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Research Paper

Ensemble Method of Multiple Decision Trees with Crisp and Fuzzy Discretization for Axial Surface Roughness Prediction

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Abstract
AISI 1045 is a steel used to make engine components for motor vehicles and aircraft. The quality of AISI 1045 is influenced by its surface roughness, both axial and tangential. The prediction of AISI 1045 surface roughness aims to produce quality products in a shorter time and at a lower cost. The axial surface roughness is in the form of certain grades according to ISO. This method is a prediction technique that combines several single prediction models to obtain better prediction results. In this work, the ensemble method is built using a voting system from an odd number of single prediction models of the decision trees. The proposed Single Model consists of one decision tree model with crisp discretization (DT1) and three models with fuzzy discretization (DT2, DT3, and DT4). The research data were obtained through experiments measuring the axial surface roughness of AISI 1045 steel using a wet machining system by considering cutting speed, feed motion, axial depth of cut, and tangential surface roughness. The study's results indicate that not all proposed ensemble models are built to have better performance than single prediction models. Of the four proposed single prediction models, only one model has an accuracy above 80%, namely the decision tree model with fuzzy discretization using a combination of linear-trapezoidal fuzzy membership functions (DT4 model). The model performance based on accuracy, recall, precision, F1-score, and AUC is 80.73%, 48.53%, 73.47%, 58.44%, and 67.72%, respectively. For the four ensemble models formed from the combination of three Single decision tree models, only the combination of DT1, DT2, and DT3 does not perform better than the Single model. The other three ensemble methods have better accuracy, recall, and AUC than the performance of all proposed Single models with values of 81.33 - 82.67%, 51.62 - 55.19%, and 69.04 - 71.02%, respectively.

Keywords
Decision Tree, Crisp and Fuzzy Discretization, Ensemble, Surface Roughness

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1. INTRODUCTION

The ensemble method is an approach in statistical machine learning that seeks the best prediction solution by combining several single prediction methods in one algorithm (Wang et al., 2022; Livieris et al., 2019) and then using an average or voting system depending on the purpose of the assignment (Karlos et al., 2020; Dutt et al., 2016). The ensemble method is one solution when a single method does not or has not been able to provide satisfactory performance (Zhao and Ye, 2024; Lu et al., 2023; Ganaie et al., 2022; Tinh and Mai, 2021). To obtain good ensemble method performance, it is sometimes necessary to improve the performance of a single method (Resti et al., 2024).

Discretization is a statistical technique that attempts to gather information by converting data from a ratio or interval scale to an ordinal or nominal scale (Resti et al., 2023; Chen and Huang, 2021; Roy and Pal, 2003). This method can also be employed to enhance the efficacy of prediction methods such as decision tree (Kresnawati et al., 2024; Altay and Cinay, 2016) or naive Bayes (Resti et al., 2023; Femina and Sudheep, 2020), especially fuzzy discretization which uses the Mathematical concept of set membership in the interval [0.1] to represent ambiguous class interval groups in the dataset (Resti et al., 2023). Decision trees do not require specific statistical assumptions, whereas naive Bayes has several statistical assumptions, so decision trees are more flexible in their application. The model performance has been significantly enhanced by the use of fuzzy discretization in prediction methods, which has been observed in a variety of disciplines of study, including health (Algehyne et al., 2022; Femina and Sudheep, 2020; Yazgi and Necla, 2015), agriculture (Resti et al., 2023; Chen and Huang, 2021), occupational safety (Fernández et al., 2022), and others. However, all of them are implemented in single prediction methods and generally use the same fuzzy membership function for all categories in each variable such as triangular function (Femina and Sudheep, 2020), trapezoidal (Algehyne et al., 2022; Yazgi and Necla, 2015), or Gaussian (Muludi et al., 2024). Several combinations of different fuzzy membership functions can also improve the performance of prediction models (Resti et al., 2023). The type and number of fuzzy membership functions used play a major role in obtaining model performance (Chen and Huang, 2021; Shanmugapariya et al., 2017).

High, robust, and stable prediction model performance is required in many industrial processes, including the AISI 1045 milling process in the manufacturing industry. In the current 4.0 era, the manufacturing industry is required to compete in improving product quality, manufacturing process speed, reducing production costs, safe production, and being environmentally friendly. AISI 1045 is a type of steel used to make engine components, in motor vehicles and aircraft. The quality of the AISI 1045 milling results is indicated by the quality of its surface roughness (Alajmi and Almeshal, 2021), while the milling process depends on the machining system involving coolant (Baldin et al., 2023) and machining parameters such as cutting speed, feed motion, and axial depth of cut (Qasim et al., 2015), cutting fluid (Alajmi and Almeshal, 2021), and tool wear (Woo and Lee, 2015).

The quality of AISI 1045 axial surface roughness will affect the machine element components' performance (Baldin et al., 2023; Alajmi and Almeshal, 2021). Low quality can reduce product efficiency and component service life, increase production costs, and shorten the remaining service life of the equipment. For this reason, a mathematical model that optimizes surface roughness needs to be built based on the machining system and machining factors or significant interactions between factors (Kandananond, 2021; Qasim et al., 2015). On the other hand, although experiments play a major role in obtaining optimal surface roughness, experiments are limited due to high costs and inefficiency (Dubey et al., 2022). For this reason, it is also necessary to predict AISI 1045 surface roughness with accurate results indicated by high, robust, and stable performance so that the demands of the manufacturing industry in the 4.0 era can be realized (Pimenov et al., 2017). We proposed an ensemble model of multiple decision trees with crisp and fuzzy discretization for axial surface roughness prediction in certain grades according to the International Standard Organization (ISO). One decision tree model with crisp discretization and three models with fuzzy discretization. Each of the last three models is created using a different combination of fuzzy membership functions. Factors considered in predicting axial surface roughness are cutting speed, feed motion, axial depth of cut, and tangential surface roughness where the machining system uses wet machining.

2. EXPERIMENTAL SECTION

In general, this research consists of two stages. The first stage is an experiment that measures the axial surface roughness of AISI 1045 milling results. The second stage is to predict the axial surface roughness of AISI 1045 using a statistical machine learning approach, in the form of an ensemble method. In the first stage, the experiment on the milling process was carried out using a wet machining system with Bromus liquid. Measurement of the axial surface roughness of AISI 1045 was carried out by setting the cutting speed, feed motion, and axial depth of cut on the OPTImill F 105 CNC milling machine. Tangential surface roughness can also be measured based on the experiment. The AISI 1045 used in this study has dimensions of 200×100×25 mm with a material hardness of 40-45 HRC. This high hardness and durability require a tool capable of cutting and has a low risk of wear. For this purpose, a coated end mill carbide tool is used, which has a hardness of 90-93 HRC, as given in Figure 1.

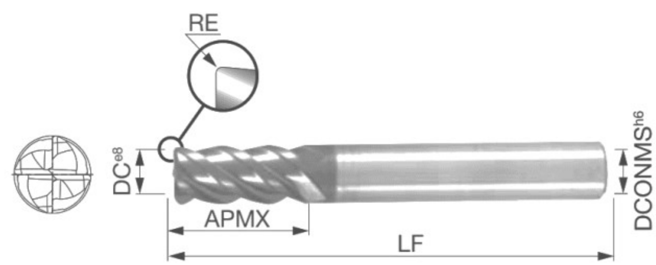

Figure 1. Coated End Mill Carbide

The cutting method used is the face milling process with a down-milling cutting direction. The surface roughness of the machined product was measured using the Handysurf Accretech E-35B instrument and a measurement pattern with an accuracy of 0.01 μm, a measurement length of 4 mm, and a cutoff of 0.8.

In the second stage, predictive modeling using the ensemble method is built from single models in the form of decision trees with crisp and fuzzy discretization. To transform data using the concept of crisp set theory, we postulated that the number of predictor variable classes indicates of prior knowledge or expert experience. Assume that X_d is the d-th independent variable of continuous type and has a value within an interval [min(x_d), max(x_d)]. The crisp discretization of x_d into m categories is achieved by identifying m pairs of lower and upper classes limit with an interval width of r(x_d) that do not intersect.The upper-class limit $u_1^c(x_d), u_2^c(x_d), u_3^c(x_d), \ldots, u_{m-1}^c(x_d), u_m^c(x_d)$ is the intersection points of the variable value, which is derived by (Resti et al., 2023):

Table 1. Research Variable

Independent Variable	Min	Q1	Mean	Q3	Max
Cutting speed m/min (V_c)	7.5	10	13.8	17.5	20
Feed motion mm/gear (f_z)	0.05	0.08	0.1	0.13	0.15
Axial depth of cut (a_x)	0.75	0.94	1.13	1.31	1.5
Tangential surface roughness at point 1 (Rt_1)	0.4	4.39	6.2	7.73	16.7
Tangential surface roughness at point 2 (Rt_2)	0.5	4.3	6.18	7.75	23.8
Tangential surface roughness at point 3 (Rt_3)	0.4	4.09	5.86	7.57	16.4
Tangential surface roughness at point 4 (Rt_4)	0.33	3.64	5.59	6.97	14.72
Tangential surface roughness at point 5 (Rt_5)	0.4	4.07	5.84	7.25	18.7
Tangential surface roughness at point 6 (Rt_6)	0.35	4.26	6.41	7.68	32.3
Dependent Variable					
Axial surface roughness μm (R_a)	Number of Samples for Each Grade				
	N_3	N_4	N_5	N_6	N_7
	2	17	44	52	5

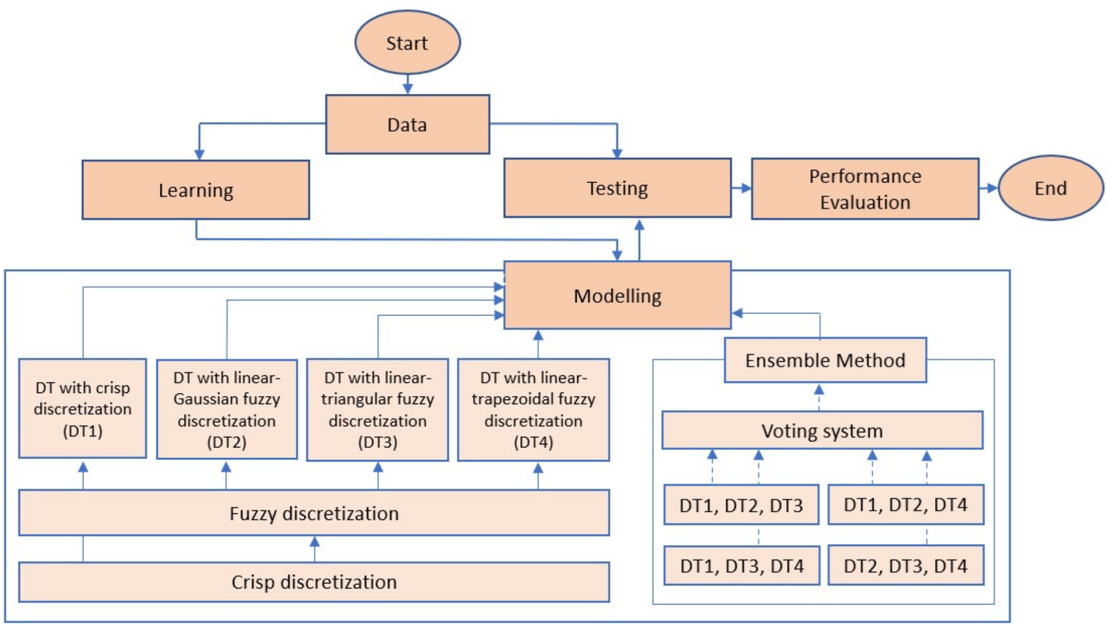

Figure 2. Ensemble Method of Multiple Decision Tree

$$
\begin{aligned}
u_1^c(x_d) &= \min(x_d) + r(x_d) \\
u_2^c(x_d) &= \min(x_d) + 2r(x_d) \\
u_3^c(x_d) &= \min(x_d) + 3r(x_d) \\
&\vdots \\
u_{m-1}^c(x_d) &= \min(x_d) + (m-1)r(x_d) \\
u_m^c(x_d) &= \max(x_d)
\end{aligned}
\tag{1}
$$

The width of the interval r is obtained by:

$$r(x_d) = \frac{\max(x_d) - \min(x_d)}{m} \tag{2}$$

The minimum value is the lower limit of the first class. The utmost value is the upper limit of the m-th class. The upper limit and the value of k, which is the magnitude of the gap between classes are used to determine the lower limits of the subsequent class up to the m-th class. This ensures that the class boundaries do not overlap (Resti et al., 2023),

$$
\begin{aligned}
l_1^c(x_d) &= \min(x_d) \\
l_2^c(x_d) &= u_1^c(x_d) + k \\
l_3^c(x_d) &= u_2^c(x_d) + k \\
&\vdots \\
l_{m-1}^c(x_d) &= u_{m-2}^c(x_d) + k \\
l_m^c(x_d) &= u_{m-1}^c(x_d) + k
\end{aligned}
\tag{3}
$$

To transform using the concept of fuzzy set theory, let X be the universal set, $\tilde{X}_d$ be the fuzzy set is obtained from X. The fuzzy set $\tilde{X}_d$ in the universal set X is defined as set of ordered pairs x_f and the fuzzy membership function $\mu_{x_d}(x_f)$ (Resti et al., 2023),

$$\tilde{X}_d = \{(x_f, \mu_{x_d}(x_f)) \mid x_f \in X\} \tag{4}$$

The fuzzy membership function $\mu_{\tilde{X}_d}(x_f)$ visualize the degree of membership of each given fuzzy set value $\tilde{X}_d$. This function is given as $\mu_{\tilde{X}_d}(x_f) : X \to [0, 1]$ where each element x_f of X is mapped to a value in the interval $[0, 1]$. Fuzzy membership functions can represent or combine all categories of input variables. Variations in the combination of these fuzzy membership functions can produce different performances (Kresnawati et al., 2024).

In this work, we proposed four combinations of the fuzzy membership functions in constructing the DTID3 single model which composes an ensemble model. Each combination consists of three membership functions representing the first to the third category. The first combination consists of fuzzy membership functions: decreasing linear, triangular, and increasing linear. The second and third combinations are similar to the first combination, but for the second category, the fuzzy membership functions are Gaussian, triangular, and trapezoidal, respectively.

Equations 5 and 6 provide the decreasing and increasing linear fuzzy membership function, separately. Let a and b be real numbers with a<b, the decreasing linear fuzzy membership function with two parameters, a,b, is represented by Resti et al. (2023) and Bhattacharyya and Mukherjee (2021),

$$\mu_{\tilde{X}_d}(x_f; a, b) = \begin{cases} 1, & x_f \le a \\ \frac{b-x_f}{b-a}, & a \le x_f \le b \\ 0, & x_f \ge b \end{cases} \tag{5}$$

The decreasing linear fuzzy membership function has also two parameters, a,b and represented by Resti et al. (2023) and Bhattacharyya and Mukherjee (2021),

$$\mu_{\tilde{X}_d}(x_f; a, b) = \begin{cases} 0, & x_f \le a \\ \frac{x_f-a}{b-a}, & a \le x_f \le b \\ 1, & x_f \ge b \end{cases} \tag{6}$$

Equations 7, 8, and 9 define the Gaussian, triangular, and trapezoidal fuzzy membership function, successively. A Gaussian fuzzy membership function with two parameters a,b, is written as in 8, where a is the mean (center) and b is the standard deviation (width) of the data (Muludi et al., 2024; Setiawan et al., 2020; Rutkowski, 2004),

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

Suppose a, b, and c are real numbers with $a<b<c$. The triangular fuzzy membership function with three parameters a,b,c, is written as Resti et al. (2023) and Rutkowski (2004),

$$\mu_{\tilde{x}_d}(x_f; a, b, c) = \begin{cases} 0, & x_f \le a \\ \frac{x_f-a}{b-a}, & a \le x_f \le b \\ \frac{c-x_f}{c-b}, & b \le x_f \le c \\ 0, & x_f \ge c \end{cases} \tag{8}$$

Let a b,c, and d are real numbers with $a<b<c<d$, the trapezoidal fuzzy membership function with four parameters, a,b,c,d, is presented as Resti et al. (2023) and Rutkowski (2004),

$$\mu_{\tilde{x}_d}(x_f; a, b, c, d) = \begin{cases} 0, & x_f \le a \\ \frac{x_f-a}{b-a}, & a \le x_f \le b \\ 1, & b \le x_f \le c \\ \frac{d-x_f}{d-c}, & c \le x_f \le d \\ 0, & x_f \ge d \end{cases} \tag{9}$$

The discretized data using both crisp set and fuzzy set membership concepts are then used to predict the axial surface roughness using a decision tree model. The fuzzy discretization parameters are obtained using a tuning system. The concept of the decision tree model is to break down the complex decision-making process into simpler ones based on information gain and entropy of predictor variables. Let S and S_c provide the total number of objects and the total number of objects in the c-category of the predictor variable X. P_c and P_{cf} be the prior probabilities of the c-th category of the predictor variable X, which are discretized using the crisp and the fuzzy sets, respectively. Equations 10 - 13 presents the information gain, the crisp entropy, the fuzzy entropy, and the fuzzy probability (Kresnawati et al., 2024).

$$\text{Information Gain}(S, X) = Entropy(S) - \sum_{c=1}^{k_X} \frac{|S_c|}{|S|} Entropy(S_c) \tag{10}$$

$$Entropy(S_c) = \sum_{c=1}^{k_X} -P_c \log_2 P_c \tag{11}$$

Table 2. Crisp and Fuzzy Discretization Parameter

Predictor variable of decision tree model	Category (m)		
	1	2	3
Crisp Discretization (DT1)	$[a, b]$	$[a, b]$	$[a, b]$
V_c	[0, 0.332]	[0.333, 0.666]	[0.667, 1]
f_z	[0, 0.332]	[0.333, 0.666]	[0.667, 1]
a_x	[0, 0.332]	[0.333, 0.666]	[0.667, 1]
Rt_1	[0, 0.332]	[0.333, 0.666]	[0.667, 1]
Rt_2	[0, 0.332]	[0.333, 0.666]	[0.667, 1]
Rt_3	[0, 0.332]	[0.333, 0.666]	[0.667, 1]
Rt_4	[0, 0.332]	[0.333, 0.666]	[0.667, 1]
Rt_5	[0, 0.332]	[0.333, 0.666]	[0.667, 1]
Rt_6	[0, 0.332]	[0.333, 0.666]	[0.667, 1]
Fuzzy Discretization using Linear-Gaussian Function (DT2)	$[a, b]$	$[\mu, \sigma^2]$	$[a, b]$
V_c	[0, 0.867]	(0.500, 0.118)	[0.833, 1]
f_z	[0, 0.667]	(0.525, 0.075)	[0.833, 1]
a_x	[0, 0.667]	(0.500, 0.140)	[0.833, 1]
Rt_1	[0, 0.667]	(0.241, 0.019)	[0.833, 1]
Rt_2	[0, 0.667]	(0.343, 0.017)	[0.833, 1]
Rt_3	[0, 0.667]	(0.364, 0.033)	[0.833, 1]
Rt_4	[0, 0.667]	(0.297, 0.022)	[0.833, 1]
Rt_5	[0, 0.667]	(0.199, 0.018)	[0.833, 1]
Fuzzy Discretization using Linear-Triangular Function (DT3)	$[a, b]$	$[a, b, c]$	$[a, b]$
V_c	[0, 0.567]	[0.233, 0.650, 0.857]	[0.833, 1]
f_z	[0, 0.517]	[0.258, 0.468, 0.917]	[0.833, 1]
a_x	[0, 0.667]	[0.233, 0.558, 0.967]	[0.833, 1]
Rt_1	[0, 0.767]	[0.333, 0.469, 0.957]	[0.913, 1]
Rt_2	[0, 0.767]	[0.383, 0.609, 0.957]	[0.913, 1]
Rt_3	[0, 0.747]	[0.508, 0.785, 0.947]	[0.873, 1]
Rt_4	[0, 0.867]	[0.343, 0.715, 0.937]	[0.873, 1]
Rt_5	[0, 0.667]	[0.333, 0.575, 0.417]	[0.833, 1]
Fuzzy Discretization using Linear-Trapezoidal Function (DT4)	$[a, b]$	$[a, b, c, d]$	$[a, b]$
V_c	[0, 0.567]	[0.283, 0.404, 0.525, 0.767]	[0.833, 1]
f_z	[0, 0.517]	[0.258, 0.423, 0.588, 0.917]	[0.833, 1]
a_x	[0, 0.667]	[0.233, 0.472, 0.705, 0.957]	[0.833, 1]
Rt_1	[0, 0.767]	[0.333, 0.479, 0.625, 0.957]	[0.913, 1]
Rt_2	[0, 0.767]	[0.383, 0.527, 0.670, 0.957]	[0.913, 1]
Rt_3	[0, 0.747]	[0.373, 0.509, 0.645, 0.947]	[0.873, 1]
Rt_4	[0, 0.747]	[0.408, 0.543, 0.678, 0.947]	[0.873, 1]
Rt_5	[0, 0.667]	[0.333, 0.554, 0.375, 0.417]	[0.833, 1]

$$Entropy(S_{cf}) = \sum_{c=1}^{k_X} -P_{cf} \log_2 P_{cf} \tag{12}$$

$$P_{cf} = \sum_{f=1}^{F} P_c \mu_{cf} \tag{13}$$

This model is nonparametric so it does not use any statistical assumptions generally related to prediction models. For examples normality, homogeneity, linearity, and so on.

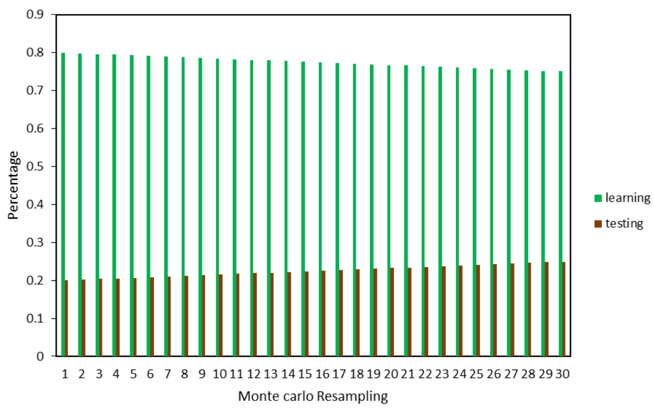

Figure 3. Monte Carlo Resampling

Each of the proposed models is then evaluated for its performance using metrics determined based on a confusion matrix for each class. Determining the model performance of AISI1045 surface roughness prediction for multiclass J, j=1,2 … , J based on accuracy, recall, precision, F1-score, and area under curve (AUC) values (Kresnawati et al., 2024; Sokolova and Lapalme, 2009), respectively, use Equations 14-18.

$$Accuracy = \frac{\sum_{j=1}^{J}(TP_j + TN_j)}{\sum_{j=1}^{J}(TP_j + FP_j + FN_j + TN_j)} \tag{14}$$

$$Precision = \frac{\sum_{j=1}^{J} TP_j}{\sum_{j=1}^{J}(TP_j + FP_j)} \tag{15}$$

$$Recall = \frac{\sum_{j=1}^{J} TP_j}{\sum_{j=1}^{J}(TP_j + FN_j)} \tag{16}$$

$$F_1 Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{17}$$

$$AUC = \frac{1}{2}\left(\frac{\sum_{j=1}^{J} TP_j}{\sum_{j=1}^{J}(TP_j + FN_j)}\right) + \frac{1}{2}\left(\frac{\sum_{j=1}^{J} TN_j}{\sum_{j=1}^{J}(TN_j + FN_j)}\right) \tag{18}$$

For the j-th surface roughness type, let true positives (TP_j) and true negatives (TN_j) be the proper prediction. False positives (FP_j) occur when an outcome is incorrectly predicted as the j-th surface roughness type when it is, in fact, not the j-th surface roughness type (negative). A false negative (FN_j) occurs when a result is incorrectly predicted as not the j-th surface roughness type when it is the j-th surface roughness type (positive).

We proposed an ensemble method of multiple decision trees, as described in Figure 2. The single prediction model consists of one DT model with crisp discretization (DT1) and three DT models with fuzzy discretization, each of which has a different combination of membership functions, namely linear-Gaussian (DT2), linear-triangular (DT3), and linear-trapezoidal (DT4). Linear in the last three models represents the functions used for the first and third categories, which are decreasing and increasing linear fuzzy membership functions respectively. In contrast, Gaussian, triangular, and trapezoidal each represent the second category in each model. Three of the four single prediction models are combined to build an ensemble method so that there are four ensemble models (Resti et al., 2024). The final prediction is obtained by integrating the predictions of these models through a voting system (Karlos et al., 2020).

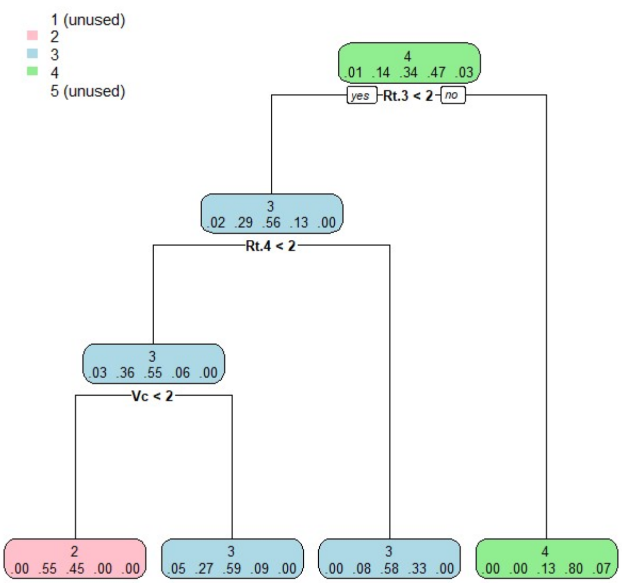

Figure 4. Surface Roughness Prediction Based on Crisp Discretization in Decision Tree

3. RESULTS AND DISCUSSION

3.1 Modeling of Surface Roughness

The data obtained in this study for both predictor (independent) and dependent variables are summarized in Table 1. The independent variables are machining factors and tangential surface roughness. The machining factors are cutting speed m/min (V_c), feed motion mm/tooth (f_z), and axial depth of cut (a_x). The dependent variable is axial surface roughness (R_a) is obtained in five grades according to International Standard Organization (ISO). The five grades are N_3 - N_7.

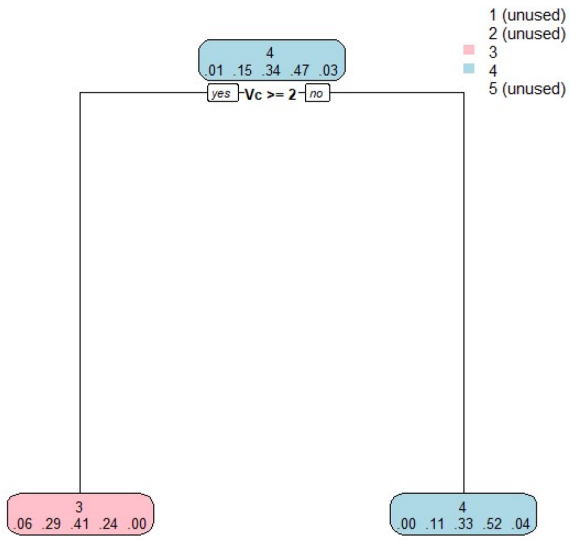

Figure 5. Surface Roughness Prediction Based on a linear-Gaussian fuzzy Discretization in Decision Tree

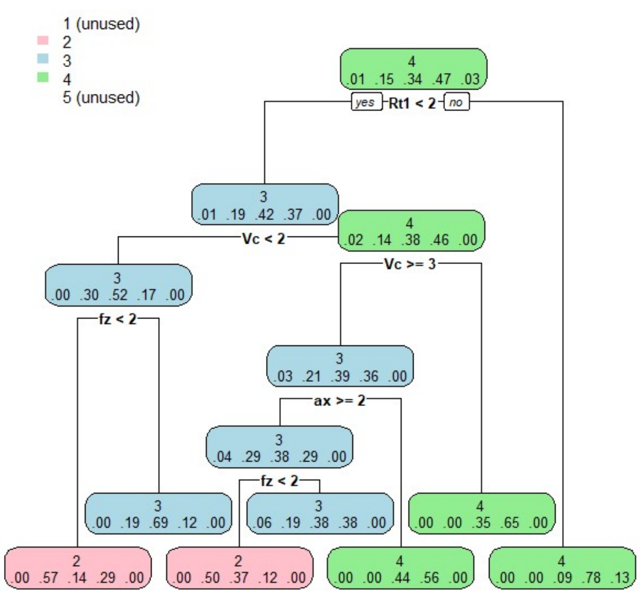

Figure 6. Surface Roughness Prediction Based on a Combination of Linear-Triangular Fuzzy Discretization in Decision Tree

The axial surface roughness is a universal standard for steel surface roughness. It is the arithmetic average of the absolute value of the distance between the measured profile and the center profile. The tangential roughness (Rt) is the distance between the reference profile and the base profile. Both axial and tangential surface roughness are taken at 6 points from each parameter variation.

In this work, each of the predictor variables is discretized into three categories with the assumption that each category represents a linguistic term of slow, moderate, fast (for V_c, f_z, and a_x), and smooth, moderate, and rough (for Rt_1 - Rt_6). The result of our proposed crisp and fuzzy discretization is given in Table 2. The parameters of each fuzzy discretization are obtained through system tuning.

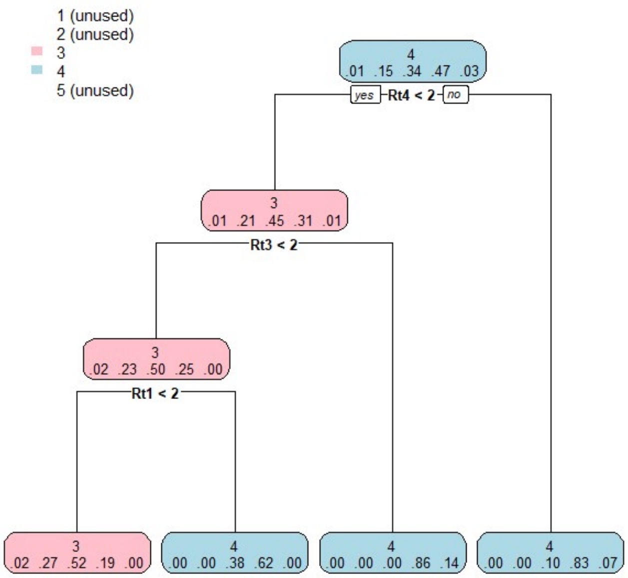

Figure 7. Surface Roughness Prediction Based on a Combination of Linear-Trapezoidal Fuzzy Discretization in Decision Tree

In this work, we create multiple datasets randomly thirty times based on Monte Carlo resampling as presented in Figure 1. The composition of learning and testing data used have a ratio between 0.75 – 0.8 and the rest, 0.20 – 0.25 (Resti et al., 2023). Research Kresnawati et al. (2024) and Resti et al. (2023) shows that the performance of a model from a sampling based on the same holdout can produce different performance. This occurs due to random sampling, therefore sampling based on the Monte Carlo concept is needed (Figure 3).

The modeling results using crisp sets and fuzzy sets are given in a tree diagram that displays the splits and rules in generating surface roughness-type predictions. Although the dataset has five classes, the random division of learning data and testing data means that not all learning data contains all classes of surface roughness in the dataset. For the decision tree model with crisp discretization, the tree diagrams based on the first Monte Carlo resampling are presented in Figure 4.

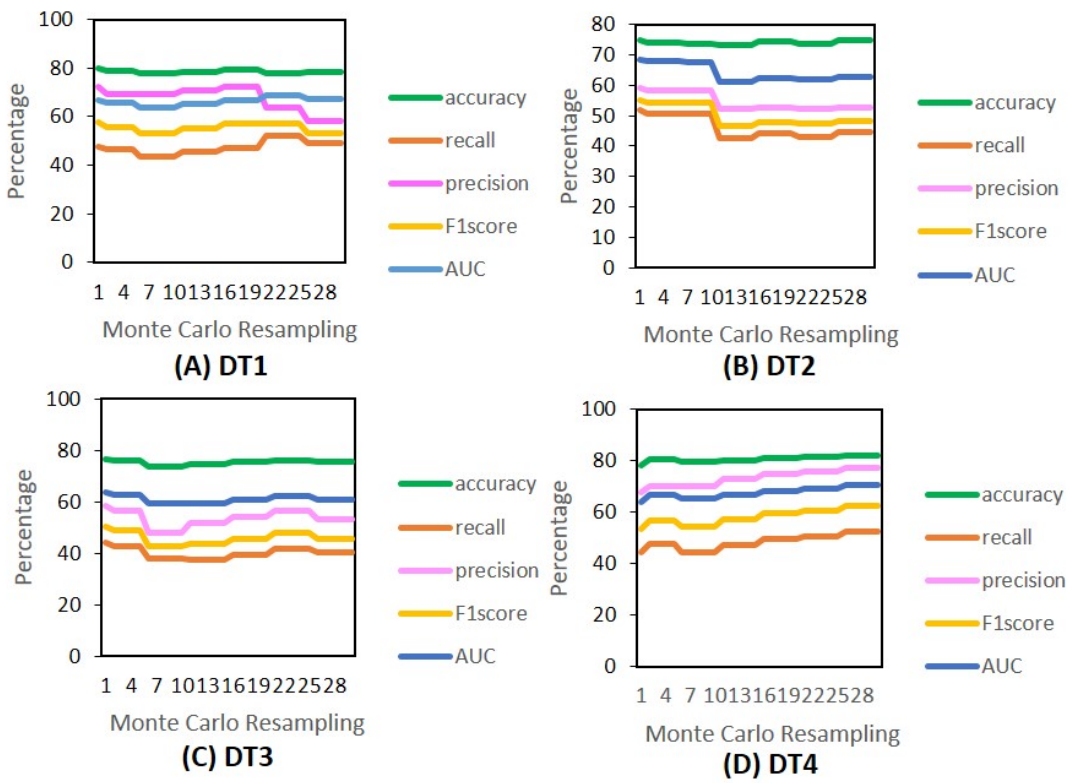

Figure 8. Performance of Single DT models

As shown at the root node in Figure 4, the initial distribution of observations in each class in this first resampling of Monte Carlo has probabilities of 0.01, 0.14, 0.34, 0.45, and 0.03, respectively for the first to fifth classes. The model in Figure 2 shows that only three classes of surface roughness of AISI 1045 are involved in the modeling, namely the second, third, and fourth classes, while the first and fifth classes are not involved. This incident occurs because the class has a very small number of observations, so in the model built, the observations are not distributed across the class. In this model, the important variables are Rt_3, Rt_4, and V_c where Rt_3 is the root node. The observation predictions into classes of surface roughness based on the predictor variables are built based on three splits and four rules, where the observations predicted into the second and fourth classes each have one rule, while the third class has two rules.

The four rules are presented below:
Rule 1: If Rt_3<2, and Rt_4<2, and V_c<2, then the observation is predicted into class 2 (grade N_4).
Rule 2: If Rt_3<2, and Rt_4≥2, then the observation is predicted into class 3 (grade N_5).
Rule 3: If Rt_3<2, and Rt_4<2, and V_c≥2, then the observation is predicted into class 3 (grade N_5).
Rule 4: If Rt_3≥2, then the observation is predicted for class 4 (grade N_6).

The tree diagram for the decision tree model with a linear Gaussian fuzzy discretization, which is based on the initial Monte Carlo resampling, is illustrated in Figure 5.

The model in Figure 7 shows there are only two classes of surface roughness of AISI 1045 involved in the modeling, third and fourth classes. The important variable of this model is V_c, that is the root node. The observation has one split and two rules, the observations are predicted into the two and third classes. The third class has one rule, while the fourth class has three rules.

The four rules are presented below:
Rule 1: If V_c≥2, then the observation is predicted into class 3 (grade N_5).
Rule 2: If V_c<2, then the observation is predicted for class 4 (grade N_6).

Figure 6 illustrates the tree diagram for the decision tree model with linear-triangular fuzzy discretization, which is predicated on the initial Monte Carlo resampling. Each Monte Carlo resampling of each model has the initial distribution of observations in each class including the first resampling. In this work, the largest to the smallest probability is owned by the fourth, third, second, fifth, and first classes respectively. The model in Figure 5 also shows there are only three classes of surface roughness of AISI 1045 involved in the modeling, namely the second, third, and fourth classes since the fifth and first classes have a very small number of observations and are not included in the observations involved in the model. In this model, the important variables are Rt_1, V_c, f_z, and a_x where Rt_1 is the root node. The observation has six splits and seven rules, the observations predicted that the second and third classes each have two rules, while the fourth class has three rules.

The seven rules are presented below:
Rule 1: If Rt_1<2, and V_c≥3, and f_z<2, and a_x≥2, then the observation is predicted into class 2 (grade N_4).
Rule 2: If Rt_1<2, and V_c<2, and f_z<2, then the observation is predicted into class 2 (grade N_4).
Rule 3: If Rt_1<2, and V_c≥3, and f_z≥2, and a_x≥2, then the observation is predicted into class 3 (grade N_5).
Rule 4: If Rt_1<2, and V_c<2, and f_z≥2, then the observation is predicted into class 3 (grade N_5).
Rule 5: If Rt_1<2, and V_c≥3, and a_x<2, then the observation is predicted for class 4 (grade N_6).
Rule 6: If Rt_1<2, and V_c=2 to 3, then the observation is predicted into class 4 (grade N_6).
Rule 7: If Rt_1≥2, then the observation is predicted for class 4 (grade N_6).

Table 3. Average Performance of Single DT Models

Single Model	Accuracy	Recall	Precision	F1 score	AUC
DT1	78.50	47.36	67.25	55.39	66.28
DT2	74.02	46.02	54.42	49.87	64.05
DT3	75.34	40.05	53.48	45.79	61.10
DT4	80.73	48.53	73.47	58.44	67.72

For the decision tree model with linear-trapezoidal fuzzy discretization, the tree diagram based on the first Monte Carlo resampling is presented in Figure 7.

The model in Figure 7 shows there are only two classes of surface roughness of AISI 1045 involved in the modeling, third and fourth classes. The important variables of this model are Rt_1, Rt_3, and Rt_4, where Rt_4 is the root node. The observation has three splits and four rules, the observations are predicted into the third and fourth classes. The third class has one rule, while the fourth class has three rules. The four rules are presented below:
Rule 1: If Rt_4<2, and Rt_3<2, and Rt_1<2, then the observation is predicted for class 3 (grade N_5).
Rule 2: If Rt_4<2, and Rt_3<2, and Rt_1≥2, then the observation is predicted for class 4 (grade N_6).
Rule 3: If Rt_4≥2, then the observation is predicted for class 4 (grade N_6).
Rule 4: If Rt_4<2, and Rt_3≥2, then the observation is predicted for class 4 (grade N_6).

3.2 Model Performance of Surface Roughness Prediction

The performance of the surface roughness prediction model with the Monte Carlo resampling technique using each of the single DT models is presented in Figure 8.

The average and standard deviation of the performance of the four single DT models are presented in Table 3 and Table 4.

Table 4. The Standard Deviation of The Performance of The Single DT Models

Single Model	Accuracy	Recall	Precision	F1 score	AUC
DT1	0.63	2.89	5.00	0.56	1.73
DT2	0.47	3.59	2.88	2.09	3.31
DT3	0.99	2.01	2.98	0.70	2.33
DT4	1.00	2.72	2.87	1.08	2.84

Based on the seven performance measures in Table 2, it can be seen that the average performance of the DT4 model provides the highest value. Further exploration is needed to obtain surface roughness prediction performance.

Table 3 shows that the models that have the lowest standard deviation for average accuracy, recall, precision, F1 score, and AUC are DT2, DT3, DT4, DT1, and also DT1 for F1 score, respectively. None of the models have the lowest standard deviation for all performance metrics. Likewise for the highest standard deviation. Further exploration is needed to obtain surface roughness prediction performance with a standard deviation that is inversely proportional to its performance. The single method or model that composes the ensemble model must be a different method or model. Table 4 and Table 5 present statistical tests to support their use in building ensemble models.

ANOVA as presented in Table 4 shows that with a 5% error rate, all four proposed single DT prediction models are significantly different. Exploration related to the details of which pairs of prediction models are different including the measured metrics is presented in Table 5.

With critical Q values of 0.57, 2.01, 2.5, 0.88, and 1.84 respectively for accuracy, recall, precision, specificity, and F1 score, Table 5 strengthens the evidence that the four proposed Single DT prediction models differ in all performance metrics, except precision in the DT with fuzzy discretization model. However, in the multiclass case for surface roughness prediction, the F1 score metric is more important than precision, because the F1 score balances the false negative and false positive values in each class. The statistical test also informs that there is a significant performance improvement from the DT1 model to the DT4 model.

For ensemble model performance of the four single predictions for surface roughness prediction is given in Table 7. It shows that the ensemble model of all proposed DT with fuzzy discretization (DT2, DT3, and DT4) has the highest value on all metrics considered in measuring model performance, so it is decided that the ensemble model of all proposed DT with fuzzy discretization (DT2, DT3, and DT4) is the best.

The prediction methods proposed in this paper, both single

Table 5. ANOVA of DT Single Models

Metrics	Source of Var.	Sum of Squares	Mean Squares	F	p-Value	F-Criteria
Accuracy	between	832.86	277.62	428.61	1.41×10^{-62}	
	within	75.14	0.65			
Recall	between	1277.40	425.80	52.12	2.08×10^{-21}	
	within	947.62	8.17			
Precision	between	8673.25	2891.08	229.36	1.36×10^{-48}	2.68
	within	1462.17	12.60			
F1 score	between	2864.44	954.81	139.17	2.81×10^{-38}	
	within	795.86	6.86			
AUC	between	749.98	249.99	62.06	5.22×10^{-24}	
	within	467.28	4.03			

Table 6. Ad Hoc Post-Test of DT Single Models

Models Comparison	Absolute Mean Difference				
	Accuracy	Recall	Precision	F1 score	AUC
DT1 vs DT2	4.49	32.48	24.08	28.64	14.46
DT1 vs DT3	3.17	38.85	25.02	32.71	17.41
DT1 vs DT4	2.23	29.97	5.03	20.06	10.78
DT2 vs DT3	1.32	39.66	0.54	28.22	12.92
DT2 vs DT4	6.72	25.48	0.55	15.57	6.29
DT3 vs DT4	4.49	26.80	1.87	16.89	7.62

methods involving crisp or fuzzy discretization, and ensemble methods built from combinations of single methods, do not require certain statistical assumptions such as normality, homogeneity, linearity, or others so that they are nonparametric types. It's just that to carry out the discretization process, the predictor variables must be of numeric type. These methods can be implemented for all cases or materials, there are no restrictions related to dataset size. In statistical machine learning, the generalization of model performance for small sizes can be handled using bootstrap resampling, of them. By using a prediction model that uses a statistical machine learning approach as proposed in this work, it is expected to save time and costs compared to traditional methods.

Table 7. Ensemble Performance of Multiple Decision Tree

Ensemble Model	Accuracy	Recall	Precision	F1 score	AUC
DT1, DT2, DT3	73.33	35.22	36.79	35.90	58.02
DT1, DT2, DT4	82.64	51.62	53.72	52.56	69.62
DT1, DT3, DT4	81.33	51.62	56.29	53.86	69.04
DT2, DT3, DT4	82.67	55.19	53.97	54.57	71.02

4. CONCLUSIONS

This paper predicts the axial surface roughness of AISI 1045 steel using ensemble methods. Four single prediction models are proposed, one decision tree model with crisp discretization (DT1) and three decision tree models with fuzzy discretization (DT2, DT3, and DT4). The ensemble method is then built from the combination of three single decision tree prediction models because the final prediction system uses a voting system. The results of this study indicate that not all proposed ensemble models are built to have better performance than the performance of single prediction models. For the four ensemble models formed from the combination of three single decision tree models, only the combination of DT1, DT2, and DT3 did not perform better than the single model. The other three ensemble methods had better accuracy, recall, and AUC than all the proposed single models with values of 81.33 - 82.67%, 51.62 - 55.19%, and 69.04 - 71.02%, respectively. Thus, the research objective has been achieved, although the performance improvement has not covered all metrics. Further research needs to explore different types and combinations of fuzzy membership functions with different numbers of categories as prediction methods. For the axial surface roughness level of AISI 1045, it is also necessary to explore other machining systems such as minimum quantity lubrication (MQL).

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