes of maneuvers performed in the process of stopping. We employ a disciplined methodology, which generally involves data quality assurance, partitioning and statistically-based feature optimization. Then we use jointly Pearson correlation analysis with significance testing, variance inflation factor analysis and Recursive Feature Elimination to select an informative and non-redundant subset of features. Advanced ensemble learning models like Random Forest, Gradient Boosting, LightGBM, XGBoost and a Voting Classifier are created to enhance the resilience and generalization of the models. Explainability is model agnostic and achieved using LIME and SHAP and interpretability is further enhanced using a Flask based deployment framework that allows real-time user engagement. It offers a solid, easy and scalable eco-driving evaluation for smart electric bus applications.



"Fig. 1. System Architecture"

Incorporating real-world driving datasets with a structured ML pipeline is suggested as a system design for this. Topics in scope include data preparation, visualization, feature engineering and ensemble (classification models). Through model evaluation, performance reliability and implementation into XAI and Flask tools for interpretable real-time eco-driving level assessment are guaranteed.

A) Dataset Collection

The data in this research was taken from a public research resource for the purpose of eco-driving analysis: driving_data_entering_stops. This data set contains 271 samples, 29 normalized characteristics that represent speed profiles, acceleration, deceleration, jerk, braking behavior, and temporal driving behavior. There are two classes of eco-driving and non-eco-driving behaviors for each case. Class size distribution is nearly even. The balanced labelling of the data and richness in the kinematic properties make it an appropriate data set for training and testing of ML algorithms for the prediction of the eco-driving behaviour in bus stop entrance 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	1.039708
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"

The dataset in this study is from a publicly available research resource called driving_data_leaving. The collection consists of 271 samples, with 29 defined parameters such as speed statistics, deceleration/acceleration patterns, jerk parameters, temporal driving proportions, and pedal usage. The samples are classified, and a balanced proportion of them is labelled as eco-, and non-eco driving. The dataset presented low class imbalance and a comprehensive kinematic representation of the situations, which makes it highly suited for accurate evaluation of eco-driving behavior during bus stop departure situations by means of ML.

	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	-0.629678	-0.254723	-1.632775	-0.849689	-1.390675	...	0.737280	-0.422747	-0.460192	0.061495
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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	1.039708
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 Entering"

B) Pre-Processing

Finally, in the preprocessing stage, data cleaning, analysis, and selection are performed to ensure data quality as well as the relevance of the features and the statistical robustness of the data, ensuring that the data are useful for the development of eco-driving behavior prediction models that are valid and accurate.

Data Cleaning and Integrity Verification: This stage is to explore missing data and duplicated data to ensure that the data is good quality and trusted. It was observed that the data does not have any missing values and duplicate data in the study, hence indicating good data integrity. Removing inconsistencies helps to avoid biased learning and decreases noise and enhances model generalization. The index is reset to ensure proper alignment of the data for future use. This stage allows a consistency that is very important to avoid distorted statistical correlations, so as to give a reliable basis for a reliable feature analysis and forecasting.

Categorical Attribute Verification: The data are analysed to see if there are categorical attributes that require encoding or transformations. The analysis revealed a set of all numerical characteristics, thus there was no need for any categorical preprocessing. It makes modelling process easier and prevents any unnecessary transformation that can cause redundancy or loss of information. This makes it possible to calculate uniformly coded numbers that can be used for correlation analysis, in an efficient manner, and for feature selection using regression analysis, while at the same time maintaining the semantic meaning of the original driving behavior indications.

Class Distribution Analysis: The class distribution was investigated to show an equal distribution of labels for the eco-driving and non-eco-driving occurrences. To avoid classification bias, the dataset was almost equally split between both classes. Additionally, make sure that there is a balanced distribution of classes in the model otherwise it will be unfairly trained because of one class dominating the other. This balance increases the reliability of the prediction and provides a more stable assessment metrics and excludes the need for re-sampling processes, thus preserving the natural characteristics of the data set and real world driving behaviour patterns.

Data Visualization: The distribution of each sample in each class was presented using visualization, and also the intuitive understanding of the data structure in constructing data was performed. Graphical information gives a sense of possible imbalance, prepareness for data, and provides explanations of data characteristics. These visualizations can lead to early detection of skewed distributions and higher transparency in the processing of data. This can improve the interpretability and provide a visual check of the suitability of the datasets to supervised classification problems for the prediction of eco-driving behavior.

Correlation Analysis for Feature Relevance: To measure the amount and direction of intercorrelations among the driving features and the target variable, a Pearson correlation analysis was performed. In this step, features are selected which are found to be playing important role in the classification of the behavior of driving. The knowledge of feature relevance can be helpful in dimensionality reduction, discarding weak predictors and better interpretability of the model. Using correlation analysis, the features selected will include relevant information that will not only increase the learning efficiency and reduce the calculation workload, but also maintain the accuracy that can be predicted.

Statistical Significance-Based Feature Filtering: Next, a statistical significance testing was performed in order to further reduce the number of selected features based on both the correlation strength and the probability values. Cross-correlated, redundant and statistically significant features (above set thresholds) were removed. This stage reduces the chances of over-fitting and preserves only informative (non-dominant) variables. The statistical rigor integration helps to make the model robust and also to ensure that the subset of features selected to the model generalize well to unknown data while retaining the key driving behavior patterns.

Feature Selection: A forward stepwise selection procedure was repeated in order to identify those features whose contribution to the explanatory power is highest. This method uses individual features to be evaluated based on their performance for the overall prediction task. It provides a best trade-off between the simplicity of model and the performance. Stepwise selection reduces the dimensionality, increasing interpretability and avoiding entry of irrelevant variables to create efficient learning and stable predictive frameworks with regression.

Multicollinearity Removal Using Variance Analysis: Variance-based analysis was used to detect the multicollinearity among the selected parameters and determining the highly associated predictors. To ensure the stability of the model the features above the accepted variance criteria were discarded. Coefficients can get over-estimated because of multicollinearity; reducing the multicollinearity increases the numerical stability. This step added to models makes them more predictable and ensures that all the features chosen contain new information, which in turn creates stronger and more universal predictive models.

C) Training and Testing:

The final refined data set was then divided into training data and testing data to assess the model performance in an objective manner. This is ensured by the unobserved nature of the data separation and ensures a fair assessment of the generalization capability. This helps prevent information leakage, and it generates a powerful method for checking how well the forecasts are working. The fix split ratio guarantees uniformity of the tests, which guarantees reliable comparisons between the models, and avoids the models learning patterns from their training set because of memorization.

D) Algorithms

RF: RF is an ensemble based classification technique, which aggregates the predictions from many decision tree models to increase the accuracy and robustness. It avoids overfitting by randomly choosing features and instances, it is able to catch complicated feature relationships, and it generalizes equally well in varying operating conditions.

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

Light Gradient Boosting Machine (LGBM): LGBM is a sequential gradient boosting system which is used to generate DT to reduce the classification errors. This unique leaf-wise growth method and its rapid learning rate provides excellent power of prediction, scaling abilities and representational power of non-linear relationships in complex data sets.

Gradient Boosting: GB is an ensemble technique that takes advantage of weak learners repeatedly, and aims to minimize the prediction error in subsequent steps. Emphasize the residual errors at every stage: gives increased accuracy, less bias and more reliable generalization in high dimensional feature spaces.

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

XGBoost: XGBoost is an extension of gradient boosting with the aim of improving the prediction accuracy by using regularized tree ensembles. It provides powerful learning capability, parallel processing and overfitting control, which allows for high-performance and adaptability to different operational conditions.

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

Voting Classifier (RF, XGB, LGBM): This is a combination of several ensemble models, using the maximum voting among them. The technique integrates the best of each model and reduces variability and enhances the stability of categorical decision making, providing reliable and consistent outcomes in complex decision making.

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

E) Integration of XAI and Flask Framework:

For the purpose of making the eco-driving prediction models more interpretable and transparent, XAI methods like LIME and SHAP were applied. We used LIME for single predictions to build local explanations that show the importance of each characteristic for the prediction result. To provide interpretability at both the global and local levels, SHAP computed the relevance of a feature with respect to each example, obtaining the impact of these driving parameters on the eco-driving level predictions. This combination helps users understand the model behavior, helps to validate the decision logic and helps to identify the most influential driving characteristics that lead to energy-efficient or non-eco driving behavior.
The learned ML models were deployed using a Flask based web framework to give an interactive user experience. Real-time or historical driving data can be entered and projections of eco-driver levels can be obtained straight away, with explanations provided by XAI. This is a seamless deployment of models and interpretability that ensure accessibility, usability and transparency, enabling optimal decision-making and implementation of energy-efficient driving evaluation tools for electric bus operations.

4. EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test refers to its capacity to appropriately identify patient and healthy instances. The percentage of true positive and true negative cases in all analyzed measures is used to measure the accuracy of a test. mathematically written as this:

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

Precision: Number of correctly predicted positive cases / Number of actual positive cases. Thus, the formula to calculate the precision is provided as:

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

Recall: Recall is a ML measure of how well a model is able to identify all instances that belong to a class. It's the proportion of positive samples that predict positive out of all the positive samples. It gives an idea of how well a model can capture all the instances of a particular class.

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

F1-Score: F1 score is one of the statistics used in ML to evaluate the accuracy of the model. This is the combination of model precision score and recall score. Accuracy statistic: the number of times a model was correct on the entire data set.

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

AUC-ROC Curve: AUC-ROC Curve is a statistic to measure the performance of the classification task at multiple thresholds. ROC plots FPR on the X-axis against TPR on the Y-axis. The total ability of the model to differentiate different classes is indicated by the AUC with a larger AUC indicating better model performance.

$$\text{AUC} = \sum_{i=1}^{n-1} (\text{FPR}_{i+1} - \text{FPR}_i) \cdot \frac{\text{TPR}_{i+1} + \text{TPR}_i}{2} \quad (9)$$

“Table. 1. Performance Evaluation Table – Dataset 1”

ML Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
RF	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

The comparison of ML models based on accuracy, precision, recall, F1-score and ROC-AUC are presented in the Table.1. Overall LGBM has the poorest performance, while XGBoost has the highest metrics and outperforms the other models.

“Table.2 Performance Evaluation Table – Dataset 2”

ML Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
RF	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

The Table.2 presents a comparison of the ML models with respect to Accuracy, Precision, Recall, F1-Score and ROC-AUC. Overall, XGBoost is the best performing model, while among all models LGBM performs worst on all measures.

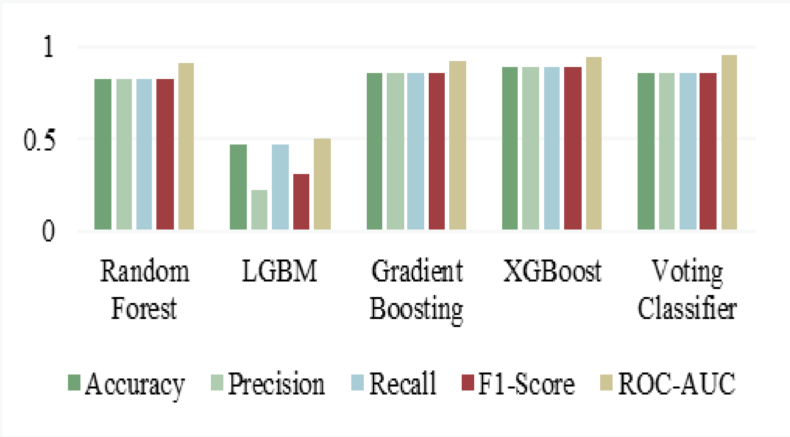

Fig. 4. Comparison Graph – Dataset 1"

This graph Fig.4 compares the performances of five ML models and their measures; namely the accuracy, precision, recall, f1 score and ROC-AUC. XGBoost has the best performance under most parameters while LGBM has the worst performance under all evaluation measures.

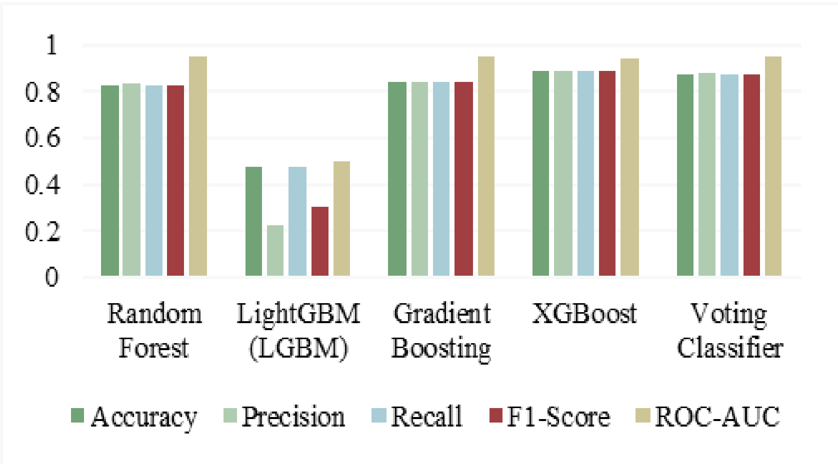

Fig. 3. Comparison Graph – Dataset 1

The comparison graph given in Fig.5 depicts Accuracy, Precision, Recall, F1-Score and ROC-AUC of five ML models. XGBoost is the best in terms of performance while LightGBM is consistently the lowest in all criteria.

Fig.6 Enter the input Data

The input interface (see figure 6) enables the user to input eco-driving data on vehicle speed, acceleration, braking and jerk to predict eco-driving behavior upon leaving bus stop.

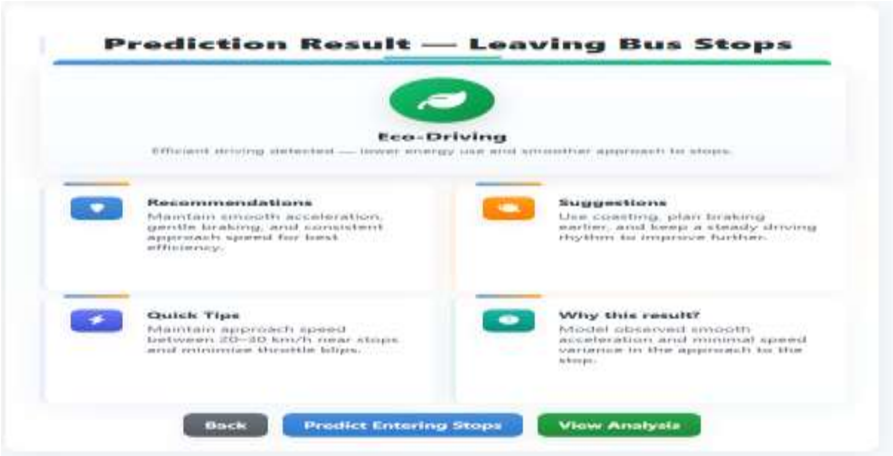

Fig.7 Predicted Result

As can be seen in Fig.7, the output screen shows the expected effect of the driving behaviour of Eco-Driving; the driving behaviour is economic and has a reduced energy consumption as well as a smoother acceleration on departure from bus stops.

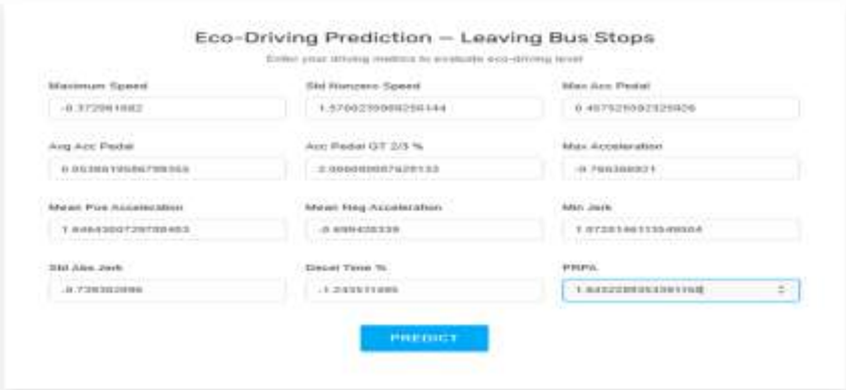

Fig.8 Enter the input Data

The input data panel of speed, acceleration, jerk, braking and pedal information for eco-driving prediction outside bus stops is presented in Fig.8.

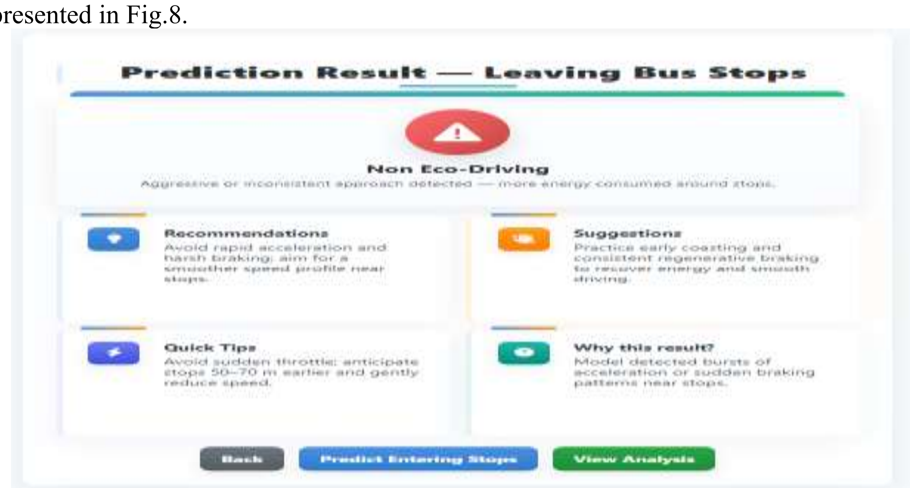

Fig.9 Predicted Result

In Fig.9, Output is predicting Non Eco-Driving which would be the case of aggressive or inconsistent driving, leading towards higher energy consumption in leaving the bus stop.

5. Conclusion

To summarize, the main purpose of this system was to effectively evaluate the eco-driving behavior of electric buses in the entrance and departing stop scenarios to promote energy-efficient and sustainable public transportation operations. In doing so, natural driving data consisting of operational, kinematic and behavioral data was obtained from actual public bus trips for the electric buses. A linear statistical feature analysis methodologies (correlation analysis and multi-collinearity control) followed by ML classifiers (RF, Gradient Boosting and LightGBM) have been used to build models for predicting complex driving patterns. Boosting and voting methods were used for more accurate classification and robustness, as an advance over advanced ensemble learning. The experimental results using standard test measures for system efficiency showed that the system is efficient and for both datasets the XGBoost model resulted in more effective predictions with an accuracy of 89.0% from the baseline models. Additionally, model-agnostic interpretation techniques were added to improve explainability and a light-weight deployment framework was provided to facilitate practicality for real-time prediction. Overall, the developed system provides a reliable, explainable, and automatic method for EWL evaluation within electric buses for use as a valuable decision support system for intelligent electric bus drive, thereby helping to decrease energy consumption and environmentally friendly transportation.

Future improvements may involve merging bigger and more diverse data sets for various roads, traffic situations and driving conditions to enhance the robustness and model's generalizability. Moreover, the accuracy of eco-driving assessment could be further improved if real-time vehicle sensor data and environmental parameters, such as traffic density, road gradient and weather parameters, are also involved. More complex deep learning architectures and on-line learning processes can be explored to dynamically adapt to changing driving patterns. In addition, the system implementation in Intelligent Transportation Systems can enable real-time monitoring and driver input for proactive energy management and sustainable applications of electric buses at scale.

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