Research Article

A Model of High-Dimensional Feature Reduction Based on Variable Precision Rough Set and Genetic Algorithm in Medical Image

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Aiming at the shortcomings of high feature reduction using traditional rough sets, such as insensitivity with noise data and easy loss of potentially useful information, combining with genetic algorithm, in this paper, a VPRS-GA (Variable Precision Rough Set--Genetic Algorithm) model for high-dimensional feature reduction of medical image is proposed. Firstly, rigid inclusion of the lower approximation is extended to partial inclusion by classification error rate β in the traditional rough set model, and the ability dealing with noise data is improved. Secondly, some factors of feature reduction are considered, such as attribute dependency, attributes reduction length, and gene coding weight. A general framework of fitness function is put forward, and different fitness functions are constructed by using different factors such as weight and classification error rate β. Finally, 98 dimensional features of PET/CT lung tumor ROI are extracted to build decision information table of lung tumor patients. Three kinds of experiments in high-dimensional feature reduction are carried out, using support vector machine to verify the influence of recognition accuracy in different fitness function parameters and classification error rate. Experimental results show that classification accuracy is affected deeply by different weight values under the invariable classification error rate condition and by increasing classification error rate under the invariable weigh value condition. Hence, in order to achieve better recognition accuracy, different problems use suitable parameter combination.

1. Introduction

Rough set theory was developed by Pawlak in 1982 [1], and it is a mathematical tool to deal with vagueness and uncertainty. The classification ability unchanged in its main idea, decision or classification rules of problem are derived by knowledge reduction [2]. The Variable Precision Rough Set (VPRS) theory, proposed by Ziarko, and is an extension of original rough set model. For inconsistent information system, the VPRS model allows a flexible approximation boundary region by a precision variable β [3]. When β = 0, Pawlak rough set model is a special case of variable precision rough set model. The main task of variable precision rough set model is to solve the problem of data classification with no function or uncertainty. The hierarchical model of attribute reduction for variable precision rough set is studied by Xiaowei [4]. There is abnormal phenomenon in existing attribute reduction models; therefore, a variable precision rough set attribute reduction algorithm with the property of interval is proposed, and the reduction abnormal problem is transformed into a hierarchical model representation, and the reduction anomaly is gradually eliminated by the layer-by-layer reduction model; Jie and Jiayang [5] puts forward that there may be a reduction...
jump phenomenon in variable precision rough set feature reduction, which affects the quality of reduction and brings the problem of attribute reduction of variable precision rough set; Pei and Qinghua [6] proposes an FCM clustering algorithm based on variable precision rough set; according to the threshold characteristics of the variable precision rough set model, the algorithm divides the objects in the edge of the cluster into the positive, negative, and boundary regions, to improve the accuracy of clustering. Two different solutions of variable precision rough set attribute reduction algorithm are proposed by Hao and Junan [7]; based on tolerance matrix and minimal reduction of attribute core, the attribute kernel idea of variable precision rough set is proposed. The experimental results show that the two algorithms can reduce the search space and improve the efficiency of the algorithm.

Feature reduction is one of the core contents of rough set theory; in the condition of keeping the classification ability for knowledge base unchanged, we delete irrelevant or unimportant knowledge, which can reduce the dimension of the decision system, reduce the time complexity, and improve the efficiency of the algorithm [8]. People want to find the minimum reduction, but it has been proved to be an NP-Hard problem [9]; the main research is how to find the second optimal solution. Genetic algorithm is a computational model which is based on the natural selection and evolution mechanism; its core idea is inspired by the natural selection rule of the survival of the fittest, can achieve a highly parallel, random, and adaptive search, is not easy to fall into local optimal [10], can find the global optimal solution with high probability, and has great advantage in solving the NP-Hard problem.

In this paper, a new algorithm of PET/CT high-dimensional feature selection is proposed based on genetic algorithm and variable precision rough set model. On one hand, the algorithm considers the value of chromosome coding, the minimum number of attributes, and the dependency of attributes to construct a general fitness function framework and adjusting weight coefficient of each factor to achieve different fitness function; on the other hand, aiming at the limitation of Pawlak rough set model, introducing the classification error rate of $\beta$, it extends rigid inclusion of the lower approximation for traditional rough set to partial inclusion, not only improving the concept of approximate space, but also enhancing the ability to deal with noise data and changing the range of $\beta$ to achieve different fitness function. Finally, through extracting PET/CT lung cancer ROI 98-dimensional feature to construct the information decision table of lung cancer patients, 8 group experiments of high-dimensional features selection are done by using support vector machine to classify and recognize reduction subsets, to verify the degree of influence on the different weights and different classification error rate, and find a set of parameters suitable for this problem ($\omega_1 = 1, \omega_2 = 1, \omega_3 = 0; \beta = 0.6$). The experimental results show that different parameters can be used to get different experimental results, so we should choose the appropriate parameter combination according to different problems so as to get better recognition accuracy.

2. Materials and Methods

2.1. PET/CT. PET/CT is a kind of advanced medical imaging technology, which is a combination of the good performance of PET and CT on the same device, and provides the anatomical and functional metabolism of the subjects under the same conditions [11]. PET is a functional image; it can provide metabolic information of tissue and organ and reflect functional changes of the human body from the molecular level, such as the physiological, pathological, biochemical, and metabolic, but has poor spatial resolution, cannot be accurately located, and cannot display the anatomical information of the lesions [12]. CT belongs to the anatomical structure of images, with high spatial resolution and density resolution; it has unique advantages in displaying the anatomical structure and density of the body [13], it also can provide detailed anatomical information of human organs and tissues, but can not reflect the functional information of tissues and organs [14] (Figure 1).

2.2. Genetic Algorithm. Genetic algorithm is a computational model which is based on the natural selection and evolution mechanism; its core idea is inspired by the natural selection rule of the survival for the fitness, so the search algorithm is an iterative process of survival and detection, is a very effective search and optimization technique, can achieve a highly parallel, random, and adaptive search, cannot easily fall into local optimum, and can find the global optimal solution with high probability and its robustness is good [15]. General use of genetic algorithm for reduction is achieved by a binary coding, 1 indicates that the position selects the corresponding attribute, while 0 indicates that the corresponding attribute is not selected. Genetic algorithm consists of four parts: encoding and decoding, fitness function, genetic operator, and control parameters, genetic operators include selection operator, crossover operator, and mutation operator. The selection operation is generally selected by roulette wheel selection method, according to the selection probability $p_i = \left( f_i / \sum_{i=1}^{M} f_i \right)$, crossover operator is a single point crossover, with a certain probability $p$ to select individuals to participate in crossover, mutation operator selects the individual with the probability $p$ and randomly selects the corresponding gene of the variant individuals to operate [16]. The general steps are as follows: determining the initial population and calculating the target value of each individual in the population and the corresponding value of the fitness function, choosing the chromosomes with high fitness value, and forming a matching set (selection), according to certain rules of reproduction (crossover and mutation), to meet the conditions to stop the genetic iteration, or return to step 3 (Figure 2).

2.3. Variable Precision Rough Set. Ziarko proposed the variable precision rough set model in 1993, he first proposed the concept of classification error rate; in the case of a given classification error rate, the objects with the same attributes can be classified into classes as many as possible [17].
Definition 1 (equivalence class). Assuming that $R$ is an equivalence relation on $K$, a collection of all elements equivalent to an element $k$ in $K$ is called an equivalence class of $k$, denoted as $[k]$.

Definition 2 (indiscernibility relation). If $P \subseteq R$ and $P \neq \emptyset$, then $\cap P$ is also an equivalence relation, it is called the indiscernibility relation on $P$, denoted as $\text{ind}[P]$.

Definition 3 (upper approximation and lower approximation). The knowledge base of $K = (U, R)$, $X \subseteq U$, $R$ is equivalent to the relationship between $U$. The lower approximation of $X$ can be understood as all of the classification errors that are not greater than $\beta$ are included in the $R$ equivalence class in $X$. The upper approximation of $X$ can be understood as the intersection of all those with classification error not greater than $\beta$ and equivalence classes with $X$ is not empty [18]. Expressions are as follows:

\[
\begin{align*}
\overline{RX}_\beta &= \cup \left\{ Y \in \frac{U}{R} \mid Y \subseteq X \right\}, \\
\underline{RX}_\beta &= \cup \left\{ Y \in \frac{U}{R} \mid Y \cap X \neq \emptyset \right\}.
\end{align*}
\]

Assume that the decision information table $S = (U, A, V, f)$, where $U$ is a sample of the universe and a nonempty finite sample set, $U = \{x_1, x_2, x_3, \ldots, x_n\}$, and $X_i$ represents each sample. $A = P \cup Q$, $P$ represents a collection of conditional attributes, $Q$ represents a set of decision attributes, $V$ represents the range of attribute, $f: U \times A \longrightarrow V$ is an information function that gives an attribute value for each attribute of each $x_i$, that is, $\forall a \in A, x \in U, f(x, a) \in V_a$. $X$ and $Y$ represent nonempty set in finite field $U$. $P, Q \subseteq A$ represents the condition attribute set and decision attribute set; $\text{ind}(P)$, $\text{ind}(Q)$ is an indiscernibility relation determined by $P$, $Q$; $\text{ind}(P)$ is a collection of equivalence classes called condition class, expressed in $U/P$, i.e., $U/\text{ind}(P) = \{P_1, P_2, P_3, \ldots, P_n\}$; $\text{ind}(P)$ is a collection of equivalence classes called decision class, expressed in $U/Q$, that is $U/\text{ind}(Q) = \{Q_1, Q_2, Q_3, \ldots, Q_n\}$.

Definition 4 (majority inclusion relation). If there is a $e \in Y$ for each $e \in X$, then $Y$ contains $X$, denoted as $Y \supseteq X$, then

\[
c(X, Y) = \begin{cases} 
1 - \frac{|X \cap Y|}{|X|}, & |X| > 0, \\
0, & |X| = 0,
\end{cases}
\]

(2)

where $|X|$ represents the cardinality of the set $X$ and $c(X, Y)$ is the relative classification error rate of set $X$ on set $Y$.

Make $(0 \leq \beta < 0.5)$; the majority inclusion relation is defined as $Y \geq X \iff c(X, Y) \leq \beta$; the “majority” requirement implies that the number of common elements in $X$ and $Y$ is greater than 50% of the number of elements in $X$.

Definition 5 ($\beta$-reduction). Conditional attribute set $P$ is a subset of $P$ for $\beta$-reduction or approximate reduction of decision attribute set $Q$, and the subset is $\text{red}(P, Q, \beta)$ and meets the following two conditions [19]:

1. $\gamma(P, Q, \beta) = \gamma(\text{red}(P, Q, \beta), Q, \beta)$
2. To remove any attribute from $\text{red}(P, Q, \beta)$, condition (1) is not valid
2.3.1. Attribute Dependency

Definition 6. The dependency of the decision attribute set $Q$ and the conditional attribute set $P$ is defined as

$$\gamma(P, Q, \beta) = \frac{|\text{pos}(P, Q, \beta)|}{|U|}$$

where $\text{pos}(P, Q, \beta) = \bigcup_{Y \subseteq U/\text{ind}(P)} Q$, $|U|$ is the number of objects contained in the domain, $|\text{pos}(P, Q, \beta)|$ is the number of objects contained in the positive domain of all equivalence classes that are not greater than the $\beta$ classification error, which indicates that the conditional attributes can correctly divide the object to $U|Q$. $\gamma(0 \leq \gamma \leq 1)$ is the $\beta$ dependency of the decision attribute $Q$ to the conditional attribute $P$ and it is an evaluation of the ability to classify objects with the classification error $\beta$. $\gamma = 0$ means that $P$ cannot be used to divide objects into equivalence classes in $Q$, $\gamma = 1$ means that $P$ can be used to divide objects into equivalence classes in $Q$ completely, $0 < \gamma < 1$ means that $P$ can be used to divide objects into equivalence classes in $Q$ partly.

2.3.2. Attribute Importance

Definition 7. Assume that the decision information table is $S = (U, A, V, f)$, $A = P \cup Q$, $s \in h$, the relative importance of attribute $s$ is

$$Z(s) = \frac{\gamma(P, Q, \beta) - \gamma(P - \{s\}, Q, \beta)}{\gamma(P, Q, \beta)} = 1 - \frac{\gamma(P - \{s\}, Q, \beta)}{\gamma(P, Q, \beta)}.$$

An attribute is able to distinguish an object; the greater the value, the stronger the ability.

The selection of threshold $\beta$ for variable precision rough set needs to meet the following requirements.

The choice of $\beta$ to make the classification accuracy as high as possible:

1. $0 \leq \beta < 0.5$
2. $\beta$ makes the attributes contained in the reduction results as little as possible

2.4. SVM. Support vector machine (SVM) is a supervised learning model for data analysis, pattern recognition, and regression analysis in the field of machine learning. The best compromise between model complexity (the learning accuracy of a particular training sample) and learning ability (ability to identify an arbitrary sample without error) should be found based on limited sample information. In order to obtain the best generalization ability, the basic idea is to use the structural risk minimization principle to construct the optimal classification hyperplane in the attribute space. SVM has some advantages such as good generalization ability, simple data structure, low computational complexity, short training time, few parameters selection, high fitting precision, strong robustness, and so on [20, 21]. It has great advantages in dealing with small sample, nonlinear, and high-dimensional pattern recognition. It is often used in pattern recognition [12, 22], regression estimation, and so on.

(1) After the introduction of kernel function and penalty parameter by SVM, the optimal discriminant function model is

$$f(x) = \text{sgn} \left( \sum_{i=1}^{n} a_i y_i k(x_i, x) + b \right).$$

Among it, $0 < a < C$, $y_i \in \{1, -1\}$.

(2) The optimization function of SVM is

$$Q(a) = \sum_{i=1}^{n} a_i - \frac{1}{2} \sum_{i,j=1}^{n} a_i a_j y_i y_j k(x_i, x_j).$$

(3) The radial basis kernel function is a widely used kernel function; the kernel function is used in this paper:

$$k(x, y) = \exp \left( -g\|x - y\|^2 \right).$$

Among them, $g > 0$, $g$ is an important parameter in the kernel function, which affects the complexity of SVM classification algorithm.

The kernel function parameter $g$ and penalty coefficient $C$ of support vector machine (SVM) is an important parameter which affects the performance of SVM classification, so $(C, g)$ is used as the optimization variable. In the process of learning SVM, 5-fold cross validation is used to calculate the optimal classification performance of kernel function parameter and penalty coefficient, and then the diagnosis result of optimization is applied to the SVM classifier for lung cancer, the final selection of the sensitivity, specificity, accuracy, and computation time as the evaluation indexes of related experiments.

3. Results and Discussion

3.1. Main Idea. The main idea of the model is as follows.

3.1.1. Parameters. Population size $M$, chromosome length $N$ (the number of condition attributes), crossover probability $Pc$, mutation probability $Pm$, fitness function $F(x)$, and the maximum number of iterations $K$ are the parameters.

3.1.2. Coding. The binary coding method is used, which is represented by a binary string whose length is equal to the number of condition attributes; each bit corresponds to a condition attribute, a bit of 1 indicates that the corresponding condition attribute is selected, 0 indicates that the condition attribute is not selected, e.g., [0011001] represents a chromosome with a length of 8, and it is known that the corresponding 1, 2, 3, 5, 7 of 0 indicates that the corresponding condition attribute is not selected, then $\{c_3, C_4, C_6, c_8\}$ is the last individual to choose the attributes set.
generate (M), \( Lr = 98 \) //Initial population M, 01 sequence of Chromosome length 98
Setting \( \beta, \omega, \) crossover probability \( P_c, \) mutation probability \( P_m, \) iteration number \( K \)
Begin
for \( i = 1 : K \)
\( \text{target1} = (|\text{pos}_\beta^\delta(Q)|/|U|) \)
\( \text{target2} = ((|P| - |Lr|)/|P|) \)
\( \text{target3} = (\sum \text{abs}(r \times (r - 1)))/|r| \)
Fitness
function \( = -\omega_1 \times \text{target1} - \omega_2 \times \text{target2} + \omega_3 \times \text{target3}; \)
//Fitness function
\( P = \text{Select}(M, 2, P_c); //\text{Crossover probability} \ P_c \)
\( Q = \text{Crossover}(P, 2, P_c); //\text{Crossover algorithm} \)
\( Q' = \text{Mutation}(Q, P_m); //\text{Mutation algorithm} \)
End

3.3. Experimental Environment and Data

3.3.1. Hardware Environment. Intel Core i5 4670-3.4 GHz with 8.0 GB memory and 500 GB hard disk were used.

3.3.2. Software Environment. Matlab R2012b, LibSVM, and Windows 7 operating system were used.

3.3.3. Experimental Data. The PET/CT images of 2000 lung cancer patients were collected as the study samples (1000 cases of benign lung tumor, 1000 cases of malignant lung tumor). Firstly, ROI was extracted from the lung tumor and pretreated; then 8-dimensional shape features, 7-dimensional gray features, 3-dimensional Tamura features, 56-dimensional GLCM features, and the 24-dimensional frequency domain features were extracted from the lung tumor ROI, and 98-dimensional feature vectors are discreted and normalized. In the decision attribute, 1 represents the lung malignant tumor and –1 represents the lung benign tumor. Figure 4(a) shows four PET/CT images, ROI of Lung malignant tumor, and Figure 4(b) shows four PET/CT images’ ROI of lung benign tumor. Table 1 gives the feature values of two patients with lung cancer (one patient was a malignant tumor and the other was a benign tumor).

3.4. Analysis of Experimental Results. In this paper, 3 kinds of experiments are designed according to the weight value \( \omega = (0, 1, 2, 3) \) of the fitness function and the classification error rate \( \beta = [0.4, 0.2, 0] \) (namely, the inclusion degree \( 1 - \beta = [0.6, 0.8, 1] \)). For first type of experiments, \( 1 - \beta = 0.6 \), according to the different values of \( \omega \) to do the three groups of experiments totally. For second type of experiments, \( \omega_1 = 1, \omega_2 = 1, \omega_3 = 0 \), according to the different values of \( \beta \) to do three groups of experiments. For third type of experiments, \( 1 - \beta = 0.6 \), by increasing the \( \omega \)
value to achieve the best fitness function, to achieve the best results.

3.4.1. Experiment 1—Research on Different Weight Coefficients under the Condition in the Same Classification Error Rate. \( \varpi \) values and \( \beta \) values of experiment 1 are shown in Table 2, and \( 1 - \beta = 0.6 \).

(1) 1st Group Experiment. \( \{ \varpi_1, \varpi_2, \varpi_3 \} = \{1, 0, 0\} \): The algorithm is run 5 times according to this group weights; the results of the 5 groups are given in Table 3, including the reduction of the conditional attributes, the length of reduction, the optimal fitness value, the attribute dependency degree, and the time. The convergence of VPRS-GA under the variation for fitness function value in one time is shown in Figure 5.

Each reduction is classified by SVM classifier, using the method of 5-fold cross validation, through changing the training samples and test samples; the results of the five groups were obtained, including accuracy, sensitivity, specificity, and time (training samples are constructed by 800 malignant samples and 800 benign samples; testing samples are constructed by 200 malignant samples and 200 benign samples; the experiment is repeated 5 times by changing training samples and testing samples). Finally, the average values of these five groups are obtained as the final result of the reduction and shown in Table 4.

The weight value in this group experiment is \( \{ \varpi_1, \varpi_2, \varpi_3 \} = \{1, 0, 0\} \), attribute dependency degree are
Table 1: ROI feature values of lung tumor PET/CT image.

| Types of disease | Shape feature | Gray feature | Tamura texture | Texture features of GLCM 0 degree | Texture features of GLCM 45 degrees | Texture features of GLCM 90 degrees | Texture features of GLCM 135 degrees | Texture feature of wavelet Norm | Standard deviation | Energy |
|------------------|---------------|--------------|----------------|----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|---------------------------------|-------------------|--------|
| Lung malignant tumor | 6.0000 | 122.2810 | 14.7000 | 0.0808 | 0.0779 | 0.0790 | 0.0611 | 649.2580 | 37.1752 | 1.0000 |
| Lung benign tumor | 4.0000 | 50.3912 | 10.1616 | 0.8087 | 0.7915 | 0.8077 | 0.7864 | 379.9170 | 2.6741 | 1.0000 |
|                  | 0.0033 | 6.0006 | 1.8835 | 0.4324 | 0.4732 | 0.4370 | 0.4840 | 5.7551 | 0.8211 | 0.0002 |
|                  | 0.0000 | 2.4496 | 2.6329 | 0.0433 | 0.0621 | 0.0469 | 0.0679 | 1.1745 | 0.1677 | 0.0000 |
|                  | 0.0000 | 0.5649 |          | 9.4899 | 7.8127 | 9.2429 | 9.2429 | 3.4684 | 0.4955 | 0.0001 |
|                  | 0.0000 | 2.8589 |          | 0.8082 | 0.7905 | 0.8072 | 0.7853 | 2.0823 | 0.2972 | 0.0000 |
|                  | 0.0000 | 3283 |          | 0.0433 | 0.0621 | 0.0469 | 0.0679 | 2.1821 | 0.3117 | 0.0000 |
|                  | 0.0000 | 3.2559 |          | 7.8367 | 7.8363 | 7.8396 | 7.8363 | 0.8937 | 0.1276 | 0.0000 |

Table 2: Fitness function weight proportion and $\beta$ value.

| Experiment times | $\omega_1$ | $1-\beta = 0.6$ | $\omega_2$ | $\omega_3$ |
|------------------|------------|-----------------|------------|------------|
| First group experiment | 1   | 0               | 0          | 0          |
| Second group experiment | 1   | 0               | 1          | 0          |
| Third group experiment | 1   | 1               | 1          | 1          |

Table 3: Results of VPRS-GA running 5 times when $1-\beta=0.6$, $\{\omega_1 = 1, \omega_2 = 0, \omega_3 = 0\}$.

| Experiment times | $C_0$ reduction | Reduction length | Optimal fitness value | Attribute dependency degree | Time (s) |
|------------------|-----------------|------------------|-----------------------|-----------------------------|----------|
| 1                | [4 5 8 9 11 12 13 17 20 22 23 24 27 30 32 33 35 38 42 48 49] | 41 | -0.9705 | 0.9705 | 971.9144 |
|                  | [52 57 59 61 62 63 64 65 68 70 72 73 75 77 78 80 87 88 91 92] | 49 | -0.9685 | 0.9685 | 1007.6907 |
| 2                | [4 6 11 15 17 18 24 25 26 28 31 36 38 39 42 43 45 47 49] | 37 | -0.9695 | 0.9695 | 1043.2000 |
|                  | [53 56 65 68 69 72 76 77 79 80 81 83 85 88 91 92] | 34 | -0.9790 | 0.9790 | 947.3111 |
| 4                | [4 8 9 11 12 13 14 15 17 23 29 34 35 39 40 43 47 48 50 53 55 56 60 61 64 68 70 75 80 81 82 83 84 86] | 35 | -0.9775 | 0.9775 | 964.5092 |
| 5                | [3 4 6 8 10 11 12 13 15 17 19 20 21 24 26 29 31 39 42 44 45 48 50 53 54 56 59 64 68 77 83 84 87 89 92] | 39.2 | -0.9730 | 0.9730 | 986.9251 |
regarded as fitness function. The average attribute dependency degree is 0.973, the average length of reduction is 39.2, and the average optimal fitness value is $-0.973$. The average recognition accuracy of the experiment is 96.92%. The premature phenomena are shown in Figure 5, and evolution progress is terminated early.

### (2) 2nd Group Experiment

\(\omega_1, \omega_2, \omega_3 = \{1, 1, 0\} \): This experiment introduces an objective function to control the length of reduction (the shorter the length of reduction, the better it is), the influence degree of the objective function which controls the reduction on the fitness function and the final recognition accuracy is verified. The algorithm is run 5 times according to this group weights, and the results of the 5 groups are given in Table 5, including the reduction of the conditional attributes, the length of reduction, the optimal fitness value, the attribute dependency, and the time. The convergence of VPRS-GA under the variation for fitness function value in one time is shown in Figure 6.

Each reduction is classified by SVM classifier, using the method of 5-fold cross validation, through changing the training samples and test samples, the results of the five groups were obtained, including accuracy, sensitivity, specificity, and time (training samples are constructed by

![Best: –0.9695 Mean: –0.944425](image_url)

**Figure 5:** The variation of fitness function value in a running process for Experiment 1-first group.

| Experiment times | Accuracy (%) | Sensitivity (%) | Specificity (%) | Time (s) |
|------------------|--------------|-----------------|-----------------|----------|
| Reduction 1      |              |                 |                 |          |
| 1                | 92.50        | 86.00           | 99.00           | 33.2607  |
| 2                | 97.25        | 97.50           | 97.00           | 34.5051  |
| 3                | 99.00        | 99.00           | 99.00           | 35.8677  |
| 4                | 98.00        | 99.50           | 96.50           | 35.1075  |
| 5                | 99.25        | 100.00          | 98.50           | 35.5948  |
| Average value    | 97.20        | 96.40           | 98.00           | 34.8672  |
| Reduction 2      |              |                 |                 |          |
| 1                | 93.25        | 87.00           | 99.50           | 43.6533  |
| 2                | 97.25        | 98.00           | 96.50           | 44.5900  |
| 3                | 98.75        | 98.50           | 99.00           | 43.9506  |
| 4                | 97.50        | 99.00           | 96.00           | 44.5064  |
| 5                | 99.25        | 100.00          | 98.50           | 44.8513  |
| Average value    | 97.20        | 96.50           | 97.90           | 44.3103  |
| Reduction 3      |              |                 |                 |          |
| 1                | 92.75        | 87.50           | 98.00           | 32.6916  |
| 2                | 95.75        | 97.50           | 94.00           | 33.7209  |
| 3                | 98.00        | 98.00           | 98.00           | 33.3174  |
| 4                | 97.50        | 98.50           | 95.50           | 33.3257  |
| 5                | 98.50        | 99.50           | 97.50           | 33.3257  |
| Average value    | 96.40        | 96.20           | 96.60           | 33.4251  |
| Reduction 4      |              |                 |                 |          |
| 1                | 93.75        | 88.50           | 99.00           | 30.6485  |
| 2                | 96.50        | 97.50           | 95.50           | 31.9240  |
| 3                | 97.50        | 97.00           | 98.00           | 32.4082  |
| 4                | 97.75        | 99.00           | 96.50           | 32.5419  |
| 5                | 99.00        | 100.00          | 98.00           | 36.1516  |
| Average value    | 96.90        | 96.40           | 97.40           | 31.8806  |
| Reduction 5      |              |                 |                 |          |
| 1                | 94.00        | 89.00           | 99.00           | 31.9557  |
| 2                | 96.50        | 97.50           | 95.50           | 33.6909  |
| 3                | 97.25        | 97.00           | 97.50           | 33.0159  |
| 4                | 97.75        | 99.00           | 96.50           | 39.9980  |
| 5                | 99.00        | 100.00          | 98.00           | 32.5692  |
| Average value    | 96.90        | 96.50           | 97.30           | 34.2459  |
800 malignant samples and 800 benign samples; testing samples are constructed by 200 malignant samples and 200 benign samples; the experiment is repeated 5 times by changing training samples and testing samples). Finally, the average values of these five groups are obtained as the final result of the reduction and shown in Table 6.

The experimental weight of this group is \( \omega_1 = 1, \omega_2 = 1, \omega_3 = 0 \); attribute dependency degree and the length of reduction are regarded as fitness function. As can be seen from Table 5, the reduction length is 13, 17, and so on. The average length of reduction was 17, which was significantly reduced compared with the average length of the reduction in Table 3 in the experiment of the first groups, which reduced the time, improved the efficiency of the algorithm, and increased the attribute dependency of the algorithm, even up to 1. The average recognition accuracy of the experimental group was 96.98%, which was increased by 0.06% compared with that in the first groups.

(3) 3rd Group Experiment. \( \omega_1 = 1, \omega_2 = 1, \omega_3 = 1 \): On the basis of attribute dependency degree and attribute reduction length, this experiment introduces gene coding weight function, in order to verify the effect of gene coding weight function on fitness function and the final recognition accuracy. The algorithm are run 5 times according to this group weights, the results of the 5 groups are given in Table 7, including the reduction of the conditional attributes, the length of reduction, the optimal fitness value, the attribute dependency, and the time. The convergence of VPRS-GA under the variation for fitness function value in one time is shown in Figure 7.

Each reduction is classified by SVM classifier, using the method of 5-fold cross validation, through changing the training samples and test samples; the results of the five groups were obtained, including accuracy, sensitivity, specificity, and time (training samples are constructed by 800 malignant samples and 800 benign samples; testing samples are constructed by 200 malignant samples and 200 benign samples; the experiment is repeated 5 times by changing training samples and testing samples). Finally, the average values of these five groups are obtained as the final result of the reduction and shown in Table 8.

The experimental weight of this group is \( \omega_1 = 1, \omega_2 = 1, \omega_3 = 1 \); attribute dependency degree, the length of reduction, and gene coding weight value are regarded as fitness function. However, the premature phenomena are shown in Figure 7, and evolution progress is terminated early. From Table 7, we can see that the attribute dependency decreases gradually and even the attribute dependency of Reduction 1 is reduced to 0.759. The average recognition accuracy of the experimental group was 96.85%. The accuracy of recognition was decreased compared with the second groups, and hence, using gene encoding weight function in the fitness function to improve recognition accuracy is useless, only for the samples with different results, to analyze specific issues. The 3 experiment runs of experiment 1 verified the necessity of the fitness function, by continuously introducing fitness objective function, such as target1, target2, and target3, the conclusion is that the fitness function is better when it is not bigger, but after the introduction of target3, the accuracy declines; therefore, the introduction of target1 and target2 in this algorithm can get better results.
Experiment 2—Research on Different Classification Error Rates under the Condition in the Same Weight Coefficient.

According to experiment 1, we can see that when $\omega_1 = 1$, $\omega_2 = 1$, $\omega_3 = 0$, the experimental results are the best, so in experiment 2, the case of the weight value of was unchanged, $\omega_1 = 1$, $\omega_2 = 1$, $\omega_3 = 0$, and the $\beta$ value was changed, and they are shown in Table 9.

(1) 1st Group Experiment. $1 - \beta = 0.6$: The algorithm is run 5 times according to this group weights; the results of the 5 groups are shown in Table 5, including the reduction of the conditional attributes, the length of reduction, the optimal fitness value, the attribute dependency, and the time. The convergence of VPRS-GA under the variation for fitness function value for one time is shown in Figure 6 (i.e., not repeated in the second group of experiment 1).

(2) 2nd Group Experiment. $1 - \beta = 0.8$: The algorithm are is 5 times according to this group weights, the results of the 5 groups are given in Table 10, including the reduction of the conditional attributes, the length of reduction, the optimal fitness value, the attribute dependency, and the time. The
convergence of VPRS-GA under the variation for fitness function value for one time is shown in Figure 8.

Each reduction is classified by SVM classifier, using the method of 5-fold cross validation, through changing the training samples and test samples; the results of the five groups were obtained, including accuracy, sensitivity, specificity, and time (training samples are constructed by 800 malignant samples and 800 benign samples; testing samples are constructed by 200 malignant samples and 200 benign samples; the experiment is repeated 5 times by

| Experiment times | Accuracy (%) | Sensitivity (%) | Specificity (%) | Time (s) |
|------------------|--------------|----------------|-----------------|----------|
| Reduction 1      |              |                |                 |          |
| 1                | 92.75        | 86.00          | 99.50           | 9.2492   |
| 2                | 97.25        | 97.50          | 97.00           | 10.7461  |
| 3                | 98.50        | 98.50          | 98.50           | 11.3811  |
| 4                | 97.75        | 99.00          | 96.50           | 11.5560  |
| 5                | 98.75        | 100.00         | 97.50           | 11.7022  |
| Average value    | 97.00        | 96.20          | 97.80           | 10.9269  |
| Reduction 2      |              |                |                 |          |
| 1                | 93.50        | 87.50          | 99.50           | 14.8245  |
| 2                | 97.00        | 96.50          | 97.50           | 16.1535  |
| 3                | 97.75        | 98.50          | 97.00           | 16.6452  |
| 4                | 98.00        | 97.50          | 98.00           | 17.5450  |
| 5                | 98.75        | 99.50          | 97.50           | 17.2348  |
| Average value    | 97.00        | 96.10          | 97.90           | 16.4806  |
| Reduction 3      |              |                |                 |          |
| 1                | 91.25        | 83.00          | 99.50           | 20.1904  |
| 2                | 96.50        | 97.00          | 96.00           | 21.8535  |
| 3                | 98.00        | 98.00          | 98.00           | 21.9605  |
| 4                | 96.25        | 99.00          | 93.50           | 22.3091  |
| 5                | 98.25        | 100.00         | 96.50           | 23.6896  |
| Average value    | 96.05        | 95.40          | 96.70           | 22.0006  |
| Reduction 4      |              |                |                 |          |
| 1                | 93.00        | 87.00          | 99.00           | 16.5454  |
| 2                | 96.75        | 96.00          | 97.50           | 17.2432  |
| 3                | 98.75        | 98.50          | 97.00           | 18.9560  |
| 4                | 99.00        | 99.50          | 98.50           | 18.5249  |
| 5                | 99.00        | 99.50          | 98.50           | 18.5249  |
| Average value    | 97.10        | 96.00          | 98.20           | 17.8399  |
| Reduction 5      |              |                |                 |          |
| 1                | 92.75        | 86.00          | 99.50           | 14.1173  |
| 2                | 97.25        | 98.00          | 96.50           | 16.1295  |
| 3                | 99.00        | 99.50          | 98.50           | 15.8992  |
| 4                | 97.75        | 99.50          | 96.00           | 16.4876  |
| 5                | 98.75        | 100.00         | 97.50           | 16.6070  |
| Average value    | 97.10        | 96.60          | 97.60           | 15.8481  |

| Table 9: Fitness function weight proportion and β value. |

| Experiment times | 1 − β = 0.6 | 1 − β = 0.8 | 1 − β = 1 |
|------------------|--------------|--------------|------------|
| First group experiment | ○           |       |          |
| Second group experiment | ○          |       |          |
| Third group experiment | ○              |       |          |
changing training samples and testing samples). Finally, the average values of these five groups are obtained as the final result of the reduction and shown in Table 11.

In the case of constant weight $\omega$ and classification error rate $\beta = 0.2$ (which contains $1 - \beta = 0.8$), the classification error rate is changed on the basis of the attribute dependency and the length of control reduction. The premature phenomena are shown in Figure 8, and evolution progress is terminated early, such that the attribute dependency of reduction 5 was 0.8405, appeared in attribute dependency on less than 0.9, compared with first groups of experiment 2 attribute dependency declined. The average recognition accuracy of the experimental group was 96.74%, which was decreased by 0.24% compared with the classification error rate of 0.4 and inclusion degree of 0.6, the accuracy was decreased by 0.24%.

(3) 3rd Group Experiment. $1 - \beta = 1$: The algorithm is run 5 times according to the group weights, and the results of the 5 groups are shown in Table 12, including the reduction of the conditional attributes, the length of reduction, the optimal fitness value, the attribute dependency, and the time. The convergence of VPRS-GA under the variation for fitness function value for one time is shown in Figure 9.

Each reduction is classified by SVM classifier, using the method of 5-fold cross validation, through changing the training samples and test samples, the results of the five groups were obtained, including accuracy, sensitivity, specificity, and time (training samples are constructed by 800 malignant samples and 800 benign samples; testing samples are constructed by 200 malignant samples and 200 benign samples; the experiment is repeated 5 times by changing training samples and testing samples). Finally, the average values of these five groups are obtained as the final result of the reduction and shown in Table 13.

In the case of constant weight $\omega$ and classification error rate of $\beta = 0$ (which contains $1 - \beta = 1$), the classification error rate is reduced and the inclusion degree is improved on the basis of the attribute dependency and the length of control reduction. The premature phenomena are shown in Figure 9, and evolution progress is terminated early. The average recognition accuracy of the experimental group was 95.73%, which was decreased by 0.06% compared with that in the second group. In experiment 2, the effect of changing the classification error rate on the recognition accuracy was verified by the 3 groups of experiments. By continually reducing the classification error rate, the final recognition accuracy has been declining, when inclusion degree is 1, $\beta = 0$; variable precision rough set becomes Pawlak rough set, the recognition accuracy of the recognition accuracy of is minimum, which was verified the advantages of variable precision rough set.

3.4.3. Experiment 3—Research on Increasing the Weight Coefficient under the Condition in the Same Classification Error Rate. According to experiment 1 and experiment 2, we can know that when $\beta = 0.6$, $\omega_1 = 1$, $\omega_2 = 1$, $\omega_3 = 0$, the recognition accuracy is the best; therefore, in the third experiment, by increasing the weight of $\omega$, 3 groups of experiments are performed, fitness goals: target 1 (attribute

| Experiment times | C_ reduction | Reduction length | Optimal fitness value | Attribute dependency degree | Time (s) |
|------------------|--------------|------------------|-----------------------|-----------------------------|----------|
| 1                | [8 9 11 12 15 16 17 18 25 26 29 31 35 39 40 41 42 48 58 65 67 68 70 83 84 91] | 26               | -6.7816               | 0.9490                      | 1000.2827 |
| 2                | [1 6 8 9 11 12 15 17 21 23 26 28 30 31 34 44 50 56 58 59 62 63 64 68 71 75 77 82 89 92] | 30               | -6.7797               | 0.9615                      | 947.7387  |
| 3                | [6 8 12 14 15 16 17 21 28 35 38 39 45 49 55 58 61 62 64 65 77 82 85] | 23               | -6.8694               | 0.9070                      | 1286.6181 |
| 4                | [4 6 7 8 11 12 13 16 17 20 25 26 31 32 34 35 41 42 44 49 50 55 58 68 72 74 76 78 79 85 89 92] | 32               | -6.7225               | 0.9540                      | 1051.0220 |
| 5                | [3 6 8 9 10 16 17 26 27 34 36 37 38 40 42 44 46 51 52 62 66 67 84 86 87] | 25               | -6.5892               | 0.8405                      | 846.9324  |

Average value | 27.2 | -6.7484 | 0.9224 | 1026.5188 |
### Table 11: The statistical results of the second group for experiment 2 with the SVM classifier.

| Experiment times | Accuracy (%) | Sensitivity (%) | Specificity (%) | Time (s)  |
|------------------|--------------|-----------------|-----------------|-----------|
| 1                | 93.00        | 86.50           | 99.50           | 22.8007   |
| 2                | 95.75        | 97.00           | 94.50           | 23.7646   |
| 3                | 97.00        | 96.00           | 98.00           | 23.3250   |
| 4                | 97.50        | 98.50           | 96.50           | 24.4491   |
| 5                | 99.25        | 100.00          | 98.50           | 24.4816   |
| **Average value** | **96.50**    | **95.60**       | **97.40**       | **23.7642** |

Reduction 1

| 1                | 93.75        | 88.00           | 99.50           | 25.2403   |
| 2                | 96.25        | 97.50           | 95.00           | 26.5289   |
| 3                | 98.00        | 97.00           | 99.00           | 26.5523   |
| 4                | 98.00        | 99.00           | 97.00           | 26.8212   |
| 5                | 99.50        | 100.00          | 99.00           | 27.5880   |
| **Average value** | **97.10**    | **96.30**       | **97.90**       | **26.5461** |

Reduction 2

| 1                | 92.75        | 87.50           | 98.00           | 19.2992   |
| 2                | 96.75        | 97.50           | 96.00           | 19.2992   |
| 3                | 97.75        | 96.50           | 99.00           | 20.3507   |
| 4                | 98.75        | 100.00          | 97.50           | 20.3507   |
| 5                | 99.50        | 100.00          | 98.00           | 29.1471   |
| **Average value** | **96.60**    | **96.10**       | **97.40**       | **19.4601** |

Reduction 3

| 1                | 92.00        | 86.50           | 97.50           | 14.3715   |
| 2                | 97.00        | 97.50           | 96.00           | 15.2637   |
| 3                | 97.75        | 98.00           | 97.00           | 15.8929   |
| 4                | 97.50        | 99.00           | 96.50           | 16.2997   |
| 5                | 99.00        | 100.00          | 98.00           | 28.1554   |
| **Average value** | **96.65**    | **95.90**       | **97.40**       | **27.5125** |

Reduction 4

| 1                | 92.75        | 87.50           | 98.00           | 14.3715   |
| 2                | 96.75        | 96.00           | 97.50           | 15.2637   |
| 3                | 97.50        | 98.50           | 97.00           | 15.8929   |
| 4                | 97.75        | 99.00           | 96.50           | 16.2997   |
| 5                | 99.50        | 100.00          | 99.00           | 16.6792   |
| **Average value** | **96.85**    | **96.10**       | **97.60**       | **15.7014** |

### Table 12: Results of VPRS-GA running 5 times when \( 1 - \beta = 1, \{ \omega_1 = 1, \omega_2 = 1, \omega_3 = 0 \} \).

| Experiment times | \( C_{\_ \_} \) reduction | Reduction length | Optimal fitness value | Attribute dependency degree | Time (s)  |
|------------------|-----------------------------|-------------------|-----------------------|-----------------------------|-----------|
| 1                | {15 44 68 73 79 84}         | 6                 | –2.7313               | 0.7965                      | 1144.9901 |
| 2                | {34 51 54 75 80 90}         | 6                 | –2.7047               | 0.8460                      | 969.9391  |
| 3                | {2 34 49 70 71 72 76 81}    | 8                 | –3.4057               | 0.7535                      | 1123.3489 |
| 4                | {12 25 78 85}               | 4                 | –2.2872               | 0.9285                      | 1166.8133 |
| 5                | {6 7 12 13 42 44 55 57 65 66 69 77 81 86 87} | 15               | –3.3230               | 0.8665                      | 1323.6077 |
| **Average value** |                             |                   |                      |                             | 1145.7398 |

**Figure 9:** The variation of fitness function value in a running process for experiment 2-third group.
dependency), target 2 (the minimum number of attributes reduction), and target 3 (gene encoding weight function), the three objective functions play an important role in the evaluation of fitness function. However, the importance of fitness function is reduced in these three objectives. Therefore, in this experiment, when the other conditions are unchanged, the weight coefficient of the target 1 is increased, to verify the influence of the change in the weight coefficient on the experimental results, and they are shown in Table 14.

(1) 1st Group Experiment. $\omega_1 = 1$, $\omega_2 = 1$, $\omega_3 = 0$: The algorithm are run 5 times according to this group weights, the results of the 5 groups are given in Table 5, including the reduction of the conditional attributes, the length of reduction, the optimal fitness value, the attribute dependency and the time. The convergence of VPRS-GA under the variation for fitness function value in one time is shown in Figure 6 (i.e., not repeated for the second group of experiment 1).

(2) 2nd Group Experiment. $\omega_1 = 2$, $\omega_2 = 1$, $\omega_3 = 0$: The algorithm is run 5 times according to this group weights, the results of the 5 groups are given in Table 15, including the reduction of the conditional attributes, the length of reduction, the optimal fitness value, the attribute dependency, and the time. The convergence of VPRS-GA under the variation for fitness function value in one time is shown in Figure 10.

| Experiment times | Accuracy (%) | Sensitivity (%) | Specificity (%) | Time (s) |
|------------------|--------------|----------------|----------------|----------|
| Reduction 1      |              |                |                |          |
| 1                | 92.25        | 84.50          | 100.00         | 8.1271   |
| 2                | 95.50        | 97.00          | 94.00          | 9.4583   |
| 3                | 95.75        | 94.00          | 97.50          | 8.8198   |
| 4                | 96.00        | 98.00          | 94.00          | 9.3754   |
| 5                | 97.25        | 99.00          | 95.50          | 9.8691   |
| Average value    | 95.35        | 94.50          | 96.20          | 9.1299   |
| Reduction 2      |              |                |                |          |
| 1                | 92.00        | 84.50          | 99.50          | 6.4894   |
| 2                | 96.25        | 95.50          | 97.00          | 8.0198   |
| 3                | 95.25        | 93.00          | 97.50          | 7.7337   |
| 4                | 96.00        | 97.50          | 94.50          | 7.6012   |
| 5                | 98.00        | 100.00         | 96.00          | 8.2763   |
| Average value    | 95.50        | 94.10          | 96.90          | 7.6241   |
| Reduction 3      |              |                |                |          |
| 1                | 92.75        | 85.50          | 100.00         | 7.6726   |
| 2                | 96.75        | 96.00          | 97.50          | 7.8467   |
| 3                | 96.00        | 94.50          | 97.50          | 7.3022   |
| 4                | 95.75        | 97.50          | 94.00          | 7.9460   |
| 5                | 98.00        | 100.00         | 96.00          | 8.4184   |
| Average value    | 95.85        | 94.70          | 97.00          | 7.6479   |
| Reduction 4      |              |                |                |          |
| 1                | 92.00        | 84.50          | 99.50          | 11.4719  |
| 2                | 96.25        | 97.50          | 95.00          | 12.8705  |
| 3                | 98.50        | 99.00          | 98.00          | 13.2049  |
| 4                | 97.75        | 99.50          | 96.00          | 13.3513  |
| 5                | 98.50        | 100.00         | 97.00          | 13.3144  |
| Average value    | 96.60        | 96.10          | 97.10          | 12.8426  |

Each reduction is classified by SVM classifier, using the method of 5-fold cross validation, through changing the training samples and test samples, the results of the five groups were obtained, including accuracy, sensitivity, specificity, and time (training samples are constructed by 800 malignant samples and 800 benign samples; testing samples are constructed by 200 malignant samples and 200 benign samples; the experiment is repeated 5 times by changing training samples and testing samples). Finally, the average values of these five groups are obtained as the final result of the reduction and shown in Table 16.

The experimental group in the case of $1 - \beta = 0.6$ unchanged, the weight of $\omega_1$ was increased. The attribute dependency and the optimal fitness function are relatively high; the average precision of reduction 1, reduction 2, and reduction 3 in Table 16 is more than 97% and that of reduction 2 is even up to 97.25%. The average recognition accuracy of the experimental group is 97.03%, which is higher than that of the first group.

| Experiment times | $1 - \beta = 0.6$ |
|------------------|------------------|
| $\omega_1$       | $\omega_2$       | $\omega_3$       |
| First group experiment | 1 | 1 | 0 |
| Second group experiment | 2 | 1 | 0 |
| Third group experiment | 3 | 1 | 0 |
Table 15: Results of VPRS-GA running 5 times when $1 - \beta = 0.6$, $\omega_1 = 2, \omega_2 = 1, \omega_3 = 0$.

| Experiment times | Cm, Reduction length | Optimal fitness value | Attribute dependency degree | Time (s) |
|------------------|----------------------|------------------------|-----------------------------|----------|
| 1                | [2 3 4 5 11 13 16 18 24 30 34 37 39 41 42 51 55 64 70 77 78 82] | 22 | −3.4859 | 0.9060 | 2151.5464 |
| 2                | [8 9 11 12 14 15 23 25 26 29 30 33 37 42 43 45 46 50 60 61 69 74 80 87 89] | 25 | −3.0845 | 0.9390 | 4276.1634 |
| 3                | [8 11 12 13 16 18 19 24 29 36 37 43 64 65 68 71 86 91 92] | 19 | −3.5039 | 0.9150 | 2619.7164 |
| 4                | [2 3 4 8 10 11 12 13 15 16 19 23 25 30 48 55 64 65 68 74 77 80 81 83 84 86 89] | 27 | −2.9150 | 0.9575 | 4427.1631 |
| 5                | [5 8 9 11 12 15 17 23 25 29 31 36 39 41 48 54 59 63 80 83 86 89] | 22 | −2.9920 | 0.9525 | 4316.1464 |
| Average value    |                      | 23 | −3.1962 | 0.9340 | 3558.1471 |

Best: ~2.915 Mean: ~2.91446

Figure 10: The variation of fitness function value in a running process for experiment 3-second group.

Table 16: The statistical results of the second group for experiment 3 with the SVM classifier.

| Experiment times | Accuracy (%) | Sensitivity (%) | Specificity (%) | Time (s) |
|------------------|--------------|-----------------|-----------------|----------|
| Reduction 1      |              |                 |                 |          |
| 1                | 92.75        | 86.00           | 99.50           | 18.8497  |
| 2                | 97.25        | 98.00           | 95.50           | 15.7162  |
| 3                | 98.50        | 99.00           | 98.00           | 15.8691  |
| 4                | 98.00        | 99.00           | 97.00           | 16.4603  |
| 5                | 99.50        | 100.00          | 99.00           | 16.1914  |
| Average value    | 97.20        | 96.40           | 98.00           | 16.6173  |
| Reduction 2      |              |                 |                 |          |
| 1                | 94.50        | 89.50           | 99.50           | 19.0813  |
| 2                | 96.75        | 98.00           | 95.50           | 20.0251  |
| 3                | 97.75        | 98.00           | 97.50           | 19.7008  |
| 4                | 98.50        | 99.00           | 98.00           | 20.9924  |
| 5                | 98.75        | 99.00           | 98.50           | 20.9245  |
| Average value    | 97.25        | 96.70           | 97.80           | 19.9648  |
| Reduction 3      |              |                 |                 |          |
| 1                | 94.00        | 88.00           | 100.00          | 13.1369  |
| 2                | 97.25        | 98.00           | 96.50           | 14.4797  |
| 3                | 98.00        | 98.00           | 98.00           | 14.2662  |
| 4                | 97.25        | 98.50           | 96.00           | 14.7190  |
| 5                | 99.25        | 100.00          | 98.50           | 14.8799  |
| Average value    | 97.15        | 96.50           | 97.80           | 14.2963  |
| Reduction 4      |              |                 |                 |          |
| 1                | 93.50        | 87.50           | 99.50           | 24.0456  |
| 2                | 97.00        | 97.50           | 96.50           | 25.2082  |
| 3                | 98.00        | 98.00           | 98.00           | 25.1175  |
| 4                | 97.75        | 99.50           | 96.00           | 27.0188  |
| 5                | 98.25        | 100.00          | 96.50           | 26.7471  |
| Average value    | 96.90        | 96.50           | 97.30           | 25.6274  |
| Reduction 5      |              |                 |                 |          |
| 1                | 93.25        | 88.00           | 98.50           | 18.0959  |
| 2                | 96.00        | 98.00           | 94.00           | 19.6563  |
| 3                | 97.50        | 97.50           | 97.50           | 19.6723  |
| 4                | 98.00        | 99.00           | 97.00           | 20.7829  |
| 5                | 98.50        | 99.50           | 97.50           | 21.9703  |
| Average value    | 96.65        | 96.40           | 96.90           | 20.0355  |
Table 17: Results of VPRS-GA running 5 times when $1 - \beta = 1$, $\{\omega_1 = 1, \omega_2 = 1, \omega_3 = 0\}$.

| Experiment times | $C_\alpha$ reduction | Reduction length | Optimal fitness value | Attribute dependency degree | Time (s) |
|------------------|-----------------------|------------------|-----------------------|-----------------------------|----------|
| 1                | [3 4 5 8 9 11 12 17 19 29 34 35 38 46 52 53 55 59 63 66 72 75 77 78 79 87 92] | 27 | -3.8867 | 0.9550 | 2898.1789 |
| 2                | [4 8 9 11 12 15 17 29 33 37 38 42 43 48 55 67 73 78 81 83 84 88 89 90] | 25 | -3.8167 | 0.9715 | 5578.3772 |
| 3                | [2 3 4 8 9 10 11 12 13 15 16 19 24 25 30 36 49 54 55 60 64 67 68 70 74 77 83 85 86 91] | 30 | -3.8807 | 0.9530 | 3483.1096 |
| 4                | [4 5 7 11 12 14 15 17 25 33 36 39 41 42 47 48 50 55 56 58 62 67 69 72 74 77 84 86 90 91] | 31 | -3.9430 | 0.9665 | 3574.2822 |
| 5                | [3 4 5 8 9 11 12 17 19 29 34 35 38 46 52 53 55 59 63 66 72 75 77 78 79 87 92] | 27 | -3.8867 | 0.9550 | 2791.9582 |
| Average value    |                      | 28 | -3.8827 | 0.9602 | 3665.1812 |

Figure 11: The variation of fitness function value in a running process for experiment 3-third group.

Table 18: The statistical results of the Second group for experiment 3 with the SVM classifier.

| Experiment times | Accuracy (%) | Sensitivity (%) | Specificity (%) | Time (s) |
|------------------|--------------|-----------------|-----------------|----------|
| Reduction 1      |              |                 |                 |          |
| 1                | 92.00        | 87.00           | 97.00           | 21.8717  |
| 2                | 97.50        | 97.50           | 97.50           | 21.0550  |
| 3                | 98.50        | 98.50           | 98.50           | 20.3206  |
| 4                | 98.00        | 99.00           | 97.00           | 22.1164  |
| 5                | 99.25        | 100.00          | 98.50           | 27.2536  |
| Average value    | 97.05        | 96.40           | 97.70           | 22.5235  |
| Reduction 2      |              |                 |                 |          |
| 1                | 94.00        | 88.50           | 99.50           | 23.3123  |
| 2                | 95.75        | 97.50           | 94.00           | 24.3349  |
| 3                | 97.50        | 97.00           | 98.00           | 24.4202  |
| 4                | 97.75        | 99.00           | 96.50           | 25.6607  |
| 5                | 99.00        | 99.50           | 98.50           | 25.9071  |
| Average value    | 96.80        | 96.30           | 97.30           | 24.7270  |
| Reduction 3      |              |                 |                 |          |
| 1                | 92.75        | 86.50           | 99.00           | 25.2584  |
| 2                | 96.25        | 97.50           | 95.00           | 26.2412  |
| 3                | 97.75        | 98.00           | 97.50           | 26.0127  |
| 4                | 97.75        | 99.00           | 96.50           | 26.8670  |
| 5                | 98.75        | 100.00          | 97.50           | 26.5387  |
| Average value    | 96.65        | 96.20           | 97.10           | 26.1836  |
| Reduction 4      |              |                 |                 |          |
| 1                | 91.50        | 85.50           | 97.50           | 25.3231  |
| 2                | 96.25        | 97.50           | 95.00           | 26.4943  |
| 3                | 97.50        | 97.00           | 98.00           | 27.5283  |
| 4                | 98.00        | 99.50           | 96.50           | 32.2954  |
| 5                | 98.25        | 99.50           | 97.00           | 27.7432  |
| Average value    | 96.30        | 95.80           | 96.80           | 27.8769  |
| Reduction 5      |              |                 |                 |          |
| 1                | 92.00        | 88.00           | 96.00           | 19.5196  |
| 2                | 97.00        | 97.00           | 97.00           | 21.4889  |
| 3                | 98.25        | 98.00           | 98.50           | 20.3612  |
| 4                | 98.50        | 100.00          | 97.00           | 21.3361  |
| 5                | 99.00        | 99.00           | 99.00           | 22.5526  |
| Average value    | 96.95        | 96.40           | 97.50           | 21.0517  |
(3) 3rd Group Experiment. \( \omega_1 = 3, \omega_2 = 1, \omega_3 = 0 \): The algorithm is run 5 times according to the group weights, and the results of the 5 groups are given in Table 17, including the reduction of the conditional attributes, the length of reduction, the optimal fitness value, the attribute dependency, and the time. The convergence of VPRS-GA under the variation for fitness function value for one time is shown in Figure 11.

Each reduction is classified by SVM classifier, using the method of 5-fold cross validation, through changing the training samples and test samples; the results of the five groups were obtained, including accuracy, sensitivity, specificity, and time (training samples are constructed by 800 malignant samples and 800 benign samples; testing samples are constructed by 200 malignant samples and 200 benign samples; the experiment is repeated 5 times by changing training samples and testing samples). Finally, the average values of these five groups are obtained as the final result of the reduction and shown in Table 18.

The experiment in the case of \( 1 - \beta = 0.6 \) unchanged, increase the weight of the \( \omega_1 \). \( \omega_1 = 3, \omega_2 = 1, \omega_3 = 0 \). In Table 18, the recognition accuracy of reduction 1 is over 97% only. The average recognition accuracy of the experimental group is 96.75%, and the accuracy is decreased by 0.28% compared with that in the other second groups. The three groups of experimental group 3, the purpose is to verify whether the experimental accuracy is influenced by increasing the weight. The experimental results show that the accuracy of second group for experimental weight \( \{2, 1, 0\} \) compared with first group experiment when \( \{1, 1, 0\} \) is high, but the third groups of experimental weight was \( \{3, 1, 0\} \), and the accuracy declined; therefore, the weight of \( \{2, 1, 0\} \) is the best choice for this experiment.

4. Conclusions

Aiming at the deficiency of the traditional rough set model, this paper proposes a new feature selection model based on genetic algorithm and variable precision rough set; by introducing the \( \beta \) value, the rigid inclusion of the approximation for the traditional rough set is relaxed, and then we design the 3 kinds of experiments by constructing the decision information table of the PET/CT feature for lung tumor ROI. The first type of experiment is the inclusion of \( 1 - \beta = 0.6 \), and different values of \( \omega \) made a total of three groups of experiments; the experimental results show that the better recognition accuracy can be obtained when the weight is \( \{1, 1, 0\} \), and the results show that the gene coding weight function has no effect on the fitness function. For the second type of experiments, \( \{1, 1, 0\} \), \( \omega_3 = 0 \), according to the different values of \( \beta \) to do three groups of experiments, the results show that the recognition accuracy of \( 1 - \beta = 0.6 \) is the best, which shows that the larger the \( \beta \) value is, the lower approximate cardinality will be larger, then the relative accuracy will increase. For the third type of experiments, \( 1 - \beta = 0.6, \omega \) value is increased to achieve the best fitness function, in order to achieve the best results. The experimental results show that the recognition accuracy is better than the others when the weight value is \( \{2, 1, 0\} \), so it is better to solve the problem by increasing the proportion of attribute dependency. Through the above experiments, it is shown that the high-dimensional feature selection algorithm based on genetic algorithm and variable precision rough set can solve the multiobjective optimization problem well. However, when the fitness function and its parameters are applied in the specific application, it is necessary to analyze the specific problems.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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References

[1] S. Luo, D. Miao, Z. Zhang, Y. Zhang, and S. Hu, "A neighborhood rough set model with nominal metric embedding," Information Sciences, vol. 520, pp. 373–388, 2020.
[2] B. Barman and S. Patra, "Variable precision rough set based unsupervised band selection technique for hyperspectral image classification," Knowledge-Based Systems, vol. 1936, Article ID 105414, 2020.
[3] Y. Chenyi and L. Jinjin, "Approximate attribute reduction under variable precision rough set \( \beta \)," Journal of Shandong University, vol. 11, pp. 17–21, 2011.
[4] S. Xiaowei, Research on Hierarchical Model of Attribute Reduction in Variable Precision Rough Set, Central South University, Changsha, China, 2013.
[5] Z. Jie and W. Jiayang, "Analysis of reduction feature of variable precision rough set model," Computer Application Research, vol. 7, pp. 12–13, 2007.
[6] Z. Pei and Z. Qinghua, "FCM clustering algorithm based on variable precision rough set," Journal of Shandong University, vol. 3, pp. 342–348, 2016.
[7] C. Hao and Y. Junan, "Attribute kernel and minimum attribute reduction algorithm of variable precision rough set," Acta Sinica Sinica, vol. 5, pp. 1011–1017, 2012.
[8] S. Xu, X. Yang, H. Yu, D.-J. Yu, J. Yang, and E. C.C. Tsang, "Multi-label learning with label-specific feature reduction," Knowledge-Based Systems, vol. 104, pp. 52–61, 2016.
[9] I. Maryam and G. Hassan, "Feature space discriminant analysis for hyperspectral data feature reduction," ISPRS Journal of Photogrammetry and Remote Sensing, vol. 102, pp. 1–13, 2015.
[10] S. Q. Wang, C. Y. Gao, C. Luo, G. M. Zheng, and Y. N. Zhou, "Research on feature selection/attribute reduction method based on rough set theory," Procedia Computer Science, vol. 154, pp. 194–198e, 2019.
[11] A. W. Omar, M. Azzam, O. Hadi, and B. Jamal, "CEAP: SVM-based intelligent detection model for clustered vehicular ad
hoc networks,” *Expert Systems with Applications*, vol. 50, pp. 40–54, 2016.

[12] H. Lee and Y.-P. P. Chen, “Image based computer aided diagnosis system for cancer detection,” *Expert Systems with Applications*, vol. 42, no. 12, pp. 5356–5365, 2015.

[13] J. A. Guy and P. L. Harold, “After detection: the improved accuracy of lung cancer assessment using radiologic computer-aided diagnosis,” *Academic Radiology*, vol. 23, no. 2, pp. 186–191, 2016.

[14] E. Kiyonori, T. Shodayu, J. Binghu et al., “Pleural invasion by peripheral lung cancer: prediction with three-dimensional CT,” *Academic Radiology*, vol. 3, pp. 310–319, 2015.

[15] B. Koohestani, “A crossover operator for improving the efficiency of permutation-based genetic algorithms,” *Expert Systems with Applications*, vol. 1511, Article ID 113381, 2020.

[16] N. K. Lee, X. Li, and D. Wang, “A comprehensive survey on genetic algorithms for DNA motif prediction,” *Information Sciences*, vol. 466, pp. 25–43, 2018.

[17] S. Shibao and Y. Leilei, “Research on variable precision rough set model and its application,” *Computer Engineering and Application*, vol. 07, pp. 10–13, 2009.

[18] T. Xiaolong, *Several Problems of Multi Granularity Variable Precision Rough Set*, Guangxi University For Nationalities, Nanning, China, 2015.

[19] W. Xueming, *Research on Several Rough Set Models and Neural Network*, University of Electronic Science and Technology of China, Chengdu, China, 2013.

[20] T. Sun, J. Wang, X. Li et al., “Comparative evaluation of support vector machines for computer aided diagnosis of lung cancer in CT based on a multi-dimensional data set,” *Computer Methods and Programs in Biomedicine*, vol. 111, no. 2, pp. 519–524, 2013.

[21] Z. Yang, T. Ouyang, X. Fu, and X. Peng, “A decision-making algorithm for online shopping using deep-learning-based opinion pairs mining and q -rung orthopair fuzzy interaction Heronian mean operators,” *International Journal of Intelligent Systems*, vol. 35, no. 5, pp. 783–825, 2020.

[22] W. Chen, C. Lin, C. Li et al., “Tracing the evolution of 3D printing technology in China using LDA-based patent abstract mining,” *IEEE Transactions on Engineering Management*, vol. 36, pp. 1–11, 2020.