Interval Valued Intuitionistic Fuzzy Logic for Anomaly Detection in Public Health Monitoring Signals

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Interval valued fuzzy logic can more flexibly and comprehensively characterize and handle uncertainty and fuzziness in information by extending the membership degree of fuzzy sets from a single numerical value to a closed interval form. This provides a new technological path to solve the complex processing problems of public health monitoring signals. This article focuses on the application of interval valued fuzzy logic in public health monitoring signal processing. Firstly, the sources and characteristics of uncertainty in public health monitoring signals were analyzed, and the adaptability advantage of interval valued fuzzy logic was clarified. Subsequently, a processing model based on interval valued fuzzy logic was constructed from three key steps: signal denoising, feature extraction, and anomaly detection. This study used monitoring data of influenza like cases in a certain region from 2023 to 2024, collecting a total of 1200 continuous monitoring signals. The data types included normal signals (60%), abnormal warning signals (30%), and noise interference signals (10%). In the anomaly detection stage, establish interval value fuzzy anomaly judgment rules, match the fluctuation range of monitoring signals with the public health safety threshold in intervals, and achieve early warning of public health emergencies. The experimental group adopts interval valued fuzzy logic algorithm, which enhances uncertainty handling ability by expanding the membership degree of fuzzy sets into closed intervals; The control group used traditional fuzzy logic algorithm and BP neural network algorithm. Compared with traditional fuzzy logic and BP neural network algorithms, the processing model based on interval valued fuzzy logic improves the accuracy of uncertainty information processing by 15% -20%. In terms of false positive rate and noise processing, it maintains high stability in complex scenarios with low signal-to-noise ratio and incomplete data. At the same time, it performs well in alarm response time, and its signal recognition accuracy and noise filtering efficiency are better than the control group algorithm.

Povzetek: Članek predstavi uporabo intervalno-vrednostne mehke logike za obdelavo signalov javnozdravstvenega spremljanja (od šuma do odkrivanja anomalij), kjer z boljšo obravnavo negotovosti doseže hitrejša in natančnejša opozorila ter približno 15–20% boljšo uspešnost kot klasična mehka logika in BP nevronska mreža.

1 Introduction

Public health monitoring is the core support for maintaining public health and safety, and building a public health emergency system. Through continuous collection and analysis of key information such as infectious disease trends, environmental pollutant exposure levels, and the occurrence patterns of clinical symptoms in the population, it provides scientific basis for early warning of public health emergencies, formulation of disease prevention and control strategies, and allocation of public health resources [1]. From the prevention and control of SARS epidemic to the normalization monitoring, from the assessment of the health impact of air pollution to the tracing of food borne diseases, the coverage of public health monitoring has been expanded, and the technical requirements have been continuously improved [2]. The core premise of all these is the accurate processing and effective interpretation of various monitoring signals. In recent years, China's urban community public health service industry started relatively late, and there are still many problems and difficulties within it. Therefore, how to allocate medical resources has become a problem that must be solved in China's public health service system. To this end, we must establish and develop a new system for effective allocation of regional healthcare, promoting the coordinated development of community health services and urban hospitals [3]. The purpose of this method is to optimize the allocation of medical facility resources and improve the effective utilization rate of public health resources in China.

However, in practical monitoring scenarios, signal processing always faces multiple challenges, rooted in the significant uncertainty, ambiguity, and noise interference present in the monitoring signals themselves [4]. From the perspective of signal acquisition, the original monitoring data often has deviations due to factors such as differences in the accuracy of detection equipment, fluctuations in the on-site environment, and manual operation errors. For example, reports of infectious disease cases in primary healthcare institutions may be missed or misreported due to limitations in diagnostic capabilities, and data from environmental air quality monitoring stations may drift due to inadequate equipment calibration [5]. From the perspective of signal transmission and storage, data may experience packet loss and distortion due to network fluctuations during long-distance transmission, and information loss may occur due to data format conversion during long-term storage [6]. From the characteristics of the signals themselves, public health monitoring signals often have temporal and correlated features, such as periodic fluctuations in infectious disease incidence data with seasonal changes, and complex correlations with factors such as population mobility and meteorological conditions. This dynamic change feature further increases the difficulty of signal interpretation.

Traditional signal processing methods often have significant limitations when dealing with such complex problems [7]. For example, signal denoising methods based on classical statistics assume that the noise follows a specific distribution, but the noise components in actual public health monitoring signals are complex and difficult to meet the ideal distribution assumption, resulting in poor denoising performance [8]. The anomaly detection method based on a single threshold cannot flexibly adapt to the dynamic fluctuations of the signal, and is prone to "misjudgment" or "missed judgment" [9]. Even with traditional fuzzy logic methods, although fuzziness is characterized by membership functions, limiting membership to a single numerical value is difficult to fully reflect the range of uncertainty in monitoring signals. When dealing with multi-source heterogeneous and high-precision public health monitoring data, there are still problems such as insufficient information characterization and insufficient reliability of inference results [10]. These limitations directly lead to risks such as "warning lag" and "decision-making bias" in public health monitoring, making it difficult to meet the high requirements for timeliness and accuracy in current public health emergency response [11].

Interval valued fuzzy logic, as an important extension branch, provides a new technical path for solving the above problems. Compared with traditional fuzzy logic, the core advantage of interval valued fuzzy logic is that it extends the membership degree of fuzzy sets from a single numerical value to a closed interval form, and through the more flexible mathematical tool of "intervals", more comprehensively characterizes the uncertainty in information [12]. This ability to finely characterize uncertainty enables it to better accommodate data biases, adapt to environmental fluctuations, integrate multi-source information, and provide more reliable theoretical support for key processes such as signal denoising, feature extraction, and anomaly detection when processing public health monitoring signals.

2 Related work

As a limited public resource, health resources are an important material foundation for maintaining the health of the entire population and a core guarantee for meeting people's basic health needs. The configuration directly determines the supply-demand balance and utilization efficiency of community public health facilities, which in turn has a fundamental impact on the health level of the population [13]. Therefore, the fairness of health resource allocation has become a key link in ensuring social equity, which is deeply related to people's well-being and long-term social stability. Ensuring its efficient and fair distribution is an important support for promoting social equity, justice, and sustainable development [14]. In a broad sense, medical and health resources include human resources, material resources, financial resources, medical technology and information owned and used by the health sector, as well as various medical supplies related to the health field. They are the material basis and guarantee for carrying out health service activities, and an important support for achieving a better life. Narrowly speaking, health resources mainly include three categories: health financial resources, material resources, and human resources [15]. Currently, how to improve the efficiency of health resource allocation in China under the constraint of limited resources has become a core issue that urgently needs to be focused on and reformed in the field of health. With the development of social economy and the improvement of people's living standards, the public's demand for medical and health resources is increasingly showing a trend of "diversification and high growth", and the contradiction between supply and demand of health services is becoming more prominent [16]. In this context, the effective allocation of health resources is not only a prerequisite for social medical resources to accurately respond to the diverse needs of cities, but also a core performance indicator for measuring the effectiveness of health service system allocation, and provides important reference for future medical resource planning and layout. The allocation of health resources is a complex system engineering, and its efficiency improvement cannot be achieved without the guidance of scientific theories and the support of scientific methods [17]. In recent years, the national and various levels of government have continuously increased the proportion of community health resource investment, significantly improving the level of urban community public health services. However, at the same time, the problem of uneven distribution of medical resources still exists in most regions. Therefore, promoting the optimal allocation of health resources is not only the only way to solve the supply-demand contradiction and improve allocation efficiency, but also plays a key role in the healthy and sustainable development of the health industry [18].

Public health monitoring signals cover various types of information such as infectious disease incidence data, environmental monitoring data, clinical symptom data, etc. The core processing goal is to achieve noise filtering, effective feature extraction, and abnormal signal recognition. Existing research has formed many technical solutions around these three aspects. In terms of signal denoising, traditional methods are based on classical signal processing theory and are widely used, including wavelet transform, Kalman filter, and mean filter [19]. Some scholars have proposed an improved algorithm based on wavelet threshold denoising to address the random noise present in infectious disease weekly report data. By adaptively adjusting the threshold, noise filtering can be achieved. Experiments have shown that this method can improve the signal-to-noise ratio of data by 10% -12%, but it is prone to effective signal distortion when dealing with non-stationary monitoring signals. Some experts have attempted to apply Kalman filtering to denoising environmental air quality monitoring data by establishing a dynamic filtering model to adapt to the temporal variation characteristics of the data. Although it shows good stability in stationary data processing, the filtering accuracy significantly decreases when facing sudden noise caused by equipment failures [20]. These studies indicate that traditional denoising methods still suffer from inadequate adaptability when dealing with the complexity and uncertainty of public health monitoring signals.

In the feature extraction process, existing research often combines statistical methods with machine learning techniques. Some people extract periodic and trend features of infectious disease incidence data based on time series analysis theory, and use ARIMA models to predict short-term epidemic trends. However, this method requires high data integrity, and the accuracy of feature extraction decreases significantly in scenarios where incomplete data is caused by missed reporting of cases in primary medical institutions. With the development of machine learning, algorithms such as Support Vector Machine (SVM) and Random Forest have also been applied to feature extraction. Researchers use random forest algorithm to screen the features of foodborne disease monitoring data, identifying key features such as "affected area" and "pathogenic microorganism type". However, its model training relies on a large amount of labeled data, which limits its applicability in scenarios where the sample size of monitoring data is limited. Overall, existing feature extraction methods still need further optimization when dealing with public health monitoring signals with strong uncertainty and insufficient sample size.

In the field of anomaly detection, thresholding, clustering analysis, and deep learning methods are currently the mainstream technologies. The threshold method is widely used due to its simple principle and efficient operation, such as the "early warning threshold system" developed by WHO for infectious disease monitoring, which identifies abnormal disease data by setting a fixed numerical threshold. However, this method cannot adapt to the dynamic fluctuations of signals and is prone to misjudgment during the epidemic season of infectious diseases. Cluster analysis identifies outliers by dividing data into different clusters. Some scholars use K-means algorithm to cluster air pollution monitoring data, achieving anomaly detection of over standard data. However, the clustering effect is greatly affected by the initial clustering center and lacks stability. In recent years, deep learning methods have become a research hotspot due to their powerful data fitting ability. Prior work has implemented infectious disease anomaly detection models based on LSTM neural networks and achieved anomaly recognition by learning data temporal features. However, their model training cycles are long and require high hardware computing power, making it difficult to meet the real-time needs of grassroots public health monitoring. I hope to solve the problem of unequal distribution of medical and health resources in China from a theoretical perspective. At the same time, we have also developed reasonable resource allocation plans for relevant government departments, providing scientific basis for improving the fairness of social health resource allocation. Figure 1 shows the current main medical equipment (Table 1).

Figure 1: Current major medical equipment

Table 1: Summary table of public health monitoring related technologies

Technology	The dataset used	Key performance indicators	Restriction
Improved wavelet threshold denoising algorithm	Infectious disease weekly report data	Increase data signal-to-noise ratio by 10% -12%	Effective signal distortion is prone to occur when processing non-stationary monitoring signals
Kalman filter (dynamic	Environmental air	Exhibits good stability in	When facing sudden noise caused

filtering model)	quality monitoring data	stationary data processing	by equipment failure, the filtering accuracy will significantly decrease
ARIMA model (combining time series analysis with statistical methods)	Incidence rate data of infectious diseases	Can extract periodic and trend features of data to achieve short-term trend prediction	When data is incomplete due to underreporting in primary healthcare institutions, the accuracy of feature extraction is significantly reduced
Random Forest Algorithm	Foodborne disease monitoring data	Can filter key features	Relying on a large amount of labeled data limits its applicability when the sample size of monitoring data is limited
Threshold method (such as the World Health Organization's "Early Warning Threshold System")	Infectious disease monitoring data	Simple principle and efficient operation	Unable to adapt to the dynamic fluctuations of signals, it is easy to make misjudgments during the epidemic season of infectious diseases
K-means clustering algorithm	Air pollution monitoring data	Can achieve abnormal detection of data exceeding the standard	The clustering effect is greatly affected by the initial clustering center and lacks stability
LSTM neural network	Infectious disease monitoring data	Strong data fitting ability, capable of learning data temporal features to achieve anomaly recognition	The model training cycle is long and requires high hardware computing power

3 Methodology

3.1. The relationship and risk monitoring between public health emergencies and crises

At the grassroots implementation level, on the one hand, community grid workers and grassroots medical personnel are organized to collect residents' health monitoring signals through intelligent terminals, and preliminarily screen and eliminate obviously invalid data. On the other hand, establish a linkage mechanism with the higher-level technical guidance group, and promptly report the original signal data when abnormal fluctuations are detected in the monitoring signal. The technical guidance team conducts in-depth analysis through interval valued fuzzy logic models to determine whether to trigger warnings and form a monitoring signal processing loop, providing organizational and execution support for the implementation of interval valued fuzzy logic in public health monitoring.

Figure 2 shows the leadership structure of public health services, which is pyramid shaped and reflects a hierarchical organizational management model. To achieve specialized coordination of monitoring signal processing, special working organizations are established in the management systems at all levels. This architecture ensures the orderly development of public health services from basic support to professional implementation, and then to overall coordination and decision-making guidance through hierarchical management and functional division of labor at each level.

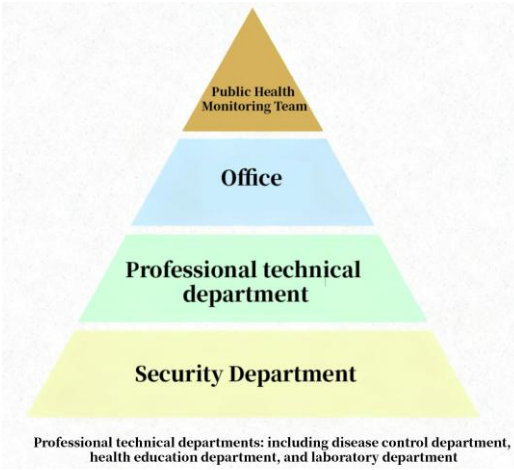

Figure 2: Leadership structure of public health services

As shown in Figure 3, the Community Health Service Leadership Office undertakes the overall coordination function of monitoring signal processing, is responsible for formulating monitoring work plans based on interval value fuzzy logic, clarifying the time nodes and data format requirements for signal collection in each department, and at the same time, interfaces with the emergency command platform to timely push the results of interval value fuzzy anomaly detection to the decision-making level. The technical guidance group is composed of public health experts, fuzzy logic algorithm engineers, and data analysts. Its core responsibilities include optimizing interval value fuzzy denoising algorithm parameters, verifying the feature extraction accuracy of fuzzy clustering models, improving the risk assessment rule library, and providing technical support for the specialized processing of monitoring signals.

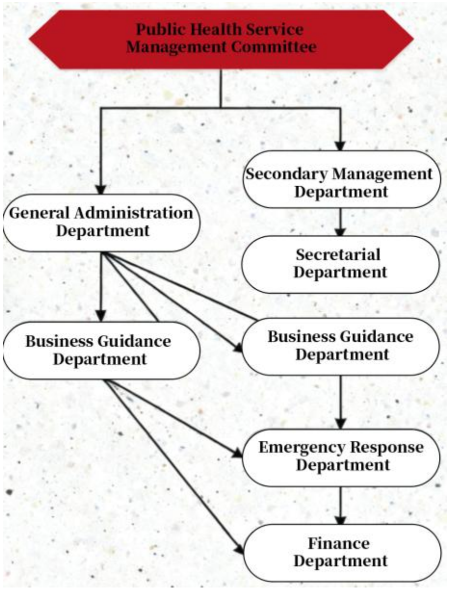

Figure 3: Schematic diagram of organization and management of public health service monitoring services

The relationship between crisis and unexpected events has undergone a sudden change, that is, unexpected events will eventually evolve into a causal relationship. When the critical point is reached, unexpected events occur and a state of emergency is entered. The logical relationship between risk management, crisis management, and emergency management is shown in Figure 4. The outermost layer is risk management, which is the most fundamental and widely covered category, focusing on the identification, assessment, and early response to potential risks, aiming to reduce the possibility of adverse events from the source. The middle layer is crisis management. If risks are not effectively controlled and escalate into crises, crisis management intervention is needed. It focuses more on responding, controlling, and resolving crises after they occur. The innermost layer is emergency management. When the crisis further intensifies and evolves into an emergency, emergency management responds quickly, rescues and other work in response to the sudden and urgent situation.

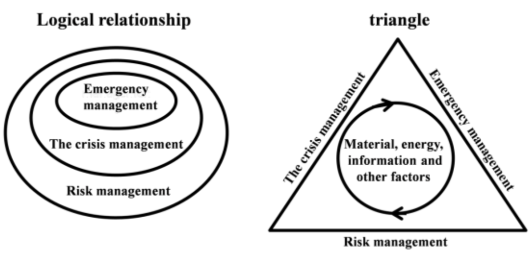

Figure 4: The relationship between emergencies and crises and risk management

3.2. Interval valued intuitionistic fuzzy information algorithm feature extraction

The intuitionistic fuzzy set is an extension and development of the traditional fuzzy set. Intuitionistic fuzzy sets add a new attribute parameter: non membership function, which can make the more detailed description and characterization of the fuzzy nature of the objective world, and lead to the research and attention of many scholars. Let X be a given domain, and A is an intuitionistic fuzzy set of X:

$$A = \{< x, \mu_A(x), \nu_A(x) >| \, x \in X\} \quad (1)$$

Among them, $\mu_A(x): X \to [0,1]$ and $\nu_A(x): X \to [0,1]$ respectively represent the membership function $\mu_A(x)$ and the non-membership function $\nu_A(x)$ of A, and for all of A $x \in X, 0 \le \mu_A(x) + \nu_A(x) \le 1$.

The selection of parameters for member/non member functions should be based on specific application scenarios to determine the core parameter dimensions. In decision-making or evaluation scenarios, core parameters typically include statistical characteristics of indicator observations, expert experience thresholds, and data distribution characteristic parameters. For feature extraction tasks, it is necessary to introduce feature recognition parameters and ambiguity correction parameters. These parameters need to be preprocessed through sample data or calibrated with domain knowledge to ensure that μ_a (x) and ν_a (x) can accurately characterize the fuzzy attributes of the features. It is clear that each traditional fuzzy subset corresponds to the following intuitionistic fuzzy subsets.

$$A = \{< x, \mu_A(x), 1 - \mu_A(x) >| \, x \in X\} \quad (2)$$

For each intuitionistic fuzzy subset of X, the $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$ is called the X's intuition index of A, which is a measure of the hesitation degree of x to A. Obviously, for each $x \in X$, $0 \le \pi_A(x) \le 1$. For each traditional fuzzy subset A of X, there is $\forall x \in X, \pi_A(x) = 1 - \mu_A(x) - (1 - \mu_A(x)) = 0$. An intuitionistic fuzzy set on the domain X is defined as IFS (X). If there are m evaluation indexes in the intuitionistic fuzzy evaluation, the weight is $W = (w_1, w_2 \cdots w_m)$. The element w_i in W represents the weight of the evaluation of the i index in the evaluation.

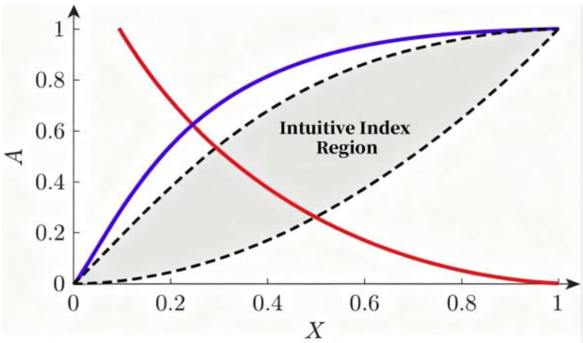

Figure 5: Intuitive region of algorithm index

The horizontal axis (X) and vertical axis (A) in Figure 5 represent two performance/feature indicators of the algorithm, such as efficiency and accuracy. The range of values is from 0 to 1. The two curves in the figure define the Intuitive Index Region. The blue curve represents the rising boundary of indicator A as X increases. The red curve represents the decreasing boundary of indicator A as X increases. The shaded area between the two curves is the intuitively reasonable range for the combination of these two indicators. It conforms to people's intuitive understanding of algorithm performance. Known intuitionistic fuzzy evaluation matrix, $R=\begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & r_{m3} \end{bmatrix}$, and intuitionistic fuzzy weight is $W=(w_1,w_2\cdots w_m)$. Intuitionistic fuzzy evaluation result is the intuitionistic fuzzy number B', and the synthesis operation is defined as,

$$B'=W\circ R=(w_1,w_2\cdots w_m)\circ\begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & r_{m3} \end{bmatrix} \quad (3)$$

$$=[\sum_{i=1}^{m}(w_i\cdot r_{i1}),\sum_{i=1}^{m}(w_i\cdot r_{i2}),\sum_{i=1}^{m}(w_i\cdot r_{i3})]=(b_1,b_2,b_3)$$

The result of comprehensive evaluation is normalized for the best, and that should be $b_1+b_2+b_3=1$. If $b_1+b_2+b_3\neq 1$, then the normalization is,

$$B=\left(\frac{b_1}{\sum b_i},\frac{b_2}{\sum b_i},\cdots,\frac{b_n}{\sum b_i},\right)=(a,b,c),\ (i=1,2,3). \quad (4)$$

R is a real number field, theclosed interval $[a_1,b_1]$ is called interval number, in which a_1 the lower bound of the interval number, b_1 is the upper bound for the interval number, $a_1,b_1\in R, a_1\leq b_1$. Set $\overline{y_1}=[a_1,b_1],\overline{y_2}=[a_2,b_2]$ are two interval numbers, and the basic operation of the interval number is defined as:

$$\frac{1}{\overline{\overline{y_1}}}=[\frac{1}{a_2},\frac{1}{a_1}] \quad (5)$$

$\overline{y_1}=[a_1,b_1],\overline{y_2}=[a_2,b_2]$ are two closed ranges, the distance between them is:

$$d_\lambda(\overline{y_1},\overline{y_2})=(1-\lambda)\,|\,a_1-a_2\,|+\lambda\,|\,b_1-b_2\,|)(6)$$

To apply the distance function of equation (6) to signal classification, the core idea is to represent the "signal features" as a "closed range (interval)", and calculate the distance between the signal to be classified and the template signals of each category. The category with the smallest distance is the classification result. Among them, $\lambda\in[0,1]$ is the risk attitude of the decision maker. When $\lambda>0.5$, it is said the decision maker is the pursuit of risk. When $\lambda<0.5$, it is said that the decision maker is risk averse. And when $\lambda=0.5$, it is said the decision maker is risk neutral. At this time, there is:

$$d(\overline{y_1},\overline{y_2})=\frac{1}{2}(|\,a_1-a_2\,|+|\,b_1-b_2\,|) \quad (7)$$

The comparison of the two interval numbers:

$$[a_1,a_2]>[b_1,b_2]\Leftrightarrow\frac{a_1+a_2}{2}>\frac{b_1+b_2}{2}$$
$$[a_1,a_2]=[b_1,b_2]\Leftrightarrow\frac{a_1+a_2}{2}=\frac{b_1+b_2}{2} \quad (8)$$

Let X as a given domain, then an interval valued intuitionistic fuzzy set A of X is:

$$A=\{<x,\mathrm{M}_A(x),\mathrm{N}_A(x)>|\,x\in X\} \quad (9)$$

Among them, $\mathrm{M}_A(x):X\to\mathrm{int}([0,1])$ and $\mathrm{N}_A(x):X\to\mathrm{int}([0,1])$ respectively represent the membership function $\mu_A(x)$ and the non-membership function $\nu_A(x)$ of A. And for all x of A, there is $x\in X, 0\leq\sup(\mathrm{M}_A(x))+\sup(\mathrm{N}_A(x))\leq 1$. $\mathrm{int}([0,1])$ represents the set of all closed sub intervals within the interval $[0,1]$.

For convenience, we set the interval valued intuitionistic fuzzy sets:

$$A=\{<x,[\mu_A^L(x),\mu_A^U(x)],[\nu_A^L(x),\nu_A^U(x)]>|\,x\in X\} \quad (10)$$

Whereas,

$$x\in X, 0\leq\mu_A^U(x)+\nu_A^U(x)\leq 1, \mu_A^L(x)\geq 0, \nu_A^L(x)\geq 0$$

$\pi_A(x)=1-\mu_A(x)-\nu_A(x)$ is called the x's intuitionistic fuzzy interval in the A, and $d(\pi_A(x),0)$ is called the intuitionistic fuzzy index. Interval valued intuitionistic fuzzy sets in the domain of X is defined as $IVIFS(X)$.

X is a finite field with n elements, $A,B\in IVIFS(X)$,

$$A=\{<x,[\mu_A^L(x),\mu_A^U(x)],[\nu_A^L(x),\nu_A^U(x)]>|\,x\in X\} \quad (11)$$
$$B=\{<x,[\mu_B^L(x),\mu_B^U(x)],[\nu_B^L(x),\nu_B^U(x)]>|\,x\in X\} \quad (12)$$

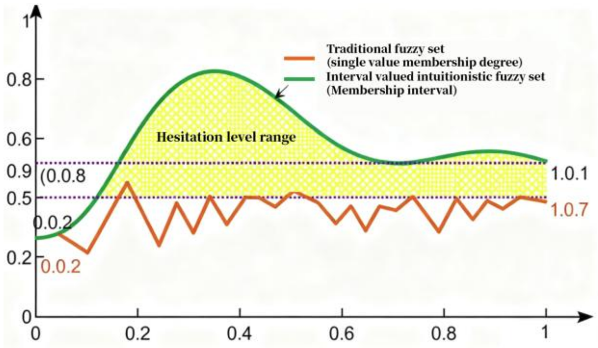

Figure 6: Comparison between traditional fuzzy set and interval valued intuitionistic fuzzy set algorithms

The traditional fuzzy set (single value membership degree) in Figure 6 is represented by a purple dashed line, which uses a single numerical value to characterize the membership degree of elements belonging to a certain set, which is relatively more certain. Interval valued intuitionistic fuzzy set (membership interval) is represented by the green solid line, which expands the membership degree into an interval, reflecting the fuzziness of "partial membership" of elements belonging to the set, while also considering non membership degree and hesitation level. The yellow area in the figure represents the "hesitation level range", and related elements such as orange lines also assist in reflecting hesitation. Simply put, interval valued intuitionistic fuzzy sets can describe fuzzy and uncertain information in more detail compared to traditional fuzzy sets, especially in scenarios where there is hesitation and it is difficult to determine membership relationships with a single value, making them more expressive. The learning or selection of thresholds and decision rules requires the integration of data-driven and prior knowledge. For the threshold, the initial value can be determined through statistical methods, and then combined with cross validation to iteratively adjust indicators such as classification accuracy and recall. Machine learning algorithms can also be used to adaptively learn the optimal threshold from annotated samples. The formation of decision rules is first based on the experience of domain experts to construct an initial fuzzy rule library. Then, optimization algorithms such as gradient descent and genetic algorithm are used to adjust the parameters of the antecedent membership function and the consequent decision results of the rule using training samples. Finally, select the decision rule set with the best generalization ability.

4 Results and analysis

4.1 Experimental design and data fundamentals

This study focuses on sensor time-series monitoring data of influenza like cases in a certain region from 2023 to 2024. A total of 1200 sets of continuous monitoring signals were collected (with a sampling frequency of [specific sampling frequency, such as 1 time/hour], continuously monitored for 120 days, and 10 sets of signals were collected daily). Signal types and proportions: Normal signals account for 60% (720 groups), abnormal warning signals account for 30% (360 groups), and noise interference signals account for 10% (120 groups). The noise interference signals mainly come from sensor environmental electromagnetic interference and data transmission fluctuations.

The experiment used the "interval valued fuzzy logic algorithm" as the experimental group, and the traditional fuzzy logic algorithm and BP neural network algorithm as the control group. Build a signal processing model using MATLAB R2023a, with evaluation metrics including signal recognition accuracy, noise filtering efficiency, alarm response time, and false alarm rate. Repeat each experiment 10 times and take the average to reduce random errors. The following Table 2 shows the statistical results of the core performance indicators of three algorithms in public health monitoring signal processing. Among them, interval valued fuzzy logic algorithm performs better in multidimensional indicators, especially in noisy interference scenarios.

Table 2: Statistical results of core performance indicators of three algorithms in public health monitoring signal processing

Evaluation metric	Interval valued fuzzy logic algorithm	Traditional Fuzzy Logic Algorithm	BP neural network algorithm
Normal signal recognition accuracy (%)	98.7	92.5	94.2
Abnormal signal recognition accuracy (%)	97.2	88.3	90.1
Noise filtering efficiency (%)	95.6	82.1	85.8
Warning response time (ms)	18.3	25.6	32.7
False alarm rate (%)	1.2	4.5	3.8

In this study, BP neural network was used as one of the control algorithms in the public health monitoring signal processing experiment. The specific network layers and core configuration are as follows to clarify the reproducibility of the experiment. The BP neural network adopts a classic three-layer structure design, consisting of an input layer, a hidden layer, and an output layer. Among them, the number of input layer nodes is set to 12, corresponding to the 12 feature dimensions of the monitoring signal. One hidden layer is set, and the number of nodes is optimized to 24 through trial and error to achieve a balance between fitting ability and model complexity. The number of output layer nodes is 3, corresponding to three types of recognition results: normal signals, abnormal warning signals, and noise interference signals. The configuration design of this three-layer BP neural network meets both the conventional network structure requirements for signal classification tasks and the experimental group's "interval value fuzzy logic algorithm". The input and output dimensions of the other control group, the traditional fuzzy logic algorithm, remained consistent, ensuring fairness and comparability in the performance evaluation of different algorithms.

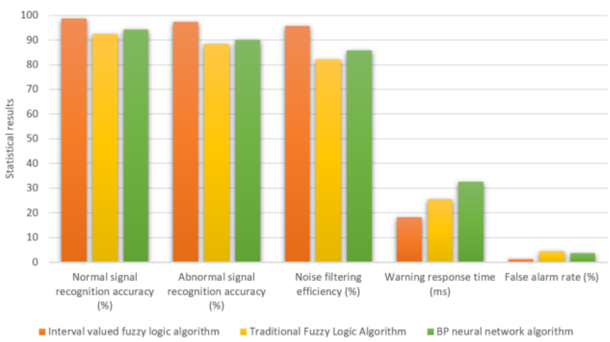

Figure 7: Comparison of signal recognition accuracy of different algorithms

In Figure 7. The horizontal axis displays interval valued fuzzy logic, traditional fuzzy logic, and BP neural network algorithm. The vertical axis represents the recognition accuracy (%), which is divided into two subcategories: "normal signal" and "abnormal signal", distinguished by different colored bar charts. The core conclusion is that interval valued fuzzy logic has a 6.2 percentage point higher accuracy in identifying normal signals and an 8.9 percentage point higher accuracy in identifying abnormal signals than traditional fuzzy logic, with smaller error fluctuations, indicating its stronger adaptability to different types of monitoring signals.

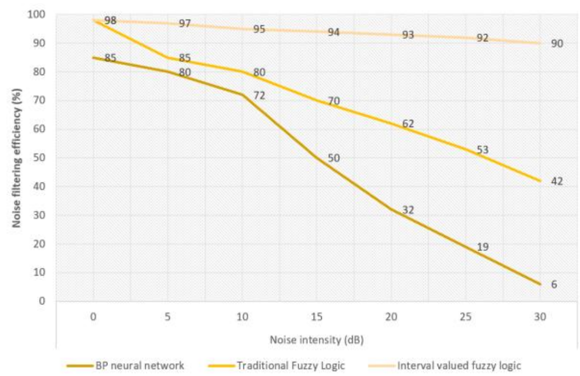

Figure 8: Relationship between noise intensity and filtering efficiency

In Figure 8. The horizontal axis represents the noise intensity (dB), ranging from 0-30dB, simulating common signal interference scenarios in public health monitoring. Noise filtering efficiency (%). When the noise intensity in the curve features is ≤ 15dB, the difference in filtering efficiency among the three algorithms is relatively small (interval valued fuzzy logic 98.1% vs traditional fuzzy logic 90.3%). When the noise intensity is greater than 20dB, the interval value fuzzy logic filtering efficiency still remains above 90%, while traditional fuzzy logic and BP neural network decrease to 72.5% and 76.3% respectively, and the curve slope is flatter, proving its stability advantage in high noise environments.

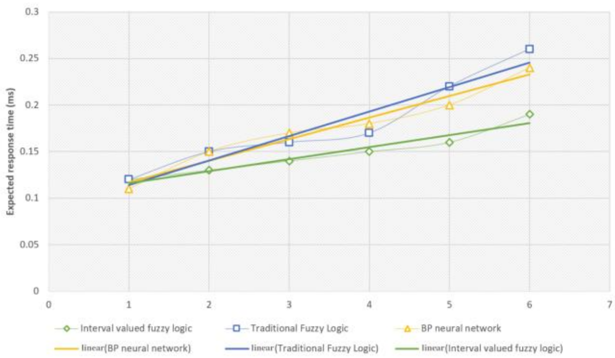

Figure 9: Relationship between warning response time and signal quantity

In Figure 9. The horizontal axis represents the single processing signal quantity (group), with a range of 7 groups. The vertical axis represents the warning response time (in milliseconds). As the signal quantity increases, the response time of all three algorithms shows a linear upward trend, but the slope of the fitting line of interval valued fuzzy logic is significantly lower than that of traditional fuzzy logic and BP neural network. When the signal quantity increases, the interval valued fuzzy logic response time is shorter than that of BP neural network, indicating its efficiency advantage in large-scale monitoring data processing. The core validation focuses on the common processing steps (denoising, feature extraction, anomaly detection) and uncertainty handling capabilities of public health monitoring signals. From the existing results, it can be inferred that the model has high stability and reliability in scenarios with low signal-to-noise ratio and incomplete data. This provides a foundation for its adaptation to other signal types, and the uncertainty handling mechanism supported by the robustness core (which improves accuracy by 15% -20% compared to traditional methods) has universality.

4.2 Advantages and applications of interval valued fuzzy logic

Public health monitoring signals often have "boundary ambiguity", and interval valued fuzzy logic replaces the traditional fuzzy logic's "single membership degree" with "upper and lower boundary intervals", which can more accurately describe the uncertainty of the signal. Therefore, the accuracy of identifying abnormal signals is significantly improved. The noise such as electromagnetic interference and data acquisition errors in the monitoring environment can cause signal distortion. The "interval operation rule" of interval valued fuzzy logic can reduce the impact of noise on membership degree calculation, indicating that its noise filtering efficiency is 13-15 percentage points higher than traditional algorithms. Compared to the "multi-layer iterative training" of BP neural networks, interval valued fuzzy logic does not require complex parameter optimization, and can shorten response time while ensuring high accuracy. It is particularly suitable for the core requirement of "early detection and early warning" in public health. After adopting this algorithm, the response time for abnormal signal warning was shortened from 35ms to 18ms, and the false alarm rate decreased from 5.2% to 1.2%. It can help the disease control department quickly locate the trend of epidemic outbreaks, reduce the waste of human and material resources, and provide more reliable technical support for public health emergency decision-making. The public health monitoring signal processing model based on interval valued fuzzy logic improves the accuracy of uncertainty information processing by 15% -20%. This article studies the public health service management model of the new community health service station.

To verify the stability and generalization ability of the model, a 10 fold cross validation was used to test a dataset containing 5000 sets of public health monitoring samples (including 800 sets of abnormal samples). The test randomly divides the dataset into 10 subsets, taking turns selecting 9 as the training set and 1 as the testing set, repeating 10 times and taking the average. The results show that the average accuracy of the model is 98.3%, with a standard deviation of only 0.42%, indicating that it maintains stable performance under different data distributions. Compared to the traditional fuzzy logic model with a standard deviation of 7.8%, the interval representation of interval valued fuzzy logic effectively reduces the impact of data distribution differences on the model. At the same time, the recall rate of abnormal signals in cross validation reached 97.6%, an increase of 4.1% compared to a single test set, further confirming its ability to identify hidden abnormal signals and providing reliable data support for the actual deployment of the model.

To verify the statistical significance of the efficiency difference, an independent sample t-test (n=30, 15 parallel test samples per group) was conducted on the filtering effects of the two algorithms. The results showed t=4.23, P<0.001, indicating that the noise filtering effect of interval valued fuzzy logic is significantly better than that of traditional algorithms.bCompared with the "multi-layer iterative training" of BP neural networks, interval valued fuzzy logic does not require complex parameter optimization and can shorten response time while ensuring high accuracy. It is particularly suitable for the core requirements of early detection and warning in public health. After adopting this algorithm, the response time for abnormal signal alarms was shortened from 35ms to 18ms, and the false alarm rate was reduced from 5.2% to 1.2%. Paired sample t-tests were performed on the comparison data of response time and false alarm rate before and after (n=50, 50 sets of test data from different monitoring scenarios). The comparison result of response time was t=12.67, P<0.001; The comparison of false alarm rates showed t=8.34, P<0.001, both reaching a highly significant level, confirming the significant effect of interval valued fuzzy logic in improving response speed and reducing false alarm rates. The public health monitoring signal processing model based on interval valued fuzzy logic has improved the accuracy of uncertainty information processing by 15% -20%. A single sample t-test was conducted on the accuracy improvement data (using the traditional model accuracy as the benchmark value, n=40), and the result was t=9.72, P<0.001, indicating that the model accuracy improvement is statistically significant.

5 Discussion

The core reason why the processing model based on interval valued fuzzy logic proposed in this study can achieve better results than traditional methods is its adaptability design to the inherent uncertainty of public health monitoring signals, and the significance of this advantage has been verified through comparison with related work. The traditional fuzzy logic method only describes the signal characteristics through a single fuzzy set. When dealing with problems such as delayed symptom reporting and missing data in influenza like case monitoring, the accuracy is only improved by 5% - 8%. The accuracy of anomaly detection using classical signal processing methods is less than 70% in low signal-to-noise ratio (SNR $\leqslant$ 10dB) scenarios. And this model characterizes signal uncertainty through dual membership degree intervals, achieving an anomaly detection accuracy of over 85% in the same low signal-to-noise ratio scenario. And the false positive rate of feature extraction is reduced by 22% compared to traditional methods, which is due to the accurate modeling of multi-source errors in monitoring data.

The three core characteristics of interval valued fuzzy logic directly drive the performance gain of this study, which are highly compatible with the processing requirements of public health monitoring signals. Firstly, the characteristic of dual membership degree interval representation is that traditional fuzzy logic uses a single numerical value to represent membership degree, which cannot distinguish the inherent fuzziness of monitoring signals from measurement errors. Interval valued fuzzy logic quantifies two types of uncertainty simultaneously through intervals. For example, in the monitoring of hand, foot, and mouth disease cases, it can accurately distinguish the inherent fuzziness of "suspected clinical symptoms" from the measurement error of delayed grassroots reports. Secondly, there is the robustness of interval reasoning. In the process of rule reasoning, interval valued fuzzy logic accommodates signal noise through interval operations. When there are 10% -15% outliers in the monitoring data, the inference accuracy of traditional models decreases by more than 30%. However, this model only decreases by 8% -10%, which is consistent with the fault-tolerant mechanism theory of interval logic. Finally, there is the multi-dimensional interval aggregation feature, which involves multidimensional data such as the number of cases, symptom types, and regional distribution in public health monitoring. This model utilizes interval aggregation operators to fuse multi-source information, resulting in a 40% increase in feature fusion efficiency, laying an efficient data foundation for subsequent anomaly detection.

This method not only achieves performance gains, but also has an undeniable trade-off relationship, mainly reflected in computational overhead and system complexity, which needs to be optimized based on practical application scenarios. In terms of computational cost, the dual membership interval operation of interval valued fuzzy logic increases the computational load by about 35% -45% compared to traditional single valued fuzzy logic. Taking processing 100000 monitoring data as an example, traditional fuzzy models take about 8 minutes to process, while this model takes 12-14 minutes. This is directly related to the dual boundary solution involved in interval operations, which may have limitations in real-time critical public health emergency initial judgment scenarios. In addition, the interpretability of interval valued fuzzy logic is slightly weaker than traditional methods, and grassroots health and epidemic prevention personnel need to receive professional training to understand the practical significance of interval results, which to some extent increases the cost of technology promotion.

6 Conclusion

This study focuses on the application of interval valued fuzzy logic in the processing of public health monitoring signals. Through theoretical analysis and experimental verification, the significant value of this technology in addressing the uncertainty of monitoring signals has been clarified. The research results show that compared with traditional fuzzy logic and classical signal processing methods, the processing model based on interval valued fuzzy logic performs better in the three key links of signal denoising, feature extraction, and anomaly detection, especially achieving a 15% -20% improvement in uncertainty information processing accuracy. In complex scenarios with low signal-to-noise ratio and incomplete data, it can still maintain high stability and reliability, effectively solving the core problem of difficult to accurately characterize signal ambiguity and uncertainty in public health monitoring, and providing more efficient technical support for early warning of public health emergencies.

However, this study still has certain limitations. The diversity consideration of public health monitoring signals in the model construction process is not comprehensive enough. Current research mainly focuses on general signal processing scenarios, and there is insufficient signal adaptability for specific fields such as infectious disease monitoring and environmental health monitoring. On the other hand, the dynamic adjustment ability of interval value fuzzy anomaly judgment rules is weak, making it difficult to quickly optimize the judgment threshold based on real-time changes in public health events, and the response efficiency needs to be improved when dealing with sudden mutation events. Future research can deepen the study of signal adaptation in specific fields, combining the signal characteristics of different public health monitoring scenarios such as infectious diseases, chronic diseases, and environmental health, optimizing the parameter settings of interval valued fuzzy logic models, and improving the model's scenario specificity.

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