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Research Paper

The Symmetric Pattern Fuzzy Discretization in Predicting Plastic Type for a Sorting System Using Decision Tree Methods

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Abstract

Plastics made from petroleum as the main ingredient cannot decompose quickly like organic materials, but rather take 500 years to 1000 years. Recycling plastic waste can significantly reduce the negative impacts that damage the environment. In addition, it can also reduce the use of natural resources as raw materials and energy use in the extraction process from mining to ready-for-use. In the process of recycling plastic bottle waste in industry, a sorting system is needed to sort the types of plastic bottle waste automatically, effectively, and efficiently. The system needs a prediction model with satisfactory performance. This research aims to build the prediction models of a plastic bottle waste sorting system with a fuzzy approach using the Decision Tree method. The main focus is fuzzy discretization with a symmetric pattern where the membership functions for the first and the last categories are balanced. Seven Decision Tree models are proposed in this study, six models with symmetric fuzzy discretization and one model with crisp discretization as a comparison. Three types of plastics are the objects of the study, namely Polyethylene Terephthalate (PET/PETE), High-Density Polyethylene (HDPE), and Polypropylene (PP). All three are types of plastics that are widely found in household waste. The unique contribution of this paper is that the symmetric pattern fuzzy discretization in the decision tree method can improve the performance of the decision tree model, but the combination of fuzzy membership functions used also contributes. Not all combinations used can improve the performance of the prediction model. Four of six models of symmetric fuzzy discretization have better performance than the decision tree model with crisp discretization. The combination of fuzzy membership functions consisting of linear and triangular functions provides the highest performance. Two models that do not perform better than crisp discretization are the linear-trapezoidal combination and the linear-Gaussian combination.

Keywords

Decision Tree, Fuzzy Discretization, Plastic Type Prediction, Sorting System, Symmetric Pattern

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1. INTRODUCTION

Plastic consumption of plastic has increased approximately 180 times between 1950 and 2018 (Pilapitiya and Ratnayake, 2024). In 2019, the global annual production of plastic has increased by more than two-thirds from 234 million tons in 2000 (OECD, 2022). Global plastic use is predicted to increase to 884 million tons in 2050 from 464 million tons in 2020 (Doki et al., 2024). The plastic production process also results in pollution, land degradation, and greenhouse gas emissions. One of the biggest problems facing the world today is plastic waste, which has far-reaching impacts. It can endanger species, disrupt ecosystems, and endanger human health (Abubakar et al., 2022). Plastic waste also has the potential to decompose into micro to nano-sized particulates, which are more easily dispersed in the environment, including the air, water, and soil (Pilapitiya and Ratnayake, 2024).

Indonesia is currently the second-largest producer of plastic waste in the world (Wang and Karasik, 2022). Recycling has been identified as a viable alternative for plastic waste management (Alaghemandi, 2024). Separation of plastic types is an important initial procedure in the plastic recycling industry. Inadequate sorting can lead to cross-contamination between different types of plastics, increasing operational costs for industrial facilities (Pivnenko et al., 2016). Sorting plastic types often faces challenges (Ruj et al., 2015). The ability to accurately predict plastic types is very useful in the context of the advancement of sorting systems in the recycling industry (Howard et al., 2024). Since manual approaches have proven to be ineffective and inefficient, an automatic plastic sorting system has emerged as a viable solution to this dilemma (Yani and Resti, 2023). An economical, effective, and efficient automatic plastic sorting system can be created by applying machine learning techniques to digital images as datasets (Lubongo et al., 2024). Intelligent computing based on high-performance machine learning prediction models is required to build this system. In addition, the use of digital images as a database in an intelligent computing system is cheaper than other technologies (Ngugi et al., 2021). Several prediction models in machine learning have been implemented to build intelligent computing on a digital image-based plastic waste sorting system, among the decision trees (Yani and Resti, 2023). However, ambiguity problems often occur when processing of processing digital image data, especially the data transformation process. Fuzzy approaches in building predictive models are currently popular because they can handle ambiguity in data and often improve model performance Chen and Huang (2021); Altay and Cinar (2016) including discretization techniques that use the concept of fuzzy set membership where the membership of each element has a degree in the interval (0.1) (Resti et al., 2022, 2023).

This research aims to build a prediction model of a plastic bottle waste sorting system with a fuzzy approach using the Decision Tree method. This approach builds a predictive model using a discretization technique that transforms data using the concept of fuzzy set membership (Roy and Pal, 2003), where the membership of each element has a degree in the interval (0,1). The research database is digital images of the three types of plastic that are most widely used as packaging: Polyethylene Terephthalate (PET/PETE), High-Density Polyethylene (HDPE), and Polypropylene (PP). Seven models are proposed in this paper, six decision tree models with symmetric pattern fuzzy discretization and one decision tree model with crisp discretization as a comparison. The six models consist of all triangular combinations Femina and Sudheep (2020); Shanmugapriya et al. (2017), all trapezoidal combinations Algehyne et al. (2022); Yazgi and Necla (2015), all-Gaussian combinations (Muludi et al., 2024, Setiawan et al., 2020), linear-triangular and linear-trapezoidal (Resti et al., 2023), and linear-Gaussian combination. For the last combination not found in previous research, the implementation of discretization using this combination in the Decision Tree method needs to be explored especially in the case of plastic type prediction based on RGB images.

2. EXPERIMENTAL SECTION

In this study, collected data by capturing digital images of plastic waste placed on a conveyor belt. The as given in Figure 1. The digital images of plastic waste were then processed into the red, green, and blue (RGB) color space model. The RGB model of digital objects is frequently employed as a dataset to address prediction or identification issues due to their affordability (Ngugi et al., 2021). This is in contrast to other technologies, including infrared sensors Bonifazi et al. (2023), image sensors (Choi et al., 2023), and multi-wavelength transmission spectrum (Shi et al., 2022). The number of samples used in this study was 450 used plastics consisting of 150 plastics for each type of plastic, PET, HDPE, and PP.

Plastic digital image processing into an RGB color space model producing numerical data with a ratio scale. The process of data transformation into categorical type can be done using crisp and fuzzy discretization while modeling the plastic type using the decision tree method.

Figure 1. Capturing the Digital Images of Plastic Waste

Globally, building a decision tree involves three main tasks; selecting the best predictor variables, partitioning the dataset, and repeating the process until the stopping criteria are met. Selecting the best predictor variables serves to provide alternative decisions. As in Equation (1), information gain is usually used as the underlying metric for this selection. The dataset is partitioned into several subsets based on the selected predictor variables. The process is repeated recursively for each subset, creating new internal or leaf nodes until the stopping criteria are met (Yani and Resti, 2023; Resti et al., 2022, 2023).

$$\text{Information Gain}(S, X) = \text{Entropy}(S) - \sum_{c=1}^{k_X} \frac{|S_c|}{|S|}\text{Entropy}(S_c) \quad (1)$$

The entropy is written as,

$$\text{Entropy}(S_c) = \sum_{c=1}^{k_X} -P_c \log_2 P_c \quad (2)$$

Both require a categorical type predictor variable Dougherty et al. (1995) so that the ratio-scale data resulting from digital image processing to the RGB color space model needs to be transformed. This problem-solving approach uses a combination of fuzzy membership functions to transform ratio-scale variables through discretization that can provide predictive performance for the decision tree method. Variations in the combination of these fuzzy membership functions can produce different performances (Resti et al., 2022, 2023). The membership functions proposed in this paper are decreasing and increasing linear for the first and third categories. Both functions are presented in Equations (3) and (4), respectively (Hudec, 2016; Bhattacharyya and Mukherjee, 2021).

$$\mu_{\tilde{x}_d}(x_f; a, b) = \begin{cases} 1 & x_f \leq a \\ \frac{b-x_f}{b-a} & a \leq x_f \leq b \\ 0 & x_f \geq b \end{cases} \tag{3}$$

$$\mu_{\tilde{x}_d}(x_f; a, b) = \begin{cases} 0, & x_f \leq a \\ \frac{x_f-a}{b-a}, & a \leq x_f \leq b \\ 1, & x_f \geq b \end{cases} \tag{4}$$

The triangular, trapezoidal, and Gaussian membership functions are presented in Equations (5) - (7) successively (Hudec, 2016; Bhattacharyya and Mukherjee, 2021).

$$\mu_{\tilde{x}_d}(x_f; a, b, c) = \begin{cases} 0, & x_f \leq a \\ \frac{x_f-a}{b-a}, & a \leq x_f \leq b \\ \frac{c-x_f}{c-b}, & b \leq x_f \leq c \\ 0, & x_f \geq c \end{cases} \tag{5}$$

$$\mu_{\tilde{x}_d}(x_f; a, b, c, d) = \begin{cases} 0, & x_f \leq a \\ \frac{x_f-a}{b-a}, & a \leq x_f \leq b \\ 1, & b \leq x_f \leq c \\ \frac{d-x_f}{d-c}, & c \leq x_f \leq d \\ 0, & x_f \geq d \end{cases} \tag{6}$$

$$\mu_{\tilde{x}_d}(x_f; a, b) = \exp\left(-\left(\frac{x-a}{b}\right)^2\right) \tag{7}$$

The symmetric form of the fuzzy discretization proposed in this work when presented in graphical form can be illustrated as in Figure 2.

Four of the six combinations of fuzzy membership functions with symmetric patterns as presented in Figure 2 can also be found in various studies such as all triangular combinations (Femina and Sudheep, 2020; Shanmugapriya et al., 2017), all trapezoidal (Algehyne et al., 2022; Yazgi and Necla, 2015), linear-triangular and linear-trapezoidal (Resti et al., 2023). Two combinations were also proposed, namely the all-Gaussian combination (Muludi et al., 2024; Setiawan et al., 2020) and the linear-Gaussian combination. The last combination was not found in the majority of related research. The parameter values in each membership function used in fuzzy discretization are obtained using a tuning system.

The prediction method's model performance is assessed by utilizing the confusion matrix for each class Dinesh and Dash (2016) as given in Figure 3.

For the j-th class, let true positives (TP_j) and true negatives (TN_j) be proper classifications. False positives (FP_j) occur when an outcome is incorrectly predicted as the j-th class (or positive) when it is, in fact, not the j-th class (negative). A false negative (FN_j) occurs when a result is incorrectly predicted as not the j-th class (negative) when it is the j-th class (positive). The model's performance based on the confusion matrix in this paper is assessed using the accuracy, recall, precision, F1-score, and Kappa as described in the study (Sokolova and Lapalme, 2009; Ramasubramanian and Singh, 2019).

3. RESULTS AND DISCUSSION

3.1 Discretization

Discretization using the concept of crisp set membership is done based on prior information. Each red, green, and blue color channel consists of three categories; dark, moderate, and light. The brighter the color of the channel, the higher the pixel value. The other two predictor variables, namely variance and entropy, also consist of three categories: low, medium, and high. The results of discretization using the concept of crisp set membership and all fuzzy discretization with the symmetry pattern are presented in Table 1 and Table 2, respectively.

Table 1. Crisp Discretization

Pred.	Category (m)		
Var.	1	2	3
X_1	[0.33, 0.55]	[0.55, 0.78]	[0.78, 1]
X_2	[0.35, 0.57]	[0.57, 0.78]	[0.78, 1]
X_3	[0.33, 0.55]	[0.55, 0.78]	[0.78, 1]
X_4	[0, 0.33]	[0.33, 0.67]	[0.67, 1]
X_5	[0, 0.04]	[0.04, 0.08]	[0.08, 1]

Using the concept of fuzzy set membership, each category in each variable has overlapping intervals in all combinations. These intervals are obtained using a tuning mechanism (Resti et al., 2022, 2023).

3.2 The Proposed Decision Tree Model

A decision tree model with proposed crisp discretization (DT1) in the first iteration is in the form of a decision diagram presented in Figure 4.

In the model, the number of splits, including the root node, is thirteen while the number of rules is fourteen. The fourteen rules consist of five rules for the first type of plastic (PET), three rules for the second type of plastic (HDPE), and six rules for the third type of plastic (PP). Five rules for the first type of plastic:

1. If $X_5 \geq 2$, and $X_3 \geq 2$, and $X_4 < 2$, then the plastic type is PET.
2. If $X_5 < 2$, and $X_3 < 2$, and $X_4 < 2$, and $X_2 \geq 2$, and $X_1 < 3$, then the plastic type is PET.
3. If $X_5 < 2$, and $X_3 < 2$, and $X_4 < 2$, and $X_2 \geq 2$, and $X_1 \geq 3$, then the plastic type is PET.
4. If $X_5 < 2$, and $X_3 \geq 2$, and $X_4 < 2$, and $X_2 < 2$, then the plastic type is PET.
5. If $X_5 < 2$, and $X_3 < 2$, and $X_4 < 2$, and $X_2 < 2$, then the plastic type is PET.

Three rules for the second type of plastic:

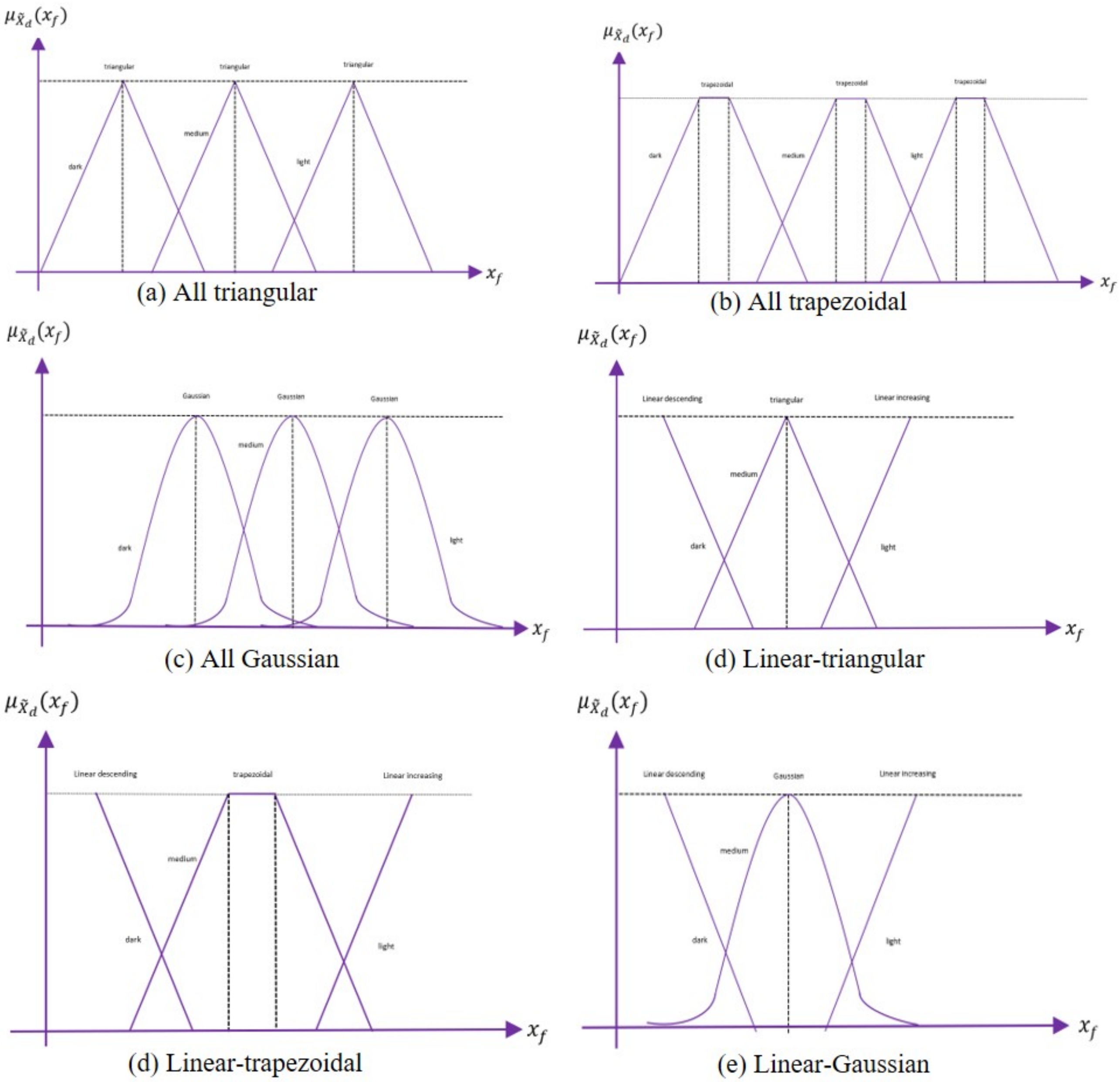

Figure 2. The symmetric pattern of fuzzy discretization

		actual		
	plastic type	PET	HDPE	PP
prediction	PET	TP	FN	FN
	HDPE	FP	TN	TN
	PP	FP	TN	TN

(g) First class

		actual		
	plastic type	PET	HDPE	PP
prediction	PET	TN	FP	TN
	HDPE	FN	TP	FN
	PP	TN	FP	TN

(h) Second class

		actual		
	plastic type	PET	HDPE	PP
prediction	PET	TN	TN	FP
	HDPE	TN	TN	FP
	PP	FN	FN	TP

(i) Third class

Figure 3. Confusion Matrix for Each Class of Plastic Type

Table 2. Fuzzy Discretization with Symmetric Pattern

Combination	Pred. Var.	Category (m) 1	2	3
All Triangular	X_1	[0.33, 0.49, 0.78]	[0.41, 0.84, 0.87]	[0.82, 0.91, 1]
	X_2	[0.35, 0.51, 0.78]	[0.42, 0.45, 0.87]	[0.83, 0.91, 1]
	X_3	[0.33, 0.49, 0.78]	[0.41, 0.64, 0.87]	[0.82, 0.91, 1]
	X_4	[0, 0.27, 0.67]	[0.14, 0.48, 0.83]	[0.77, 0.88, 0.99]
	X_5	[0, 0.03, 0.08]	[0.01, 0.15, 0.28]	[0.04, 0.52, 1]
All Trapezoidal	X_1	[0.33, 0.46, 0.58, 0.70]	[0.52, 0.61, 0.71, 0.90]	[0.89, 0.92, 0.94, 1]
	X_2	[0.35, 0.48, 0.59, 0.71]	[0.53, 0.67, 0.71, 0.90]	[0.89, 0.92, 0.95, 1]
	X_3	[0.33, 0.46, 0.58, 0.70]	[0.52, 0.61, 0.71, 0.90]	[0.89, 0.92, 0.94, 1]
	X_4	[0.00, 0.13, 0.30, 0.67]	[0.31, 0.48, 0.83, 0.87]	[0.83, 0.87, 0.92, 1]
	X_5	[0.00, 0.03, 0.06, 0.09]	[0.05, 0.06, 0.08, 0.11]	[0.10, 0.11, 0.12, 0.13]
All Gaussian	X_1	(0.63, 0.02)	(0.93, 0.02)	(0.72, 0.03)
	X_2	(0.67, 0.01)	(0.93, 0.02)	(0.74, 0.02)
	X_3	(0.71, 0.01)	(0.94, 0.02)	(0.74, 0.03)
	X_4	(0.76, 0.03)	(0.24, 0.07)	(0.63, 0.02)
	X_5	(0.02, 0.01)	(0.11, 0.01)	(0.03, 0.01)
Linear - Triangular	X_1	[0.33, 0.78]	[0.55, 0.95, 0.94]	[0.89, 1]
	X_2	[0.35, 0.78]	[0.57, 0.66, 0.95]	[0.89, 1]
	X_3	[0.33, 0.78]	[0.55, 0.75, 0.94]	[0.89, 1]
	X_4	[0, 0.67]	[0.33, 0.63, 0.92]	[0.83, 1]
	X_5	[0, 0.08]	[0.04, 0.30, 0.55]	[0.10, 1]
Linear - Trapezoidal	X_1	[0.33, 0.78]	[0.55, 0.75, 0.94, 0.95]	[0.89, 1]
	X_2	[0.35, 0.78]	[0.57, 0.71, 0.66, 0.95]	[0.89, 1]
	X_3	[0.33, 0.78]	[0.55, 0.65, 0.75, 0.94]	[0.89, 1]
	X_4	[0, 0.67]	[0.33, 0.48, 0.63, 0.92]	[0.83, 1]
	X_5	[0, 0.08]	[0.04, 0.17, 0.30, 0.55]	[0.10, 1]
Linear - Gaussian	X_1	[0.33, 0.98]	(0.76, 0.04)	[0.89, 1]
	X_2	[0.35, 0.78]	(0.79, 0.03)	[0.89, 1]
	X_3	[0.33, 0.98]	(0.80, 0.03)	[0.89, 1]
	X_4	[0, 0.67]	(0.55, 0.09)	[0.83, 1]
	X_5	[0, 0.08]	(0.05, 0.03)	[0.10, 1]

1. If $X_5 \geq 2$, and $X_3 \geq 2$, and $X_4 \geq 3$, and $X_1 < 3$, then the plastic type is HDPE.
2. If $X_5 < 2$, and $X_3 < 2$, and $X_4 < 2$, and $X_2 \geq 2$, and $X_4 < 2$, and X_1 is 2 to 3, then the plastic type is HDPE.
3. If $X_5 \geq 2$, and $X_3 \geq 2$, and X_4 is 2 to 3, then the plastic type is HDPE.

Six rules for the third type of plastic:

1. If $X_5 < 2$, and $X_3 < 2$, and $X_4 \geq 2$, and $X_2 < 2$, and $X_1 < 3$, then the plastic type is PP.
2. If $X_5 \geq 2$, and $X_3 \geq 2$, and $X_4 \geq 3$, and $X_1 \geq 3$, then the plastic type is PP.
3. If $X_5 < 2$, and $X_3 \geq 2$, and $X_4 < 2$, then the plastic type is PP.
4. If $X_5 < 2$, and $X_4 \geq 2$, and $X_4 \geq 2$, then the plastic type is PP.
5. If $X_5 < 2$, and $X_3 \geq 2$, and $X_4 \geq 2$, and $X_2 < 2$, then the plastic type is PP.
6. If $X_5 \geq 2$, and $X_3 < 2$, then the plastic type is PP.

For six other proposed models of DT with fuzzy discretization that have a similar pattern, the form of the decision diagram in the first iteration is presented in Figures 5-10. Each figures has different splits and rules where the number of rules is the number of splits in the tree minus 1. The rules presented in each of these decision diagrams can be interpreted in

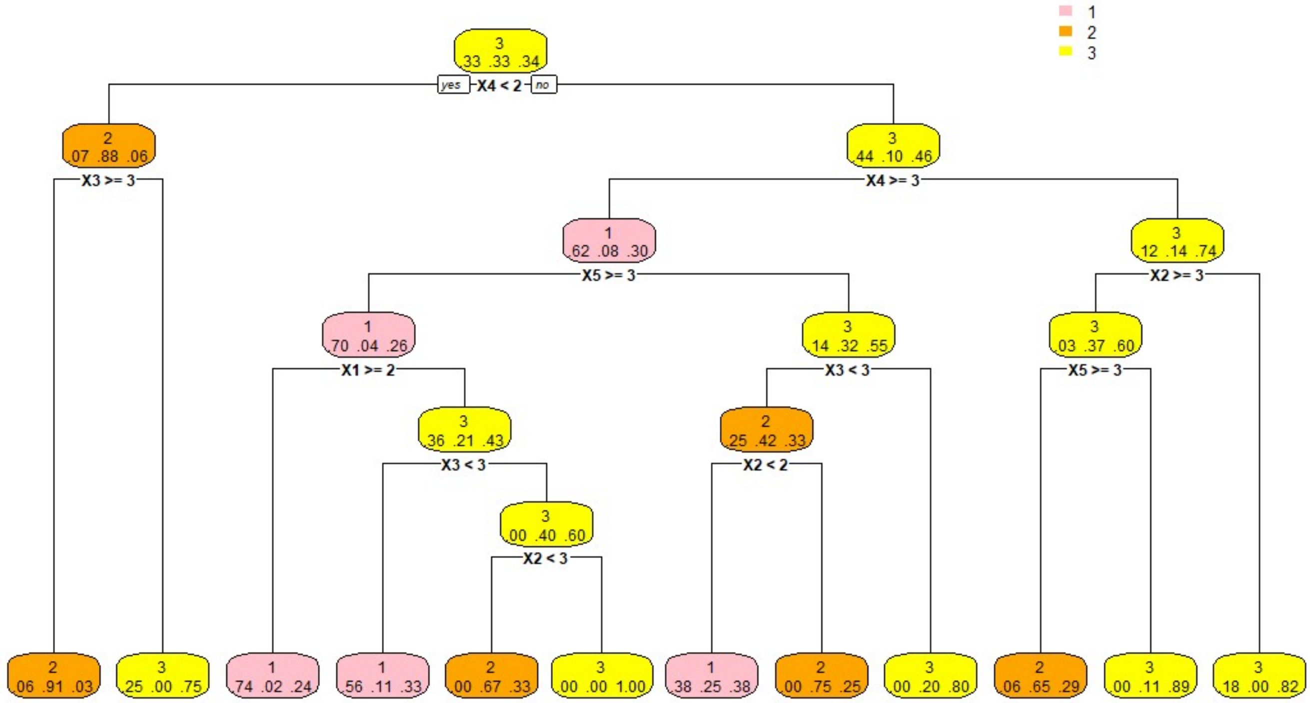

Figure 4. Decision Diagram of DT with Crisp Discretization (DT1)

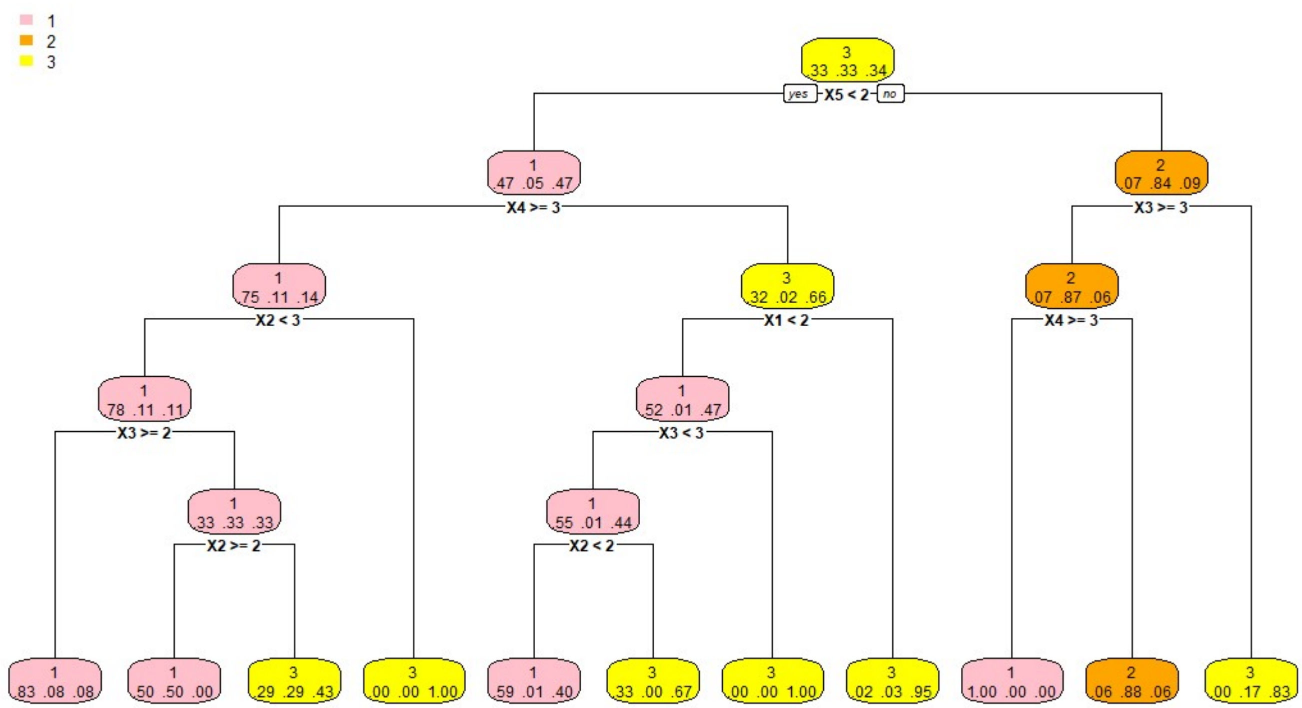

Figure 5. Decision Diagram of DT with All-Triangular Fuzzy Discretization (DT2)

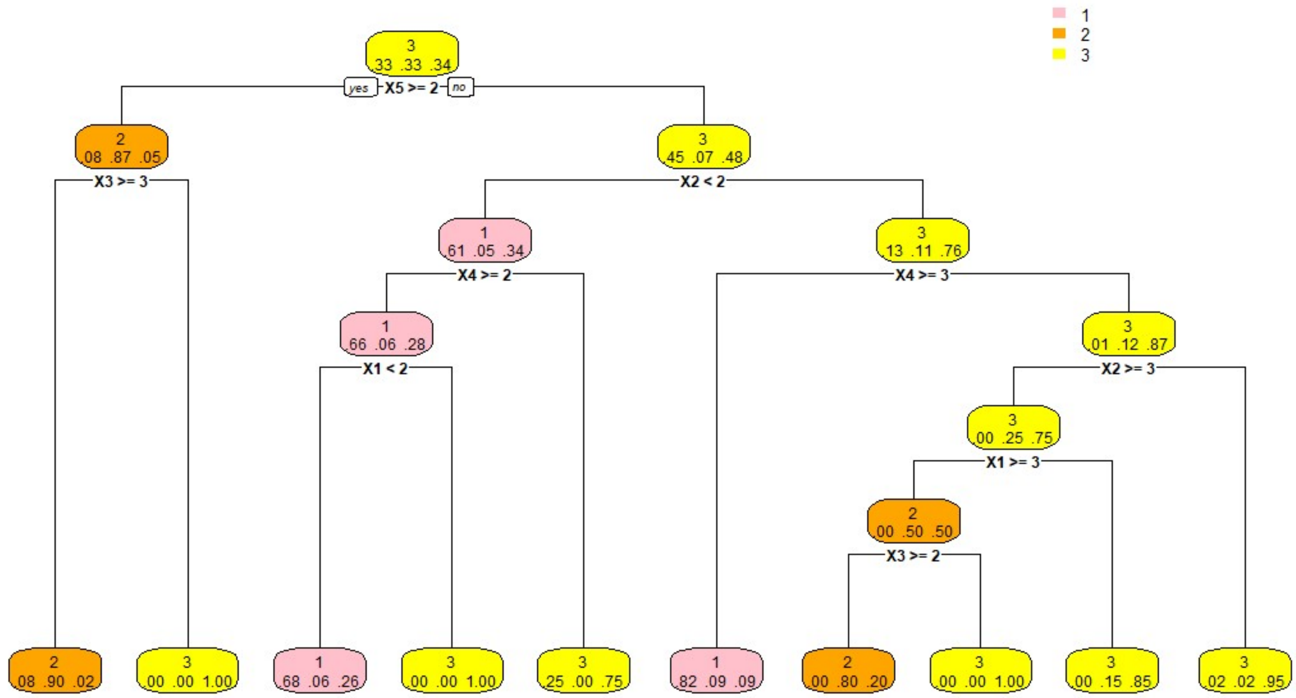

Figure 6. Decision Diagram of DT with All-Trapezoidal Fuzzy Discretization (DT3)

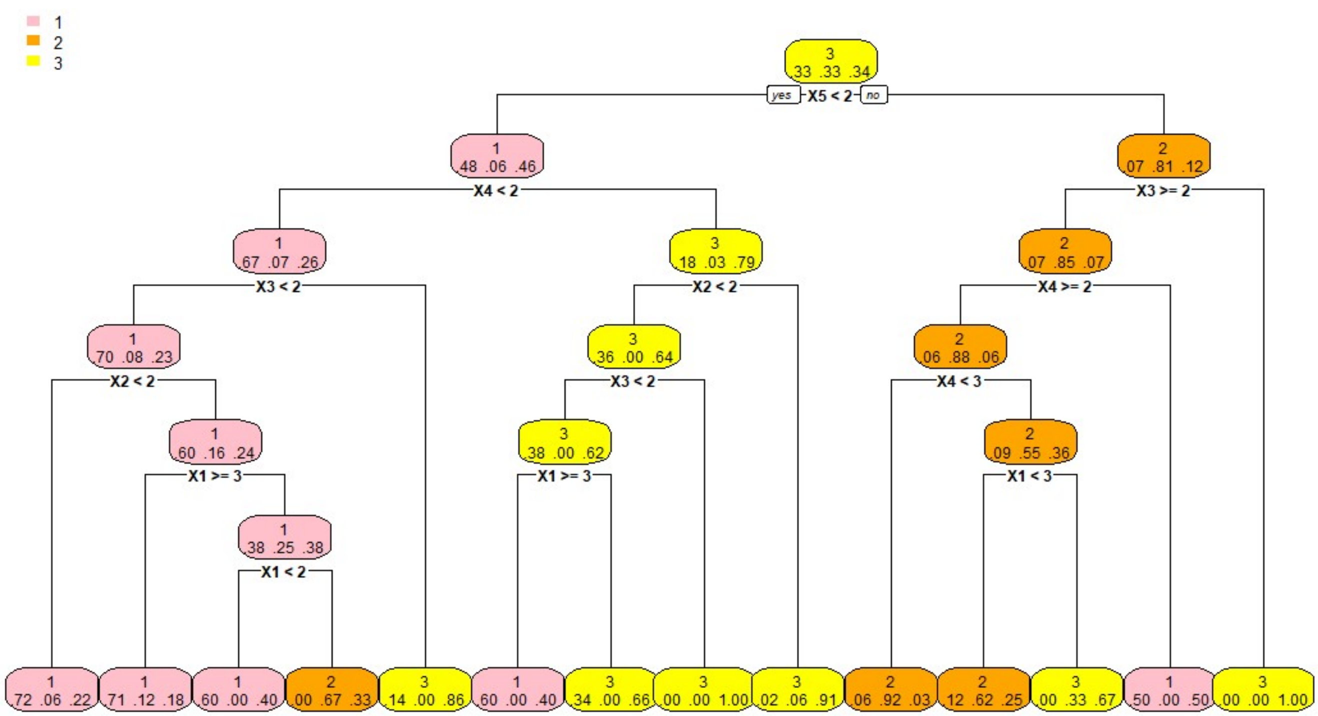

Figure 7. Decision Diagram of DT with All-Gaussian Fuzzy Discretization (DT4)

Table 3. Model Performance of DT in Each Iteration

Proposed Discretization		Metric Performance				
DT Model	Iteration	Accuracy	Recall	Precision	F1-score	Kappa
Crisp(DT1)	1	81.48	71.27	75.68	80.48	57.96
	2	80.74	71.94	73.10	78.52	55.65
	3	82.22	71.39	72.18	78.82	59.39
	4	84.44	76.29	76.70	82.12	64.92
	5	82.96	73.93	76.43	81.50	61.55
All Triangular (DT2)	1	85.93	78.42	80.73	84.83	68.19
	2	84.44	77.38	79.71	83.60	64.35
	3	83.70	73.69	74.54	80.59	62.64
	4	81.48	71.59	72.26	78.58	58.17
	5	80.74	69.78	74.20	79.30	55.96
All Trapezoidal (DT3)	1	83.70	74.96	79.30	83.25	63.09
	2	86.67	80.63	83.33	86.34	69.40
	3	89.63	83.62	85.02	88.49	76.37
	4	86.67	78.06	83.15	86.69	66.63
	5	82.96	73.27	77.10	81.69	61.10
All Gaussian (DT4)	1	80	69.24	70.4	76.98	54.72
	2	78.52	69.04	69.58	75.78	50.74
	3	82.22	70.65	71.43	78.29	59.18
	4	86.67	79.85	79.95	84.70	69.98
	5	86.67	79.40	82.14	85.82	69.76
Linear Triangular (DT5)	1	84.44	75.92	82.03	84.98	64.73
	2	86.67	80.98	84.83	87.18	69.51
	3	90.37	84.77	85.85	89.23	78.09
	4	82.96	73.99	79.05	82.96	61.60
	5	85.19	76.72	82.02	85.12	66.15
Linear Trapezoidal (DT6)	1	80.74	71.17	72.18	78.35	56.74
	2	78.52	68.59	70.76	76.48	50.38
	3	82.22	70.65	70.60	76.48	59.28
	4	80.00	69.40	69.46	76.48	54.90
	5	80.00	69.67	71.68	77.79	54.89
Linear Gaussian (DT7)	1	83.7	75.08	75.37	81.1	63.23
	2	76.3	66.26	66.7	73.44	46.05
	3	85.93	76.91	78.28	83.42	67.64
	4	75.56	62.61	61.94	70.47	44.85
	5	78.52	66.49	68.04	75	50.96

a similar way to the decision diagram of model DT with crisp discretization.

In DT model with Linear-Gaussian fuzzy discretization, as shown in Figure 9, the number of splits is 11 including the root node, while the number of rules is 12 consisting of four rules for the first plastic type (PET), three rules for the second plastic type (HDPE), and five rules for the third plastic type (PP). There is no significant difference in terms of computation between crisp and fuzzy discretization. It is just necessary to explore the combinations of fuzzy membership functions used and their parameter settings.

3.3 Model Performance

The performance of the seven proposed models of decision trees with crisp discretization and the symmetric pattern fuzzy discretization in each iteration is presented in Table 3. Each decision tree model with the proposed discretization has a different range of values. In all iterations, the decision tree model with the linear-triangular combination has an accuracy and F1-score value above 82%. For the models: crisp discretization, all trapezoidal combinations, and linear-triangular have recall

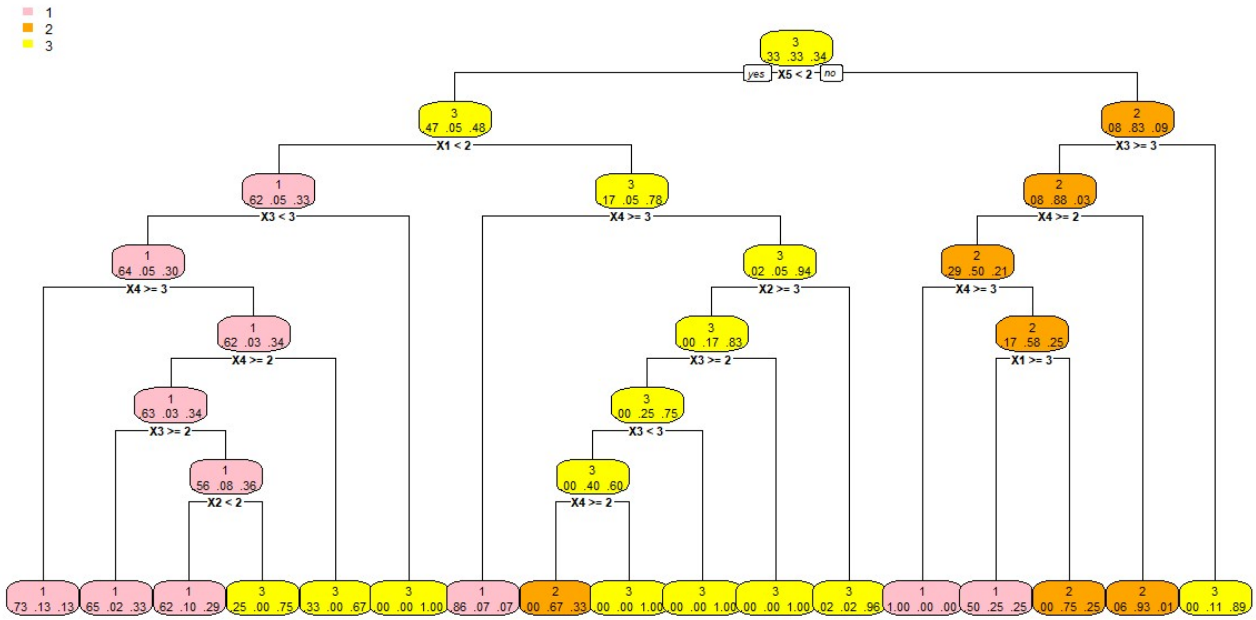

Figure 8. Decision Diagram of DT with Linear-Triangular Fuzzy Discretization (DT5)

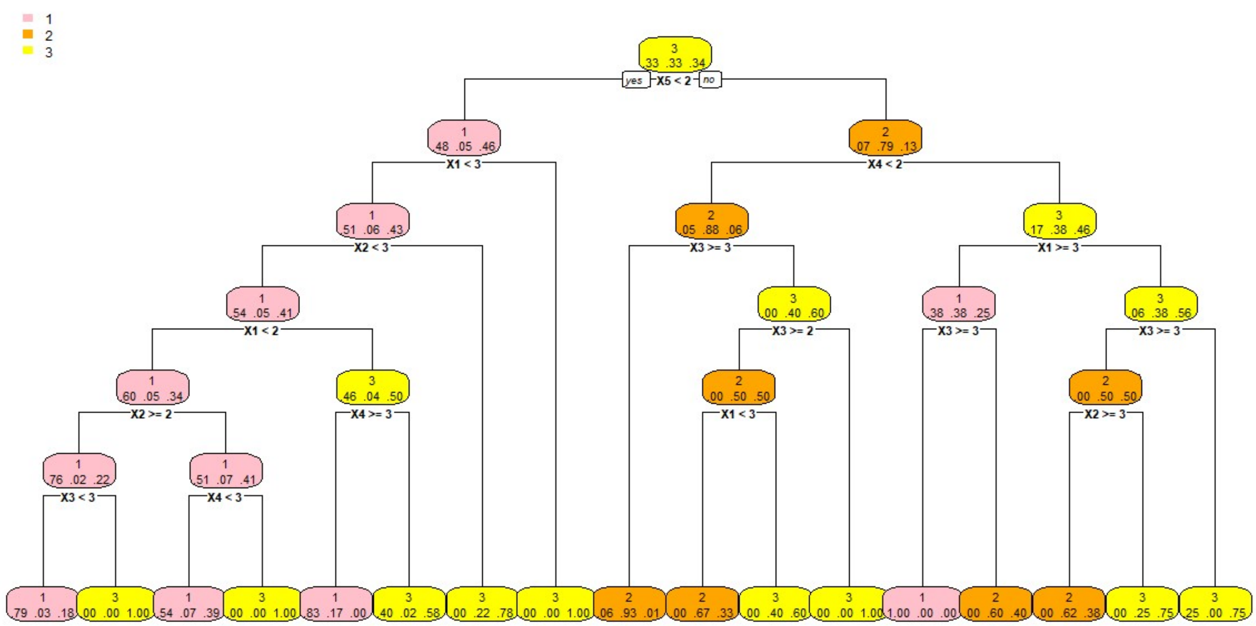

Figure 9. Decision Diagram of DT with Linear-Trapezoidal Fuzzy Discretization (DT6)

and precision values above 70%, while the linear-trapezoidal combination has a Kappa value below 60%.

Figure 11 shows the average performance of the seven proposed models. Four out of six DT models with symmetric fuzzy discretization with symmetric patterns have higher performance than the DT model with crisp discretization (DT1). DT model with fuzzy discretization using the combination of linear and triangular functions (DT5) gives the highest performance with the average performance for each accuracy, recall, precision, F1-score, and kappa being 85.93%, 78.48%, 82.76%, 85.89%, and 68.02%. Followed in turn by the performance of the DT model with fuzzy discretization which is a combina-

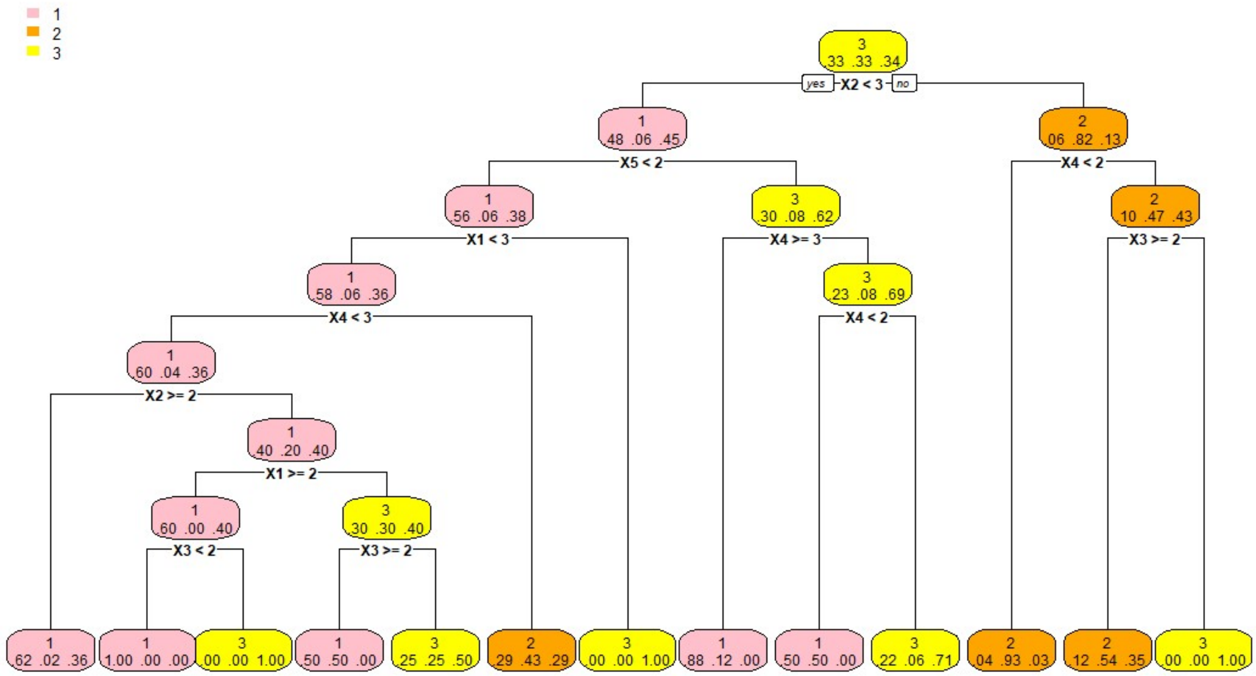

Figure 10. Decision Diagram of DT with Linear-Gaussian Fuzzy Discretization (DT7)

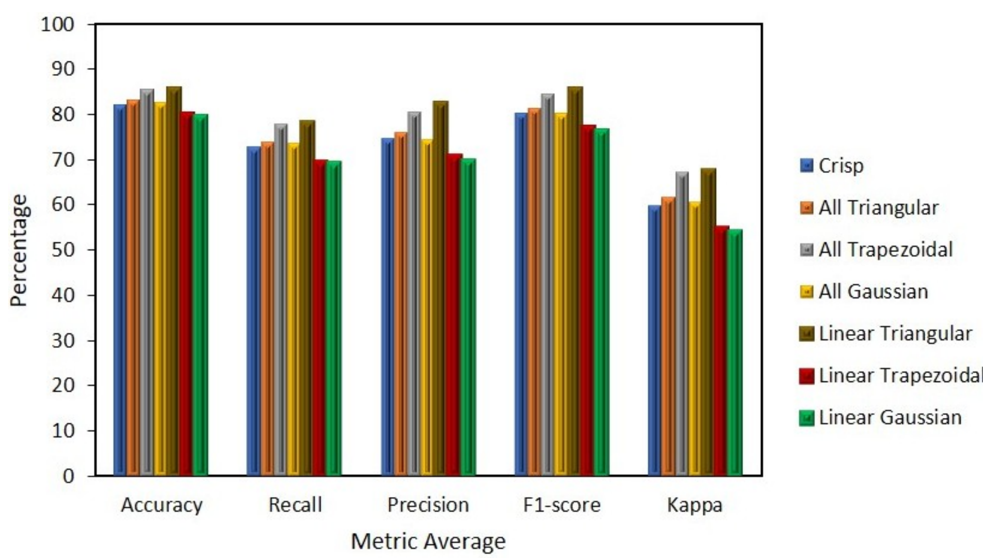

Figure 11. Model Performance Comparison of Seven Proposed DT

tion consisting of all trapezoidal (DT3) and all triangular fuzzy membership functions (DT2).

Only two decision tree models with fuzzy discretization have lower performance than decision tree models with crisp discretization in this work. Both DT models with combinations of linear-trapezoidal (DT6) and combinations of linear-Gaussian (DT7).

Statistical tests on the performance of the seven proposed decision tree models in the form of ANOVA and post hoc tests using Tukey-Cramer with thirty-five resampling as presented in Table 4 and Table 5, show significant differences in the seven proposed models based on five performance metric measures. The different model pairs based on each metric size as presented in Table 5, show that not all pairs of the proposed decision tree models with crisp or fuzzy discretization with similar patterns have different performances, but the major-

Table 4. ANOVA of Seven Proposed Models

Metrics	Source of Var.	Sum of Squares	Mean Squares	F	p-Value	F-Criteria
Accuracy	between	161.04	26.84	3.21	0.02	2.45
	within	234.44	8.37			
Recall	between	371.58	61.93	3.50	0.01	
	within	495.26	17.69			
Precision	between	644.77	107.46	6.43	0.00	
	within	467.78	16.71			
F1 score	between	345.96	57.66	5.42	0.00	
	within	297.94	10.64			
Kappa	between	829.49	138.25	3.17	0.02	
	within	1221.43	43.62			

Table 5. Ad Hoc Post-Test of DT Single Models

Models	Absolute Mean Difference				
Comparison	Accuracy	Recall	Precision	F1 score	Kappa
DT1 vs DT2	3.56	3.89	0.39	3.53	14.35
DT1 vs DT3	2.07	12.49	11.32	4.93	27.13
DT1 vs DT4	2.37	12.90	12.30	5.68	27.82
DT1 vs DT5	0.89	8.20	6.08	0.99	20.51
DT1 vs DT6	3.26	4.38	1.81	2.22	15.05
DT1 vs DT7	0.45	8.66	7.67	2.05	21.49
DT2 vs DT3	5.63	16.04	14.88	8.49	30.69
DT2 vs DT4	5.92	16.46	15.86	9.24	31.38
DT2 vs DT5	4.01	11.75	9.64	4.55	24.06
DT2 vs DT6	0.30	7.94	3.56	1.34	18.61
DT2 vs DT7	3.11	12.23	11.23	5.61	25.05
DT3 vs DT4	0.29	0.43	1.02	0.31	0.64
DT3 vs DT5	2.96	6.12	4.01	1.08	18.43
DT3 vs DT6	5.33	2.31	0.27	4.29	12.98
DT3 vs DT7	2.52	6.59	6.50	0.02	19.42
DT4 vs DT5	3.26	5.83	3.71	1.38	18.14
DT4 vs DT6	5.63	2.02	0.56	4.58	12.68
DT4 vs DT7	2.81	6.29	5.30	0.31	19.13
DT5 vs DT6	2.37	5.27	2.70	1.33	15.94
DT5 vs DT7	0.44	9.55	8.56	2.94	22.38
DT6 vs DT7	2.81	11.92	10.93	5.32	24.75

ity differ. Each performance metrics has a Q-critical of 2.18, 3.17, 3.08, 2.46, and 4.98 respectively. Based on this fact, the seven proposed models are different even though not all of their performance metrics are different. Of the six proposed decision tree models with fuzzy discretization, where the six models have symmetric patterns, four models perform better performance than the decision tree model with crisp discretization. This means that fuzzy discretization in the decision tree method can affect the performance of the decision tree model. However, the combination of fuzzy membership functions used can provide different performances.

4. CONCLUSIONS

A plastic sorting system that can sort plastic bottle waste types automatically, effectively, and efficiently requires a prediction model with good performance. This study has used the discretization in decision tree method for predicting plastic type in a sorting system, both crisp and fuzzy, especially symmetric pattern fuzzy discretization, namely the membership function for the first category and the last category forming a symmetric pattern. The results of the study show that there are significant differences in the seven proposed models based on five performance metric measures. Almost all decision tree models with fuzzy discretization with a symmetric pattern performance better than decision tree models with crisp discretization. Only two decision tree models with fuzzy discretization performance less than decision tree models with crisp discretization. Both models are a combination of linear trapezoidal and linear Gaussian combinations. The combination of fuzzy membership functions consisting of linear and triangular functions is the decision tree model that provides the highest performance.

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