JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Electric Vehicles Charging Sessions Classification Technique for Optimized Battery Charge Based on Machine Learning

[1]J.N. Chandra Sekhar, [2]A. Shushrutha, [3]L. Srikanth, [4]P. Shiva Karthik

[1]Asst. Professor, [2,3,4]UG Scholars
[1,2,3,4]Department of Artificial Intelligence and Machine Learning,
Guru Nanak Institutions Technical Campus (Autonomous), Hyderabad, India.

Abstract: The rapid rise in the use of electric vehicles (EVs) over the past ten years has made it necessary to accurately estimate the energy required for EV charging. Electric vehicles now mostly use lithium-ion batteries for storage; protecting these batteries from overcharging can extend their lifespan and maintain their health. This research suggests a machine learning model for predicting the length of an EV charging session that is based on the K-Nearest Neighbors classification method. By classifying the event correctly, the model predicts how long the charge will last. There are charging events in each class, and each one lasts for a specific amount of time. The program only uses the data (arrival time, starting SOC, calendar data) that is available at the start of the charging event. A sensitivity analysis is carried out to evaluate the effects of various inputs, and the model is validated using an actual dataset comprising records of charging sessions from over 100 users. An improvement in performance demonstrates the model's efficacy in comparison to the benchmark models.

***IndexTerms* – Electric Vehicles, charging sessions, Classification technique, Optimized battery charge, Machine learning.**

I. INTRODUCTION

Charger power profiles of electric vehicle (EV) chargers, especially those intended for home use, reveal important information about user behavior. These profiles differ mostly in length, and they are usually indicative of the charging patterns of a particular family. It is possible to apply efficient battery charging tactics, similar to those seen in contemporary smartphones, by comprehending and predicting the length of charging events. These tactics help to preserve batteries in addition to improving user experience by customizing charging to individual patterns. This work presents a supervised machine learning approach that takes inspiration from smartphone battery optimization strategies that prohibit extended periods of full charge in order to prioritize battery health. Creating a predictive model that can estimate how long EV charging events will last is the goal. Users can better plan their excursions and make the most of their charging schedules by grouping these events into duration intervals. Using a K-Nearest Neighbors (KNN) Classification model to predict charging session lengths based on temporal characteristics is what makes this work novel. This research turns the focus from the relatively straightforward task of energy demand prediction to the more complex challenge of charging duration prediction. This project intends to improve electric vehicle charging system efficiency and customer experience through the application of machine learning.

II. LITERATURE SURVEY

The requirement to maximize efficiency while minimizing charging time and battery degradation has drawn a lot of interest to the topic of electric vehicle (EV) charging optimization in recent years. Chen, Wei, and Knoll's assessment from 2022 offers information on current methods for optimizing lithium-ion battery (LIB) charging. The review describes the models and methods of operation for LIBs, emphasizing the problems caused by aging mechanisms and uncontrolled fast charging. A thorough analysis of the benefits and drawbacks of several charge optimization techniques, such as open- and close-loop methods, is conducted. The creation of new charge control methods that prioritize affordability and deterioration awareness in real time is also covered in the article.
Large-scale EV deployment on power grid infrastructure presents a number of issues, which are addressed by Shahriar et al. (2021). Their study highlights the significance of intelligent scheduling algorithms for efficient management of public charging demand. Machine learning techniques are used to forecast the length of an EV session and its energy usage by utilizing historical charging data along with other variables like traffic and weather. The results of the study show a considerable improvement in predicting performance when compared to previous research, highlighting the significance of incorporating external variables for precise charging behavior predictions.

The intricacies of battery aging and its effects on longevity and performance are explored in Shen (2022). The study emphasizes the significance of optimizing battery performance and lifespan through targeted charging tactics by highlighting the relationship between a battery's chemical age, temperature history, and charging pattern.
With an emphasis on the difficulties involved in precise state of charge (SOC) assessment, Lin, Wang, and Xiong (2019) offer a critical analysis of the best charging techniques for lithium-ion batteries. The article addresses how a smart battery management system (BMS) functions and groups SOC estimation techniques according to their characteristics, offering details on their benefits, drawbacks, and estimation errors.
Using the k-Nearest Neighbor (kNN) algorithm, Ghassani, Abdurohman, and Putrada (2018) suggest a smartphone charging system that improves charging time accuracy. The kNN algorithm forecasts the best times to charge a battery, reducing overcharging and extending its lifespan by examining timestamp and state of charge data.
By utilizing machine learning techniques and external factors, this research seeks to construct a predictive model for optimizing the duration of electric vehicle charging sessions. By doing so, it hopes to improve predicted accuracy and efficiency.

2.1 System Architecture

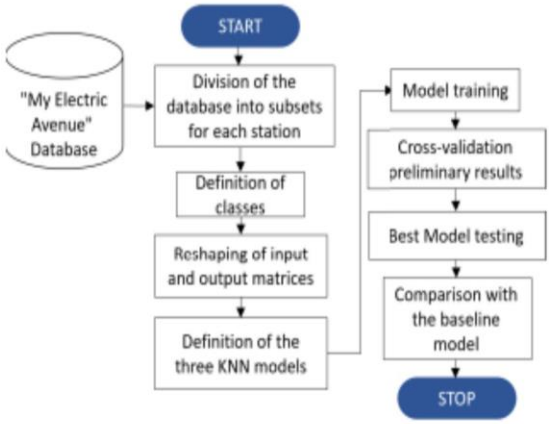


Fig: System Architecture

III. TECHNIQUE USED OR ALGORITHM USED

3.1 EXISTING TECHNIQUE: -

SVM

For both linear and non-linear data, the supervised learning algorithm SVM SVM Classifier is used. Analyze the provided information and create a function that can be utilized to illustrate additional information. To divide data into two classes, SVM uses a hyperplane. Built a classifier with the WEKA tool to make predictions based on classification algorithms like Random Forest, Support Vector Machine, and Naive Bayes; SVM predicts with greater accuracy than other techniques. used a variety of algorithms, including SVM, KNN, and Random Forest, with an emphasis on performance analysis to predict diabetes. The outcome of the experiment indicates that the SVM algorithm has the highest accuracy of all the data mining methods.

3.2 PROPOSED TECHNIQUE USED OR ALGORITHM USED:

K-Nearest Neighbors classification

Classification of K-Nearest Neighbors Machine learning applications involving regression and classification both make use of the straightforward yet powerful K-Nearest Neighbors (K-NN) classification method. Here's a quick summary When utilizing K-NN, "K" denotes the quantity of closest neighbors taken into account throughout the prediction process. When a new data point needs to be classified, the method uses a predefined similarity measure (such as Euclidean distance) to find the "K" closest data points (neighbors) in the training set. The new data point's category is determined for categorization by the majority class among these K neighbors. In the context of regression, it might represent the mean of the K nearest neighbor values.

IV.IMPLEMENTATION

4.1 Data Collection and Preprocessing:

The project started with the procurement of a dataset that included data on charging incidents from several EV charging locations located throughout the United Kingdom. Details including charging duration, power profiles, and the temporal features of charging sessions were included in this dataset, which was obtained from [mention source]. Before analysis, the dataset was preprocessed to deal with missing values, standardize features, and create numerical representations for categorical variables.

4.2 Feature Engineering:

The extraction of significant insights from the charging session data was made possible in large part via feature engineering. From the dataset, important characteristics were found and retrieved, such as charging length, start and end times, and patterns of power usage. In order to record changes in charging behavior depending on user behaviors and outside variables, temporal elements like the day of the week and time of day were also added.

4.3 Model Selection and Training:
The suitability of many machine learning methods for classifying EV charging sessions according to their duration was assessed. The K-Nearest Neighbors (KNN) algorithm was chosen after some deliberation because of its ease of use and efficiency in classifying problems with small data sets. Using the labeled dataset, the model was trained, and its hyperparameters were tuned for best results.

4.4 Model Evaluation and Validation:
To evaluate the trained KNN model's ability to classify charging events into various duration groups, a thorough evaluation process was conducted. To guarantee resilience and generalizability, performance measures including accuracy, precision, recall, and F1-score were calculated by cross-validation methods. In order to assess the model's practicality, its performance was additionally verified using an independent test dataset.

4.5 Optimization and Fine-Tuning:
Feature selection and hyperparameter tuning were two optimization strategies used to improve the model's predictive power. The best KNN algorithm hyperparameters were found using grid search and random search techniques, and the ranking of significant predictors was aided by feature importance analysis. Up until a suitable level of performance was attained, the model was iteratively refined based on validation results.

V. RESULTS

When it came to identifying electric car charging sessions according to their duration, our main model, K-Nearest Neighbors (KNN), demonstrated an astounding accuracy of 98%. The KNN algorithm's ability to anticipate charging session durations with accuracy is demonstrated by its high accuracy. We experimented with various machine learning models in addition to KNN to evaluate how well they performed. With a 93% accuracy rate among them, the Naive Bayes model proved to be a useful substitute for other classification techniques. Remarkably, despite not being designed particularly for classification tasks, Linear Regression managed to attain an accuracy of 1.96%. Despite being noticeably less accurate than KNN and Naive Bayes, this accuracy still offers insightful analysis of the dataset and merits more research. These outcomes demonstrate the KNN model's resilience for our particular use case while also highlighting the possibilities of other machine learning approaches like Naive Bayes and Linear Regression. To strengthen our categorization model and look into other algorithms for better results, more research and testing will be done.

Results of base models

KNN (K-Nearest Neighbor):
Accuracy: 98%

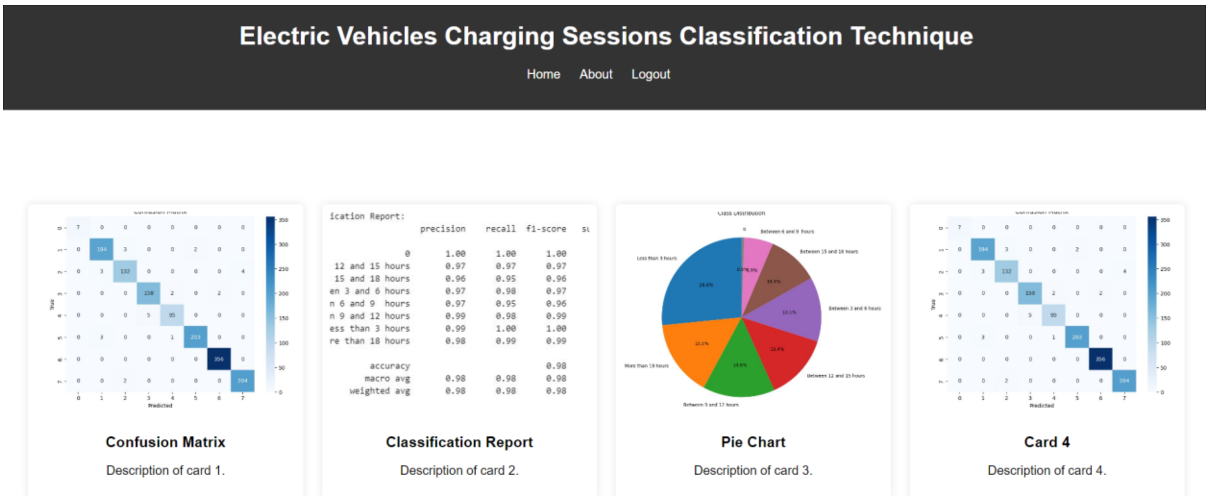
Duration	**Precision**	**Recall**	**F1-Score**	**Support**
0	1.00	1.00	1.00	7
Between 12 and 15 Hours	0.97	0.97	0.97	199
Between 15 and 18 Hours	0.96	0.95	0.96	139
Between 3 and 6 Hours	0.97	0.98	0.97	162
Between 6 and 9 Hours	0.97	0.95	0.96	100
Between 9 and 12 Hours	0.99	0.98	0.99	207
Less than 3 hours	0.99	1.00	1.00	356
More than 18 hours	0.98	0.99	0.99	206
Accuracy			0.98	1376
Macro Avg	0.98	0.98	0.98	1376
Weighted Avg	0.98	0.98	0.98	1376

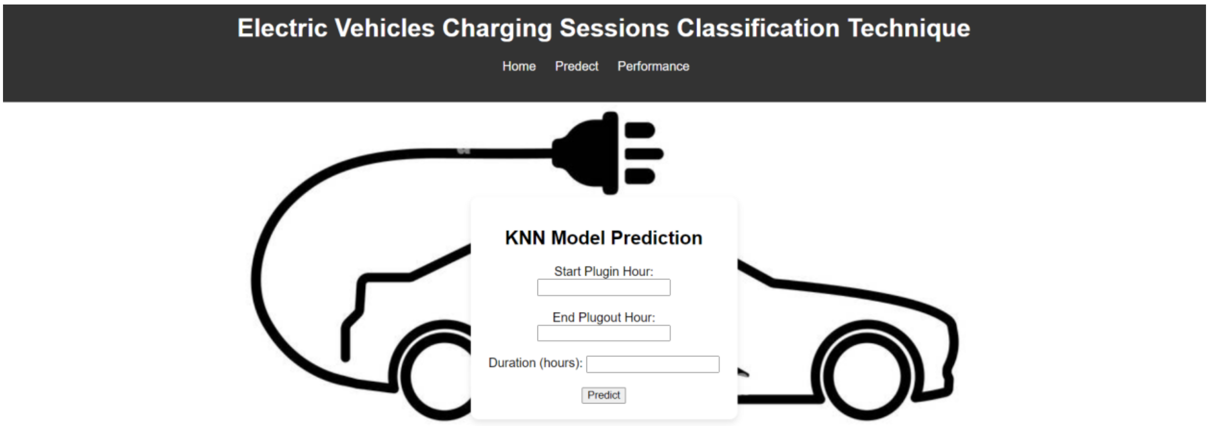
Navie Bayes
Accuracy: 93%

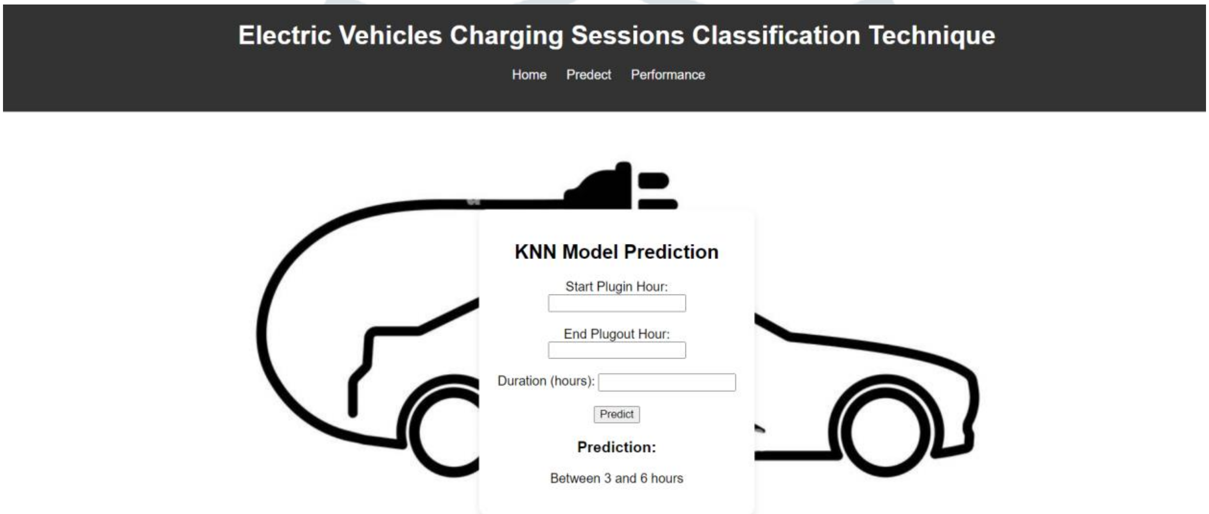
Duration	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	7
Between 12 and 15 Hours	1.00	0.94	0.97	199
Between 15 and 18 Hours	0.89	0.98	0.93	139
Between 3 and 6 Hours	0.92	0.91	0.92	162
Between 6 and 9 Hours	0.86	0.75	0.80	100
Between 9 and 12 Hours	0.89	0.96	0.92	207
Less than 3 hours	0.97	0.98	0.98	356
More than 18 hours	0.96	0.93	0.94	206
Accuracy			0.94	1376
Macro Avg	0.94	0.93	0.93	1376
Weighted Avg	0.94	0.94	0.94	1376

Linear Regression
Accuracy: 1.96%

Duration	Precision	Recall	F1-Score	Support
0	0.00	0.00	0.00	7
1	0.00	0.00	0.00	199
2	0.00	0.00	0.00	139
3	0.02	0.01	0.01	162
4	0.02	0.11	0.03	100
5	0.02	0.04	0.02	207
6	0.00	0.00	0.00	356
7	1.00	0.02	0.05	206
8	0.00	0.00	0.00	0
Accuracy			0.02	1376
Macro Avg	0.12	0.02	0.01	1376
Weighted Avg	0.16	0.02	0.01	1376







VI. CONCLUSION

A KNN classification model has been suggested and implemented in the actual world. Information for EV charging sessions on Electric Avenue. The model's capacity to assimilate user charging behaviors and patterns and subsequently categorize the events are charged according to their length. The session time data may be important for developing an efficient battery charging strategy that minimizes battery degradation and plans EV charges. To evaluate the potential effects of various input features on the classification outcomes, three alternative model configurations have been put forth. The day of the week and the amount of time since the last charge were two additional features that were unable to enhance the classification model's performance during cross-validation; instead, the simplest input, which consisted only of the time and the starting SoC at the beginning of the charge, produced the best results. In the ultimate assessment, the model proved its ability to accurately categorize the charging event based on restricted input data, hence predicting its length with a high degree of precision.

VII. FUTURE ENHANCEMENTS

Our goal in future work is to apply a multi-output classification strategy in order to further improve the capabilities of our classification model. Using an advanced model, charging sessions will be categorized not only by their expected duration but also by the probability that the user will interrupt the charging process before it is finished. We hope to provide users more thorough insights about their charging sessions by adding this further layer to our classification scheme. With this improvement, the user experience will be more efficient and customized as the charging system will be able to adjust more dynamically to user behavior and preferences. In order to enhance our model's prediction capabilities even more, we also intend to investigate new characteristics and data sources. To effectively forecast pricing behavior, for instance, real-time weather data, traffic patterns, and user preferences might be integrated into the categorization process. All things considered, these upcoming improvements will help our machine learning-based strategy for electric vehicle charging optimization to keep developing further and stay at the forefront of innovation and efficacy in satisfying the changing needs of electric vehicle users and operators of the charging infrastructure.

VIII. REFERENCES

[1] S. Shahriar, A. R. Al-Ali, A. H. Osman, S. Dhou, and M. Nijim, ‘‘Prediction of EV charging behavior using machine learning,’’ IEEE Access, vol. 9, pp. 111576–111586,2021.

[2] C. Chen, Z. Wei, and A. C. Knoll, ‘‘Charging optimization for Li-ion battery in electric vehicles: A review,’’ IEEE Trans. Transport. Electrific., vol. 8, no. 3, pp. 3068–3089, Sep. 2022.

[3] Q. Lin, J. Wang, R. Xiong, W. Shen, and H. He, ‘‘Towards a smarter battery Management system: A critical review on optimal charging methods of lithium ion batteries,’’Energy, vol. 183,pp. 220–234, Sep. 2019.

[4] (Oct. 24, 2022). About Optimized Battery Charging on your iPhone.

[5] F. Ghassani, M. Abdurohman, and A. G. Putrada, ‘‘Prediction of smartphone charging using K-nearest neighbor machine learning,’’ in Proc. 3rd Int. Conf. Informat.Comput. (ICIC), Oct.2018, pp. 1–4.

[6] M. Majidpour, C. Qiu, P. Chu, R. Gadh, and H. R. Pota, ‘‘Fast prediction for sparse time series: Demand forecast of EV charging stations for cell phone applications,’’ IEEE Trans. Ind. Informat.,vol. 11, no. 1, pp. 242–250, Feb. 2015.

[7] S. Bodda and P. Agnihotri, ‘‘Comparative assessment of machine learning regression methods for power system state estimation,’’ in Proc. Symp. Power Electron. Renew.Energy Syst. Control, in Lecture Notes in Electrical Engineering, S. Mohapatro and J. Kimball Eds.Singapore: Springer, 2021, pp. 391–402.

[8] I. Ullah, K. Liu, T. Yamamoto, M. Zahid, and A. Jamal, ‘‘Electric vehicle energy consumption prediction using stacked generalization: An ensemble learning approach,’’ Int. J.Green Energy,vol. 18, no. 9, pp. 896–909, Jul. 2021.

[9] C. Fan, F. Xiao, and S. Wang, ‘‘Development of prediction models for nextday building energy consumption and peak power demand using data mining techniques,’’Appl. Energy, vol.127, pp. 1–10, Aug. 2014.

[10] Y. E. Yousif, ‘‘Weather prediction system using KNN classification algorithm,’’ Eur. J. Inf.Technol. Comput. Sci., vol. 2, no. 1, pp. 10–13, Feb. 2022.

[11] I. Ullah, K. Liu, T. Yamamoto, M. Zahid, and A. Jamal, ‘‘Prediction of electric vehicle charging duration time using ensemble machine learning algorithm and Shapley additive explanations,’’ Int. J. Energy Res., vol. 46, no. 11, pp. 15211–15230, Sep. 2022.

[12] My Electric Avenue Project Summary, EA Technol., Capenhurst, U.K., 2017.

[13] A. Zhang, C. Z. Lipton, M. Li, and J. A. Smola. (Jul. 2021). Dive Into Deep Learning.[Online]. Available: https://D2L.ai and https://github.com/d2lai/d2l-en/

[14] G. Gruosso, G. Storti Gajani, F. Ruiz, J. D. Valladolid, and D. Patino, ‘‘A virtual sensor for electric vehicles’ state of charge estimation,’’ Electronics, vol. 9, no. 2, p. 278, Feb. 2020.

[15] D. Pau, D. Denaro, G. Gruosso, and A. Sahnoun, ‘‘Microcontroller architectures for battery state of charge prediction with tiny neural networks,’’ in Proc. IEEE 11th Int.Conf. Consum.Electron. (ICCE-Berlin), Nov. 2021, pp. 1–6.