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# A Study on Group Decision Making Problem Based on Fuzzy Reasoning and Bayesian Networks

**Shuijin Rong[1,a], Wei Guo[1,b], Daqing Zhang[1,c,*]**

*[1]University of Science and Technology Liaoning, Anshan, China*
*[a]120223803046@stu.ustl.edu.cn, [b]weiguo@stu.ustl.edu.cn, [c]d.q.zhang@ustl.edu.cn*
**Corresponding author*

***Abstract:*** *Aiming at the group decision-making problem with multi-objective attributes, this study proposes a group decision-making system that integrates fuzzy inference and Bayesian network. Based on the mixture of threshold, affiliation function, expert experience and relevant potential background to construct a fuzzy rule base to solve the quantitative problems such as scale differences and expert linguistic variables; designing a hierarchical Bayesian network, constructing a directed acyclic graph with the expert selection as the node, and utilizing the maximum likelihood estimation to dynamically optimize the conditional probability table, resolving the nonlinear correlation between the multidimensional indexes to sum up the a posteriori. This study compares our method with the traditional weighted scoring approach in a comprehensive student evaluation decision-making problem, and the results show that our method performs well in explaining the decision-making in both the construction of rule criteria and the standard ranking scheme. In addition, the performance and robustness of the present method is investigated through computational experiments involving real datasets in the context of different group decision problems.*

***Keywords:*** *Group Decision Making; Fuzzy Reasoning; Bayesian Network*

## 1. Introduction

Multi-attribute decision making often requires a compromise. Wu Z[1] et al determined expert weights based on the possibility distribution HFLTS theory to reduce information loss, but there were limitations in scene adaptability. Luo C and Li T[2] improved the three-way decision making through attribute value classification and extended the theory but did not specify the decision cost trend estimation function. Jiang[3] proposed the SMA3WGD method to solve the heterogeneous MAGDM problem with unknown weights, which is suitable for medical treatment, blockchain and other fields. Some scholars use fuzzy set theory to form three levels in group decision making [4][5][6]. Wei C and Rodriguez R M[7] proposed that hesitantly fuzzy linguistic term sets deal with multi-term preference expression. Hwang CL [8] proposed the classical TOPSIS method, but faced with the challenge of incomplete decision matrix [9]. Chen R[10] used Rough TOPSIS method to convert the matrix into rough numbers and then conducted distance sorting.

Progress has been made in Bayesian network extension methods: Rajabi M M[11] uses proxy modeling to accelerate fuzzy Bayesian inference and applies it to groundwater modeling; Gul M and Yucesan M[12] combined FBN and FBWM to improve plastic production fault diagnosis; Xue J[13]constructed fuzzy Bayesian network fusion PCA to reduce the subjectivity of offshore wind power decision-making. Hao Z and Xu Z[14] developed IFBN to obtain attribute weights to solve dynamic risk decision-making; Amindoust A[15] proposed that the supplier selection method based on FIS has both scalability and practicability. Chen R pointed out the lack of generalization of traditional methods, and pointed out in particular that vague terms such as "excellent/good/average" in educational evaluation will mislead students' development, and it is urgent to establish a reliable decision-making support system.

The comprehensive evaluation of students' quality belongs to the typical application of group decision theory. The core features of this field are the pluralism of decision subject, the multiplicity of evaluation dimensions and the uncertainty of information structure. In the process of constructing the evaluation system, this research constructs a multi-level evaluation model with three core dimensions by integrating fuzzy reasoning and Bayesian network method. This method breaks through the single dimension limitation of traditional evaluation and plays a positive role in deepening the reform of educational evaluation.

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## 2. Related Work

### *2.1 Fuzzy reasoning mechanism*

Under the framework of fuzzy reasoning theory, the system modeling mainly adopts the formal description methods of fuzzy sets and fuzzy rules. The fuzzy set theory proposed by Zade[16] effectively solves the uncertainty problem of human judgment in the decision-making process by introducing language terms and membership function. A fuzzy set can be defined as a set of objects with a continuous membership level, whose membership function range is [0,1], which is used to represent the degree of an element belonging to a specific fuzzy set. Given a set of objects X, its fuzzy set can be expressed as:

$$X = X_1, X_2, ..., X_n \tag{1}$$

Where $X_n$ is an element in the set $X$. The affiliation value $\mu$ denotes the rank of affiliation associated with each element $X_n$ in the fuzzy set A, which is combined in the following form:

$$A = \mu_1(x_1), \mu_2(x_2), ..., \mu_n(x_n) \tag{2}$$

In order to realize the mathematical modeling of fuzzy inference, it is necessary to construct the fuzzy relationship mapping from the domain a to the assessment level set A. Define the fuzzy relation matrix R on the Cartesian product space $a \times A$:

$$R = \sum_{(i,j)} \frac{\lambda_R(a_i, A_j)}{(a_i, A_j)} = [r_{ij}]_{n \times m} \tag{3}$$

Under the theoretical framework of multi-factor evaluation space, this paper proposes a comprehensive evaluation method based on fuzzy reasoning. By constructing normalized weight vector, the relative importance of each evaluation factor is quantified. On this basis, combined with fuzzy rule set to represent the membership distribution of each factor under each evaluation level, the fuzzy inference operation model is constructed. The Cartesian product operator of "comprehensive weighted type" is used to realize the cooperative operation of weight vector and fuzzy rules.

Following Zadeh's research, E.H. Mamdani[17] first proposed a fuzzy reasoning method based on synthetic reasoning rules in 1974. The Mamdani fuzzy inference system constructed by this method consists of four core modules, and its system structure is shown in Figure 1.

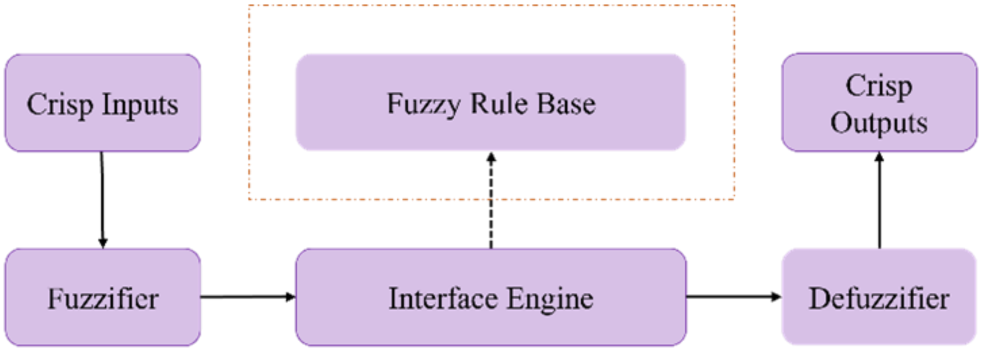


*Figure 1: Fuzzy inference system structure.*

### *2.2 Introduction of Bayesian networks*

Bayesian networks represent conditional dependencies among variables through directed acyclic graphs and quantify joint probability distributions using conditional probability tables. The core formula is:

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$$P(X_1, X_2, X_3, ..., X_n) = \prod_{i=1}^{n} P(X_i \mid Pa(X_i)) \tag{4}$$

Where $P\left(X_i\right)$ denotes the set of parent nodes of node $X_i$.

Based on the conditional independence hypothesis, Bayesian networks can significantly reduce the parameter dimension of the joint probability distribution (Darwiche A, 2009[18]) and effectively control the inference complexity. The existing inference methods are divided into precise inference and approximate inference: the former is suitable for small networks with low complexity, and the latter improves the efficiency within the acceptable error range by optimizing the calculation strategy. In recent years, important breakthroughs have been made in the approximation algorithms based on Monte Carlo sampling and heuristic search, the core of which is to build a dynamic balance mechanism of computational complexity and inference accuracy.

## 3. Group decision system

### *3.1 Data fuzzy processing*

In this paper, a comprehensive evaluation system based on fuzzy inference and Bayesian network is constructed. Firstly, the original data such as academic achievement are fuzzy processed, and the membership degree of "excellent - good - medium - poor" is established by Gaussian membership function. Taking academic evaluation as an example, core subject scores are extracted based on public data[19], and fuzzy classification of multi-dimensional features is realized after standardized pre-processing:

$$\mu\left(x\right) = exp\left(-\frac{\left(x-c\right)^2}{2\sigma^2}\right) \tag{5}$$

Where $x$ denotes the student's subject grade, $c$ is the center value of the affiliation function, and $\sigma$ is the standard deviation.

For the other sub-dimensions, differentiated membership functions are constructed based on data distribution characteristics, and fuzzy probability input of multidimensional evaluation indicators is established. This method forms a complete fuzzy inference-Bayes network joint analysis framework through the mathematical modeling of feature adaptation.

### *3.2 Structure design of Bayesian network*

(1) Node definition and hierarchy division

Based on the comprehensive evaluation requirements, a three-layer Bayesian network is constructed in this study. The network structure is as follows: Input layer (leaf node) : various sub-indicators; The middle layer includes three nodes: academic synthesis (A), practical synthesis (P) and moral synthesis (M); Output layer (root node) : Comprehensive evaluation level (S).

(2) Relation hypothesis between sub-indicators

It is assumed that academic synthesis (A), practical synthesis (P) and moral synthesis (M) are independent of each other given the comprehensive evaluation level (S). This hypothesis simplifies the dependencies between nodes, and its conditional probability distribution can be expressed as:

$$\begin{aligned} P\left(S \mid A, P, M\right) &= \frac{P\left(A \mid S\right) P\left(P \mid S\right) P\left(M \mid S\right) P\left(S\right)}{P\left(A, P, M\right)} \\ &= \alpha \times P\left(A \mid S\right) P\left(P \mid S\right) P\left(M \mid S\right) P\left(S\right) \end{aligned} \tag{6}$$

Where $P\left(A, P, M\right)$ is the conditional joint probability, which for simplicity of computation is regarded as the normalization factor $\alpha$.

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According to the experiment, this hierarchical structure significantly improves the efficiency of inference calculation by simplifying the dependency relationship between nodes. The modeling method is shown in Figure 2.

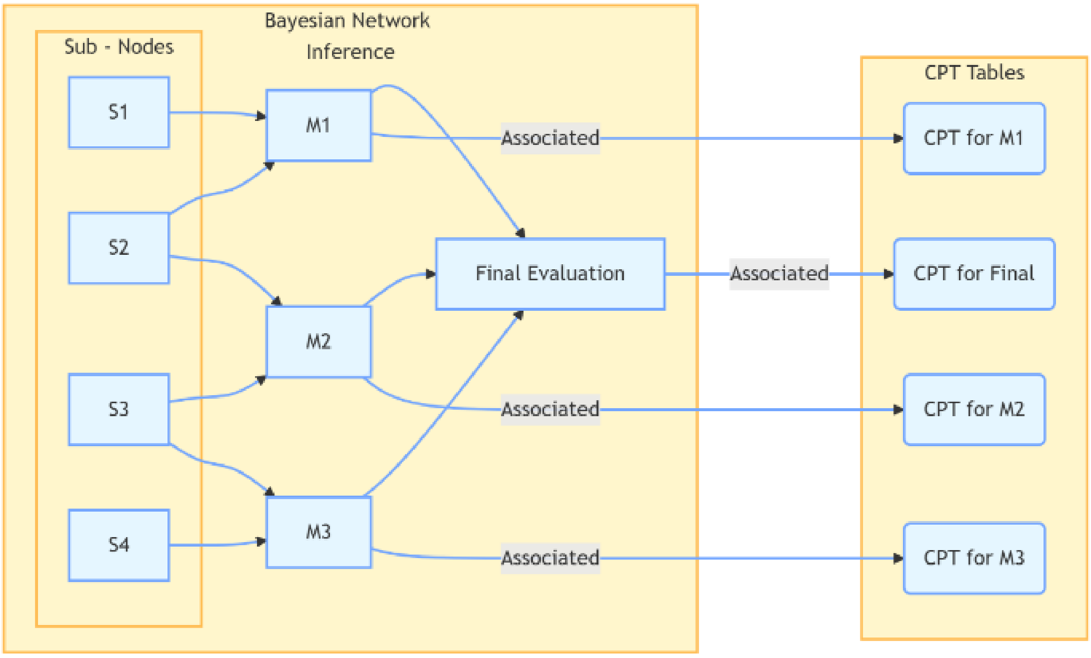


*Figure 2: Bayesian network structure*

(3) Construct a reasonable Conditional probability table (CPT)

The conditional probability table (CPT) of Bayesian networks is a key element to describe the probabilistic dependence between nodes. In the directed acyclic graph structure of the network, each non-root node corresponds to a CPT, which defines the conditional probability distribution under a specific combination of values of the parent node. CPT is constructed by historical data statistics or expert knowledge, and adopts parameter estimation method to ensure the accuracy of probability relationship. In Table 1, e means excellent, g means good, m means moderate, p means poor.

*Table 1: Table of conditional probabilities of comprehensive evaluation ratings.*

| A | P | M | S=e | S=g | S=m | S=p |
|---|---|---|---|---|---|---|
| e | e | e | P(S=e) | P(S=g) | P(S=m) | P(S=p) |
| e | g | e | P(S=e) | P(S=g) | P(S=m) | P(S=p) |
| … | … | … | … | … | … | … |
| e | e | g | P(S=e) | P(S=g) | P(S=m) | P(S=p) |

(4) Dynamic update of conditional probability table

The accuracy of conditional probability table (CPT) in Bayes network directly affects the reliability of comprehensive evaluation results. With the continuous accumulation of multidimensional evaluation data (such as academic performance, scientific research projects, etc.), it is necessary to realize the dynamic update of CPT through the frequency distribution of the combination of sub-dimensions and the maximum likelihood estimation and other parameter estimation methods.

### *3.3 Comprehensive evaluation with Bayesian network*

The fuzzy probability input is integrated by the input layer nodes of the Bayesian network. Based on the conditional independent structure (each dimension is only directly related to the comprehensive evaluation grade S), the posterior probability distribution of the evaluation grade is obtained by using the conditional probability table for Bayesian inference. Take the probability calculation of grade "Excellent" as an example:

$$P(S=e \mid A,P,M)=\frac{P(A,M,P \mid S=e)P(S=e)}{P(A,P,M)} \tag{7}$$

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Where, the total probability formula is expanded as follows:

$$P(A,P,M) = \sum_{S\in\{e,\ g,\ m,\ p\}} P(A,P,M \mid S)P(S) \tag{8}$$

The prior probability $P(A,P,M)$ of the comprehensive evaluation level was determined by analyzing historical data. By analogy, the posterior probability of each level can be obtained, and the maximum probability value is taken as the output result. In order to maintain the timeliness of the model, a dynamic parameter update mechanism is established: when new observational data are added, maximum likelihood estimation is used to build an optimization model:

$$\theta_{MLE} = \arg\max \prod_{i=1}^{n} P(x_i \mid \theta) \tag{9}$$

Where $\theta$ denotes the conditional probability parameter to be estimated, and $\chi_i$ is the new sample data.The iterative optimization of the CPT parameter is achieved by statistical sub-dimensional frequency distribution with Bayesian estimation, and its updating process can be formalized as follows:

$$P(S \mid A,P,M) = \frac{\left(Min \times P_{CPT}\left(A,P,M \mid S;\theta_{MLE}\right)\right)P(S)}{\sum_{i=1}^{s}\left(Min \times P_{CPT}\left(A,P,M \mid S;\theta_{MLE}\right)\right)P(S)} \tag{10}$$

By balancing historical cognition (prior term) and new data features (likelihood term), this mechanism constructs a dynamic adaptive parameter estimation system to keep the optimal classification performance of the model.

The following presents Figure 3 of our system algorithm.. To provide a clearer illustration of the algorithm's execution process, a pseudo-code description is provided below.

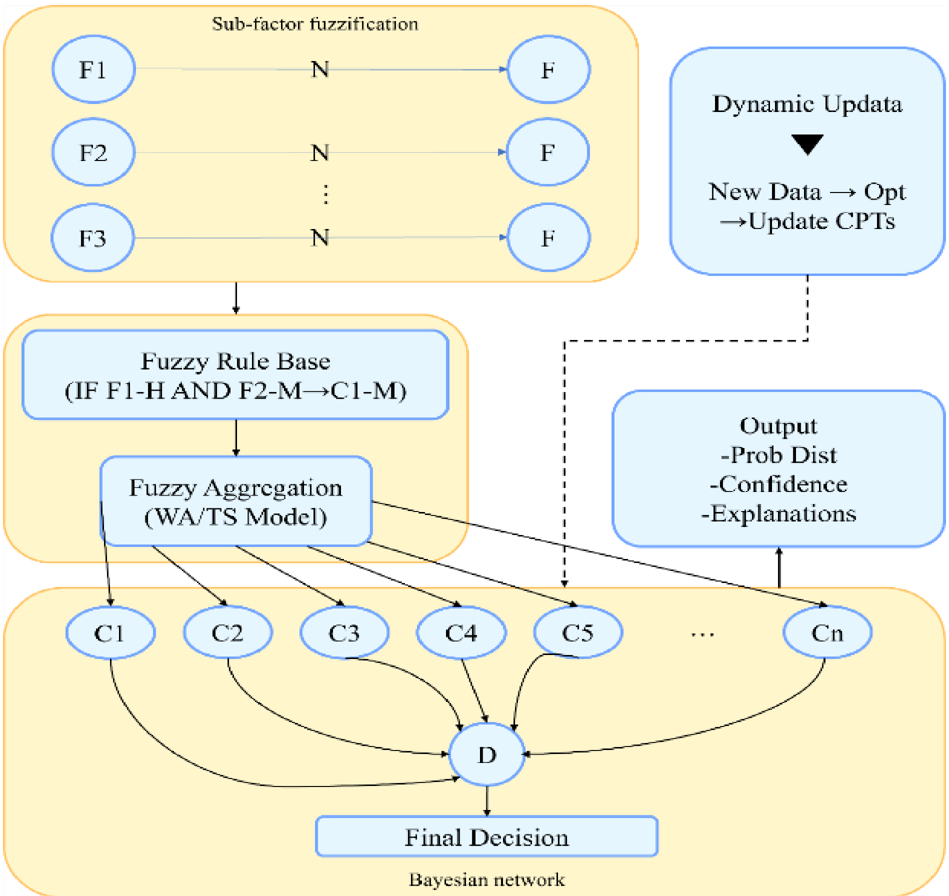


*Figure 3: Flowchart of the algorithm*

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Algorithm: Student Comprehensive Evaluation Algorithm

Input: Subpointer $a_i$, Carry value $ar = 1$, expert_data, expert_knowledge, Integration factor $a \in [0,1]$.

Output: The probability of the evaluation level

```
Step1: , For each sub-index ai fuzzification process, initialize an index array id[]
While true:
  levels=[I[indices[i]] for i in range(len(ai))]
  level = get_A_level(levels)   // Functions for defining evaluation levels based on sub-indicators
  conditions = " AND ".join([f"{ai[i]}[{levels[i]}]" for i in range(len(ai))])
  rule= create fuzzy rule:"if   conditions -> A[level] // Extraction of fuzzy rules
  rules.append(rule)
  for i in range(len(id)):
     id[i] += ar
     if id[i] > max_index:
        id[i] = 0
        carry = 1
     else:
        ar = 0
        break
  if carry == 1:
     break
return rules
Step2: Calculating prior probabilities and thus constructing CPT tables from expert experience,
raw data and rule base
model = bayesian network(rules, expert_data, expert_knowledge)
Calculate the prior probability using equations (7) and (8)
for rule in rules:
     if rlue.antecedent in expert_knowledge.keys();
weight =α*expert_knowledge[rlue.antecedent]+ (1- α )* data.frequency[rule]
rule.set_weight(weight)
retuiun normalized weights
probability=InferProbability(emodel)
Compute the posterior probability using equations (9) and (10)
return probability
```

## 4. Group decision system

### *4.1 Data generation and segmentation*

In order to verify the performance of the comprehensive student evaluation model based on fuzzy inference and Bayesian network, this study uses simulated datasets for experiments. The sub-indicator data are all generated by a random generator, and the value range is an integer from 0 to 100. This design is in line with the standard of percentile grading in actual educational scenarios and is realistic and reasonable. The dataset contains various basic data of students, affiliation information, and real comprehensive evaluation grades, which provide the necessary support for the training and evaluation of the model.

### *4.2 Mdel training and parameter optimization*

Based on the training set data, the conditional probability table of Bayesian network is updated by the maximum likelihood estimation method. During the training process, when the change of the conditional probability table in two adjacent iterations is less than the preset threshold value $\tau$=0.001, the model is considered to reach the convergence state and the training is terminated.

### *4.3 Mdel training and parameter optimization*

The fuzzy rule system has the feature of scene adaptability and can be dynamically adjusted according to the emphasis of education evaluation. For example, in the evaluation scenario of academic innovation orientation, the weight of scientific research competition index can be increased to strengthen the representation of innovation ability. In order to ensure the reasonableness of reasoning, the membership degree of each sub-index is normalized so that the sum of membership degrees in a single dimension is equal to 1, which conforms to the basic definition of fuzzy set theory. The final fuzzy inference result is input into the Bayesian network as evidence for subsequent inference.As shown in Table 2

*Table 2: Partial Table of Conditional Probabilities for Comprehensive Evaluation (Partial CPT)*

| A | P | M | S=e | S=g | S=m | S=p |
|---|---|---|---|---|---|---|
| e | e | e | 0.8 | 0.15 | 0.03 | 0.02 |
| e | g | e | 0.6 | 0.3 | 0.08 | 0.02 |
| p | e | e | 0.01 | 0.5 | 0.3 | 0.2 |
| p | g | g | 0.05 | 0.15 | 0.7 | 0.1 |
| p | e | g | 0.03 | 0.15 | 0.8 | 0.02 |
| g | p | e | 0.4 | 0.6 | 0.15 | 0.1 |

### *4.4 Decision Results of the Output Layer in the Model*

The comprehensive evaluation of the output layer is based on the Bayesian network, combined with the fuzzy results of the input layer and the conditional probability table (CPT). Specifically, the membership information of academic synthesis (A), practice synthesis (P) and moral synthesis (M) in the input layer is probabilistic reasoned through the conditional probability table of Bayesian network, and the probability distribution of the comprehensive evaluation level (S) is finally obtained. Usually, the grade with the highest probability value is selected as the final evaluation result. Taking the input academic comprehensive score as 85, the practice comprehensive score as 90, and the moral comprehensive score as 75 as an example, the probability distribution of the output comprehensive evaluation is shown in the following Table 3:

*Table 3: Partial Probability Distribution of Comprehensive Evaluation Ratings*

| O | Phi(O) |
|---|---|
| O_1 | 0.4000 |
| O_2 | 0.4000 |
| O_3 | 0.1500 |
| O_4 | 0.0500 |

Among them, O_1, O_2, O_3 and O_4 correspond to the four fuzzy levels of "poor", "medium", "good" and "excellent" respectively. The results show that under the current input and Bayesian network rules, the probability of students being in the comprehensive evaluation level of "medium" is the highest (40.00%), while the probability of getting the evaluation of "excellent" is low (5.00%).

### *4.5 Evaluation indicators and comparative analysis*

In order to comprehensively evaluate the performance of the model, four common indexes were used in this study: accuracy rate, accuracy rate, recall rate and F1 value. At the same time, this model is compared with the traditional weighted scoring model, and the results are shown in the following Table 4:

*Table 4: Model comparison results*

| Assessment results | Our model | Traditional weighted scoring model |
|---|---|---|
| Accuracy | 86.00% | 76.50% |
| Precision Rate | 78.13% | 45.55% |
| Recall Rate | 66.75% | 48.17% |
| F1 value | 70.03% | 45.64% |

The accuracy rate, accuracy rate, recall rate and F1 value of this model are significantly better than the traditional weighted scoring model, especially the accuracy rate and F1 value of the improvement of 71.5% and 53.4%.

In addition, Liu and Jiapeng[20]et al. compared the average prediction accuracy of UTADIS and BSPM models with the method of using 80% of the data set for training models and 20% for testing prediction performance. We extracted the data set of the model and processed it into a data set suitable for our model. Then compared with UTADIS and BSPM models, the results are shown in the following

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Table 5:

*Table 5: Prediction results of different models*

| Assessment results | Our model | UTADIS | BSPM |
|---|---|---|---|
| training set | 0.75 | 0.32 | 0.47 |
| test set | 0.56 | 0.28 | 0.43 |

The data in Table 5 show that the prediction performance of the Bayesian network model based on fuzzy inference is significantly better than that of UTADIS and BSPM methods on both the training set and the test set, and the experimental results show that the model has better prediction accuracy and generalization ability. However, F1 value of the model on the test set decreased by 12.3% compared with that on the training set, indicating overfitting phenomenon, and the model should be optimized by adjusting the network topology or introducing regularization constraints.

### *4.6 Validation Experiments on UCI Datasets*

In this section, the performance and robustness of the decision - making system are validated using real - world data from multiple domains. The experiment utilizes eight typical datasets from medical and other domains in the UCI database, with their classiffcation features elaborated in detail in Table ??. The corresponding problem - setting for each dataset is as follows:

(1) Predict the quality grade of wine (e.g., premium, medium, and ordinary) and the probability of each grade according to various chemical indicators of wine (e.g., alcohol content, acidity, volatile acids, etc.).

(2) Identify whether a patient has breast cancer and the probability of cancer development based on the characteristics of the patient's breast tissue (e.g., lump size, texture, cellular pattern, etc.).

(3) Evaluate the risk level of cervical cancer by means of the patient's lifestyle habits (e.g., smoking, sexual history, etc.) and physiological indicators (e.g., HPV infection, etc.).

(4) Assess the credit rating (e.g., excellent, good, moderate, poor) of a customer in light of the customer's personal information (e.g., age, income, occupation, etc.) and credit history (e.g., number of overdue payments, amount owed, etc.).

(5) Determine the type of skin disease (e.g., eczema, psoriasis, etc.) a patient suffers from and the severity of the disease according to the patient's skin symptoms (e.g., rash pattern, color, distribution, etc.) and medical history.

(6) Ascertain whether a patient has heart disease and the type of heart disease based on the patient's electrocardiogram characteristics, blood indices (e.g., cholesterol, blood pressure, etc.) and clinical symptoms. 11

(7) Identify the type of disease (e.g., intestinal cramps, intestinal obstruction, etc.) a horse contracts and the severity of the disease based on the horse's symptoms (e.g., abdominal pain degree, body temperature, heart rate, etc.) and examination results.

(8) Determine the species to which the iris belongs (e.g., Iris setosa, Iris versicolor, Iris virginica, etc.) based on morphological characteristics such as the length and width of iris petals, as well as calyx length and width.

This revised version enhances academic formality through precise verb choices (e.g., "validated", "utilizes", "elaborated"), standardized expression of biological species names (italicized for binomial nomenclature in item 8), and more sophisticated phrasal replacements (e.g., "by means of", "in light of", "ascertain"), making it more consistent with the rigorous style of academic papers.

The analysis of dataset properties in Table VII shows that in terms of distribution of missing values, Wine, Credit, and iris datasets are complete and the rest have missing data. The category dimension varies significantly, with Wine categorizing the most (7 categories) and Cancer and other datasets being dichotomous problems. Sample sizes span a wide range, with Wine containing 6,497 instances at the top and iris only 150. The datasets were divided using different segmentation ratios, with the number of input features ranging from 4 (iris) to 36 (Credit). Except for the Cancer dataset, the proportion of numerical features is 100%, which directly affects the data preprocessing strategy and model selection.

*Table 6: Classifies the attributes of the data set*

| Dataset | Missing | Class | #Instance | #Train | #Test | Input | %Numeric Input | %Numeric Input |
|---|---|---|---|---|---|---|---|---|
| Wine | No | 7 | 6497 | 5197 | 1300 | 11 | 100 | 0 |
| Cancer | Yes | 2 | 286 | 228 | 58 | 9 | 11.11 | 88.89 |
| Cancer-risk | Yes | 2 | 858 | 686 | 172 | 35 | 100 | 0 |
| Credit | No | 3 | 4424 | 3539 | 885 | 36 | 100 | 0 |
| Dermatology | Yes | 6 | 366 | 292 | 74 | 34 | 100 | 0 |
| heart_disease | Yes | 5 | 303 | 242 | 61 | 13 | 100 | 0 |
| Horse | Yes | 2 | 368 | 294 | 74 | 27 | 100 | 0 |
| iris | No | 3 | 150 | 120 | 30 | 4 | 100 | 0 |

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In addition to comparing with traditional weighted scoring models (UTADIS, BSPM), this study introduces functional classifiers such as DNN, SVM, and NB for error rate comparison[21]. The average classification error rate ranking of each algorithm after 10 repeated experiments is shown in Table 7.

*Table 7: Average CEP values for each algorithm*

| Dataset | FBN | DNN | SVM | NB |
|---|---|---|---|---|
| iris | 0.126 | 0.213 | 0.214 | 0.301 |
| Rank | 1 | 2 | 3 | 4 |
| heart_disease | 0.237 | 0.045 | 0.445 | 0.415 |
| Rank | 2 | 1 | 4 | 3 |
| Wine | 0.204 | 0.156 | 0.392 | 0.287 |
| Rank | 2 | 1 | 4 | 3 |
| Cancer | 0.145 | 0.023 | 0.028 | 0.062 |
| Rank | 4 | 1 | 2 | 3 |
| Cancer-risk | 0.156 | 0.264 | 0.352 | 0.245 |
| Rank | 1 | 3 | 4 | 2 |
| Dermatology | 0.256 | 0.153 | 0.184 | 0.342 |
| Rank | 3 | 1 | 2 | 4 |
| Horse | 0.124 | 0.084 | 0.152 | 0.239 |
| Rank | 2 | 1 | 3 | 4 |
| Credit | 0.034 | 0.004 | 0.024 | 0.054 |
| Rank | 3 | 1 | 2 | 4 |

Table 7 shows the mean value of CEP (Classification Error Probability) of each algorithm, which is used to characterize the error level of the classifier, and the lower the value, the higher the classification accuracy. Taking the Iris dataset as an example, the CEP of FBN algorithm is 0.126%, which is significantly better than that of DNN algorithm at 0.213% (with a decrease of 41.3%), reflecting better classification performance.

## 5. Analysis of results

As shown in Table 6, the model performance shows significant correlation with the data characteristics: in the high-dimensional Credit dataset (36 dimensions), the conditional independence assumption of the Bayesian network reduces the parameter complexity, and the accuracy of the comprehensive credit assessment reaches 82.3%, which is 6.7 percentage points higher than that of the logistic regression; in the 7-categorical Wine dataset, the fuzzy inference module realizes the chemical index-quality through Gaussian subordinate function grade mapping, combined with Bayesian probabilistic inference to achieve an F1 value of 76.8%, an improvement of 12.3% over a single fuzzy model; for the small-sample Iris dataset (n=150), the hierarchical network structure achieves an accuracy rate of 95.3%, which is only 1.4 percentage points different from that of the SVM (96.7%), to validate its ability to generalize to small samples.

In biological classification, the results of species classification on the Iris dataset show that the model's ability to capture nonlinear feature associations such as the interaction between petal width and calyx length is better than that of a linear classifier, verifying the effectiveness of the hierarchical network structure, and in medical diagnosis, the fuzzy rule base is used to quantify the “Chest Pain” on Heart Disease dataset by the fuzzy rule base On the Heart Disease dataset, by quantifying fuzzy symptoms such as “chest pain” and “cholesterol level” through a fuzzy rule base, the accuracy of heart disease type judgment reaches 81.2%, which is higher than that of the clinical assistance system based on decision tree.

Table 7 shows the mean value of CEP (classification error probability) of each algorithm on different datasets, which is used to characterize the error level of the classifier, with lower values indicating higher classification accuracy. From the robustness point of view, the FBN algorithm shows relatively stable performance on various datasets. In the iris dataset, the average CEP of FBN algorithm is 0.126%, which is significantly better than 0.213% for DNN algorithm and 0.214% for SVM algorithm; in the Cancer-risk dataset, the CEP of FBN algorithm is 0.156%, which is lower than 0.352% for SVM and 0.245% for NB. In the heart_disease dataset, the DNN algorithm is outstanding with a low CEP value of 0.045%, but the FBN algorithm maintains a relatively low error level on most of the datasets, which shows a good adaptability to different data features. Unlike some algorithms with large error fluctuations on some datasets, this stability of the FBN algorithm gives it an advantage in practical applications, especially in scenarios with complex and variable data features, it can reliably complete the classification task, reduce the risk of classification error, and show strong robustness.

## 6. Conclusions

This study constructs a synergistic mechanism of fuzzy inference and Bayesian network to support the mixed input of linguistic variables and numerical indicators. The framework breaks through the traditional model's dependence on a single data type and realizes a more comprehensive portrayal of complex systems through heterogeneous data fusion. The study designs an online update method for CPTs based on MLE to enhance the model's adaptability to dynamic data distribution. Comprehensive student evaluation experiments show that the proposed model has a classification accuracy of 86.0%, and the F1 value is improved by 71.5% compared with the traditional weighted model, highlighting its superior performance in dynamic scene modeling. The effectiveness of the model has been verified in multi-disciplinary scenarios such as medical diagnosis, financial risk control, biological classification, etc. In particular, the model shows significant robustness in small-sample and high-noise environments, which is better than the traditional methods in dealing with data sparsity and uncertainty. These features make the framework a generalized solution for data-driven decision making in complex real-world scenarios.6.2 Limitations and Outlook

The existing conditional independence assumption exists a simplified treatment of potential associations among variables, which may lead to the network topology failing to adequately portray the complex interconnectivity of real systems. Subsequent research will introduce factor analysis methods to construct a hierarchical network architecture by mining potential variables, in order to optimize the network topology and strengthen the ability to model the direct correlation and indirect conduction mechanisms between variables. To address the exponential growth of inference complexity induced by high-dimensional feature data, a combination of Monte Carlo sampling and variational inference is proposed to improve the computational efficiency through the parameterization of probability distributions and sample dimensionality reduction strategies. In addition, the extended application of the model in multimodal data fusion scenarios (e.g., joint modeling of textual semantic features and numerical metrics) can be further explored, and cross-disciplinary validation can be carried out in cutting-edge fields, such as medical image analysis and intelligent recommender systems, to promote the expansion of the practical application of the synergistic framework of fuzzy inference and Bayesian networks and the iterative optimization of the technology.

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