CLASSIFICATION OF ELECTRIC VEHICLE CHARGING SESSIONS: A MACHINE LEARNING–BASED TECHNIQUE FOR OPTIMIZED BATTERY CHARGING

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ABSTRACT

Given how quickly EV use has increased over the past ten years, it is now necessary to accurately estimate how much energy an EV will use when charging. The primary energy source for electric cars nowadays is lithium-ion batteries; keeping them from being overcharged can protect them and increase their lifespan. The machine learning model for EV charging session length prediction presented in this paper is based on the K-Nearest Neighbors classification technique. Assigning the event to the appropriate class allows the model to predict how long the charge would last. The charging events, which last for a specific amount of time, are included in each class. The program only uses the data (arrival time, starting SOC, calendar data) that is available at the start of the charging event. The model has been proved accurate A sensitivity analysis is conducted to evaluate the effects of various input data sets on a real-world dataset that includes records of charging sessions from over 100 users. A performance gain indicates how effective the model is in comparison to the benchmark models.

INTRODUCTION

The charging power profiles of a charging unit are indicative of the user behavior (often a family) when it comes to Electric Vehicle (EV) chargers used for personal use. The fact that just one car is most likely charged at a time with the EV charger guarantees a consistent charging profile. The primary characteristic that sets charging events apart is their length. It would be helpful to predict in advance the "type" (short/long, complete/incomplete) of charging event (short/long, complete/incomplete) that will take place at the precise moment the charging car is plugged in, taking into account the previously mentioned factors. The charging control system may incorporate more capabilities if it could anticipate how long the electric vehicle will remain in charge system, such turning on an enhanced battery charging feature like to that present in certain smartphones today. Additionally, the charging system has the option to initiate a "slow" or "fast" charge, which will differ in their effect on the household's overall power load requirement. In addition to providing the customer with a better charging experience tailored to their habits, this new optimized charge would protect the battery's condition. For example, starting with the iOS 13 system, the phone's optimized charging mechanism charges the battery to approximately 80% before finishing it just before the predicted end time, all because it can predict the user's daily habits. Because of this, the battery is never fully charged for an extended length of time, a scenario that could lead to degeneration from voltage overflow at full charge. The paper's goal is to demonstrate a supervised machine learning model that, by classifying each event according to its appropriate time interval, can "predict" how long the next EV charging event at a certain EV charging station will last. With minimal features as input, a K-Nearest Neighbors (KNN) model is selected to carry out the classification assignment. Previous studies on EV charging sessions use the KNN as a regressive prediction model, despite the fact that it has already been applied in literature; on the Instead, a KNN classification model is proposed in this paper to categorize charging events according to temporal features into distinct duration categories. Furthermore, the bulk of research in the literature place more emphasis on predicting energy demand than just the amount of time it will take to charge a device based on user activity. The projected session length is expected to assist users in organizing their travel.

OBJECTIVE

There are several goals behind using machine learning to optimize battery charging in electric vehicles. Its primary goal is to improve charging processes' efficiency by developing predictive models that can simplify parameters and shorten charging times while preserving the battery health of the car. This project also aims to save costs by employing clever techniques that take advantage of off-peak times or variations in grid demand, which lowers costs for car owners as well as operators of the charging infrastructure. In addition, one of the main objectives is to increase battery longevity by developing charging strategies that reduce deterioration and guarantee consistent and dependable performance throughout the vehicle's lifespan.

PROBLEM STATEMENT

In order to maintain battery health, the increasing popularity of electric vehicles (EVs) requires precise energy usage forecasts during charging. A K-Nearest Neighbors classification approach is suggested in this work to forecast the length of EV charging sessions. The model divides events into duration intervals by utilizing only the initial charging event data, which includes arrival time, starting state of charge (SOC), and calendar information. Its efficacy in comparison to benchmark models is demonstrated via validation on a dataset that includes billing records from more than 100 customers, exhibiting enhanced performance.

EXISTING SYSTEM

The proposed paper's innovation is in its ability to predict the class of EV charge power profiles with high accuracy using fewer features, including duration—a crucial metric for both DSOs (Distribution System Operators) and EV charging stations. The conventional load power curve methodology, which often uses time-series forecasting techniques, has changed its viewpoint in this way. The suggested model is verified using an actual dataset that includes details on charging incidents that took place in over 100 EV charging locations around the United Kingdom. The suggested KNN method can be implemented and made to function completely locally on any kind of charging tower because of its speed and simplicity as well as the ability to generalize the model.

Disadvantages of the Existing System

- When there is sounder in the data set, i.e., when target classes overlap, it performs poorly. Should each data point have more attributes than there are training data specimens, the model will function poorly.
- Because it requires more time to train, it performs poorly when we have large data sets.

PROPOSED SYSTEM

A supervised machine learning method for handling both regression and classification issues is the KNN algorithm. It is predicated on the idea that similar objects are located close to one another. When an unlabeled point is provided as input, it can classify it according to the class to which the k nearest labeled points belong—that is, the points that are actually its closest neighbors. A positive integer k of neighbors, a test observation x0, and a training set of labeled data are provided to the KNN classifier. The classifier first finds the k points in the training data that are nearest to x0, creating the domain N0. Finding the distance between x0 and every point in the training set—a widely used metric—reveals the closest neighbors is equal to the normal Euclidean metric when p = 2 and is Minkowski.

Advantages of the Proposed System

- The complete training dataset is stored and utilized immediately for inference.
- K-NN can easily adapt to new data without requiring the model to be retrained.
- Since K-NN doesn't assume anything about the underlying data distribution, it can be used on a variety of datasets.
- It performs well with smaller datasets when it is possible to compute the distances between data points.

RELATED WORKS

In order to maintain battery longevity and health, it is imperative that energy consumption during electric vehicle (EV) charging sessions be precisely predicted. This study tackles this critical issue. The work suggests a unique method for predicting charging session durations using the K-Nearest Neighbors classification algorithm, taking advantage of the ubiquitous use of lithium-ion batteries in EVs. The model produces accurate projections by grouping events into periods according to initial charging data, such as arrival time, starting state of charge (SOC), and calendar information. The model's efficacy is validated on a real-world dataset that includes billing records from more than 100 users; a sensitivity analysis reveals the influence of various input variables. The outcomes demonstrate enhanced efficiency in comparison to reference models, highlighting the possibility of utilizing machine learning to optimize electric vehicle charging procedures.

METHODOLOGY OF THE PROJECT

In light of the sharp increase in EV usage, the project's main goal is to anticipate how long EV charging sessions will last. This is because long-term battery health and longevity are critical. By classifying events into distinct periods, the model uses a Machine Learning technique based on the K-Nearest Neighbors classification method to estimate charging durations. The model is trained and validated on a real-world dataset that includes records from over 100 users, utilizing just initial charging event data, such as arrival time, starting state of charge (SOC), and calendar information. To demonstrate the resilience of the model, a sensitivity analysis is carried out to assess its performance under various input conditions. By comparing the model's output to benchmark models, the study shows how well the model forecasts the length of EV charging sessions with increased accuracy and dependability.

MODULES

1) Data Gathering

Getting a variety of information on the charging procedure, how the car is used, and climatic conditions is necessary when it comes to optimizing battery charge for electric vehicles. I will elaborate on this now.

2) Data Evaluation

When it comes to optimizing battery charging for electric vehicles, data analysis entails looking through the gathered information to find patterns and insights that might guide the creation of charge optimization techniques.

3) Data Preparation

An essential stage in the pipeline for data analysis and machine learning is data pretreatment. It entails preparing raw data for analysis and modeling by cleaning and formatting it. Here is an explanation of the main elements of data preparation in the context of electric vehicle battery charge optimization:

4) Train Model

Iterative experimentation and fine-tuning are used in the training process to create a model that reliably forecasts the ideal charging conditions for electric vehicles based on historical data.

5) Data Evaluation

Evaluating data entails determining how successfully a machine learning model carries out its assignment. This entails verifying its precision, accuracy, or other particular metrics pertinent to the issue it's resolving, such as forecasting the best time to charge electric cars. It's similar to putting the model to the test on fresh, untested data to make sure it can provide correct predictions rather than just memorize past data.

6) Outcomes

For all intents and purposes, "results" refer to the outputs of applying machine learning models or data analysis techniques, which support decision-making processes, generate insights, and direct subsequent actions toward accomplishing the goals established for optimizing battery charging in electric vehicles or any other pertinent task.

ALGORITHM USED IN PROJECT

K-Nearest Neighbors classification

- In machine learning, the K-Nearest Neighbors (K-NN) classification algorithm is a straightforward yet powerful method for both classification and regression problems. Here's a quick summary: The "K" in K-NN stands for the number of nearest neighbors that are taken into account while forming a prediction. The algorithm considers the "K" nearest data points (neighbors) in the training set based on a predetermined similarity metric (such as Euclidean distance) whenever a new data point needs to be classified.The new data point's category is determined by the majority class among its K neighbors for categorization purposes. The average of the values from the K nearest neighbors could be used for regression.

DATA FLOW DIAGRAM

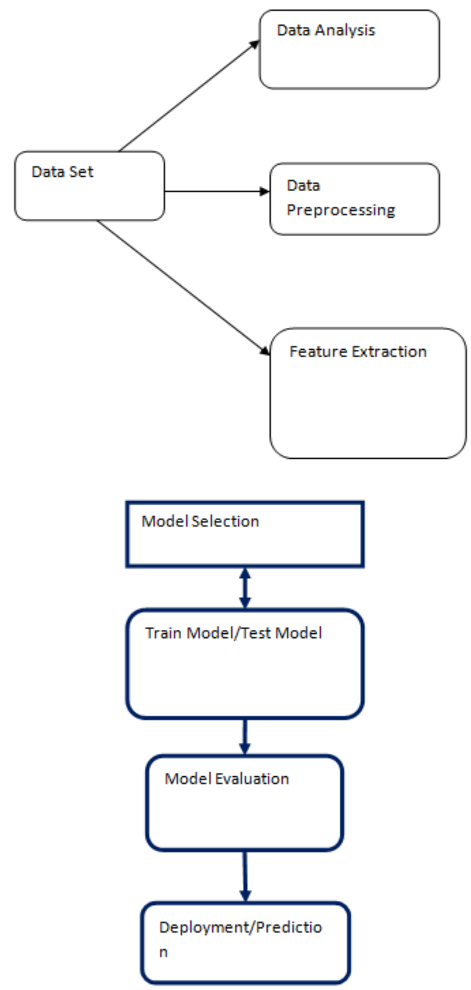


Fig: 1 Flow Diagram of Modules

SYSTEM ARCHITECTURE

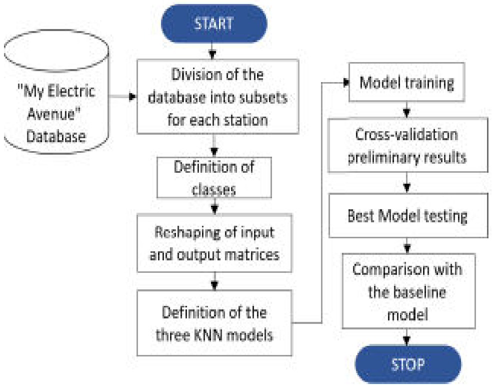
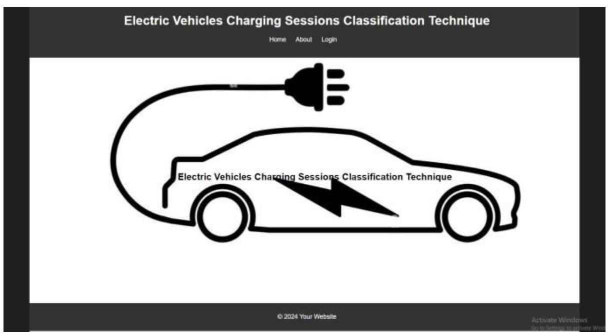
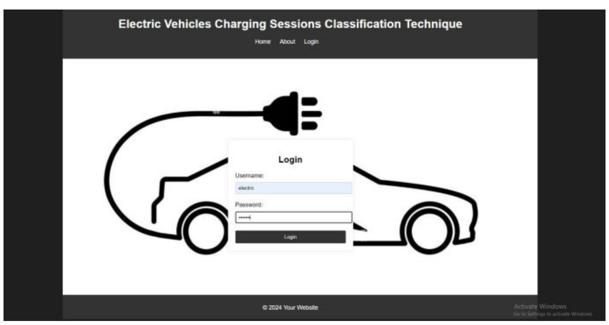
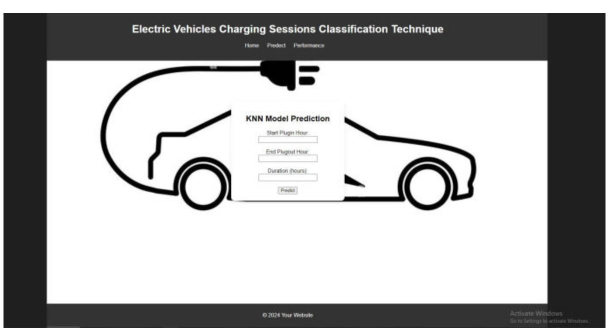


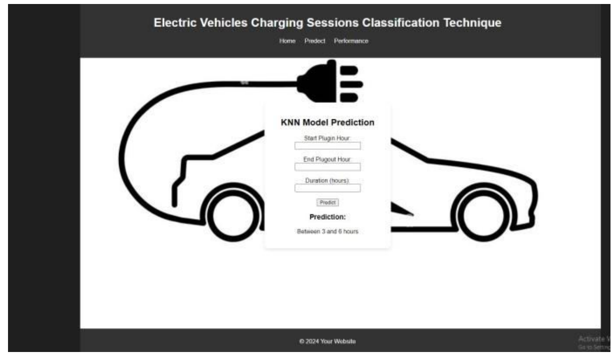
Fig: 2 System Architecture Of Project

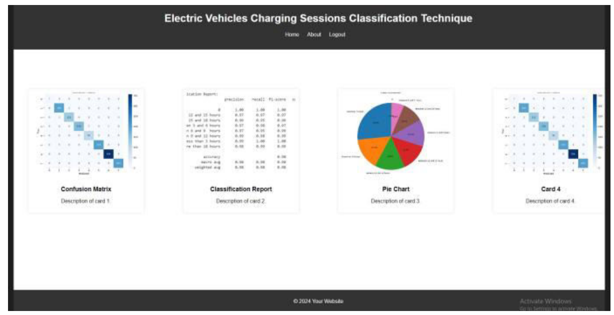
RESULTS











FUTURE ENHANCEMENT

In the future, we might put into practice a new multi-output classification model that can categorize both situations according to the anticipated duration and the likelihood that the user would terminate the charge before it is finished.

CONCLUSION

Using the actual My Electric Avenue EV charging sessions dataset, a KNN classification model has been proposed and adopted. Classifying the charging events according to their duration, the model has demonstrated its ability to learn the charging routines and behavior of the user. Regarding the scheduling of EV charges and preventing battery degradation, the session time data may be important in developing an optimal battery charging strategy. To evaluate how various input variables might affect the categorization outcomes, three alternative model configurations have been put forth. Both the day of the week and the amount of time since the last charging of the classification model were insufficient to enhance the model's performance during cross-validation. With only the time and the starting SoC at the start of the charge, the simplest input produced the best results. In the last test, the model proved to be able to accurately classify the charging event based on a small amount of input data, and as a result, predict the charging event's duration almost exactly.

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