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RESEARCH ARTICLE

Capacitance Classification for Supercapacitors Using Machine Learning

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ABSTRACT Supercapacitors are considered key components in many industrial and technological applications, due to their high ability to store energy and rapid charging and discharging. In this study, machine learning techniques were used for analyzing specific capacitance data of supercapacitors and developing a classification technique that helps to improve the efficiency of systems that rely on supercapacitors. Kernel Naïve Bayes model was used in this study to classify the data of supercapacitors to improve understanding of their performances. MATLAB program was used to apply the model to a dataset of supercapacitors, taking into account specific capacitance, voltage window, electrode materials, and electrolyte used. Supercapacitors were divided into five classes according to the level of their specific capacitance values. The results showed high accuracy in classifying the data – more than 95% – as the model was able to distinguish between different categories effectively while displaying the percentage of correct and incorrect predictions for each class.

INDEX TERMS Machine learning, kernel Naïve Bayes, supercapacitors.

I. INTRODUCTION

Due to the increasing global demand for energy resources and energy storage, and the exhaustion of traditional energy sources, and the increasing demand for addressing climate change, the increase in population and heavy industrialization have imposed the need to generate, store and use energy with high efficiency. Improving energy use with high efficiency and using renewable energy has become extremely important, there is a need to develop environmentally friendly, clean and renewable energy resources. At the same time, improving and development of existing energy storage technologies is a necessity. Energy is considered one of the primary inputs for the development of countries, also the energy is one of the most important areas of global attention [1], [2], [3], [4], [5], [6], [7], [8], [9], [10]. Efficient electrical energy storage systems with a long cyclic life have become an important thing in our lives, it is necessary to improve or replace current energy storage technologies. Environmentally friendly and efficient energy storage devices are essential for sustainable development. With the increasing environmental problems, clean energy is gaining more and more attention. The need to use green energy is significantly increasing, especially lithium-ion batteries and supercapacitors, in the energy structure of different countries Energy storage technologies, especially supercapacitors, have gained a lot of attention recently, Supercapacitors are one of the most preferred storage devices due to their high capacity, supercapacitors also it's known as supercapacitors or electrical double-layer capacitors (EDLCs) [11], [12], [13], [14], [15], [16], [17]. are the most common electrical storage devices, Supercapacitors have gained significant importance as a means of storing energy due to their advantages, including their high capacity, energy density, long life cycles, stability, safe operating mode, and rapid ability to charge and discharge compared to batteries, However, the energy that supercapacitors can store, is much less than that of batteries [18], [19], [20], [21], [22]. Supercapacitors have the ability to operate at high-speed charge and discharge rates, over an almost unlimited number of cycles, within a few seconds, these devices can be fully charged and discharged [22], [23], [24]. Recently, research activities related to supercapacitors (SCs) have increased significantly, with a focus on materials and energy storage capabilities. Extensive efforts have been made to enhance

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their competitiveness compared to other energy storage options, like rechargeable batteries [19]. The electrical properties of supercapacitors, especially their fast charging and discharging times, are very interesting for some applications, due to their advantages, they are widely used in different applications in the automotive, consumer electronics, renewable energy, railways, defense, energy industries, etc., where supercapacitors can completely replace batteries [25]. Supercapacitors are becoming more and more popular as components for electrical energy storage in renewable energy sources because renewable systems require high cycle efficiency and frequently experience high charge-discharge cycles [26]. Supercapacitors (SCs) have gained attention as potential replacements for aluminum electrolytic capacitors (AECs). Researchers have explored different carbon materials with open-pore structures, such as vertically oriented graphene (VOG), edge-oriented graphene (EOG), and vertically aligned carbon nanotubes (VACNTs), to achieve fast SCs for AC line filtering. Aqueous electrolytes with high ionic conductivity and low viscosity, such as KOH, H2SO4, and Na2SO4, have been widely used in high-frequency SCs. Non-aqueous electrolytes, such as organic and ionic liquid electrolytes, have also shown promise for high-rate capability [27]. Machine learning (ML) techniques are one of the most important tools for solving various scientific and engineering problems [22]. Recently, machine learning has played an important role in the design of supercapacitors. Reference [5] (ML) is the focus of recent studies aimed to improving supercapacitor and battery technology, Machine learning methods have been used in several studies to estimate the life, state of charge, and capacitance of supercapacitor. Machine learning can help design supercapacitors with target characteristics [21], [28], [29].

Several studies have been performed, to study the development of accurate and efficient forecasting models for supercapacitor performance. Artificial intelligence (AI) techniques, such as Artificial Neural Networks (ANN), can be employed. These ML approaches enable the prediction of the specific capacitance of carbon-based supercapacitors by analyzing various structural qualities and physicochemical test features of the electrode materials. The ANN model developed in previous studies exhibits exceptional accuracy in capacitance prediction compared to other models. It achieves a root mean square error (RMSE) 30.82 and a correlation coefficient (R) of 0.89537. Furthermore, the analysis of input features using the Shapley Additive exPlanations (SHAP) framework reveals that the specific surface area (SSA) significantly influences the ANN model, this underscores the importance of SSA in determining the performance of supercapacitors [30]. The performance of supercapacitors based on fractal nanocomposites has been studied by using cyclic voltammetry (CV), gradient tree boosting (XGBoost), and a machine learning (ML) model. These nanocomposites provide a large surface area, excellent electrical conductivity, and impressive mechanical stability. By taking advantage of the experimental dataset of Co-CeO_2/rGO nanocomposites, the successful development of an intelligent prediction model provides valuable insights into generating novel nanocomposite structures with high accuracy [31]. Ding et al., proposed a new feed forward Artificial Neural Network (ANN) structure with two hidden layers and back propagation training for modeling the complex dynamic behavior of supercapacitors. The ANN provides output values with a total correlation of 0.9426 compared to target values. Measurement of the performance of an ANN is done through the Mean Squared Error (MSE) function, which quantifies the deviation of outputs from targets. Effective modeling of supercapacitors using ANNs can assist in designing and optimizing supercapacitor-based energy storage systems [32]. Eddahech et al., suggested utilizing a single-layer feed forward (ANN) in which the back-propagation algorithm is applied to describe the behavior of supercapacitors used for automotive applications. In this model, the neural network is constructed based on the temperature, current, and voltage of the supercapacitor, and it shows a very high degree of accuracy compared with measurements obtained from power-cycling tests. Overall, this study proposes a method for modeling and adaptive control of supercapacitors in automotive applications using ANN and is validated through simulation and experimental results [26]. Wang et al., developed (ANN) model to predict the electrochemical performance of (nitrogen- and oxygen-co-doped) activated carbon electrodes. The researchers utilized a back propagation algorithm during the training process. To evaluate the model's performance, the dataset was divided randomly into three subsets: training (70%), validation (15%), and testing (15%). The model takes into account various factors such as structural parameters (micropore and mesopore surface areas), chemical features (nitrogen and oxygen doping percentages), and electrochemical parameters (cyclic voltammetry scan rate), to accurately forecast the performance of the electrodes, thus contributing to the advancement of energy storage technology [33]. Jamaluddin1 et al., employed Machine Learning (ML) to forecast the capacitance of supercapacitors, with the Random Forest (RF) model demonstrating the most favorable outcomes, concentrating on graphene characteristics and experimental parameters. Graphene characteristics that were analyzed encompassed the specific surface area, pore volume, pore size, defect ratio, carbon, oxygen, and nitrogen content, while experimental parameters included electrolyte concentration, voltage window, and current density. The research emphasized that graphene possessing a high specific surface area and porous configuration could result in elevated capacitance values in supercapacitors. The study underscored the significance of optimizing graphene characteristics and experimental parameters to enhance supercapacitor efficiency, providing valuable insights for forthcoming material science investigations [34].

Only a few number of features are employed in the studies in the literature to classify supercapacitors using ML techniques. Because of this, the categories that were produced are either insufficiently useful or have restricted applicability.

The studies in the literature on supercapacitor design and categorization were used to construct the dataset for this investigation. However, some studies were not incorporated to the model since some articles did not share their whole data.

This study underscores the potential of applying machine learning in the field of capacitor manufacturing, as it can significantly reduce the time and effort required to develop these devices. By utilizing machine learning techniques such as classification learner, we cannot only improve their performance but also open up new possibilities for supercapacitor applications.

In this study,

- Kernel Naïve Bayes model was used to classify supercapacitors,
- Specific capacitance, voltage window, electrode materials, and electrolyte used were taken into account,
- Supercapacitors were divided into five classes according to the level of their specific capacitance values,
- The model was able to distinguish between different categories with high accuracy.

The paper was organized as follows: the model establishment with Kernel Naïve Bayes method was described in Section II. In Section III data collection and classification were then explained. After that the methodology was described in Section IV. Results and discussion was provided in Section V and the model's performance was evaluated in Section VI. Lastly, key findings and future work were explained in Section VII.

II. MODEL ESTABLISHMENT

In this paper a supercapacitor specific capacitance classification method was developed based on a kernel Naïve Bayes classifier, consisting of steps as shown in Fig. 1.

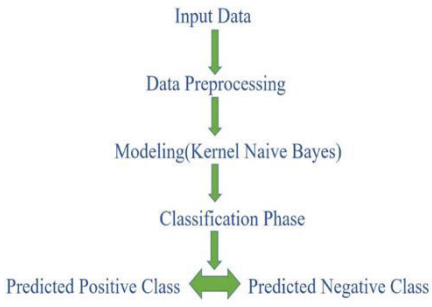

FIGURE 1. Model proposed methodology.

III. DATA COLLECTION AND CLASSIFICATION

The data was collected from scientific papers related to supercapacitors, which totaled 542 studies. Moreover, the data was collected based on properties of supercapacitors. It included the types of materials used in manufacturing supercapacitors, most of which were carbon-based, such as, graphene, carbon nanotubes, and carbon nanofibers, as well as the type of electrolyte, voltage window (ΔV), specific surface area



FIGURE 2. Confusion matrix for a classification model.

of the electrode material (m^2/g). Within the scope of the study, all available data regarding the supercapacitors were used. The aim here is to retain and include in the study all factors affecting supercapacitor classification as positive or negative. For this reason, no feature elimination was performed. The supercapacitor specific capacitance data (F/g), has been divided into five categories for easy classification and analysis. The first category includes values $<$ 106 F/g, reflecting the lowest capacitance (Class 1), while the second category starts from 106 to 159 F/g, indicating a slightly higher level (Class 2). The third category includes values from 160 to 216 F/g, and is considered an average level of capacitance (Class 3). The fourth category ranges between 217 and 302 F/g, and indicates a relatively high capacitance (Class 4), while the fifth category covers values $>$ 302 F/g, and is the category with the highest capacitance (Class 5).

Kernel Naïve Bayes theorem is used with a kernel function to nonlinearly estimate the conditional probabilities of each class. The main equations used in the classification process. In the Naïve Bayes model, we use Bayes' theorem to update the conditional probabilities. The basic equation is:

$$P(C|X) = P(C|X) \cdot P(C)/P(X)$$
$$X = (X_1, X_2, \ldots, X_d) \quad (1)$$

where, P(C|X) is the conditional probability of class C given the inputs X, P(X|C) is the conditional probability of the input X provided that the class exists C, P(C) is the prior probability of class C, P(X) is the input probability X. Conditional probability P(X|C) was calculated with the following equation:

$$P\left(X_j \middle| C\right) \prod_{j-1}^{d} = P(X|C) \quad (2)$$

where, d is the number of features in the input X. Conditional probability P(Xj|C) is estimated with the following equation:

$$K\left(X_j, X_{i,j}\right) \sum_{i=1}^{C^n} 1/C^n = P\left(X_j \middle| C\right) \quad (3)$$

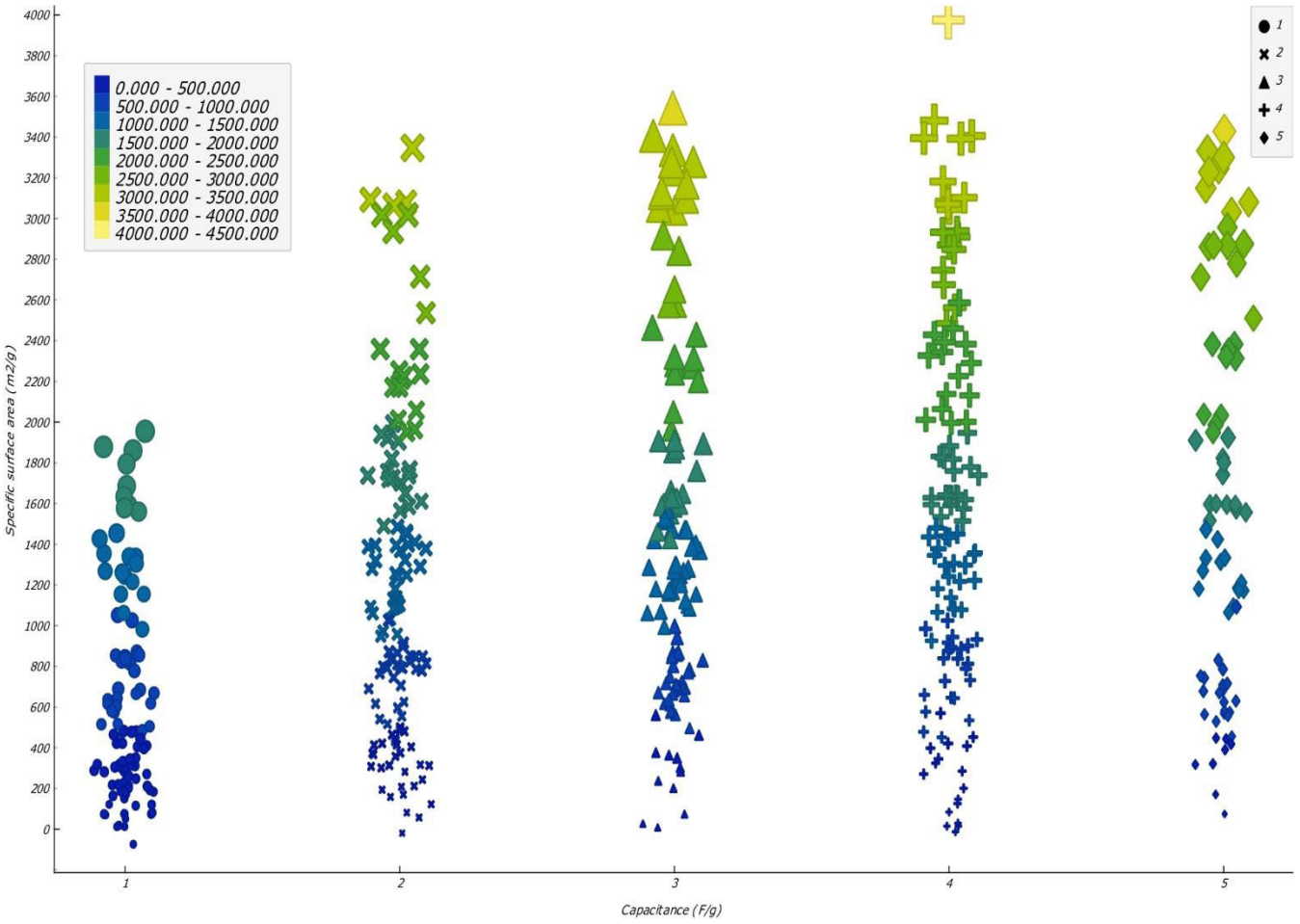

FIGURE 3. The relationship between specific capacitance (F/g) and specific surface area (m^2/g).

where, C^n is the number of samples in class C, K (X_j, $X_{i,j}$) is the kernel function that measures the similarity between the feature X_j and the j-th feature in the i-th sample. Gaussian Kernel function was calculated using the equation below:

$$K\left(X_j, X_{i,j}\right) = \exp\left(-\left(X_j - X_{i,j}\right)^2 \Big/ 2\sigma^2\right) \tag{4}$$

where, σ is a parameter controlling the width of the kernel.

IV. METHODOLOGY

Using software tools such as MATLAB in data classification operations is an effective way to develop advanced models and analyze performance. In this paper, we discuss the scientific research steps that were followed to classify data using a classification learner. The focus was on how to collect, process, and classify data using MATLAB, in addition, how to evaluate the model through the confusion matrix. To evaluate model performance, the confusion matrix was used across five classes. The matrix shows the proportion of true and false predictions for each class.

V. RESULTS AND DISCUSSION

Fig. 2 presents the confusion matrix of the model, where the proportions of predictions for each class are shown in the figure. The diagram shows the confusion matrix for a classification model using kernel Naïve Bayes.

VI. MODEL PERFORMANCE

The data was classified into five different categories. The percentages inside the blue boxes represent the percentage of correct classification. The model shows great performance in classifying classes, especially Classes 3 and 4, where the correct classification rate was more than 98%. This indicates that the model has a high ability to accurately recognize most of the valid samples within Classes 3 & 4. While a wrong classification was obtained in the following classes. Class 1 (7.5%) and Class 2 (7.0%), these classes have a relatively high false negative rate (FNR).

The true positive rate (TPR) and false negative rate (FNR) were calculated for each class. The results show that most of the classes showed high true positive rates. While the rates of false negatives were very low as shown in Table 1. TPR reflects the proportion of positive cases that are correctly

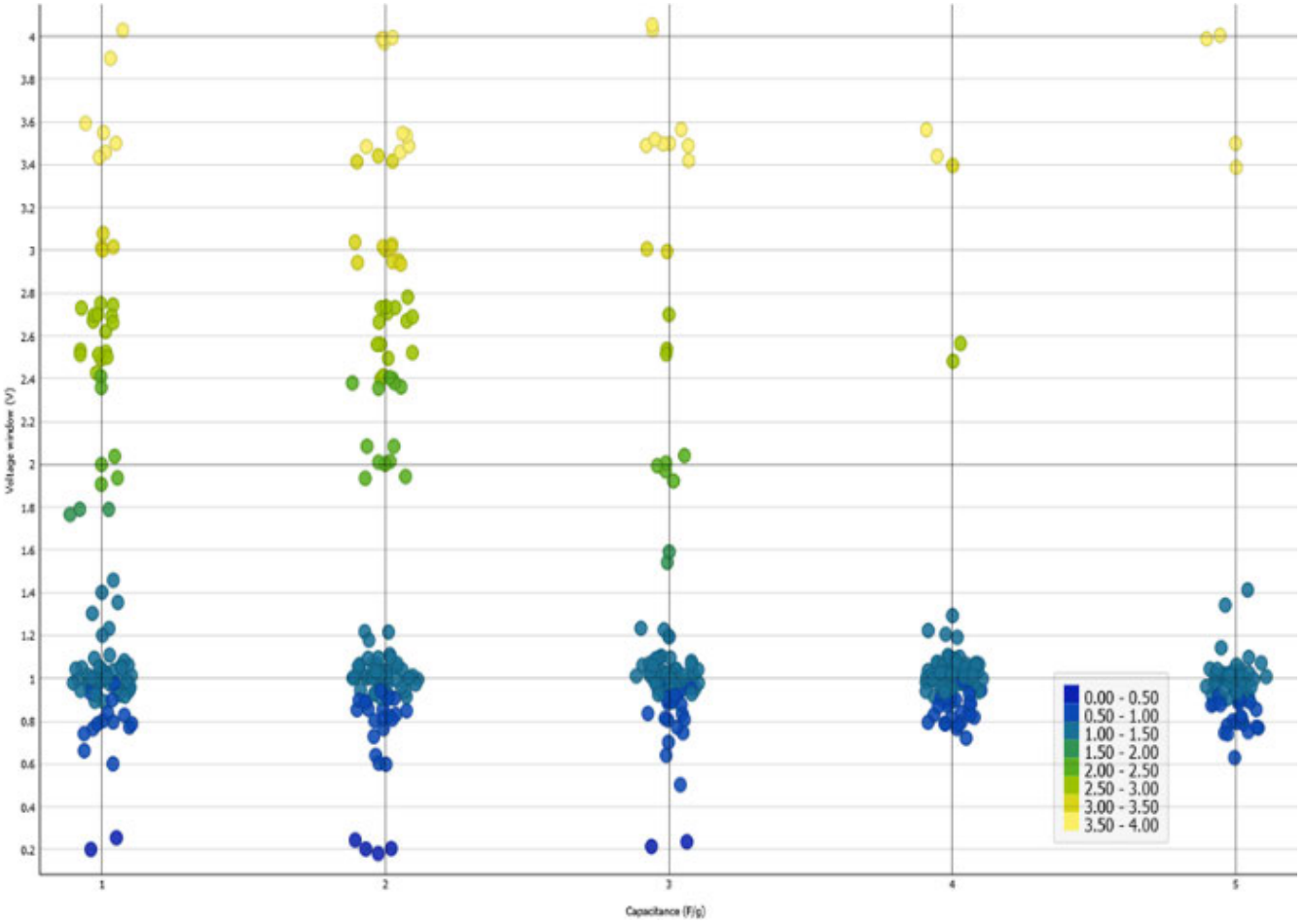

FIGURE 4. The relationship between the voltage window (ΔV) and specific capacitance (F/g).

TABLE 1. Performance rates of the model.

Class	True positive rate (TPR)	False negative rate (FNR)
1	92.5%	7.5%
2	93.0%	7.0%
3	98.1%	1.9%
4	98.1%	1.9%
5	94.2%	5.8%

detected by the model used. The true positive rate is calculated by dividing the number of correctly detected positive cases by the total number of positive cases. In the table, the false negative rate ranges between 92.5% and 98.1%, which indicates that the model used is capable of detecting positive cases most of the time. FNR reflects the proportion of negative cases that were detected by the model and classified as negative cases. The false negative rate is calculated by dividing the number of negative cases detected by the total number of positive cases. The percentage of negative cases detected in the table ranges from 1.9% to 7.5%. Classifications 3 and 4: TPR was the highest at 98.1% and FNR was the lowest at 1.9%. This indicates that these two classifications are the most accurate in detecting positive cases and the least negative ones. Class 1 showed the lowest TPR of 92.5% and the highest FNR of 7.5%. This means that the Class 1 is less accurate than other classes in detecting positive cases. In Class 1, 92.5% of the data were correctly classified, while 7.5% were incorrectly classified as other categories. In Class 2, 93.0 % of the data were correctly classified, while 7% were incorrectly classified as other classes (3.5% as Class 1, 1.8% as Class 2, 0.9% as Class 4, and 0.9% as Class 5). In Class 3, 98.1% of the data were correctly classified, while 0.9% were incorrectly classified as Class 2 and 0.9% as Class 4. In Class 4, 98.1% were correctly classified while 1.0% was incorrectly classified as Class 2 and 0.9% as Class 3. In Class 5 94.2% were correctly classified while 2.9% were incorrectly classified as Class 1 and, 2.9% as were incorrectly classified as Class 2.

The graph shows the relationship between the electrical capacity (F/g) and the specific surface area (m^2/g) of a set of electrical capacitors. The horizontal axis shows the electric capacity of the capacitors, while the vertical axis shows the specific surface area. The distribution of samples is shown within a wide range of values for both capacity and

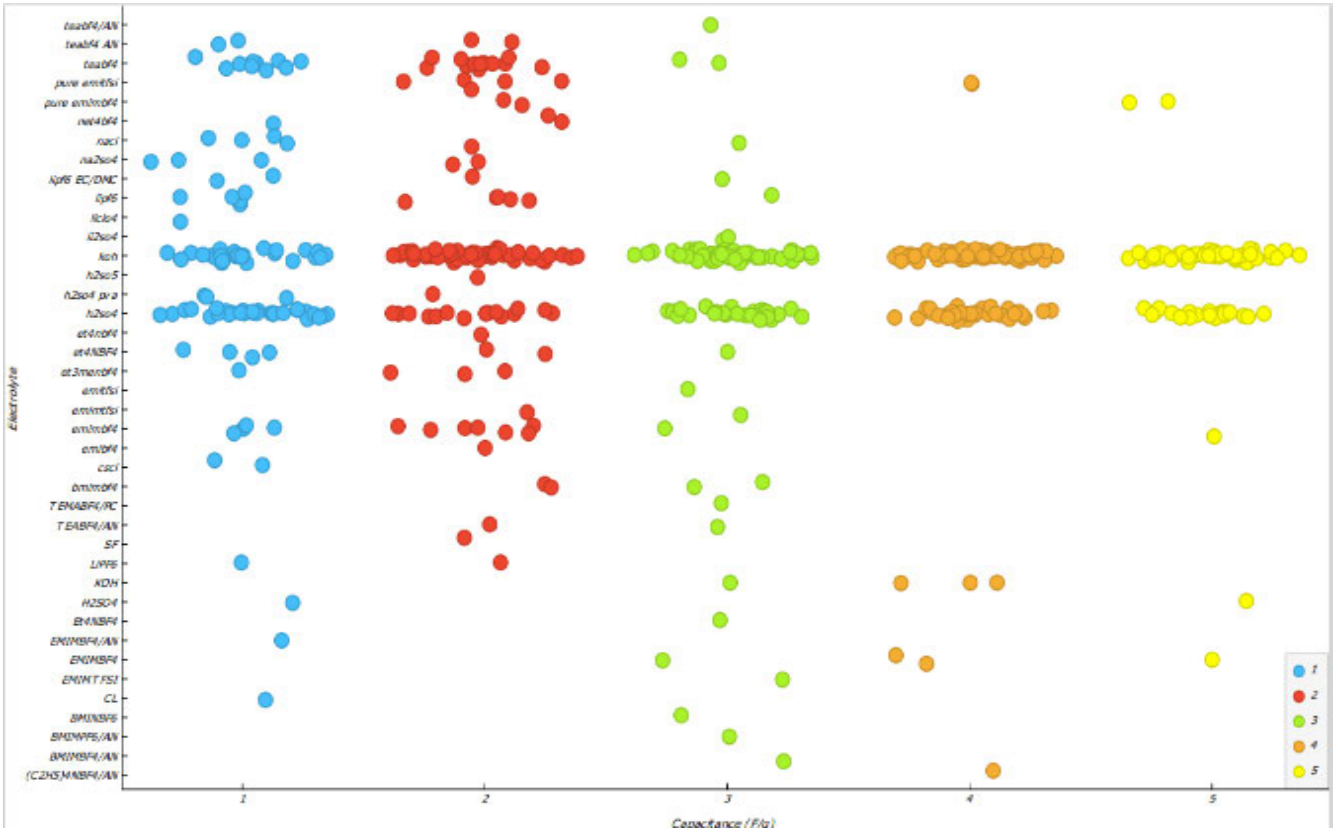

FIGURE 5. The relationship between different types of electrolytes and specific capacitance (F/g).

surface area. There is a direct relationship between increasing the surface area and increasing the electrical capacity. As the surface area increases, the electrical capacity increases with it, where samples with higher capacity are collected in areas with large surface areas. It can be concluded that capacitors with greater surface area may show greater electrical capacity, but data dispersion is also observed, indicating that additional factors may affect electrical capacity and surface area. This chart provides an overview of the relationship between electrical capacity and the specific surface area of the capacitors, and highlights the importance of the surface area as a factor in improving the electrical performance of supercapacitors.

This graph shows the relationship between the voltage window (ΔV) and specific capacitance (F/g) for a data set of supercapacitors. The voltage window is dispersed throughout a range of capacitance values. The diagram's colored dots, each representing a distinct electrolytic capacitor measurement, indicate the capacitance and voltage window values associated with that measurement. The distribution of amplitudes may be viewed throughout various voltage ranges since the dots are color-coded based on the amplitude values. It is seen that the colors gradually change from dark blue for lower amplitude applications (0.00–0.50 F/g) to green and finally yellow for higher amplitude applications (3.50–4.00 F/g). Analyzing the distribution shows that data with lower amplitudes are more concentrated in lower voltage ranges. In contrast, data with bigger amplitudes extend to higher voltage ranges but have a less dense distribution. Higher capacitance supercapacitors may be able to function across a greater voltage range, according to this distribution.

This figure compares different types of electrolytes and their effect on the capacitance of a supercapacitor, where capacitance is measured in farads per gram (F/g). The multiple bars in the graph represent different types of electrolytes, including H_2SO_4, BMIMBF$_4$/AN, and KOH, with the length of the bars reflecting the specific capacitance of each electrolyte. The graph clearly shows that capacitance varies widely from electrolyte to electrolyte, reflecting the impact of the physical and chemical properties of each electrolyte on the performance of the capacitor. Electrolytes with high electrical conductivity, such as, H_2SO_4, exhibit higher capacitance than other electrolytes. This is due to their ability to improve the movement of ions inside the supercapacitor, thus increasing charge storage efficiency. In contrast, electrolytes such as KOH exhibit lower capacitance, primarily due to increased ionic resistance within the electrolyte or less effective surface interaction with the active material within the capacitor. Viscosity, on the other hand, plays an important role in determining the overall performance of an electrolyte. Low viscosity electrolytes facilitate ion migration, resulting in improved electrical performance and increased capacitance.

However, high viscosity electrolytes conversely hinder ion migration and decrease capacitance. Overall, this figure illustrates the importance of carefully selecting an electrolyte based on the specific performance requirements of the application. Whether the goal is to increase capacitance, improve electrochemical stability, or strike a balance between these two factors, understanding how different electrolytes affect capacitance provides a foundation for meeting the needs of diverse applications and improving capacitor design. This study provides a foundation for improving supercapacitor design to meet the needs of a wide variety of applications.

The results show that the kernel Naïve Bayes model has a high ability to classify data with great accuracy. The confusion matrix showed that the model has a high accuracy rate of more than 92% in most categories, which indicates the effectiveness of the model in identifying different patterns in the data. Additionally, this model has a high ability to distinguish between different classes accurate

VII. CONCLUSION

This study demonstrated the possibility of achieving accurate and efficient classification of supercapacitor data based on a set of distinct characteristics. This model has proven highly efficient in classifying data, due to its ability to deal with complex and multidimensional data. The most notable benefits of this model are its high classification accuracy and ease of implementation, making it an excellent choice for supercapacitor data analysis. These results contribute significantly to improving the performance and efficiency of applications that rely on supercapacitors. This model provides a powerful framework for accurate analysis and classification of electrical data, opening the way for broader applications in areas such as energy storage, electric transportation, and advanced electronic systems.

In this study data on supercapacitor design and categorization in the literature were used to construct the dataset for this investigation. We were unable to incorporate supercapacitor information into our study since some articles did not share it that could be incorporated to the dataset. Furthermore, the article's focus was on the model that incorporates as many features as feasible and all of the descriptive features of supercapacitors to create the most successful classification, rather than a detailed analysis of each feature's impact on classification.

The results of this study reflect the strong performance of this model in classifying data, and this is clearly evident in Classes 3 and 4, where the prediction accuracy reached 98.1%. This high performance indicates that the model is capable of providing accurate assessments of the performance of supercapacitors, enhancing its potential as an effective tool in practical applications. In addition, this model achieved high true positive rates and low false negative rates for most classes. This indicates the model's ability to accurately distinguish different classes and respond well to the data provided. Based on the data presented, it can be said that the model used in these classifications generally performs well in detecting positive cases, but there is slight variation in performance between different classifications. Classes 3 and 4 show the best performance.

In future studies, it is planned to use the classification model that was developed to divide the classification into narrower capacitance ranges and thus enabling more specific capacitance estimates. Additionally, it is aimed to make feature selection more effectively by determining the SHAP values of the features used.

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