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Clustering Machine-Learning Technique for Administration and Economic Development: Focusing on Predicting the Purchase of Electric Vehicles to Improve Business Decision Making for Companies

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Abstract: There are several ways to forecast electric vehicle sales to help businesses make better decisions. One strategy is to use prescriptive and predictive analysis techniques to examine consumer preferences and buying behavior regarding electric vehicles. Additionally, models for predicting electric vehicle sales can be developed using logistic regression and decision trees. These models let businesses make well-informed judgments about their sales by offering patterns regarding customer mining, classification accuracy, and prediction effects. In this study, we collected survey data from approximately 452 respondents in Qassim State through an online questionnaire to analyze factors influencing electric vehicle (EV) adoption. The data consists of 23 conditional attributes that were evaluated during the analysis. This study suggests evaluating the features of the customer that may influence their decision to purchase electric vehicles. The clustering algorithm was implemented to segment customers based on these features. The current study's findings demonstrated the effectiveness of the model created using the K-means clustering algorithm derived from data mining in predicting the purchase of electric vehicles. The accuracy of the correctly classified instances was evaluated using three distinct classification techniques: BayesNet-D, NaiveBayes, and J48. According to the evaluation results from these algorithms, the overall accuracies in terms of correctly identified cases were 90.4867%, 88.0581%, and 91.8142%, respectively. Through a series of tests on real electric vehicle datasets gathered from individual users, the effectiveness of these classifier-based rule-based models is evaluated. The overall experimental findings and discussions can assist businesses of electric vehicle companies in making decisions on the development of intelligent systems for electric vehicle users. The data-mining algorithm's extraction of information in this study improved our comprehension of the customer base's composition regarding purchasing electric vehicles and the company's assessment of the appropriate course of action for offering guidance, training, and expertise.

Keywords: Electric vehicles; Distribution networks; Vehicle-to-Grid (V2G); Photovoltaics; Wind generation; Power loss reduction; Voltage regulation.

1. INTRODUCTION

The data pertaining to multiple electric car models, encompassing details such as battery capacity, range, acceleration, charging speed, cost, and additional pertinent qualities. Using a clustering method on this data, we may potentially find multiple unique clusters or groups of electric vehicles that have similar attributes.

One cluster might stand for less expensive, entry-level electric vehicles with smaller battery packs and less powerful engines. High-end, luxury electric cars with extended ranges, quick acceleration, and premium pricing may make up another cluster. And a third group might consist of mid-range electric vehicles that strike a compromise between features, performance, and price.

The clustering outcomes would vary based on the underlying data structure, the variables analyzed, and the technique applied. Nonetheless, the overall concept is to determine logical clusters or divisions within the electric vehicle industry by means of the vehicles' technical attributes and additional pertinent variables.

The global automotive sector is witnessing a major revolution as electric vehicles (EVs) emerge as a greener and more ecologically sound option compared to traditional vehicles dominant in the market [1]. As businesses build up plans to be part of this transformation, their understanding and accurate forecasting of EV sales have proved to be central to strategic decision-making processes [2]. Estimating the sales of electric vehicles requires a thorough consideration of consumer preferences, market options, and technological developments, making it necessary to employ advanced analytical instruments to gain knowledge concerning individual customers [3].

The use of prescriptive and predictive analysis in forecasting the sales of EVs is one of the approaches that seeks to employ positive measures. [4]. Consideration of consumer preferences and buying behavior towards electric vehicles offers valuable information that guides the company in structuring its sales strategy and the products it will sell [5]. To build predictive analytics in EV sales, companies must use logistic regression analysis and decision tree models, which are common and allow the company to make decisions about customer segmentation, classification, and prediction accuracy, and even the outcome of the predictions made [6].

In order to enhance business strategies and support automotive companies in increasing EV adoption, this study also examines the use of prescriptive and predictive analysis techniques to examine consumer preferences and buying behavior about electric vehicles. By implementing and preparing a clustering algorithm, the study aims to develop a predictive model that can effectively and more accurately predict EV purchases. The effectiveness of the model is evaluated using different classification techniques, including BayesNet-D, NativeBayes, and J48 [7], [8], which demonstrate high accuracy rates in correctly identifying potential EV buyers. Also, through experimental tests on real-world EV datasets derived from individual users, the study evaluates the effectiveness of classification-based rule models in predicting EV purchases [9]. The results and discussions from these experiments provide valuable insights that can guide companies in developing intelligent systems tailored specifically for EV users. Moreover, data mining algorithms can be leveraged to extract valuable information about customer preferences and behaviors [10], which can help companies improve their strategies and offerings to meet evolving market demands and contribute to the sustainable growth of the electric vehicle sector [11].

Clustering, an important dynamic technique in machine learning, offers great potential to improve administrative functions and drive economic growth [12]. By focusing on predicting the purchasing habits of electric vehicle consumers, companies can improve their decision-making tactics, thereby encouraging expansion and innovation in this area [13]. Electric vehicles represent a rapidly expanding market segment, and understanding customer trends in this area is essential for companies aiming to capitalize on this trend. Clustering algorithms skilfully classify customers according to their purchasing patterns, allowing companies to tailor marketing strategies and product offerings to meet distinct customer needs [14]. This focused approach not only increases customer satisfaction but also enhances business profitability by aligning offerings with consumer preferences [15]. In the field of economic development, the implementation and adoption of clustering techniques to predict electric vehicle purchases can have wide-ranging impacts [16].

Through the use of clustering algorithms, examining customer data can gain powerful insights into market dynamics and consumer behavior trends [17]. By identifying groups of customers with similar purchasing tendencies, companies can adjust their marketing strategies and optimize their product offerings to better match consumer expectations and desires [18]. Through accurately predicting consumer behavior, companies can mitigate risks associated with product development and marketing strategies, leading to more informed and profitable business decisions [19].

The emphasis on predicting EV purchases through clustering technologies also contributes to broader economic progress [20]. As EVs gain traction and profitability, companies that can accurately predict customer demand and preferences are guaranteed to gain a competitive advantage in the market [21]. This, in turn, stimulates the role of innovation and drives economic growth by encouraging investment in sustainable technologies and advocating environmentally friendly practices [22]. Adopting predictive analytics and machine learning tools, companies can enhance their strategic planning processes, unlock new business opportunities, and drive overall economic progress [23].

1.1. Purpose of the Study

The ability of national economies to generate and utilize knowledge is becoming more and more crucial to their ability to compete globally, as information, education, and innovation are the main indicators of economic progress in a globalizing world. Within economics, it is widely accepted that the main driver of a country's, region's, or city's economic growth is technology. The ability to produce more and better goods and services more efficiently is a prerequisite for prosperity, and technical innovation makes this feasible.

Customers value progress in businesses, especially in the case of electric vehicle companies, as a strong profit margin on products like these is one of the standards for a high-quality business. However, the abundance of data and variety of brands available on the market have made it more difficult to predict the trajectory of electric vehicle sales.

As electric cars become more popular, it's essential to grasp what drives people's buying choices. This research sets out to pinpoint key features that sway purchase decisions and to look at how outside forces, like government rules and tech breakthroughs, have an impact on how consumers act. By folding these factors into our cluster analysis, we can get a fuller picture of what's happening in the market. This wider view will help car makers line up their plans with shifting customer wants, boosting their edge in the changing car world.

This study's primary goal is to suggest a set of characteristics that will enhance the process of evaluating potential buyers of electric vehicles. Adopting a clustering method to assess client data is the second goal, which is designed to improve the standard of electric vehicle manufacturers.

1.2. Significance of the Study

The importance of this study lies in the ability to carry forward the understanding of consumer behavior in the rapidly developing electric vehicle (EV) market. Due to global concerns about climate change and environmental stability, electric vehicles are deployed as an important option for traditional combustion vehicles. The purpose of this research is to provide valuable insights that can help manufacturers, policy makers, and stakeholders navigate the complications of this infection. Exact predictions of EV sales are essential for an effective strategic scheme in the motor vehicle industry. By employing clustering techniques to analyze consumer preferences and behaviors, this study identifies different market segments and their distinguishing characteristics. Understanding these sections allows manufacturers to tailor their marketing strategies, optimize their product offerings, and increase customer satisfaction. In addition, this targeted perspective can increase sales and market share, promoting competitive advantage in a cumbersome industry. Additionally, the findings of this study can contribute to the comprehensive economic and environmental goals. By facilitating the adoption of electric vehicles, manufacturers can play an important role in reducing carbon emissions and promoting permanent practices. This aligns with global initiatives aimed at creating a green future, as governments rapidly apply policies that encourage EV adoption. Thus, the insight from this research not only benefits individual companies but also supports national and international efforts for environmental stability.

1.3. Motivation of the Study

The motivation behind this study is an immediate need to understand consumer behavior in the context of adopting electric vehicles. As the market expands for EVS, it is important to understand the factors affecting the purchase decisions. Traditional market analysis methods cannot catch the nuances of consumer preferences in this dynamic scenario. The purpose of this research is to provide that difference by using advanced analytical techniques, such as clustering algorithms, to provide a more comprehensive understanding of consumer motivations. In addition, the increasing variety of electric vehicle models and features presents both challenges and opportunities for consumers. With many options available, understanding which properties are the most valuable to potential buyers can greatly affect the success of a manufacturer. By examining external factors, such as government incentives and technological progress, the study wants to provide a holistic approach to the market, empowering manufacturers to align their strategies with consumer expectations. Finally, the inspiration for this study is inspired by the desire to contribute to the permanent development of the electric vehicle sector. By providing actionable insights into consumer behavior, the purpose of this research is to support the motor vehicle industry in navigating the challenges of this infection, promoting innovation, and promoting environmentally friendly practices.

1.4. Saudi Arabia's Vision 2030

Saudi Arabia's Vision 2030 is a comprehensive initiative aimed at transforming the country's economy and reducing its dependence on oil. Launched in 2016, the initiative seeks to diversify economic activities by promoting sectors such as tourism, entertainment, and renewable energy, including electric vehicles (EVs). As part of this vision, the Saudi government is actively investing in the development of EV infrastructure, such as charging stations and maintenance facilities, to encourage widespread adoption.

The implications for the EV market are significant. By fostering a favorable environment for EV development, Saudi Arabia aligns itself with global sustainability goals, particularly the reduction of greenhouse gas emissions and the combat against climate change. The initiative emphasizes the importance of sustainable transportation solutions, which are essential for improving air quality and reducing the carbon footprint.

Additionally, Vision 2030 aims to position Saudi Arabia as a leader in sustainable technologies, attracting foreign investment and fostering cooperation with global EV manufacturers. This strategic focus not only promotes innovation but also creates job opportunities and stimulates economic growth, contributing to a more flexible and diversified economy. Through these efforts, Saudi Arabia is taking meaningful steps toward a sustainable future, enhancing its global competitiveness in the emerging EV market.

The structure of this paper is as follows: Section 2 provides the background and literature review; Section 3 describes the proposed model; Section 4 discusses the experiments and evaluation of this study; Section 5 outlines the limitations; Section 6 illustrates the contributions of the study; and the concluding remarks are presented in the final section.

2. INTRODUCTION

Electric vehicles (EVs) have gained significant popularity in recent years due to their environmental benefits and advancements in technology. Unlike traditional internal combustion engine vehicles, EVs produce zero tailpipe emissions, making them an attractive solution for reducing greenhouse gas emissions and air pollution [24]. In addition, improvements in battery technology have increased the range and efficiency of EVs, contributing to their growing adoption [25]. Governments worldwide are also providing incentives and investing in charging infrastructure to encourage EV adoption, which is expected to accelerate the transition towards more sustainable transportation [26].

Artificial intelligence (AI) is increasingly being integrated into electric vehicles (EVs) to enhance their performance, safety, and efficiency. AI-driven systems enable advanced driver-assistance features, such as autonomous driving, collision avoidance, and adaptive cruise control, making EVs safer and more convenient for users [27]. Moreover, AI optimizes energy management in EVs by predicting driving patterns and efficiently controlling battery usage, which can extend the vehicle's range and lifespan [28]. Additionally, AI-based predictive maintenance helps in diagnosing potential issues before they occur, reducing downtime and maintenance costs [29].

Saudi Arabia has been implementing policies and regulations to promote the adoption of electric vehicles (EVs) as part of its Vision 2030 initiative, which aims to diversify the economy and reduce dependence on oil. The Saudi government has taken steps to develop the necessary infrastructure, such as establishing charging stations and offering incentives to attract EV manufacturers [30], [31]. In 2022, [32] introduced new technical regulations to ensure the safety and quality of EVs and charging equipment, which is expected to accelerate the growth of the EV market in the country (Arab News, 2022). Additionally, Saudi Arabia has entered partnerships with global EV manufacturers to establish production facilities, contributing to the country's aim to be a leader in sustainable transportation [33].

Sales of electric vehicles (EVs) in Saudi Arabia have been steadily rising as the country continues to make significant improvements in the EV market. This growth is driven by the government's efforts to invest in charging infrastructure, offer incentives, and raise awareness about the benefits of EVs [34]. The launch of the first domestically produced EV brand, Ceer, in partnership with global manufacturers, has also contributed to increasing consumer interest and confidence in the market [35]. As a result, EV sales in Saudi Arabia are expected to grow by 28% annually, with projections indicating that EVs could account for 20% of all vehicles on the road by 2030 [36].

Recently, artificial intelligence procedures have been increasingly applied in various areas, and data-mining algorithms have a number of applications, such as in banking, economics, education, and communications [37]–[43].

Competition in the global markets for electric vehicles is very high due to the increasing number of manufacturers and the growing global need. Therefore, it is crucial to make informed decisions based on accurate and up-to-date data to stay competitive and ahead. The use of data mining rule-based classifiers has emerged in various products to predict demand and consumer behavior and help make business decisions that provide a competitive advantage [44]. Rule-based classifiers are used in data mining, such as if-then rules, to classify data into several different categories [45]. These classifiers could have been extracted from historical data to identify patterns and predict future outcomes [46].

In the study by [47] on the use of database-based classifiers that help make predictions based on several factors, including residential composition, product, and price, the results demonstrated the effectiveness of these rule-based classifiers in accurately predicting brand preferences. The study provided valuable and effective insights into strategies to build product marketing and brand promotion, as well as interpretability in outcome-based predictive process monitoring.

Machine learning algorithms play an important and prominent role in enhancing the accuracy and effectiveness of classifiers based on data mining rules, such as relying on deep learning techniques and neural networks in artificial intelligence, which allows for the availability of more accurate and efficient information for decision-making that helps discover more opportunities for consumer behavior [48]. Clustering is a powerful machine-learning technique that combines similar data points depending on the underlying characteristics, making it invaluable for administration and economic development. By identifying separate customer segments, businesses can tailor their strategies to meet specific requirements and preferences. Electric vehicles (EVs) procurement in terms of predictions, clustering organizations helps understand consumer behavior, which is able to make more informed decisions. This approach not only enhances marketing efforts but also supports the development of targeted policies that promote permanent practices and economic growth. Since industries rely on rapid data-driven insight, it is necessary to apply clustering techniques to improve efficiency in the economic sector and improve driving innovation.

Applying classifiers based on data mining rules to predict the market regarding electric vehicle commerce can help businesses continuously improve their marketing strategies, design their products, and enhance customer satisfaction [47].

[49] emphasized the effectiveness and performance efficiency of data mining techniques in extracting valuable insights from customer reviews and social media data. Rule-based classifiers contribute significantly to providing accurate and interpretable data, enabling companies to have a broad understanding of making informed decisions that support brand preference [50].

The study by [51] proposed a neural network to enable learning, retrieve information from texts, and respond to questions. [52] presented the idea of linking SVM notions to Pawlak's rough sets in a single classification system. [53] proposed deep-learning models to significantly improve systems based on artificial intelligence. The article by [54] suggests a summary of attribution-based post hoc explanations for analyzing and tracking bias in information. Research by [55] has been successfully applied to various sequences of decision-making assignments, machine learning applications, and time series predictions.

One popular prediction technique is the decision tree. Due to its simplicity and ability to uncover small or large data structures and predict their value, it has been used by a large number of researchers [56]–[61]. According to [62]–[68], decision tree models are easy to understand because of their reasoning process, and they can be directly converted into a set of IF–THEN rules. Rule induction is an efficient, accurate prediction strategy [69]–[71].

[72] developed data mining methods to forecast patient recovery using healthcare datasets. The framework for data mining classification of patient healthcare records was the Cross-Industry Standard Process for Data Mining. The researcher used WEKA software.

In a study by [7], the characteristics of remote learning that may impact student performance were assessed. Based on the results, a classification system was implemented to suggest changes to higher education institutions, using WEKA software. In a subsequent study [73], the researcher investigated the impact of various qualities, instructional methods, and neural network topologies on the accuracy of heart attack diagnosis.

The assessed outcomes about electric vehicle brands are meant to enable management and companies to build the framework themselves. The techniques depend on the attributes of the framework, which are applied to explore their feasibility. The characteristics and attributes are generally used to measure which brand of electric vehicle customers prefer, and factors such as vehicle features, brand features, and customers. Therefore, this study introduces a set of attributes that evaluate electric vehicle companies from a customer perspective to predict which brand is used. The attributes are divided into three factors: vehicle features, brand features, and customers.

3. THE PROPOSED MODEL

A cross-industry standard procedure for data mining strategy [74] was being established in order to create a recognized classification model. The method can be broken down into five main stages: (1) collecting pertinent features associated with the issue under investigation; (2) getting the data ready; (3) creating the classification model; (4) assessing the model using one of the evaluation techniques; and (5) applying the possible prediction model for cell phone brands. The ensuing subsections go over these phases.

3.1. Description of Influence Factors and Attributes

In this study, we collected survey data from approximately 452 respondents in Qassim State through an online questionnaire to analyze factors influencing electric vehicle (EV) adoption. The data consists of 23 conditional attributes, which we categorized into four main groups:

Customer Attributes: This category includes factors directly related to the consumers, such as gender (CF1), age (CF2), education (CF3), income (CF4), place of residence (CF5), and product attributes like cost of battery replacement (CF7), level of EV recognition (CF8), battery performance and safety (CF9), operating conditions (CF10), and the effects of subsidies (CF11). Understanding these attributes helps us gauge consumer preferences and behaviors regarding EV purchases.

Infrastructure and Environment: This group focuses on external factors affecting EV adoption, including subjective norms and difficulties in servicing (I-EF13), lack of charging infrastructure (I-EF14), charging services (I-EF15), charging infrastructure (I-EF16), environmental perceptions (I-EF17), and the reduced impact on environmental pollution (I-EF18). These attributes provide insight into the environmental and societal aspects that may influence consumer decisions.

Government Policy: Within this category, we consider the lack of information and government policy on electric vehicles (GF19), along with subsidy policy (GF20). These factors help assess how governmental support and information dissemination can affect consumer trust and willingness to adopt EVs.

EV Features: This category includes brand image (EVF21), advanced features (EVF22), and price (EVF23) of electric vehicles. These attributes are essential for understanding consumers' perceptions of the actual vehicles offered in the market.

The attributes encompass a comprehensive view of the factors influencing electric vehicle adoption, enabling us to conduct a robust analysis and derive meaningful insights from the collected data. By categorizing these attributes into customer characteristics, infrastructure and environmental factors, government policies, and vehicle features, we can better understand the multifaceted landscape surrounding EV adoption. Each category sheds light on critical dimensions: customer attributes reveal individual preferences and socio-economic backgrounds; infrastructure factors highlight the importance of charging facilities and environmental perceptions; government policies underscore the role of regulatory support and incentives; and EV features provide insights into consumer expectations and valuation of technology. In Figure 1, we visually represent the characteristics of these four groups, illustrating their interconnectedness and the various influences they exert on consumers' decisions to adopt electric vehicles. This visualization enhances our understanding of how these factors interplay, guiding stakeholders such as policymakers, manufacturers, and businesses in crafting strategies that effectively address barriers and promote the adoption of electric vehicles.

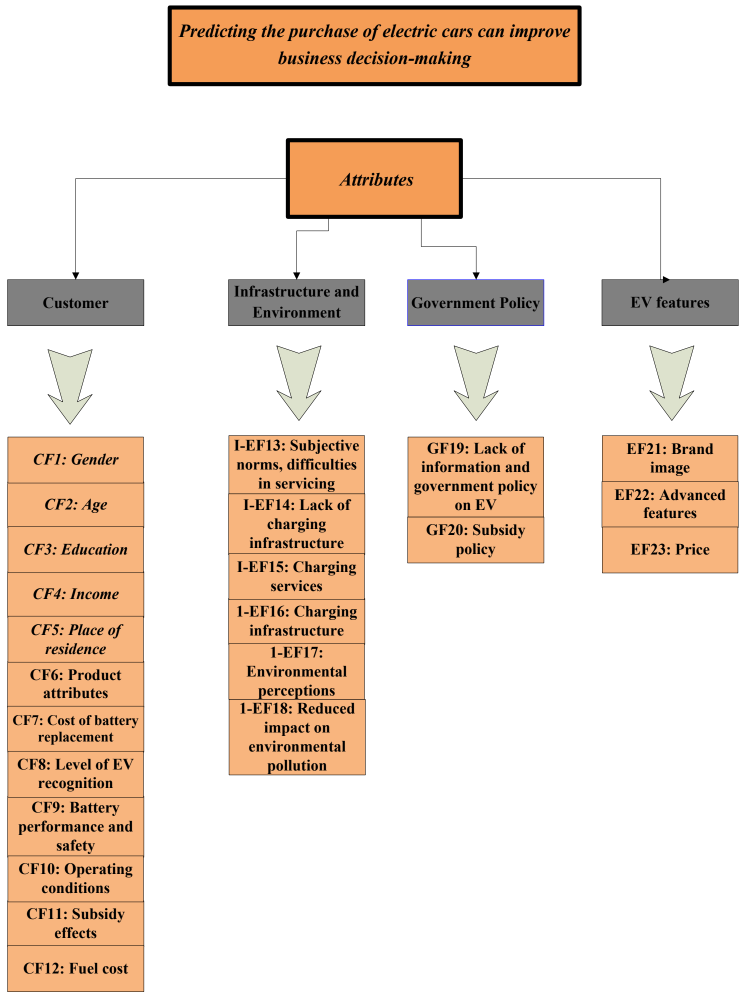
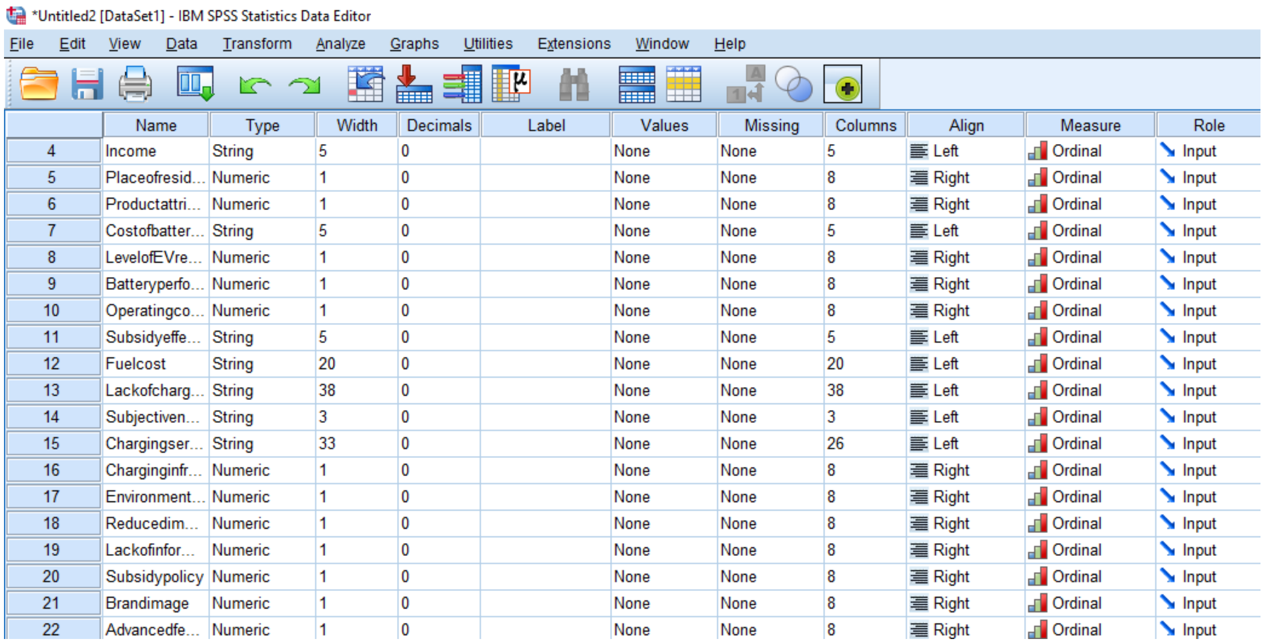


Figure 1: Influence features and attributes

3.2. Collecting the Relevant Features

Targeted responders gathered relevant data from Qassim State customers during this period. 23 conditional qualities in total were taken into account. The properties and potential representation values of respective attributes are described in Table 1. Figures 2 and 3 display the pertinent properties and data views, respectively.



*Untitled2 [DataSet1] - IBM SPSS Statistics Data Editor

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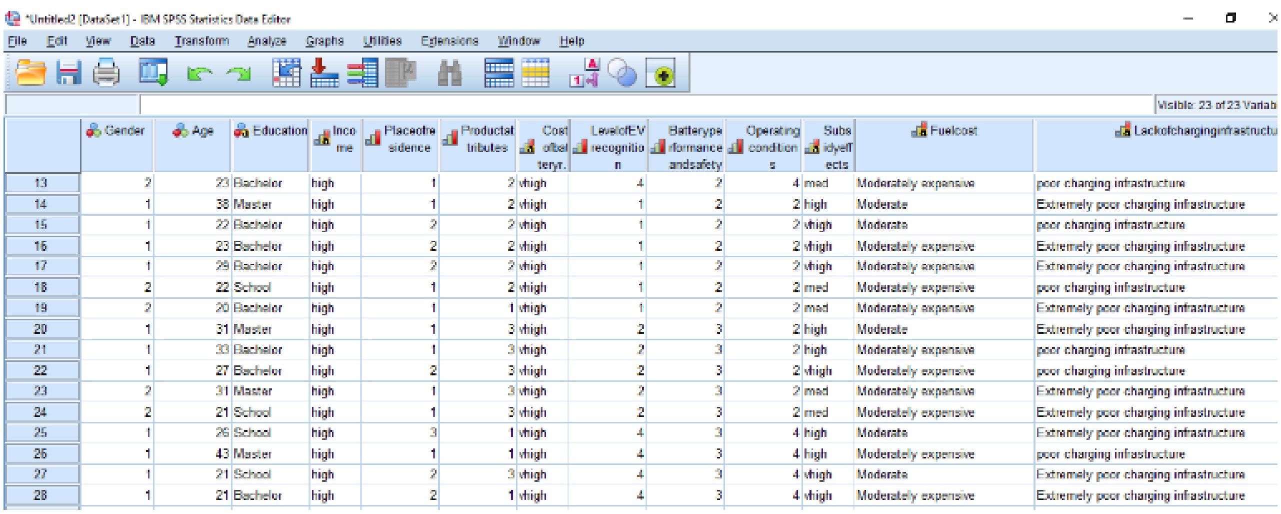
	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure	Role
4	Income	String	5	0		None	None	5	Left	Ordinal	Input
5	Placeofresid...	Numeric	1	0		None	None	8	Right	Ordinal	Input
6	Productattri...	Numeric	1	0		None	None	8	Right	Ordinal	Input
7	Costofbatter...	String	5	0		None	None	5	Left	Ordinal	Input
8	LevelofEVre...	Numeric	1	0		None	None	8	Right	Ordinal	Input
9	Batteryperfo...	Numeric	1	0		None	None	8	Right	Ordinal	Input
10	Operatingco...	Numeric	1	0		None	None	8	Right	Ordinal	Input
11	Subsidyeffe...	String	5	0		None	None	5	Left	Ordinal	Input
12	Fuelcost	String	20	0		None	None	20	Left	Ordinal	Input
13	Lackofcharg...	String	38	0		None	None	38	Left	Ordinal	Input
14	Subjectiven...	String	3	0		None	None	3	Left	Ordinal	Input
15	Chargingser...	String	33	0		None	None	26	Left	Ordinal	Input
16	Charginginfr...	Numeric	1	0		None	None	8	Right	Ordinal	Input
17	Environment...	Numeric	1	0		None	None	8	Right	Ordinal	Input
18	Reducedim...	Numeric	1	0		None	None	8	Right	Ordinal	Input
19	Lackofinfor...	Numeric	1	0		None	None	8	Right	Ordinal	Input
20	Subsidypolicy	Numeric	1	0		None	None	8	Right	Ordinal	Input
21	Brandimage	Numeric	1	0		None	None	8	Right	Ordinal	Input
22	Advancedfe...	Numeric	1	0		None	None	8	Right	Ordinal	Input

Figure 2: Relevant attributes



*Untitled2 [DataSet1] - IBM SPSS Statistics Data Editor

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	Gender	Age	Education	Income	Placeofresidence	Productattributes	Costofbatteryr.	LevelofEVrecognition	Batteryperformanceandsafety	Operatingconditions	Subsidyeffects	Fuelcost	Lackofcharginginfrastructu
13	2	23	Bachelor	high	1	2	vhigh	4	2	4	med	Moderately expensive	poor charging infrastructure
14	1	38	Master	high	1	2	vhigh	1	2	2	high	Moderate	Extremely poor charging infrastructure
15	1	22	Bachelor	high	2	2	vhigh	1	2	2	vhigh	Moderate	poor charging infrastructure
16	1	23	Bachelor	high	2	2	vhigh	1	2	2	vhigh	Moderately expensive	Extremely poor charging infrastructure
17	1	29	Bachelor	high	2	2	vhigh	1	2	2	vhigh	Moderately expensive	Extremely poor charging infrastructure
18	2	22	School	high	1	2	vhigh	1	2	2	med	Moderately expensive	poor charging infrastructure
19	2	20	Bachelor	high	1	1	vhigh	1	2	2	med	Moderately expensive	Extremely poor charging infrastructure
20	1	31	Master	high	1	3	vhigh	2	3	2	high	Moderate	Extremely poor charging infrastructure
21	1	33	Bachelor	high	1	3	vhigh	2	3	2	high	Moderately expensive	poor charging infrastructure
22	1	27	Bachelor	high	2	3	vhigh	2	3	2	vhigh	Moderately expensive	poor charging infrastructure
23	2	31	Master	high	1	3	vhigh	2	3	2	med	Moderately expensive	Extremely poor charging infrastructure
24	2	21	School	high	1	3	vhigh	2	3	2	med	Moderately expensive	Extremely poor charging infrastructure
25	1	26	School	high	3	1	vhigh	4	3	4	high	Moderate	Extremely poor charging infrastructure
26	1	43	Master	high	1	1	vhigh	4	3	4	high	Moderately expensive	poor charging infrastructure
27	1	21	School	high	2	3	vhigh	4	3	4	vhigh	Moderate	Extremely poor charging infrastructure
28	1	21	Bachelor	high	2	1	vhigh	4	3	4	vhigh	Moderately expensive	Extremely poor charging infrastructure

Figure 3: Data view

3.3. Preparing the Data and Selecting the Relevant Attributes

Tables containing the obtained data were organized according to the data-mining techniques employed in this study. To enhance the classification model's effectiveness, the most relevant features were meticulously selected, keeping in mind that superfluous attributes could undermine the model. After cleansing the data, each attribute was standardized to ensure consistency across the dataset. Preparing the inputs for data-mining research demands a significant investment of time and effort. The symbolic qualities are detailed in Table 1, and the most important features identified were: Gender, Age, Education, Income, Place of Residence, Product Attributes, Cost of Battery Replacement, Level of EV Recognition, Battery Performance and Safety, Operating Conditions, Subsidy Effects, Fuel Cost, Lack of Charging Infrastructure, Charging Services, Environmental Perceptions, Reduced Impact on Environmental Pollution, Lack of Information and Government Policy on EVs, Subsidy Policy, Brand Image, Advanced Features, and Price. For the attributes Income, Cost of Battery Replacement, and Price, the possible values were categorized as very high, high, medium, and low. Additionally, the irrelevant attributes "Subjective Norms" and "Difficulties in Servicing" was removed to further refine the analysis.

Table 1: The attribute description

No	Attribute	Description	Possible Values
Customer			
1	CF1	Gender	M =1, F =2
2	CF2	Age	Integer
3	CF3	Education	School, Bachelor, Master, Ph.D
4	CF4	Income	very high, high, med, low
5	CF5	Place of residence	City =1, Village =2, Other =3
6	CF6	Product attributes	1 to 5 (5 highest)
7	CF7	Cost of battery replacement	very high, high, med, low
8	CF8	Level of EV recognition	1 to 5 (5 highest)
9	CF9	Battery performance and safety	1 to 5 (5 highest)
10	CF10	Operating conditions	1 to 5 (5 highest)
11	CF11	Subsidy effects	very high, high, med, low
12	CF12	Fuel cost	Expensive, Moderately expensive Moderate, Affordable, Inexpensive
	Infrastructure and Environment		
13	I-EF13	Subjective norms, difficulties in servicing	1 to 5 (5 highest)
14	I-EF 14	Lack of charging infrastructure	Extremely poor charging infrastructure Poor charging infrastructure Average charging infrastructure Good charging infrastructure Excellent charging infrastructure
15	I-EF15	Charging services	Very Poor Charging Services Poor Charging Services Neutral/Average Charging Services Good Charging Services Excellent Charging Services
16	I-EF 16	Charging infrastructure	1 to 5 (5 highest)
17	I-EF17	Environmental perceptions	1 to 5 (5 highest)
18	I-EF18	Reduced the impact on environmental pollution	1 to 5 (5 highest)
Government Policy			
19	GF19	Lack of information and government policy on EV	1 to 5 (5 highest)
20	GF20	Subsidy policy	1 to 5 (5 highest)
EV Features			
21	EVF21	Brand image	1 to 5 (5 highest)
22	EVF22	Advanced features	1 to 5 (5 highest)
23	EVF23	Price	very high, high, med, low

There are situations where attribute datatypes need to be converted to numeric attributes, even though certain AI algorithms are skilled at handling small datasets [48]. Numerical attributes are necessary for a multilayer perceptron artificial neural network to execute calculations [72], [75]–[80]. The use of numerical qualities was considered in the creation of the support vector machine algorithm, which is currently in use. For the best classification results, characteristics should also be in a consistent numerical form, according to best practices for managing the multilayer perceptron neural network approach.

3.4. Building the Classification Model

The next objective was to create the model using the clustering algorithm. It is an effective and useful method. The information gain index is the main tool used to assess if an attribute is typically more valuable. The entropy measure is necessary for the information gain. The gain ratio, which ranks and locates each attribute, served as the foundation for the construction. Figures 4, 5, and 6 show the preprocess for a number of the attributes , while Figure 7 presents clusterer output. Figure 8 visualizes the clusters generated by the Weka clusterer. Figure 9 and Figure 10 presents the number of cluster and the number of iteration and clustered instances, respectively. Figure 11 and Figure 12 present clustered instances based on education and price attributes.

Initial starting points (random) for cluster 0, 1,2,3 and 4 respectively:

- 1,23,Bachelor,low,2,1,vhigh,3,5,1,vhigh,Moderate,'Extremely poor charging infrastructure','Good Charging Services',4,1,2,3,3,5,4,vhigh
- 1,32,Bachelor,med,1,1,vhigh,1,5,1,high,Affordable,'Extremely poor charging infrastructure','Very Poor Charging Services',2,1,1,3,3,5,2,vvhigh
- 1,48,Bachelor,med,2,2,high,1,2,2,vhigh,Affordable,'Average charging infrastructure','Neutral/Average Charging Services',2,1,3,1,1,2,2,high
- 2,38,Bachelor,high,1,1,high,1,5,2,med,'Moderately expensive','Average charging infrastructure','Poor Charging Services',2,2,1,1,1,5,2,med
- 1,22,Bachelor,high,2,2,vhigh,1,2,2,vhigh,Moderate,'poor charging infrastructure','Poor Charging Services',2,1,2,3,3,2,2,vhigh

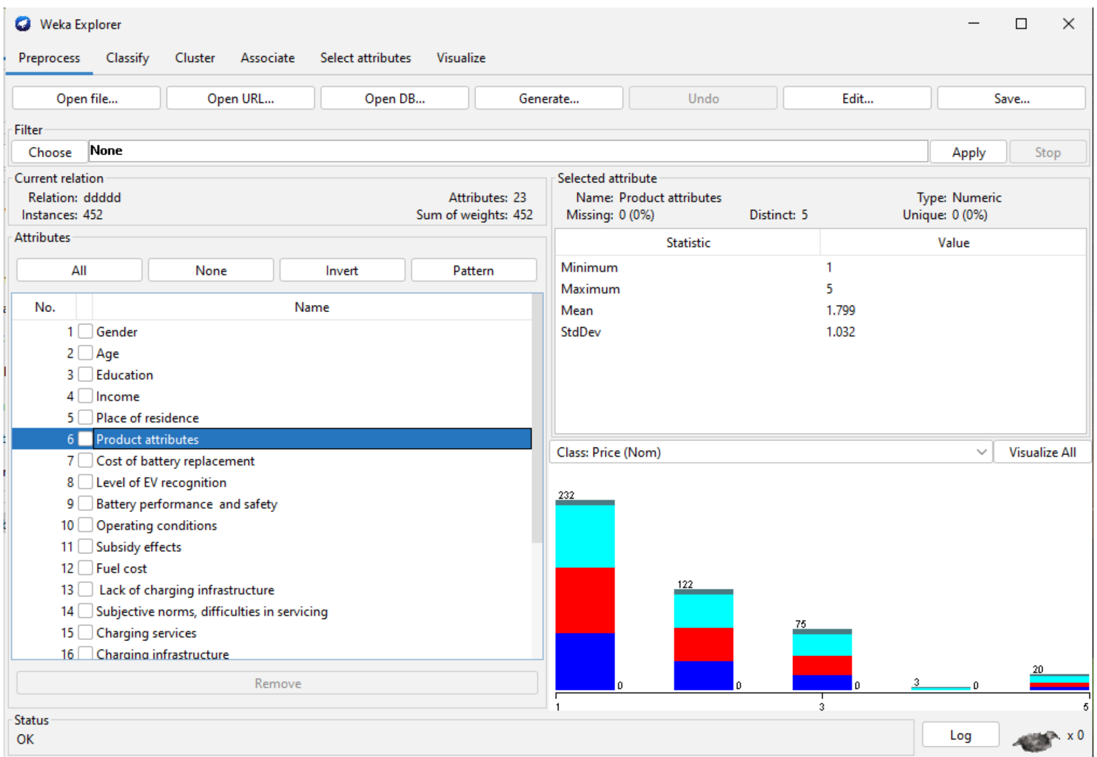

Figure 4: Preprocess Weka explorer for Product attribute

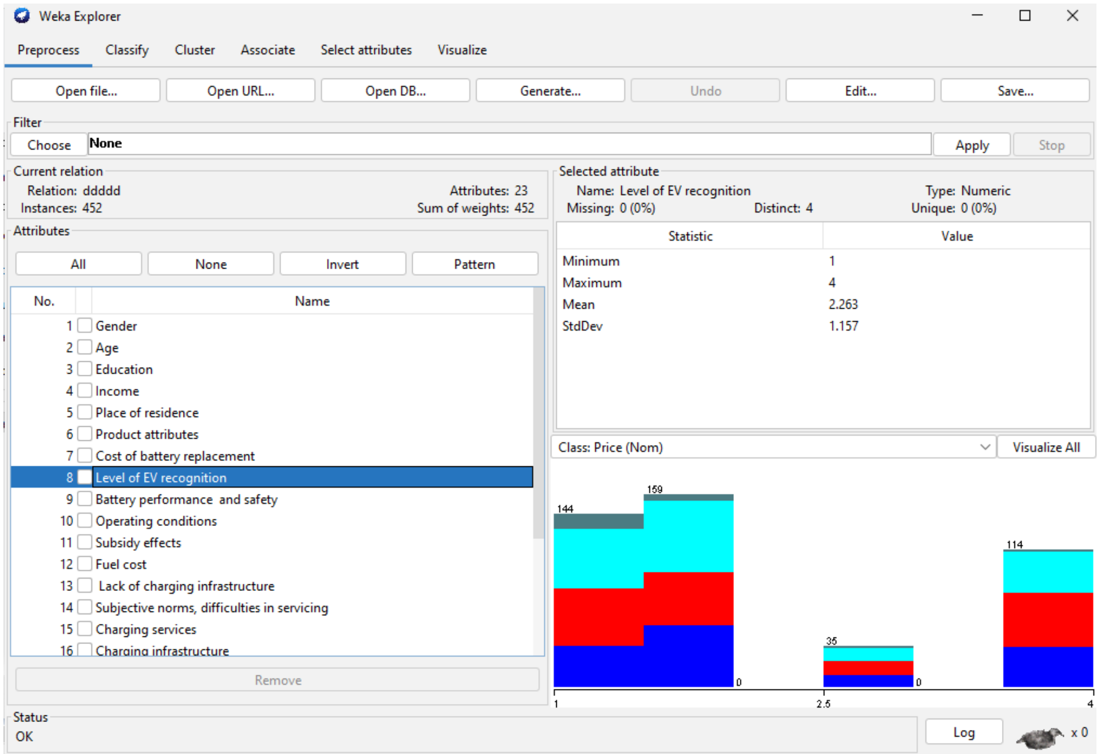

Figure 5: Preprocess Weka explorer for the Level of EV recognition attribute

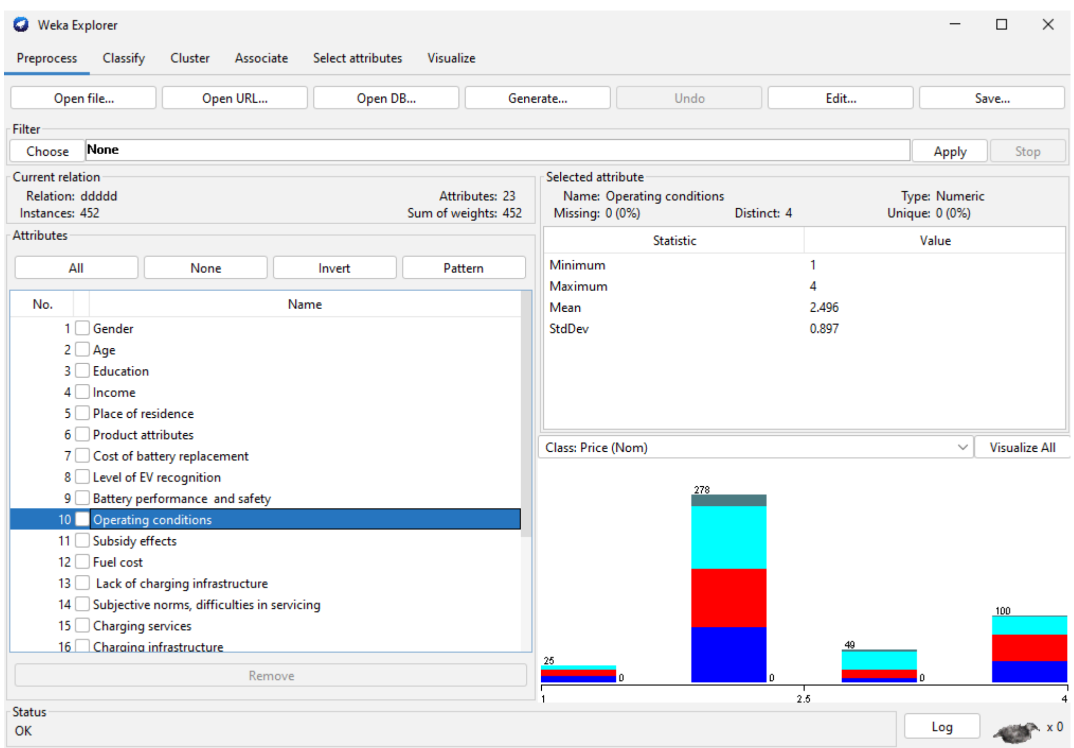

Figure 6: Preprocess Weka explorer for operating conditions attribute

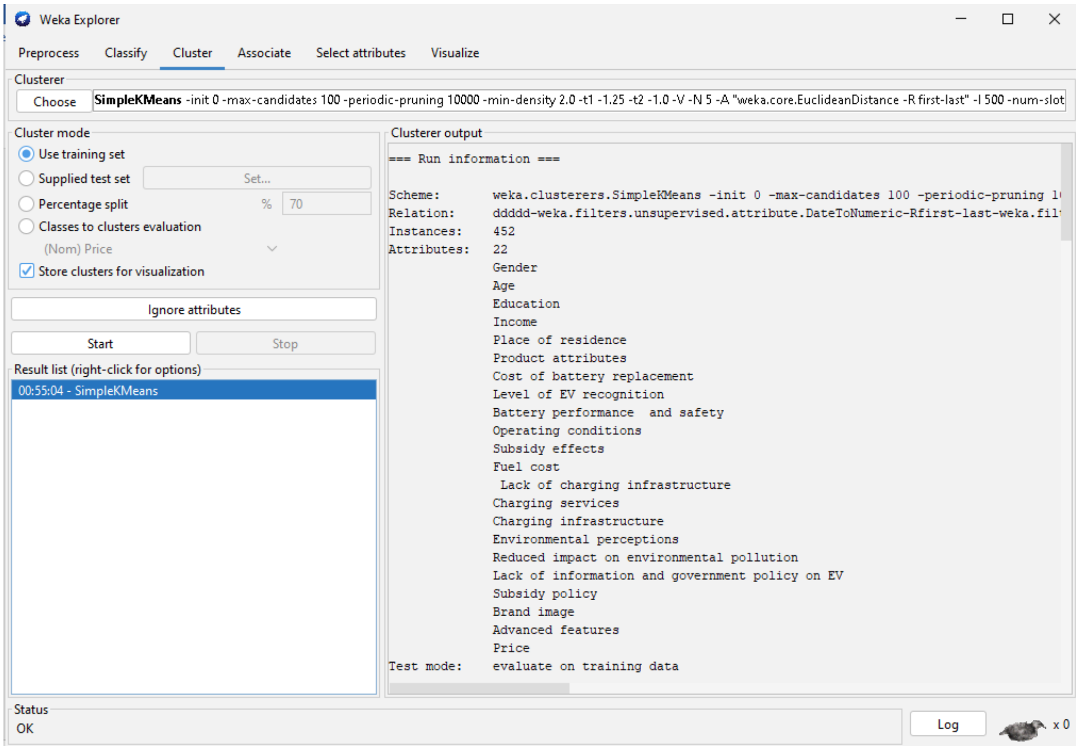

Figure 7: Clusterer output

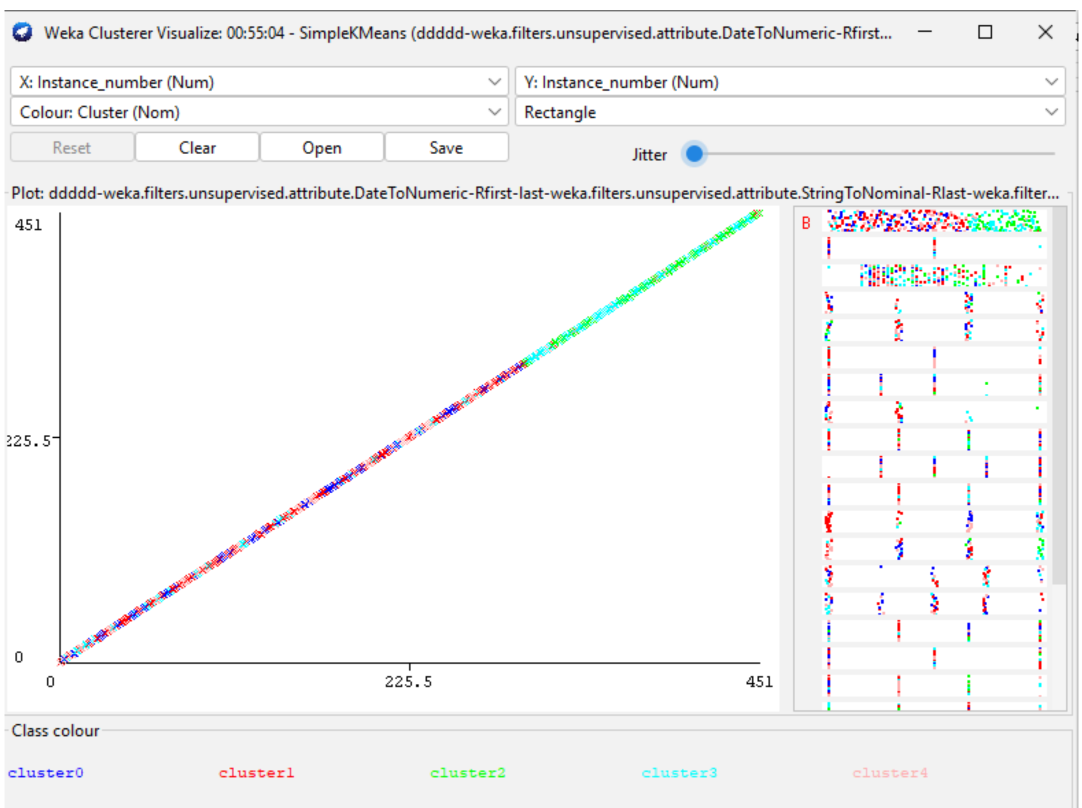

Figure 8: Visualize the clusters generated by the Weka clusterer

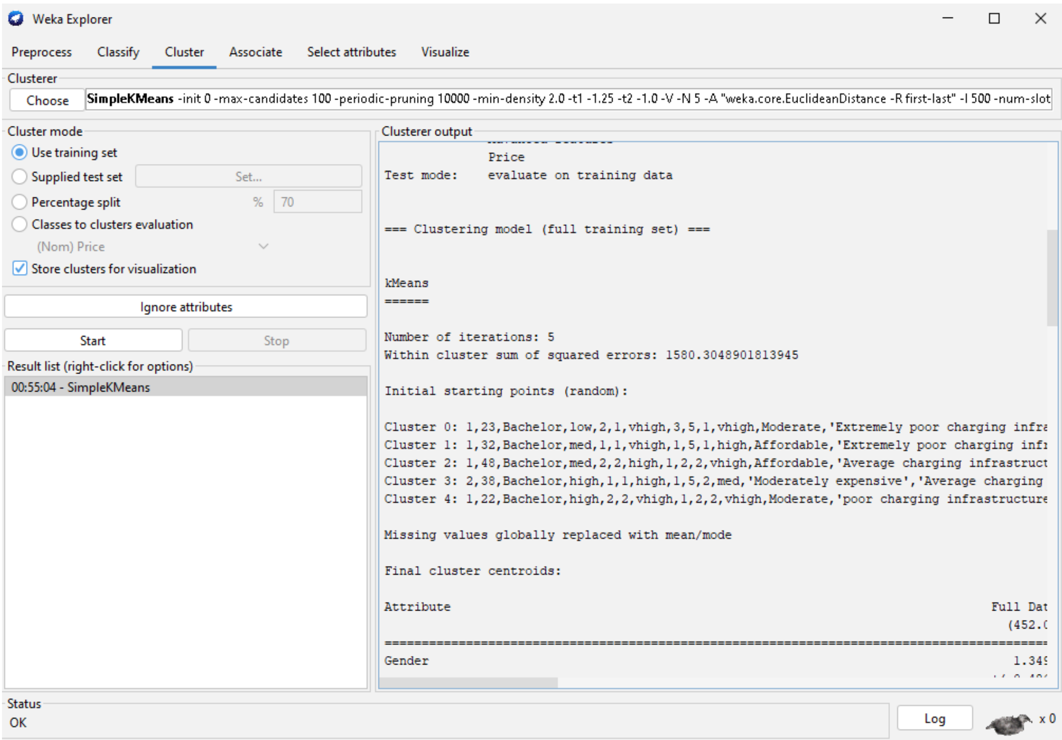

Figure 9: The number of clusters and the number of iterations

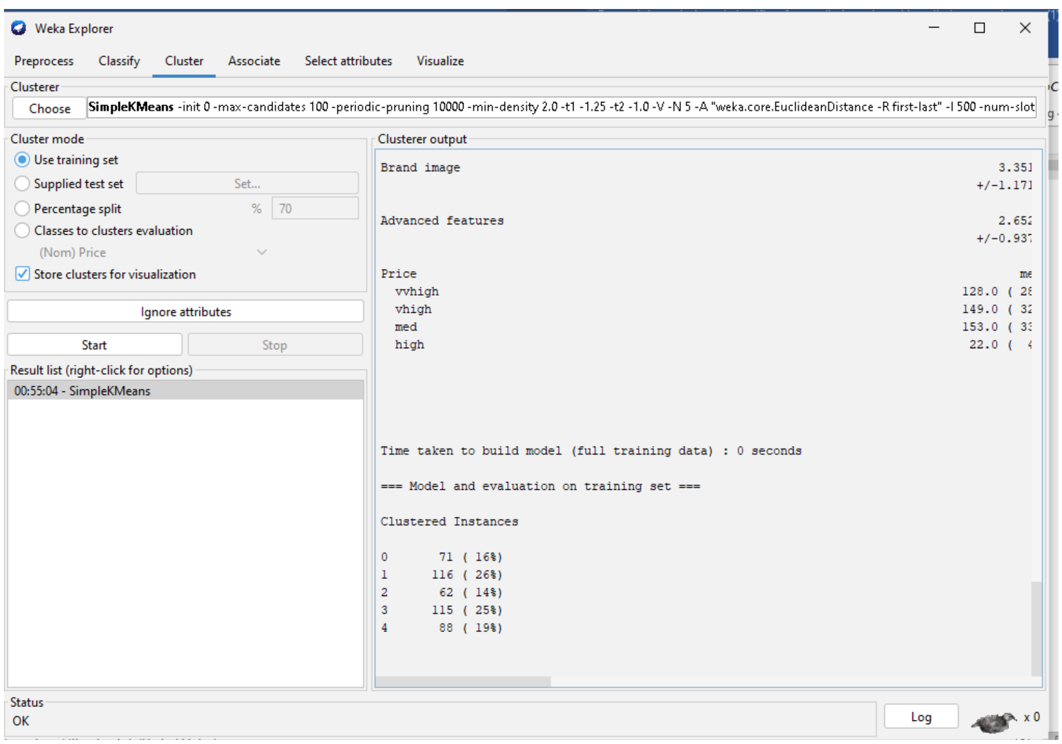

Figure 10: Clustered Instances

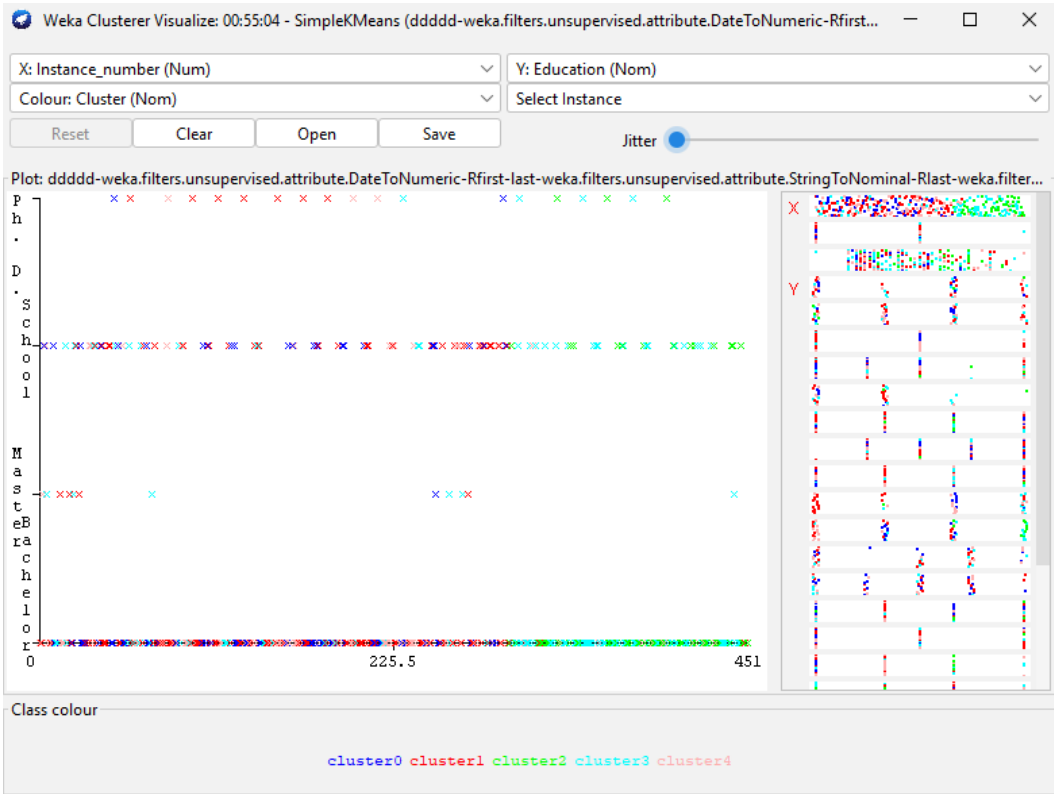

Figure 11: Clustered Instances based on education attribute

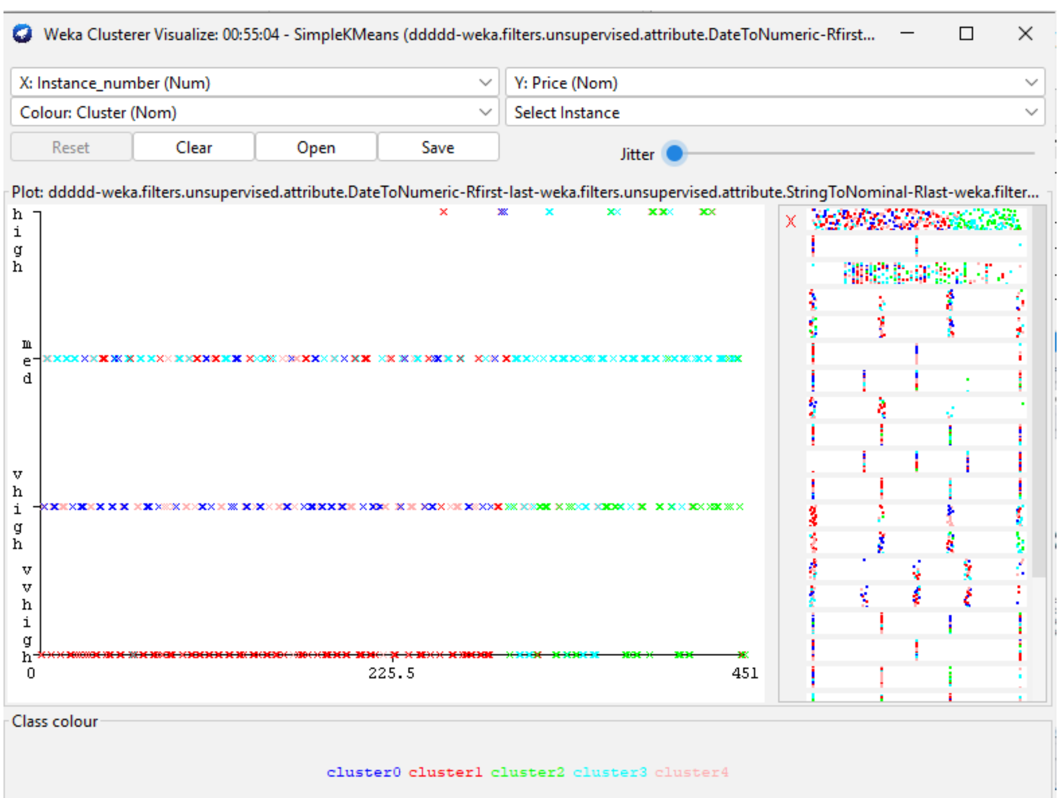

Figure 12: Clustered Instances based on price attribute

4. EXPERIMENT AND EVALUATION

Predicting sales is crucial for companies and retailers to foster customer loyalty, enhance brand recognition, and optimize product allocation. This study explored the identification of significant features within a relatively small dataset, employing the K-Means Clustering Algorithm to construct a robust prediction model. To enhance model accuracy, we evaluated key indicators using various machine learning techniques, which allowed for a comprehensive analysis of consumer data.

The primary findings of this study underscore the effectiveness of data-mining algorithms and machine learning in analyzing consumer behavior, demonstrating their capacity to train on small datasets while maintaining commendable accuracy rates. This reliability not only affirms the potential of these methods for delivering valuable insights but also highlights their applicability in real-world scenarios.

By analyzing customer purchasing intentions and behaviors, we identified distinct consumer segments poised to emerge. These segments provide businesses with the opportunity to implement targeted marketing strategies that cater to the unique preferences and needs of different groups. This tailored approach is anticipated to deepen customer engagement and optimize sales outcomes, ultimately driving growth in the electric vehicle market. By leveraging these insights, companies can make data-driven decisions that enhance their marketing effectiveness and improve overall operational efficiency.

4.1 Cluster 0 (16% of Respondents)

Demographic Profile: Typically younger individuals (median age 32), with higher incomes, residing in urban areas.

Key Attributes: Exhibits strong environmental awareness (attributes I-EF17 and I-EF18), a willingness to pay a premium for advanced EV features (attribute EVF22), and a significant influence from government incentives (attribute GF20).

Interpretation: This cluster represents tech-savvy, environmentally conscious consumers eager to adopt electric vehicles. However, their adoption is contingent upon continued government support and accessibility to advanced EV models.

Business Implications: Companies should consider developing marketing campaigns that highlight the ecological benefits of EVs, while also promoting advanced features that appeal to this segment. Creating partnerships with government agencies to enhance subsidy awareness could effectively engage this demographic.

4.2 Cluster 1 (26% of Respondents)

Demographic Profile: Generally middle-aged (median age 45), with middle-range income, living in suburban settings.

Key Attributes: Highly sensitive to upfront costs (CF4, CF7), concerned about the availability of charging infrastructure (I-EF14, I-EF16), and in need of more detailed information about EVs and their benefits (GF19).

Interpretation: Cost-conscious customers who hesitate to adopt EVs due to perceived high upfront and operating costs. Their hesitance is further compounded by concerns about charging accessibility.

Business Implications: Targeted education campaigns could assist in alleviating their concerns, focusing on lower total ownership costs and the long-term savings associated with EVs. Providing information sessions and community test-drive events could increase confidence and interest in EV adoption.

4.3 Cluster 2 (14% of Respondents)

Demographic Profile: Older consumers (median age 49) with lower incomes, primarily residing in rural areas.

Key Attributes: Exhibits low recognition of EVs (CF8), skepticism regarding EV performance and safety (CF9, CF10), and is influenced by potential savings on fuel costs (CF12).

Interpretation: This cluster comprises risk-averse consumers who require more substantial evidence of EV reliability and tangible cost savings before they consider adoption.
Business Implications: Outreach efforts should focus on building consumer confidence through informative campaigns, testimonials, and hands-on test-drive events. Simulations or demonstrations that showcase the operational cost savings and performance of EVs could address their skepticism effectively.

4.4 Cluster 3 (25% of Respondents)

Demographic Profile: Predominantly higher-educated individuals (bachelor's degree or above) living in urban areas.
Key Attributes: This group is strongly influenced by brand image and advanced features (EVF21, EVF22) and shows less sensitivity to upfront costs (CF4).
Business Implications: Marketing strategies should emphasize cutting-edge technology and the premium nature of the EVs. Collaborations with well-known brands or influencers might enhance credibility and appeal to this segment as they seek products that align with their lifestyle and values.

4.5 Cluster 4 (19% of Respondents)

Demographic Profile: Higher-educated individuals (bachelor's degree or above) primarily in urban settings.
Key Attributes: This group shows definite plans to purchase an EV and is highly influenced by the environmental benefits of using EVs (I-EF16, I-EF18).
Business Implications: Since this cluster has a clear intention to purchase, marketing efforts should reinforce their decision by highlighting sustainable practices and the overall impact of EV usage on the environment. Tailored promotions, early access to new models, or exclusive events can further enhance engagement and conversion in this segment.

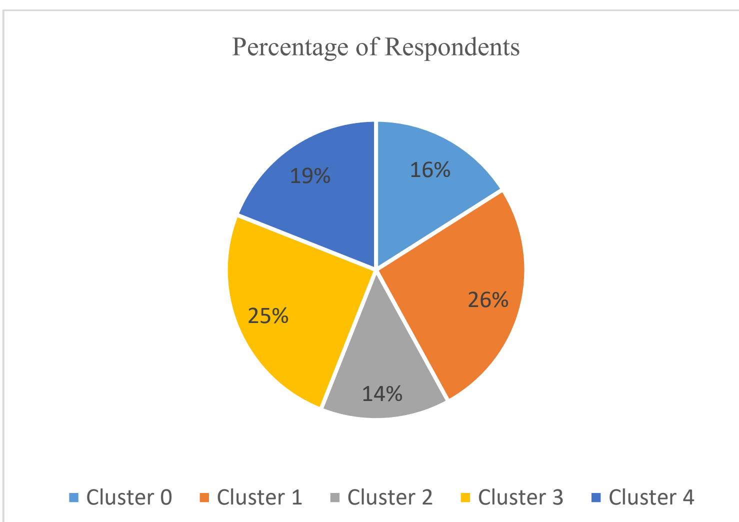

Figure 13: Percent of respondents

Table 2 presents the demographic and behavioral characteristics of different customer clusters based on survey responses. Each cluster is defined by its percentage of respondents, median age, income level, and location. Additionally, key attributes highlight the distinct motivations and concerns of each group regarding electric vehicle (EV) adoption. This information helps in understanding the diverse profiles of potential EV customers and their preferences.

Table 2: Cluster characteristics

Cluster	Percentage of Respondents	Median Age	Income Level	Location	Key Attributes
Cluster 0	16%	32	Higher	Urban	Strong Environmental Awareness, Willing to Pay Premium
Cluster 1	26%	45	Middle	Suburban	Cost-Sensitive, Concerned About Charging Infrastructure
Cluster 2	14%	49	Lower	Rural	Low EV Recognition, Skeptical of EV Performance
Cluster 3	25%	N/A	N/A	Urban	Higher Education (Bachelor's or above), Influenced by Brand Image
Cluster 4	19%	N/A	N/A	Urban	Higher Education (Bachelor's or above), Plans to Purchase EV, Environmental Benefits

Crucially, we also showed how well they worked when applied to the analysis and training of a tiny dataset, yielding a respectable Clustering with precise and consistent test rates.

4.6 Cluster Validation

The accuracy or error rate of the classification was typically used to examine how well the Clustering method performed on the test dataset. After the cluster's accuracy was processed from the testing dataset, it was possible to assess how several clusters in the same domain were displayed overall. Nonetheless, it was also necessary to determine the class labels for the test records, and the evaluation process was supposed to evaluate the correctness and sequence of the clustering. This study aimed to answer the following questions: What is the best machine learning Clustering model for predicting electric vehicles with a fair and meaningful accuracy rate using a limited dataset size? What are the most important attributes that could assist in the design of a Clustering model for predicting buyers of electric vehicles? The Weka software was used to obtain the reliability of the study model.

To ensure the robustness and effectiveness of the clustering model developed for predicting electric vehicle (EV) buyers, the study employed three distinct machine learning algorithms: BayesNet-D, NativeBayes, and J48. The dataset was divided into training and testing subsets, with the training set used to form the clusters and the testing set to evaluate their accuracy.

BayesNet-D, a Bayesian network classifier, was utilized for its ability to model the conditional dependencies between variables, providing probabilistic interpretations of the data. NativeBayes, a simpler version of Bayesian classification, assumes independence among predictors, making it effective for high-dimensional datasets and serving as a baseline for comparison. J48, an implementation of the C4.5 decision tree algorithm, was chosen for its transparency, allowing for easy interpretation and identification of decision rules based on the clusters.

The accuracy of each algorithm was assessed by calculating the percentage of correctly classified instances in the testing dataset, comparing the predicted class labels with the actual labels. The evaluation results revealed that all three algorithms performed well, with J48 achieving the highest accuracy rate of 91.81%. This demonstrated that the clustering model effectively captured the underlying patterns in the dataset, allowing for reliable predictions of customer segments. Overall, the validation process confirmed the model's robustness and its potential to inform strategic business decisions in the electric vehicle market. Three different methods were tested: BayesNet-D, NativeBayes, and J48 as shown in figures 15, 16 and 17. The evaluation results of the proposed model are shown in Table 3 and Figure 14.

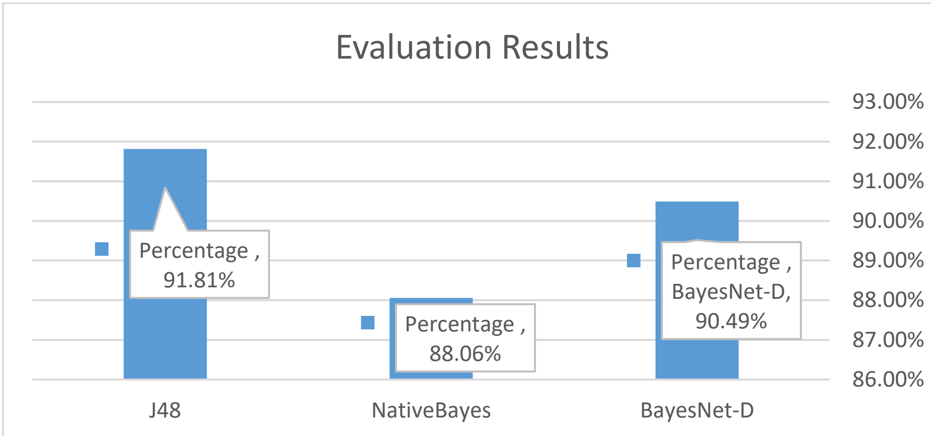

Figure 14: Evaluation results

Table 3: Accuracy of the 3 different algorithms

Algorithm	**Percentage**
BayesNet-D	90.4867%
NativeBayes	88.0581%
J48	91.8142%

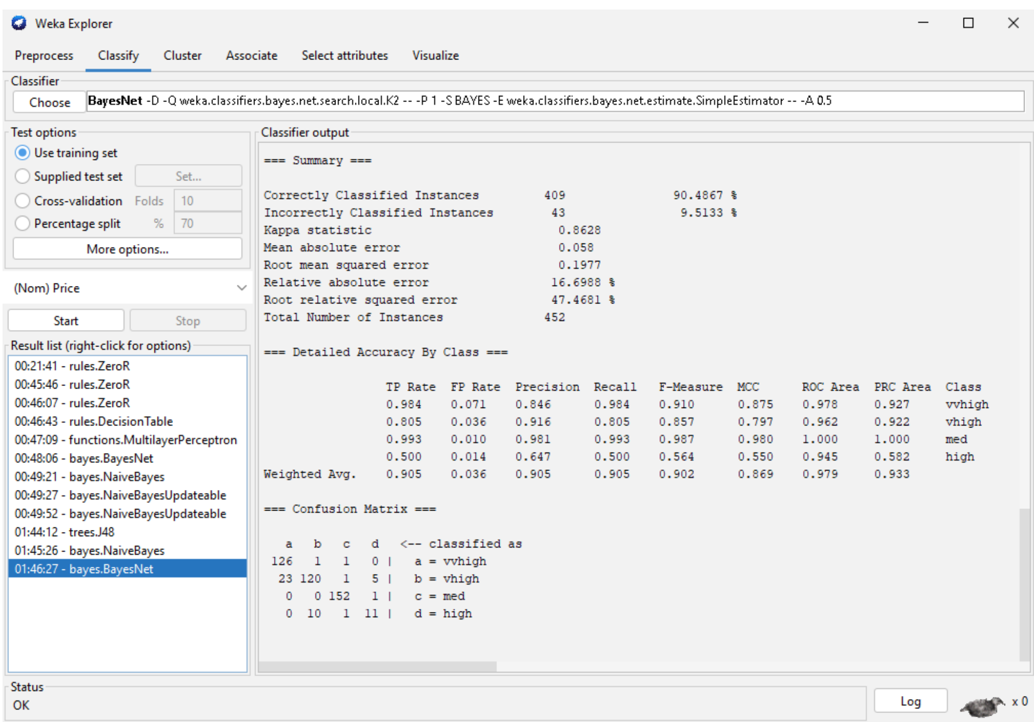

Figure 15: BayesNet-D cross-validation folds

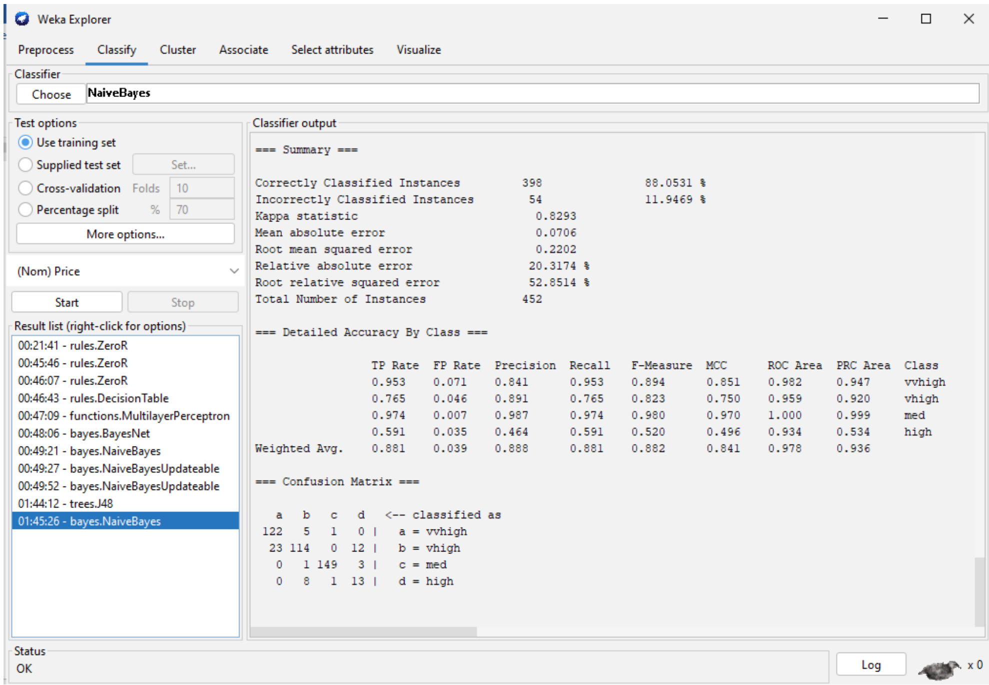

Figure 16: NativeBayes cross-validation folds

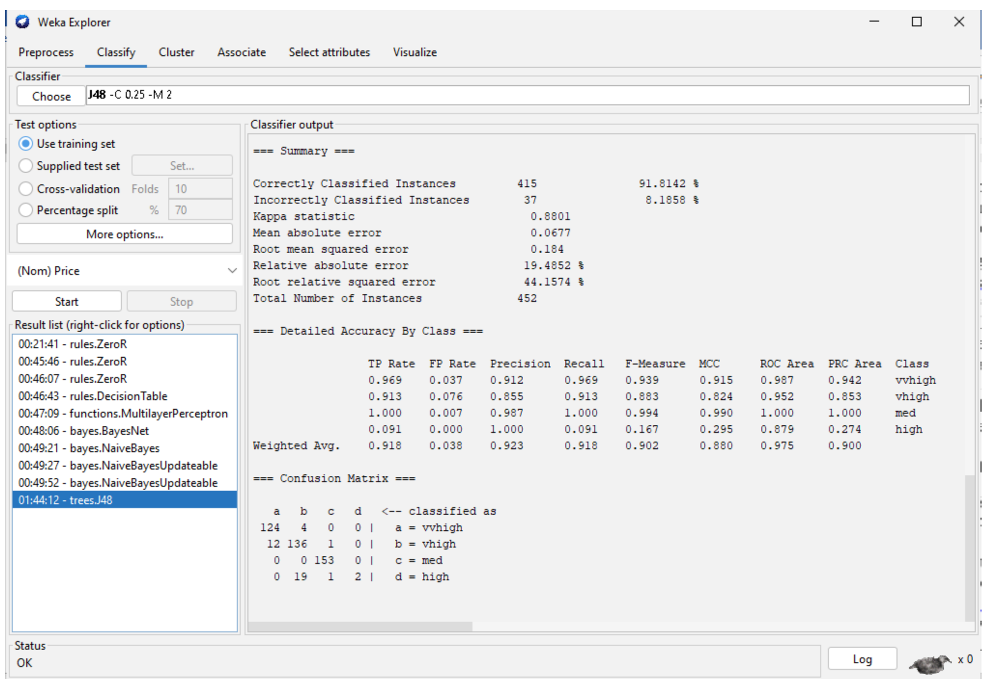

Figure 17: J48 cross-validation folds

To validate the clusters, we assessed the following aspects:

1. Consistency Across Algorithms: The relatively high accuracy rates across all algorithms indicated that the clusters were stable and could be reliably reproduced, reinforcing the robustness of the clustering results.
2. Interpretability: The decision tree generated by the J48 algorithm provided clear insights into the characteristics of each cluster. This interpretability is crucial for informing marketing strategies and understanding customer behavior.

3. Cross-Validation: Each algorithm was subjected to cross-validation techniques to further ensure the reliability of the results. This involved partitioning the dataset into multiple subsets, training the model on some subsets while testing it on others, which helped mitigate overfitting.

The validation process confirmed that the clustering model, supported by various machine learning algorithms, effectively identified distinct customer segments for electric vehicle (EV) purchases. This robust approach enhances predictive accuracy while providing valuable insights that help businesses optimize their strategies to meet the diverse needs of different consumer groups. The findings emphasize the necessity of employing reliable machine learning techniques to validate clustering outcomes, ensuring consistency and interpretability. By applying comprehensive validation methods, businesses are empowered to make informed decisions in the EV market. Therefore, the observations gained from these clustering efforts not only support targeted marketing initiatives but also deepen the understanding of consumer behavior, fostering strategic innovation in the rapidly evolving landscape of electric vehicles.

5. DISCUSSION

The findings of this study underscore the critical role of advanced data mining techniques, such as K-Means Clustering, in predicting consumer behavior in the electric vehicle (EV) market. By leveraging these methods, we successfully identified distinct consumer segments that exhibit varying preferences and purchasing behaviors. This nuanced understanding allows businesses to tailor their marketing strategies effectively, aligning them with the specific characteristics and needs of each segment. For instance, the differentiation between tech-savvy consumers willing to pay a premium for advanced features and cost-sensitive individuals hesitant due to upfront costs highlights the necessity for targeted outreach and educational initiatives.

Moreover, the impressive accuracy rates achieved across multiple machine learning algorithms confirm the robustness of the clustering model. With J48 achieving the highest accuracy of 91.81%, the results validate the effectiveness of employing various analytical methods to derive actionable insights from small datasets. The interpretability of the decision tree generated by J48 provides businesses with clear guidance on the attributes that influence consumer decisions, thus facilitating more informed marketing and product development strategies.

Therefore, the ability to cluster consumers based on their purchasing intentions not only enhances marketing effectiveness but also fosters deeper customer engagement. By understanding factors such as environmental awareness and brand loyalty, companies can refine their product offerings and communication strategies, thereby driving growth in the EV sector. This study emphasizes the importance of adopting data-driven approaches to understand consumer behavior fully, enabling businesses to navigate the challenges of a rapidly evolving market landscape while ensuring sustainable growth and customer satisfaction.

5.1 Implications for Practice

Previous studies have really underscored how crucial it is to analyze consumer behavior in the electric vehicle (EV) market. However, many of them leaned on traditional forecasting methods that might not capture the full spectrum of what consumers actually want. For example, research that relied on basic statistical analyses often missed the intricate details of consumer segmentation, which can result in marketing efforts that aren't as targeted as they could be.

However, this study takes a different approach by using advanced data mining techniques, which allows for a much more accurate segmentation of customers. By pinpointing specific consumer groups based on their preferences and anticipated buying behavior, companies can roll out marketing campaigns that truly resonate with each segment. This strategy could boost customer engagement and lead to higher sales conversions.

Moreover, the findings indicate that grasping the factors that sway consumer decisions, like environmental concerns, cost factors, and brand loyalty, can empower companies to craft more effective product offerings and communication strategies. This is a shift from earlier research that mainly focused on broad market trends without really digging into the specific motivations that drive consumer choices.

This study really highlights the need for a shift towards data-driven decision-making in the electric vehicle industry. By embracing these advanced analytical methods, businesses can boost their strategic planning and operational efficiency, which in turn can help drive the market adoption of electric vehicles.

The results from this research offer valuable perspectives that could greatly influence practices in the electric vehicle (EV) sector. By using predictive models like K-means clustering and logistic regression, companies can gain a better grasp of consumer preferences and buying habits. This deeper understanding allows them to categorize their customer base into distinct groups based on shared traits, paving the way for more personalized marketing strategies.

Armed with this knowledge, businesses can craft targeted marketing campaigns that truly resonate with different consumer segments. For example, messages aimed at environmentally conscious buyers can focus on the ecological advantages of EVs, while those directed at cost-sensitive consumers can emphasize long-term savings. Plus, knowing what consumers want can steer product development, helping manufacturers fine-tune features that cater to specific needs, like battery life and charging convenience.

Embracing predictive analytics nurtures a culture of data-driven decision-making within organizations, enabling smarter choices about pricing, promotions, and distribution channels. This proactive stance boosts competitiveness in a fast-changing market. Additionally, the findings from this study can guide strategic partnerships, such as collaborations with charging infrastructure providers, and make things more convenient for customers.

By understanding the factors that influence consumer decisions, companies can build long-term relationships with their customers, encouraging loyalty and repeat purchases. Overall, the application of predictive models equips businesses with the tools needed to improve their marketing strategies, product offerings, and operational efficiency, which is essential for increasing the adoption of electric vehicles in a competitive market.

5.2 Future Work

Future research should broaden the geographic scope beyond Qassim State to include diverse markets, enhancing the generalizability of findings. Longitudinal studies would be beneficial to track how consumer attitudes toward electric vehicles (EVs) evolve over time, particularly in response to changing market dynamics and technological advancements. Integrating qualitative methods, such as interviews or focus groups, could provide deeper insights into the motivations and experiences of consumers, complementing quantitative findings.

Moreover, exploring external factors like economic fluctuations and regulatory changes would offer a more holistic understanding of the market. Future work could also develop and test targeted marketing strategies for specific consumer segments identified in this study. Investigating the impact of improved charging infrastructure on adoption rates will provide actionable insights for both businesses and policymakers.

Lastly, researchers should consider applying advanced machine learning techniques to improve predictive model accuracy and systematically integrating consumer feedback into product development and marketing strategies. This multifaceted approach will contribute to more effective strategies for promoting sustainable transportation and enhance the overall understanding of EV adoption.

6. LIMITATIONS AND CONSTRAINTS

In addition to the challenges of fitting machine learning models to smaller datasets, this research has several other drawbacks. Relying on data from just one area might not accurately reflect how consumers in different markets behave when buying cars, which could limit the applicability of the results. Furthermore, the models may not account for external factors like economic changes, new government regulations, and technological advancements, all of which significantly influence people's decisions about purchasing electric cars.

Another issue is the potential for skewed survey answers. Respondents might not provide truthful or precise feedback regarding their buying intentions, which can hurt the quality of the data used to train the models. Additionally, the study predominantly focuses on quantitative data analysis, which might overlook valuable qualitative insights that could deepen our understanding of what drives consumer preferences.

Moreover, the timeframe of the study may not capture long-term trends in electric vehicle adoption, as consumer desires and market dynamics can change quickly. Future research should aim to utilize larger, more diverse datasets, consider long-term studies, and integrate qualitative methods to provide a more comprehensive view of the factors that influence electric car purchases.

7. CONTRIBUTION OF THE STUDY

This study makes several significant contributions to the domains of market analysis for electric vehicles and machine learning:

Enhanced Understanding of Customer Segmentation*:* This study utilizes the K-Means Clustering Algorithm to identify distinct customer segments based on their purchasing intents and habits. By categorizing consumers into specific groups, businesses can tailor their marketing campaigns and product offerings to meet the unique preferences of different demographics. This granular insight is invaluable for optimizing marketing strategies and improving customer engagement.

Application of Advanced Machine Learning Techniques*:* The research illustrates the predictive capabilities of data mining and machine learning algorithms for understanding electric vehicle purchases. By employing multiple algorithms, including Naive Bayes, J48, and BayesNet-D, the study provides a comprehensive overview of how these models perform with small datasets. This comparison highlights varying degrees of accuracy and informs businesses of the most effective algorithms to deploy in their predictive models.

Practical Implications for Businesses: The findings translate into actionable strategies for electric vehicle manufacturers. To address consumer concerns and enhance adoption rates, the study recommends clear tactics such as targeted educational initiatives and financial incentives. These recommendations aim to foster a more informed consumer base, ultimately leading to higher sales and a stronger market presence for electric vehicles.

Contributions to Predictive Sales Modeling: By utilizing prescriptive and predictive analysis techniques, this study offers a robust framework for forecasting electric vehicle sales. The integration of logistic regression analysis and decision tree models not only improves classification accuracy but also provides businesses with insights into consumer behavior patterns. Such models enable companies to make well-informed, strategic decisions regarding their sales and marketing efforts.

Real-World Testing and Validation: The study underscores the importance of tested methodologies by validating the effectiveness of the models using real electric vehicle datasets collected from survey respondents in Qassim, Saudi Arabia. The high accuracy rates achieved (90.49% for BayesNet-D, 88.06% for Naive Bayes, and 91.81% for J48) affirm the reliability and robustness of the developed models, offering businesses confidence in utilizing these predictive analytics tools for strategic planning and consumer engagement.

8. CONCLUSION

The maker needs to be aware of the elements that affect consumers' purchasing choices. The product has undergone a thorough assessment of the research's acceptance in recent years. Sadly, manufacturers frequently fail to recognize the true demands of their customers, and the main challenge in product development is determining how to more accurately assess the product's acceptability. Predicting the arrival of electric vehicles is therefore very helpful to businesses in terms of enhancing their planning, allocating, and overseeing production resources. It goes without saying that managers could detect and address their production challenges with the use of product sales prediction.

The purpose of this study was to predict customer purchasing behavior for electric vehicles using a data-mining technology in order to enhance business performance. Company managers should create plans to boost company sales and decision-making by utilizing the clustering model to improve electric vehicle sales outcomes. The data-mining algorithm's extraction of information in this study improved our comprehension of the customer base's composition when it came to purchasing electric vehicles and the company's assessment of the appropriate course of action for offering guidance, training, and expertise.

However, the managers and management systems of the institutions are able to update and enhance their judgments, policies, and procedures thanks to the clusters created by the suggested model and patterns, which increases the control system's efficacy. Furthermore, by applying this knowledge, the management of the company's system can enhance its plans, modernize its processes, and enhance the structure of the board.

Through the analysis of customer data, this study identified a collection of characteristics and traits that can help enhance the quality of companies by identifying the factors that have the greatest impact on customer performance. In this study, customer data was evaluated for the characteristics most impacted by the circumstances, and a set of characteristics and features that can be used to enhance the quality of electric vehicle purchase behavior was discovered. Technological developments are having a fast effect on all aspects of life, including business. Artificial intelligence has shown encouraging results in decision-making through data analysis. Additionally, companies can use electric vehicle projection to better plan their marketing and production strategy. They can use it to assess the likelihood that they will be successful or unsuccessful with a specific product.

Finally, early adopters are prepared to shell out more money for luxurious, feature-rich EVs. To appeal to this market, marketing initiatives should highlight the brand's image and technological prowess.

Electric vehicle (EV) manufacturers, politicians, and infrastructure providers can create more focused plans to address the specific needs and obstacles experienced by each group by comprehending the diverse client segments identified by this clustering research. To speed up EV adoption across the industry, this may entail customized product offerings, incentive schemes, awareness campaigns, and infrastructural expenditures.

This study also highlights how crucial it is to do continuous market research and gather customer input in order to inform future product development. Manufacturers may better match their products to consumer needs by being in constant communication with consumers and learning about their changing preferences. In the end, this proactive strategy contributes to the long-term success of electric vehicle firms by increasing customer happiness and brand loyalty. Maintaining awareness of consumer insights will be essential as the industry changes in order to modify marketing tactics and guarantee that items remain relevant in a cutthroat market.

Acknowledgment

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تقييم أثر دمج المركبات الكهربائية ومصادر الطاقة المتجددة على أداء نظام التوزيع

الملخص: يشكّل التزايد السريع في تبنّي المركبات الكهربائية (EV) ضغوطًا جديدة على مغذّيات التوزيع، بينما لا تزال الأدلة الكمية حول الكيفية التي يمكن بها للتوليد المتجدد المُنسَّق وتشغيل المركبة-إلى-الشبكة (V2G) التخفيف من هذه التأثيرات محدودة، خاصةً في الشبكات الشعاعية ذات الفروع الطويلة والطلب ذي الذروة المسائية. في هذه الدراسة، أُجريت محاكاة تدفّق قدرة زمنية عالية الدقة (كل 15 دقيقة) على نظام شعاعي معياري مكوَّن من 69 حافلة لتقييم الشحن غير المُدار للمركبات الكهربائية، والشحن المُدار مع محفزاتV2G ، وسيناريوهات مشتركة مع محطات كهروضوئية (PV) وتوليد توربينات رياح (WTG) مدمجة على المغذّي. استُخدم نموذج وصول عشوائي للمركبات، وتتبع لحالة شحن البطارية(SOC) ، ونموذج مبسّط للشاحن (2.3 كيلوواط لكل طور، ومعامل قدرة ≈0.95)؛ ويتم تفعيل تفريغ V2G عندما يهبط الجهد المحلي إلى أقل من 0.95 وحدة نسبية (p.u.) ويتوقف التفريغ حين تنخفض حالة الشحن إلى حد أدنى محدّد. اتّبعت مخرجات PV/WTG ملفات يومية واقعية مع معاملات قدرة متأخرة تمثل حدود العواكس. أتاح أسلوب المسح الأمامي/الخلفي في تدفّق القدرة الحصول على جهود العقد، وتيارات الفروع، وإجمالي فواقد المغذّي على أفق 25 ساعة، ثم جرى تلخيص النتائج عبر خرائط حرارية ومخططات صندوقية ومنحنيات توازن القدرة اليومية. وتبيّن أن تنسيق V2G مع موارد PV/WTG على مستوى المغذّي يقلّل ماديًا تيار المصدر الأقصى، ويخفف التحميل الزائد على العمود الرئيسي وأجزاء منتصف المغذّي، ويخفض إجمالي فواقد القدرة الفعالة، مع رفع الجهود الدنيا نحو الحدود المقبولة خلال النوافذ المسائية الحرجة. وكانت الفوائد أقوى عندما تزامن إنتاج المتجدّدات زمنيًا مع طلب الشحن، وحين كانت الموارد الموزعة قريبة كهربائيًا من الفروع المُجهَدة؛ ومع ذلك، استمرت قيود متبقية خلال ذرى آخر الليل مع ضعف دعم المتجدّدات. وبصورة عامة، تشير النتائج إلى أن عتبات V2G البراغماتية، وقدرًا متواضعًا من المتجدّدات المتموضعة على المغذّي، مع إدارة أساسية للشحن، يمكنها تحسين سعة الاستضافة بدرجة كبيرة من دون الحاجة إلى تعزيز فوري للشبكة.

كلمات مفتاحية: المركبات الكهربائية؛ شبكات التوزيع؛ من المركبة إلى الشبكة (V2G)؛ الخلايا الكهروضوئية/الطاقة الشمسية الكهروضوئية (PV)؛ التوليد بالرياح؛ تقليل فواقد القدرة؛ تنظيم الجهد.