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Enhancing Audio Accessory Selection through Multi-Criteria Decision Making using Fuzzy Logic and Machine Learning

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Abstract

This research paper aims to investigate the significance of electrical products, specifically earbuds and headphones, in the digital world. The processes of decision-making and purchasing of audio accessories are often characterized by a significant investment of time and effort, as well as a complex interplay of competing priorities. In addition, various methodologies are employed for the selection and procurement of audio equipment through the utilization of machine learning algorithms. This study aimed to gather responses from a diverse group of participants regarding their preferences for the latest functionalities and essential components in their gadgets. The data was collected through a questionnaire that provided multiple options about the specifications of the audio accessories for the participants to choose from. The study employed seven distinct input factors to elicit responses from participants. These factors included brand, type, design, fit, price, noise cancellation, and folding design. The quantification of each input parameter was executed through the utilization of a scaling function in the Fuzzy Logic Interface, which assigned the labels “Yes” or “No” to each parameter. In this study, the Mamdani approach, which is a widely used fuzzy reasoning tool, was employed to develop a fuzzy logic controller (FLC) consisting of seven input and one output processes. In this study, standard fuzzy algorithms were employed to enhance the accuracy of the process of selecting an audio accessory in accordance with the user's specific requirements on the basis of Fuzzy threshold where “Yes” signifies about the availability of such audio accessory and “No” refers to the non-availability and readjustment of the input parameters.

Keywords: ML Models, Mamdani approach, FLC, MCDM, audio accessories

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1. Introduction

The act of decision-making can also be characterized as a empirical process that culminates in the to select a particular viewpoint or course-of-action from a range of feasible alternatives. The objective of this research is to investigate the process of finding and selecting alternatives based upon user ideals and preferences taken into consideration. The process of multi-criteria decision-making – ‘MCDM’ involves evaluation of each substitute based on a set of attributes or criteria, with the aim of selecting the optimal choice from a pool of available options [1]. The act of assessing, ordering, or electing a group of options based on a multitude of often contrasting, conflicting, or competing standards is commonly referred to as multi-criteria decision-making [2].

The present state of affairs in India and globally has been adversely affected by the cut-throat competition among audio accessory manufacturers, who are incessantly introducing novel models and upgrading their existing ones. The market for earphones and headphones offers a wide range of prices, spanning from premium to budget options, with varying additional features across different models. The primary objective of most laptop manufacturers is to enhance their profitability, which is achieved through the introduction of upgraded versions of their devices with enhanced capabilities. The implementation of novel technology is often accompanied by a rapid escalation in costs, thereby presenting consumers with a challenging task of selecting from a plethora of available alternatives. Designers and manufacturing companies face the challenge of creating earphones or headphones that cater to the needs of their clients while simultaneously enhancing their satisfaction. The task of selecting a suitable audio accessory for the general public and an audio accessory for the music industry business is a multi-criteria decision-making – 'MCDM' issue. This is due to the fact that it involves the consideration of various criteria related to input and output operations as well as their variations [3].

2. Related Work

MCDM techniques were evaluated using a range of models, which include:

- Technical for Order Preference By Similarity To The Ideal Solution – 'TOPSIS'
- Analytical Network Process – 'ANP'
- Analytical Hierarchy Process – 'AHP'

These along with fuzzy sets, to find out the finest model designed to meet the needs correct situation [3].

The Analytical Hierarchy Process is essential to the Data-Mining process since it upholds logical progression. It also claims that the Analytical Hierarchy Process and human behaviour in the Data Mining process are extremely similar, and that pair-wise comparison ensures that all options are considered in order to get the best results. Chen's (2005) claim that Analytical Hierarchy Process may be used for both quantitative and qualitative elements because it provides the best option based on the scenario [4] further supports this proof. A clear and easy model is the analytical hierarchy pro-cess. It addresses complex problems that demand a lot more mathematics since it is more versatile than AHP. There are only a few solid applications for the analytical hierarchy process because of how difficult and time-consuming it is to use. Analytical Network Process, as opposed to Analytical Hierarchy Process, considers the interconnectedness of the criteria and variations, producing much more precise computations and observations. Olsen, who suggested TOPSIS in 2004, asserted that it would be more certain than the MCDM algorithms that the best alternative would be chosen with the least amount of subjective input. In some cases, TOPSIS performs better than another model. Although in a limited sense, TOPSIS seems to be an effective way of tackling the MCDM issue. However, it relies on subjective information, which could skew the findings [5]. With inconsistent data, none of the MCDM problem-solving techniques are effective. According to Saaty (2007c), users increasingly use fuzzy sets to find out the type of information. While Analytical Hierarchy Process is constant, fuzzy is the least reliable technique. It is challenging to simulate any decision-making process that involves a variety of variables and human judgement. Decisions are made using professional judgements, which are frequently based on incomplete data. Both depending on subjective judgement and making judgements based on dubious data are acceptable uses of machine learning [5].

3. Methodology

3.1. Participants

This study involved 207 undergraduate students, ages 18 to 23, from the engineering, research, and management departments at the VIT-AP University in Amaravati, Andhra Pradesh, India. The study was carried out on university property. Before making a contribution, participants were made aware of the opportunity to participate in research that included a competitive analysis of audio accessories. The research participants were mandated to complete a written authorization as a prerequisite for their involvement in the study.

3.2. Language Variables Selected

The study incorporated 'seven' input factors, namely Brand, Type, Design, Fit, Noise Cancellation, Foldable Design, and Price, along with an output variable that participants could opt to choose or not choose. The data was collected through surveys. In this study, language-based variables were utilized to represent the input parameters. Specifically, the variables low, medium, and high were employed to express the varying degrees of each parameter. During the decision-making process, the participants were requested to provide their comments.

3.3. Measuring the Variables

The participants of this survey were told to select their preferred selection for each specification by checking the box next to it. After analysing the answers, we assessed the selections to each issue based on the ranges and values given for all the variables. Each dimension was evaluated on a three-point scale, with "L" denoting the dimension's lowest value and "H" denoting its maximum value.

The stepwise implementation of fuzzy logic is displayed in **Fig. 1.**

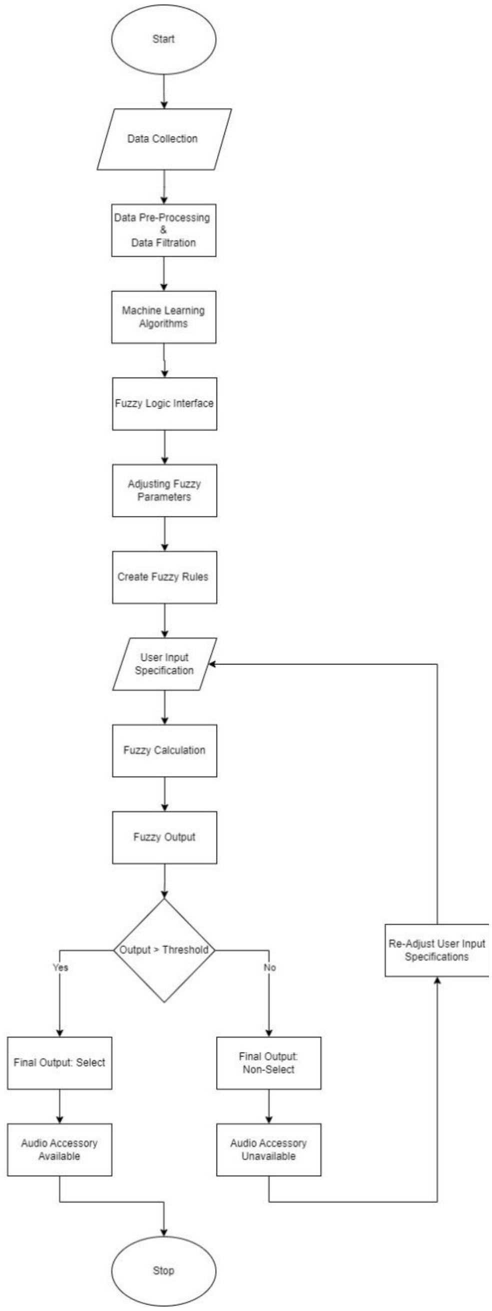

Figure 1. Data Flow Diagram

4. System based on Fuzzy-Rules

This is the body text with no indent. This The two fundamental components of System based on Fuzzy-rules – 'FRBS' are the Knowledge Base - 'KB' and the Inference Engine - 'IE'. The KB serves as a repository of knowledge, while the IE is responsible for processing the knowledge and making decisions based on it. The representation of data can be achieved through various methods. The utilization of natural language for the purpose of expressing human comprehension is widely considered to be the predominant approach. Upon provision of an input, the inference engine (IE) is required to execute the fuzzy inference process and subsequently produce an output from the fuzzy rule-based system (FRBS). The knowledge base (KB) is a repository of information that pertains to the problem at hand, presented in the form of IF-THEN fuzzy rules of language. The present study concerns a specific type of articulation, namely the rule-based articulation, which is formulated in the IF-THEN form. This type of articulation is characterized by the utilization of two key components, namely the IF premise (also known as the antecedent) and the THEN conclusion (also known as the consequence).

Fig. 2. depicts an illustrative representation of the systems based on fuzzy rules.

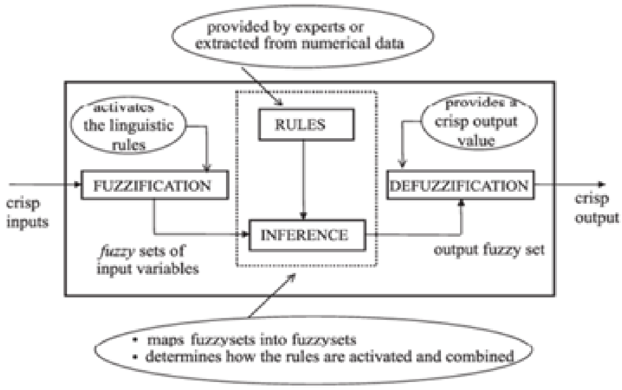

Figure 2. FRBS Illustrative View

The present system is composed of three fundamental components, namely fuzzification, defuzzification, and inference. The present study outlines a procedure for the process also known as fuzzification, which includes the conversion of input parameter factors into fuzzy-sets. The primary objective of this procedure is to facilitate effective communication of measurement uncertainty. Following the evaluation of rules for control by the IE, an fuzzified output is generated. This output is based on the fuzzified measurements that are stored in the database for fuzzy-rules. Subsequently, the output is fuzzified gets transformed into a singular crisp value. The phenomenon of effecting a transition from a fuzzy set to a crisp set is commonly referred to as defuzzification [6,7].

4.1. Membership functions and fuzzy linguistic variables

The fuzzy-linguistic procedure is a systematic approach that enables the expression of language factors in a precise evaluation process, as described in reference [8]. The utilization of a fuzzy set is a viable means of expressing a fuzzified input, which manifests as a fuzzy linguistic label, as posited by previous research [9]. Fuzzy-sets possess are capable to manipulate 'uncertainty' through the utilization of estimation methodologies [8].

Fuzzy sets consist of two primary components:

- The first, the element ‘x’
- The secondly, is the membership value ‘$\mu_{\propto}(x)$’, which value can orbit from 0 to 1, as demonstrated.

$$\propto = \{(x,\ \mu_{\propto}(x))\ :\ x \in X\} \quad (1)$$

Triangular membership functions were used for the inputs and outputs of the FLCs to simplify their design. Figure 2 depicts the use of a degree of two overlapping. A discourse universe with a normalized range of [0.0, 1.0] was also utilized. The degree of membership, also known as the membership value, is a numerical representation that measures the extent to which a constituent in ‘X’ belongs to the fuzzy-set – ‘A’ (as subsequently defined).

$$\mu_{\lambda(x)} = \begin{cases} 0,\ x \le a \ or\ x \ge b \\ \frac{x-a}{m-a},\ a < x \le m \\ \frac{b-x}{b-m},\ m < x < b \end{cases} \quad (2)$$

In the present case, the variables a, b, and m hold significant values. The current formula computes the median value of variable A as m, while also determining the upper and lower boundaries of A’s support as b and a, respectively.

4.2. What fuzzy input variables are and how they work

The study utilized seven input fuzzy variables, namely V1 (Brand), V2 (Type), V3 (Design), V4 (Fit), V5 (Noise Cancellation), V6 (Foldable Design), and V7 (Price). Each variable was denoted using three linguistic terminologies, namely Low – ‘L’, Medium – ‘M’ and High – ‘H’, as illustrated in **Fig. 3.**

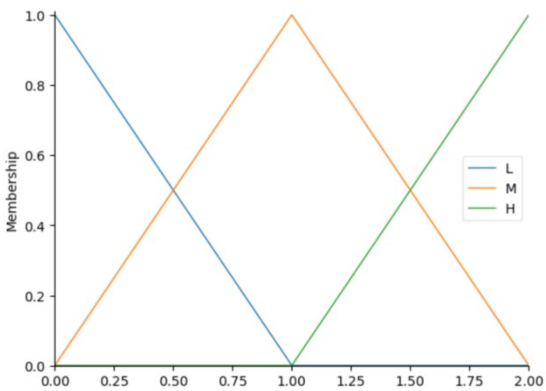

Figure 3. Input variables ‘Brand’, ‘Type’, ‘Design’, ‘Fit’, ‘Noise Cancellation’, ‘Foldable Design’, ‘Price’

4.3. Description of fuzzy output variable

The output variable in question was denoted by a pair of linguistic expressions, namely “select” and “not-select”, with V8 serving as the decision output (as shown in **Fig. 4**). The present study employed the Mamdani min-operator for the purpose of accumulation, and the center of the sums i.e., COS approach was employed for defuzzification.

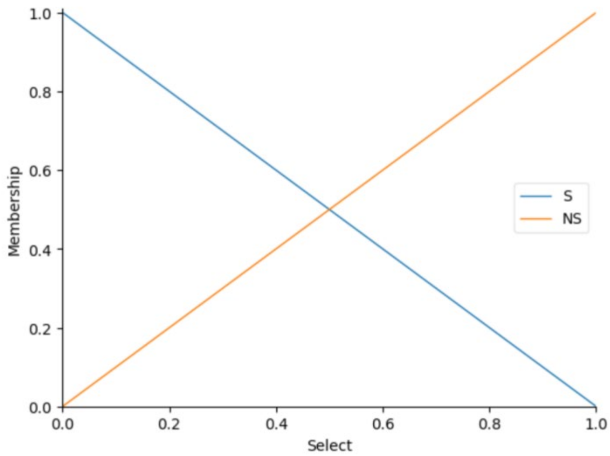

Figure 4. Distributions of membership functions for output fuzzy variables: V8 = {Select/Not-select}

4.4. Establishing the fuzzy rule basis using the interplay between inputs and outcomes

The fundamental components of Fuzzy Rule-Based System (FRBS), commonly referred to as rules, serve as the connections between its inputs and outputs. The present study involved the consideration of seven input factors, with each factor being characterized by three distinct language elements. Consequently, the Federal Reserve Banking System (FRBS) may incorporate a multitude of limitations to the extent that they are practicable.

For this study, we constructed 621 fuzzy rules.

Here's an example of the first and last rules:

The present study outlines a decision-making algorithm for selecting a suitable au-dio device based on specific criteria. The algorithm utilizes a set of seven variables, namely V1 (brand), V2 (type), V3 (design), V4 (fit), V5 (noise-cancellation feature), V6 (foldable design), and V7 (price). The output of the algorithm is a recommendation to select an appropriate audio device that meets the specified criteria.

In the case where (“V1” – “Sennheiser”), (“V2” – “wired”), (“V3” – “in-ear canal-phone”), (“V4” – “behind the neck”), ("V5" – "Y"), ("V6" – "N"), and ("V7" – "M"), the output is "Select."

This algorithm can be useful for individuals seeking to purchase an audio device that meets their specific needs and preferences.

In this study, it was found that when the variables 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', and 'V7' are present in a certain configuration, the output is determined to be "Not-Select". Specifically, if V1 represents a boat, V2 represents being wired, V3 represents being on-ear, V4 represents being over-the-head, V5 is "Y", V6 is "N", and V7 is "H", then the outcome is determined to be "Not-Select".

5. Mamdani Method

The Fuzzy Logic Controller (FLC) is a control system that operates based on a set of rules. These rules which are then formatted as 'IF-THEN; statements, where conditional clauses are evaluated, and a corresponding set of outcomes is generated. The FLC is a type of controller that utilizes fuzzy logic, which is a mathematical framework that deals with uncertainty and imprecision. The FLC is widely used in various applications, including robotics, process control, and artificial intelligence. The FLC's ability to handle imprecise and uncertain data makes it a valuable tool for controlling complex systems. In this particular scenario, the authority to take action for the system according to authority is the consequent, whereas the antecedent is an occurrence within its application domain. The utilization of specific language is employed to articulate the antecedents and consequences of the IF-THEN principles. Fuzzification is an essential process in providing inputs to Fuzzy Rule-Based Systems (FRBSs) as it necessitates the use of fuzzy sets instead of crisp inputs. Moreover, it is imperative to note that the outcome of a Fuzzy Logic Controller (FLC) invariably constitutes a 'fuzzy-set'. Thus, to obtain the precise value tallying with it, a 'defuzzification' technique becomes indispensable. This The two fundamental components of System based on Fuzzy-rules – 'FRBS' are the Knowledge Base - 'KB' and the Inference Engine - 'IE'.

The process i.e 'fuzzification' of the input parameters involves a series of steps, which are as follows:

a) The input variables are to be assessed.
b) Transforming the ranges of input variables into compatible spheres of discussion is what scale mapping is all about.
c) The 'fuzzification' procedure is a crucial step in fuzzy logic systems because its job is to transform unprocessed data into meaningful labels for fuzzy-sets using natural language processing. This process is typically carried out by the fuzzifier component of the system, which is designed to accurately map input data to their corresponding linguistic values. The resulting linguistic values are then used to define the membership functions of the fuzzy sets, which are essential for making accurate decisions and predictions in the system.

The rule base incorporates a comprehension in the field of application by leveraging information from the 'database'. It facilitates the acquisition of essential data required for the formulation of control regulations utilizing linguistic expressions. The utilization of a set of language control rules enables the rule base to furnish the domain experts with control objectives and policies.

The Intelligent Engine (IE) of a Fuzzy Logic Controller (FLC) has the ability to emulate human decision-making processes by utilizing imprecise concepts and subsequently deducing control operations based on fuzzy applications and rules. In order to obtain a precise numerical value from the fuzzy output, a defuzzification method is employed. This approach enables the retrieval of a crisp value that corresponds to the previously fuzzified output. The present investigation utilized the Centres Of Sum defuzzification technique, which will be expounded upon in subsequent sections.

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

In this study, we consider the following variables:

$U'_{f"}$, which represents the 'controller' output;
A (α), which refers to the 'firing area' of the jth-rule;
P, which indicates the total no. of fired rules;
f_j, which denotes the area of the centre under consideration.

6. Result

The conventional approach to fuzzy reasoning was constructed using a set of seven inputs, namely Brand, Type, Design, Fit, Noise Cancellation, Foldable Design, and Price. Each input was associated with three potential responses, namely low, medium, high, and extremely high. As previously mentioned, a compendium of 621 regulations was meticulously crafted through manual means.

The present study showcases that the selection of an audio accessory necessitates the consideration of crucial criteria such as Brand, Type, Design, Noise Cancellation, and Price [refer from **Fig.** 5(a) to 5(g)]

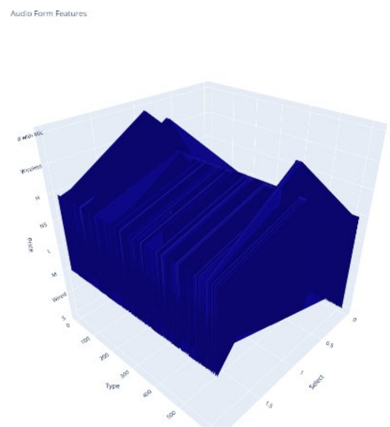

Figure 5. a

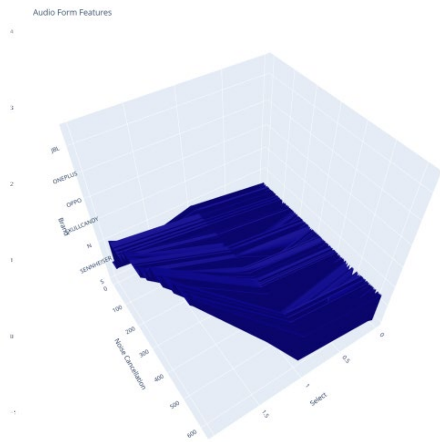

Figure 5. b

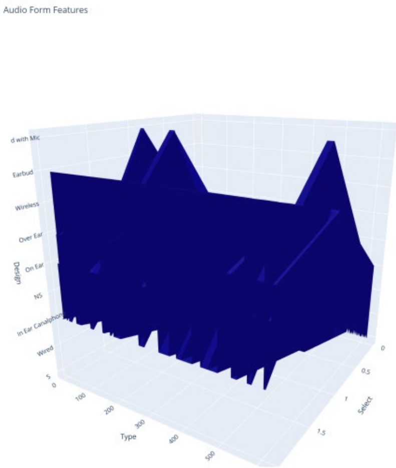

Figure 5.c

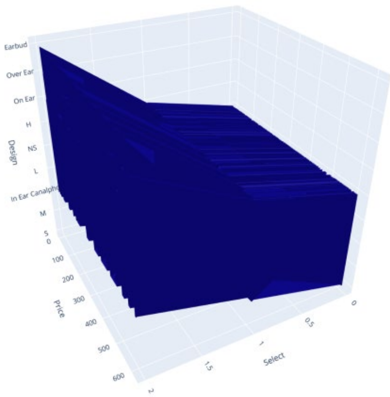

Figure 5. d

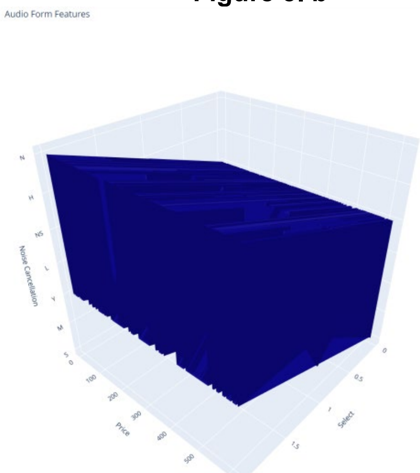

Figure 5. e

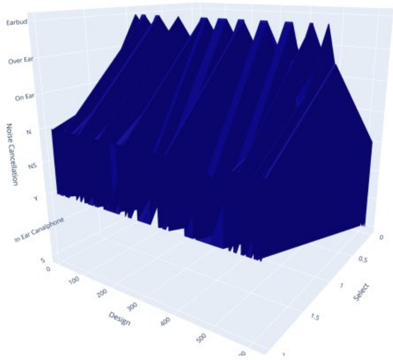

Figure 5.f

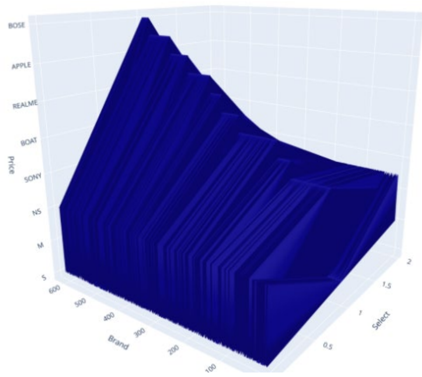

Figure 5.g

7. Machine Learning Models

The present study employs a data science approach, specifically machine learning, to develop a model utilizing training data. In its fundamental essence, a machine learning model is a mathematical expression that produces an output value by taking into account distinct weights and values assigned to each training variable. The model's relationship with the goal value can be determined by analyzing the matching weights assigned to each variable in every record. These weights typically range between 0 and 1. Adequate training data is necessary to determine the optimal weights for each variable. Achieving the highest level of accuracy in weight learning enables a model to accurately predict the target value or output of a given test data record.

7.1. Machine Learning Techniques Utilized

The anticipated results of this investigation are discrete values that can be classified into distinct categories.

The present study employs a range of analytical tools, including Artificial Neural Network (ANN) (as shown in **Fig.** 6), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Logistic Regression, Random Forest Regression (RFR), Decision Tree, Naive Bayes classifier, and XG Boost. These tools have been selected based on their established efficacy in analyzing complex data sets and their ability to generate accurate predictions. By utilizing a diverse range of analytical tools, this study aims to provide a comprehensive and nuanced analysis of the data under investigation and hence the accuracy and validation in displayed in **Table 1**.

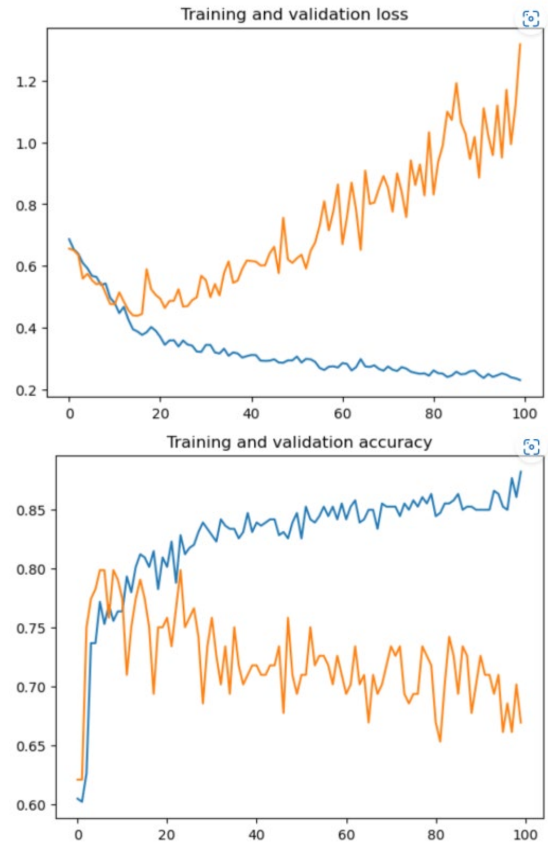

Figure 6. Performance of Artificial Neural Network Model

Table 1. Machine Learning Performance

Different Approaches	Train Accuracy (%)	Validation Accuracy (%)	Test Accuracy (%)	Precision (%)	Recall (%)	Cross Validation Accuracy (%)
ANN	86.12	77.45	67.25	---	---	---
MLP Classifier	73.65	75.00	76.00	75.57	76.00	68.26
KNN	68.01	62.90	61.60	58.08	61.60	68.31
Logistic Regression	67.74	66.12	68.80	67.92	68.80	69.71
Support Vector Machine	71.23	71.77	70.40	69.43	70.40	75.99
Random Forest	89.24	70.16	73.60	73.09	73.60	72.45
Decision Tree	90.05	71.77	80.80	80.80	80.80	67.79
Naïve Bayes	72.58	69.35	67.20	66.75	67.20	77.12
XG Boost	90.05	72.58	78.40	---	---	65.31

8. Conclusion

The present study investigates the procurement of audio accessories for data pro-cessing in the context of data mining. The research employs a fuzzy reasoning tool system that is grounded in the Mamdani technique. The current investigation utilized conventional fuzzy reasoning techniques that rely on the Mamdani method to establish the input-output associations of the process. The present approach is based on empirical observations and subjective experiences of human beings. The present study focuses on a novel perspective regarding the concept of fuzziness in the context of in-formation processing. In this study, we present a novel approach for selecting audio accessories that combines machine learning and fuzzy logic. Our technique leverages the power of these two methodologies to provide a more accurate and efficient means of choosing the optimal audio accessories. Specifically, we demonstrate the effective-ness of our approach through a series of experiments and analyses. Our results indicate that our technique outperforms traditional methods and offers a promising avenue for future research in this domain. The implementation of machine learning technology has facilitated the development of intelligent models that provide a more user-friendly option compared to traditional physical models. The technology under con-sideration offers notable advantages such as the ability to operate on a wide range of computing devices, including mobile ones, and the utilization of fewer resources.

The findings of our assessment indicate the beneficial characteristics of machine learning models in discerning the most suitable headset that possesses the necessary attributes. The present study refrained from investigating the computational complexity of the devised methodologies, albeit it remains a potential avenue for future research. This study utilized a total of seven input parameters as independent factors. It is important to note that future studies may incorporate additional input parameters. Under such circumstances, the size and number of parameters of the categorization model would experience an increase. The objective of enhancing the effectiveness and precision of machine learning models is to streamline the process. Future developments in personalized audio algorithms, sustainable design, and biometric integration hold great promise for the research paper's future focus on choosing the ideal audio accessory based on user specifications. Advanced machine learning techniques can be used to construct audio algorithms that analyze user preferences, hearing capacities, and acoustic settings to provide personalized sound profiles for different people. Future studies could also concentrate on developing eco-friendly audio accessories that use renewable resources, energy-saving technology, and recycling practices to minimize their negative effects on the environment. Furthermore, the incorporation of biometric sensors into audio accessories offers new opportunities for tracking users' health and wellbeing and enables customized audio experiences that change according to the user's physiological state. By offering specialized solutions that prioritise user preferences, sustainability, and general wellbeing, these integrated fields of research have the potential to revolutionize the audio accessory market.

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