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Implementation of Supervised Machine Learning Algorithm to Classify Multi-Criteria Interval Valued Inventory Data

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Abstract **Original Research Article**

A good management system ensures that the organization has enough goods and materials to meet organization's needs without causing material shortages or surpluses. But in some cases, uncertainties or imprecisions may exist in the measurement of inventory levels. Interval Valued Data (IVD) allows a more flexible representation of the associated uncertainty. Multi-Criteria interval valued inventory data refers to the inventories those are expressed as intervals based on different criteria. Organizations classify inventory into different classes, allowing managers to set appropriate policies for sourcing, storing, manufacturing, and distributing items. ABC classification based on Pareto Principle (Named after the Italian economist Vilfredo Pareto) is a well-known technique to classify items. In this work, initially classify the dataset into ABC classes using Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) model. A new approach has proposed based on Supervised Machine Learning (ML) Algorithms for IVID which will be used to classify an item in an appropriate class. Supervised ML is a type of ML where the computer uses labeled dataset (splitted into a training set and a test set) to train algorithms that to predict outcomes accurately. Numerical experiments are carried out by applying the approach on some benchmarking data set.

Keywords: Inventory Management; Interval Valued Inventory Data, MCDM; ABC Classification; TOPSIS.

1. INTRODUCTION

A decision-making challenge is the process of selecting the best option from among all variable options [6]. One of the most common decision-making challenges is multi-criteria decision-making (MCDM), which seeks to identify the optimal choice by taking into account more than one factor throughout the selection process. Benjamin Franklin pioneered multi-criteria decision-making with his study on moral algebra. Since the 1950s, scientists have studied MCDM methods to develop a framework for structuring decision-making problems and generating preferences from alternatives [2]. Multi-Criteria Decision Making (MCDM) approaches are a common decision assistance tool when an issue becomes tough for an individual to handle [12]. MCDM encompasses several strategies that differ from one another in various ways, which will be addressed in the following sections [2].

Supervised learning is a type of machine learning where a computer trains algorithms to classify data or predict outcomes using labeled datasets. In supervised learning, labeled data is split into a training set and a testing set. The model is trained on the training set, and its performance is assessed on the testing set.

In the real world, many situations involve significant information that may be inaccurate, unclear, or variable. In such cases, interval-valued data is more effective at expressing data variability and uncertainty than point data. All products, materials, and merchandise that are represented in interval forms those are kept by a firm for sale in the market to generate profit are collectively referred to as interval-valued inventory. Proper management of interval-valued inventory data is crucial in market research and various fields, including medical, educational, social, economic, and business research.

Inventory management is the practice of keeping track of the products that are stored. Inventory management is essential for keeping track of inventory levels, orders, and sales in the retail industry [14]. Effective inventory management is a skill required to succeed in the global market. Most organizations and supply chains rely on effective inventory management to run smoothly. Inventory management offers functions that prevent product overstocking and outages, lowering carrying costs. Inventory management in marketing has an impact on customer satisfaction. In finance, inventory investment is a company's main asset. Every day in the modern business sector, a massive amount of data about stocked items is generated and collected. With increasingly demanding customers and rising operating costs, it is critical for the organization to use inventory management systems to manage business transactions and choices [15, 16].

G. D. Lekha *et al.,* [9] have focused on developing a hybrid methodology that integrates Ma chine Learning Algorithms (MLA) with Multi-Criteria Decision-Making (MCDM) to enable comprehensive multi-attribute inventory analysis. K. Balaji *et al.,* [3] have proposed the Multi Criteria Inventory Classification (MCIC) method for the classification of the inventory of an automobile rubber component manufacturing industry. Z. Farrukh *et al.,* proposed a simple equal weighted normalized methodology for multi-criteria inventory classification to help inventory managers of each organization, whether small, medium or large [7]. It was advised to use the Simple Additive Weighting (SAW) method, which is well-established for generating multi-quality judgments. The author has used ABC analysis [11] for classification purposes. R. Krol *et al.,* [4] have analyzed the performance of the TOP SIS Method in a crisp and fuzzy environment. In [5], S. Chakraborty has provided an extensive simulation-based comparison and mathematical analysis of two popular methods, TOPSIS and Modified TOPSIS, to clarify confusion about their selection for solving Multiple Attribute Decision Making (MADM) problems. A. Kaczynska *et al.,* [12] have proposed a new approach to handling interval-valued data in the TOPSIS method based on the Cartesian product of boundaries. This approach is compared with the most popular extension proposed by Jahanshahloo. A modification of the TOP SIS method for a dataset that is nondeterministic, like interval data has been approached by F. H. Lotfi et al.in [6]. In [13], F. H. Lutfi have addressed multi-criteria models for complex decision-making.

All the above motivate us to use the extended TOPSIS method for decision-making problems with the dataset mixing of classical and interval valued. Therefore, the aim of this paper is to classify an unknown alternative into appropriate class by using the concept of Machine Learning and ABC analysis.

Our main contributions in this work are

- Initially, this paper uses an unsupervised dataset that mixes classical and interval-valued inventory. Then, the TOPSIS method is extended to the dataset after converting it into a classical dataset.
- Convert the original dataset into a supervised form based on ABC analysis.
- Then the idea of Machine Learning is applied to the supervised training data, yielding positive and negative ideal solutions.
- Finally, a new approach to classifying testing alternatives is applied using these solutions. The proposed approach is implemented on benchmarking data set.

The rest of the paper is designed as follows.

The following section 2 includes the brief review of MCDM, SAW method, TOPSIS method for different type of datasets, Pareto Principle, ABC classification. This section also covers the new approach of classification based on Machine Learning Algorithms. In section 3, Numerical Experiment will be applied on one benchmarking data set for classification purpose. Finally, the conclusion of this work has drawn in section 4.

2. FORMULATION

2.1 Multi-Criteria Decision-Making Approach

One of the primary decision-making challenges is multi-criteria decision-making (MCDM), which seeks to identify the optimal option by taking into account multiple criteria during the selection process [2]. This approach takes into account several qualitative and quantitative factors that should be adjusted in order to identify the optimal resolution. For instance, one of the most prevalent criteria in many decision-making challenges is cost or price and the quality of the procedures. MCDM can be applied to common issues that people face in their daily lives. MCDM has numerous uses in a variety of fields and professions, including engineering design, medical, economics, and finance [9].

Over the past few decades, various writers have developed or refined a variety of MCDM approaches. Simple Additive Weighting (SAW) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) are two important MCDM approaches those will be introduced bellow. These two approaches can quantify the relative performance of decision alternatives in a straightforward mathematical format and are straightforward, intuitive, and efficient.

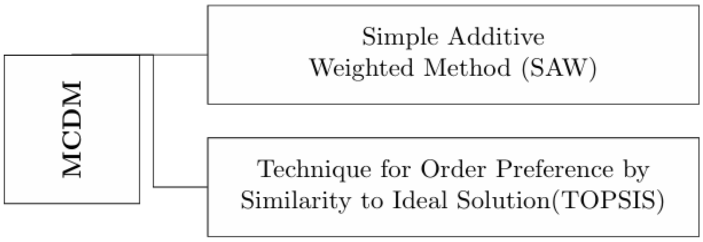

Figure 1: Types of MCDM

2.1.1 Simple Additive Weighting (SAW) Method [7,8]

The basic principle of the weighted summation methodology, commonly known as the Simple Additive Weighting (SAW) method, is to determine the weighted average of the performance of each alternative for each characteristic. In the multi-process decision-making system, it was advised to use the Simple Additive Weighting method to complete a settlement. The Simple Additive Weighting (SAW) method is a well-liked method for generating multi-quality judgments.

Suppose that one problem contains 'J' number of inventories (items) that have to be classified with respect to 'K' number of criteria.

Let, a_{jk} denote the value of inventory item 'j' with respect to 'k' number of criteria, where

$$j = 1, 2, \cdots, J$$

and

$$k = 1,2, \cdots, K$$

Then an equal weighted additive function is used to find normalized score of items which will convert all measurements in a 0-1 scale for all items.

$$\boldsymbol{Score\ (j'\ th\ item\ w.r.t\ k'th\ criteria) = P_{jk}} = \frac{a_{jk}-min_{j=1,2,\cdots,J}a_{jk}}{max_{j=1,2,\cdots,J}a_{jk}-min_{j=1,2,\cdots,J}a_{jk}} \quad (1)$$

The sum of item scores for all criteria will be calculated using the following equation.

$$\boldsymbol{P_j = \sum_{j=1}^{J}\{P_{jk}\}} \quad (2)$$

where, $\boldsymbol{P_j}$ is the sum of transformed score for 'j'th item with respect to multiple criteria 'k'.

To rank the sum of items score

$$\boldsymbol{P_j - P_{(j+1)} >= 0, j = 1, 2, \cdots, (j+1)} \quad (3)$$

After ranking in the descending order, the classification will be done according to Vilfredo Pareto rule.

2.1.2 Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

Hwang and Yoon [10] introduced the technique known as Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS). A multiple criteria approach called TOPSIS is used to select solutions from a limited number of options. The fundamental premise is that the alternatives that are selected should be the closest to the perfect solution and the furthest from the less-than-ideal solution [10, 19]. An overall index derived from the separations between the perfect solutions and the alternatives is used to rank them. The weighted matrices are normalized and then ranked using the TOPSIS algorithm. A sequence of steps can be used to describe the TOPSIS technique, those are given as follows:

- Find the decision matrix that has been normalized.
- Compute the decision matrix that is weighted and normalized
- Determine the positive-ideal and negative-idea solutions
- Utilizing the n-dimensional Euclidean distance, compute the separation measures
- Determine the relative closeness to the ideal solution
- Rank the preference order

Categories of TOPSIS method:

1. TOPSIS for Classical Data set
2. TOPSIS for Interval Valued Data set (Jahanshahloo TOPSIS)
3. Extension of Jahanshahloo TOPSIS (for mixed type dataset)

2.1.3 TOPSIS Method for Classical Dataset [12]

Since, our considered dataset is of mixing of classical and interval valued type that's why only TOPSIS Method for Interval Valued type (Jahanshahloo TOP SIS) and TOPSIS Method for mixing type (the extension of Jahanshahloo TOPSIS) is discussed below.

2.1.4 TOPSIS for Interval Valued Dataset (Jahanshahloo TOPSIS) [12,13]

Consider the following decision matrix:

$$B = \begin{bmatrix} [b_{11}^L, b_{11}^U] & [b_{12}^L, b_{12}^U] & \cdots & [b_{1n}^L, b_{1n}^U] \\ [b_{21}^L, b_{21}^U] & [b_{22}^L, b_{22}^U] & \cdots & [b_{2n}^L, b_{2n}^U] \\ \cdots & \cdots & \cdots & \cdots \\ [b_{m1}^L, b_{m1}^U] & [b_{m2}^L, b_{m2}^U] & \cdots & [b_{mn}^L, b_{mn}^U] \end{bmatrix}$$

Then the procedure of TOPSIS for interval valued data can be expressed by the following steps:

Step 1: Calculate the normalized interval decision matrix as:

$$\bar{e}_{ij}^{L} = \frac{b_{ij}^{L}}{\sqrt{\sum_{j=1}^{m}\left[\left(b_{ij}^{L}\right)^2 + \left(b_{ij}^{U}\right)^2\right]}}, j = 1,2,\cdots,m, i = 1,2,\cdots,n$$

$$\bar{e}_{ij}^{U} = \frac{b_{ij}^{U}}{\sqrt{\sum_{j=1}^{m}\left[\left(b_{ij}^{L}\right)^2 + \left(b_{ij}^{U}\right)^2\right]}}, j = 1,2,\cdots,m, i = 1,2,\cdots,n$$

Step 2: Calculate the weighted normalized interval decision matrix as:

$$\bar{f}_{ij}^{L} = \alpha_i \bar{e}_{ij}^{L}, j = 1,2,\cdots,m, i = 1,2,\cdots,n$$

$$\bar{f}_{ij}^{U} = \alpha_i \bar{e}_{ij}^{U}, j = 1,2,\cdots,m, i = 1,2,\cdots,n$$

Step 3: Calculate the positive and negative ideal solution as:

$$\bar{A}^{+} = \{\bar{f}_1^{+}, \bar{f}_2^{+}, \cdots, \bar{f}_n^{+}\} = \{(max_j \bar{f}_{ij}^{U})|i \in I, (min_j \bar{f}_{ij}^{L})|i \in J\}$$

$$\bar{A}^{-} = \{\bar{f}_1^{-}, \bar{f}_2^{-}, \cdots, \bar{f}_n^{-}\} = \{(max_j \bar{f}_{ij}^{L})|i \in I, (min_j \bar{f}_{ij}^{U})|i \in J\}$$

Where I is associated with benefit criteria and J is associated with cost criteria.

Step 4: Calculate separations from positive and negative ideal solution respectively as:

$$\bar{s}^{+} = \sqrt{\sum_{i\in I}\left(\bar{f}_{ij}^{L} - f_i^{+}\right)^2 + \sum_{i\in J}\left(\bar{f}_{ij}^{U} - f_i^{+}\right)^2}, j = 1,2,\cdots,m$$

$$\bar{s}^{-} = \sqrt{\sum_{i\in I}\left(\bar{f}_{ij}^{U} - f_i^{-}\right)^2 + \sum_{i\in J}\left(\bar{f}_{ij}^{L} - f_i^{-}\right)^2}, j = 1,2,\cdots,m$$

Step 5: Calculate Relative Closeness of each alternative to the ideal solution as**:**

$$\overline{RC}_j = \frac{\bar{s}_j^{-}}{\bar{s}_j^{+} + \bar{s}_j^{-}}, j = 1,2,\cdots,m$$

Step 6: Rank the preference order by arranging the Relative Closeness in descending order.

2.1.5 Extension of Jahanshahloo TOPSIS [12]

Step 1-3: Perform Steps 1-3 from the Jahanshahloo TOPSIS Method.

Step 4: All the other steps will perform according to step 4 for each alternative $A_j, j = 1,2,\cdots,m$.

1. Generate a crisp matrix for the alternative by taking different combination of the vertices of each interval.
2. On the newly generated decision matrix, per form classic TOPSIS, substituting for positive and negative ideal solutions values $\bar{A}^{+}$, $\bar{A}^{-}$ obtained in Step 3.

- **(a)** Calculate separations from positive and negative ideal solution respectively.
- **(b)** Calculate relative closeness of each alternative to the ideal solution.

Table 1: Crisp Decision Matrix

	Criteria (C_j)					
Alternatives (A_j')	C_1	C_2	$\cdots$	C_{n-2}	C_{n-1}	C_n
A_1'	$\bar{e}_1^L$	$\bar{e}_2^L$	$\cdots$	$\bar{e}_{n-2}^L$	$\bar{e}_{n-1}^L$	$\bar{e}_n^L$
A_2'	$\bar{e}_1^L$	$\bar{e}_2^L$	$\cdots$	$\bar{e}_{n-2}^L$	$\bar{e}_{n-1}^L$	$\bar{e}_n^U$
A_3'	$\bar{e}_1^L$	$\bar{e}_2^L$	$\cdots$	$\bar{e}_{n-2}^L$	$\bar{e}_{n-1}^U$	$\bar{e}_n^L$
A_4'	$\bar{e}_1^L$	$\bar{e}_2^L$	$\cdots$	$\bar{e}_{n-2}^L$	$\bar{e}_{n-1}^U$	$\bar{e}_n^L$
A_5'	$\bar{e}_1^L$	$\bar{e}_2^L$	$\cdots$	$\bar{e}_{n-2}^U$	$\bar{e}_{n-1}^L$	$\bar{e}_n^L$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
A_m'	$\bar{e}_1^U$	$\bar{e}_2^U$	$\cdots$	$\bar{e}_{n-2}^U$	$\bar{e}_{n-1}^U$	$\bar{e}_n^U$

1. **Then for each alternative, A_j, *Choose:***

$RC_j = \{min\, RC_j', max\, RC_j'\}, j = 1,2,\cdots,m.$

2.1.6 Pareto Principle and ABC Classifications

The Pareto Principle, first introduced in 1896, is named after the Italian economist Vilfredo Pareto [11]. This principle suggests that approximately 80 percent of the consequences for most outcomes stem from just 20 percent of the causes. In other words, a small pro portion of causes can lead to a significant impact. Pareto later expanded this concept to other areas of economics, such as the distribution of income and wealth.

The ABC classification method, based on the Pareto Principle, is commonly used to categorize stock goods into three classes: A, B, and C. By categorizing goods into three groups—"A," "B," and 'C"—inventory management efforts can be tailored to meet the specific needs of each category. It is an effective inventory management technique that focuses on prioritizing and allocating resources to the most important inventory items. This classification helps reduce the risk of overstocking and supply shortages, while also enabling individuals and organizations to optimize their resource utilization. This approach ensures that resources and efforts are used both effectively and efficiently.

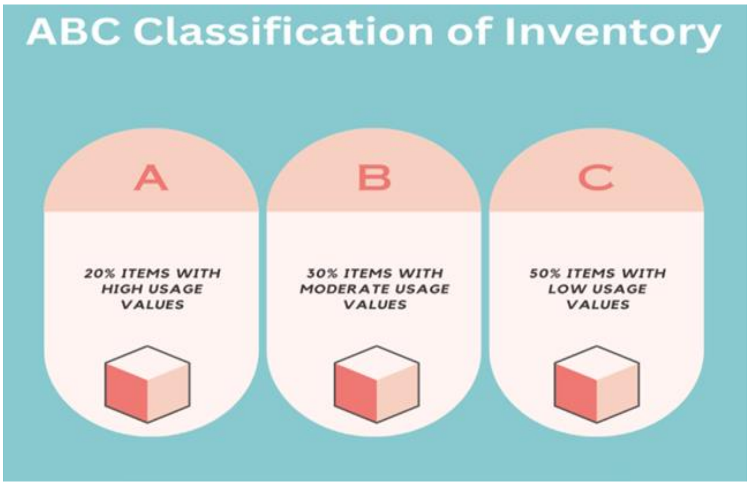

Figure 2: Percentage of uses of items in ABC Classification [11]

2.2 Working Procedures

To apply the appropriate method for the classification purpose, the nature of the considered dataset plays a pivotal rule. As the paper uses the data set of mixed type that is combination of classical and interval valued, the extension of Jahanshahloo TOPSIS will be applied. The complete working procedure is given by the following steps.

The extended Jahanshahloo TOPSIS

- Calculate the Separations from Positive and Negative Ideal solutions and Relative Closeness RC_j of each alternative by using newly generated crisp matrix.
- Label the alternatives into three different classes depends on the sorted values of Relative Closeness.

New Classification Approach: **S**plit the reconstructed dataset into training and testing set.

Training set:

- Obtain the positive and negative ideal solutions from the training dataset.
- Use these two ideal solutions to calculate the separations from the crisp dataset.

Testing set:

- Normalized the testing data by using the information from the training set.
- Identify the class of the testing alternatives by checking the value of Relative Closeness RC_j ei ther lie inside the range of RC_j or very close to the range.

3. Numerical Experiment

This section presents a numerical experiment to illustrate the implementation of MCDM. To demonstrate this, we utilize a well-known mixed type interval-valued dataset: The Electric Bicycle Selection Problem Data set (collected from A. Kaczynska *et al.,* [12]). According to [7], the extended TOPSIS method gives better result for the mixed type from SAW. That's why we will apply the extended TOPSIS Method to classify the alternatives.

3.1 Experiment on Electric Bicycle Selection Problem Data set

Description of Dataset: The Electric Bicycle Selection Problem Dataset contains 10 Bicycles models (Al-ternatives) and the following 8 different criteria (Cost and Benefit).

- C1- battery capacity, expressed in Ampere hours (Ah),
- C2- charging time of the battery, expressed in hours (h),
- C3- number of gears (derailleur), expressed in units,
- C4-power of the engine, expressed in Watts (W),
- C5-themaximumspeedreachedsolelybyelectric mode, expressed in kilometers per hour, (km/h),
- C6- driving range of the bicycle by electric mode using fully loaded battery, expressed in kilometers (km),
- C7- weight of the bicycle, including battery ex pressed in kilograms (kg), and
- C8-price in US dollars.

Here, the criteria C2, C7 and C8 are considered as Cost criteria and the remaining criteria are considered as Benefit. The complete dataset is given in the **Table 2.**

Table 2: The Electric Bicycle Selection Problem Data set [12]

Alternatives	Name	Criteria (C_j)							
A_j		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	Emu Crossbar	14.5	[6, 8]	7	250	25	[55, 100]	23	1560
A_2	Xiaomi QiCycle	5.8	3	3	250	20	45	14.5	950
A_3	ANCHEER Plus	8	5	21	250	25	[25, 50]	23	615
A_4	Ecotric	12	[5, 8]	7	500	32	55	24.9	999
A_5	Merax 26" Aluminium	8.8	[5, 6]	7	350	32	[35, 45]	22	690
A_6	Kemanner	8	[4, 6]	21	250	[35, 70]	20	23	[615, 700]
A_7	Rattan	10.4	[4, 5]	7	350	32	50	23.5	740
A_8	Aceshin	8	[4, 6]	21	250	30	40	22.2	730
A_9	Shaofu 6AH	4.4	3	1	350	25	20	12	390
A_{10}	Carrera Crossfuze	11	[6, 7]	9	400	25	80	20.3	2300

Table 3: Ranges of relative closeness of each alternative

Alternatives (A_j)	A_1	A_2	A_3	A_4	A_5
Ranges of (RC_j)	[0.4562, 0.4562]	[0.5188, 0.5360]	[0.4311, 0.4311]	[0.4528, 0.4763]	[0.5132, 0.5924]
Alternatives (A_j)	A_6	A_7	A_8	A_9	A_{10}
Ranges of (RC_j)	[0.3711, 0.4800]	[0.4651, 0.4977]	[0.5100, 0.5471]	[0.4859, 0.4959]	[0.3648, 0.3787]

Since the Electric Bicycle Selection Problem Data set is of mixed of classical and interval valued, so all the steps of the extension of jahanshaloo TOPSIS method have applied on the dataset of Table 2 to compute the Relative Closeness of each alternative. The ranges of Relative Closeness of each alternative are enlisted in the following Table 3.

Then Classify the Alternatives into three classes (A, B and C) according to Pareto Principle. Depends on the sorted values of the midpoint of the ranges of relative closeness this classification has done which is en listed in the Table 4.

Table 4: Labeling of all Alternatives based on Pareto principle

Lower limit of RC_j	Upper limit of RC_j	Mid Value of RC_j (RCM)	Sorted (RCM)	Alternatives (A_j)	Class
0.3771	0.4800	0.4286	0.5528	A_6	A
0.4311	0.4311	0.4311	0.5286	A_3	A
0.5100	0.5471	0.5286	0.5274	A_8	B
0.4651	0.4911	0.4814	0.4909	A_7	B
0.4528	0.4763	0.4645	0.4814	A_4	B
0.5132	0.5924	0.5528	0.4645	A_5	C
0.4859	0.4959	0.4909	0.4562	A_9	C
0.5188	0.5360	0.5274	0.4311	A_2	C
0.4562	0.4562	0.4562	0.4286	A_1	C
0.3648	0.3787	0.3717	0.3717	A_{10}	C

3.2 Classification Process of Testing Alternatives Set

Consider the original reconstructed dataset as training set and taking 12 different set of alternatives as the testing set.

Training Set: Original Dataset

Testing Set: Consider 12 different set of Alternatives

Figure 3: Training and Testing Set

3.3 RESULTS

The following Table 5 illustrates the class information of the first Testing set1 containing 10 different alternatives. It is observed that Out of 10 Alternatives, 9 testing alternatives have been identified correctly.

Table 5: Class information of Testing set 1 contains 10 Alternatives

Testing Alternatives A_j (RC_j)	Class of Testing Alternatives	Matching Alternatives	Class of matching Alternatives
A_1 (o.4053)	C	A_1 [0.3711, 0.4800]	C
A_2 (0.4299)	C	A_1 [0.3711, 0.4800]	C
A_3 (0.5241)	A	A_3 [0.5100, 0.5471]	A
A_4 (0.4904)	B	A_4 [0.4651, 0.4977]	B
A_5 (0.4643)	C	A_1 [0.3711, 0.4800]	C
A_6 (0.5492)	A	A_3 [0.5100, 0.5471]	A
A_7 (0.4959)	B	A_4 [0.4651, 0.4977]	B
A_8 (0.5360)	A	A_3 [0.5100, 0.5471]	B
A_9 (0.4650)	C	A_1 [0.3711, 0.4800]	C
A_{10} (0.3716)	C	A_1 [0.3711, 0.4800]	C

Similar classification process has applied to the rest of the11 set of testing alternatives. **Table 6** illustrates the class information of all testing alternatives sets.

Table 6: Class information of all 12 test Alternatives sets

Test Set	No. of Alternatives	Classified Alternatives	Misclassified Alternatives	Unclassified Alternatives
1	10	9	1	0
2	15	14	1	0
3	10	10	0	0
4	10	9	1	0
5	15	13	1	1
6	8	7	1	0
7	10	9	1	0
8	10	10	0	0
9	15	14	1	0
10	20	19	1	0
11	20	18	1	1
12	10	10	0	0
	Total Alternatives = 150	**Total Classified = 139**	**Total Misclassified = 09**	**Total Unclassified = 02**
Accuracy = 92.67%				

3.4 Performance analysis

It is evident from the Table 6, Testing set 3, 8 and 12 are fully classified. For the test set 5 and 11, number of unclassified is 1 respectively which indicates that the alternatives lie more than one class. On the other hand, for the test set 1, 2, 4, 5, 6, 7, 9, 10 and 11, number of misclassified alternative is 1 respectively that means alter natives belong to wrong class. Overall Accuracy rate of classification is 92.67%.

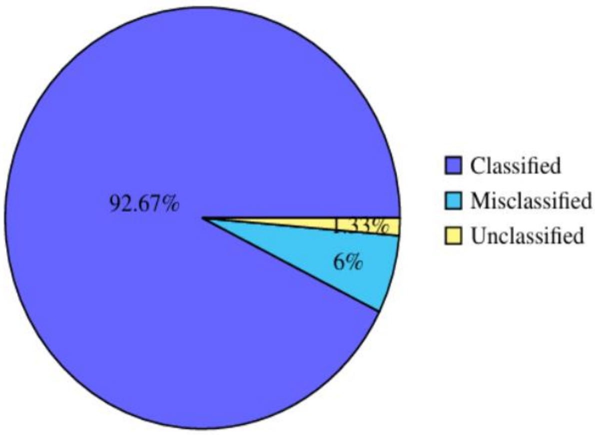

Figure 4: Performance Analysis of identification of testing Alternatives (in %)

4. CONCLUSION

In this study, Supervised Machine Learning (ML) algorithms and Multi-Criteria Decision-Making (MCDM) techniques are combined in a novel way to categorize multi-criteria interval-valued inventory data. To handle mixed datasets containing both classical and interval-valued data, the proposed solution first employs the expanded TOPSIS method. The dataset is subsequently transformed into a supervised form using Pareto-based ABC classification, and machine learning algorithms are trained on the rebuilt data to categorize new test options efficiently.

A numerical experiment conducted on the dataset for the Electric Bicycle Selection Problem illustrates the effectiveness of the proposed method in managing unpredictability and uncertainty in real decision-making scenarios. The overall accuracy achieved was 92.67\%, with 139 out of 150 test alternatives correctly identified, nine misclassified, and only two unclassified. These results confirm that the integration of multi-criteria decision-making (MCDM) techniques with machine learning (ML) significantly enhances decision accuracy and resilience when dealing with interval-valued data.

The fundamental benefit of this strategy is that it can be applied across a variety of domains, including engineering, economics, and inventory management, where decisions must be made with imprecise or unclear information. The technique facilitates applying contemporary machine learning methods to traditional MCDM problems by converting unsupervised interval-valued data into a supervised format.

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