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Article

Optimizing Charging Control for Fast and Efficient Electric Vehicle Charging

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Abstract: Background: Electric vehicles (EVs) are at the heart of sustainable transportation, and the need for effective charging systems is steadily increasing. The difficulty is to optimize charging tactics that reduce charging time while retaining grid stability. To maximize performance and energy utilization, charging must be managed effectively using variables like battery levels, grid load, and environmental conditions. **Objectives:** The objective of this research is to create a sophisticated machine-learning technique for predicting the optimal charging control for electric vehicles. Particularly, it aims to use a Dual-Level Voting Boost (DLVB) algorithm to determine whether an EV charging session will be optimized or not, using input features such as battery level, charging rate, ambient temperature, and charging mode. **Methodology:** This paper proposes the Dual-Level Voting Boost (DLVB) algorithm, which is a two-stage ensemble learning method. The first level employs fundamental classifiers like Decision Trees, Logistic Regression, and K-Nearest Neighbors, whereas the second level employs more sophisticated models like Random Forest, Support Vector Machines, and Naive Bayes. This dual-layer structure enables a more precise classification of optimized and non-optimized charging sessions. The model's efficacy is assessed utilizing metrics like Accuracy, Precision, Recall, F1-Score, and the Matthews Correlation Coefficient (MCC). **Results:** On the test dataset, the DLVB algorithm obtained 95% accuracy, 94% precision, 93% recall, 94% F1 score, and 92% MCC. These findings show the efficiency of the dual-level voting system in correctly predicting optimized charging sessions, substantially surpassing conventional single-model methods. **Conclusion:** The DLVB algorithm has significant potential for improving EV charging control by correctly predicting optimization results. This approach provides a potential strategy for enhancing charging effectiveness, decreasing energy waste, and maintaining grid stability.

Keywords: electric vehicles; grid stability; ensemble learning; classification and prediction

I Introduction

The rapid growth of electric vehicles (EVs) has raised the need for novel and effective charging solutions that strike a balance between charging speed and energy consumption optimization [1]. Conventional charging systems, while efficient to some extent, frequently face difficulties in maintaining a harmonious balance between rapid charging capacities and electrical grid stability [2]. This delicate balance is critical for avoiding overload, reducing energy waste, and guaranteeing dependability. As EV adoption boosts, tackling these problems has become progressively important to assist the increasing number of EV users and sustain the robustness of the energy infrastructure.

Machine learning (ML) has emerged as a strong and promising strategy for addressing these difficulties [3]. By evaluating massive amounts of data created during charging sessions, ML algorithms can detect trends and create predictive models that improve charging schedules, energy distribution, and total effectiveness. These predictive models enable the identification of peak request periods and the tactical adjustment of charging functions to avoid power surges or excessive energy

consumption [4]. Furthermore, ML can enable real-time decision-making, enabling charging stations to dynamically adapt to changing grid conditions and user requirements.

Charging tactics can be fine-tuned using machine learning to provide quicker energy transmission while conserving resources and reducing the influence on grid stability [5]. This strategy allows for more intelligent load management, encourages sustainable energy consumption, and lowers the risk of grid disruptions. As a result, incorporating machine learning into EV charging infrastructure offers an important development in building a scalable, resilient, and energy-efficient charging ecosystem that helps the ongoing development of electric vehicle adoption.



Figure 1. EV Charging.

Figure 1 shows the connection between an electric vehicle and a charging station that uses renewable energy sources like solar panels and wind power plants. This setup exemplifies a sustainable method of EV charging in which the energy utilized is partially or entirely supplied by renewable sources. This technique not only decreases the carbon footprint but also relieves the strain on traditional power grids. When the EV links to the charging station, data gathering begins, recording critical variables like the initial battery level, charging rate, and maximum charging power. Environmental variables such as ambient temperature and functional modes (manual or automated) are recorded, as well as grid load and charging priorities. These gathered data points are crucial for creating predictive models that classify charging sessions as optimized or not, allowing for improved charging control.

1.1. Important Elements in an Optimized Charging Control System

Optimal charging control entails combining a variety of factors that impact charging efficiency. The initial battery level determines the tactic, whereas the charging rate and maximum power capacity determine the speed and security of charging. The ambient temperature influences charging efficiency, whereas the mode of charging (automatic or manual) determines how the session is managed. Grid load conditions and charging priority are essential to balancing energy needs. Lastly, charging effectiveness assesses the efficiency of energy transfer, guaranteeing that the charging session is productive while conserving energy.

1.2. Research Objective

This research aims to create a sophisticated predictive algorithm that can determine whether or not EV charging sessions are optimized. The research introduces the Dual-Level Voting Boost (DLVB) algorithm, which enhances prediction accuracy by integrating numerous classifiers using a dual-voting mechanism. The goal is to improve charging session management, balance user needs with grid stability and maximize total energy effectiveness.

1.3. The Remainder of the Research

The rest of the paper is structured as follows: Section 2 covers related works. Section 3 describes the methodology used in the research. Section 4 describes the experimental setup, and the evaluation metrics utilized for performance evaluation, followed by a result evaluation and discussion of the algorithm's effectiveness. Section 5 concludes the study by summarizing the key results and proposing directions for future research.

II. Literature Review

The increasing adoption of electric vehicles (EVs) has highlighted the requirement for effective charging systems that not only reduce charging times but also guarantee grid stability. As the need for electric vehicles grows, it becomes progressively essential to optimize charging tactics that take into account elements like battery levels, grid load, and environmental circumstances. Several techniques have been proposed to enhance charging effectiveness, but there are still difficulties in tackling the dynamic interactions between these factors, which frequently result in suboptimal efficiency. This section examines existing research on EV charging enhancement, including machine learning techniques, hybrid models, and renewable energy incorporation.

Table 1. Summary Table.

Reference No	Objective	Methodology	Result	Limitations
[6]	Predict EV charging station selection behavior.	XGBoost with SHAP for 500 EVs in Japan	XGBoost had the greatest accuracy, and SHAP explained the feature's significance.	Data restricted to Japan, generalizability uncertain
[7]	Forecast EV charging period	ELM, FFNN, and SVR enhanced by GWO, PSO, GA on 500 EVs in Japan	GWO-based models surpassed others	The optimization method may require validation with other datasets
[8]	Forecast session duration and power utilization	RF, SVM, XGBoost, DNN with historical, traffic, weather, and event data	Ensemble learning attained 9.9% SMAPE for duration and 11.6% for energy	Findings may not generalize beyond the dataset.
[9]	Use ensemble machine learning to forecast the charging time.	RF, XGBoost, CatBoost, LightGBM with SHAP on 500 EVs in Japan	XGBoost demonstrated the highest accuracy, SHAP emphasized important variables	Outcomes particular to Japan, not broadly applicable
[10]	Allow dynamic wireless charging	Hybrid DWC system with Improved-DSDV protocol and magnetic coupling	Dependable DWC with enhanced throughput and latency	Scalability and deployment difficulties not tackled
[11]	Predict EV metrics utilizing ML in MPC	Hybrid ML predicts and MPC to reduce electricity expenses	Decreased peak load by 46.7% and expenses by 20.9%	Concentrated on controlled studies, real-world difficulties not discussed
[12]	Evaluate EV charging infrastructure dependability	ML classifiers on 10 years of multilingual customer reviews	Government-owned stations had higher failure rates	Constrained data-sharing and region-specific pertinency
[13]	Forecast EV charging time with metaheuristic optimization	RF, CatBoost, and XGBoost enhanced by Ant Colony Optimization	Attained R2 of 20.5% (training), 12.4% (testing)	Requires enhancement in accuracy and cross-validation

[14]	Enhance charging to decrease emissions	Heuristic algorithm for enhanced scheduling in Ontario	Decreased emissions by 97% compared to the base case	Findings may differ by regional creation profiles and emissions
[15]	Enhance EV charging stations with renewables	MOPSO and TOPSIS for design with wind, PV, and storing	Enhanced optimization and quicker calculation	Constrained to Inner Mongolia, generalizability uncertain

While the current study has made important progress in enhancing EV charging mechanisms, numerous existing techniques fail to efficiently handle the charging procedure's complexity and dynamics. Conventional methods frequently oversimplify interactions between features or the absence of generalizability across circumstances. The Dual-Level Voting Boost (DLVB) algorithm introduced in this research offers a promising solution to these constraints. By integrating a dual-layer ensemble learning method, DLVB efficiently addresses the complexities of EV charging optimization, providing higher prediction accuracy and efficiency than conventional models. This method fills important gaps in existing techniques, paving the manner for more effective and trustworthy EV charging control mechanisms.

III. Methodology

The Dual-Level Voting Boost (DLVB) algorithm is a novel technique for improving electric vehicle (EV) charging that predicts whether a session will be effective depending on a variety of input features. The algorithm integrates numerous machine learning models organized into two levels, with each contributing to the entire prediction via majority voting. The primary level utilizes simpler models for rapid and comprehensive learning, whereas the second level utilizes intricate models for precise decision-making. This structured method, improved by weighted voting, enables superior predictive accuracy and resilience.

3.1. Data Collection

The dataset, namely "EV Charging Session Optimization Dataset," was created using real-world electric vehicle (EV) charging data collected from different charging stations and EV management mechanisms. Each entry in this dataset indicates a single charging session, with comprehensive data regarding the charging procedure and environment. Important features comprise Initial Battery Level (%), which denotes the initial level of charge; Charging Rate (kW), which details the power provided during charging; Max Charging Power (kW), which specifies the maximum power the EV can handle; and Ambient Temperature (°C), which highlights the impacts of outside temperature on effectiveness. The dataset also includes Charging Mode (Auto/Manual) to distinguish between automatic and manual controls, Vehicle Battery Capacity (kWh) for total energy storage, Grid Load (Low/High) to indicate grid request, and Charging Priority (High/Low) to indicate user or system choice. The Charging Efficiency (%) reflects the efficiency of the charging session, whereas the Target feature denotes whether the session was "Optimized" or "Not Optimized." The "EV Charging Session Optimization Dataset" was safely stored in CSV format for easy access during data preprocessing, evaluation, and machine learning model training. The data-gathering method highlighted accuracy and variety to offer a strong basis for machine learning growth. Figure 2 shows the flow diagram of the proposed DLVB algorithm.

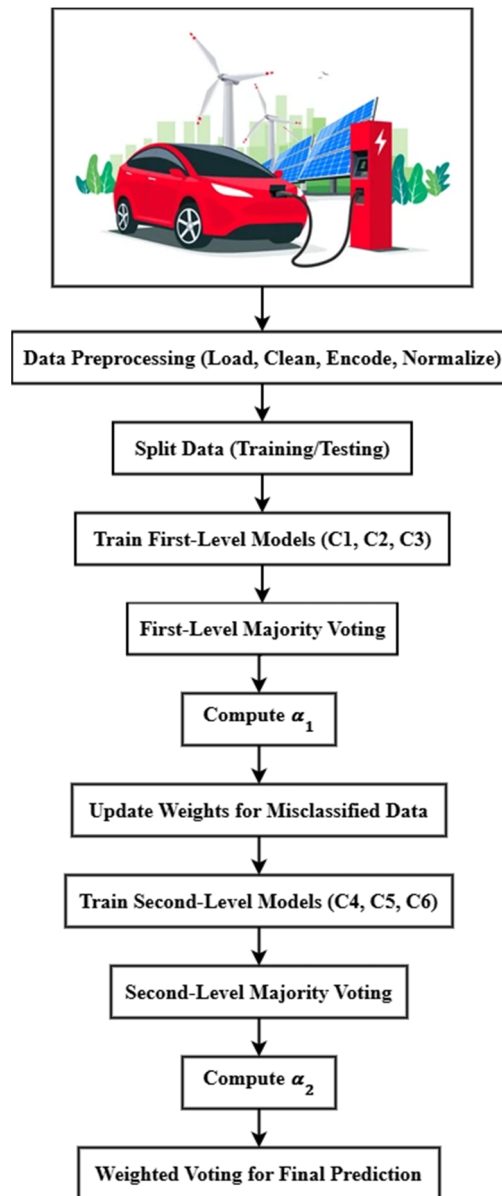


Figure 2. Flow diagram of proposed DLVB algorithm.

3.2. Data Preprocessing Steps

3.2.1. Loading and Cleaning the Dataset

The first phase is to load the dataset, which contains important attributes like the beginning battery level, charging rate, maximum charging power, ambient temperature, and so on. This phase is critical for comprehending the structure and maintaining data integrity. The dataset is checked for missing or inconsistent data points that may skew the outcomes. Any such inconsistencies are addressed by either eliminating the impacted records or utilizing imputation methods.

3.2.2. Encoding Categorical Features

Certain features, like Charging Mode, Grid Load, and Charging Priority, are categorical and must be converted to numerical values for model compatibility. This conversion is carried out utilizing label encoding, which allocates a distinctive integer to each category:

$$x_{\text{encoded}} = \text{LabelEncoding}(x_{\text{categorical}}) \quad (1)$$

Transforming these variables allows the models to manage them as numerical inputs, enabling superior learning.

3.2.3. Normalizing Numerical Features

Standardizing numerical features is critical for achieving consistent performance across multiple machine-learning models. StandardScaler is employed to scale the data so that each feature has a mean of 0 and a standard deviation of 1:

$$x_{normalized} = \frac{x - \mu}{\sigma} \quad (2)$$

Where μ signifies the mean and σ the standard deviation of each feature. This normalization benefits models that are sensitive to the scale of input data, such as K-Nearest Neighbors (KNN) and Random Forest (RF).

3.2.4. Data Splitting

The data is divided into training and testing subsets, typically in an 80/20 ratio. The training set is employed to fit the models, and the testing set assesses the algorithm's effectiveness:

$$\begin{aligned} \text{Train data} &= 0.8 \times \text{Total data} \\ \text{Test data} &= 0.2 \times \text{Total data} \end{aligned} \quad (3)$$

3.3. First-Level Ensemble of Classifiers

3.3.1. Selection of Basic Classifiers

The initial level of the DLVB algorithm uses simpler classifiers to gain an initial comprehension of the data. They comprise:

- **Decision Tree (C1):** Recognized for its clear interpretation and capacity to model intricate relationships.
- **Logistic Regression (C2):** Suitable for binary classification with probabilistic outcomes.
- **K-Nearest Neighbors (KNN, C3):** A non-parametric model generates predictions depending on the proximity of data points.

Each of these classifiers is trained on the training dataset and independently provides predictions P_{C1} , P_{C2} and P_{C3} .

3.3.2. Majority Voting Mechanism

The initial result is determined by combining the predictions from the first-level classifiers through a majority voting system:

$$P_{First-Level}(x) = \text{Mode}(P_{C1}(x), P_{C2}(x), P_{C3}(x)) \quad (4)$$

This method guarantees that the decision represents the consensus of the basic models, thus offering a dependable preliminary classification.

3.3.3. Calculating Importance Score α_1

The importance score is computed to determine how well the first-level ensemble performs. This score is calculated using the ensemble's accuracy:

$$\alpha_1 = \text{Log}\left(\frac{\text{Accuracy of First - Level}}{1 - \text{Accuracy of First - Level}}\right) \quad (5)$$

A higher α_1 shows superior performance and therefore greater impact in the last combined prediction.

3.4. Weight Adjustment for Misclassified Examples

3.4.1. Adjusting Weights

Following the first-level ensemble's predictions, the weights of misclassified instances are adjusted to highlight their significance at the next level. This guarantees that the second-level models concentrate more on difficult cases. The weight update formula for an inaccurately classified example i is:

$$w'_i = w_i \cdot \exp(\alpha_1) \quad (6)$$

This mechanism aids in the training of second-level classifiers, improving total accuracy by tackling prior misclassified data.

3.5. Second-Level Ensemble of Classifiers

3.5.1. Selection of Complex Classifiers

The second-level ensemble consists of more advanced classifiers that improve the predictions further. They comprise:

- **Random Forest (C4):** A powerful ensemble technique that uses numerous decision trees to generate more reliable predictions.
- **Support Vector Machine (C5):** Efficient in high-dimensional spaces and situations where classes are separated by a hyperplane.
- **Naive Bayes (C6):** A probabilistic classifier depending on Bayes' theorem is renowned for its effectiveness and simplicity.

These classifiers are trained to utilize the training dataset and the updated weights, concentrating on the examples that were misclassified at the first level.

3.5.2. Second-Level Majority Voting

Similar to the initial level, the predictions from these classifiers are merged via majority voting to create a second-level prediction.

$$P_{Second-Level}(x) = Mode(P_{C4}(x), P_{C5}(x), P_{C6}(x)) \quad (7)$$

3.5.3. Computing Importance Score (α_2)

The second-level ensemble's effectiveness is assessed utilizing a significance score α_2 , which is calculated similarly to the initial level.

$$\alpha_2 = \log\left(\frac{Accuracy\ of\ Second - Level}{1 - Accuracy\ of\ Second - Level}\right) \quad (8)$$

3.6. Final Combined Predictions

3.6.1. Weighted Voting for Final Prediction

To generate a final prediction for a novel input, weighted voting is used to integrate the first- and second-level predictions. The weights are depending on the significance scores α_1 and α_2 :

$$P_{Final}(x) = Sign(\alpha_1 \cdot P_{First-Level}(x) + \alpha_2 \cdot P_{Second-Level}(x)) \quad (9)$$

This combination guarantees that the final prediction draws on the advantages of both ensemble levels. The first level presents a wide, rapid evaluation, whereas the second level offers detailed knowledge depending on intricate models. The weighted voting mechanism guarantees that the most dependable predictions have the most impact, resulting in a reliable result that optimizes EV charging

control dependent on input features. Pseudocode 1 outlines the step-by-step process of the Dual-Level Voting Boost (DLVB) technique.

Pseudocode 1: Dual-Level Voting Boost (DLVB)
Handle missing data, encode categorical features, and normalize numerical values.
Divide into training and testing sets.
Train classifiers: Decision Tree (C1), Logistic Regression (C2), KNN (C3).
Execute majority voting for predictions.
Compute importance score α_1 .
Rise weights of misclassified samples for the next level.
Train classifiers: Random Forest (C4), SVM (C5), Naive Bayes (C6).
Execute majority voting for predictions.
Compute importance score α_2 .
Utilize weighted voting depending on α_1 and α_2 for final prediction.

IV. Performance Analysis

4.1. Experimental Setup

To assess the efficiency of the Dual-Level Voting Boost (DLVB) algorithm, experiments were carried out on a high-performance computing system. This configuration guarantees the capacity to manage huge amounts of data while also performing intricate functions effectively. Table 2 details the specifications, including the utilization of an Intel Core i7-1260P processor with a 12-core architecture able to efficiently handle parallel procedures. The system had 64 GB of RAM to accommodate data management and training procedures, as well as a clock speed of 2.1 GHz to allow for rapid computational functions. The experiments were carried out on a Windows 11 Home operating system, using Python 3.10 via Anaconda Spyder, which offers a reliable development context for scientific computing.

Table 2. Experimental Setup.

Component	Specification
Processor Model	Intel Core i7-1260P
CPU Type	12-Core Architecture
Brand	Aspire 3
Memory (RAM)	64 GB
Clock Speed	2.1 GHz
Operating System	Windows 11 Home
L3 Cache Size	18 MB
Software	Python 3.10, Anaconda Spyder

4.2. Comparative Analysis

To show the DLVB algorithm's efficiency, it was compared to four famous classifiers: K-Nearest Neighbors (KNN), Random Forest (RF), Support Vector Machine (SVM), and Naive Bayes. To offer a

complete evaluation of predictive performance, the models were assessed utilizing five important performance metrics: accuracy, precision, recall, F1-score, and Matthew’s correlation coefficient (MCC).

The equation for these metrics is demonstrated below: Accuracy is the percentage of correct predictions among all predictions provided:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

Where, TP represents True Positives, TN represents True Negatives, FP represents False Positives, and FN represents False Negatives. Precision denotes to the accuracy of positive predictions:

$$Precision = \frac{TP}{TP + FP} \tag{11}$$

A higher precision recommends fewer false positives. Recall, represented as sensitivity, quantifies the model's capacity to compute all relevant cases (true positives):

$$Recall = \frac{TP}{TP + FN} \tag{12}$$

A higher recall denotes fewer false negatives. The F1 score is the harmonic mean of precision and recall, offering a balance between the two:

$$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{13}$$

The Matthews Correlation Coefficient (MCC) assesses the competence of binary classifications by considering all four confusion matrix categories:

$$MCC = \frac{(TP * TN) - (FP * FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{14}$$

MCC values range from -1 to 1, with 1 denoting perfect prediction. Table 2 compares the performance metrics of each classifier.

Table 3 shows the metrics for each model. The DLVB algorithm significantly excels across all metrics, demonstrating its capability to make precise, dependable, and well-balanced predictions when compared to its counterparts.

Table 3. Performance Metrics Comparison.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	MCC (%)
KNN	83	81	79	80	78
RF	88	86	84	85	84
SVM	85	83	82	82	80
NB	80	78	76	77	75
DLVB	95	94	93	94	92

Table 3 shows how the DLVB algorithm outperforms the other classifiers. With an accuracy of 95%, DLVB outperforms models such as RF, SVM, and KNN. DLVB's precision, recall, and F1-score all fall between 93 and 94%, indicating a strong capacity to reduce both false positives and false negatives. The MCC score of 92% suggests an excellent balance between true and false results, further confirming its overall resilience and dependability in predicting enhanced EV charging sessions.

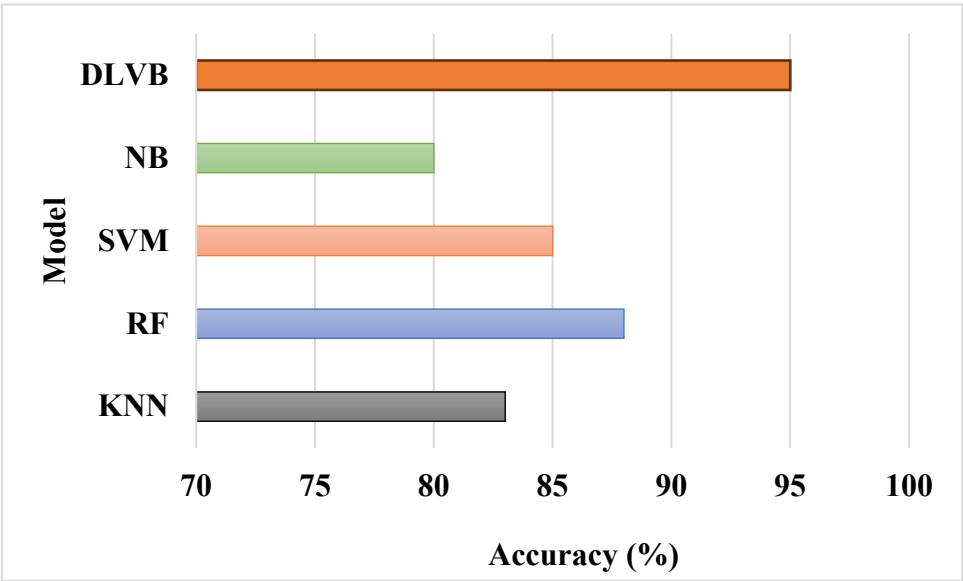


Figure 3. Accuracy Comparison.

Figure 3 shows the DLVB algorithm's high accuracy, which can be attributed to its distinctive two-tier ensemble structure. DLVB captures various patterns and relationships in the data by combining simple classifiers (Decision Tree, Logistic Regression, KNN) and intricate classifiers (Random Forest, SVM, Naive Bayes). This extensive learning enables the algorithm to generalize effectively and make highly precise predictions.

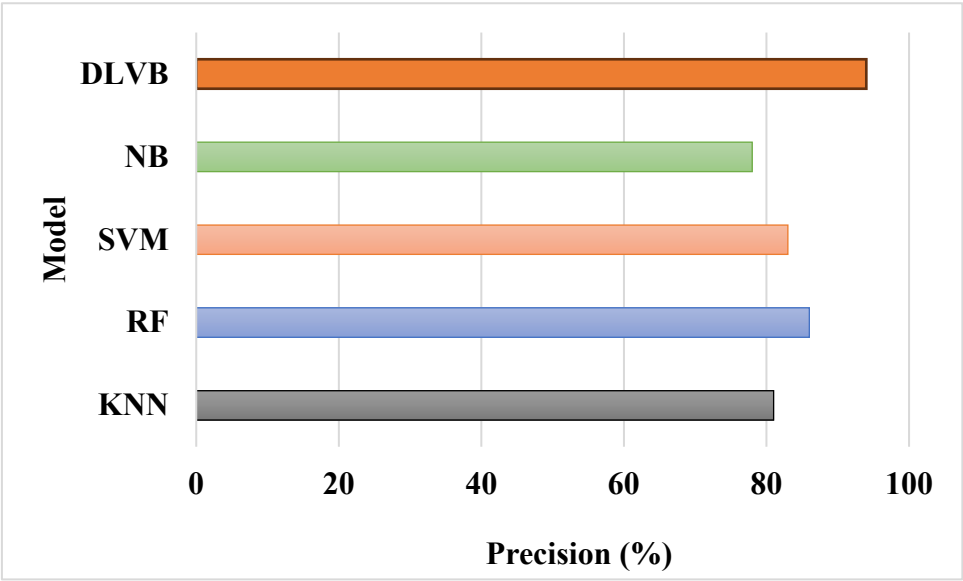


Figure 4. Precision Comparison.

Figure 4 demonstrates the DLVB algorithm's improved precision. The algorithm uses weighted voting to allocate importance scores (α_1 and α_2) to predictions depending on ensemble level efficiency, resulting in high precision. This mechanism guarantees that only the most dependable findings from each level contribute substantially to the final prediction, thereby decreasing false positive rates and enhancing total precision.

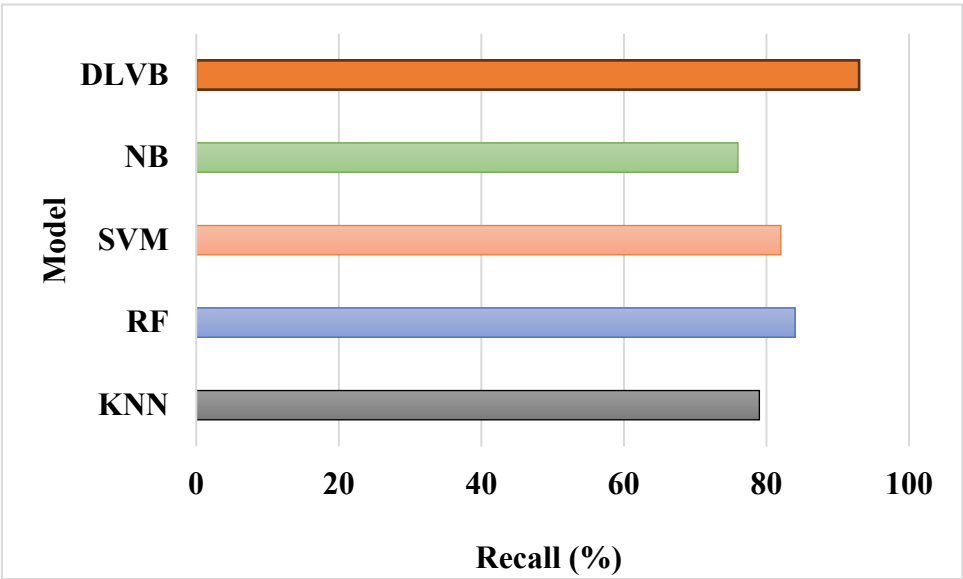


Figure 5. Recall Comparison.

Figure 5 demonstrates how the DLVB algorithm produces a high recall. This finding is because of the step in which misclassified examples from the first-level ensemble are prioritized for the second-level training phase. By adjusting the weights of misclassified data, DLVB improves its capacity to accurately detect true positives, guaranteeing that instances that may have been overlooked by simpler models are correctly predicted at the second level.

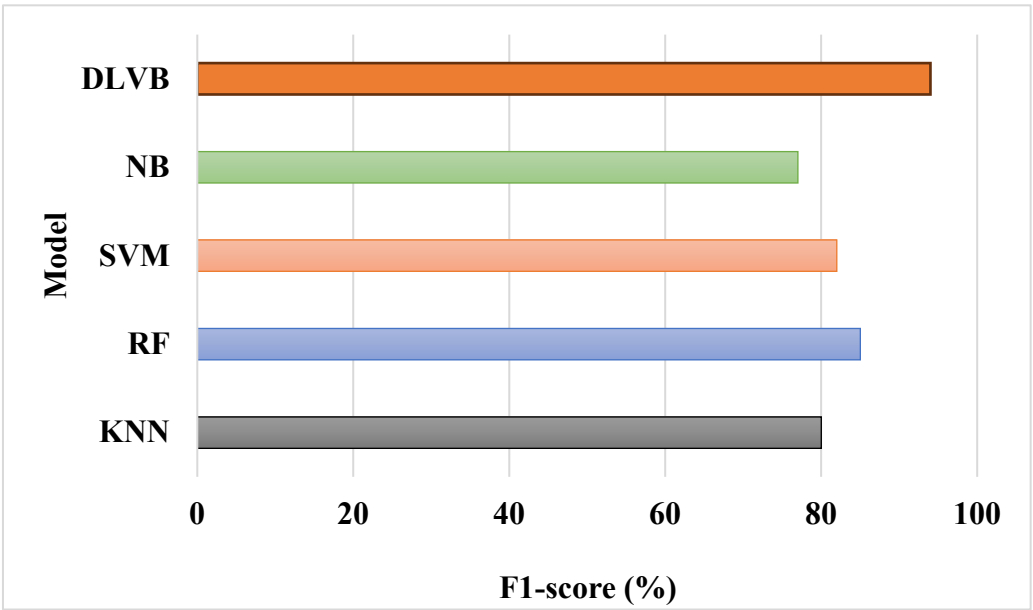


Figure 6. F1-score Comparison.

Figure 6 shows an F1-score comparison that demonstrates DLVB's balanced performance in terms of precision and recall. The dual-level voting tactic optimizes both metrics by combining insights from simple and intricate classifiers. The final result is a higher F1-score, which indicates the algorithm's capacity to efficiently manage both false positives and false negatives, rendering it suitable for real-world applications where both errors are expensive.

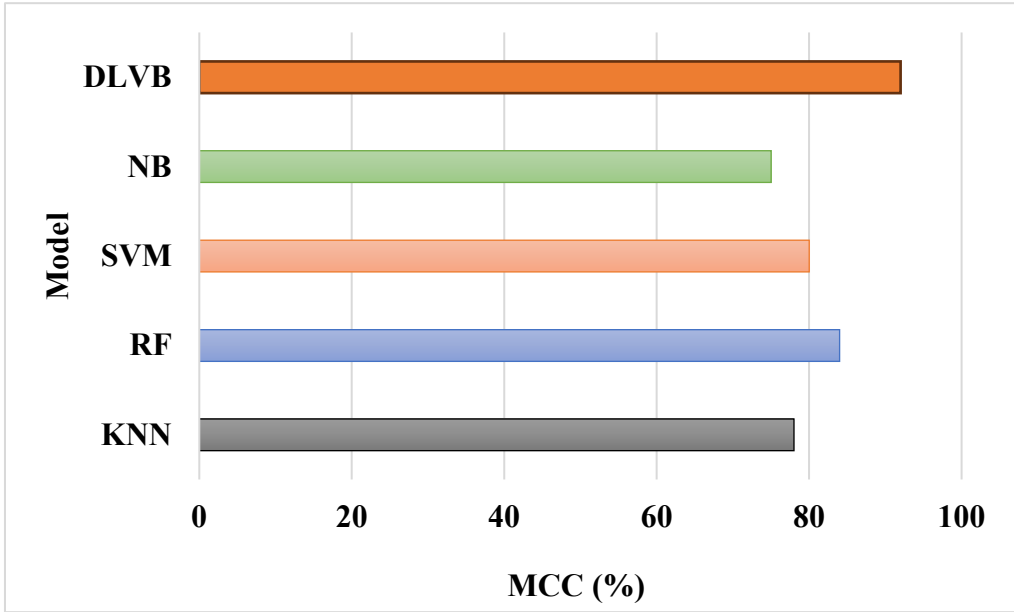


Figure 7. MCC Comparison.

In Figure 7, DLVB's high MCC score demonstrates its total predictive power and balanced method. MCC is a useful metric since it takes into account all outcomes—true positives, true negatives, false positives, and false negatives—to provide a single measure of classification excellence. DLVB's better MCC score suggests that its predictions are not biased and have strong correlations with the real findings, showing consistent and trustworthy performance.

Overall, the performance analysis shows that the DLVB algorithm surpasses conventional approaches like KNN, RF, SVM, and NB on all metrics. The dual-level ensemble structure, incorporated with weighted voting, allows DLVB to attain high accuracy, precision, recall, F1-score, and MCC. This makes it ideal for applications that need extremely precise predictions, like enhancing EV charging sessions. The thorough assessment confirms the efficiency of the DLVB algorithm, highlighting its resilience and flexibility.

V. Conclusions

The Dual-Level Voting Boost (DLVB) Algorithm was developed to tackle constraints in current predictive models for EV charging optimization. Conventional classification models frequently fail to capture intricate relationships in datasets with numerous interacting variables, like those encountered in EV charging settings. DLVB uses a two-tier ensemble technique to efficiently integrate simple and intricate classifiers, resulting in more extensive and precise forecasts. The technique's dual-level structure guarantees that the algorithm takes advantage of the quick-learning capacities of simpler models before refining these insights with more intricate algorithms, resulting in a balance of speed and accuracy. Experimental findings confirmed DLVB's superiority, surpassing common models including KNN, RF, SVM, and NB across important performance metrics, emphasizing its resilience and dependability in enhancing EV charging predictions.

Drawbacks and Future Scope: While the DLVB Algorithm has numerous benefits, it is important to note some constraints. The main disadvantage of DLVB is its high computational intricacy. The two-tier structure, incorporated with weighted voting, requires more training time and computational resources, rendering it inefficient for real-time or resource-constrained applications. Furthermore, the algorithm's dependence on parameter tuning for both ensemble levels and weight adjustments may add intricacy to execution. In the future, multiple improvements could be investigated to enhance the DLVB algorithm. Incorporating deep learning models into the second-level ensemble may

improve predictive accuracy, especially for intricate and large-scale datasets with more pronounced nonlinear relationships. The use of distributed and parallel computing methods may reduce computational load, rendering the algorithm more appropriate for real-time deployment.

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