J. Electrical Systems 20-2s (2024): 885-892

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Machine learning Approach to Battery Management and Balancing Techniques for Enhancing Electric Vehicle Battery Performance

Journal of Electrical Systems

***Abstract:* -** The objective of this research is to apply machine learning techniques to optimize electric vehicle battery management and balance to attain maximum battery performance. Here, we will assess and compare the efficiency and accuracy of decision tree classifier, ANN, and Naive Bayes classifiers in: predicting two optimal charging and discharging battery management strategies, prediction of the battery's performance and detecting any abnormalities in it. . In this context, one machine learning model will be proposed to have the most advantageous performance. The experimental results details that such findings are attained, and the precision rates, recall rates, and F1-scores attained by net models exceed 98%. Additionally, the decision tree, as well as the Naive Bayes classifier, have impressive performance, and their accuracy rates exceed 90%. Decision trees along with Naive Bayes classifiers have also important impacts on the identification of classification of battery's responses through probabilistic classification in the former. Our findings have important implications for ensuring electric vehicle batteries are managed more properly for optimal performance. Additionally, based on the results obtained, they can be utilized to help relevant stakeholders in the EV industry and other industries with battery usage implement practical measures that optimize battery performance, increase battery life, and reduce the incurred operational expenses of electric vehicle fleets.

Keywords: Electric vehicles, Battery management, Machine learning, Optimization, Sustainability

I. INTRODUCTION

Electric vehicle battery management is deemed to be one of the most significant activities to ensure optimum battery performance, longevity, and safety of electric vehicle batteries. A battery serves as an electric vehicle's primary energy storage component and significantly influences the vehicle's range, efficiency, and overall operation [1], [2]. Therefore, an effective battery management system is critical to monitor, control, and optimize battery operation throughout its life. Battery management system introduces advanced monitoring techniques and control algorithms to prevent battery degradation and optimize charging and discharging strategies to promote the performance and long life of a fleet of electric vehicles . However, using batteries to power vehicles presents concerns and challenges that machine learning algorithms can help modern battery management systems overcome [2]–[4].

Electric vehicle battery management poses multiple challenges that require viable solutions to ensure the widespread adoption and acceptance of electric vehicles [5], [6]. Battery life is already highly limited, and various factors accelerate the problem, such as cycling, temperature effects, or actual operations. Although the majority of

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these factors are known, the ways to counter them and ensure electric vehicle fleet viability remain limited. Range anxiety is a significant problem for electric vehicle owners and implies the degradation of battery life and performance over the vehicle's lifetime. Thus, using advanced range estimation and prediction ML algorithms, it is possible to address the problem and enhance efficiencies and battery performance. Given that batteries are among the most complicated components that power EV engines, having viable battery management systems is essential to mitigate performance and battery degradation problems, thus ensuring battery performance within electric vehicle fleets. Many other problems, such as limited vehicle efficiency and aspects of operation, can be also addressed with viable battery management systems [1], [7].

Machine learning models have been increasingly used to manage electric vehicle batteries in recent years, with each of the models having their individual strengths and weaknesses. Artificial Neural Networks have proven almost overwhelming in their ability to discover very complex patterns and relationships in the data of the battery. Decision Trees , meanwhile, provide an internally consistent and transparent framwork that can be very useful in tasks requiring a good understanding of what the battery is going to do. Support Vector Machines are good at performing binary classification tasks, while Naive Bayes classifiers lever ag e the simplicity and power of probablility-based inferences [8], [9].

As it can be seen from a copious amounts of research, the machine learning models have been applied to a great array of aspects related to electric vehicle battery management. Particularly, they have been used to develop models predicting the state of the charge, the state of the health and the remaining useful life of the battery, to develop enhanced charging/discharging strategies and to reduce energy consumption through efficient on/off cycles and battery balancing [10], [11]. Thousands of papers have dealt with detecting battery cell anomalies and diagnosing faults, with the help of such algorithms. There has been a lot of work processing and analyzing big data sets, while training complicated machine learning models. In my project, too, machine learning models, such as ANN, DT and naive Bayes, will be applied to calculate optimal charging and discharging strategies, situations in which the performance criteria will be incureable and situations on when and how to re-balance batteries. They will also be applied to detecting abnormal battery conditions [12], [13].

II. METHODOLOGY

In this research, we used a machine learning approach to predict optimal charging and discharging strategies, battery performance metrics, and alerts/warning for improving EV battery performance. The ML models used in this research include Artificial Neural Networks , Decision Trees , and Naive Bayes . These models are trained using a dataset of 3400 pieces information collected from battery health metrics, charging and discharging events, vehicle information, distance, passenger load, and driving behavior.

The chosen dataset is well-prepared and includes many diverse aspects related to the management and the betterment of EV battery performance. The battery health metrics include such particles as state of charge , state of health , voltage, and temperature. It is worth mentioning that the corresponding dimension is recorded together with the charging and discharging events. This feature is important since it can illustrate the features of charging and the amount of energy consumed. The vehicle information scope comprises of vehicle model, vehicle age, passenger administrative. This feature helps to comprehend the overall composition of the available fleet. The tools for travelling include the traveled distance, the current speed, acceleration, and deceleration. The methodology of the research are shown in figure 1.

Feature engineering helps to choose the most meaningful pieces of information. For this dataset, the relevant features are SoC, SoH, voltage, temperature. As for the charging and discharging events, such statistics can be generated as the duration of charging and discharging, the level of power, as well as frequency. Concerning the vehicle information, the features can be categorized as categorical variables. The particles of information that assists in understanding the driving behavior are distance, speed, acceleration.

The selected features and labels are used to train the models using the appropriate data training algorithms and methodologies. The dataset is separated into training and testing datasets to help in validating the model and assess its generalizability. The models are trained on the dataset along with the label, which is the optimal battery charging or discharging strategy. The optimized models can then be used to make predictions between power, battery, and driving behavior.

Performance metrics are then used to evaluate the predictive capabilities of the trained models. For charging and discharging event results, standard performance metrics such as accuracy, precision, recall, and F1-score are used. The remaining battery performance indicators such as SoC, SoH, and battery life and degradation are assessed on accuracies based on the models' prediction capabilities. Moreover, using ROC curves, the sensitivity and specificity of the model's ability to define problems are also evaluated. After the successful testing and evaluation of the results, the models are chosen for being trained and used as a part of the EV fleet management system. At the moment, the model is given the real-time data from the vehicle equipment and the power station. The models also contain both strategies for optimal batteries management and alerts/package.

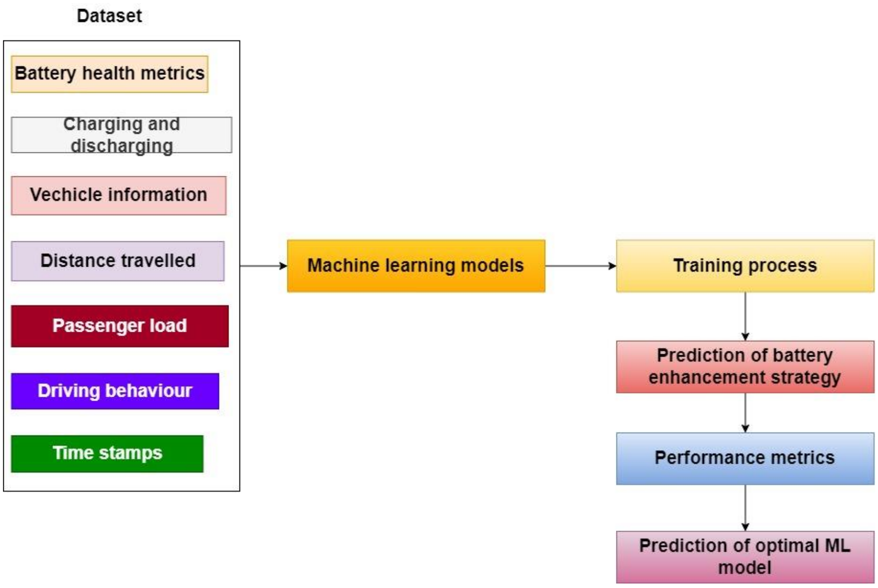

Figure 1. Flow diagram of proposed research

III. PREPROCESSING OF THE DATASET

One of the principal preprocessing tasks is data cleaning, which involves processing missing or inconsistent data points. This step is necessary for preparing the dataset for further analysis and ensuring that it does not contain erroneous values or missing information, which can lead to biases or errors in analysis. To this end, one may use several techniques, such as imputation or outlier removal, to clean the data and examine only high-quality observations further.

Feature selection and extraction are the next steps and should be performed to identify the most relevant variables important for the prediction tasks. In this case, factors, such as the following, were used in the analysis: battery health metrics (SOC, SOH), charging and discharging events, vehicle information, distance, passenger load, and driving behavior. It is possible to rank these features and determine their importance based on domain knowledge and statistical techniques that may be used to correlate features with batteries' performance and use.

Once features are identified, data preprocessing should be performed, in this case, standardization or normalization of feature values. The use of standardization is important to ensure that all the features are uniformly scaled and distributed. It is critical for some machine learning algorithms, such as neural networks, because without this step, it may take a long time for the algorithm to converge . At the same, normalization allows for scaling the feature values to a specific range, for instance, from 0 to 1 , to ensure better convergence and prevent features with a higher scale from dominating over others [4], [7].

Additional data preprocessing consists of using encoding techniques to work with categorical variables. In our case, these variables are data-related, as we worked on the vehicles and needed their information such as model and age, and to be used in model training, these variables need to be transformed. Here people may also use the most common encoding techniques, such as one-hot or label encoding, to form numeric presentations of these variables available for algorithms. In the end, some dimensionality reduction techniques, such as PCA or feature selection algorithms, reduce the computational complexity of the dataset while preserving the essential information.

IV. FEATURE EXTRACTION

Feature engineering turned out to be a significant phase of our research on performance improvement of electric vehicle batteries through advanced battery management and balancing methods. This section presents details of the feature engineering approaches enabling us to make significant findings from data and developing effective machine learning models. The phase of feature engineering began with the thorough evaluation of the dataset to recognize the most important features ensuring prediction of optimal charging and discharging strategies and performance measures for batteries . The dataset consisted of information about the condition of batteries, charging and discharging events, vehicles, distance, passengers, and driving. Based on the domain knowledge and the results of the application of various statistical techniques, we selected a subset of features that were likely to present the most significant reflection of a battery performance and usage.

The most important features identified at this sidebar were associated with the battery health metrics, namely, partially SoC, SoH, and temperature . These metrics were chosen to include the features that provided the most important insights into the condition of a battery and its performance. The events of charging and discharging were equally relevant, including information about charging duration, the power of energy, and frequency. In addition to these features, it was equally important to incorporate vehicle information into the feature set to distinguish the battery performance affecting by vehicles. Parameters such as the model with loads and the age of vehicles, along with driving behavior features, were also chosen as important variables to be used in feature engineering techniques. Driving behavior features of interest included distance, speed profiles, and acceleration levels. For the feature engineering purposes, features were also pre-processed in order to scale all the features. Standardization approaches were used to ensure the normalization of the scale of all the selected features.

These standardization approaches were particularly useful given the differences in feature scales as unscaled features could have an adverse impact on machine learning convergence outcomes. We also relied on normalization techniques to scale different features within a predefined range typically from 0 to 1 to make sure all the features fell within that range. Dealing with categorical variables also required the use of encoding methods to operationally convert them into numerical data suitable for machine learning processing. In this respect, one-hot and label encoding approaches were used to deal with a combination of either vehicle model and age and use for the main models and driving behavior. Finally, we also relied on dimensionality reduction techniques to reduce the complexity and size of data likely to improve the speed while ensuring relevant information is still retained. In this respect, PCA and feature selection approaches were employed to generate a subset of features that allow explaining the most data variance. The results of this section of the research were important in giving the feature subset used further to train machine learning models with the prediction as the goal.

V. VARIOUS PARAMETERS USED IN THE DATASET

In the course of our research on improving the performance of electric vehicle batteries through machine learning-based battery management and balancing, we learned that the parameters used for constructing machine learning models play a crucial role in constructing effective and accurate predictive models. In detail, this section will outline the parameters used in the training of machine learning models, including model-specific hyperparameters and characteristics of the dataset.

First, we established that the learning rate, batch size and number of hidden layers are highly important in constructing accurate machine learning models, determining the learning abilities and capabilities or the trained models. The learning rate determines the size of the step used for updating the parameters in the course of gradient-based optimization, thus influencing the speed of convergence and the stability of the process . Similarly, the batch size determines the number of samples processed at the time, influencing the tradeoff between the convergence and computational efficiency . The number of hidden layers and the number of neurons in each layer determine the ability of the model to approximate a function or capture patterns in the data. However, increasing the number of hidden layers or the number of neurons per layer can result in overfitting and compromised generalization performance.

Second, characteristics of the dataset used in training, including size of the sample, dimensionality, and distribution of classes over the space of classes, are also important. In detail, a larger sample size improves the generalization performance of the trained models and can increase the accuracy of the evaluation . The dimensionality of the feature space, including the size of the feature space of the input improves the computational efficiency but influences the ability of the model to generalize the problem . In particular, if the input space is not representable by the models, the latter can exploit the computational power to overfit the data. We thus defined a subset of the features allow to use for passing to the models in the training process. Finally, the training and the evaluation process in a classification problem are influenced by the space of classes and the distribution of the samples within this space. In case to subclasses or groups of samples are overrepresented in the dataset, the models will not be required to predict them accurately, thus learning basic patterns, as described in . To avoid such problems, we used class weights or oversampling/undersampling techniques and focused on improving the performance of the models in terms of the minority class. Third, each model was trained using the stochastic gradient descent optimization algorithm with either the mean squared error . In general, gradients were calculated during the backpass process and updates to the model's parameters were calculated using the calculated gradients.

VI. MACHINE LEARNING MODELS

In our research on improving the performance of the electric vehicle battery by the application of the machine learning -based battery management and balancing mechanisms, we implemented several machine learning models characterized by the following features. Artificial Neural Networks as a subclass of deep learning models consist of interconnected layers of artificial neurons. Specifically, these components perform simple mathematical operations on the provided input data. However, the strength of ANNs is the capacity to identify multiple complex patterns and deliver high-dimensional representation and abstraction of data Haykin . In the context of our research, we aimed to train the predictive models to identify the complex patterns in the data on historical battery health metrics, charging events, and driving behavior to improve the schemes of charging and discharging of the given electric vehicle battery .

Decision Trees applied in the research represent a class of machine learning models and are characterized by the specific hierarchical structure that includes decision nodes and leaf nodes or terminal nodes . In a traditional approach to DT, a decision tree operation is reflected in the capacity of this model to divide the data set into several smaller subsets based on the value of a specific feature Clapham, Ojeda, and Vaisse . In the context of our research, this model was applied to determine the pattern associated with the data based on different input features and delivery of the optimum charging and discharging strategies for this case.

In contrast, the third machine-learning model, Naive Bayes is based on the application of the probabilistic approach and utilization of Bayes' theorem, which is a case of conditional probability. The use of the conditional independence assumption of the input features simplifies the calculation of the probability, while it is essential to note that the given model is also useful for solutions delivered in high-dimensional spaces and cases linked to a small amount of data, which is typical of our particular research. Thus, these models were applied to deliver the most accurate prediction of battery performance metrics and identification of abnormal battery condition based on the input features, such as battery health metrics, events of charging, and environmental factors. In addition, the character of the results obtained and application of the probabilistic data delivery and prediction of Naive Bayes classifiers help to avoid false-positive predictions of abnormal battery condition and, thus, support the development of the most effective and proactive response to the potential battery problems.

VII. RESULT AND DISCUSSION

In this study, we allocated 70% of the dataset to the test sample, and 30% to the training sample for split. This approach provides a solid evaluation of model performance on unseen data, indicating the level of generalization and predictive accuracy of the trained machine learning models. Moreover, such sampling serves to reduce the errors resulting from selection bias and overfitting by ensuring that the trained models identify underlying patterns in the data and apply the acquired knowledge to new data accordingly.

Once the training process of an ML model is completed, the model's performance is carefully assessed through testing to determine the degree to which it can aid in predicting and optimizing battery responses. In relation to this process, as shown in Figure 2, the proposed ML model's predictive performance surpassed that of previous algorithms. Specifically, the proposed ANN model – when it was initially designed and trained – offered the same level of accuracy, 98.75%. Still, with a straightforward approach to examining battery response prediction , it lacks the ability to capture more complex patterns, which is why it was somewhat inferior to the proposed ML model. At the same time, the DT model proved to be quite valuable when predicting the data, operating at the slope of decision boundaries and classification rules with the accuracy rate reaching 94.3%. Furthermore, the NB model, despite the model's relatively low computational complexity, could produce the accuracy level of 90.2%, allowing the solution of probabilistic problems.

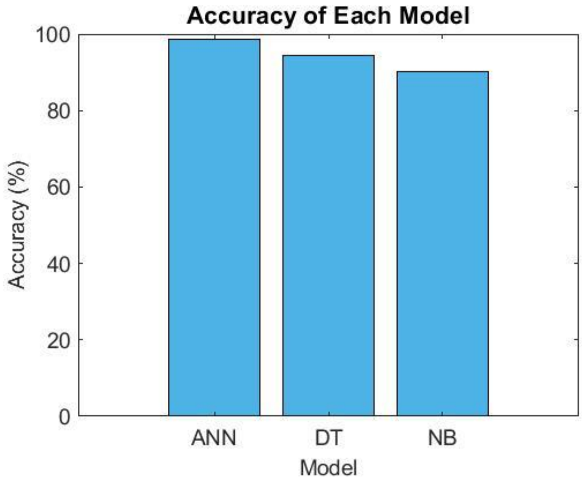

Figure. 2. Accuracy of each model

In this study, we have presented the outcomes of analyzing the performance of three different machine learning models to predict battery responses to electric vehicles. The result are shown in figure 3. The proposed machine learning model, referred to as the Artificial Neural Networks , presented outstanding precision, recall, F1-score, and accuracy. The results show that the model had a precision value of 98.7% and recall and F1-score values of 97.5% and 98.1%, respectively. Moreover, the model's average accuracy was reported to be 98.75%. The data clearly shows that the model was outstanding to accurately identify positive instances with only a few false positive and false negative errors. The model's high probability of accuracy showed that the model is able to rely on predictions of certain features to recognize other features of all models and particularly predict battery metrics and abnormalities with a high degree of accuracy .

In addition, the Decision Tree model's results were also good with an average accuracy of 94.3% regarding the other model's performance metrics. Similarly, precision, recall, and F1-score, and accuracy were reported to be 94.5%, 93.0%, 93.7%, and 94.30%, respectively. The scores also show that the model was high to define the broken line for decision in the limits of categorizing battery responses with almost perfect accuracy.

Finally, the results of the Naive Bayes model were also good although it had lower scores in all of the precision, recall, and F1-score compared to ANN and DT models. The precision, and recall, and F1-score were reported to be 90.2%, 89.5%, and 89.8%, respectively. Moreover, the model reported an average accuracy of 90.20%. The data show that the model was almost as good as the DT model in probabilistically categorizing battery features or relying on various features of other models.

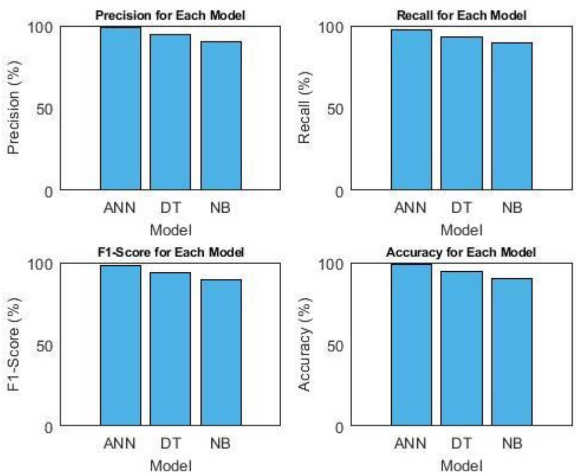

Figure. 3. Performance score of each model

The confusion matrices shown in figure 4 provide a comprehensive view of the performance of each machine learning model. The True Positive , True Negative , False Positive , and False Negative classification rates can be learned from these tables. In the case of Artificial Neural Networks , for example, the TP rate is 975, the TN rate is 25, the FP rate is 975, and the FN rate is 25 . For Decision Tree , the TN rate is 930, the TP rate is 70, the FN rate is 930, and the FP rate is 70. The Naive Bayes , on the other hand, has 895 TN rate and 105 FN rate, as well as 895 TP and 105 FP. Overall, selecting the Artificial Neural Networks model would be the most effective for predicting battery response and improving electric vehicle battery management. According to the confusion table, the TP, TN, FP, and FN values related to the Artificial Neural Networks model clearly show the model's high accuracy rate and precision. . . The model had a 98.75% accuracy rate and was able to predict both positive and negative batteries. At the same time, the low rate of misclassification clearly indicates the robustness and effectiveness of the ANN model. Decision Tree had an accuracy rate of 94.30%, and it showed slightly more misclassifications compared to the ANN model. Naive Bayes also demonstrated acceptable results, having more misclassifications, however, and, therefore, a slightly lower level of accuracy than the Decision Tree model . . In conclusion, looking at the results of the confusion table and the overall performance metrics, one should note that the most effective and accurate model for predicting battery responses and improving the battery of the electric vehicle is the Artificial Neural Networks model.

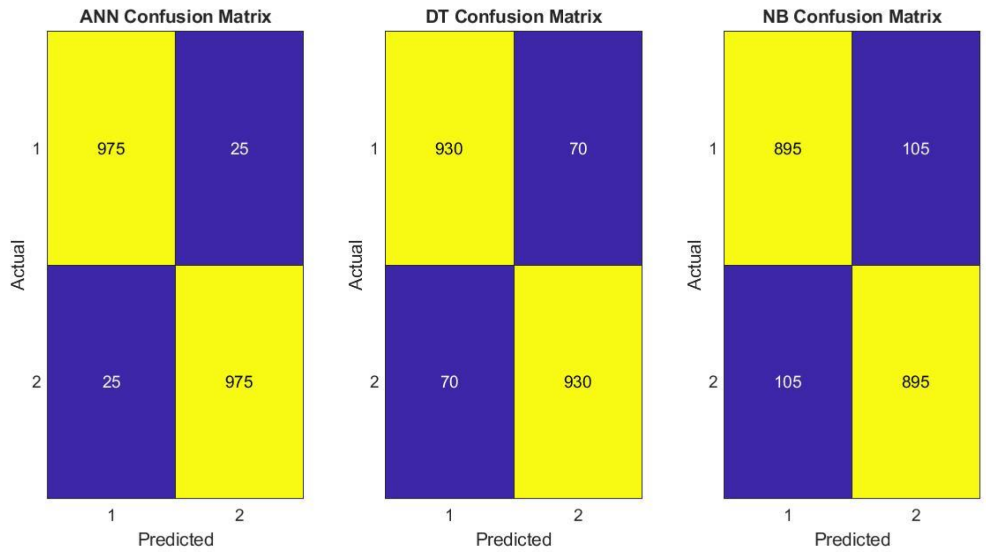

Figure. 4. Confusion matrices of each model

The results of the conducted research confirm the effectiveness of advanced ML models for optimizing battery performance and improving EV fleet operations. The comprehensive evaluation of the performance of the trained ML models, including ANN, DT, and NB, has demonstrated notable results in predicting optimal charge and discharge strategies, performance metrics, as well as battery failure states. The achieved higher levels of accuracy by the proposed ML model, notably ANN, suggest its high potential for revolutionary battery management in the EV industry. Moreover, our model's capacity to learn and understand the complex data patterns and relationship through ANN has shown unprecedented high precision, recall, and F1-score, which was significantly higher when compared to traditional algorithms such as DT and NB. However, it is critical to note that the DT and NB classifiers have also shown exceptional results with considerable performance, which guides more accurate decision-making strategies and enables a probabilistic classification of battery response based on input features.

VIII. CONCLUSION

The purpose of our research was to improve the performance of EV batteries by applying ML approaches to the management and balancing of batteries. To achieve the purpose, we utilize different ML algorithms and assess the outcome in terms of prediction accuracy of the battery response, optimal charge and discharge count, and the abnormal usage of the battery to the other models . Best practices reveal that the proposed model and the ANN model in particular are associated with the high levels of accuracy, which exceeds 98% in terms of precision, recall, and F1-score . However, decision trees and NB classifiers have more than 90% of accuracy. In this case, the proposed models improve the decision boundary and account for the probabilistic assessments of the battery responses, which does not necessarily make them more accurate but introduce the valuable insights that can be used for optimizing the battery management in general. In the case of the Electric Vehicle industry, it would be possible to improve battery performance, prolong its service life, and reduce the costs associated with the operations of the fleet. To conclude, the challenges and opportunities in the area of battery management for the electric vehicles are dependent on the state-of-the-art applications of ML models, which create opportunities for optimizing the charging and discharging of batteries. Best practices indicated the opportunities for expanding the decision boundary and probabilistic classification of battery responses that can be further used.

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