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Research Article

Design of Intelligent Fire Alarm System Based on Multisensor Data Fusion

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With the rapid development of today's alarm system, the market demand for an intelligent alarm system is increasing. The traditional alarm system needs technological progress/advancement to meet the needs of the society, and the alarm system needs to develop in the direction of integration, both digitally and professionally. The intelligent fire warning systems using integrated multisensor digital data integration techniques can obtain the data information of the measured object more accurately and comprehensively from multiple dimensions, to improve the system alarm accuracy. This article aims to study the application of multisensor data fusion technology in intelligent fire alarm systems. For the issue of multivalued bias of the ID3 algorithm, this paper proposes the CAC_ID3 algorithm. Through the C4.5, the CART and the ID3 algorithm are compared and analyzed on the $F1$ value and the correct rate of the multisensor intelligent fire alarm data is set, and experiments show that the correct rate and $F1$ value of the CAC_ID3 algorithm are 1, which are higher than the other three algorithms. This shows that the CAC_ID3 algorithm has good classification effect and superior performance.

1. Introduction

With the growth of the community, all walks of life have generally entered the stage of informatization. However, with the diversification and complexity of information, it has become extremely difficult to collect information. In the actual large industrial field, the data collected by a single sensor are relatively simple, which is not conducive to analyzing the data and making decisions. Therefore, the fusion of multiple sensors is required by the market and is one of the prerequisites for leading various fields to a higher/advanced level. The integrated multiple sensor solutions were mainly used in the military at first, and its main work was to collect the military information of the blue party or locate the blue party's position. In a fire alarm system, the occurrence of fire is a comprehensive phenomenon which is accompanied by changes in light, smoke, temperature rise, radiation and gas concentration, and in order to detect and capture these information, various fire sensors need to be used. The multisensor data fusion solution can enhance decision-making precision and productivity. This technology has been applied extensively in all walks of life and has achieved good results by greatly improving decision-making capabilities.

The development of social science and technology has brought earth-shaking changes to people's lives. In people's daily life, multisensor data fusion algorithms are found in every corner of their life. The alarm system based on a multisensor can combine the information of each sensor through the network to form a tight alarm system. In the multisensor alarm system, each sensor can monitor any abnormal information in real-time [1, 2]. As long as there is an abnormal situation, the sensor will send an alarm indication, so that the alarm system can be analyzed through the multisensor fusion algorithm in time. When the analysis result gives an alarm command, the system will immediately send the alarm information to the relevant staff, so that the staff can immediately take corresponding protective measures. Therefore, the development of an intelligent fire alarm system based on the multisensor data fusion not only makes the corresponding security work accurate and efficient but also makes the alarm system intelligent, so that the relevant security personnel do not need to do a lot of repetitive patrol work. At the same time, the management efficiency of the alarm system is improved. Through the multisensor data fusion technology, the temperature and humidity of the environment can be effectively monitored, and the dangers such as floods and fires can be well prevented. Therefore, exploring the alarm system of the data fusion technology not only promotes the intelligent development of an alarm system but also provides a reference for the use and management of various alarm systems of the same type and provides a reference for future academic research in the field of multiple sensors digital integration method.

Recently, a number of professionals and scholars focused primarily on the study of the multisensor data fusion. However, it does not pay enough attention to the fire alarm system. If we only talk about the advantages of data fusion in the development of fire alarm systems, security systems, and other systems, there will be a lack of research and exploration of specific concepts. Thus, in this article, a smart fire alarm is designed based on a multisensor digital integration approach to promote the development of multisensor digital integration approach and offer future information for the relevant studies on fire alarm systems.

2. Related Work

The multiple sensors message integration method is also known as the multiple sensors digital integration method. Although the growth of the multiple sensors message integration method started relatively late, it has developed rapidly. Hwang K H considered a multisensor data fusion system using load cells and vision sensors when developing a flounder classifier for fish management in aquaculture systems. In a single-sensor measurement approach, each sensor has its own shortcomings. The load cell showed high performance in adult fish measurements, but fry measurements were significantly affected by the water weight. The vision sensors show high performance in fry measurements, but the fish movement can affect the accurate measurements in adults. Therefore, the effects of water weight disturbance and motion disturbance are addressed using a data fusion algorithm, and its performance is evaluated by comparing the single-sensor measurement results and the multisensor data fusion results [3]. To protect the seniors against falling, a live falling forecast system is fitted to the wrist known as the wearable intelligent device, which can promptly trigger an alert to minimize unintentional damage resulting from falls. Currently, most algorithms built on individual sensor dates do not provide an exact representation of fall states, while fall recognition methods integrated with multiple sensor data can increase the flexibility and precision of forecasts. Pan D devised a fell recognition system based on multiple sensors digital integration. The three characteristic parameters representing the human acceleration and posture changes were extracted using a digital integration method, and the efficiency of the multisensor digital integration algorithm was verified [4]. In the purpose of improving the practical value of multimedia browser web, it is essential to integrate space data and antimedia messages in antimedia browser web. Therefore, the method of spatial data and information fusion in multisensor networks cannot express the local change of the local dynamics in great detail, which causes the error of large fusion of data and multisensor messages. Zhang J presents a way to fuse the space data and multisensor networks in the multisensor systems using the superfluous data. The test outcomes indicate that this approach can decrease the power expenditure of converging space data and multimedia messages in multimedia sensor webs, and the integration precision is also good [5]. Yao W focused on how to optimize the energy consumption of LEDs. Firstly, based on the energy optimization algorithm (EOA), combined with the characteristics of the algorithm's collective operation and information integration, an LED energy consumption optimization algorithm control based on the multisensor data fusion is proposed. In order to ensure that the energy consumption optimization at this time does not lead to an increase in computational complexity, the proposed algorithm is improved in real-time. The optimal processing angle (OPA) is introduced to realize the efficient transformation of the energy consumption problem of multisensor coordination behavior, and the equivalent linear programming problem is obtained. Finally, a multisensor LED energy consumption optimization control is realized [6]. At the same time, policy discussions in Europe have resulted in the introduction of green economics principles to strike a favorable break between the sustainability of farming and profits by making it more efficient. This attitude poses small businesses with legal issues in terms of technical and financial difficulties. Decision support systems (DSSs) can be an efficacious answer to surmount these constraints; therefore, Aiello G proposes a multisensor solution for decision fusion. This approach is an easily used and low-cost solution to reducing the use of agricultural fertilizers and fertilizers on covered crops [7]. The use of simultaneous phasor measures in wide-area surveillance applications allows real-time grid access to system operations. Intentional injection of the wrong synchrophasor measured values, nevertheless, can lead to unsuitable control actions that impair the safety and stability of the power transmission network. To solve this problem, Khalid H M presents a model prediction based on multisensor track-level fusion. The results indicate that the TFMP proposed by him can precisely extract swing variables from pollution measures in the existence of multiple system disruptions and stochastic data infusion [8]. In summary, multisensor data fusion technology has been applied to various fields, including real-time prediction systems and industrial internet of things while countries around the world are working on upgrading security measures; however, in the development of intelligent fire alarm systems, there are not many research studies on the use of the multisensor data integration method, so more in-depth exploration is needed.

3. Theories Related to the Design of Intelligent Fire Alarm System Based on Multisensor Data Fusion

3.1. Theory of Multisensor Data Fusion. The multiple sensor digital integration technology is a technology about the comprehensive processing of the multiple resource information [9]. It intelligently synthesizes the multisource information from the system to generate more accurate and complete estimates and judgments than a single source of information, thereby improving the reliability of the early fire warning system and effectively reducing the false alarm rate [10, 11]. The advantages of the multiple sensor message integration method over the information obtained by a single sensor are summarized as follows: firstly, the accuracy of the system is greatly improved. The information collected by each sensor can be confirmed more accurately, reducing the probability of false positives and false negatives. Secondly, it improves the judgment of the system and reduces the alarm time. The fusion analysis of the information collected by the sensor greatly reduces the data processing time. Thirdly, the robustness and reliability of the system are enhanced. When the signal has a transmission delay, distortion, and so on, the multisensor shows good robustness. Moreover, the information between the multiple sensors can be exchanged and transmitted, thus increasing the fault tolerance rate of the system. Fourthly, it enhances the accuracy of the system. Through the proper fusion of multisource information, the ambiguity and uncertainty of the system are greatly reduced. Fifthly, it reduces the overall cost of the system. With the advancement of technology, the cost of building a multisensor system is often much lower than that of building a single-sensor system [12].

Data fusion is a fundamental function that exists in both humans and other biological systems [13]. Humans can use the information detected by the various organs of the body and prior knowledge to synthesize instinctively. The multiple sensors digital integration refers to the fusion of the data collected by the multiple homogeneous or heterogeneous sensors at different locations on the same detection target, thereby weakening some redundant data information that may exist between the sensors. The complementarity of the information between each sensor in time or space is used to reduce the ambiguity caused by a single sensor in the acquisition process and to increase the accuracy of system decision-making. Based on different types of measured objects and according to the actual needs of the measured objects, the level of data fusion is also different [14, 15]. In actual implementation, the level of multisensor digital integration can be categorized into 3 levels as follows: decision-level integration, feature-level integration, and data-level integration.

Decision-level fusion first needs to complete a preliminary decision result of the local decision on the measured object and then proceed to the next step of digital integration processing. The next step is to monitor whether the data collected by each sensor involved in the digital integration come from the same measured object, that is, to associate the preliminary decision results of each sensor [16, 17]. Finally, the decision results of all sensors on the same measured object are fused to obtain the final result. Decision-level fusion belongs to the upper-layer fusion method, and the schematic diagram of the decision-level fusion is shown in Figure 1.

The information extracted by feature-level integration is the complete message of the object under test which is to extract the features from the bottom-level data collected by each sensor in the system and then classify and fuse the extracted multisensor feature information [18, 19]; it belongs to the fusion of the middle level. Figure 2 displays a diagram of feature-level fusion.

In the data-level integration, each individual sensor needs to perform data fusion on the data messages gathered from the identical target and then process the fused data, such as classification and recognition, data estimation, and feature extraction. Finally, the final data of the tested target are obtained [20, 21]. Data-level fusion is to directly fuse and analyze the raw signal data captured by the transducers without preprocessing, which is the lowest-level data fusion method. Figure 3 shows a schematic diagram of data-level fusion.

3.2. Multisensor Data Fusion Algorithm. The multiple sensors digital integration intelligent algorithm is applied in most multisensor systems, and the intelligent fire alarm system of this paper mainly uses the multisensor data fusion intelligent algorithm for fusion decision-making. The following is an introduction to the commonly used fuzzy logic and artificial intelligence-related algorithms.

In the multiple sensors digital integration system, the fuzzy logic inference method is actually equivalent to a kind of multivalued logic. It assigns a real value from 0 to 1 to each logical proposition and inference operator to indicate its credibility in the fusion process, which is also called a certainty factor in some places. Then, the multivalued logical reasoning method is used, and various operators are used to combine the data and information collected by each sensor, so as to achieve the purpose of multiple sensors digital integration. Figure 4 shows the principle diagram of fuzzy logic reasoning [22, 23].

Artificial intelligence algorithms are a method of data fusion handling techniques method produced by simulating the human head. It uses a large number of simple processing units that interact and connect with each other in a certain way to process data information. The core of AI deals with computer science and engineering. Using machine learning, machines can perform the same kind of learned events as humankind. They can not only constantly obtain fresh learning but also enhance that knowing and refine that knowledge progressively and methodically. A number of generalized approaches to inductive training are available in machines for machine learning, and decision trees are one of them, which can be used for data classification and system construction [24, 25]. Based on the advantages and disadvantages of the two, it is found that in general, the fire alarm system can achieve the expected effect only through the

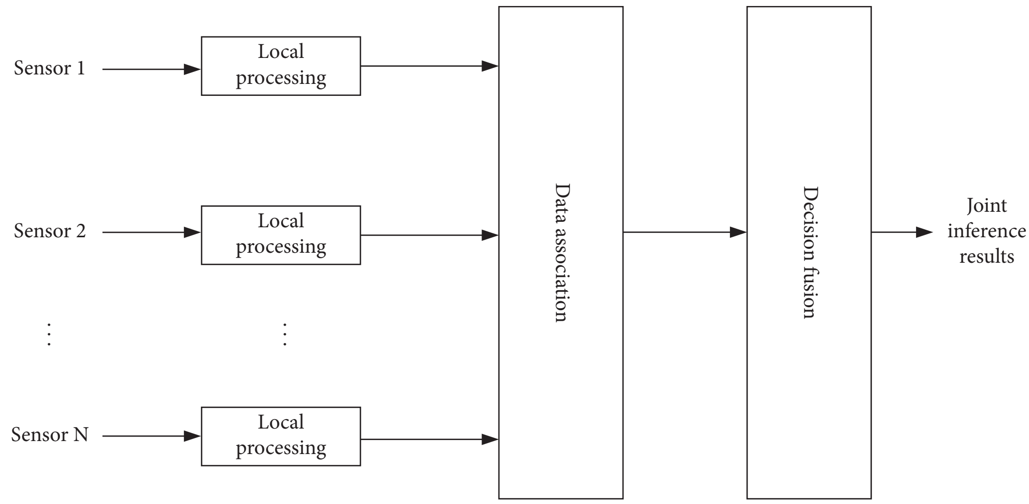


Figure 1: Schematic diagram of the decision-level fusion.

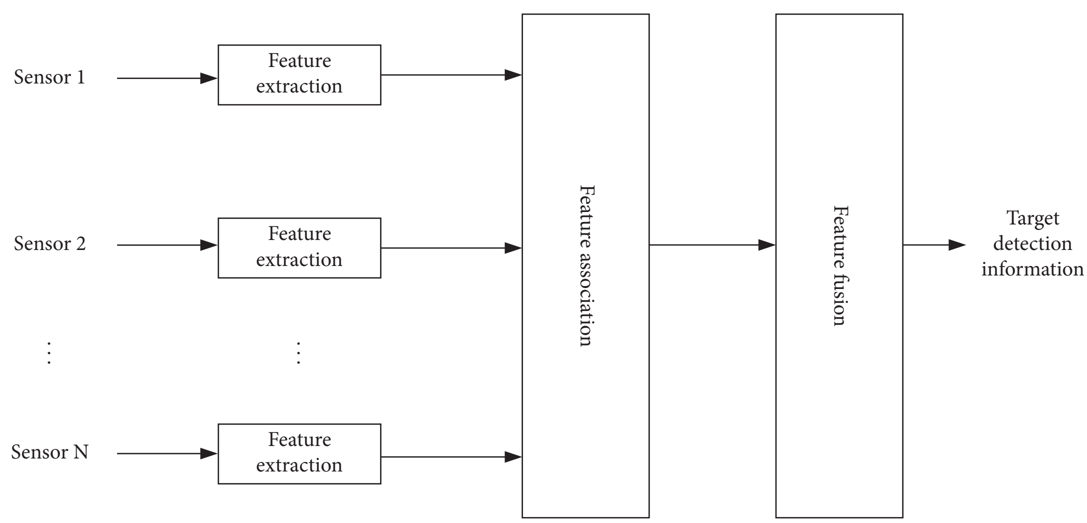


Figure 2: Schematic diagram of the feature-level fusion.

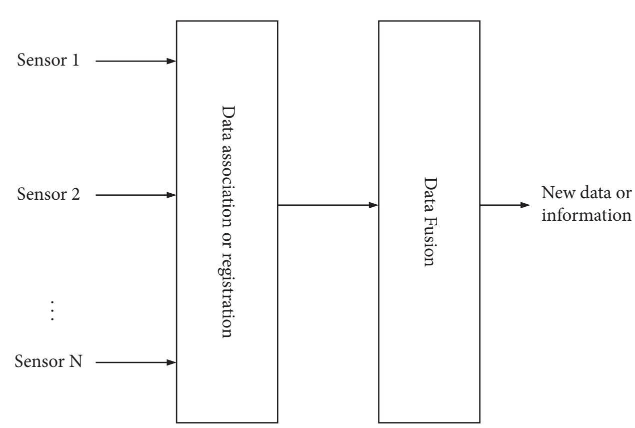


Figure 3: A schematic diagram of the data-level fusion.

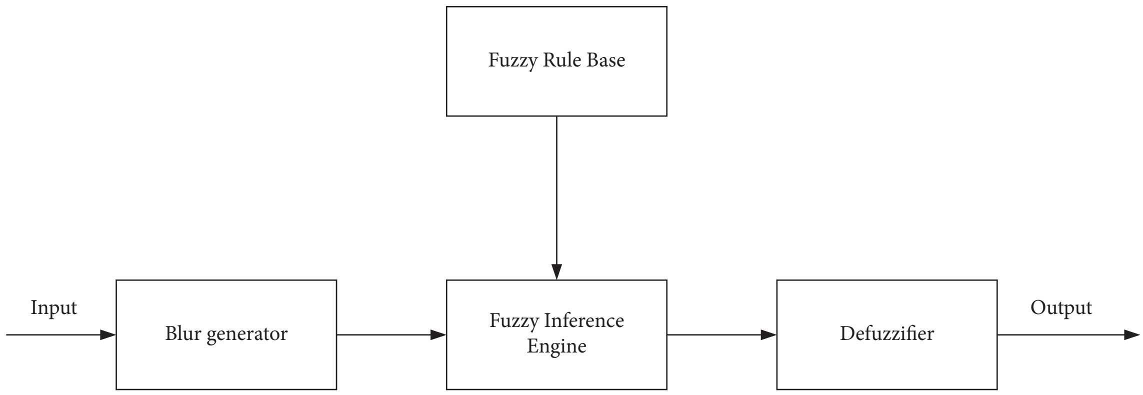


FIGURE 4: A schematic diagram of the fuzzy logic system.

decision tree algorithm, so the policy-making tree algorithm in machine learning is selected to control the fire alarm system.

3.3. Different Decision Tree Algorithms

3.3.1. ID3 Algorithm. For the issue that the ID3 method tends to have more attributes, this paper proposes the CAC_ID3 algorithm, which is an extended algorithm built on the ID3 method. And the algorithm is applied to the multisensor intelligent fire alarm system. The algorithm adjusts the information gain by introducing the attribute confidence and correlation function ratio and improves the classification accuracy.

The ID3 algorithm takes the properties with message benefits as knots and builds various branching for the goal of decision-making tree formation. The idea of the ID3 algorithm is to first consider all instances as the rooting knots of the decision-making tree, calculate the message degree of all properties based on their entropy using information-theoretic methods, and then select the properties based on the message degree. The tree is further split through the attribute value to establish branch nodes. Then, each branch node is regarded as the root node, and this process is repeated until the last branch node belongs to the same category, thus constructing a decision tree. The calculation formula of the ID3 algorithm is shown in the following formula:

$$I(F,B) = -\frac{F}{F+B}\log\frac{F}{F+B} - \frac{B}{F+B}\log\frac{B}{F+B},$$

$$I(A) = \sum_{i=0}^{v}\frac{f_i+b_i}{F+B}I(f_I,b_i), \tag{1}$$

$$I(f_i,b_i) = -\frac{f_i}{f_i+b_i}\log\frac{f_i}{f_i+b_i} - \frac{b_i}{f_i+b_i}\log\frac{b_i}{f_i+b_i},$$

where R means a vector space; F represents the large positive and negative sample level in vector space R; B represents a small positive and negative example level in the vector space R; f_i stands for the amount of positive examples included in the subset R_i; and b_i stands for the amount of counterexamples included in the subset R_i.

The information gain rooted at attribute A is as follows:

$$\mathrm{Gain}(A) = I(F,B) - I(A). \tag{2}$$

The CAC_ID3 algorithm introduces attribute correlation and confidence and uses a new method to calculate the information gain, which effectively weakens the multivalue bias in the ID3 algorithm so that the classifying precision of the decision-making trees becomes higher. The formulation is shown in equations (3) and (4).

The confidence of the attribute A is expressed as follows:

$$0\angle\lambda(A)\angle 1,$$
$$I'(A) = (1-\lambda(A))\sum_{i=0}^{v}\left(\frac{f_i+b_i}{F+B}I(f_i,b_i)\right), \tag{3}$$

$$\mathrm{CAC}(A) = \frac{\sum_{i=1}^{n} x_{i1}/x_{i1}+x_{i2}}{n}, \tag{4}$$

where $x_{ij}(j=1,2)$ means that the dataset S takes the i-th value in the attribute A; the decision attribute C takes the j-th value of the sample total; and n represents the number of value types of the attribute A.

Among them, the usage of formula (4) is as follows:

$$\mathrm{CAC}(\mathrm{RFID}_d) = \frac{x_{11}/x_{11}+x_{12}+x_{21}/x_{21}+x_{22}}{n}, \tag{5}$$

where x_{11} indicates the total number of samples whose intrusion value is "Yes" when the attribute " *RFI D* detection" is "Yes" and x_{12} represents the total number of samples whose intrusion value is "No" when the attribute " *RFI D* detection" is "Yes."

Among them, n is the number of value types detected by the attribute *RFI D*; here, $n=2$.

$$W(A) = \frac{CAC(A)}{\sum_{k=1}^{i}CAC(k)},$$
$$\mathrm{Gain}' = (I(F,B) - I'(A))W(A), \tag{6}$$

where i represents the quantity of attributes in the database; W stands for the weight of every attribute association; and Gain' represents the new information gain.

3.3.2. CAC_ID3 Algorithm. The algorithm CAC_ID3 obtains the recalculated information gain Gain′, and Gain′ is employed to build new decision-making trees. In this writing, decision-making trees construction test is carried out through Table 1 (softball decision table), and the attribute confidence of each attribute of the dataset in Table 1 is set as $\lambda(\text{outlook}) = 0.1$, $\lambda(\text{temperature}) = 0.3$, $\lambda(\text{humidity}) = 0.5$, and $\lambda(\text{wind}) = 0.3$.

By calculating the informational benefit of every property from Table 1, the final decision tree can be obtained. Figures 5 and 6 are the decision trees constructed by the ID3 and the CAC_ID3 algorithm, respectively. From Figures 5 and 6, the CAC_ID3 algorithm can well solve the shortcomings of the multivalue bias of the ID3 algorithm.

3.3.3. C4.5 Algorithm. C4.5 algorithm is an enhanced version of the decision tree algorithm based on the ID3 algorithm. The algorithm uses the information gain rate instead of the information gain degree to select attributes, which can complete the discrete processing of the continuous attributes and can increase the processing ability of the continuous data. And before the decision tree is established, the tree is prepruned, and if there are problems with the data, they can be dealt within time. There is no need to wait for the tree to be pruned after it is built, which greatly improves the efficiency of the algorithm. The calculation formula of this algorithm is shown in the formula.

$$\begin{aligned} P\left(C_j\right) &= \frac{\left|C_j\right|}{|T|} = \text{freq}\left(C_j, T\right), \\ P\left(v_i\right) &= \frac{\left|T_i\right|}{|T|}, V = v_i, \\ P\left(C_j \middle| v_j\right) &= \frac{\left|C_{jv}\right|}{\left|T_i\right|}, \end{aligned} \tag{7}$$

where T represents the dataset and $\{C_1, C_2, \ldots C_k\}$ represents the set of categories in the dataset T.

The category information entropy is calculated as follows:

$$\begin{aligned} \text{Info}(C) &= -\sum_j P\left(C_j\right)\lg P\left(C_j\right), \\ \text{Info}(C) &= -\sum_{j=1}^{k} \frac{\text{freq}\left(C_j, T\right)}{|T|} \lg \frac{\text{freq}\left(C_j, T\right)}{|T|} = \text{Info}(T). \end{aligned} \tag{8}$$

The class conditional entropy is calculated as follows:

$$\begin{aligned} \text{Info}\left(\frac{C}{V}\right) &= -\sum_j P\left(v_j\right) \sum_i P\left(\frac{C_j}{v_j}\right) \lg P\left(\frac{C_j}{v_i}\right), \\ \text{Info}\left(\frac{C}{V}\right) &= -\sum_{i=1}^{n} \frac{\left|T_i\right|}{\left|v_i\right|} \text{Info}\left(T_i\right) = \text{Info}(T), \end{aligned} \tag{9}$$

Table 1: Softball decision table.

Numbering	Outlook	Humidity	Wind	Temperature	Activity
1	Sunny	High	Strong	Hot	No
2	Overcast	High	Weak	Hot	Yes
3	Rain	Normal	Strong	Cool	No
4	Overcast	High	Strong	Mild	Yes
5	Sunny	Normal	Strong	Mild	Yes
6	Rain	Normal	Weak	Mild	Yes

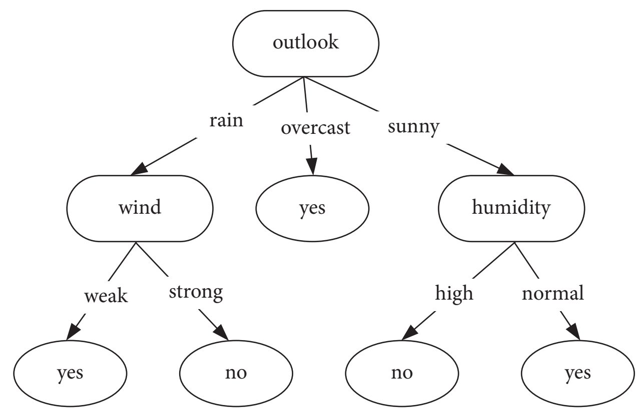


Figure 5: Decision tree constructed by the ID3 algorithm.

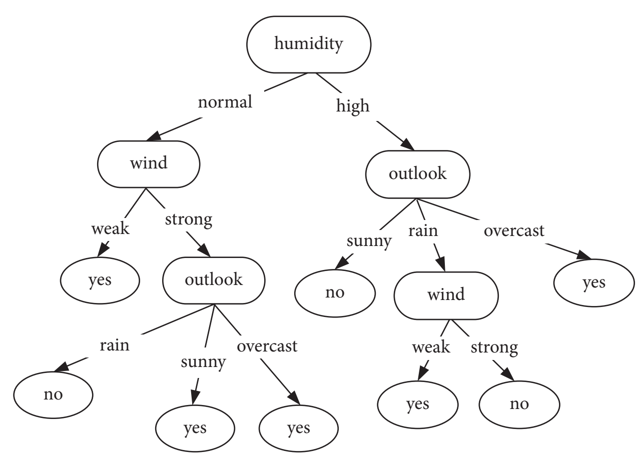


Figure 6: Decision tree constructed by the CAC_ID3 algorithm.

where V represents an attribute in the dataset T and $\{v_1, v_2, \ldots v_n\}$ means that the attribute V has n values that do not overlap with each other.

The informational benefit is as follows:

$$\begin{aligned} I(C, V) &= H(C) - H\left(\frac{C}{V}\right) \\ &= \text{Info}(T) - \text{Info}_v(T) = \text{gain}(v). \end{aligned} \tag{10}$$

Informative entropy of attributes v is as follows:

Table 2: Dataset description.

Serial number	Dataset name	Totality of instances	Amount of attributes	Amount of class labels	With or without missing values
1	Car	1473	5	13	N/A
2	Krkopt	20020	10	2	No
3	Nursery	28056	6	17	No
4	Tic-tac-toe	210300	24	3	N/A

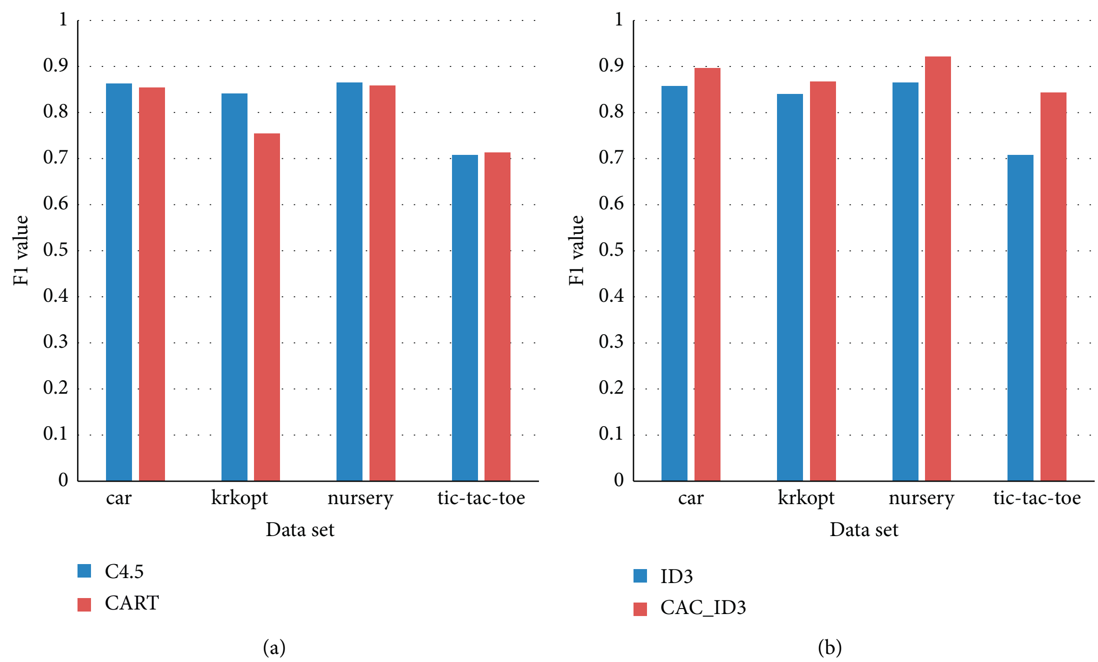


Figure 7: $F1$ values of the four algorithms in the four datasets. (a) $F1$ values of the C4.5 algorithm and the CART algorithm in the four datasets. (b) $F1$ values of the ID3 algorithm and the CAC_ID3 algorithm in the four datasets.

$$\begin{aligned}\text{Info}(V) &= -\sum_{i} P(v_i)\lg P(v_i)\\ &= -\sum_{i=1}^{n}\frac{|T_i|}{|T|}\lg\frac{|T_i|}{|T|} = \text{split\_Info}(v).\end{aligned} \tag{11}$$

The information gain rate is as follows:

$$\text{gain\_ration}(v) = \frac{I(C,V)}{H(V)} = \frac{\text{gain}(v)}{\text{split\_Info}(v)}, \tag{12}$$

where $\{T_1, T_2, \ldots T\}$ represents the n subsets into which the dataset T is divided; v_i represents the value of all instances in the subset T_i; $|T_i|$ represents the number of examples in the dataset T; and $|C_j| = \text{freq}(C_j, T)$ represents the number of instances of C_j.

3.3.4. CART Algorithm. The full name of the algorithm CART is classification and regression tree. It employs a binary reciprocal partitioning technique to split the present example set into two subset samples so that each non-leaf node generated has two branches. The decision-making tree produced by the CART algorithm is a binary tree with a straightforward construction. There are two basic ideas for the classification tree method of the algorithm CART: the first method is to construct a tree by recursively dividing the training samples into the independent variable spaces and the second is to prune the classification tree with a subset of the validation data, that is, the decision tree.

The article further verifies the capability of the algorithm by a comparative study of the four algorithms: $CAC\_I\ D3$ algorithm, $I\ D3$ algorithm, $C4.5$ algorithm, and CART algorithm. The first is $F-$measure, and the second is the correct rate. The calculation formulas of the two performance evaluation indicators are shown in the formulas. The empirical dataset is the one in UCI, which is shown in Table 2.where P means accuracy; R means recall rate; and β indicates parameters.

$$\begin{aligned}F_\beta &= \frac{(\beta^2+1)PR}{\beta^2 P + R},\\ \text{accuracy} &= \frac{(\text{TP}+\text{TN})}{(\text{P}+\text{N})}.\end{aligned} \tag{13}$$

As can be observed in Figure 7, in the four sets of datasets, the $F1$ result of the CAC_ID3 algorithm is the best. In the tic-tac-toe dataset, the C4.5, the CART, and the ID3 algorithms are similar. The $F1$ values of the three algorithms are all around 0.71, while the $F1$ value of the CAC_ID3

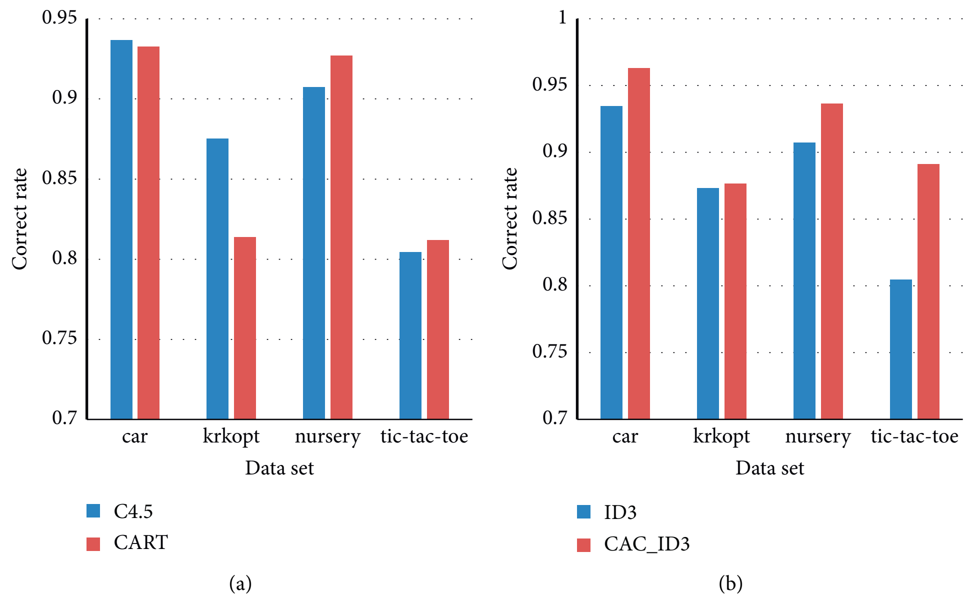


Figure 8: The accuracy of the four algorithms in the four datasets. (a) The correct rate of the C4.5 algorithm and the CART algorithm in four datasets. (b) The correct rate of the ID3 algorithm and the CAC_ID3 algorithm in four datasets.

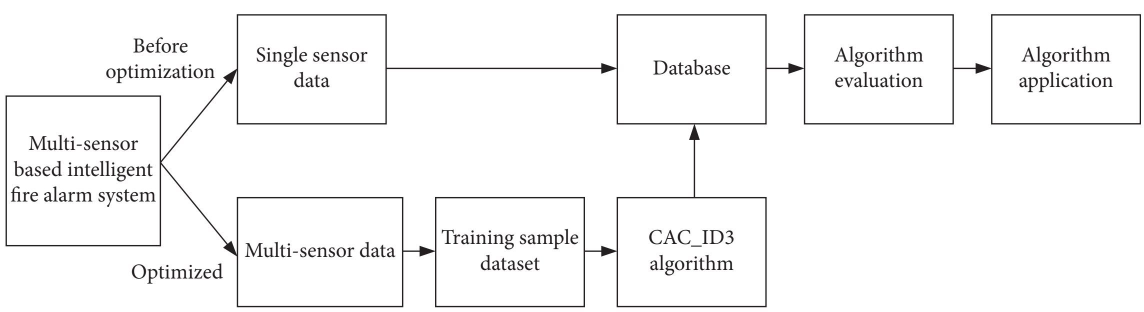


Figure 9: The experimental schematic diagram of the decision tree algorithm to predict the multisensor intelligent fire alarm system.

Table 3: Fragments of datasets based on the multisensor intelligent fire alarm system.

Numbering	RFID	Infrared	Human face	Surroundings	Video	Whether to invade
1	0	1	0	2	0	Yes
2	1	0	1	0	0	Yes
3	0	1	1	0	1	Yes
4	0	0	0	0	0	No
5	0	1	1	0	0	No
6	1	1	0	2	1	Yes
7	1	1	1	0	1	Yes
8	1	1	0	2	1	Yes
9	0	0	0	1	0	No
...	...	...	...	...	...	...

algorithm reaches 0.8431. This shows that the CAC_ID3 algorithm has superior performance.

As shown in Figure 8, in general, the CAC_ID3 algorithm performs well on the four datasets. On the dataset car, the accuracy rates of the C4.5, the CART, and the ID3 algorithm are basically the same. The CAC_ID3 algorithm is at least 0.0263 higher than the other three algorithms. This shows that the execution efficiency of the CAC_ID3 algorithm is high.

4. Experiment Analysis of CAC_ID3 Algorithm

Data analysis plays an important role in the intelligent fire alarm system. The quality of the data analysis is directly related to the accuracy of the information. When a large amount of data is collected, it first needs to be classified. So, this paper proposes the CAC_ID3 algorithm. Through the comparative analysis of the CAC_ID3 algorithm and other decision tree algorithms, it can be seen that the CAC_ID3

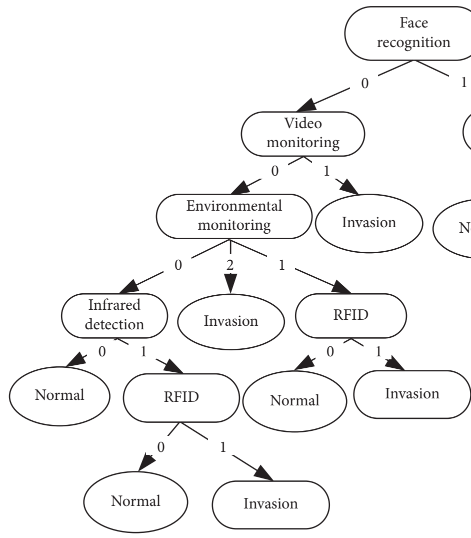
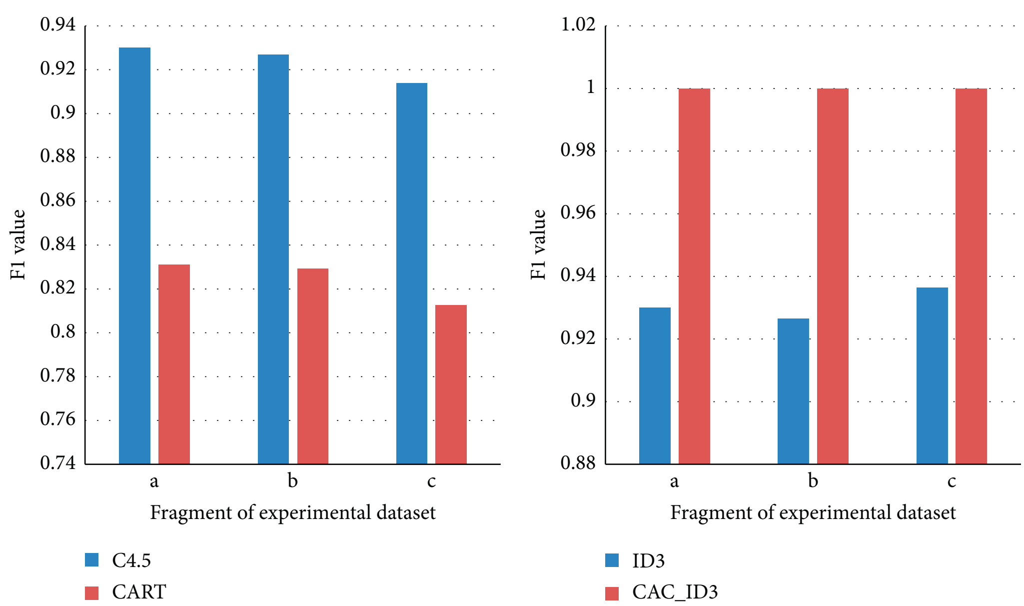


Figure 10: The decision tree generated based on the CAC_ID3 algorithm.



(a) (b)

Figure 11: *F*1 value of the four algorithms in the system experimental dataset. (a) The *F*1 value of the C4.5 and the CART algorithm in the system experimental dataset. (b) *F*1 values of the ID3 algorithm and the CAC_ID3 algorithm in the system experimental dataset.

algorithm can realize the data classification well. Therefore, this article classifies the intelligent fire alarm data based on the multisensors through the CAC_ID3 algorithm. Figure 9 is the experimental schematic diagram of the decision tree algorithm to predict the multisensor intelligent fire alarm system.

This system applies the C4.5 algorithm, CART algorithm, ID3 algorithm, and CAC_ID3 algorithm to the multisensor intelligent fire alarm system by using the developing environment and developing language and then conducting experimental comparisons. The performance of the algorithm is judged by the correct rate and F1 value. The data segment set of the multisensor intelligent fire alarm system is shown in Table 3. Table 3 divides the dataset into two parts, from which 80% are arbitrarily picked as the trainer set and 20% as the validation set.

In Table 3, 1 in RFID attribute, infrared attribute, face attribute, and video attribute means alarm and 0 means normal; 0 in the environment attribute is normal, 1 is a warning, and 2 is an alarm. The attribute of the class label is whether to invade or not, and it contains two values of “Yes” and “No.”

The confidence and information gain of each attribute are calculated by the CAC_ID3 algorithm. It is calculated

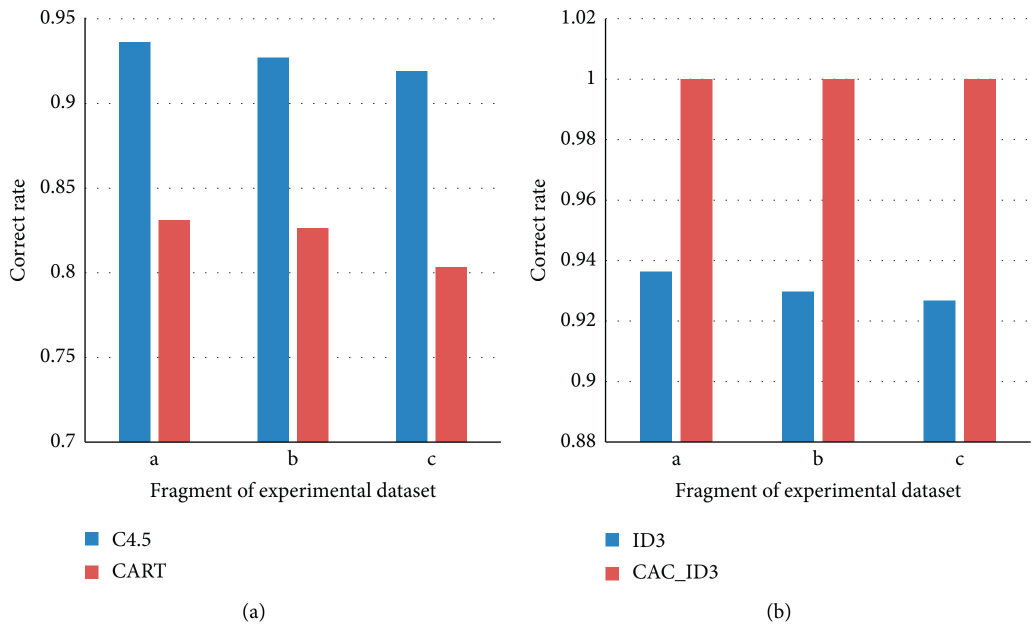


FIGURE 12: The accuracy of the four algorithms in the system experimental dataset. (a) The correct rate of the C4.5 and the CART algorithm in the system experimental dataset. (b) The correct rate of the ID3 algorithm and the CAC_ID3 algorithm in the system experimental dataset.

that the information gain of the face attribute is the largest; that is, the face attribute is selected as the division attribute. Figure 10 shows the decision tree based on the CAC_ID3 algorithm.

The decision-making trees generated based on the CAC_ID3 method are evaluated through Table 3, which shows that the accuracy ratio of the validation set is 100%. This article compares and analyzes the accuracy rate and the F1 value of the different algorithms to judge the performance of the algorithm.

According to the experimental results in Figures 11 and 12, it is observed that the accuracy and F1 value of the CAC_ID3 algorithm in the system experimental dataset are both 1, which are higher than those of the other three algorithms.

5. Discussion

According to the fast growth of the domestic market and the progress of the society, the construction industry is developing rapidly and many large buildings are rising. At the same time, the diversity of building styles and uses changes, and the probability of fire occurrence also increases to a certain extent. It may be due to a variety of fire sources, or it may be caused by human factors. Not only fires caused by buildings but also car fires, forest fires, and so on are also included. Different fires have different fire sources, but when a fire occurs, there will be different physical and chemical reactions, and there will be characteristics such as smoke, temperature, and gas concentration, and the characteristics will be different in different places. Therefore, the accuracy of the fire alarm system is particularly important. Based on the multisensor data fusion technology, it can dramatically decrease the false alarm rate of the fire and can increase the accuracy of fire judgment. Through the comparative analysis of the F1 value and the correct rate of the C4.5, the CART, and the ID3 algorithm on the four datasets, it is concluded that the F1 value and the correct rate of the CAC_ID3 algorithm are higher than those of the other three algorithms. It shows that the CAC_ID3 algorithm has an ideal classification effect.

Finally, through the comparative analysis of the F1 value and the correct rate of the four algorithms in the system experimental dataset, it is concluded that the classification correct rate and F1 value of the CAC_ID3 algorithm are slightly higher than those of other algorithms. Therefore, the CAC_ID3 algorithm has a certain practical significance in the application of a multisensor intelligent fire alarm system.

The entire comparison measurement figures indicate that the CAC_ID3 algorithm outperforms alternative algorithms in terms of performance comparison of algorithms, with datasets based on multisensor intelligent fire alarm systems. The feasibility and superiority of the CAC_ID3 algorithm in data classification are verified.

6. Conclusion

The multiple sensors message integration method is developed by imitating the sensory organs of humans and animals. The paper first expounds on the theoretical basis of multisensor data fusion and then determines the machine learning technology in artificial intelligence as an intelligent algorithm for fire signal processing. Aiming at the problem of multivalue bias in the ID3 algorithm, this article presents an improved approach. The first aspect is to introduce confidence into the expected entropy. The second aspect is to introduce attribute correlation information. Its purpose is to weaken the information gain of the attributes with small attribute value and category relationship. To further validate the capability of the CAC_ID3 method, the article compares the C4.5, the CART, the ID3, and the CAC_ID3 algorithm through experiments, showing that the execution performance of the CAC_ID3 method is more efficient than that of the other three algorithms. Then, this article uses the CAC_ID3 algorithm to classify the data of the multisensor intelligent fire alarm system and compares it with the other three algorithms. The testing outcome indicates that the classification precision of the CAC_ID3 algorithm is better than that of other algorithms. The accuracy and classification speed of the CAC_ID3 algorithm are more suitable for the real conditions of an intelligent fire alarm system based on multiple sensors digital integration. Therefore, it facilitates the advancement of work related to intelligent fire alarm systems and has a good application value. The multisensor intelligent fire alarm system is highly sophisticated and involved. Because of the authors' limitation of time and efforts as of resources, there are some deficiencies in this paper, such as the elaboration and scaling of the multisensor smart fire alarm system; other interferences that impact the decision tree algorithm classification precision are not considered such as the compatibility of the multisensor data fusion technology to intelligent fire alarm system.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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