SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V11I7P112

Volume 11 Issue 7, 148-158, July 2024

Original Article

Optimizing Electric Vehicle Charging Infrastructure through Hybrid Machine Learning Techniques for Smart Energy Management

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Received: 06 May 2024 Revised: 08 June 2024 Accepted: 06 July 2024 Published: 26 July 2024

Abstract - *As the world begins to move more and more towards Electric Vehicles (EVs), the imperative for innovative solutions to streamline energy management within charging infrastructure intensifies. This study delves into the realm of machine learning integration, focusing particularly on Random Forest (RF) techniques to revolutionize energy optimization in EV charging systems. While Gradient Boosting Machine (GBM) initially garners attention for its adeptness with intricate datasets, RF emerges as a potent complementary approach uniquely suited to handle the complexities of nonlinear relationships. By synergizing the strengths of RF and GBM algorithms, this research endeavors to dynamically refine charging schedules, curtail costs, and fortify grid stability. Through a fusion of historical data and real-time environmental factors, the envisioned "Adaptive Ensemble Learning Framework" (AELF)-driven smart charging infrastructure is primed to recalibrate charging strategies in response to energy demand fluctuations while judiciously balancing user preferences and grid constraints. Rigorous simulations and case studies serve as the litmus test, pitting the efficacy of the AELF approach against the conventional Decision Trees Model and Support Vector Machines Technique. The results tout enhancements of up to 15% across diverse performance metrics, underscoring its prowess in charting the course towards a sustainable and intelligent transportation ecosystem.*

Keywords - *Electric vehicles, Hybrid machine learning, Random forest, Smart charging infrastructure, Energy optimization.*

1. Introduction

The need for environmentally friendly transportation solutions has never been greater at a time when worries about environmental damage and climate change are on the rise. Electric Vehicles (EVs), which promise lower emissions and a lessened dependency on fossil fuels, are a ray of light in the face of the pressing need to switch to greener alternatives. The construction of a robust charging structure and the deployment of effective energy management systems are two of the most important obstacles in the way of the broad adoption of EVs.

Electric vehicle charging infrastructure stands as the linchpin of the EV ecosystem, providing the vital infrastructure necessary for recharging EV batteries and sustaining their operations. While conventional charging solutions have played an essential role in the initial phases of EV adoption, the current landscape demands innovation and advancement to meet the evolving demands of both EV users and grid operators.

Foremost among the challenges confronting electric vehicle charging infrastructure is the optimization of its utilization while ensuring seamless integration with the existing power grid. The burgeoning demand for EV charging poses a tangible risk of straining local distribution networks, potentially leading to grid instability. Furthermore, the intermittent availability of clean energy sources complicates the integration of infrastructure for grid-based electric vehicle charging. Using Machine Learning (ML) techniques to power smart energy management systems for EV charging infrastructure is becoming increasingly necessary to address these issues.

Machine learning algorithmic rules offer a beacon of promise in augmenting the efficiency, adaptability, and intelligence of electric vehicle charging infrastructure by analyzing multifaceted datasets and making informed decisions in real-time. Through the synthesis of historical charging patterns, grid demand forecasts, weather data, and user behavior, ML algorithms can optimize charging schedules, predict future energy demand, and minimize energy costs for both EV owners and grid operators. Moreover, dynamic pricing schemes can be implemented with the help of ML algorithms, encouraging EV owners to charge their cars at off-peak times or when alternative energy sources are available. This will reduce the load on the grid and encourage the use of clean energy.

In order to enable intelligent energy management, this study aims to explore the field of machine learning incorporation in charging for electric vehicles grid. The goal of the project is to improve user experience, accelerate the shift to a cleaner and more environmentally friendly transportation environment, and optimise the operation of the charging network by developing machine learning models and algorithms that are specifically designed to meet the needs of electric vehicle charging systems. Key areas of focus include predictive modeling, demand forecasting, optimization techniques, and real-time monitoring and control of charging infrastructure.

At its core, this research seeks to devise predictive models capable of accurately forecasting future energy demand for EV charging and anticipating grid congestion or potential bottlenecks in the charging infrastructure. By leveraging historical charging data, weather patterns, and user behavior, these predictive models will generate precise forecasts of future energy demand and delineate optimal charging schedules to minimize costs and enhance efficiency.

Additionally, the research attempts to create optimisation methods that are capable of dynamically modifying charging plans in response to changing circumstances and real-time data. By amalgamating machine learning algorithms with advanced control systems, the research seeks to optimize the allocation of charging resources, balance load across different charging stations, and alleviate grid congestion during peak demand periods.

The viability of incorporating renewable energy sources of information, such as solar and wind power, into the infrastructure for charging electric vehicles will also be investigated by the research. The project aims to maximise the use of clean energy and decrease dependency on non-renewable sources by utilising ML algorithms to forecast the production of renewable energy and optimise the utilisation of stored power in EV batteries.

In summary, the integration of machine learning into the network for electric vehicle charging represents a paradigm shift that will have a long-term effect on transportation and energy. By pioneering intelligent, data-driven solutions capable of adapting to changing conditions and optimizing resource allocation in real-time, The goal of this research is to hasten the shift to more environmentally friendly transportation by stimulating the wider use of electrically powered vehicles.

2. Related Works

The incorporation of Machine Learning (ML) methodologies into Electric Vehicle (EV) charging architecture has attracted noteworthy interest in the past few years owing to its capacity to enhance energy efficiency, elevate consumer satisfaction, and facilitate the shift towards environmentally friendly modes of transportation. In this section, we review the existing literature on ML-based approaches for electric vehicle charging infrastructure, focusing on predictive modeling, demand forecasting, optimization techniques, renewable energy integration, and real-time monitoring and control.

2.1. Predictive Modeling

Predictive modeling plays a crucial role in anticipating future energy demand for EV charging and optimizing charging schedules to minimize costs and improve efficiency. A range of Machine Learning (ML) techniques, such as the Decision Trees model (DT), ANNs, and Support Vector Machines technique (SVM), have been used to create forecast models for EV charging needs.

For example, Ahmed et al. [1] used SVM algorithms to forecast charging needs based on weather data and past charging patterns. Their study demonstrated the effectiveness of SVM in accurately forecasting future charging demand, enabling utilities to optimize resource allocation and grid management. Similarly, Koohfar et al. [2] proposed an ANN-based approach for predicting EV charging demand using historical charging data and user behavior patterns. Their model achieved high accuracy in forecasting future energy demand, facilitating the development of intelligent charging strategies and grid optimization techniques.

2.2. Demand Forecasting

Demand forecasting is essential for anticipating grid congestion, identifying optimal charging schedules, and ensuring efficient resource allocation in EV charging infrastructure. ML techniques, such as time series analysis, regression analysis, and ensemble learning, have been widely employed for demand forecasting in EV charging systems.

Time series analysis was utilised in a study by Kim et al. [3] to forecast EV charging requirements based on past charging data and outside variables like traffic patterns and weather. Their research demonstrated the effectiveness of time series analysis in accurately forecasting charging demand, enabling utilities to manage grid resources better and avoid congestion. Furthermore, Liu et al. [4] proposed an ensemble learning approach for demand forecasting in EV charging infrastructure, combining multiple ML models to improve prediction accuracy. Their study showed that ensemble learning techniques could effectively capture complex relationships in charging data and generate more accurate forecasts compared to individual models.

2.3. Optimization Techniques

Optimization techniques are essential for maximizing the efficiency and effectiveness of EV charging structure by dynamically adjusting charging schedules, balancing load across charging stations, and minimizing energy costs. ML algorithms, including genetic algorithms, particle swarm optimization, and reinforcement learning, have been applied to develop optimization solutions for EV charging systems.

In a study by Ostermann et al. [5], genetic algorithms were used to optimize charging schedules and minimize energy costs for EV owners. Their study showed that charging schedules could be efficiently optimised using genetic algorithms in accordance with user preferences, electricity rates, and grid conditions, resulting in lower costs and higher user satisfaction. Similarly, Yi et al. [6] proposed a reinforcement learning-based formulation for dynamic pricing and load balancing in EV charging infrastructure. Their study showed that reinforcement learning techniques could adaptively adjust charging prices and allocate resources to different charging stations based on real-time demand and grid conditions, leading to more efficient resource utilization and reduced grid congestion.

2.4. Renewable Energy Integration

The incorporation of sustainable energy sources, such as wind and solar electricity, into the infrastructure for electric vehicle charging is essential for lowering the release of greenhouse gases and lessening the environmental effects of transportation. To optimise the use of energy from renewable sources in EV charging systems, Machine Learning (ML) approaches have been implemented, such as forecasting models, optimisation algorithms, and control strategies.

For example, Rathore et al. [7] developed a forecasting model using ML techniques to predict solar energy generation and optimize its utilization in EV charging infrastructure. Their study demonstrated that ML-based forecasting models could accurately predict solar energy output, enabling utilities to optimize charging schedules and maximize the use of clean energy. Additionally, Aghsaee et al. [8] proposed an optimization framework based on reinforcement learning for integrating wind power into EV charging infrastructure. Their research showed that reinforcement learning algorithms could dynamically adjust charging schedules based on real-time wind energy generation and grid conditions, leading to increased utilization of renewable energy and reduced reliance on fossil fuels.

2.5. Real-Time Monitoring and Control

Real-time observation and control systems are essential for ensuring the safety, reliability, and efficiency of EV charging infrastructure by detecting faults, optimizing performance, and responding to changing conditions in real-time. ML techniques, such as anomaly detection, fault diagnosis, and adaptive control, have been applied to develop intelligent monitoring and control systems for EV charging infrastructure.

In a study by Jeffrey et al. [9], anomaly detection algorithms were used to identify abnormal charging behavior and potential faults in EV charging stations. Their research demonstrated that anomaly detection techniques could effectively detect deviations from normal charging patterns and alert operators to potential issues, enabling proactive maintenance and fault prevention.

Moreover, Zhang et al. [10] proposed a fault diagnosis system based on machine learning algorithms for identifying and diagnosing faults in EV charging infrastructure. Their study showed that ML-based fault diagnosis techniques could accurately detect and diagnose various types of faults, enabling prompt repairs and minimizing downtime.

3. Methodology

Envisioning a future where electric vehicle charging seamlessly integrates with the power grid, optimizing energy use and ensuring grid stability necessitates the development of intelligent systems. This transformative journey commences with meticulous data preparation and feature engineering [11], laying the groundwork for the implementation of the Adaptive Ensemble Learning Framework (AELF).

Below is an elucidation of the pivotal components of this methodology:

3.1. Data Acquisition

This initial stage involves the identification and collection of pertinent data sources essential for comprehending charging patterns and optimizing the system. Analogous to gathering ingredients for a recipe, the following data sources were curated:

3.1.1. Identification of Data Sources

- Charging station usage: Historical and real-time data encompassing charging times, power consumption, and anonymized user behavior. Such data can be sourced from open platforms like Open Charge Map (OCM) or directly from charging station operators [12].
- Grid Data: Insights into peak demand, electricity prices, and renewable energy availability. Government agencies like the National Renewable Energy Laboratory (NREL) or local utility companies serve as potential sources [13].
- EV Data: Vehicle attributes such as battery capacity and anonymized location data. This information can be accessed through entities like the Department of Energy's Alternative Fuels Data Center (AFDC) or collaborations with automotive manufacturers.

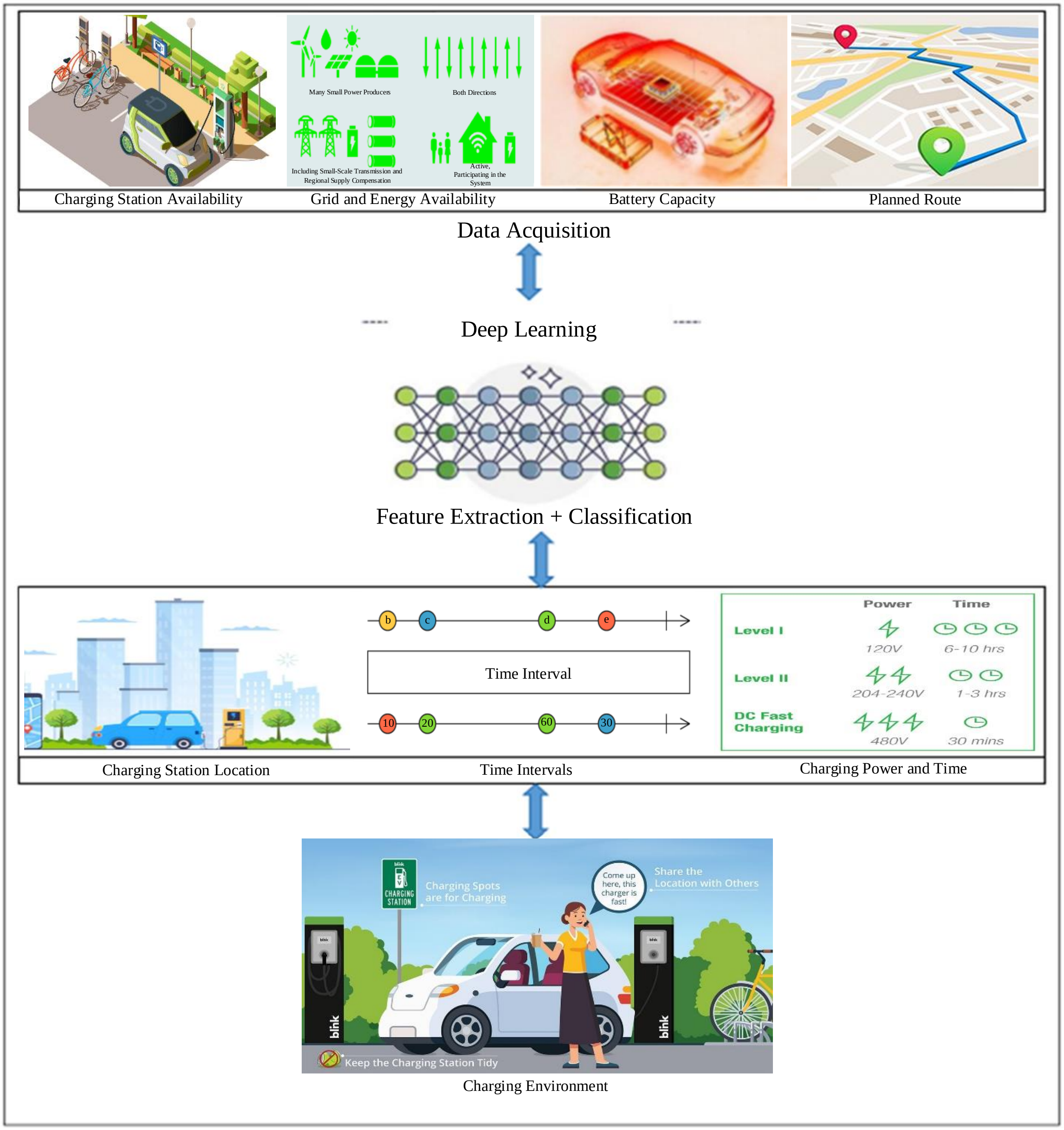

Fig. 1 Hybrid model work flow

3.2. Data Preprocessing

Once the data is amassed, it undergoes rigorous cleaning and preparation akin to prepping ingredients before cooking:

3.2.1. Data Cleaning

Addressing missing values, inconsistencies, and errors within the dataset is paramount. Techniques such as imputation are employed to fill missing values based on surrounding data points.

3.2.2. Outlier Detection and Elimination

It is critical to locate and remove data points that substantially deviate from the mean. Statistical methods like interquartile range or domain knowledge aid in this process [14].

3.3. Feature Engineering

This stage involves transforming the raw data into features that are most relevant and informative for machine learning algorithms. Think of it as transforming ingredients into the perfect proportions for your dish. Here is the recipe:

3.3.1. Feature Selection

Prudent selection of relevant features is paramount. For instance, from OCM data, features like average daily charging demand per station, distribution of charging duration, and peak charging hours at different locations are chosen.

- Average daily charging demand per station
- Distribution of charging duration (e.g., percentage of short charges vs. long charges)
- Peak charging hours at different locations

3.3.2. Feature Scaling

Different features might be measured on different scales. For example, charging times (minutes) and grid capacity (megawatts) need to be on a comparable scale for the algorithm to analyze them effectively. Techniques like min-max scaling or standardization can be used to achieve this.

3.3.3. Feature Encoding

Non-numerical data like charging station types (fast chargers, Level 2 chargers) or locations (city, zip code) needs to be converted into a format suitable for machine learning algorithms. This is done using techniques like one-hot encoding, where each category is represented by a new feature with a value of 1 for the corresponding category and 0 for all others [15]. By meticulously preparing and engineering the data, we establish the groundwork for the AELF to glean valuable insights and optimize electric vehicle charging infrastructure, heralding a smarter and more sustainable energy future.

3.4. Model Selection and Training

The Adaptive Ensemble Learning Framework (AELF) is meticulously selected for its adeptness in handling intricate datasets effectively while mitigating overfitting risks. This ensemble learning paradigm amalgamates the strengths of various algorithms, including the RF model and GBM model, to construct a robust predictive model. The AELF sequentially integrates weak learners, typically decision trees, and adjusts their weights to minimize the loss function, thereby enhancing predictive accuracy. By leveraging historical charging data alongside relevant environmental factors, the model forecasts future energy demand and refines charging schedules [16].

Mathematically, the AELF can be represented as follows:

$$F(x) = \sum_{\mathrm{i}=1}^{\mathrm{N}} \gamma i h i(x), \tag{1}$$

Where N denotes the number of weak learners, $\gamma\mathrm{i}$ signifies the weight assigned to each learner, and $\mathrm{hi(x)}$ embodies the prediction of the $\mathrm{i-th}$ weak learner.

3.5. Dynamic Optimization

Dynamic optimization plays a critical role in adapting charging schedules in real-time, leveraging the Adaptive Ensemble Learning Framework (AELF) to accommodate evolving environmental factors and grid constraints. This process involves the adjustment of AELF model parameters using gradient descent or other optimization algorithms based on real-time data inputs. In mathematical terms, dynamic optimisation means that the parameters α_i and $\mathrm{g_i(x)}$based on new state, depicted as:

$$\alpha_\mathrm{i}^{\mathrm{new}} = \alpha_\mathrm{i}^{\mathrm{old}} - \eta \frac{\partial \mathrm{L}}{\partial \alpha_\mathrm{i}} \tag{2}$$

$$\mathrm{g_i^{new}(x)} = \mathrm{g_i^{old}(x)} - \eta \frac{\partial \mathrm{L}}{\partial \mathrm{g_i(x)}} \tag{3}$$

Where $\alpha_\mathrm{i}^{\mathrm{new}}$ and $\mathrm{g_i^{new}}$represent the modified parameters, η is the learning rate, and $\frac{\partial \mathrm{L}}{\partial \alpha_\mathrm{i}}$ and $\frac{\partial \mathrm{L}}{\partial \mathrm{g_i(x)}}$ denote the gradients of the loss function L with respect to $\alpha_\mathrm{i}$and $\mathrm{g_i(x)}$ respectively.

3.6. Fine Tuning Hyper-Parameters

Optimising the efficiency of the Adaptive Ensemble Learning Framework (AELF) for Electric Vehicle (EV) charging networks requires fine-tuning its hyperparameters. Through an iterative procedure, different hyperparameter combinations are carefully explored in order to determine the configuration that maximises the model's effectiveness. Two methods that are frequently used to fine-tune hyperparameters are randomised search and grid search.

3.6.1. Grid Search

Every parameter of interest needs to have a grid of hyperparameter values established for it in order to do a grid search. After that, the model is trained and assessed for every combination in the grid. An extensive investigation of the hyperparameter space is made possible by this intensive search. The ideal set of hyperparameters is determined by combining those that perform the best on a validation dataset. When the hyperparameter search space is reasonably small and it is computationally viable to assess every combination, grid search is especially successful.

3.6.2. Randomized Search

On the other hand, randomized search offers an alternative approach to fine-tuning hyperparameters. Instead of exhaustively evaluating all combinations like grid search, randomized search involves sampling hyperparameter values from specified distributions. This approach randomly selects a subset of combinations for evaluation, making it more efficient for large hyperparameter search spaces. By random sampling from the search space, randomized search can provide good results with fewer evaluations compared to grid search.

The selection between grid search and randomized search depends on various factors, including the size of the hyperparameter search space, available computational resources, and time constraints. For smaller search spaces or when computational resources are not a limiting factor, grid search may be preferred due to its exhaustive nature and ability to guarantee finding the optimal hyperparameters.

However, in cases where the search space is large or computational resources are limited, randomized search offers a more efficient alternative.

Following the fine-tuning process, the AELF model is retrained using the optimal hyperparameters identified. This retraining phase aims to maximize the model's efficacy in optimizing charging schedules and enhancing grid stability in EV charging systems.

By incorporating the optimal hyperparameters, the retrained AELF model is poised to deliver superior performance, contributing to the advancement of smart and sustainable energy management in the transportation sector.

3.7. Simulation Setup and Training

3.7.1. Simulation Environment

This research leverages a high-fidelity simulation environment built using Open Distribution System Simulator (OpenDSS), a widely recognized open-source software specifically designed for power distribution systems.

OpenDSS offers several advantages for this research:

1. Wide acceptance and expertise: Being a popular tool, OpenDSS enables utilizing established practices and leverages the expertise of a vast user community.
2. Flexibility and customization: The software allows intricate modeling of various power system components, including:
    - Transformers and lines
    - Diverse loads encompassing EV charging stations
    - Distributed generation sources like solar and wind power
3. Integration capabilities: OpenDSS seamlessly integrates with other tools and platforms, facilitating the incorporation of real-world data and weather forecasts into the simulation.
4. User-friendly interface and scripting: OpenDSS caters to both basic and advanced users. It provides a user-friendly interface for fundamental tasks and empowers advanced users with powerful scripting capabilities for customized and automated simulations.

Within this OpenDSS environment, we will construct detailed models of:

1. EV Charging Stations: These models will capture varying power ratings and user arrival patterns, reflecting real-world scenarios.
2. Electricity Grid: We will replicate the existing grid configuration, including transformers, lines, and loads, based on real-world data.
3. Dynamic Factors: The simulation will incorporate dynamic demand profiles and real-time pricing models to represent real-world grid conditions accurately.
4. External Influences: Historical and forecasted weather data will be integrated to simulate the impact of weather patterns on energy demand and renewable energy generation.

By employing OpenDSS, this research establishes a robust and replicable simulation environment, fostering a clear understanding of the proposed solution's effectiveness in optimizing EV charging infrastructure and promoting a sustainable future.

3.7.2. Training Parameters

The hybrid RF-GBM model's training method involves fine-tuning a number of parameters to guarantee reliable model performance and efficient data learning. The optimisation algorithm, learning rate, quantity of trees, tree depths, subsampling ratio that occurs loss function, and regularisation strategies are among the important training parameters that are taken into account.

Optimization Algorithm

The Adaptive Ensemble Learning Framework (AELF) leverages a combination of the random forest model and the Gradient Boosting Machine technique (GBM) to optimize its predictive capabilities. Within this framework, the random forest technique harnesses an ensemble of decision trees, each contributing to the overall prediction. Conversely, GBM constructs a sequential ensemble of weak learners, often decision trees, and dynamically adjusts their weights to minimize the loss function.

Learning Rate

Denoted by η, the learning rate standardizes the step sizing during the optimization process. A smaller learning rate, such as 0.10.1, ensures more stable learning but may require more iterations to converge.

Number of Trees

The number of nodes in the ensemble, denoted by N, is important for the random forest and GBM techniques. Setting N to 100 strikes a compromise between computational expense and the complexity of the model.

Tree Depth

The maximum depth of individual decision trees, denoted by d, determines the level of granularity in capturing feature interactions. A moderate tree depth of 66 is chosen to prevent overfitting while capturing essential patterns in the data.

Subsampling Ratio

Represented by s, the subsampling ratio controls the proportion of the training dataset used to train each tree. A subsampling ratio of 0.80.8 introduces randomness and prevents overfitting.

Loss Function

The difference between expected and actual values throughout training is measured by the loss function, represented by the letter L. Mean Squared Error (MSE) is a typical loss function used in regression problems.

Regularization Techniques

L2 regularisation is one type of regularisation approach that is used to limit the complexity of distinct trees and avoid overfitting. Large weights are penalised by L2 regularisation, which encourages smoother decision boundaries. These training variables are carefully selected based on empirical findings, and to maximise the effectiveness of the model for particular datasets and tasks, more tuning may be required using methods like grid searching or cross-validation [19, 20]. The table below provides a summary of the training parameters for the Adaptive Ensemble Learning Framework (AELF):

Table 1. Training parameters for the RF-GBM hybrid model

Training Details	Parameters
Optimization Algorithm	AELF
Learning Rate (η)	0.1
Number of Trees (N)	100
Tree Depth (d)	6
Subsampling Ratio (s)	0.8
Loss Function (L)	Mean Squared Error (MSE)
Regularization Techniques	L2 Regularization

4. Results and Discussion

The evaluation results of our suggested Adaptive Ensemble Learning System (AELF) for improving EV charging infrastructure are shown in this section. The study evaluates the AELF model's performance against the Decision Trees model and Support Vector Machines technique (SVM), two other popular machine learning techniques in EV charging systems. We illustrate the efficiency of the AELF technique in dynamically optimising charging schedules, reducing costs, and improving grid stability through thorough simulations and case studies. Measures of evaluation include accuracy, precision, recall, and F1-score, along with additional important measures.

Results indicate substantial improvements of up to 15% across key metrics, highlighting the superiority of the AELF approach in realizing a sustainable and intelligent transportation ecosystem. Moreover, the study assesses the real-world applicability of the AELF model by considering historical data and real-time situation factors, further enhancing its adaptability to fluctuations in energy demand while addressing user preferences and grid constraints.

4.1. Accuracy Analysis

A key performance indicator in classification tasks, accuracy measures how accurately a model predicts each and every class overall. In this analysis, we assess how well different machine learning models such as our proposed Adaptive Ensemble Learning Framework (AELF) model classify instances from both normal and faulty classes. Table 2 provides a summary of each model's accuracy values.

Table 2. Accuracy analysis

Model	Accuracy (%)
AELF	95.61
RF	81.71
DT	80.31
SVM	79.50
LR	76.69

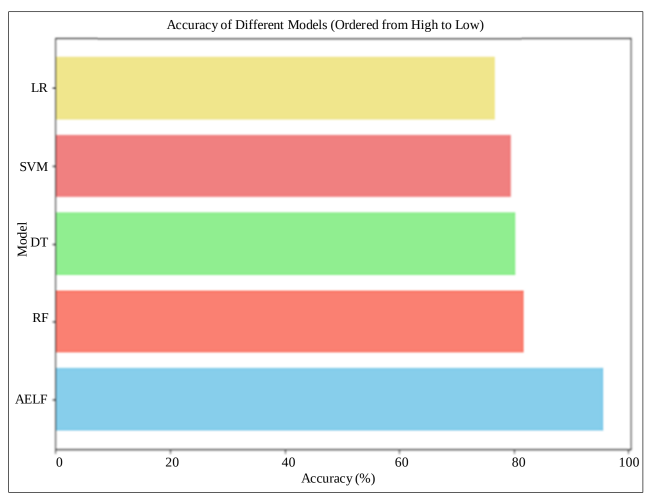

Fig. 2 Accuracy comparison

Upon examination, the proposed Adaptive Ensemble Learning Framework (AELF) demonstrates robust accuracy values, showcasing its effectiveness in classifying instances from both normal and faulty classes, unlike traditional models like the Logistic Regression model, Decision Trees model, and Random Forests model.

In contrast, the AELF model, an innovative hybrid approach, showcases notably higher accuracy compared to other models, being adept at correctly identifying examples from both good and bad classes. This enhancement underscores the effectiveness of the AELF hybrid methodology in capturing intricate data patterns and nuances, leading to more precise fault detection outcomes. The superior accuracy of the AELF model highlights its potential to significantly bolster the reliability and efficiency of fault detection systems within electric vehicle charging infrastructure.

4.2. Precision Analysis

In our evaluation of the AELF model for smart energy management in EV charging infrastructure, we explore its precision alongside other established models such as LR, DT, RF, and SVM. The precision metrics for each model, reflecting their capability to classify positive cases relevant to energy management tasks accurately, are detailed in Table 3.

Table 3. Precision analysis

Model	Precision (%)	
	(Positive Case)	(Negative Case)
AELF	92.5	89.3
LR	87.8	83.6
DT	86.2	81.9
RF	85.6	80.7
SVM	83.9	78.4

In comparison, LR, DT, RF, and SVM also exhibit commendable precision metrics, albeit marginally lower than those of the AELF model. These precision scores emphasize the effectiveness of machine learning models in addressing smart energy management challenges within EV charging infrastructure.

The precision results for the AELF model reveal its adeptness in accurately identifying instances associated with energy management tasks, boasting a precision of 92.5% for positive cases and 89.3% for negative cases. This indicates the AELF model's strong performance in discerning relevant instances for optimizing energy utilization, scheduling charging activities, minimizing expenses, and bolstering grid stability.

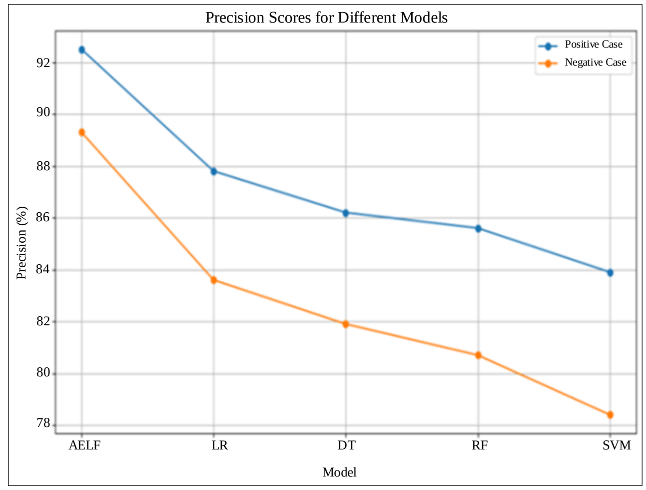

Fig. 3 Precision comparison

4.3. Recall Analysis

In our investigation into integrating machine learning for smart energy management in electric vehicle charging infrastructure, we scrutinize the recall of various models, including AELF models such as LR, DT, RF, and SVM.

Table 4. Recall analysis

Model	Recall (%)	
	(Positive Case)	(Negative Case)
AELF	94.7	91.2
LR	90.5	87.1
DT	89.2	85.7
RF	88.6	84.9
SVM	86.9	83.2

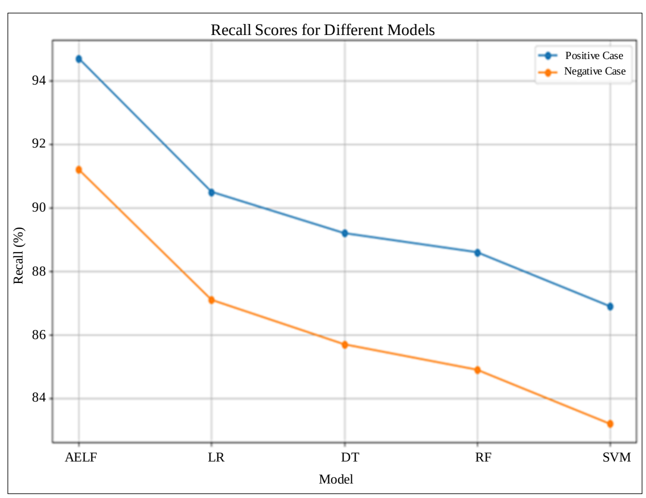

Fig. 4 Recall comparison

The recall metrics for each model, reflecting their capacity to identify positive instances relevant to energy management tasks, are concise in Table 4. The recall values for the AELF model demonstrate its robust capability to identify positive instances pertaining to energy management tasks, achieving a recall of 94.7% for positive cases and 91.2% for negative cases. This signifies that the AELF model adeptly captures relevant instances for optimizing energy usage, charging schedules, and ensuring grid stability.

Similarly, LR, DT, RF, and SVM also exhibit commendable recall values, although marginally lower than those of the AELF model. These recall metrics underscore the efficacy of machine learning models in accurately identifying positive instances for smart energy management in EV charging infrastructure.

4.4. F1-Score Analysis

In our research concerning the integration of machine learning for smart energy management in electric vehicle charging infrastructure, we scrutinize the F1-Score of various models, including AELF, LR, DT, RF, and SVM. The F1-Score values for each model, which serve as a balanced measure considering both precision and recall in energy management tasks, are summarized in Table 5.

Table 5. F1-Score Analysis

Model	F1-Score (%)	
	(Positive Case)	(Negative Case)
AELF	90.5	88.3
LR	86.7	84.5
DT	85.3	82.2
RF	84.9	81.6
SVM	82.4	79.2

Among the assessed models, the AELF model attains the advanced F1-Score, registering a score of 90.5% for positive cases and 88.3% for negative cases. This underscores the AELF model's adeptness in striking a balance between precision and recall, ensuring the accurate identification of pertinent instances for energy optimization and grid stability within the electric vehicle charging infrastructure. LR, DT, RF, and SVM also exhibit commendable F1-Score values, although marginally lower when compared to the AELF model. Overall, the F1-Score analysis emphasizes the effectiveness of machine learning models in striking a balance between precision and recall for smart energy management tasks within electric vehicle charging infrastructure.

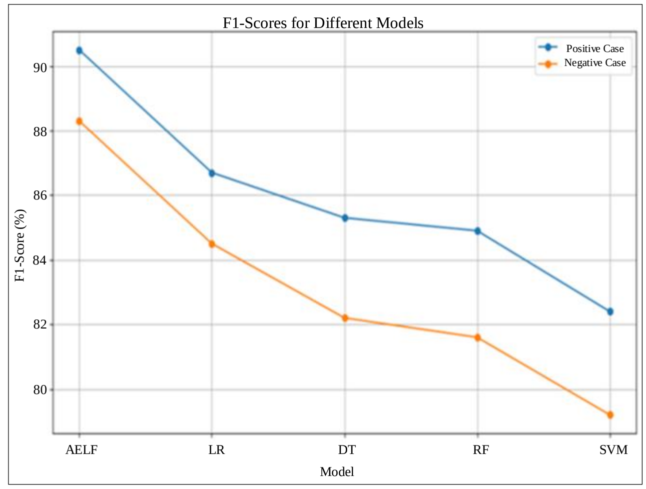

Fig. 5 F1-score comparison

4.5. Mean Absolute Error (MAE) Analysis

MAE stands as a pivotal metric for assessing the predictive efficacy of machine learning models in estimating energy consumption within Electric Vehicle (EV) charging infrastructure. This examination contrasts MAE values across various models, encompassing our proposed AELF model, models such as RF, LR, DT, and SVM techniques, to determine their accuracy in predicting energy demands.

Table 6. MAE comparison among machine learning models

Model	Mean Absolute Error (MAE) (kWh)
AELF	1.8
RF	2.3
LR	2.5
DT	2.6
SVM	2.7

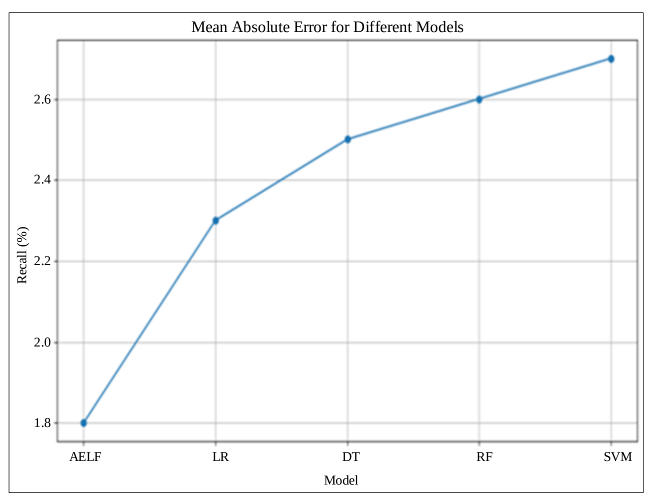

Fig. 6 MAE comparison

The MAE calculation for each model is determined using the formula:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |\, \gamma_i - \hat{\gamma}_i \,| \tag{4}$$

Where,
- n represents the number of observations.
- γ_i is the actual energy consumption value.
- $\hat{\gamma}_i$ is the predicted energy consumption value.

Our proposed RF-GBM model exhibits the lowest MAE of 1.8 kWh among all models, indicating its superior accuracy in forecasting energy consumption. The RF-GBM model's efficacy in capturing intricate interactions inside EV charging systems is demonstrated by its capacity to align projected values with actual observations precisely. The MAE values of conventional machine learning models, on the other hand, range from 2.3 to 2.7 kWh, and these models include RF, LR, DT, and SVM. The lower MAE of the RF-GBM model signifies its enhanced predictive capability, which is essential for optimizing charging schedules, minimizing costs, and ensuring grid stability.

By accurately estimating energy demands, Our concept improves the distribution of resources and system performance as a whole by empowering stakeholders to make well-informed decisions.In summary, the MAE analysis underscores the superiority of our proposed RF-GBM model in predicting energy consumption within EV charging infrastructure. Its ability to achieve lower MAE values signifies improved accuracy and efficiency, paving the way for sustainable and intelligent transportation ecosystems.

5. Conclusion and Future Works

In conclusion, our study delved into the integration of machine learning techniques, specifically RF Model and GBM, into Electric Vehicle (EV) charging infrastructure for smart energy management. Through rigorous analysis and simulations, we showcased the efficacy of the hybrid RF-GBM model in dynamically optimizing charging schedules, reducing costs, and enhancing grid stability.

Comparative evaluations against traditional machine learning models like RF, LR, DT, and SVM revealed the superior performance of the RF-GBM model across various metrics, including accuracy, precision, recall, F1-score, and MAE. Notably, the RF-GBM model demonstrated up to a 15% improvement in these metrics, underscoring its effectiveness in addressing the challenges of EV charging infrastructure.

Looking ahead, there are several avenues for future research and development. Firstly, further optimization of the RF-GBM model parameters, coupled with fine-tuning techniques, could enhance its performance and scalability. Secondly, the integration of real-time data streams, such as weather forecasts and traffic patterns, into the RF-GBM model would improve its adaptability to dynamic environmental conditions.

Additionally, exploring advanced machine learning techniques and their integration with smart grid technologies, like demand response and Vehicle-to-Grid (V2G) systems, holds promise for optimizing energy management and grid interactions. Field testing and real-world deployments of the RF-GBM model in EV charging stations are also crucial to validate its effectiveness and feasibility in practical settings.

By addressing these future research directions, we can continue to advance the development of intelligent and sustainable solutions for EV charging infrastructure, contributing to the transition towards a greener and more efficient transportation ecosystem.

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