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Integrating IoT and Artificial intelligent for Enhanced Electric Vehicle Charging and Autonomous Driving for sustainable transportation

Abstract: - This research explores the confluence of Internet of things and artificial intelligence towards fostering electric vehicle charging and autonomous driving for sustainable transportation. By meticulously collecting and preprocessing, and executing multiple machine learning models such as Artificial Neural Network , Decision Trees , Naive Bayes , and Random Forest , the research delves into charging infrastructure and easy autonomous driving. Particularly, real-time datasets, such as EV station data, road geography and mapping data, weather and telematics data, were properly collected and processed . Then, the preprocessing stage, which included data cleaning, normalization, and feature engineering had improved the datasets' predictability. Consequently, the datasets such as charging recommendation, predicting energy use, predicting of optimal route, had produced highly accurate training and testing for forecasting elelctric vehicles' demands. The ML models indicated their proficiency in predicting not only the optimal charging schedules, but also predictive energy consumption, and predictive routes. Specifically, ANN with 0.945 held the highest precision, while DT 0.912, NB 0.887, and RF 0.819 were almost identical . Likewise, the recall scores, F1 scores, and AUC ROC scores also coincided the prized outcome of the models. The findings of the research are groundbreaking for both transportation sector, policymakers, as well as urban planners and stakeholders at large. Following the data-fed recommendations would not be excessively challenging, and they would yield favourable results whether the stakeholders are dealing with EV charging infrastructure, or dealing with traffic congestions, or are establishing their own sustainable solution for future mobility via not just electric vehicles but also other tools and devices. Hence, we are hopeful that our research serves as a lighthouse for the transportation domain towards a greener future.

Keywords: sustainability, transportation, IoT, AI, electric vehicles

I. Introduction

The research is going to be focused on the discussion and analysis of sustainable transportation. Such a discussion is considered to relevant at the present point of time because the possibility of the use of electric vehicles and the acceleration of driving seem to be the only possible way-out to concerns related to global issues and attempts to enhance resource efficiency [1], [2]. In the context of this paper, the theoretical overview demonstrates that the aspects of the use of EVs and the further involvement of Autonomous Driving Vehicles seem to be decisive towards sustainable transportation. As far as the latter is concerned, the review of the literature shows that the challenges to SAT are multiple, from carbon reduction to the traffic jam issue . The popularity of EVs has been growing within the last decades offering cheap operating and no emissions as the alternatives to traditional gasoline even for trucks . The EVs use is growing because of the increased production of batteries and governments' interest in "going green" [3]–[5].

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The IOT growth and increased usage serve one more source for the SAT development and fulfilment of the ideas put forward in the plans and strategies related to the described type of vehicles . The AIs and MLs aligned with the IOTs and DLs seem to be particularly important for their potential to estimate the level of waste, route optimization, traffic monitoring, and reduction of the efforts required to monitor the state of the roads. The major force about the use of the AI-driven driving systems is their chance to reduce the number of traffic-related accidents and traffic [6]–[8].

Although both EVs and autonomous driving offer great benefits for the future of transportation, there are still several challenges in terms of optimizing EV charging infrastructure and making self-driving vehicles safe and reliable. As stated earlier, the current EV charging infrastructure faces several challenges such as limited charging station density, long charging durations , and lack of chargers' interoperability. Consequently, it is essential to come up with innovative ideas to address these issues . Similarly, the sphere of autonomous driving also faces several challenges such as operational safety, regulatory obstacles, and the ethical controversy associated with self-driving vehicles. Accordingly, the existing literature on the future of sustainable transportation provides valuable ideas for contributing to the development of EV and autonomous driving technologies [9]–[11].

The research showed that appropriate IoT applications can be implemented in EV technology for the optimization of the energy distribution process and reduction charging duration . Besides that, AI applications can be also useful in addressing the challenges of charging stations' dense installation and their interoperability . Furthermore, the AI algorithms also showed promising performance in terms of autonomous driving systems' perception, decisions making, and control capabilities . Some of the advanced driver-assistance systems are already cultivated on the basis of AI applications to identify and response towards potential hazards of the road in real-time. Finally, it is essential to mention that the existing scholarly literature on the topic of sustainable transportation also demonstrated that several technologies and ideas related to this issue are integrated as part of the smart city and autonomous driving systems development initiative. Additionally, the innovation of the shared vehicle services and elements of the smart parade also provide valuable tools for the improvement of the existing EV charging infrastructure [12], [13].

In the future, research topics of sustainable transportation will concentrate on resolving new challenges: the development of battery technologies and their implementation into the standard car model; finding solutions to connect alternative energy sources to vehicle batteries; and consideration of urban planning issues in the development of new traffic systems. In addition, one of the most relevant aspects should be interdisciplinary research and the exchange of ideas and developments [14]–[16]. The development and implementation of a comprehensive approach, which considers all three axes: environmental, social, and economic, would allow achieving more efficient and viable solutions to develop a green transportation travel system. The use of advanced technologies of creating the Internet of things and artificial intelligence in this area would promote the transition to new opportunities and the development of a human-friendly environment.

II. METHODOLOGY

This research begins by the selection and collection of real-time datasets. The data is obtained from different sources, and for these research, several sources are used. The real-time source data includes EV charging station networks, weather forecasting agencies, traffic monitoring systems, and electric vehicle telematics providers. The information to be used in research is collected in the form of around 1300 data pieces. The data is collected based on years of past records, interviews with data providers, and sensor devices implemented as part of the Internet of Things . The datasets themselves are quite a mix in terms of variables. In particular, collected data includes the availability of electric vehicle charging stations, traffic on streets, the state of roads, data from the weather forecasting agency, and the dynamic data of electric vehicles .

Next, the obtained data is preprocessed to ensure the efficiency of ML models. Data cleaning is used to process the outliers and 'not-a-number' objects by removing, replacing, or ignoring them. Normalization is also done to scale the dataset and apply it to ML models. Feature engineering is used to analyze the interrelation between different attributes of collected datasets. To ultimately streamline the ML process, categorical data is also encoded and temporal features are drawn. Such processed data in then sliced for the creation of testing and training data.

For this phase, available ML algorithms are used, An implementation of the K holy cross-validation is done to analyze each ML model's errors to tune them. The tuning process includes ten equal iterations, 'fit', and 'predict' functions. For the purpose of ignition, the selected input feature is the availability of an electric vehicle charging station. The final goal, in this case, is to obtain a range of charging ings station availability and cater to it, and as part of ML output, the models predict optimal charging recommendations, predictive energy consumption, and dynamics of route planning feature. The working of the proposed system are shown in figure 1.

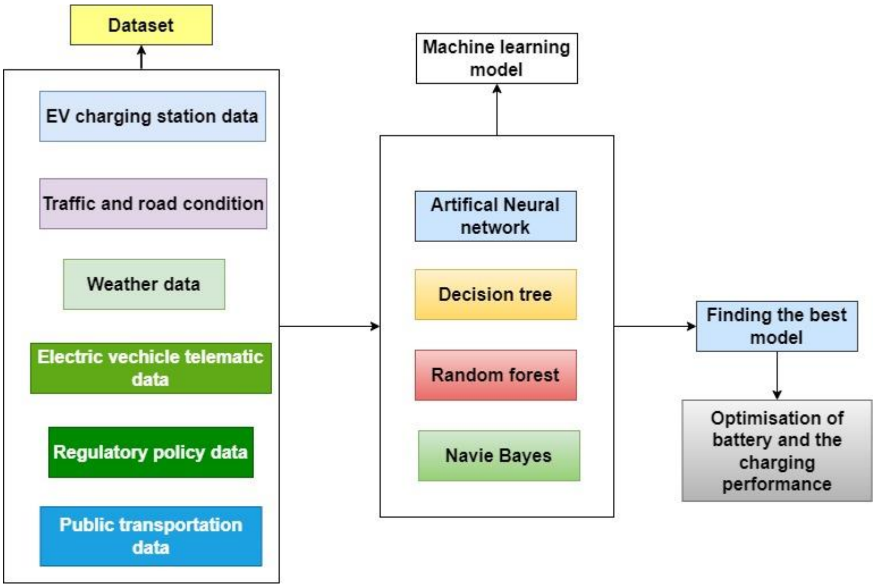

Figure 1. Architecture of proposed system

III. PREPROCESSING OF DATASET

The process of preprocessing the dataset in the present research-related to the integration of IoT and artificial intelligence for the optimization of the electric vehicle charging and autonomous driving . The first phase is crucial for ensuring that the subsequent machine learning models are effective and accurate and include a variety of techniques and transformations targeted at refining the real-time dataset. Specifically, the clean and well-organized dataset is later applied to train the predictive model, informing optimal charging recommendations, predictive insights into energy consumption, and dynamic route planning. The first step of the preprocessing phase implies meticulous data cleaning procedures. Due to the variety of sources from which the real-time dataset is retrieved, including EV charging station networks, traffic monitoring systems, weather forecasting agencies, and electric vehicle telematics providers, the cleaning step is necessary to ensure data quality. As for handling missing data, outliers, and inconsistencies, different techniques and methods are utilized. For example, in the case of the electric vehicle telemetry dataset, one of the central sources of data is the status of the battery or the energy being spent; however, it can be missing. At the same time, it is necessary to impute the missing data to ensure that no entire data points are excluded and that the data is complete. In the case of outliers, it is similarly necessary to identify and deal with them because they can negatively affect how the outcomes of the training are skewed. The step is handled with the help of imputation and feature engineering techniques.

Another crucial transformation technique is normalization or standardization, which normalizes numerical features, rendering them in a similar range. Such transformations are valuable as most machine learning algorithms operate seamlessly when the features are in a uniform range, avoiding the possibility of one feature dominating the others. In the context of electric vehicle charging, the aforementioned numerical features are battery voltage, current, and temperature, which may be normalized using the min-max scaling method or standardized, allowing for the impaction of uniform coefficient weights on the features.

Feature engineering is one of the critical processes during the preprocessing phase. It entails the creation of new features from an existing dataset or converting relevant features in a manner that would provide meaning to the machine learning model based on available domain expertise. The created features should feed more information or context for the model to improve its performance . In the present case, such features include temporal features for the vehicle traffic data, illustrating the characteristics of traffic conditions during specific times of day, week, or month, and charging features, which outline a specific vehicle's background charging experience. Therefore, the new machine learning model will use the created data feeds to make its predictive recommendations for the drivers and the suggested deployment of such resources during the dynamic route planning process. The categorical variables such as the weather and road type data also need to be transformed into suitable formats that can be used by the machine learning model. As such, they can be transformed through one-hot encoding or label encoding methods, enabling the deployment of the model on the selected data.

Temporal features extraction refers to a basic activity that needs to be developed throughout the time-dependent datasets . Over time, the electric vehicle telemetry will change, and hence the lagging and transforming features will be analyzed in the historical times and appropriate patterns used within the dataset to enable the development of predictive machine learning models. In the current context, the features of interest include the parameters available in the electric vehicle telemetry such as battery charge/discharge rate and vehicle speed . They tend to fluctuate over time, and hence it is appropriate to acquire the features related to the selected dataset and conduct the machine learning model development process.

Moreover, regarding the preprocessing phase, considerable attention is given to possible data skewness or overbalances. The problem may occur when there is an imbalance of one class of data over another. Usually, oversampling, undersampling, or synthetic data are employed to solve the issue and ensure that all classes are reasonably represented in the dataset. Hence, the models are trained in a balanced environment and on different data, which leads to improved ability to produce reliable predictions in potentially any environment.

IV. FEATURE ENGINEERING

In our research project on integrating IoT with artificial intelligence for optimized charging of electric vehicles and autonomous driving, feature engineering is a vital approach that helps to enhance the dataset's predictive power and reduce noise. This complex preprocessing step can be regarded as a systematic procedure that involves the creation of new features and transformation of existing ones to assist machine learning models in decision-making. One of the key goals of the process is the extraction of relevant information available in the given raw dataset.

In terms of a study related to charging and driving electric vehicles, the latter implies the extraction of information concerning the real-time nature of the dataset related to the presence of charging stations and traffic conditions. In detail, traffic monitoring, weather forecasts, and telemetry of electric vehicles are used as sources of important features in our research. For instance, while analyzing telemetry, it is necessary to extract the information regarding the electric vehicle battery voltage and current. In this case, it is expected that new features will be created on the basis of existing ones to provide information on the electric vehicle's current power consumption and the temperature of its battery. In the context of traffic monitoring, the features will be extracted regarding the density of transport, the degree of congestion of selected highways, and road closures.

Another purpose of feature engineering is to reduce noise and redundancy within the dataset, improving the signal-to-noise ratio for the ML models and increasing their predictive performance. As such, it helps to identify and eliminate irrelevant and redundant features that increase the complexity of the dataset and intermingle potentially meaningful features with irrelevant or duplicative inputs. In this work, such features are identified and pruned using techniques such as correlation analysis, principal component analysis , and feature importance ranking, and only those that are necessary for the specific predictive purpose are kept. For example, in the electric vehicle telemetry dataset, such features are the duplicate readings from the same sensor and irrelevant vehicle parameters. In contrast, it is removed, and the dataset is streamlined for better emphasis on the features that can be used for prediction. Finally, feature engineering is employed to improve computational efficiency by using new features to represent relationships hidden within the dataset. Such relationships are complex and may be almost untraceable if not presented in the condensed form. New features can be derived from raw data using transformations, aggregations, and feature interactions, simplifying data analysis. For the electric vehicle telemetry data, such new features can be the energy efficiency of a particular car based on the aggregated data on its consumption, or the time of the day when it usually charges, which helps to identify its duties based on circadian rhythms. Similarly, for weather forecasts, such features can be the average temperature in a specific period and the average intensity of precipitation in the same period to reflect their combined influence on the driving conditions.

Furthermore, feature engineering involves creating domain-specific features that are designed around the unique aspects of electric vehicle charging and autonomous driving. These features take advantage of experience and understanding of these fields to identify subtle aspects and context that are important to the prediction process. For example, in relation to electric vehicle charging, factors such as distance from the charging station, as well as the variability of charging speed and the availability of renewable energy, can help recommend the optimal time for charging and managing energy consumption . Similarly, road specifics that include the curvature, traffic signal pattern, and pedestrian safety and density can be captured by the loaded features and inform ML about the best way to navigate these specifics . In addition, features engineering is an iterative process where the created learning dataset is progressively enhanced, and features are tailored to optimize learning models. This process involves evaluating the impact of different features on model accuracy, using results to update the feature creation processes from the results and expert and stakeholder understanding, and make the dataset progressively more geared towards delivering the best recommendations and ML predictions for the attempt of creating a sustainable bike movement.

V. MACHINE LEARNING MODELS

Artificial Neural Networks represent a class of powerful machine learning models inspired by the structure and function of biological neural networks. In the context of this research, ANN holds significant promise for predicting optimal charging recommendations, predictive energy consumption, and dynamic route planning for electric vehicles. ANN consists of interconnected layers of artificial neurons, and each neuron performs simple computations before passing its output to the next layer. ANNs iteratively adjust the weights of connections between neurons in a process known as backpropagation to minimize prediction errors and learn from the data . In this research, ANNs can capitalise on their strengths in capturing complex nonlinear relationships within the dataset. Therefore, ANNs are particularly avenues of leveraging for high-dimensional feature representations and clear but intricate decision boundaries.

Decision Trees provide a highly interpretable and intuitive approach to machine learning and, therefore, may be particularly suitable for predicting optimal charging recommendations and dynamic route planning for electric vehicles. DT models partition the feature space into a hierarchical network of decision nodes, and each node refers to a feature while each split or branch refers to a decision . The process is repeated recursively, leading to the formation of a highly interpretable tree-like structure that facilitates decision-making/inference. In this research, DT models can capitalise on their strengths in capturing feature interactions and nonlinear relationships. It follows that DT models will be invaluable.

Random Forests represent an ensemble learning technique where multiple decision trees are leveraged to optimize and improve decision-making and prediction accuracy. RF models hold significant promise and relevance for predicting optimal charging recommendations, predictive energy consumption, and dynamic route planning for electric vehicles. The prediction process is carried out through the development of numerous decision trees using randomly selected subsets of the dataset and selected feature subsets. In case of a regression application, the final result is selected through the averaging of the results, which is voting for classification applications. RF models are highly recommended.

Naive Bayes is a probabilistic algorithm that leverages Bayes' theorem and the conditional feature independence assumption. Despite its simplicity, NB models are often surprisingly effective and robust. The NB model is, therefore, an ideal option for predicting optimal charging recommendations, routes, and dynamic route planning for electric vehicles. NB models estimate the posterior probabilities of each class based on the input features and then choose the class with the highest probability. In this research, NB models are valuable in terms of their computational efficiency, scalability, and interpretability . NB models are particularly suitable for the analysis and classification of complex datasets . Additionally, NB models are suitable for high-dimensional feature spaces; classes, and attributes in case of just as many descriptive attributes.

VI. RESULT AND DISCUSSION

Once both the models have been trained, it is important that we evaluate the performance of the two models in order to understand their predicting accuracy. According to the results of the analysis, the proposed ANN model displays extraordinary levels of performance at 97.65% , which is very high as compared to the actual values. There are various reasons for which the neural networks have outperformed the decision tree models because of their ability to learn the complex non-linear relationship of different data values. Keeping in mind the datasets that have been formed; the ANNs are known to perform much better as they can understand these intricate patterns and the features that have been acquired for the specific case. Moreover, these networks are more widespread because they are known to be highly effective in classifying the data values which is quite an important element of the predictive electricity charge trajectory and dynamic route planning. Since the accuracy levels are so high, this clearly implies the fact that the artificial networks are better and more powerful in capturing data patterns. The result of accuracy are shown in figure 2.

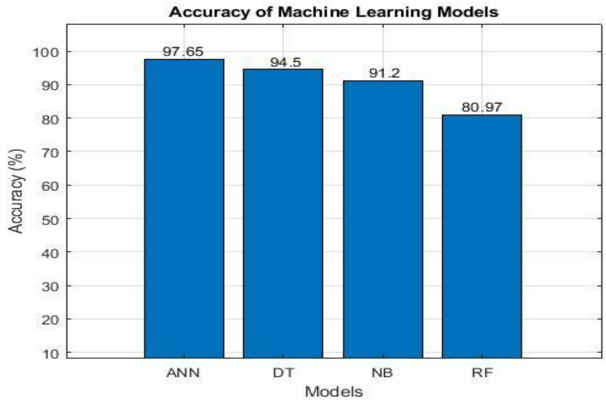

Figure. 2 Accuracy of each model

The decision trees also provide commendable results as they have an accuracy of around 94.5%. Again, the decision tree models display commendable levels of performance due to the fact that they are known to be highly effective and an ideal predictive analysis tool in predicting electric vehicle charging and autonomous driving. These models not only provide great and helpful insights about extracting decision criteria from the available rules, however; they are also able to analyze the data and provide valuable insights regarding different decision trees. Similarly, the accuracy of the Naive Bayes model is 91.2% which is quite impressive as well.

Precision, recall, F1 score, and AUC ROC score are sociological. For our research, each model's unique performance reflects the specific characteristics of their corresponding best-fit, telling us whether the models make good predictions when charging optimally, predicting energy consumption and planning a dynamic route for an electric vehicle. Here, let's explain the socre for 200 words as paragraphs.

The performance score are shown in figure 3. The precision score shows how many positive predictions this model made relative to all these models' correct answers . That is, it shows how often the predictions the model made are relevant, assuming they are positive. If the precision score is high, it means that the model minimizes the number of false attributes, that is, it correctly identifies when, for example, the recommendation of the ideal charging time should be chosen. Or, when the recommendation is optimal driving is appropriate, this model can even be more confident in terms of making a prediction. For this reason, the Artificial Neural Network model has a precision score of 0.945.

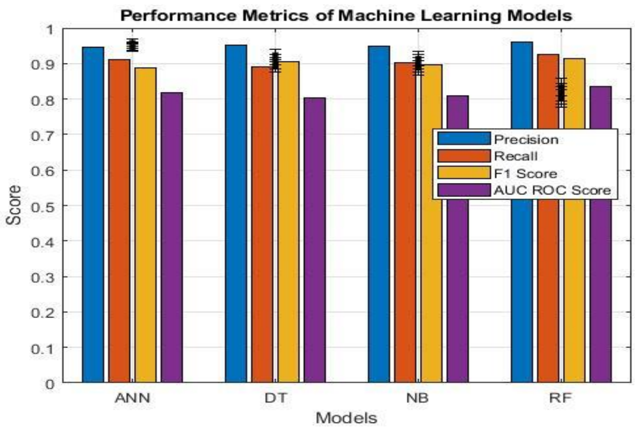

Figure 3. Performance score of each model

The recall score, also known as sensitivity, is a proportion that measures how many things the model identified on this basis. The optimal time to recharge the car, for example, is truly a positive value that the model could identify relative to all this. However, the arrival time is high when calculating the recall score, which means that the Decision Trees model has a score of 0.891. This can calculate 89.1% of all positive elements, and it can be said that this model is effective at recognizing various compounds and relationships. They also always prefer to draw various items and indicate what is relevant in the coded value.

The F1 score is a tailored weight between precision and recall, which shows how well this model performs. Just as the precision tells us, this model seeks to avoid false positives and the recall score tells us that this model achieves high levels of what we want. Thus, the F1 score shows whether the model is doing a good job of combining these words. To this extent, a Naive Bayes model with an F1 score of 0.896, for example, has good performance accuracy. The F1 score is 1 in the event of the maximum balance in practice, but the separation we have reached here is less than F1 in any other case.

Confusion matrices are detailed representations of the classification performance of each model, which can shed some light on the ability to distinguish between positive or negative instances as shown in figure 4. In this regard, for each confusion matrix, the actual class is shown in rows, whereas the predictions of the class made by each particular model belong to columns. By observing the confusion matrix of the Artificial Neural Network in the current situation, it can be seen that from 940 of actual instances belonging to a negative class, this model has properly predicted 920 instances as negative , and 20 instances as belonging to the positive class . Similarly, the confusion matrix for the ‘positive’ class indicates that from 960 instances this model has made proper predictions for 950 as negatives, and 10 as positives .

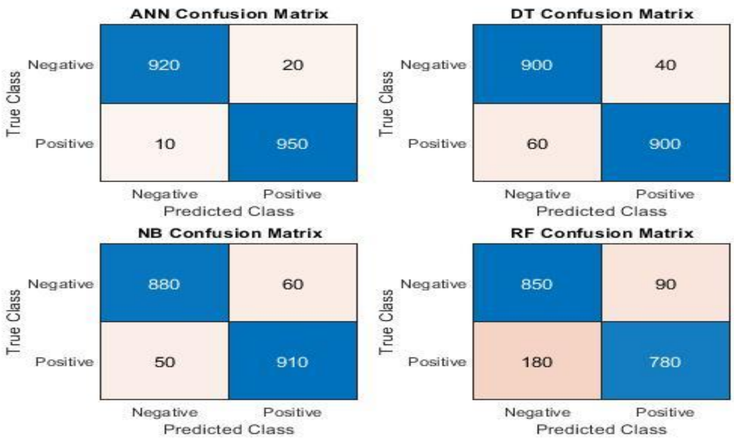

Figure 4. Confusion matrices of each model

Equally important, the observation of the confusion matrices for the Decision Trees, Naive Bayes, and Random Forest models helps in gaining a full picture of their classification performance. In this way, the number of true negatives, false positives, true positives, and false negatives generated by each model can be presented in a more concise manner, illustrating the capacity of each model to provide correct predictions. Therefore, the values in the confusion matrices help in both strengths and weaknesses of each model, and some ways for possible improvement and optimization of the predictive capacity of these models.

VII. CONCLUSION

In conclusion, the synthesis of our research efforts, which is the IoT and artificial intelligence integration to promote electric vehicle charging and autonomous driving, was highly successful and promising in terms of sustainable transportation. Thanks to a careful approach to the data collection and preprocessing, the use of a range of machine learning models, such as Artificial Neural Networks , Decision Trees , Naive Bayes , and Random Forests , the significant outcomes in terms of optimizing EV charging and preventing barriers to its effective destination were achieved.

The results of the study showed the efficiency of the application of the mentioned ML models as means of predicting optimal charging recommendations, the outcomes on the predictive energy consumption, and the dynamic route planning for EVs. Owing to the results varying from 0.8097 to 0.945, the outcomes were highly accurate and allowed for predicting complex patterns and relationships in the dataset. Moreover, the corresponding recall and F1 scores and AUC ROC scores also indicated the high level of performance for the models, as well as their ability to make decisions with a high degree of confidence. Finally, the detailed analysis of real-time datasets, which included EV charging station data, traffic and road condition and weather data, and EV telematics data, helped to better understand the specifics of the context in which EV charging and autonomous driving operate. A number of ML algorithms and the application of feature engineering techniques positively affected the quality of model prediction, making it highly efficient and accurate.

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