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Decision Trees in the Selection of Electric Vehicles Based on Various Parameters

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***Abstract*— The production of electric vehicles is highly increasing in recent days to meet the demands of alternatives to fuel-based vehicles. The automobile industries are manufacturing new variants of electric vehicles which are both economical and environmentally friendly. As the number of electric vehicles is many in the market it is quite challenging for customers to make decisions on selecting electric vehicles and also the retailers of E-vehicles are confronted with the same challenges of decision making. This paper proposes a decision-making model for selecting E-vehicles by using the machine-learning technique of Decision Trees. The decision-making on selection is based on significant parameters. The data on different E-vehicles with respect to the core parameters are subjected to treatment with the supervised learning technique of Decision Trees in the R environment. In this case, the decision trees are used to classify the E-vehicles into the two categories of feasible and infeasible based on five decision parameters. On comparing the accuracy results of classification with other machine learning techniques, decision trees are found to be more optimal.**

Keywords*— *Decision Trees, Electric vehicles, classification, compatibility.

I. Introduction

In recent days, machine learning algorithms are commonly used in making decisions on problems based on selection, classification, and prediction [1,2]. The three kinds of machine learning algorithms of supervised, unsupervised, and reinforcement are used in different kinds of decision-making problems subject to varied fields. Decision Trees are one of the supervised learning algorithms applied to solve problems based on regression and classification. A decision tree appears like a tree model with nodes and branches representing the testing conditions on attributes and outcomes respectively. Researchers have applied decision trees to several selection problems. Wu et al [3] in decision-making on teaching models, Cabo [4] in assessing the performance of the students, Liu et al [5] in classification and clustering of faults, Kamadi et al [6] in disease diagnosis, Venkat et al [7] in epidemic research, Matuszny [8] in knowledge-based decision making, Mingay [9] in legislation using rule-based decision trees. Decision trees are of various types such as decision stump, M5, Iterative Dichotomiser 3, C4.5, C5.0, Chi-squared Automatic Interaction Detector, multivariate adaptive regression splines, conditional Inference Trees, Classification and Regression Trees. These different kinds of decision trees differ from one another in the aspect of accuracy computations using various concepts of statistics. Hence the decision trees shall be broadly classified into categorical and continuous based on the values of the target variables. Thus, the consistent results of accuracy make the decision trees highly preferable. Decision Trees are the most viable classification tools employed to make interpretations on the grouping of data into two sets. In this research work the decision trees are used to classify the data set of electric vehicles into two categories of compatible and non-compatible. The electric vehicle is the order of this modern age. The increasing awareness of the importance of creating carbon-neutral communities has made nations across the world inaugurate and unveil the openings for e-vehicles of all kinds to venture into the global market. As every automobile company has vested their interest in manufacturing the components of electric vehicles, the retailers and the consumers are challenged with the decision-making problem of making optimal decisions on electric vehicles. This paper intends to provide optimal solutions to the decision-making challenges on electric vehicles using a decision trees algorithm in the R environment.

This paper presents a detailed description of the contributions of machine learning and multi-criteria decision-making in the selection of electric vehicles in section 2 together with the research gaps. The decision-making problem together with the working mechanism of decision trees is presented in section 3. The results obtained along with interpretations and inference are well sketched as in the discussion segment of section 4. The summary of the research work is presented in brief in the concluding part of this paper.

II. State of Art of Work State of Art of Work

This section presents the literature on applications of machine learning (ML) in decision-making problems associated with electric vehicles. Hu et al [10] applied ML algorithms in estimating the state of lithium-ion in the batteries of electric vehicles. Long et al employed prediction approaches of charging states. Li et al [11] used deep learning techniques in predicting the capacity of charging stations. Mohanty et al [12] used the techniques of ML in scheduling the charging of electric vehicles. Different ML algorithms are applied in the estimation and forecasting of the charging efficiency of electric vehicles. Some of the recent and significant contributions are as follows, Srinath et al [13] in charging efficacies, Shahriar et al [14], Hecht et al [15] in determining the expectancy of charging of electric vehicles, Schwenk et al [16] in smart charging, Hong et al [17] in optimizing the automatism of electric vehicles, Heroth et al [18] used efficient sampling algorithm in designing electric vehicles, Zhang et al [19] applied Nesterov Accelerated Gradient Algorithm in the estimation of the charging state, Ayman et al [20] employed data-driven approach in vehicle transit fleet, Liu et al [21] applied capacity analysis in finding the gradation of battery. Rodriguez et al [22] used automatic algorithms in designing electric vehicles. Poh et al [23], and Mehta [24], presented a comprehensive review of machine learning interferences in determining the charging status of the batteries. Nazari et al [25] applied clustering algorithms to discuss various aspects of electric vehicles. Venkitaraman, et al [26] employed deep learning techniques in charging management. Mousaei [27] built an intelligence-based algorithm. Kosuru et al [28] used deep learning in the smart battery management of electric vehicles. From the literature, it is very evident that ML algorithms are predominantly applied in predicting the charging states and capacity of electric vehicles. However, the ML algorithms are not used in selecting electric vehicles to the best of our inferences from the literature.

On the other hand, multi-criteria decision-making methods are extensively applied in the selection of electric vehicles. Buyukozkan et al [29]and Babar et al [30] briefed on the significance of electric vehicles in promoting the sustainability of the environment. Different MCDM methods are applied in the optimal selection of electric vehicles, some of the feasible methods applied are as follows: The fuzzy MCDM approach by Pradhan et al [31], the data-driven approach by Tian et al [32] and Stillic et al [33], fuzzy LMAW-grey MARCOS by Tešić et al [34], improved centroid method by Hatefi [35], MOORA and TOPSIS by Hamurcu et al [36], Fuzzy SMART by Oztaysi et al [37], consumer ethnocentrism by Wang et al [38], goal programming by Hamurcu et al [39], MEREC-CRADIS by Puska et al [40], Compromise based selection by Ziemba et al [41], Shannon's Entropy and Topsis by Dwivedi et al [42], AHP-MABAC by Sonar et al [43], Fuzzy KEMIRA by Oztaysi et al [44], Monte Carlo methods, fuzzy MCDA and stochastic interventions by Ziemba [45], Interval-Valued Spherical representations by Serap et al [46], different type of fuzzy numbers expressed by Varalakshmi [47], Miriam[48], Devados [49], Anand [50], Bharatraj [51], Anand [52-55].

These literature works vividly present the applications of MCDM in the selection of electric vehicles but at the same time, the magnitude of ML interferences is comparatively low in comparison to that of the MCDM interferences in the optimal selection problem of electric vehicles. Henceforth in this research work, the Ml algorithms are used in the selection of electric vehicles. The decision trees algorithm is used in this research work to make optimal vehicle selection. The decision Trees algorithm is applied in several fields to find solutions to selection problems. The research gaps presented in this section are

- On profound investigation on the applications of decision trees, it is found that decision tree algorithm has not been used in the context of selecting electric vehicles, to the best of our knowledge
- The intervention of Ml algorithms is almost nil in solving the electric vehicles selection problem whereas the MCDM intervention is very high

To bridge these gaps, this research work proposes Decision trees as an alternate means of solution-finding approach to the selection problems of electric vehicles.

III. Functioning Mechanism of Decision Trees

Decision Trees (DT) are one of the most viable and compatible supervised learning algorithms predominantly used in the problems of prediction and classification. In a decision tree, the nodes and branches are used in making representations of both the inputs and output at each stage. The process involved in making decisions using DT is described in the following three steps,

(i) Data Partition
(ii) Data Pruning
(iii) Selection of Trees

A. Data Partition

In this stage, the data is divided into many subsets. The splitting of data is very significant as it influences the output phase. The partition of data is attribute-based, hence the attribute similarity measure using either information gain or the Gini index is applied to choose the best attributes. Algorithms such as Chi-square are used to partition the data effectively.

B. Data Pruning

In this stage, the inessential nodes are removed to obtain an optimal tree. The complexity of reaching decisions is reduced without disturbing the optimality. Cost Complexity and reduced error pruning are the two types used primarily based on the requirements of data size.

C. Selection of Trees

The tree of the smallest size which fits the data is decided to be optimal. The selection is based on two important factors viz. Entropy and Information gain. Entropy refers to the uniformity in the given sample. The smaller values of entropy simplify the process of inference-making. Information gain is essential to make decisions on splitting up the feature at a node or not. Smaller entropy values with high maximum information gain are essential in selecting the optimal tree.

The following Table 3.1 presents the expressions of the efficacy of the classification indicators such as accuracy, precision, recall, and F scores which are determined using the values of True Positive (TP), False Positive (FP), True Negative (TN), False Negative (FN).

TABLE 3.1 INDICATORS OF BINARY CLASSIFICATION

Indicators	Expression
Accuracy (A): Relation indicating the ratio of correctly classified objects to the total classified objects	$\frac{TP + TN}{TP + TN + FP + FN}$

Precision (P): It accounts to the characterization of the correctness of the model by considering the ratio of the true positive to all the objects categorized as positive.	$\frac{TP}{TP + FP}$
Recall (R): It refers to the capacity of the model in object classification	$\frac{TP}{TP + FN}$
F-Scores (F) : Harmonic mean of between the values of precision and recall	$\frac{2(P * R)}{P + R}$

IV. Application of Decision Trees to the Selection Problem of Electric Vehicles

This section presents the decision-making problem of selecting electric vehicles using the algorithm of decision trees. As the numbers of electric vehicles are flooding the markets with different features, the optimum choice-making of electric vehicles is very essential. The interference of machine learning algorithms makes the identification of the ideal electric vehicles simple and consistent. This section makes such an attempt using a decision tree algorithm. The data on 50 different variants of electric vehicles is collected from various sources with the help of two experts in the field of marketing automobiles. The details of the experts are presented in Table 4.1

TABLE 4.1 DETAILS OF EXPERTS

Experts	Field of Expertise	Years of Experience
I	Marketing	10 years and 5 months
II	Marketing & Sales	13 years and 7 months

The following attributes make electric vehicles preferable in comparison to fuel-based vehicles.

- The maximum top speed of an electric vehicle is around 250 mph.
- The range of electric vehicles ranges from 100 to 400 miles.
- The torque of electric vehicles is very high in comparison with fuel-based vehicles.
- Electric vehicles possess the capacity to convert almost 85% of the energy into the driving force.
- In addition to the above benefit attributes the price of the electric vehicles is referred to as the cost attribute, because the cost of the electric vehicles is high in comparison to the fuel-based vehicles.

Thus, attributes such as Top speed, Maximum Range, Torque, Energy consumption, and price are considered for the selection problem of electric vehicles. The nature of the attributes is presented in Table 4.2

TABLE 4.2 DESCRIPTION OF ATTRIBUTES

Attributes	Nature of the Attributes
Top speed	Benefit Criteria
Electric Range	Benefit Criteria
Torque	Benefit Criteria
Energy Consumption	Benefit Criteria
Price	Cost Criteria

Using the packages 'caTools', 'party', 'dplyr', 'magrittr' of the decision tree algorithm in R the following results are obtained as in Table 4.3.

TABLE 4.3 DECISION TREE ALGORITHM PERFORMANCE PARAMETRIC VALUES

Indicators	Percentage Values
Accuracy (A)	86%
Precision (P)	84%
Recall (R)	96%
F-Scores (F)	89.6

The values of TP, TN, FP, and FN shall be determined from the confusion matrix.

TABLE 4.4 PREDICTED AND ACTUAL VALUE

	Predicted	
Actual	11	6
	1	32

V. Result and Discussion

To determine the consistency and efficacy of the results obtained using the Decision Tree algorithm, the same data is subjected to other algorithms such as XGB Classifier, Catboost, RUS Boost Classifier, and Balanced Random Forest Classifier. The parametric values obtained using other algorithms are presented in Table 5.1

TABLE 5.1 COMPARISON OF PARAMETRIC VALUES

Indicators	Decision Tree	XGB Classifier	Catboost	RUS Boost Classifier	Balanced Random Forest Classifier
Accuracy (A)	0.86	0.76	0.78	0.82	0.73
Precision (P)	0.84	0.69	0.72	0.81	0.62
Recall (R)	0.96	0.65	0.69	0.83	0.61
F-Scores (F)	0.87	0.67	0.70	0.82	0.62

From Table 5.1, it is very vivid that the results of the parametric values obtained using the Decision Tree are more optimal in comparison with other algorithms. As the accuracy of classification is more in Decision trees as depicted in Fig 5.1, this algorithm shall be used in decision-making on classifying the electric vehicles into the categories of compatibility and non-compatibility.

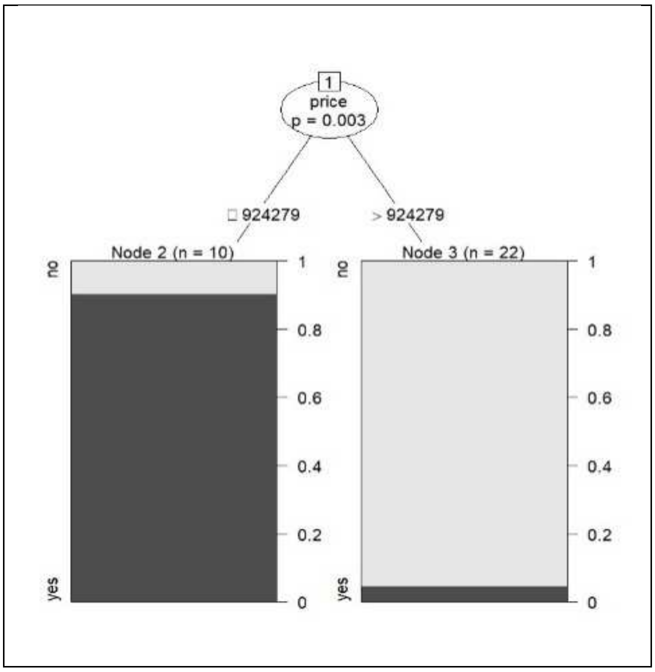

FIG. 5.1 DECISION TREES

The following Fig. 5.2 sketches the efficacy of the decision trees over the other algorithms. The diagrammatic representations make it very clear of the high values of the performance indicators.

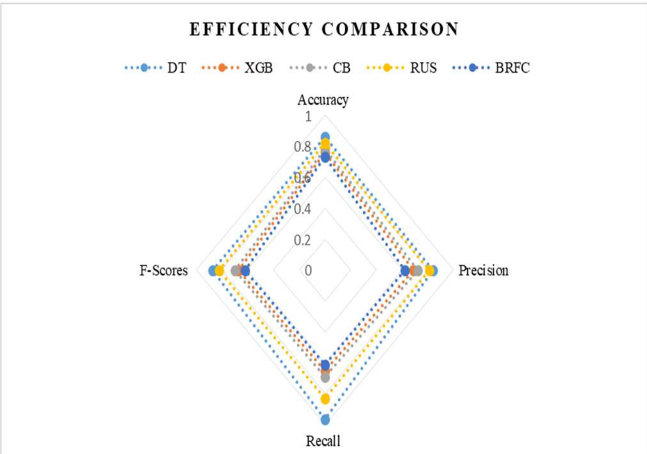

FIG. 5.2 EFFICIENCY COMPARISON

VI. CONCLUSION

This paper proposes a decision-making model for electric vehicle selection using a decision tree based on the classification category of feasibility. The accuracy results are more agreeable in comparison with other classifiers. The data shall be used as an underlying base for categorizing new data sets of electrical vehicles. Other classifying algorithms shall also be used as the extension of this research work. The same decision-making approach shall be used in other decision-making problems associated with electric vehicles.

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