Fuzzy and Machine Learning based Multi-Criteria Decision Making for Selecting Electronics Product

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Abstract

INTRODUCTION: In this study, we have considered electronics product as laptop one of the essential items in digital era. The decision-making and buying processes for laptops are time consuming and fraught with competing priorities.
OBJECTIVES: Through a questionnaire that provided them with many choices for the newest features and essential components they desire in their devices, the participants' replies were sought.
METHODS: The participants' responses were elicited from eighteen independent input variables: processor, ram capacity, gpu, graphics card, laptop brand, type of storage, storage size, ports, screen size, backlit keyboard, pc body, category, screen display, weight, webcam, battery life, operating system, and price range. Each of the input variables was quantified using a scale using the terms very low, low, medium, high, and very high.
RESULTS: Five input and one output processes were designed using the Mamdani technique, a conventional fuzzy reasoning tool (FLC). Furthermore, machine learning is used to pick and purchase laptops using a variety of strategies.
CONCLUSION: To arrive at a more precise knowledge of the procedure for choosing a laptop in accordance with the user's requirements, standard fuzzy systems were employed.

Keywords: ML Models, Fuzzy reasoning tool; FLC, Multi-criteria decision making (MCDM)

Received on 17 May 2023, accepted on 25 July 2023, published on 04 July 2023

doi: 10.4108/eetsis.3353

1. Introduction

It is conceivable to consider decision-making as the cognitive procedure that results in the selection of a point of view or a course of action from a variety of feasible alternatives. Finding and choosing choices in accordance with the decision-values maker's and preferences is the subject of this research. Multi-criteria decision-making (MCDM), where each choice is evaluated based on a range of criteria or characteristics, is a procedure for identifying the best option out of all potential possibilities [1]. It describes the procedure of assessing, ranking, or selecting a group of alternatives in light of a variety of frequently distinct, conflicting, or competing criteria [7].

The current situation in India and around the world has become more difficult as a result of the intense competition among laptop manufacturing businesses, which often release new models and upgrade existing ones. Laptops are offered at a range of prices, from high to cheap, with the inclusion of a few additional features that often change from one edition to another. Most laptop-manufacturing businesses prioritize increasing their earnings, and in order to do so, they offer new versions of their products with new features. When new technology is adopted, expenses rise dramatically, which makes it challenging for consumers to choose from the wide range of alternatives available. As a result, it's crucial to use

a process when picking the best laptop with the necessary characteristics from the range of options on the market. The difficulty of creating a laptop that meets the needs of the consumer and increases his pleasure is one that designers and manufacturing businesses confront in addition to that of the customers. The selection of an appropriate laptop for the common people is multi-criteria decision-making.
(MCDM) problem and so it is for the entire laptop industry as it involves many input/output criteria and alternatives [4].

This paper makes an effort to comprehend the thought processes that go into selecting a laptop. The paper is structured as follows: the introduction is followed by a review of the literature on MCDM, the following part discusses data collecting, and Section 4 elaborates on the approach used in this study. The report concludes with closing observations and offers guidance for further research in the last part, which also discusses the outcomes of various methodologies.

2. Related Work

To find the optimal model for the right problem, MCDM approaches were assessed using a variety of models, including analytical hierarchy process (AHP), analytical network process (ANP), technical for order preference by similarity to the ideal solution (TOPSIS), and fuzzy sets [4].

AHP plays a significant role in the DM process since it maintains procedural logic. Furthermore, it claims that AHP and human behaviour in DM are highly similar, and that the pair-wise comparison makes sure that all options are considered in order to get the optimal results. This evidence is further supported by Chen's (2005) suggestion that AHP may be utilised for both qualitative and quantitative elements because it offers the best choice based on the criteria [11]. ANP is an intuitive and straightforward model. In comparison to AHP, it is more flexible in how it solves complicated problems that call for a lot more math. ANP only has a few valid/useful applications because of how difficult and time-consuming it is to utilise it. ANP, in contrast to AHP, takes into account the interdependence of the criteria and options, producing more accurate findings. Olsen suggested TOPSIS in 2004 and claimed that it can find the optimal alternative while requiring less subjective input than some other MCDM techniques. TOPSIS provides a superior answer to another model in some circumstances. Although only in a restricted sense, TOPSIS appears to be an efficient way for addressing the MCDM issue. However, it makes use of certain subjective data that might skew the findings. For inconsistent data, none of the MCDM problem-solving strategies work [2]. According to Saaty (2007c), users now utilise fuzzy sets to identify the type of data. The least consistent method is fuzzy, AHP is constant in contrast. It is difficult to simulate any decision-making process including several factors and human judgment. Professional judgments that are frequently based on incomplete information are used to make decisions. Making choices with shaky data and using subjective judgment are both appropriate uses of machine learning [2].

3. Method

3.1. Participants

Participants in this study included graduate and postgraduate engineering students, management students, and research scholars from the VIT-AP University in Amravati, Andhra Pradesh, India, who were all between the ages of 17 and 29 (males: 336 (80.4418%), age = 24.08 years; females: 82 (19.6%), age = 23.24 years. With the head warden of the hostel's consent, the study was carried out on the hostel premises. The individuals were made aware of the chance to participate in a study including a competitive analysis of laptops prior to their involvement. Participants in this study were individuals who completed an informed consent form after being asked for their consent.

3.2. Selection under linguistic variable

The questionnaires consisted of eighteen input variables such as processor, RAM capacity, GPU, Graphics card size, Brands, types of storage, storage size, ports, screen size, backlit keyboard, pc body, price range, category, screen display, weight, webcam, battery life, Operating system, and output variable as select or not select as per the individual choice of the participants were prepared. Each input parameter was expressed in linguistic variables like low, medium, and high. The participants were asked to give opinions while making their choice.

3.3. Measuring the variables

The participants were asked to select their preferred alternative for each problem by checking the box next to it. After compiling the questionnaires, we assessed the participant's responses to each issue based on the ranges and values given for the variables of processor, ram capacity, GPU, Graphics card size, laptop brand, types of storage, storage size, ports, screen size, backlit keyboard, pc body, price range, category, screen display, weight, webcam, battery life, Operating system, price range. Each dimension was evaluated on a one-point scale, with "0" denoting the dimension's lowest value and "1" denoting its maximum value. We assessed the 418 participant options.

4. Fuzzy rule-based systems

Fuzzy rule-based systems primarily consist of an inference engine (IE) and a knowledge base (KB) (FRBS). The representation of knowledge can take several forms. Perhaps the most typical approach to communicate human understanding is through the use of natural language. The IE, which implements the fuzzy inference process, is required to derive an output from the FRBS when an input is supplied. The KB typically contains the knowledge about the issue being solved in the form of fuzzy linguistic IF-THEN rules. The IF-THEN rule-based form, which uses the IF premise (antecedent), THEN conclusion (consequence) parameters, is the name given to this type of expression. Figure 1 depicts the FRBS in schematic form.

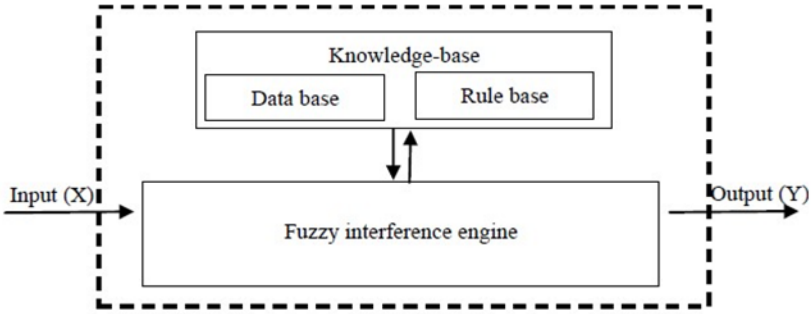


Figure 1. A schematic view of an FRBS

Fuzzification, inference, and defuzzification are the three components of a FRBS. The process of "fuzzification" transforms the input parameters into the necessary fuzzy sets to convey measurement uncertainty. The IE then assesses the control rules kept in the fuzzy rule base using the fuzzified measurements, and a fuzzified output is produced. The output that has been fuzzified is subsequently transformed into a single crisp value. Defuzzification is the term for this transformation [26,27].

4.1. Membership functions and fuzzy linguistic variables

A methodical manner to express linguistic variables in a process of natural assessment is offered by the fuzzy linguistic approach [14]. A fuzzy number, which is represented by a fuzzy set, may be used to express a fuzzy linguistic label [16]. The capacity to manage uncertainty using approximation techniques is captured by fuzzy sets [14].

A fuzzy set α is represented by a pair of two things – the first one is the element x and the second one is its membership value $\mu_\alpha(x)$ (varying in the range of [0, 1]), as given below.

$$\alpha=\{(x,\mu_\alpha(x)):x\in X\} \qquad (1)$$

In order to keep the design of the FLCs straightforward, triangular membership functions were chosen for the inputs and output. Figure 2 illustrates the utilisation of a degree of two overlapping. Additionally, a discourse universe with a normalised range of [0.0, 1.0] was used. The grade of membership of the element in X to the fuzzy set A is quantified by this value, often known as the membership value or degree of membership (as provided below).

$$\mu_A(x)=\begin{cases}0, & x\le a\\ \frac{x-a}{m-a}, & a<x\le m\\ \frac{b-x}{b-m}, & m<x<b\\ 0, & x\ge b\end{cases} \qquad (2)$$

Here, the numbers a, b, and m are real. This formula uses m as the median value of A and uses b and a, as the upper and lower limits of A's support, respectively.

4.2. Membership functions and fuzzy linguistic variables

The input fuzzy variables were V1 = {processor}, V2 = {Ram capacity} and V3 = {GPU}, V4 = {Graphics card}, V5 = {Laptop Brand}, V6 = {Storage type}, V7 = {Storage size}, V8 = {Ports}, V9 = {Screen Size}, V10 = {Backlit}, V11 = {PC Body}, V12 = {Category} V13 = {Screen Display}, V14 ={Weight}, V15 = {Webcam}, V16 = {Battery Life}, V17 = {Operating System}, V18 = {Price Range} and each of them was represented using three linguistic terms, such as Very Low (VL), Low (L), Medium (M), High(H), and Very High (VH) the linguistic terms and their ranges are shown in Figure 2.

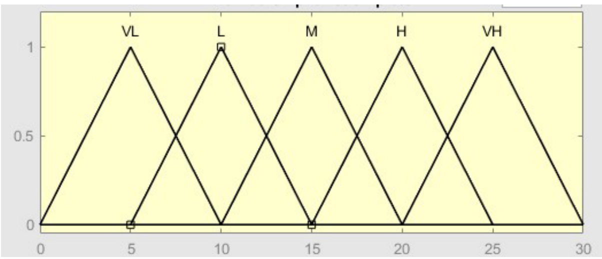


Figure 2. Input variables ‘processor’, ‘ram capacity’, ‘gpu’, ‘graphics card’, ‘laptop brand’, ‘storage type’, ’storage size’, ‘ports’, ‘screen size’, ‘backlit’, ‘pc body’, ‘category’, ‘screen display’, ‘weight’, ‘webcam’, ‘battery life’, ‘operating system’, ‘price range’

Table 1 Linguistic terms and their ranges for the variables: V1 = {processor}, V2 = {Ram capacity} and V3 = {GPU}, V4 = {Graphics card}, V5 = {Laptop Brand}, V6 = {Storage type}, V7 = {Storage size}, V8 = {Ports}, V9 = {Screen Size}, V10 = {Backlit}, V11 = {PC Body}, V12 = {Category} V13 = {Screen Display}, V14 ={Weight}, V15 = {Webcam}, V16 = {Battery Life}, V17 = {Operating System}, V18 = {Price Range}

Linguistic terms	Membership function	Range of parameter
Very Low (VL)	Trimf	[0 , 10]
Low (L)	Trimf	[5, 15]
Medium (M)	Trimf	[10, 20]
High (H)	Trimf	[15, 25]
Very High (VH)	Trimf	[20, 30]

4.3. Description of fuzzy output variable

Two linguistic terms, namely select and not-select were used to represent the output variable: V8 = {output as a decision} (refer to Figure 3). The Mamdani min-operator was utilised for aggregation and defuzzification was done using the centre of the sums (COS) method [15].

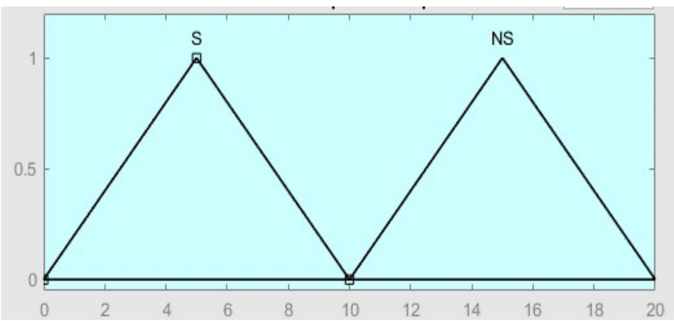


Figure 3. Membership function distributions for output fuzzy variable: V8 = {select/non select}

4.4. Establishing the fuzzy rule basis using the input and output variables

The FRBS's fundamental building blocks—called rules—represent the connections between its inputs and outputs. In the current issue, eighteen input factors were taken into account, and each of them was described by four or five linguistic elements. The FRBS might therefore contain as many regulations as possible.
We created 1672 fuzzy rules for this research.
One example of the first and last rules is as follows:

IF V_1 is Ryzen AND V_2 is H AND V_3 is M AND V_4 is AMD AND V_5 is Lenovo AND V_6 is SSD V_7 is M AND V_8 is TUHL AND V_9 is VH AND V_{10} is Y AND V_{11} is Plastic AND V_{12} is Gaming V_{13} is LED AND V_{14} is M AND V_{15} is Y AND V_{16} is H AND V_{17} is Windows AND V_{18} is H
THEN output is Select.

Similarly,
IF V_1 is Intel AND V_2 is M AND V_3 is VL AND V_4 is Nvidia AND V_5 is Hp AND V_6 is Both V_7 is H AND V_8 is TUHL AND V_9 is VH AND V_{10} is Y AND V_{11} is Plastic AND V_{12} is Gaming V_{13} is LED AND V_{14} is H AND V_{15} is Y AND V_{16} is L AND V_{17} is Windows AND
V_{18} is H
THEN output is Select.

5. Traditional FLC's functioning model (Mamdani method) [2]

An FLC is made up of a collection of regulations stated as IF (a set of criteria are met) After which (a set of consequences can be prepared). Here, the consequent is a control action for the system under control, and the antecedent is a condition in its application area. Some language words are used to express the IF-THEN rules' antecedents and consequents. Fuzzification is required since the inputs to FRBSs should be provided by fuzzy sets rather than crisp inputs. Additionally, the output of an FLC always produces a fuzzy set, therefore a defuzzification technique must be applied to obtain the matching crisp value. The following steps are involved in the fuzzification of input variables:

a) Evaluate each input variable.
b) carries out a scale mapping, which converts the input variable ranges' values into matching worlds of discourse.
c) carries out the fuzzification function, which transforms input data into appropriate linguistic values, which may be thought of as the label of fuzzy sets.

By utilising the data from the database, the rule base includes understanding of the application domain. In order to create the control rules incorporating language words, the database therefore offers the essential data. Utilizing a set of language control rules, the rule base specifies the domain experts' control objectives and policies.
An FLC's IE is capable of emulating human decision-making based on fuzzy ideas and deducing fuzzy control actions using fuzzy implications and rules. The crisp value corresponding to the fuzzified output is obtained using a defuzzification technique. This study used the COS technique of defuzzification, which is described below.

$$U'_{f'} = \frac{\sum_{j=1}^{P} A(\alpha_j) \times f_j}{\sum_{j=1}^{P} A(\alpha_j)} \tag{3}$$

where $U'f'$ is the output of the controller, A (α) represents the firing area of j^{th} rule, p is the total number of fired rules and fj represents the centre of the area.

6. Results and discussions

The results of FLC method is stated and discussed as follows.

6.1. Results of FLC

The conventional fuzzy reasoning tool was created with 18 inputs, including the processor, RAM capacity, GPU, Graphics card size, laptop brand, types of storage, storage size, ports, screen size, backlit keyboard, pc body, price range, category, screen display, weight, webcam, battery life, Operating system, and price range, each with four or five different responses (that is, very low, low, medium, high, very high). As indicated in Appendix A, a set of 1672 rules were manually created.
The outcome of this approach reveals that when choosing a laptop, factors such as weight, CPU, operating system, battery life, brand, storage space, ports, screen size, screen display, and body are crucial [refer to Figures 4(a) to Figure 4(l)].

7. ML Models

A model is built using machine learning, a data science approach, using training data. In its simplest form, a model is a formula that generates a goal value based on unique weights and values for each training variable. Each variable's matching weights in each record indicates the model of how that variable relates to the goal value (often between 0 and 1). To choose the most optimal weights for each variable, there must be enough training data. A model may predict the proper output, or the target value given a test data record when the weights are learned with the greatest degree of accuracy.

7.1. Machine Learning Techniques

The outcomes that are anticipated in this research are categorical values.
Our analytical methods include Artificial Neural Network (ANN), K-Nearest Neighbour (KNN), Logistic Regression, Support Vector Machine (SVM), Random Forest Regression (RFR), Decision Tree, Naive Bayes classifier, and XG Boost.

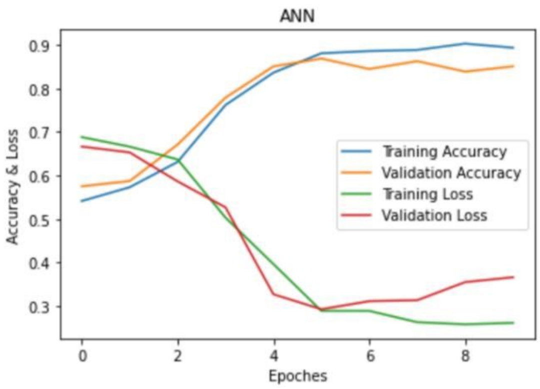
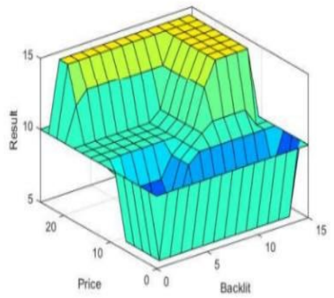


Figure 5. Performance of ANN Model

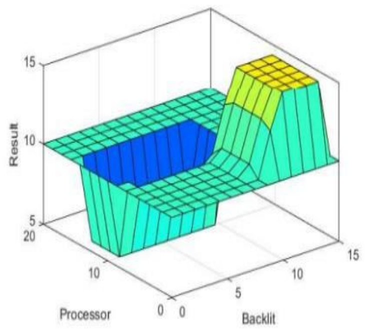
8. Conclusions

In this research, we use a fuzzy reasoning tool system based on the Mamdani technique to analyse the procurement of laptops for information processing during DM. In order to identify the input-output linkages of this process, which is based on human observations and experiences, typical fuzzy reasoning techniques built based on the Mamdani method were utilised. Our focus has been on a novel perspective on fuzziness in information processing. In addition to fuzzy, we demonstrated a machine learning-based system for laptop selection. Intelligent models may be produced by machine learning technology and are significantly more straightforward than conventional physical models. They are easier to operate on practically any computer, including mobile ones, and are less resource-hungry. Our assessment findings demonstrate the usefulness of these machine-learning models to find the desired laptop with the required components.

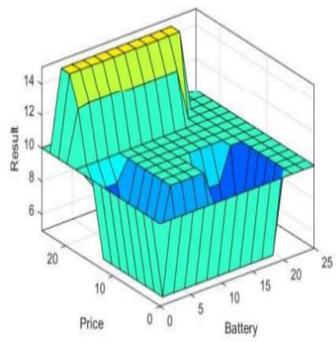
The computational complexity of the developed methodologies was not explored in this research, although it may be in the future. In addition, 18 input parameters were included in this study as independent factors; however, future research may incorporate other input components. In such cases, the number of parameters and size of the classification model would increase. The procedure will be made even simpler by attempting to enhance the effectiveness and precision of machine learning models.



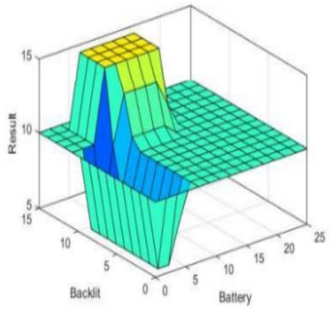
(a)



(b)



(c)



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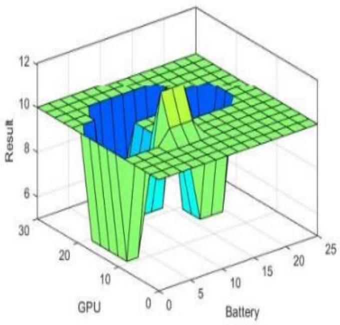
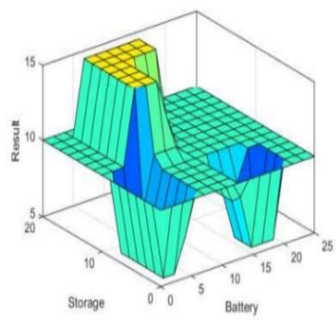


(e)



(f)

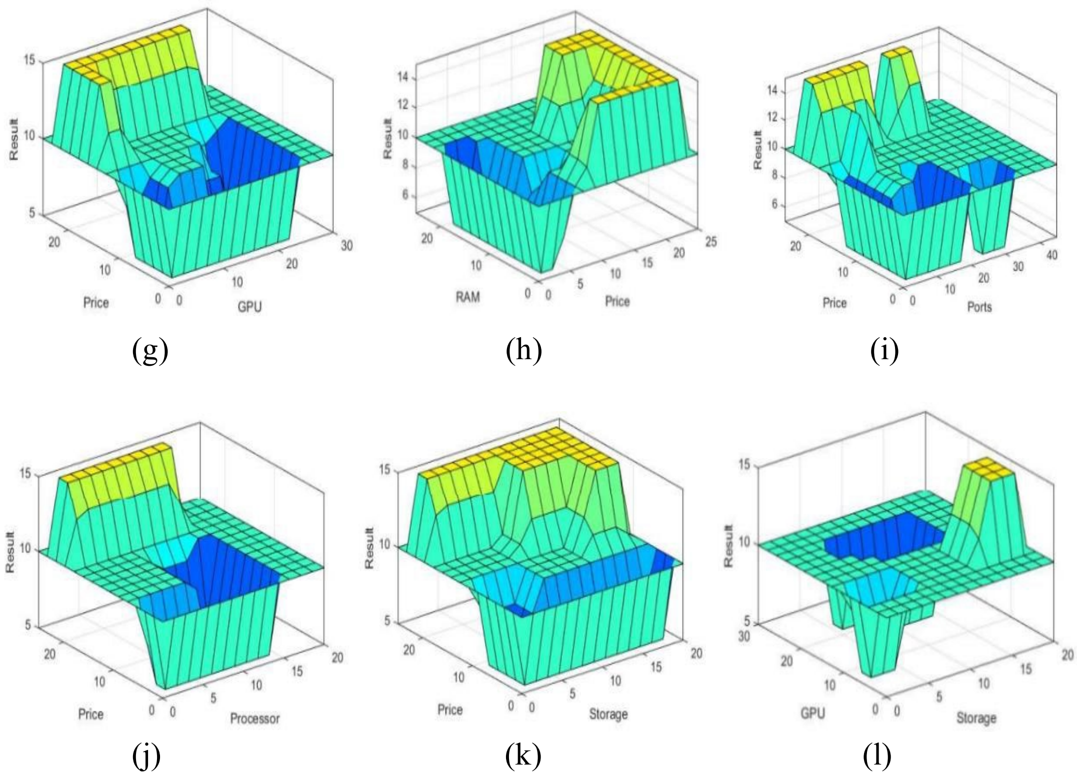


Figure 4. (a) Backlit vs Price (b) Backlit vs Processor (c) Battery vs Price (d) Battery vs Backlit (e) Battery vs gpu (f) Battery vs Storage (g) gpu vs price (h) price vs ram (i) ports vs price (j) processor vs price (k) storage vs price (l) storage vs gpu

Table 2. ML models performance

Different Approaches	Train Accuracy (%)	Validation Accuracy (%)	Test Accuracy (%)	Precision (%)	Recall (%)	Cross Validation Accuracy (%)
ANN	89.32	87.43	88.36	---	---	---
MLP Classifier	87.35	89.22	88.65	88.97	88.65	86.12
KNN	74.44	69.46	67.76	68.49	67.76	71.64
Logistic Regression	63.67	62.27	65.97	65.58	65.97	63.39
Support Vector Machine	80.42	70.65	77.01	76.91	77.01	77.99
Random Forest	99.23	87.42	88.35	88.71	88.35	85.28
Decision Tree	99.26	83.23	85.97	86.25	85.97	84.74
Naive Bayes	73.07	73.65	76.41	76.36	76.41	72.18
XG Boost	92.64	89.22	88.95	---	---	66.16

Appendix A.

The rule basis for classical fuzzy reasoning's output prediction

	Process	RAM	GPU	Graphics c	Brand	Type	Storag	Ports	Screen :	Backlit I	PC Body	Category	Screen Dis	Weight	Webcam	Battery L	Operating	Price	Result
1	Ryzen	H	AMD	M	Lenovo	SSD	M	TUHL	VH	Yes	Plastic	Gaming	LED (IPS)	M	Yes	H	Windows	H	S
2	Ryzen	H	AMD	M	Lenovo	SSD	M	TUHL	VH	Yes	Plastic	Gaming	LED (IPS)	M	Yes	H	Windows	L	S
3	Ryzen	H	AMD	M	Lenovo	SSD	M	TUHL	VH	Yes	Plastic	Gaming	LED (IPS)	M	Yes	H	Windows	M	S
4	Ryzen	H	AMD	M	Lenovo	SSD	M	TUHL	VH	Yes	Plastic	Gaming	LED (IPS)	M	Yes	H	Windows	VH	NS
5	Intel	M	Nvidia	M	Dell	SSD	M	TUHL	H	Yes	Metallic	Gaming	LED (IPS)	M	Yes	H	Windows	H	S
6	Intel	M	Nvidia	M	Dell	SSD	M	TUHL	H	Yes	Metallic	Gaming	LED (IPS)	M	Yes	H	Windows	L	S
7	Intel	M	Nvidia	M	Dell	SSD	M	TUHL	H	Yes	Metallic	Gaming	LED (IPS)	M	Yes	H	Windows	M	S
8	Intel	M	Nvidia	M	Dell	SSD	M	TUHL	H	Yes	Metallic	Gaming	LED (IPS)	M	Yes	H	Windows	VH	NS
9	Ryzen	M	AMD	M	HP	SSD	M	UHL	VH	Yes	Plastic	Gaming	LCD	M	Yes	H	Windows	M	S
10	Ryzen	M	AMD	M	HP	SSD	M	UHL	VH	Yes	Plastic	Gaming	LCD	M	Yes	H	Windows	L	S
11	Ryzen	M	AMD	M	HP	SSD	M	UHL	VH	Yes	Plastic	Gaming	LCD	M	Yes	H	Windows	H	NS
12	Ryzen	M	AMD	M	HP	SSD	M	UHL	VH	Yes	Plastic	Gaming	LCD	M	Yes	H	Windows	VH	NS
13	Ryzen	M	Nvidia	M	HP	HDD	H	UH	H	Yes	Plastic	Gaming	OLED	M	Yes	M	Windows	M	S
14	Ryzen	M	Nvidia	M	HP	HDD	H	UH	H	Yes	Plastic	Gaming	OLED	M	Yes	M	Windows	L	S
15	Ryzen	M	Nvidia	M	HP	HDD	H	UH	H	Yes	Plastic	Gaming	OLED	M	Yes	M	Windows	H	NS
16	Ryzen	M	Nvidia	M	HP	HDD	H	UH	H	Yes	Plastic	Gaming	OLED	M	Yes	M	Windows	VH	NS
17	Intel	H	Nvidia	M	Dell	SSD	M	UHL	VH	Yes	Metallic	Notebook	OLED	M	Yes	VH	Windows	H	S
18	Intel	H	Nvidia	M	Dell	SSD	M	UHL	VH	Yes	Metallic	Notebook	OLED	M	Yes	VH	Windows	L	S
19	Intel	H	Nvidia	M	Dell	SSD	M	UHL	VH	Yes	Metallic	Notebook	OLED	M	Yes	VH	Windows	M	S
20	Intel	H	Nvidia	M	Dell	SSD	M	UHL	VH	Yes	Metallic	Notebook	OLED	M	Yes	VH	Windows	VH	NS

1669	Ryzen	M	AMD	VL	HP	SSD	M	UH	M	Yes	Plastic	Notebook	LED (IPS)	L	Yes	M	Windows	VH	NS
1670	Intel	M	Nvidia	VL	HP	Both	H	TUHL	VH	Yes	Plastic	Gaming	LED (IPS)	H	Yes	L	Windows	VH	S
1671	Intel	M	Nvidia	VL	HP	Both	H	TUHL	VH	Yes	Plastic	Gaming	LED (IPS)	H	Yes	L	Windows	L	S
1672	Intel	M	Nvidia	VL	HP	Both	H	TUHL	VH	Yes	Plastic	Gaming	LED (IPS)	H	Yes	L	Windows	M	S
1673	Intel	M	Nvidia	VL	HP	Both	H	TUHL	VH	Yes	Plastic	Gaming	LED (IPS)	H	Yes	L	Windows	H	S

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