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Extracting Control Rules through Fuzzy Logic using Machine Learning Methods from Home Automation Dataset

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Abstract: Fuzzy logic is a mathematical framework that allows for uncertain or imprecise reasoning, making it particularly useful in situations where traditional binary logic is insufficient. The proposed method used decision trees, which are examples of machine learning algorithms that can analyze data and produce fuzzy logic-based control rules. The extracted rules used in process control, robotics, and automation applications of the proposed technology are highlighted, focusing on merging machine learning with fuzzy logic to build flexible and powerful intelligent systems. The paper explores methodology, core ideas, and applications related to machine learning-based extraction of control rules from fuzzy logic. Numerous rules are produced as a result of this approach to help direct desired results. The necessity for interpretability in control rules generated by machine learning algorithms is one of the major issues raised in the passage. This is a reference to the significance of comprehending and outlining how certain guidelines are created and the rationale behind specific judgements. In many fields, interpretability is essential because it promotes trust and comprehension of the system's behaviour and ensures that the judgements made by the system are sound.

Keywords: Fuzzy logic, Machine learning, Fuzzification, Smart Home, Rules Extraction.

1. Introduction

Modern technology has incorporated machine learning to help computers learn from new situations and data. The extraction of control rules from data using fuzzy logic is one application of machine learning that has shown a lot of promise. In instances where classic binary logic is insufficient, fuzzy logic is a mathematical framework that allows for uncertain or imprecise reasoning. Developing intelligent systems that can adapt to changing settings and enhance performance over time is feasible by integrating fuzzy logic and machine learning. This article will discuss how fuzzy logic can be used to extract control rules from data using machine learning approaches. It starts by giving a general introduction to fuzzy logic and its applications in control systems. The use of machine learning in control systems and how control rules can be derived from data will then be covered. It will also discuss the various machine-learning techniques that may be employed for this goal and offer illustrations of how they might be applied in actual situations.

Finally, review the difficulties and restrictions associated with applying machine learning and fuzzy logic to control systems and some future research topics.

Numerous control system applications, such as robotics, automation, and process control, utilize fuzzy logic. Fuzzy logic is used in these systems to express and control the inherent uncertainties and imprecisions. It is possible to create controllers with fuzzy logic that respond to the current environment and alter it as it does. Fuzzy logic is a mathematical paradigm that allows for vague or incorrect thinking. Fuzzy logic permits reasoning with varying degrees of truth, in contrast to standard binary program logic, which operates on the theory of right and wrong (Blasch et al., 2021). It is constructive when the input or output quantities are not clearly specified or are vulnerable to ambiguity or vagueness. According to Fuzzy logic relies on the rules of semantic variables that are stated in terms of natural linguistic or fuzzy sets (Choi, Yi, Park, & Yoon, 2021).

Machine learning is a potent technique for knowledge discovery in data. Machine learning can be used in control systems to extract control rules from data and develop intelligent controllers that can learn from their environments and adapt. With the utilization of machine learning techniques like decision trees and neural networks, fuzzy logic-based control rules may be produced from data (Dhebar & Deb, 2020). Automating the extraction of control rules is one of the main advantages of employing machine learning in control systems. The human analysis of data used in traditional control rule extraction techniques can be time-consuming and error-prone. This procedure can be automated by machine learning algorithms, allowing controllers to adapt to new data and enhance their performance over time (Díaz-Curbelo, Espin Andrade, & Gento Municio, 2020).

There are several real-world uses for fuzzy logic-based control rule extraction, which employs machine learning. Robotics is an excellent example of this. Robots frequently operate in challenging and unpredictable contexts thus, their capacity to adjust to shifting circumstances is essential to their success. Fuzzy logic and machine learning can be used to build intelligent controllers that can modify their behaviour in response to the environment, enhancing their performance and adaptability. Fuzzy logic, a variety of machine learning algorithms can be utilized to extract control rules. The decision-tree algorithm is one of the most well-liked ones. A straightforward yet effective approach for extracting control rules from data is decision trees. Recursively creating a tree that symbolizes the control rules, they operate by segmenting the data into subsets according to the values of the input variables. The neural network is another well-liked machine learning approach for extracting control rules. Decision trees are a simpler algorithm than neural networks. However, neural networks can be more beneficial for simulating complex interactions between input and output variables for home automation (Blasch et al., 2021; Iqbal, Iqbal, Ahmad, Ahmad, et al., 2021). It can be done by creating intelligent controllers to manage uncertainty and adapt to changing situations.

The use of fuzzy logic and machine learning to derive control rules from data advances the research of artificial intelligence and machine learning in addition to its practical applications. The demand for electric power has dramatically expanded as a result of increased local and worldwide electric power consumption brought on by technology. The rate of electricity use has risen both domestically and commercially. Due to increased demands brought on by load shedding, electricity shortages and crises occasionally impact home appliances. Layers of connected nodes make up a neural network, and these nodes can learn to extract features from input data and provide control rules based on the learned features (Fernandez-Quilez, 2023; Iqbal, Iqbal, Ahmad, Alassafi, et al., 2021). The requirement to create intelligent controllers capable of adapting to changing surroundings and handling uncertainties and imprecisions in the system is the problem statement for utilizing machine learning to derive control rules from data using fuzzy logic. Traditional techniques for extracting control rules take a lot of time, are prone to mistakes, and may not be able to handle the complexity and variety of contemporary control systems. Automating the process of control rule extraction and building controllers that can learn from and adapt to new data would improve the performance and robustness of the system. This approach has limitations and downsides, such as the need for machine learning algorithms to provide interpretable control rules and the need for large amounts of training data. It creates trustworthy and efficient intelligent controllers that employ fuzzy logic and machine learning, and these challenges must be overcome. The advantages of this study are listed below.

The capability of machine learning to create intelligent controllers that can adapt to changing contexts and manage uncertainties and system imprecisions is its contribution to fuzzy logic-based control rule extraction from data.

Machine learning techniques like decision trees and neural networks are used to automate the process of control rule extraction and create fuzzy logic rules that can manage uncertainties and imprecisions in the system. This method enables the development of controllers that can learn from fresh data and adjust accordingly, gradually improving performance.

The proposed method is superior over conventional methods for obtaining control rules, and this technique can help control systems perform better and be more resilient.

This method makes a contribution that goes beyond the control systems industry. It has uses in process control, robotics, and automation. It can boost the efficiency and dependability of these systems, resulting in advantages like decreased energy consumption, improved safety, and increased production. It may learn more about the possibilities of these methods and increase our understanding of them by investigating the strengths and weaknesses of machine learning algorithms in control systems.

2. Literature Review

In recent years, there has been a lot of interest in combining fuzzy logic and machine learning to extract control rules from data. Numerous industries, including robotics, automation, and process control, can benefit from this strategy. The main ideas and methods for applying machine learning to extract control rules from fuzzy logic will be examined in this literature review and the state of the art of this field of study. For many years, fuzzy logic has been employed extensively in control systems. It is especially beneficial when the input or output values are unclear, ambiguous, or not explicitly stated (Kedir, Siraj, & Fayek, 2023). Fuzzy logic enables reasoning with varying degrees of truth, which enables controllers to modify their behaviour in response to changing circumstances (Fernandez-Quilez, 2023). Automating the rule extraction process is one of the main advantages of using machine learning for control rule extraction. When using human data analysis, conventional control rule extraction techniques can be time-consuming and prone to errors.

Machine learning techniques allow controllers to automate this procedure to adapt to new data and enhance their performance over time (Ghorbani & Zamanifar, 2022). Decision trees are frequently used in machine learning for the purpose of finding control rules. They are an efficient method for quickly obtaining control rules from data. To employ decision trees, the data must first be separated into subsets according to the values of the input variables; only after this can a recursive tree reflecting the control rules be formed (Khosravi, Golkarian, & Tiefenbacher, 2022; Nadeem et al., 2023). One of the key benefits of using fuzzy logic in control systems is the ability to describe and manage uncertainties and imprecisions at the system level. This becomes especially important if the system is subjected to disturbances, noise, or other potential performance-impairing uncertainties. Fuzzy logic boosts the performance and longevity of controllers by enabling them to handle these uncertainties and adapt to their environment. Machine learning is an effective method for finding information in data. Control rules extract from data and create intelligent controllers that can learn from and adapt to their environments, and control systems can employ machine learning (Dimitrios Kontogiannis, Dimitrios Bargiotas, & Aspassia Daskalopulu, 2021; D Kontogiannis, D Bargiotas, & A Daskalopulu, 2021).

Layers of interconnected nodes make up neural networks. These networks can learn to extract features from incoming data and produce control rules based on those features (Li et al., 2023). Numerous research studies have shown how well neural networks perform when extracting control rules with fuzzy logic. For instance, a neural network-based approach was utilized in a study by Yu et al. to extract control rules for an HVAC system (Nivedetha, 2023; Rao, Chen, Liu, & Ma, 2023). When modelling intricate interactions between the input and output variables, neural networks are a more sophisticated algorithm than decision trees (Majlesi et al., 2023; Wang et al., 2023). The outcomes demonstrated that the strategy successfully enhanced controller performance and lowered energy use (Jintasuttisak, Edirisinghe, & Elbattay, 2022; Sun, Zhang, Liu, & Duan, 2023). Decision trees and neural networks are examples of machine learning algorithms that can be used to analyze data and derive fuzzy logic-based control rules. The efficiency of decision trees for fuzzy logic-based control rule extraction has been shown in numerous studies. For instance, a decision tree-based approach was utilized in a study to derive control rules for a wastewater treatment system (Yang et al., 2023). The outcomes demonstrated that the strategy successfully enhanced controller performance and lowered system variability (Erfando & Khariszma, 2023).

3. Proposed Solution

The suggested approach includes a multi-step procedure that combines data preparation, feature selection, machine learning algorithm selection, and rule generation based on fuzzy logic to extract control rules from data using fuzzy logic. To start, noise, outliers, and missing values are removed from the raw data during preprocessing. This stage is crucial to guarantee the precision and dependability of the control rules produced by the machine learning algorithm. Then, pertinent characteristics are chosen from the preprocessed data using principal component analysis or correlation analysis. As illustrated in Figure 01, this stage aids in reducing the dimensionality of the data, which makes it simpler for the machine learning algorithm to find patterns and provide management rules.

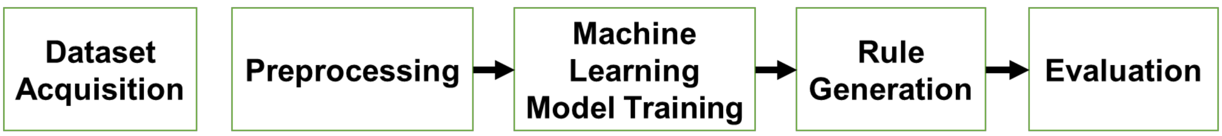

Figure 01. Proposed model for Rule Generation

The identification of the features using a machine learning method is chosen depending on the properties of the data and the desired results. Support vector machines, neural networks, and decision trees are examples of common control rule extraction algorithms. The preprocessed and feature-selected data are used to train the algorithm, and the resulting rules are assessed for accuracy and dependability. Finally, fuzzy logic is used to construct the control rules, allowing for handling system uncertainties and imprecisions. In order to create an intelligent controller that can learn from and adjust to new data, the produced rules are then implemented in the control system. It is crucial to deal with issues like the requirement for huge volumes of data for training, the requirement for interpretability of the generated rules, and the danger of overfitting or underfitting the data in order to guarantee the effectiveness and dependability of the suggested solution. The suggested method for leveraging fuzzy logic and machine learning to extract control rules from data is a viable strategy for developing smart controllers that can deal with uncertainties and adapt to changing surroundings. We can create efficient and dependable control systems with a variety of real-world applications by overcoming the difficulties and drawbacks of this method.

The dataset CSV file includes the meteorological data for that specific area as well as readings from a smart meter for 350 DAYS of home appliances in kW for 1 minute. The dataset has 503910 entries and 32 total characteristics. The dataset includes measurements for household appliances in kW from a smart meter that was displayed in Table 01. The values were taken throughout a time period of 1 minute. A sample of 10 attributes with 13802 records was used for the experimentation.

Table 01. Some attributes sample of Dataset

Sr.#	**Temperature**	**Solar [kw]**	**Icon**	**Humidity**	**Apparent temperature**	**Summary**	**Wind speed**	**Pressure**	**Wind bearing**	**Cloud Cover**
1.	36.14	0.003483	clear-night	0.62	29.26	Clear	9.18	1016.91	282	Cloud Cover
2.	36.14	0.003466	clear-night	0.62	29.26	Clear	9.18	1016.91	282	Cloud Cover
3.	36.14	0.003466	clear-night	0.62	29.26	Clear	9.18	1016.91	282	Cloud Cover
4.	36.14	0.003433	clear-night	0.62	29.26	Clear	9.18	1016.91	282	Cloud Cover
5.	36.14	0.003450	clear-night	0.62	29.26	Clear	9.18	1016.91	282	Cloud Cover
6.	36.14	0.003416	clear-night	0.62	29.26	Clear	9.18	1016.91	282	Cloud Cover
7.	36.14	0.003416	clear-night	0.62	29.26	Clear	9.18	1016.91	282	Cloud Cover
8.	36.14	0.003416	clear-night	0.62	29.26	Clear	9.18	1016.91	282	Cloud Cover
9.	36.14	0.003416	clear-night	0.62	29.26	Clear	9.18	1016.91	282	Cloud Cover
10.	36.14	0.003433	clear-night	0.62	29.26	Clear	9.18	1016.91	282	Cloud Cover

The following are the steps involved in generating fuzzy rules from data:

Step 1: Determine the domain (or universe of discourse) for the input and output spaces after preprocessing the data. For variables such as relative humidity, Temperature, and heat index, the domain is defined by the minimum and maximum observations recorded.

Step 2: Divide the intervals into three overlapping regions using triangular functions, creating the fuzzy regions of low, mid, and high. Each measurement is assigned a grade that ranges from 0-1, indicating the degree of belonging to that particular region. The sum of membership degrees for a measurement is equal to 1.

Step 3: Assign each observation to the region with the highest membership grade. For instance, a measurement that lies within the interval of the length of a ruler will belong to the sets "low," "mid," and "high" with grades of 0, 0.4, and 0.6, respectively denoted by equation 1.

$$X \Rightarrow low = 0.0, mid = 0.4, high = 0.6 \tag{1}$$

Step 4: Transform every record in the data into text, forming a rule. The rule degree is computed by multiplying the membership grades of the fuzzy sets that form part of the rule.

Step 5: Construct a summary of the rules by selecting one from a group of rules with the same antecedent. The chosen rule is the one with the highest rule degree, and its consequence is preserved. The antecedent of a rule is the assigned membership of the input variables (e.g., temperature and relative humidity), while the consequent is that of the output variable (e.g., heat index). The fuzzification process is shown in Figure 02.

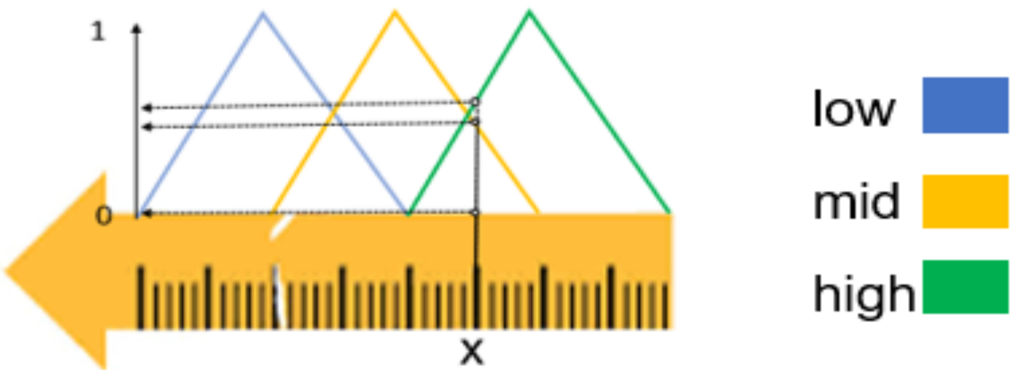

Figure 02. Fuzzification of a numerical measurement

4. Result and Discussion: Case Study for Smart Home Control

A case study of smart homes is taken for the rule generation, and rules are generated by using this case study. In the scenario of smart home control, machine learning can be used to extract control rules from sensor data to ensure optimal energy consumption and comfort for the occupants. Solar energy production vs usage in weather conditions is shown by the Circos graph in Figure 03.

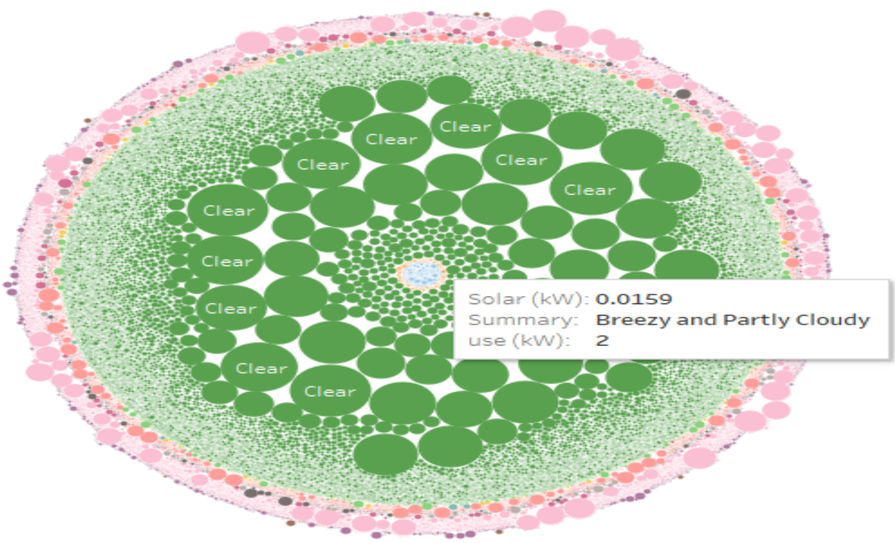

Figure 3. Solar energy production vs. Usage in Weather Conditions

The machine learning algorithm can identify patterns in the data and generate control rules based on fuzzy logic, which can account for uncertainties in the environment, such as changing weather conditions or occupancy patterns. The intervals indicated by the minimum and maximum observations collected and displayed by Tables 02, 03, 04, and 05 serve as the datasets for the preprocessing result and the domain for the variables relative humidity, Temperature, and heat index.

Table 02. Presents Relative humidity

Sr.#	Humidity	High	Mid	Low	Degree	Membership
1	75	.000000	.880503	.119497	.880503	Mid
2	76	.006135	.993865	.000000	.993865	Mid
3	83	.865031	.134969	.000000	.865031	High
4	77	.1288340	.871166	.000000	.871166	Mid
5	76	.006135	.993865	.000000	.993865	Mid
…	…	…	…	…	…	…
…	…	…	…	…	…	…
13798	79	.374233	.666667	.000000	.666667	Mid
13799	77	.1288340	.871166	.000000	.871166	Mid
13800	80	.496933	.503067	.000000	.503067	Mid
13801	74	.000000	.754717	.245283	.754717	Mid
13802	74	.000000	.754717	.245283	.754717	Mid

This strategy could increase occupants' comfort and energy efficiency because the system can adjust to their preferences and the changing environment, as demonstrated in Figure 03. Based on its maximum membership degree, the temperature value is assigned to one of three fuzzy sets (High, Mid, or Low). For instance, if the highest membership degree is "Mid," "Mid" will be allocated to this column. The dataset appears to be a component of a fuzzy logic system that employs membership functions to measure how much a given input (the temperature) fits into different high, middle, and low-level fuzzy sets.

Table 03. Presents Temperature

Sr.#	Temperature	High	Mid	Low	Degree	Membership
1	24	.000000	.689655	.310345	.689655	Mid
2	24	.000000	.689655	.310345	.689655	Mid
3	25	.333333	.666667	.000000	.666667	Mid
4	24	.000000	.689655	.310345	.689655	Mid
5	25	.333333	.666667	.000000	.666667	Mid
…	…	…	…	…	…	…
…	…	…	…	…	…	…
13798	24	.000000	.689655	.310345	.689655	Mid
13799	25	.333333	.666667	.000000	.666667	Mid
13800	25	.333333	.666667	.000000	.666667	Mid
13801	25	.333333	.666667	.000000	.666667	Mid
13802	25	.333333	.666667	.000000	.666667	Mid

The suitable classification for that temperature value is then determined by choosing the fuzzy set with the highest membership degree from the "Membership" column. When inputs have varying degrees of truth or membership in distinct categories, fuzzy logic systems are frequently employed in decision-making and control systems. This allows for more flexible and nuanced decision-making based on ambiguous or imprecise data. Using fuzzy logic and machine learning to extract control rules from data presents a potential method for developing intelligent controllers that can deal with uncertainty and adapt to changing surroundings.

Table 04. Presents Heat index.

Sr.#	Heat	High	Mid	Low	Degree	Membership
1	25.6	.851852	.148148	.000000	.851852	High
2	24.5	.037037	.962963	9.270362e-15	.037037	Mid
3	25.5	.777778	.222222	.000000	.777778	High
4	25.5	.777778	.222222	.000000	.777778	High
5	25.5	.777778	.222222	.000000	.777778	High
….	…	…	…	…	…	…
…	…	…	…	…	…	…
13798	25.6	.777778	.222222	.000000	.777778	High
13799	24.6	.111111	.888889	.000000	.888889	Mid
13800	24.5	.037037	.962963	9.270362e-15	.962963	Mid
13801	24.5	.037037	.962963	9.270362e-15	.962963	Mid
13802	25.5	.777778	.222222	.000000	.777778	High

The results of this approach could include improved safety, increased efficiency, and reduced energy consumption, leading to significant advancements in a range of industries, from automotive to manufacturing to residential. Table 5. containing information showing various combinations of heat, humidity, and temperature along with a corresponding degree value. It appears that a summary function or rule set is created using this table. The following codes apply fuzzification to all the variables in the data.

Table 05. Presents summary function is created to extract the final rule set.

Sr.#	Temperature	Humidity	Heat	Degree
1	Mid	Mid	Mid	.655623
2	Low	High	Low	.815951
3	Mid	High	Mid	.605505
4	Low	Mid	Low	.993865
5	Mid	Low	Mid	.631005
6	High	Mid	High	.503286
….	….	….	….	….
….	….	….	….	….
….	….	….	….	….

The data frame above describes the strongest relationships in the data: Temperature as 'T', Humidity as 'H, and Heat as 'Ht'. This data is probably being utilized in a fuzzy logic or machine learning system to develop rules or correlations between the input variables (heat, humidity, and temperature) and the output variable (degree) in such a situation. It can easily be translated into control rules as follows:

Rule 1: IF 'T'is Medium and 'H' is also Medium, THEN 'Ht' index is Medium

Rule 2: IF 'T' is Low and 'H'is High, then 'Ht' Index is Low

Rule 3: IF 'T'is Medium and 'H' is High, THEN 'Ht' index is Medium

Rule 4: IF 'T'is Low and the 'H' is Medium, THEN 'Ht' index is Low

Rule 8: IF 'T'is Medium and 'H' is also Medium, THEN 'Ht' index is Medium

Rule 9: IF 'T'is Low and 'H'is Medium, THEN 'Ht' Index is Low

Given that the minimum confidence or threshold is 50%, it can be concluded that the first three rules, namely L^M→O, M^O→L, and L^O→M, are the strong association rules for the given problem, as shown in Table 06.

Table 06. Presents Forward rule confidence and vice versa.

Sr.#	Rules	Rules Confidence
1.	L^M→O	Sup {(L^M)^O}/sup(L^M)=4/8=50%
2.	M^O→L	Sup {(M^O)^L}/sup(M^O)=4/8=50%
3.	O^L→M	Sup {(O^L)^M}/sup(O^L)=4/8=50%
4.	L→M^O	Sup {L^(M^O)}/sup(L)=4/12=33%
5.	M→O^L	Sup {M^(O^L)}/sup(M)=4/14=28%
6.	O→L^M	Sup {O^(L^M)}/sup(O)=4/10=40%

The table shows the degree of confidence in a rule's forward and backward implications. Both forward and backward reasoning or inference can be significant in many rule-based systems. Backward reasoning starts with the desired conclusion and looks for supporting rules, whereas forward reasoning starts with the supplied rule and infers a conclusion. Depending on whether attempting to make predictions or provide an explanation for how a particular conclusion was reached, both forward and backward confidence can be helpful in various situations.

5. Challenges and Limitations

The use of fuzzy logic and machine learning to derive control rules from data advances the research of artificial intelligence and machine learning in addition to its practical applications. Despite the promise of utilizing machine learning to derive control rules from fuzzy logic, issues and restrictions still need to be resolved. The necessity for a lot of data to train the machine learning algorithms is one of the main difficulties. This can be especially problematic when data are few or difficult to collect. The requirement that the control rules produced by the machine learning algorithms be comprehensible presents another difficulty. Knowing the controller's behaviour and making sure it runs within safe parameters are crucial in safety-critical applications.

6. Conclusion and Future Work

This study explores the use of machine learning and fuzzy logic to extract control rules from data, offering a practical method for developing intelligent controllers that can manage uncertainty and adapt to changing environmental conditions. Automating the extraction of control rules using machine learning and artificial intelligence (AI) techniques can have several advantages, including improved efficacy and dependability of control systems and a greater grasp of AI and ML. We can automate the extraction of control rules using this technology, increase the effectiveness and dependability of control systems, and gain more knowledge about AI and machine learning. This method has several difficulties and restrictions, such as the necessity for vast data sets for training, the requirement for the defined rules to be comprehensible, and the possibility of the data being over- or under-fitted. It is imperative to get over these challenges to construct dependable and efficient control systems combining machine learning and fuzzy logic. Future research in this area is the development of new algorithms that can manage more complex and dynamic control systems may be the focus of future research in this area. Other potential directions include unique approaches to data preparation, feature selection, and rule generation. It is crucial to carry out extra studies to examine the interpretability of the developed rules and their effect on the control system's overall performance. Hence, future research could also concentrate on exploring the practical applications of this approach and its potential to enhance energy efficiency, safety, and productivity.

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