Developing an Efficient Support Vector Machine Learning Model for Mobile Charging Stations.

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ABSTRACT

In the context of increasing global energy scarcity, optimizing electric vehicle (EV) mobile charging stations is critical for promoting sustainable transportation. This study introduces the use Artificial Neural Network (ANN) models, and Support Vector Machine (SVM) enhanced with the Adams optimizer, to address the challenge of efficient EV charging in energy-constrained environments. The models are designed to predict optimal charging station locations and schedules, with the ANN-Adams optimization fine-tuning the model parameters to improve accuracy and performance, while ensuring dynamic adaptation to fluctuating energy availability and demand patterns. This research contributes to the development of intelligent, adaptive systems for EV infrastructure, paving the way for more resilient and energy-efficient urban mobility solutions. The system employs supervised learning, where models were trained and tested on labeled datasets. The performance of the SVM models was compared to that of a Multilayer Perceptron Network (MLPN) with Adams optimization. The results showed that the MLPN with Adams optimization achieved an accuracy of 97.85%, while the SVM model had a prediction accuracy of 81%. The ANN recorded 91.29% accuracy. Both approaches significantly improved classification accuracy, model generalization on testing datasets, and reduced misclassification errors.

INTRODUCTION

Electric vehicle (EV) mobile charging stations are an innovative solution designed to address the growing demand for EV charging infrastructure. Unlike fixed charging stations, mobile charging units can move to different locations, providing flexibility and convenience for EV users. These mobile units are particularly useful in urban areas, events, emergencies, and locations where installing permanent charging infrastructure is not feasible. The global transition towards sustainable transportation has accelerated the adoption of EVs as a viable alternative to conventional internal combustion engine vehicles. This shift is driven by the need to reduce greenhouse gas emissions, lower dependency on fossil fuels, and mitigate the adverse effects of climate change. However, the widespread deployment of EVs presents several challenges, particularly in the realm of charging infrastructure. As EVs continue to gain popularity, the optimization of charging schedules becomes increasingly important to balance demand with grid capacity (Usman et al., 2016). Efficient and reliable charging solutions are critical to supporting the growing number of EVs on the road and alleviating concerns related to range anxiety among users. In this context, mobile charging stations have emerged as a flexible and adaptive solution to address the dynamic and distributed nature of EV charging demands. This research focuses on utilizing advanced machine learning techniques to optimize the operation and deployment of mobile EV charging stations in energy-constrained environments. The study primarily emphasizes the use of a Multilayer Perceptron Network (MLPN) enhanced with the Adams optimizer and an Artificial Neural Network (ANN), as these models achieved the highest accuracy in predicting optimal charging station locations and schedules. The MLPN with Adams optimization demonstrated superior performance, achieving an accuracy of 97.85%, followed closely by the ANN without an optimizer, which recorded an accuracy of 91.29%.These models were designed to dynamically adapt to fluctuating energy availability and charging demands, making them particularly well-suited for energy-scarce environments. The Adams optimizer, in particular, played a crucial role in fine-tuning the MLPN model parameters, leading to significant improvements in accuracy and performance. In conclusion, this research addresses the critical challenge of optimizing EV mobile charging stations in energy-scarce environments by leveraging advanced machine learning techniques and optimization methods. The proposed framework offers a scalable and resilient solution for sustainable urban mobility, with significant implications for policymakers, urban planners, and stakeholders in the transportation sector. As the world continues to embrace electric mobility, the innovative solutions presented in this study will play a pivotal role in shaping the future of transportation and energy management.

LITERATURE REVIEW

In the realm of charging EVs, various survey papers on the optimization of charging strategies have been published. For instance, the study in (Mukherjee & Gupta, 2015) examined scheduling algorithms for charging EVs in smart grids. A power and communication system has been designed for bidirectional flows of electricity and information. The authors categorized their work based on unidirectional and bidirectional charging, centralized and decentralized scheduling, and the consideration of mobility aspects. (Junming et al., 2019) introduced a Genetic Algorithm-based Emergent Charging Scheduling (GECS) scheme to address routing and scheduling optimization problems for EVs, when there is a sudden demand for rapid charging in a high-density area. Gruoss et al. (2020) developed a Markov chain framework (MCF) for describing the level of occupancy of charging infrastructure. MCF was constructed relying on information collected from about 40 public charging spots for an array of car-sharing automobiles. The suggested model’s accuracy in prediction could not be computed. The model performed flawlessly when determining the occupancy level of EV charging. Charging modes for EVs are of four main modes based on the Deltrix EVs Chargers classification (D. Chargers. EV Charging Modes, 2024 Online). The selection of an appropriate charging mode depends on various factors, such as EV battery capacity, current charging status, required driving range, user preferences, and the availability of charging infrastructure.

1. Charging mode 1: This mode is the slowest form of charging for an EV. It involved using a standard home plug to connect the EV to the power grid. Charging an EV battery in mode 1 can take several hours or even require an overnight. However, one advantage of this gradual charging process is that it generates less heat and imposes less stress on the EV battery (Ahmad et al., 2022). 2)
2. Charging mode 2: This mode also uses a home plug for charging EVs. It incorporated a specialized cable equipped with built-in shock protection against risks from both Alternating Current (AC) and Direct Current (DC), enhancing the safety of the charging process.
3. Charging mode 3: It is the most popular charging method among EV users. It can be implemented both at home and at public CSs. Like mode 2, it provides shock prevention against both AC and DC currents. In mode 3, the EV user does not need to use a specific cable for charging; instead, the necessary connecting cables are provided at the stations.
4. Charging mode 4: Often referred to as fast charging mode, it involves the use of CSs that convert AC power to DC, allowing direct charging for EVs. Typically, fast charging mode is notable for its efficiency; an average EV battery takes about 30 minutes to an hour to be fully charged. The charging rates supported in this mode vary, ranging from 5 kW units up to 50 kW and 150 kW. Future standards may even extend this range to 350 kW and 400 kW. However, these higher charging rates can generate significant heat, which may impact the battery’s lifespan. Therefore, a special cooling

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system is often required to manage this heat effectively.

The following elements are presented and examined to put the suggested architecture into execution.

(a). Datasets: The dataset was sourced from publicly made available kaggle site at "https://data.cityofpaloalto.org/dataviews/257812/ELECT-VEHIC-CHARG-STATI-83602/". A few of its features are station name, MAC address, start date, start time, end date, total duration, charging time, power split transmission (PST), pulse discharge test (PDT) and etc, With over 2000 testing and 8000 training sets making up the 10,000 dataset, the suggested collection provides a sizable dataset for building models.

Table 1: Dataset for EV (source: https://data.cityofpaloalto.org/dataviews/257812/ELECT-VEHIC-CHARG-STATI-83602/")

1	Station Name	**MAC Address**	**Org Name**	**Post User_id**
2	PALO ALTO CA / HAMILTON #1	000D:6F00:015A:9D76	City of Palo Alto	3284
3	PALO ALTO CA / HAMILTON #1	000D:6F00:015A:9D76	City of Palo Alto	4169
4	PALO ALTO CA / HAMILTON #1	000D:6F00:015A:9D76	City of Palo Alto	4169
5	PALO ALTO CA / HAMILTON #1	000D:6F00:015A:9D76	City of Palo Alto	2545
6	PALO ALTO CA / HAMILTON #1	000D:6F00:015A:9D76	City of Palo Alto	3765
—	——-	——-	——-	——
9996	PALO ALTO CA / HAMILTON #1	000D:6F00:015A:9D76	City of Palo Alto	55033
9997	PALO ALTO CA / HAMILTON #2	000D6F0000A20F47	City of Palo Alto	126779
9998	PALO ALTO CA / HIGH #4	000D:6F00:015A:9D76	City of Palo Alto	139203
9999	PALO ALTO CA / HAMILTON #1	000D6F0000A2108E	City of Palo Alto	2670
	PALO ALTO CA / BRYANT #2	000D6F0000A2108E	City of Palo Alto	134699

(b). Data pre-processing: The preprocessing is encapsulated in set of routines capable of filtering instances or attributes. The data preparation phase is utilized in order to identify and deal with erroneous values and eliminate missing data values from the current system dataset. The date and the vehicle charging parameters are preprocessed into an appropriate format prior to training. The missing value replace function was used during the preprocessing stage to fill the values for the training dataset before creating the model.

(c). Feature engineering: The feature engineering technique is employed to transform data to have meaningful representation using human knowledge. This is very important and intensive which acts as a weakness to learning models. This phase relies mainly on human ingenuity and prior knowledge to compensate for the inability of algorithms to extract and organize the discriminative information from dataset (Bengio et al. 2020).

(d). Model training: The libraries given below are used in Python to train the suggested model

(i). Scikit-learn: is a popular and freely available Python framework for machine learning predictive data analysis (Ferreira, 2018). The multi-layer perceptron neural network and the support vector machine. we imported the Sci-learn package in order to train two distinct machine learning models.

(ii). TensorFlow is an open-source deep learning system Known as the "big daddy" of deep learning frameworks. The dataset module is being used to build a unique dataset that will be fed into the training model.

(e). Metrics of Evaluation: Comparing the various outcomes requires the use of a consistent model

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diagnostic tool. Model anticipated results for scenarios involving multi-classification tasks, like the one proposed here, can be visualized in a variety of ways. Standard model evaluation metrics like accuracy, confusion matrices, and ROC learning curves are used to evaluate the efficacy of SVM algorithms. Classification accuracy is defined as the proportion of the dataset's data points that were correctly classified. The error rate can be measured with the general equation given by:

$$\text{Classification accuracy} = \frac{\text{Number of correct classifications}}{\text{Total number of classifications}} = \frac{TP+TN}{TP+TN+FP+FN}$$

Where TN represents true negative, FP is false positive, TP is true positive and FN is false negative cases.

Method 1: Adaptive Moment (Adam) Optimization

Adam is a first-order gradient-based optimization technique designed to succeed SGD in training deep learning models. It is more memory-efficient, computationally effective, eliminates gradient challenges, suitable for noisy and large dataset. Adam employs a technique that maintains a single learning rate for all weight updates that remain fixed throughout training while keeping adaptive learning rates distinct from each parameter. Adam is an optimization approach that is capable of handling sparse gradients on noisy situations by combining the best features of the AdaGrad and Root Mean Squared Propagation (RMSProp) techniques. The goal is to improve the performance of a given loss function by optimizing the model weights. The effectiveness of the MLPNN model can be determined using the loss function as a metric. It is imperative to employ optimizers such as Adams and SGD to systematically modify the network weights and improve model performance during the training process. The cross entropy loss quantifies the model's performance when the output of a classification model is a probability value that falls between 0 and 1. We employed Adam-grad optimizer in ANN model to adjust layer weights along with learning rates following each iteration phase in order to reduce losses.

Adam estimates the first and second moments of network gradients to balance the model learning rates for each network weight given as:

$$m_n = E\,[X^n] \qquad 1.0$$

Where "m" represent moment; "X" the random variable, "n" moment of random variable assigned and the expected value or power.

Adagrad adjusts the learning rate based on conditions because the actual rates are derived from parameters and the learning rates are also adjustable. The learning rate of parameters having low gradients will increase and those with large gradients will decrease.

The Adam's update equation which cannot be manually updated is represented as:

$$\nabla_{\Theta_t} = \nabla_{\Theta_t} J(\Theta_t) \qquad 1.1$$

$$\Theta_{t+1} = \Theta_t - \frac{\eta}{\sqrt{\upsilon_t + \epsilon}}\, g_t \qquad 1.2$$

Where

υ_t is the exponential moving average of the gradient

ϵ smoothing term that avoids dividing by zero.

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Θ_{t+1} the dynamic gradient of the past term

η is the learning rate

$\nabla_{\Theta_t} J(\Theta_t)$ is the gradient of the loss function

gt is the first derivative for loss function

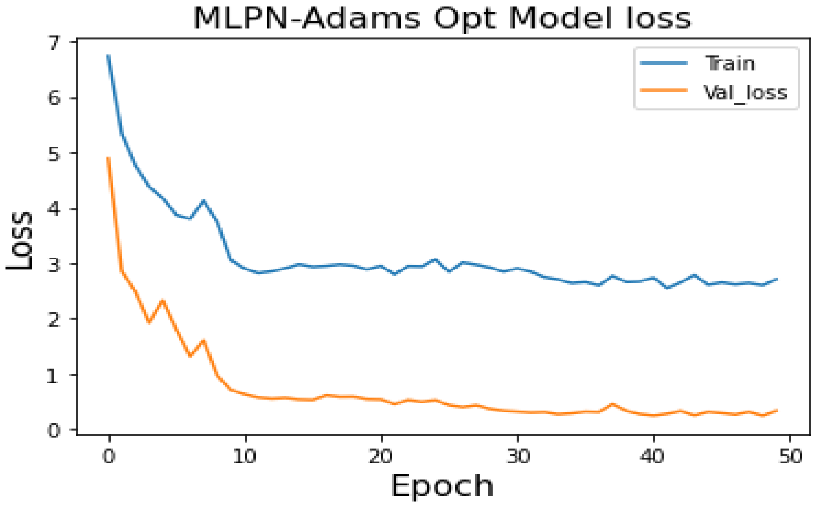

Figure 1: Train/validation loss of MLPN-Adams Optimization

The MLPN accuracy for training and validation loss is based on the ANN model weights' as randomly setup is shown in Figure 1. It provides us with further insight into how the MLPN model performs over the course of the training cycle (epoch). The validation loss dropped in the same order as the training over 50 epochs. There is a correlation between the training and validation sets from the beginning to the end.

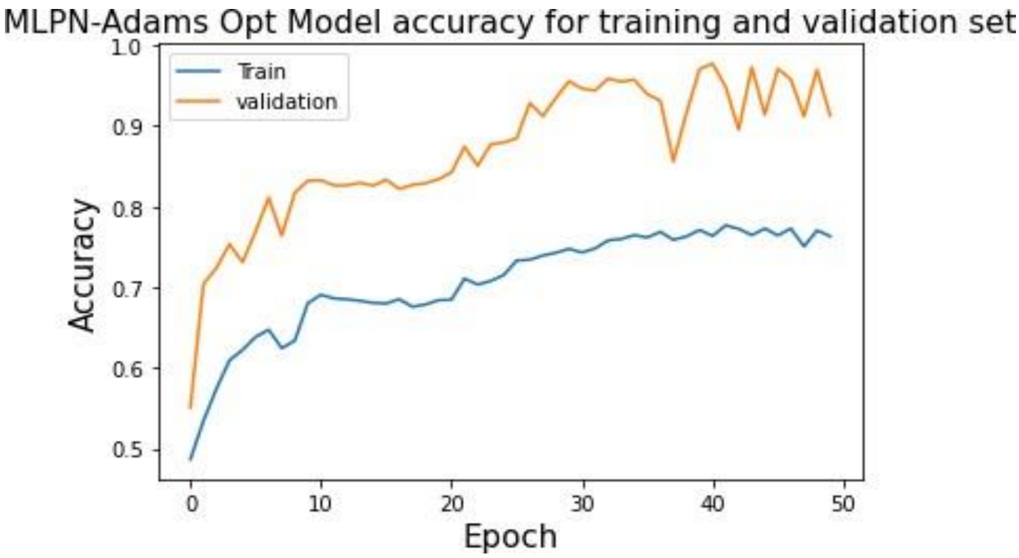

Figure 2: Train/validation plot of MLPN-Adams Optimization

The MLPN training and validation loss is shown in Figure 2. It illustrates how the predictive algorithm fails to draw valid conclusions from the testing data. The trained model performs well on training samples, but

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when tested on the validation data set, it performs poorly at the beginning, as the graph illustrates, validation loss increases once again at point 10 before declining again from 50. Model fitting happens because the artificial neural network (ANN) algorithm in this case was trained for an extended period of time, making it purely too sophisticated for the data. When the loss is gradual and mild, training can be decreased with the intention of terminating early. Over the training loss, the validation curve is bouncing up and down.

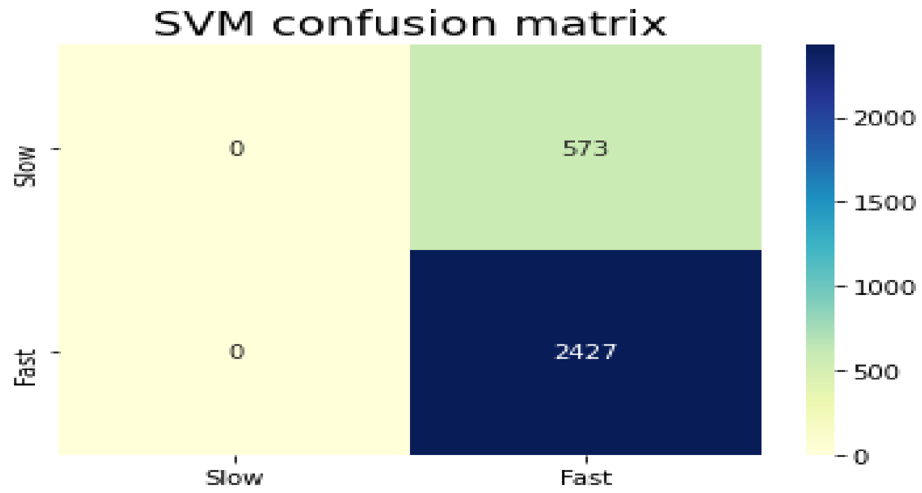

Figure 3: DT Confusion matrix (TP=0, TN=2427, FP=0 and FN=575)

Figure 3, shows the confusion matrix, which displays a table structure of the various SVM prediction results and outcomes of a binary-classification task to aid in visualizing its results. This is used to show the predicted and actual values of a classification model. Cell values above and below the main diagonal or off-diagonal elements showing the incorrectly predicted values, show the total number of correctly predicted values that are equal to the actual or true values. The greater the diagonal value, the more accurate the predicted EV Battery charging duration. According to the confusion matrix, EV Batteries with low charging time had 573 incorrectly predicted cases with zero(no) correct predictions. While EV Batteries with fast charging duration provided 2427 incorrectly predicted values with zero (0) true positive class prediction.

(b). For MLPN-Adams Optimization Technique

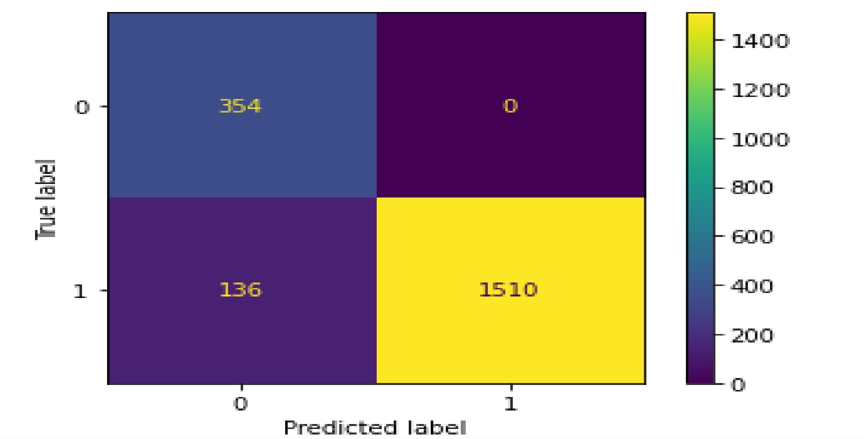

Figure 4: MLPN-Adams Confusion matrix (TP=354, TN=1510, FP=136 and FN=0S)

A 4 × 4 confusion matrix, with 4 representing the total number of target classes, is used to determine the performance of a binary classification report, as shown in Figure 2. This is done to compare the predicted values of the ANN model with the actual target values, which are divided into four mutually incompatible possibilities. Figure 2 displays the true positive and negative cases of the MLPN EV duration of battery charging rate and classification. According to the data, 136 are the correct predictions and 1864 classes were wrongly classified cases of slow and fast battery charging duration. The confusion matric help to explain how well a classification system performs on a set of experimental data for which the true values are known is the artificial neural network confusion matrix.

RESULTS AND DISCUSSION

Table 1: SVM Classification Report

SVM Classification report
SVM

	precision	recall	f1-score	support
Slow	0.00	0.00	0.00	573
Fast	0.81	1.00	0.89	2427
accuracy			0.81	3000
macro avg	0.40	0.50	0.45	3000
weighted avg	0.65	0.81	0.72	3000

The SVM classification report for shorter and longer battering charge times is shown in Table 1. It includes the precision, recall, and f1-score accuracy of the exiting. For slower (longer) battery charging times, the precision accuracy recall and f1-score produced results of 0.0 for each. The quick (shorter) battery charging duration yielded a precision accuracy of 0.81. A shorter battery charging time produced a f1-score of 0.89 and a recall score of 1.00 for shorter charging times.

Table 2: Classification Report for MLPN-Adams Optimizer

	precision	recall	f1-score	support
Low	1.00	0.84	0.92	354
Long	0.97	1.00	0.98	1646
accuracy			0.97	2000
macro avg	0.98	0.92	0.95	2000
weighted avg	0.97	0.97	0.97	2000

The classification report of the MLPN-Adams Optimizer for longer and shorter battery charging durations is displayed in Table 2, along with precession, recall, and f1-score correctness. For the slow or extended battery charging parameter, the precision accuracy score was 1.00, and for the shorter or faster charging period, it was 0.97. Recall scores for slower charging batteries were recorded at 0.84 and 1.00 for quicker charging times, respectively. The f1-score for slow charging was 0.92 and for fast charging, 0.98.

Table 3: SVM and MLPN-Adam's Optimizer

Metrics	SVM	MLPN-Adam's Optimizer
True Positive(TP)	0	233
False Negative(FN)	573	121
False Positive(FP)	0	89
True Negative(TN)	2427	1557
Correct predictions	2427	1790
Incorrect predictions	573	210
Accuracy	81%	97.85%

Performance accuracy of the models, including SVM and the suggested Adams optimization techniques, revealed the following results: The Multilayer Perceptron Network with Adams Optimization (MLPN-Adams) achieved the highest accuracy of 97.85% for predicting target EV charging class duration. The Multilayer Perceptron Network with ANN optimization achieved the second-best result, also with an accuracy of 97.85%. Both of these models improved accuracy and reduced the challenges associated with model training. In contrast, the Support Vector Machine (SVM) model had the lowest prediction accuracy at 81%.

CONCLUSION

This study effectively developed and evaluated Artificial Neural Network (ANN) and Support Vector Machine (SVM) models optimized with the Adams optimizer for mobile charging stations. The research aimed to address the challenges associated with efficient EV charging in energy-constrained environments by leveraging advanced machine learning techniques. The integration of the Adams optimizer with ANN and SVM models has proven to be a valuable approach for developing intelligent and adaptive systems. These models offer innovative solutions for predicting optimal charging station locations and schedules, enhancing the efficiency of mobile charging infrastructure. The findings of this research contribute to the advancement of sustainable transportation by providing a robust framework for improving energy utilization and service quality in dynamic urban environments. The use of these advanced models and optimization techniques paves the way for more resilient and effective EV charging solutions.

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