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GA optimization-based BRB AI reasoning algorithm for determining the factors affecting customer churn for operators

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ABSTRACT

Customer churn directly leads to the weakening of the economic efficiency of an operator and even the loss of its competitive advantage in the market share. The identification and prediction of customer churn in the era of interconnection has become more complex, as it not only is based on the analysis of customer information and customer churn data but also must take into account the intricate relationships between the market economy and culture. In the era of big data, numerous predictive models are based on more redundant features, which increases the complexity of the algorithms and the difficulty of analyzing customer churn. Therefore, in this paper, a belief rule base (BRB) artificial intelligence inference algorithm based on GA optimization to determine the factors affecting customer churn for operators proposed. First, customer churn data from a website are analyzed, and features are extracted. Second, a BRB is established from the experience of operator experts, and a BRB inference prediction model is constructed for predicting and analyzing customer churn. Finally, the BRB model is optimized by GA optimization, the input characteristics with high feature weights are obtained, and the accuracy of the churn analysis is verified according to the obtained features. The results show that this method not only outperforms the comparative SVM and BP neural network models for predicting customer churn but also provides better judgment of the main inputs of customer churn, thus reducing the reliance on input information, optimizing the complexity of the algorithm, and enabling operators to obtain a more accurate understanding of the main factors that lead to churn.

1. Introduction

Customer churn, also popularly known as customers leaving suppliers (Bhambri, 2013; Chandar et al., 2006; Phadke et al., 2013), occurs when a business suffers the loss of valuable customers to competitors, triggering a loss of business, which in turn tends to cause financial loss and reputation damage for the business. Customer churn is prevalent in all industries. Attracting and capturing customers is the most important concern in the operation of today's business market and is also a direct issue related to success or failure in the business operation industry (Nabgha et al., 2013).

In recent years, operators have been facing the problem of customer churn, which is becoming increasingly serious. According to the relevant data, When operators weigh the pros and cons of the process of attracting new customers and maintaining old ones, they find that the cost of the former is more than ten times the cost of the latter, but the benefits of the latter are much greater than those of the former (Shu, 2008; T C I, 2010). As a result, it was concluded that avoiding customer churn not only leads to significant protection of business benefits but also to effective savings in employment costs. In this regard, customer churn depends on whether customer needs and wants are being met by the current operator; the behavior of an operator in response to customer churn is complex and is often affected by the interactions and joint influences of several factors from different categories (Quanbo, 2006). Taking telecommunication operators as an example, if such an operator cannot identify customer churn behavioral factors in time, it is very likely that it will lose approximately half of its customers in five years (Idris et al., 2012). Therefore, the factors affecting customer churn for operators can be used to not only analyze the causes of customer churn more intuitively but also make changes in the operator strategy to achieve the purpose of retaining customers and reducing loss. Especially in the telecommunications industry, identifying the factors that influence customer churn can not only enhance competitive advantage and help companies offer more attractive services and pricing strategies, but

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also support the industry in making data-driven decisions. Having specific data about what factors lead to customer churn can make decision-making more scientific and precise.

With the development and rise of Artificial Intelligence (AI), many AI methods are utilized in various areas, at the same time, more and more AI methods are being applied to predict and analyze customer churn. Ahmad A K developed a predictive model for customer churn based on a big data platform, which builds a new feature engineering and selection method based on tree-based machine learning techniques, as well as extracting social network analysis (SNA) features using customers' social networks, which was shown through the results to help telecommunication operators to predict which customers are most likely to churn (Ahmad et al., 2019). Liu proposed an integrated learning model based on customer churn prediction, which firstly uses the K-means algorithm to cluster different consumers, then analyzes the main factors that different consumer groups are concerned about, and finally, in order to improve the validity and robustness of the model, the model is validated by using the telecommunication customer churn; the experimental results show that the accuracy of the integrated learning model in predicting the customer churn is satisfactory (Liu et al.). On this basis, Xiahou innovatively constructed a k-means customer classification and support vector machine (SVM) customer churn prediction fusion mechanism model, the model will be divided into three classes of customers, and will determine the core customer groups in the three classes for experimental reference and verification, and finally compare the results of predicting customer churn by the support vector machine and logistic regression model; it is demonstrated through the experiments that, on the basis of the fine-grained class division of the k-means, the accuracy of the SVM prediction is obviously superior to the accuracy of the logistic regression prediction (Xiahou & Harada, 2022). In addition, Tjeng developed an interpretable model using the concept of vector embedding based on deep learning methods, which enables the model to predict more accurately whether a customer will discontinue a service subscription through the difference in the vectors generated between churned and loyal customers (Tjeng et al., 2021). Yu uses the BP network (PBCCP) algorithm for telecom customer churn prediction based on particle classification optimization and iteratively performs Particle Classification Optimization (PCO) and Particle Fitness Calculation (PFC) based on the fitness values of the particles, which is advantageous in that the PCO classifies the particles into three categories while updating the speeds of the particles of the different categories using different equations; in addition to this the PFC can be used to calculate the BP Neural Network's fitness value of particles in each forward training step. The results show that the accuracy of PBCCP in customer churn prediction is significantly improved (Yu et al., 2018).

The above artificial intelligence algorithms assist operators in accurately predicting customer churn rates based on the characteristics of the operators' data and help operators make further policy changes and optimization decisions with respect to the amount of customer churn to retain old customers, reduce costs, and increase economic benefits. However, the above AI methods use a large amount of data to judge customer churn, and in addition, they do not do a good job of identifying and judging the factors that cause customer churn, which can easily lead to misjudgment of the causes of customer churn and confusion in policy optimization.

An initial BRB model should be established based on expert subjective experience, where data samples can be used to optimize the parameters of the model to more accurately describe the relationship between the input and output. In addition, the inferencing process of the BRB model should be transparent and interpretable, and domain experts should be able to visually inspect the BRB model and avoid errors that violate intuition. Currently, the BRB system has been widely applied in many areas, such as forecasting atmospheric pollution, detecting engineering faults, and treatments in medical diagnostics (Kabir, Islam, & Hossain, 2020; D L Xu et al., 2007; Kong, Xu, & Body, 2012). According to numerous experimental studies, this system surpasses other prediction models in handling uncertain information and plays an irreplaceable role in identifying factors.

There is a non-linear relationship between customer churn and influencing factors, and existing factor data cannot intuitively represent the intrinsic relationship between customer churn. The BRB model not only has the ability to handle nonlinearity, but the system is also a white box system, which allows experimenters to observe the inference process and correct the inference results. Therefore, it can intuitively display the relative weight of input data and determine its impact on the results. Establishing a BRB model to predict customer churn while determining the weights of influencing factors, followed by optimizing the BRB model through the GA algorithm, optimizing the relative weights of influencing factors, and further determining the main influencing factors of customer churn through the comparison of weight sizes. Therefore, this paper presents an algorithm based on GA optimization of BRB AI for judging the influencing factors of customer churn; customer churn, customer characteristics, and a customer database constructed by customer access to services and consumption are combined to establish a BRB predictive analysis model, ER algorithm for fusion activation rules, and the credibility distribution indicates the degree of support for customer churn. At the same time, combined with the experience of experts in this area, the initial BRB parameters are optimized by the GA, and the main influencing factors are judged and analyzed while ensuring that each influencing factor does not lack practical significance. Finally, by comparing the SVM (Chauhan et al., 2019) and BP Neural Network models (Zhang & Jiang, 2022), We analyzed the changes in attribute weight parameters before and after BRB optimization, verified that the BRB AI method proposed in this paper has certain accuracy and effectiveness in preventing customer churn, and judged and analyzed the factors affecting customer churn.

The remainder of the paper is organized as follows: Part 2 gives the method overview, which introduces the theory of the BRB method and the optimization model in detail; Part 3 describes the construction of the BRB inference model, which introduces the data sources and the detailed reasoning steps of the BRB model based on GA optimization; Section 4, results analysis, presents the results of the BRB model for customer churn prediction, as well as the results of parameter optimization and validation of the BRB model; and Part 5 is the conclusion, which is mainly a summary of the findings of this paper.

2. Methodological discussion

BRB theory evolved from D-S evidence theory, decision theory, and traditional "IF-THEN" rules. However, unlike traditional "IF-THEN" rules, each belief rule in rule base has a corresponding belief level associated with its posterior term. In 2006, Yang proposed a BRB inferencing method based on ER inference algorithm (Yang et al.; Xu et al., 2007b; Chen et al., 2013). The original BRB was built with the expertise of carrier data specialists, and the model parameters are optimized by the historical customer data so that the relationship between case subscriber characteristics, service characteristics, and customer churn outcomes can be described more accurately. Additionally, The inferencing process of the BRB model has the excellent characteristics of transparency and interpretability, and the parameters of the BRB model can be adjusted according to the statistical experience of experts as well as historical customer data to address the uncertainty faced in the process of predicting customer churn more efficiently. The BRB consists of two parts, namely, the BRB expression form and the reasoning.

2.1. BRB expression form

The BRB consists of a set of belief rules, where the l th rule is of the following form:

$$R_l : \text{if } \left(x_1 \text{ is } A_1^k\right) \vee \left(x_2 \text{ is } A_2^k\right) \vee \cdots \vee \left(x_m \text{ is } A_M^k\right) \\ \text{then } \left\{\left(D_1, \beta_{1,l}\right), \cdots, \left(D_n, \beta_{n,l}\right)\right\} \\ \text{with rule weight } \theta_l \tag{1}$$

where R_l denotes the lth$(l = 1, 2, \cdots, L)$ rule, $x_m(m = 1, 2, \cdots, M)$ denotes the m th input feature of a sample case of data, M denotes the number of customer churn input features, $A_m^k(k = 1, 2, \cdots, M)$ indicates the k th reference level of the m th user input feature of a sample of data, $D_n(n = 1, 2)$ denotes the customer churn outcome of the rule, $\beta_{n,l}$ denotes the belief level D_n for the n th churn outcome in rule l (here divided into churn and no-churn outcomes), and θ_l denotes the initial weight of this rule (Chang et al., 2017).

2.2. BRB model reasoning

2.2.1. Input matching

The first step in BRB inferencing is to compute the combined match between the operator's churn input characteristics, and the rule is $\alpha_{m,l}$. The combined match between the m th input feature of the sample and the l th rule is calculated as:

$$\alpha_{m,l} = \frac{\varphi\left(x_m, A_m^k\right)}{\sum \varphi\left(x_m, A_m^k\right)} \tag{2}$$

where $\varphi\left(x_m, A_m^k\right)$ is the matching degree between the m th input feature of the sample and the k th reference level (Chang et al., 2020). In this paper, the input information of the customer data sample is qualitative information, and x_m has the form of a semantic value, which can directly yield the matching degree.

2.2.2. Rule activation

The second step of BRB reasoning is to compute the activation weights ω_l of the rules, and for L rules, the procedure for computing the l th activation rule is

$$\omega_l = \theta_l \sum_{m=1}^{M} \left(\alpha_{m,l}\right)^{\overline{\delta_m}} \Big/ \sum_{l=1}^{L} \theta_l \sum_{m=1}^{M} \left(\alpha_{m,l}\right)^{\overline{\delta_m}} \tag{3}$$

$$\overline{\delta_m} = \delta_m \Big/ \max_{m=1}^{M}\{\delta_m\} \tag{4}$$

where $\omega_l \in [0, 1], l = 1, 2, \cdots, L$; δ_m denotes the initial weight of the m th input feature of the data sample example, so $\overline{\delta_m}$ is the relative weight of this input feature (Chang et al., 2015).

2.2.3. Inference from the results

The third step of BRB inferencing is to apply the ER algorithm to fuse the belief structures of the activation rule customer churn results to obtain the final BRB customer churn prediction. In this case, the process of fusion using the ER algorithm is:

$$\beta_n = \frac{\mu\left[\prod_{l=1}^{L}\left(\omega_l\beta_{n,l} + 1 - \omega_l \sum_{n=1}^{N}\beta_{n,l}\right) - \prod_{l=1}^{L}\left(1 - \omega_l \sum_{n=1}^{N}\beta_{n,l}\right)\right]}{1 - \mu\left[\prod_{l=1}^{L}(1 - \omega_l)\right]} \tag{5}$$

$$\mu = \left[\sum_{n=1}^{N}\prod_{l=1}^{L}\left(\omega_l\beta_{n,l} + 1 - \omega_l \sum_{n=1}^{N}\beta_{n,l}\right) - (N-1)\prod_{l=1}^{L}\left(1 - \omega_l \sum_{n=1}^{N}\beta_{n,l}\right)\right]^{-1} \tag{6}$$

where $\beta_{n,l}(n = 1, 2; l = 1, 2, \cdots, L)$ is the belief level of the n th churn prediction for the l th rule, ω_l is the activation weight of the l th rule, and β_n is the belief level of the n th churn prediction (Yang & Xu, 2013).

2.3. BRB model optimization

The optimization objective function used in this paper is Mean Absolute Percentage Error (MAPE), which is the absolute error between the actual value and the predicted value, and the parameters to be optimized in the model include the rule weights θ_l, the input feature weights $\delta_{l,m}$ of the data samples, and the belief level of the customer churn prediction results $\beta_{n,l}$ (Chang, 2019). The structure of the optimization model is shown in Fig. 1, and the optimization model constraints are shown in Equations (7)–(11).

$$\text{MIN MAPE}\left(\theta_l, \delta_m, \beta_{n,l}\right) \tag{7}$$

s.t.

$$0 < \theta_l \leq 1 \tag{8}$$

$$0 < \delta_m \leq 1 \tag{9}$$

$$0 \leq \beta_{n,l} \leq 1 \tag{10}$$

$$\sum_{n=1}^{N} \beta_{n,l} = 1. \tag{11}$$

3. Construction of BRB inference models

3.1. Presentation of data

In this paper, by extracting the user's personal information, access to services and consumption information, belief rule expert reasoning technology is used to combine the customer sample data with the management experience of the operator's data experts. The complex nonlinear relationship between the customer churn characteristics and the prediction of customer churn behavior is thereby established. The prediction of customer churn is made based on the customer's characteristics and the sample data. The optimization method determines the main factors that affect customer churn based on the factor weights in order to retain customers and avoid the loss of customers to competing carriers, enabling the operator to retain the advantages of competition and maintain the benefits of its business.

In this paper, the data source for predicting customer churn is the Kaggle website Telco Customer Churn, these data are the results of customer survey feedback from operators in a certain region over a certain period of time and the data are statistical data. This paper employs quantitative analysis involving data collection, mathematical analysis, and more, in order to draw conclusions or predict outcomes. Therefore, it involves deleting or correcting errors, missing, duplicate, or inconsistent data in the dataset. This includes filling in missing values, handling outliers, and removing duplicates.These data are processed as shown in Fig. 2. After the data are extracted from the website, they are cleaned and analyzed; the purpose of cleaning is to screen duplicate data, and the goal of the analysis is mainly to determine the data categories. After the analysis, the data are classified into 19 kinds of input

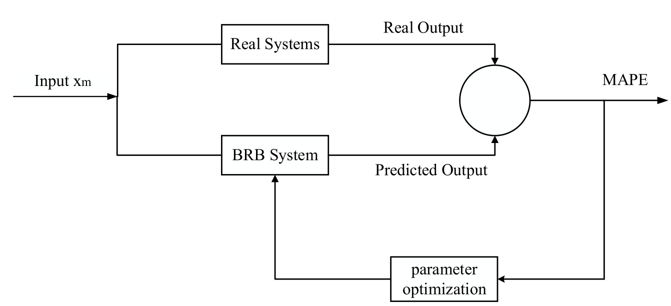

Fig. 1. Structure diagram of the BRB parameter optimization model.

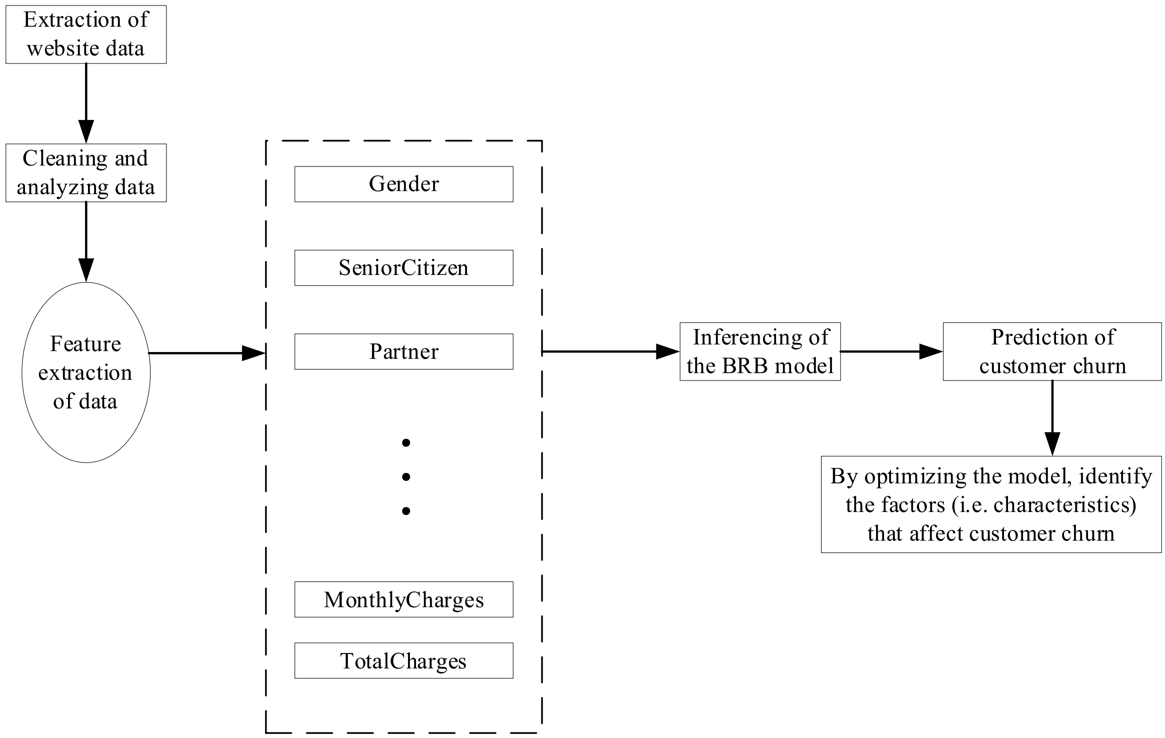

Fig. 2. Customer churn data prediction process.

customer characteristics, as follows: Gender, SeniorCitizen, Partner, Dependents, Tenure, PhoneService, MultipleLines, InternetService, OnlineSecurity, OnlineBackup, DeviceProtection, TechSupport, StreamingTV, StreamingMovies, Contract, PaperlessBill, PaymentMethod, MonthlyCharges, and TotalCharges. Finally, the BRB inference model is used to predict and analyze customer churn, and the GA optimization algorithm is used to determine and summarize the main factors (i.e., characteristics) of customer churn. The BRB inference process and GA optimization process are described in Section 3.3.

The values of the data obtained from the above division are transformed into semantic values. For example, for the Gender (x_1) feature, the male semantic value is converted to 0, while the female semantic value is converted to 1, and these discrete quantities are the reference levels of the input features. Regarding the Tenure (x_5) feature, this represents the number of months the user has been in the network, and its reference level is a numerical value equivalent to an integer greater than 0. MonthlyCharges (x_{18}) represents the monthly fees paid by the user, which is numerically equal to a continuous quantity, and it is necessary to divide this continuous quantity into reference levels for processing. In this paper, the reference levels of MonthlyCharges (x_{18}) are {29.35, 55.65, 83.25, 118.75}, and the reference levels of TotalCharges (x_{19}) are {586.8, 2288.85, 4488.85, 6688.85, 8684.8}. The output of the model has two values, indicating whether the customer is currently churning or not.

In addition, the reference levels of the customer data input characteristics are shown in Table 1.

3.2. Creation of a belief rule base

The belief rule base is generally derived from several sources: 1) extracted from expert experience, 2) obtained from historical data, and 3) learned from training data (Xu et al., 2007c). In this study, the rule base for the BRB model for churn prediction is provided by the experience of the operator's data management experts. As shown above, the input features are divided into 19 types, and each input feature is divided into corresponding reference levels, while the output results are divided into two types: customer churn (D_1) and no customer churn (D_2). The specific rule base is shown in Appendix 1.

3.3. BRB inference model based on GA optimization

3.3.1. BRB modeling

From Fig. 3, it can be seen that the BRB reasoning model can be divided into four modules, which are the feature input module, reasoning module, inference output module and GA optimization module. According to the introduction of Tables 1 and x_1, x_2, …, x_{19} in the input module correspond to the 19 input features, while the output D_n corresponds to the two outcomes of customer churn and no churn. The customer outcomes S_1 and S_2 are determined by the inference module and compared with the actual customer churn results, and the error between the actual output results and the BRB inference results is used as the objective function of the GA optimization algorithm. In addition, in the inference module, the BRB algorithm is taken as the main core algorithm, and its detailed inference process is as follows.

1) **Initial setting of the parameters of the initial belief rule base.** The rules in the belief rule base are shown in Equation (1), where the initial values of rule weight $\theta_l(l = 1, 2, ..., 200)$ and attribute weight $\delta_i(i = 1, 2, ..., 19)$ are set to 1 for all rules in the belief base.
2) **Transformation of customer input feature information into a model-recognizable confidence distribution structure.** Specifically, for a given input $\boldsymbol{X} = \{x_1, x_2, ..x_i.., x_{19}\}$, when $x^i \le A_1^1$ or $x^i \ge A_1^{J_i}$, where $i = 1,2, …,19$, J_i indicates the sum number of reference levels for the i th antecedent attributes, and x_i has a match of 1 for both A_1^1 and $A_1^{J_i}$, while the other references have a match of 0. When $A_1^j \le x_i \le A_1^{j+1}$, where $j = 1,2,...,J_i - 1$, according to Equation (2), we can calculate the reference rank match of x_i for A_1^j and A_1^{j+1} as α_1^j and α_1^{j+1}, respectively.
3) **Calculation of the activation weights.** Based on the reference grade match calculated in step 2, activation weights $w_l(l = 1, 2, ..., L)$ can be calculated from Equation (3) and Equation (4) by substituting

Table 1
Reference levels for customer data input features.

Customer Data Input Characteristic	Reference Level	Description of the Reference Level
Gender (x_1)	0; 1	0 for male; 1 for female
SeniorCitizen (x_2)	0; 1	0 for non-senior citizen, 1 for senior citizen
Partner (x_3)	0; 1	Has partner or not: 0 for no, 1 for yes
Dependents (x_4)	0; 1	Has dependents or not: 0 for no, 1 for yes
Tenure (x_5)	Any integer (>0)	Number of months in the network
PhoneService (x_6)	0; 1	Telephone service available: 0 for no, 1 for yes
MultipleLines (x_7)	0; 1; 2	Has multiline service or not: 0 for no, 1 for yes, 2 for no network service
InternetService (x_8)	0; 1; 2	Internet service provider: 0 for none, 1 for DSL, 2 for fiberoptic
OnlineSecurity (x_9)	0; 1; 2	Has online security service or not: 0 for no, 1 for yes, 2 for no network service
OnlineBackup (x_{10})	0; 1; 2	Has online backup service or not: 0 for no, 1 for yes, 2 for no network service
DeviceProtection (x_{11})	0; 1; 2	Device is protected or not: 0 for no, 1 for yes, 2 for no network service
TechSupport (x_{12})	0; 1; 2	Has technical support service or not: 0 for no, 1 for yes, 2 for no network service
StreamingTV (x_{13})	0; 1; 2	Has streaming TV service or not: 0 for no, 1 for yes, 2 for no network service
StreamingMovies (x_{14})	0; 1; 2	Has streaming movie service or not: 0 for no, 1 for yes, 2 for no network service.
Contract (x_{15})	1; 2; 3	Contract period: 1 for monthly renewal, 2 for 1-year renewal, 3 for 2-year renewal
PaperlessBill (x_{16})	0; 1	Receives paperless bill or not: 0 for no, 1 for yes
PaymentMethod (x_{17})	1; 2; 3; 4	Payment method: 1 for electronic check, 2 for mailed check, 3 for bank transfer (automatic), 4 for credit card (automatic)
MonthlyCharges (x_{18})	29.35; 55.65; 83.25; 118.75	Monthly fees paid by user
TotalCharges (x_{19})	586.8; 2288.85; 4488.85; 6688.85; 8684.8	Total historical user payments

in the reference level matchesthe. L is 200 in this paper, and it represents the magnitude of the role played by the l th rule in the process of determining the distribution of the belief in the churn outcome.

4) **Fusing the activated rules in step 3 for inference using the ER algorithm.** According to Eq. (5) and Eq. (6), the final output customer churn result (churn or no churn) corresponding to the inference of this customer data sample through the BRB algorithm and the size of its belief distribution are obtained as follows: $D = \{(D_1, \beta_1), (D_2, \beta_2)\}$.
5) **Obtaining the customer churn results according to the BRB model.** According to the belief degrees, the rules are sorted to determine customer churn. If $D_1 > D_2$, the churn belief distribution is greater than the no-churn belief distribution, from which it can be concluded that the sample data reasoning result is churn; the opposite indicates no churn. These results are represented as $D = \text{argmax}(\beta_m(m = 1, 2))$.

3.3.2. GA-based optimization modeling

GA optimization algorithms have evolved and developed according to the theory of biological evolution. Its basic principle is to simulate the processes of genetics, crossover, and mutation in nature and search for the optimal solution through continuous iteration. In the process of predicting customer churn, the accuracy of customer churn predictions is taken as the objective function, and the optimal solution with higher accuracy is determined by optimizing the attribute weights in the BRB model, which ultimately determines the main influencing factors of customer churn.

The flow of the optimization algorithm with the BRB and GA as the inference and optimization engines is shown in Fig. 4, and the main steps are as follows.

Step 1 Parameter initialization. Initialize the population of GA, i.e., the belief value of the customer churn prediction result, the customer information input feature weight value and the rule weight value for the BRB.
Step 2 Chromosome crossover mutation. This operation crosses the belief parameters of the customer churn inference results of the BRB. Here, the bits of the optimized beliefs that violate the constraints of the initial rules are adjusted and normalized to ensure the objectivity of each rule.
Step 3 Calculation of fitness

Step 3.1 BRB reasoning. The process of calculating the combined match between the customer input features of the BRB and the rule is described in Step 2 in the previous section. The calculation of the activation weights of the rules is described in Step 3 and Step 4 in the previous section.
Step 3.2 ER fusion rule. The computation process is described in Step 5 in the previous section.
Step 3.3 Calculation of the error MAPE.

$$\text{MAPE} = \sum_{i=1}^{I} error_i / I \times 100\% \tag{12}$$

$$error_i = \begin{cases} 1, output_{i,estimated} \neq output_{i,actual} \\ 0, output_{i,estimated} = output_{i,actual} \end{cases} \tag{13}$$

Step 4 Selection of the optimal fitness value. The detailed operation can be found in the specific genetic algorithm description.
Step 5 Optimization termination. It is determined whether the termination condition is satisfied; if not, jump to step 2, and if so, output the optimal parameters.

The GA-based BRB model optimization method uses a genetic algorithm as the optimization engine, with the number of individuals in the initial population set to 100 and the number of training generations set to 50. The optimized rule weights, the confidence of predicting the churn result, and the optimal customer input feature weights are finally obtained.

4. Results and analysis

4.1. BRB model prediction results

In this paper, Telco Customer Churn is used as the data source (described in detail in Section 3.1), 200 data points are selected as the rule base of the BRB inference prediction model based on expert experience, and 400 data points are randomly selected as the experimental samples in this paper because the total number of datasets is too large to illustrate the reasonableness of the experiment. To verify the effectiveness of the BRB model for customer churn inference prediction, this paper adopts the SVM model and BP neural network model as the comparison models for customer churn prediction. The experimental results are shown in Fig. 5. First, the SVM model and BP neural network are essentially block-box modeling methods, and their internal structure is not directly associated with the reasoning logic or process, which

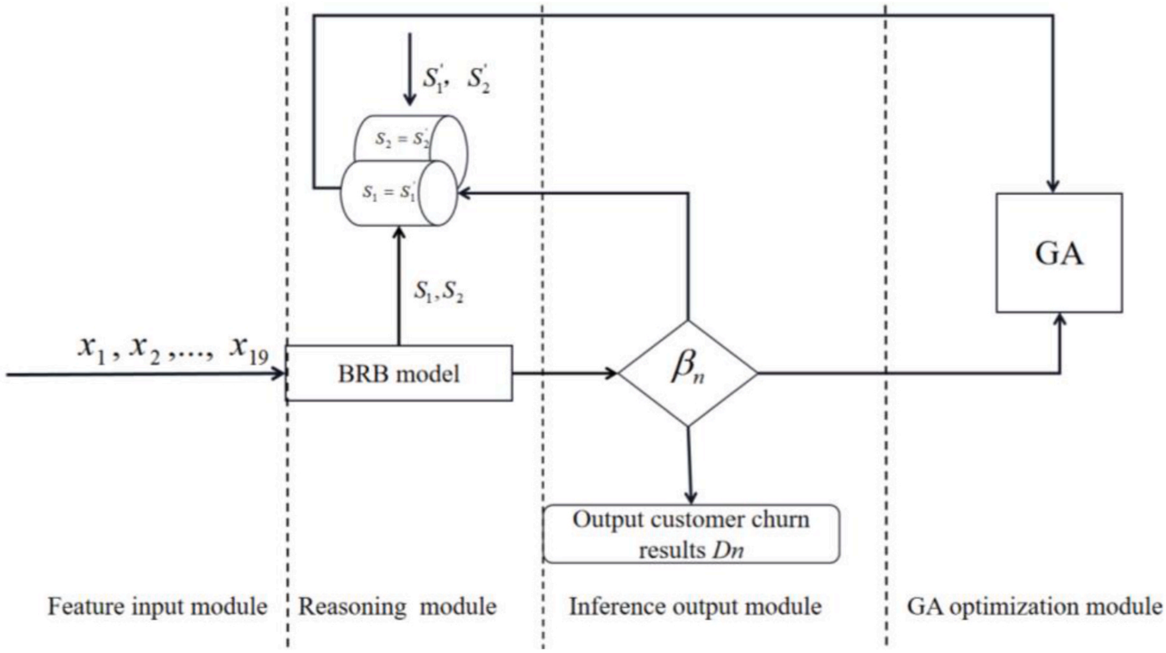

Fig. 3. BRB reasoning prediction model.

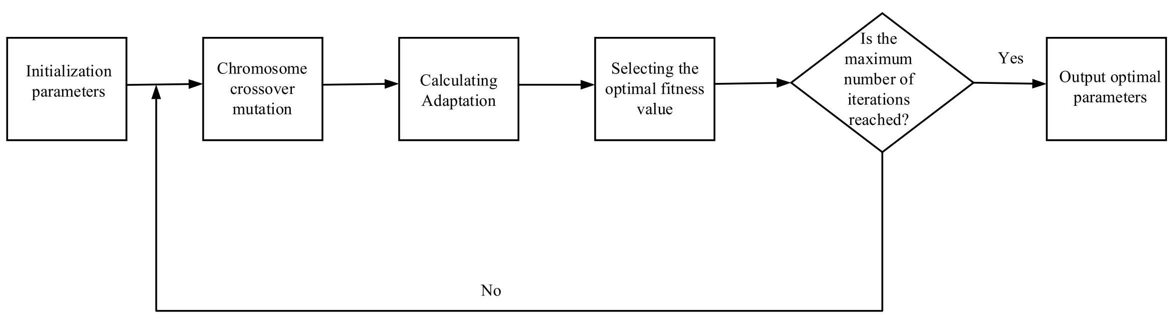

Fig. 4. Flow chart of GA optimizing the BRB parameters.

makes it difficult for the operator (manager) to determine the importance of each customer input feature information for customer churn. Second, the SVM and BP neural networks are implemented for purely nonlinear data fitting. Since operator data management experts play a crucial role in determining the resultant rule base, it is important to use customer churn data and the experience of operator data management experts to assess customer churn. In contrast, the BRB AI inference algorithm based on GA optimization for the operator customer churn inference prediction model can remove the bottleneck of estimating all the initial parameters by using domain knowledge initialization or random assignment and adjusting the rule base with attribute weights through historical churn data. In addition, different types of uncertainty information can be included in BRB inference based on the knowledge of customer characteristics since the ER algorithm can maintain the original characterization of uncertainty during the inference process, and the corresponding effects can be reflected in the final conclusions. Finally, when optimizing the initial parameters under the GA optimization algorithm, different degrees of constraints are added to the inference of the customer churn results by combining the operator's experience in data management of customer churn to ensure that each rule has an objective meaning and is in line with the actual situation to achieve a more accurate result.

Above, Fig. 5(c) shows the prediction of customer churn by the BRB model, and it can be seen that the red actual customer churn results and the blue model-predicted customer churn results overlap; the results are significantly better than those of the SVM model in Fig. 5(a) and the BP neural network model in (b). Integrating the above theories and experiments, it is clear that BRB (Belief Rule-Based system) outperforms SVM (Support Vector Machines) and BP (Back Propagation) neural networks in handling uncertain information. Additionally, based on a variety of customer characteristic data and types of churn, BRB has the capability to handle nonlinear relationships, exhibiting notably effective predictive outcomes and high accuracy in customer churn prediction. Their accuracies are shown in Table 2 below.

4.2. BRB model optimization analysis

As shown in Fig. 6, the weights of the input features of customer churn change after optimization, and as introduced in Section 3.3.1, the weights of all attributes are initially set to 1. In the figure, it can be seen that some of the weights change significantly, such as the weights of Dependents and PhoneService, which change from 1 to 0.077 and 0.294, respectively; these changes indicate that these customer characteristics are less indicative of customer churn. Other scholars have drawn the same conclusion; e.g., reference (Pamina et al., 2019) showed that PhoneService has the smallest impact on telecom customer churn, with a correlation value of 0.0119. Reference (Sanjay & Kumar, 2019) showed that customer churn is related to many factors, but Dependents is not the main factor. Therefore, the weight values of the input characteristics Dependents, PhoneService and StreamingMovies are substantially

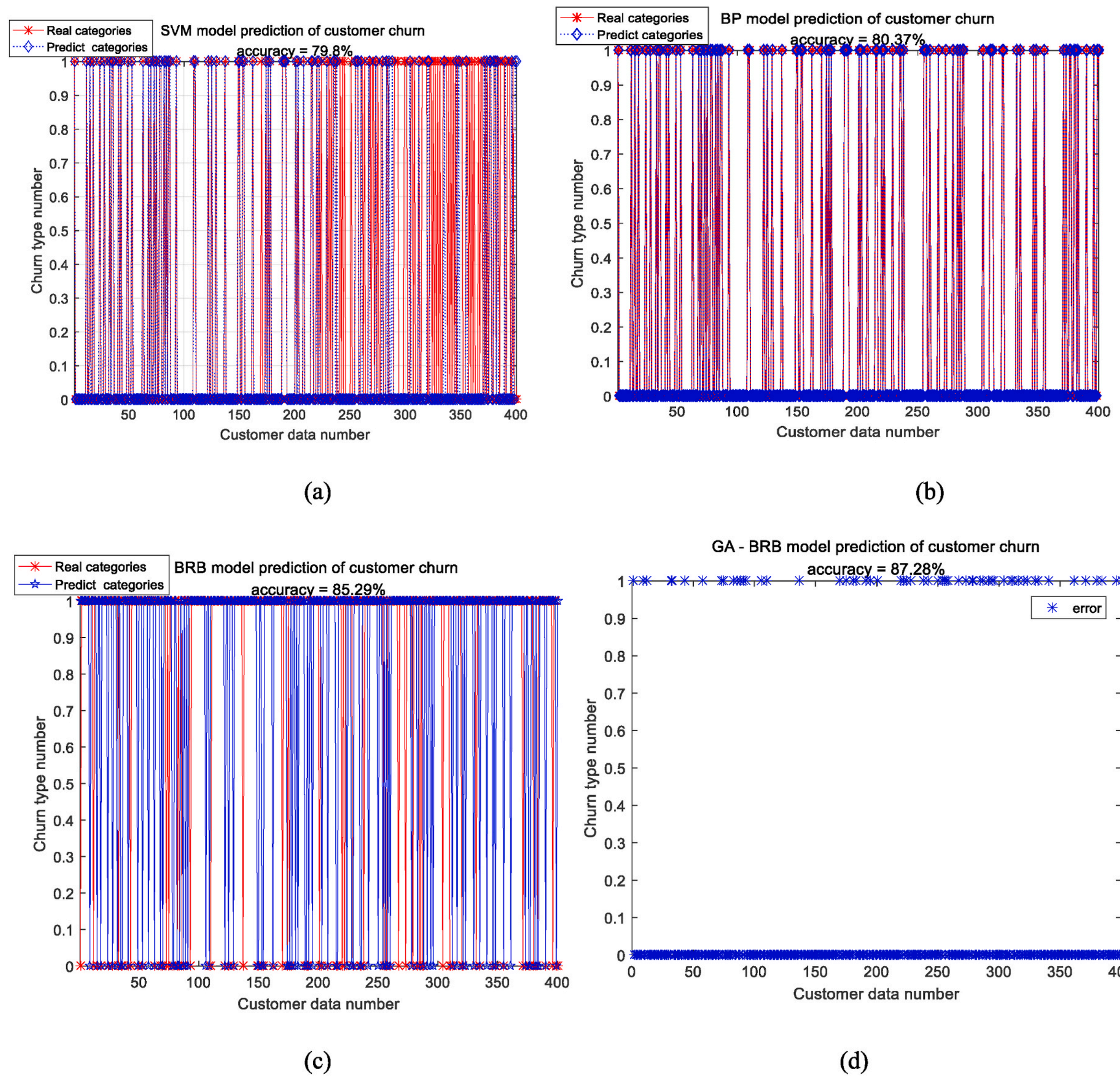

Fig. 5. Prediction of customer churn by three models.

Table 2
Prediction accuracy of customer churn for the three models.

Predictive model	SVM	BP	BRB	GA-BRB
Accuracy	79.8%	80.37%	85.29%	87.28%

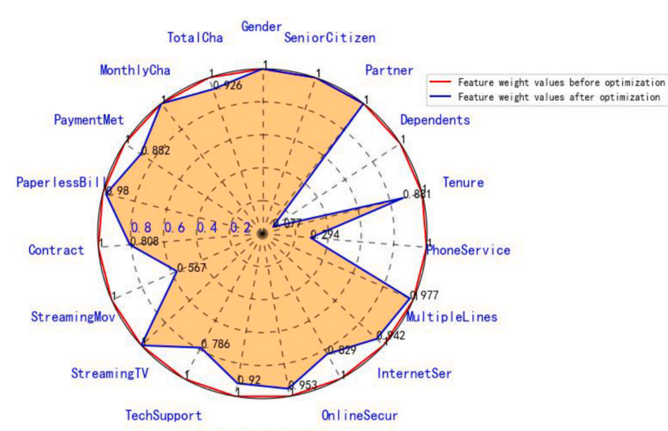

Fig. 6. Before and after optimizing the feature weight parameters.

reduced after optimization. In contrast, Gender and SeniorCitizen maintain a high weight after optimization, indicating that these customer data input features have a strong influence on the prediction of customer churn; e.g., reference (Keramati et al., 2020) showed that Gender and Age features have a significant impact on customer churn. Reference (Loukili et al., 2022) showed that SeniorCitizen has a great impact on customer churn, as churn is much greater for seniors than nonseniors. Therefore, the weights of the input features Gender, SeniorCitizen, Partner, etc., are optimized to remain at the maximum value of 1. The values of all the feature weight changes are shown in Table 3.

4.3. Validation of the model after weight optimization

It can be seen from the above section that the weights of the input features are changed after the optimization of the BRB customer churn prediction model using the GA. According to the meaning of the weights of the input features, the size of the weights affects the output of the results, and the larger the weights are, the greater the impact. Therefore, to further validate the judgment regarding the influencing factors of

Table 3
Before and after optimizing the feature weight values.

Rule number Input features	Feature weight before optimization	Feature weight after optimization
Gender (x_1)	1	1
SeniorCitizen (x_2)	1	1
Partner (x_3)	1	1
Dependents (x_4)	1	0.077
Tenure (x_5)	1	0.881
PhoneService (x_6)	1	0.294
MultipleLines (x_7)	1	0.977
InternetService (x_8)	1	0.942
OnlineSecurity (x_9)	1	0.829
OnlineBackup (x_{10})	1	0.953
DeviceProtection (x_{11})	1	0.920
TechSupport (x_{12})	1	0.786
StreamingTV (x_{13})	1	1
StreamingMovies (x_{14})	1	0.567
Contract (x_{15})	1	0.808
PaperlessBill (x_{16})	1	0.980
PaymentMethod (x_{17})	1	0.882
MonthlyCharges (x_{18})	1	1
TotalCharges (x_{19})	1	0.926

customer churn, the factors whose weights are greater than 0.9 are selected as input features, and then the BRB model is used to make predictions regarding customer churn. In this experiment, the input features are Gender, SeniorCitizen, Partner, MultipleLines, InternetService, OnlineBackup, DeviceProtection, StreamingTV, PaperlessBill, MonthlyCharges, and TotalCharges, totaling 11 features. The experimental results are shown in Fig. 7.

After the weights change, the customer churn is judged again by reducing the features with smaller weights and retaining those with larger weights. From the above figure, it can be seen that the prediction of customer churn after the weight change is similar to the results of the GA-optimized BRB prediction model and better than those of the BRB model, which indicates that the judgment of the factors affecting the operator's customer churn based on the GA-optimized BRB AI inference algorithm has authenticity and reliability.

5. Conclusions and future research prospects

In this paper, a BRB AI inference algorithm based on GA optimization is proposed, which aims to determine the factors affecting customer churn for operators. In the BRB AI inference model based on GA optimization, first, the nonlinear relationship between customer input features and customer churn is determined, and different classes of customer churn belief rule bases are established for the prediction of customer churn by incorporating the experience of the operator's data management experts regarding customer churn management. Then, the GA is used to improve the accuracy of the BRB inference model, optimize the attribute weights of the input features, and screen the input features to determine those with a greater impact on the prediction results. Finally, experiments are conducted on statistical data of customer churn, the Telco Customer Churn data, which were obtained from the Kaggle website and validated. The final experimental results show that the BRB AI inference algorithm based on GA optimization is very effective in determining the factors affecting customer churn for operators, and it has strong expandability and extensibility; it can be used to design an improved optimization model based on the experience of operator data managers and accumulated historical data.

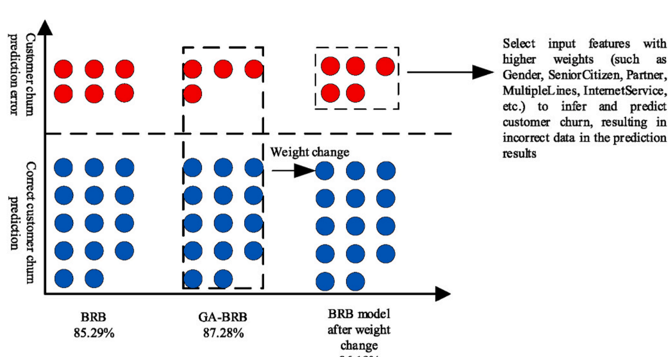

Fig. 7. Comparison of customer churn predictions after weight change.

Operators can use identified factors that affect customer churn not only for data analysis and mining, employing machine learning and statistical models to analyze customer data, which can help determine which factors are most predictive of churn tendencies; but also for customized customer experiences: Based on the analysis results, operators can design tailored customer retention strategies, offering specific discount packages or loyalty discounts for price-sensitive customers; and can improve customer service: Customer service is a crucial factor affecting customer satisfaction and loyalty, providing fast, effective, and friendly customer service during this period can significantly reduce customer churn. After identifying the influencing factors, it not only improves customer satisfaction and loyalty, increases revenue, and reduces costs, but also optimizes products and services. Understanding the reasons behind customer churn can help companies identify problems and deficiencies in their products or services, leading to improvements. Moreover, it establishes a data-driven culture by promoting a data-based decision-making process within the company, which helps to create a culture driven by data.

There are still some shortcomings in this study, such as excessive reliance on data in the BRB modeling process and empirical bias in expert experience, which leads to errors in the inference process of the confidence rule library and the prediction of influencing factors in the GA optimization process. In addition, as these data are static, they may change over time, and the influencing factors may also undergo slight changes. Due to the fact that BRB's ability to handle uncertain information is based on big data, in future research, we can expand the data on customer churn to improve the model. At the same time, different optimization algorithms can be used to optimize the BRB model, and the most important thing is to achieve dynamic updates. To further validate the effectiveness of this method in predicting customer churn, additional theoretical and practical work needs to be done. This paper mainly focuses on the factors of customer churn, with the goal of making judgments and performing verification to help operators prevent or avoid customer churn, accurately categorize customers, develop prevention strategies, improve business service quality, and thus improve the profitability and competitiveness of the whole enterprise; therefore, the idea of this paper is practical and has promotional significance. In the next study, we intend to examine customer churn from the perspective of operator policy.

CRediT authorship contribution statement

Liu Kun: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Hassan Alli:** Writing – review & editing, Validation, Supervision, Conceptualization. **Khairul Aidil Azlin Abd Rahman:** Writing – review & editing, Writing – original draft, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix I

Rule number Input Features	1	2	3	…	100	101	102	…	198	199	200
Gender(x_1)	0	0	1	…	0	0	1	…	0	0	0
SeniorCitizen(x_2)	0	0	0	…	0	1	1	…	0	0	1
Partner(x_3)	0	0	0	…	0	1	1	…	1	1	0
Dependents(x_4)	0	0	0	…	0	0	0	…	1	1	0
Tenure(x_5)	2	45	2	…	48	11	55	…	31	50	32
PhoneService(x_6)	1	0	1	…	1	1	1	…	1	1	1
MultipleLines(x_7)	0	2	0	…	1	0	1	…	1	1	1
InternetService(x_8)	1	1	2	…	2	0	2	…	2	2	2
OnlineSecurity(x_9)	1	1	0	…	0	2	0	…	1	0	0
OnlineBackup(x_{10})	1	0	0	…	1	2	1	…	0	1	0
DeviceProtection(x_{11})	0	1	0		1	2	1		1	1	1
TechSupport(x_{12})	0	1	0	…	0	2	0	…	1	0	0
StreamingTV(x_{13})	0	0	0	…	1	2	0	…	0	1	0
StreamingMovies(x_{14})	0	0	0	…	1	2	0	…	0	1	0
Contract(x_{15})	1	2	1	…	3	1	1	…	1	1	1
PaperlessBill(x_{16})	1	0	1	…	1	0	1	…	0	1	1
PaymentMethod(x_{17})	2	3	1	…	3	2	1	…	1	3	4
MonthlyCharges(x_{18})	2	2	3	…	4	1	4	…	4	4	3
TotalCharges(x_{19})	1	2	1	…	4	1	4		3	4	3
Customer Churn	1	0	1	…	0	1	1	…	0	1	0

Note: In Customer Chun, 1 represents the result of customer churn, and 0 represents the result of customer non churn.

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