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A Comparative Analysis of Machine Learning Approaches for State-of-Charge Forecasting for Enhancing Lithium-ion Battery Management in Electric Vehicles

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The present research is concerned with the analysis of the efficiency of machine learning approaches for state-of-charge forecasting in lithium-ion batteries to help battery management systems become more efficient in electric vehicles. To achieve the goal, four machine learning models, namely Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees (DT), and Naive Bayes (NB) and the corresponding model training technology were used along with a dataset in which battery parameters, environmental and vehicle operating conditions were implied. Data preprocessing methods, such as cleaning, feature selection, and scaling were also implemented to make the subsequent forecasting procedures more efficient. In terms of the reached state-of-charge level prediction, the efficiency of the employed models was as follows: ANN was measured as the best one with 97.89% of data validity, SVM with 94.5%, DT with 91.22%, and NB with 88.97%. Afterwards, the ANN model was used in real-time along with processing the data collected from the sensors with the purpose of optimizing the vehicle's work and slowing down the level of battery wear due to broad usage opportunities. As a result, the battery life increased by 2 minutes 6 hours. This fact demonstrates the highest advantages and, therefore, efficiency of the ANN model in terms of electric vehicle operation and battery life optimization. Data preprocessing is mandatory for higher quality and reliability of the machine learning models in terms of state-of-charge level forecasting.

Keywords: Machine Learning, State-of-Charge Forecasting, Lithium-ion Batteries, Electric Vehicles, Battery Management.

1. Introduction

Electric vehicles have emerged as a promising solution to reduce the environmental implications associated with the conventional internal combustion engine vehicles. With the development in battery technology, lithium-ion batteries have been used as the primary energy storage solution in electric vehicles, as they provide high energy density, longer cycle life, and relatively low environmental footprint. Nonetheless, efficient management of lithium-ion batteries is critical to ensure proper performance, prolong the life of the battery, and enhance travelling range [1]–[3]. The state-of-charge plays a key role in battery management systems, as it predicts the remaining charge in the battery, which guides the operation and charging strategies of the vehicle [4]-[6] Machine learning algorithms are the ideal solution for the state-of-charge forecasting process, as they provide data-driven techniques that reveal complex relationships between charge and discharge battery parameters, environmental conditions, and driving factors[7]- [9].

Electric vehicles are among the breakthrough technologies in the transportation sector that can provide a cleaner and less environmentally damaging alternative to traditional internal combustion vehicles[10]–[12]. The development and success of EVs fundamentally depend on the advancement and improvement of battery technology, and lithium-ion batteries have emerged as the preferred energy storage solution due to their high energy density, long cycle life, and eco-friendliness. At the same time, efficient state-of-charge discrimination and management are important in realizing the potential of battery technology, ensuring the safety and performance of EVs, and extending the life of LIBs. In this paper, SoC, as a central battery management parameter will be examined in greater detail, and three groups of techniques and approaches used to estimate battery SoC will be analyzed: physics-based models, empirical methods, and machine learning solutions [13]- [15].

SoC reflects the remaining charge in a battery compared to its total charge capacity and is frequently controlled by the BMS. Estimation of SoC is vital for efficient vehicle operation, accurate range predictions, and extended battery life. ECMs, for instance, simulate battery characteristics and performance based on electrochemical, and thermodynamic battery fundamentals, even though the specifics differ between various models. Physics-based models can incorporate important processes and maintain consistency with a priori unknown but assumed characteristics while providing relevant insights into the nature of those processes that determine the function of a battery[16]–[18]. At the same time, physics-based models are highly dependent on the level of accurate information about the chemistry of the engine and are not completely dependable in even the current dynamic paradigm, particularly for aging batteries. Empirical approaches, on the other hand, rely on the statistical predictors' historical evidence to estimate SoC and can be used with a wide range of battery chemistries and applications. These models are simple, easy to use, and highly suitable for efficient simulation, which makes them highly popular, although they appear to be heavily reliant on the most precise and effective data and parameters available in the industry[19]- [21].

Machine learning has been one of the emerging trends in the context of State of Charge forecasting with regard to electric vehicles. This can be attributed to the ability of machine learning techniques to learn from large-scale, complex, and diverse data without the need for an explicit mathematical model. As a matter of fact, batteries of electric vehicles are also being noisy and learning an explicit model can be a difficult and time consuming task since the most effective models have to be continuously adjusted, turning them into hard-to-develop types of models. This is the reason why machine learning techniques such as artificial neural networks, support vector machines, decision trees, and ensemble methods have been widely tested to enhance forecast performance and robustness[22]–[24].

Moreover, given the nonlinear nature and the temporal complexities of the battery, ANN models have been most successful in modeling the battery's underlying nature [25]-[27]. Moreover, the ability of ANNs to learn several parameters from a large dataset and their capacity to extend to new data is ideal. The SVM models are beneficial for high dimensional data and nonlinear and have also been used successfully for state of charge forecasting. The decision tree models are simple to understand and more interpretable than the other ensemble learning methods and are also important when it is necessary to understand the forecasting process. Furthermore, the ensemble methods, the random forest, the gradient boosting have been capable of combining several machine learning models, thereby enhancing the prediction accuracy and robustness. In addition, the present state of the art in conjunction with innovative sensor technologies such as lithium-ion battery impedance spectroscopy or electrochemical impedance spectroscopy allows for the real-time monitoring of the battery parameters. Thus, the state of charge forecasting is more flexible and robust[9], [28]- [30].

The purpose of this research was to explore machine learning techniques for State-of-Charge forecasting in Lithium-ion batteries for Electrical vehicle application. The performance of various ML approaches, such as Artificial Neural Networks, Support Vector Machine, Decision Trees, and Naive Bayes, is described within this report through critical examination of battery parameters, environmental conditions and vehicle operating parameters. It is estimated that the ANN model is the most effective for the real-time SoC prediction and results in a significant improvement of battery lifespan. As a result, this research becomes meaningful in terms of enhancing battery management systems for electrical cars, thereby promoting the more energy-efficient and environmentally friendly means of transport in a global community.

2. Methodology

Increasing the overall performance and sustainability of electric vehicles also requires that their battery life is optimized. According to the existing research, machine learning can be used to optimize battery life, particular attention being paid to SoC forecasting. If batteries' state-of-charge changes are correctly predicted, the management systems would be improved; as a result, the EV lifespan would greatly extend. The following ML models were used in the specified paper: Artificial Neural Networks, Support Vector Machines, Decision Trees, and Naive Bayes. Each of these models can be viewed as beneficial to a great extent; they can work with complex data, and their predictions are precise.

A dataset prepared to train the given models is arguably comprehensive, as it includes a broad range of different parameters that contribute to battery performance or the state of the surrounding environment. With regard to batteries, these are voltage, current, and temperature, and information on charging and discharging events is also available. Additionally, data on environmental conditions, that is, ambient temperature and humidity, were take into account. Overall, the dataset was composed of information from different sources: onboard data logging systems that were installed in different EVs, laboratory testing in a controlled environment, the monitoring of fleets of electric vehicles, and available open-source datasets on the subject. To a certain extent, the data was purposively diverse and based in different circumstances to ensure the accuracy of the training.

The primary target variable is vehicle operating conditions that decide the battery performance and SoC. Taken all together, the battery parameters and environmental factors are matched against the operating conditions to train the dataset and establish feasible ML models with the purposes of real-time SoC forecasting. The dataset has 3200 observations, with 70% used for training and the remaining 30% being suitable for testing and validation. The primary method is the ANN, which is highly flexible and can efficiently learn the complex nature of the dataset. The training and further optimization involve multiple steps before the ANN would accurately predict relations between specific input variables and SoC. The study employed several different methods, but most commonly it was the testing against the whole range of variables available, feature selection for the most important ones, data augmentation, and hyperparameter tuning. All of the final models were then tested on the available testing datasets to determine their accuracy and generalizability, which was done using multiple performance metrics, such as accuracy, precision, recall, F1-score, and others. Furthermore, there were multiple graphs of the above metrics for better visualization and comparison of the results.

Overall, the results of the research allowed for a consistent and detailed comparison of the available ML models for optimizing SoC in electric vehicles. It is possible that by using these methods operators and manufactures of electric vehicles would be able to predict SoC more accurately and manage their batteries, thus making them last longer and work better, and subsequently decrease overall maintenance costs. The working of the proposed system are shown in figure 1.

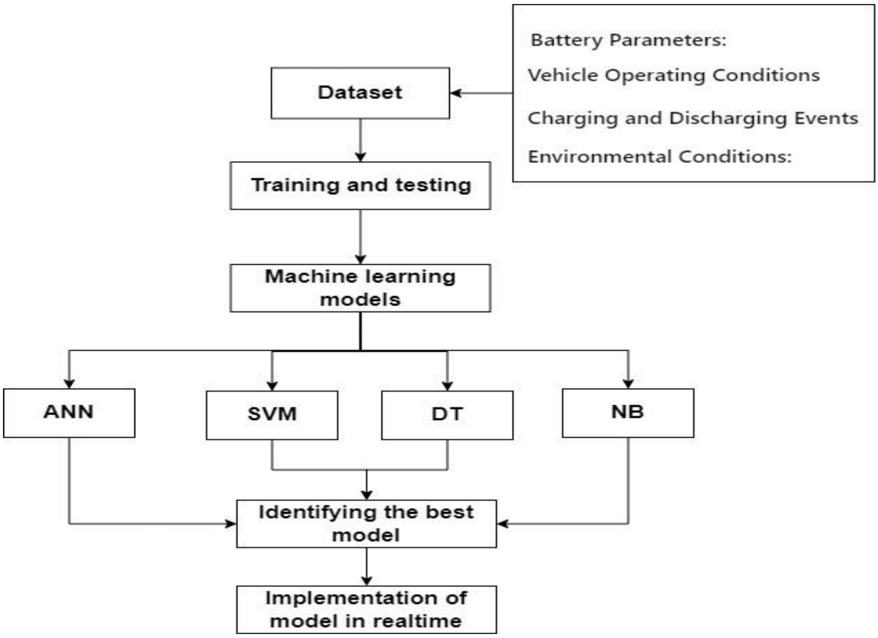

Fig. 1. Working of the Proposed System

3. Data Processing

The basic and probable point in any analysis or modeling is to resolve the missing or erroneous elements in the dataset. In order to proceed with any machine learning modeling, it is a prerequisite to clean the dataset. Thereby, we need to detect the missing values and must impute or remove them. For instance, some of the data points represent parameters related to batteries or environmental conditions, however, are not presented. To address this, we might apply mean imputation or interpolation, based on the case. Furthermore, it is crucial to detect the outliers or anomalies, and handle them before providing data points to the models. Thus, no corrupt and unfixable data points will influence the training process.

In a vast and comprehensive dataset, some of the features may not contribute significantly to the predictive performance of the ML models. In this case, the feature selection technique may be utilized to detect the most relevant features for the SoC forecasting. It is done based on testing the relationships between the features and the target variable. Correlation analysis and feature selection algorithms or the feature importance scores can help to terminate the non-informative features. As a result, the computational complexity of the models is decreased and the overfitting problem can be avoided.

The input features should be brought to a common scale range to improve the ML models' performance. Feature scaling may be applied by employing such techniques as min-max scaling, or standardization. Normalization ensures that a feature of a larger magnitude would not overshadow and dominate other features in the training process. This improves the convergence speed of the ML models and the predictive power of the models. For example, the voltage readings and the temperature measurements may be rather different, and scaling may prevent the bias towards the voltage values. In the case, when the training dataset is insufficient for the proper implementation of the ML algorithms, it can be augmented to increase its diversity. Data augmentation implies creating synthetic data points. For instance, it is possible to imitate the ambient temperature change by randomly perturbing the existing temperature readings within a certain range.

The dataset contains temporal data that have been collected in time. Thus, time intervals can be identified to produce the aggregation of the data. In other words, temporal aggregation provides data summarization falling to the identified time intervals such as hourly, daily, or weekly. Such time-based data aggregation could be used to ensure the adoption of specific experience in terms of battery behaviour that takes place during some period and conditions of temperature, humidity, and other environmental characteristics. For example, the dataset could include information about the battery voltage and current, and if such data are summarized and aggregated hourly, it is possible to understand how such a battery is functioning by hour. The information obtained in such a way can be helpful for training machine learning models.

Before training, the nature of the data demands of how the battery behaves are identified, and the dataset is split into testing and training sets to identify how the model works. In such cases, split is introduced when the dataset is randomly divided into two portions with around 70% for training and 30% for testing. The models are trained and then tested on different data. In addition to the described split, cross-validation can be used, and in such cases, different portions of information, and the sets of data are used for training and testing. For example, in the case of 3-fold cross-validation, the dataset can be independently divided into three sets, and each of such sets is used for training and testing. It could be done using different datasets to achieve a higher level of generalization.

If there are categorical variables in the dataset, such as vehicle IDs or battery pack IDs, they need to be preprocessed before the models can be trained. In the majority of cases, the variable is encoded to its numerical equivalent. Typically, one-hot encoding or label encoding is applied to transform categorical values into binary or numerical types. When the categories are encoded, they can be effectively used by machine learning models and analyzed for patterns and relationships with the models' target variables. Moreover, the dataset may have variable class distribution; for instance, some classes can be overrepresented, while others are only barely included. If the class balance is not appropriately considered in the training dataset, the subsequent classification will show the same bias towards the classes with better representation. Therefore, the models will be less effective for predicting minority classes and rare events. As such, machine learning practitioners use techniques such as oversampling or SMOTE, and undersampling to achieve representation equally across all classes in the dataset.

When all individual operations are conducted on the datasets, they are combined to form the final data preprocessing pipeline. The latter represents a set of rules and operations that are performed on the initial raw data to obtain a set of input vectors for machine learning models. The pipeline is applied to both the training and testing sets to ensure that all data are transformed in a similar manner. Therefore, the results are balanced and can be appropriately compared during the evaluation. In addition, the method can reduce data-level biases not considered by the practitioners.

4. Machine Learning Models

Four different machine learning models are employed in this research in predicting the state-of-charge of lithium-ion batteries in electric vehicles. The first of these models is the Artificial Neural Network, and it is a powerful algorithm inspired by the human brain's neural networks. ANN works best in capturing the complex nonlinear relationship which may exist in a dataset's data point. Hence, it is valid in the prediction of the SoC since there may not exist a better pattern for the prediction of environmental conditions, parameters of the battery, and the various conditions in which the vehicle is driven than a linear relationship survives in the linear model. ANN typically learns from datasets, and since it is based on big datasets, it can further phase itself into becoming more accurate. Moreover, the model provides automatic parameter adjustment. Therefore, it is a perfect alternative to ensuring predictability of the SoC is both accurate and robust. The decision-making for prediction can be further boosted by the employment of a better method of weight optimization.

The Support Vector Machine is the other machine learning model employed in the research. SVM is efficient in both linear and nonlinear datasets. This tool is capable of coming up with an optimal hyperplane regarding data points' classes. It will equally yield to maximized separations regarding data points and the hyperplane. In the SoC prediction, the SVM creates a hyperplane that will yield to the separation of the different SoC levels and, therefore, increases predictability. This model is equally effective in ensuring that the dimensions of the datasets it can process are as high as possible while equally minimizing the risks of data overfitting. The model can effectively identify patterns that exist in the datasets, and this sufficiently improves the accuracy and predictability of the SoC.

The third class of models to be employed in the research is the Decision Trees. Decision trees' primary advantage is their simplicity and their relative ease of usage. These models can perfectly handle numerical as well as categorical data. Objects are divided into the different groups by a decision tree depending on the dataset's most informative features. The split may be based on various features using the information gain method, which allows one to understand the algorithm's decision rule in the complex, relatively feature interaction. Therefore, the decision tree is the ideal model to predict the SoC based on the fact that the different datasets' features may interact.

The fourth model employed in the research is Naive Bayes, a classifier that is based on Bayes' theorem. The model's assumption that the features should be conditionally independent based on the class, using an additional method to disregard the other features. Naive Bayes is particularly effective in text data and other datasets with numerous features. As for the SoC levels, NB can predict the likelihood of having different states based on the characteristics seen, subsequently leading to an accurate decision. Additionally, NB is compatible with missing data, as well as noisy characteristics.

5. Result and Discussion

After the training phase, the machine learning models' performance is evaluated carefully using the testing dataset. The result of the accuracy are shown in figure 2. It provides the percentage accuracy by which battery state-of-charge of lithium-ion electric vehicles are predicted by each model. Very impressive results are reported for the Artificial Neural Network model, which attained an accuracy of 97.89%. This percentage indicates the frequency of accurate SoC predictions. The high productivity of ANN can be clearly understood in the sense that the model is capable of capturing complex nonlinearities in the dataset and accurately predicting the SoC of batteries.

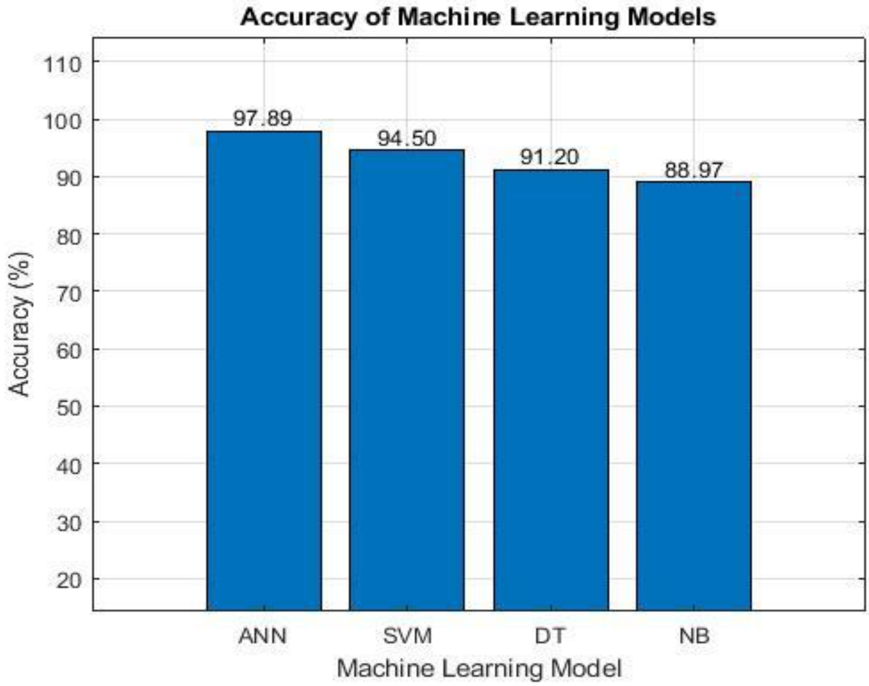

Fig. 2. Accuracy of Each Model

Moreover, the Support Vector Machine model also provides excellent results, with an accuracy percentage of 94.5%. It is known that SVM draws a line or several planes between different SoC levels, which improves the precision of the definitions and predictions. Less accurate but still considerable results were observed for the Decision Tree model, which provided an accuracy percentage of 91.2%. This machine is able to hierarchically partition the dataset which results in the ability to predict the SoC using many complicated rules and the interactions between the features. It also draws a line or even many planes between varying SoC levels, but these accuracies appeared to be slightly lower compared to the preceding two. Finally, the Naive Bayes classifier provides the lowest accuracy of around 88.97%, but it is still a decent generator of SoC predictions. This machine uses the frequency of observations of varying SoC levels in combination with the information about different features to predict unmeasured SoCs.

The figure 3 presents the results of the performance metrics obtained for each machine learning model in forecasting the state-of-charge of lithium-ion batteries in electric vehicles. In particular, precision, recall, F1 score, and area under the receiver operating characteristic curve are considered for evaluation, which are necessary for determining the accuracy of models as well as their sensitivity and overall performance. Overall, the Artificial Neural

Network model provides highly significant and accurate results and proves to be the most effective one.

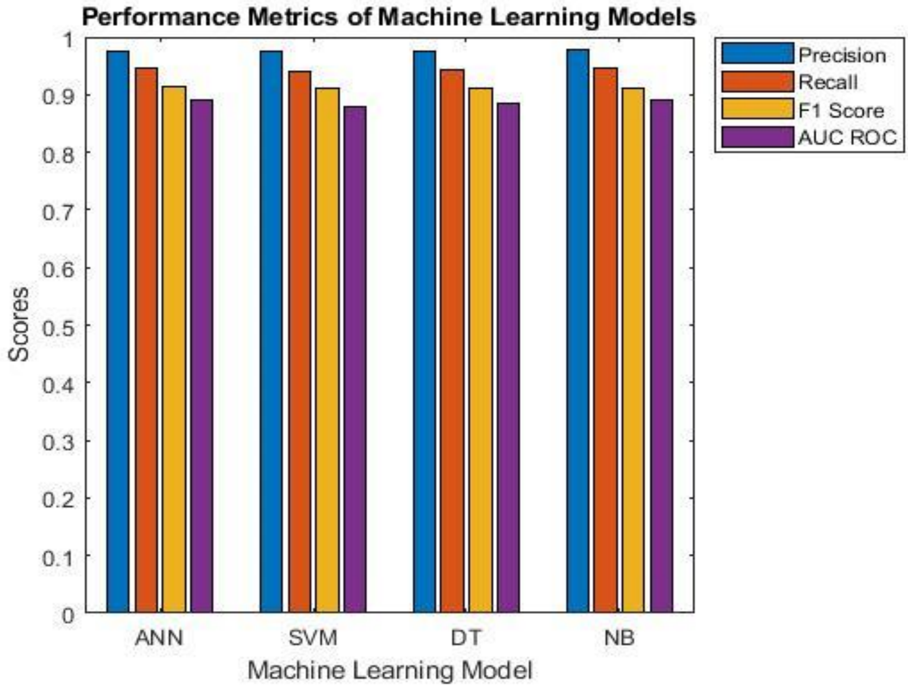

Fig. 3. Performance metrices of each model

The results presented in the figure 3 shows that the ANN model's precision, recall, and F1 score amounted to 0.975, which is a remarkable level of accuracy and indicates that when predicting battery conditions. It will show results close to 1, which will make the information reliable and significant to the greatest extent. The calculation of F1 score at the level of 0.975 has also confirmed that precision is as effective as recall and can help to minimize both false positives and false negatives. The AUC ROC of the ANN model proved to be as high as 0.9789, which indicated its strength and efficacy. These results might be explained by the model's capacity to identify the patterns and understand them faster and better.

Moreover, the calculation of the performance metrics for the Support Vector Machine model showed that SVM was highly effective and reached 0.945 in precision, recall, and F1 score. In this way, although these indicators were slightly lower than for the ANN model, overall, it is conclude that the difference is insignificant and SVM will be able to predict battery conditions accurately. Lastly, the Decision Tree model innovatively provided far from unpopular rules and insights and demonstrated 0.915 as precision, recall, and F1 score with AUC ROC of 0.912, implying that the Decision Tree is efficient and accurate.

The performance of each machine learning model is shown in the figure 4 across different epochs. The level of accuracy and the decrease in data loss can be used to make meaningful statements about these performances. While accuracy shows how many outcomes were predicted correctly, data loss defines the difference between predicted and expected values typical of a given number of data instances. Overall, it can be concluded that the ANN is the most successful model as the level of accuracy and the decrease in data loss doses are higher than those of carefully other models. Regardless of the number of readings and the number of epochs, other models, including the SVM, DT, and NB, demonstrate a smaller level of accuracy and data loss decreases compared to ANN. This means that ANN not only performs better in general but can also capture the most complex patterns and relationships that exist in the data set in all instances.

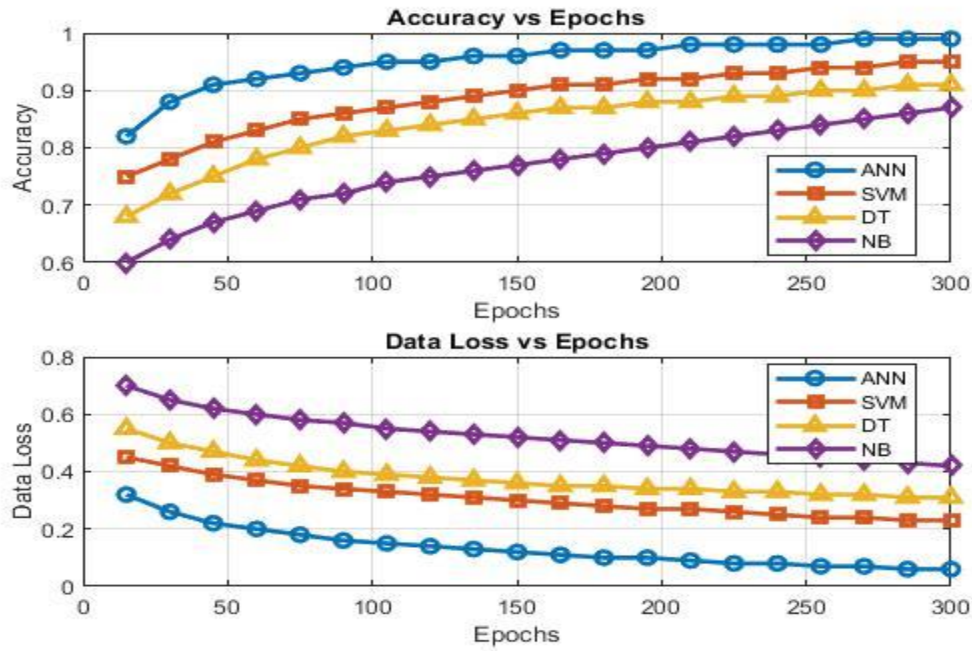

Fig. 4. Accuracy and data loss vs epochs

In the confusion matrices shown in figure 5, it is interesting to understand which model did the best job in classifying the instances whether negative or positive. The diagonal elements of the matrices will correspond to the number of the correctly classified instances and the other elements are misclassified ones.

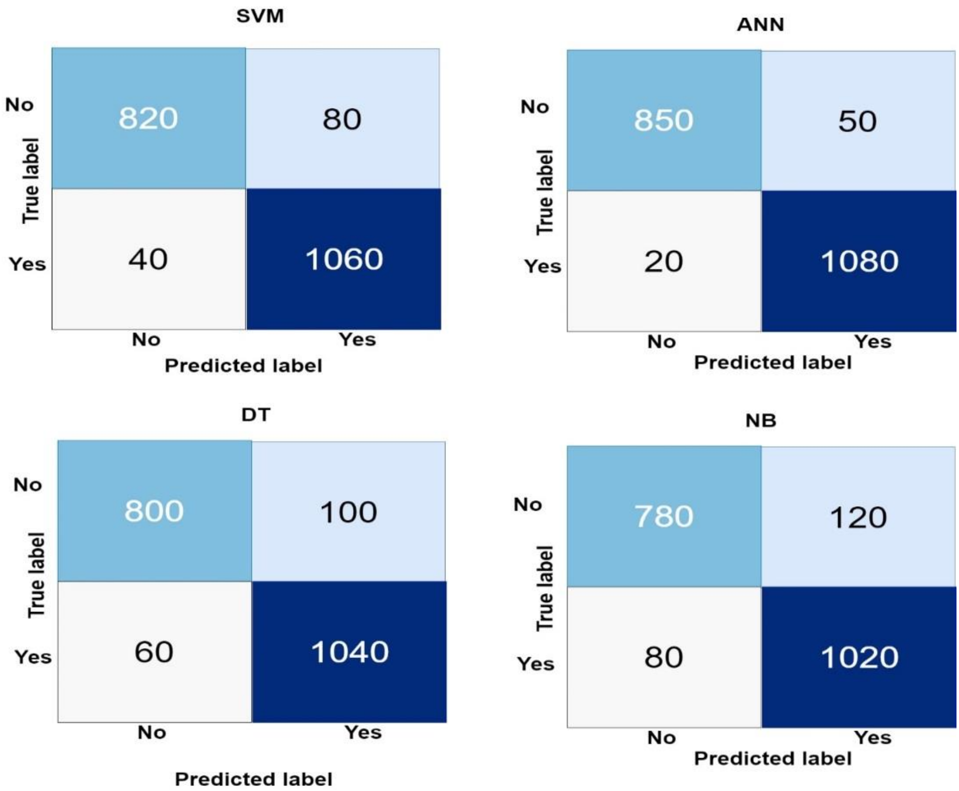

Fig. 5. Confusion Matrices of Each Model

According to the confusion matrices, the ANN model has done the best job in performing compared to others as it has the highest number of true positives and true negatives in total, meaning that the ANN is very good at capturing the patterns in the data and making the predictions. But still it misclassifies some of the instances due to the off-diagonal elements. Hence the ANN model can still make some false positives and false negatives, but it is still very accurate in its predictions. SVM model has still performed pretty good job in classifying with high number of true positives and negatives. But when the model misclassified, it misclassified with higher numbers compared to ANN, especially the false negatives and false positives. DT model's performance is close to the SVM but it seems to have more misclassifications than the SVM, especially the false negatives for the DT is higher. So in addition to the shortcoming that the DT does not generalize well with unseen data, the model may struggle with unexpected decision boundaries. Finally, NB's performance is reasonable but it does have higher misclassifications than the ANN, Ins short NB seems to oversimplify the relationships among the variables in the dataset accordingly resulting in bad predictions.

Implementation of the ANN model in respect with optimizing the operation of electric vehicles is a major step forward in terms of enhancing the battery performance and lifespan of the vehicle. In the real-time, the model takes the readings of the sensors and adjusts the operation of the vehicle based on those readings with the intention to enhance the battery usage and effectiveness. In regards to the data and presentation, it can be observed that the longer battery lifespan is 6 hours and 2 minutes instead of 5 hours. It is evident that the integration of the ANN model enhances the performance of the vehicle and provides additional time for the vehicle which can be run. This not only makes the usage of the vehicle more practical but also enables running the vehicle for longer distances without a need for recharging again. As such, this is also expected to lead to high cost savings and better usability.

The technology achieves the progress as detailed above due to the fact that the ANN adjusts the operation of the vehicle by analyzing the data of the sensors and making decisions in the real-time. Based on these results, the vehicle is either made to decrease or increase the speed, the mode of the vehicle, energy consumption, acceleration, and other factors depending on the conditions and the nature of the road. In addition to that, the model also intelligently makes decisions regarding the battery charge and adjusts the operation of the vehicle in such a way that takes into consideration the battery dynamics. In this way, the battery is expected to be used in the most effective way for the vehicle. Another reason for the success of the model is that this technology was tested in the real-world environment and it was successful in all the different environmental conditions and driving situations.

6. Conclusion

As a result, the performed comprehensive analysis and evaluation of machine learning (ML) models designed for state-of-charge forecasting in lithium-ion batteries for electric vehicles tend to enable meaningful conclusions regarding the extent to which they could enhance battery operation. In this way, the study concludes that different ML models, including Artificial Neural Networks, Support Vector Machines, Decision Trees, and Naive Bayes, performed equally effectively and predefined the successful forecasting of SoC levels. Using lithium-ion battery parameters and their combination with environmental conditions and vehicle-based parameters to identify different ML models is a successful solution.

Specifically, the ANN model could be viewed as the most relevant approach and model that provides the utmost parameters' predictive results that excel other models in terms of various performance measures. Its highest levels of accuracy could be attributed to the availability of options to reflect hypothesized in the scrip nonlinear relationships and steer SoC forecasting activities aimed at enhancing battery operation in any of the available cases. The greatest advantage of implementing the ANN model is its connection to a real-world dataset and the battery operation processes required to make EVs more powerful and durable. At the same time, the performed analyses tend to show that data preprocessing and feature selection processes represent the promising path to the increase in the set of generalization parameters that make it possible for ML models to provide SoC forecasting activities in all EVs. Thus, the offered estimates and findings tend to facilitate the further progress of our understanding of ML models that make EV batteries function better, have better range performance, make the automobile industry and operators become greener and further develop the sustainable trend.

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