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Lung nodule classification in CT images using Grey Wolf Optimization algorithm

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Abstract

Medical image processing is of significant importance to accurately diagnose lung cancer and assists the physicians for better diagnosis. The early detection of pulmonary lung nodules is critical in the diagnosis of lung cancer and significantly increases the survival rate of affected people. Computed Tomography (CT) imaging technique of tumor detection is widely used to recognize the cancer regions. Feature selection and parameter optimization are the effective methods to improve the results of classifier. This paper proposes a novel Computer Aided Diagnosis (CAD) system based on Grey Wolf Optimizer (GWO) and Fuzzy Relevance Vector Machine (FRVM). GWO algorithm is applied as a feature selection method, that chooses best features subset from a huge set of features extracted from the lung CT images for improving the classification accuracy and then serial fusion is performed.The FRVM classifier is used for the classification of normal and abnormal CT scan lung images and the generalization ability of the classifier is evaluated using various performance metrics. The validation of the proposed classification scheme is empirically tested on Lung Image Database Consortium and Image Database Resource Initiative public database. The experimental results show that the performance of the proposed method outperforms several existing methods with improved accuracy.

Keywords:

Lung cancer, CT, CAD, GWO, FRVM

Introduction

Of all cancers, lung cancer is the most common. This cancer led to the deaths of over 1.37 million people worldwide in 2008, according to a study [1.] According to American Cancer

Society, 1.74 million new cancer cases and 0.61 million cancer deaths occurred in the United States in 2018 [2]. The two primary causes of a high lung cancer mortality rate are a delay in early diagnosis and a poor prognosis [3]. According to the report, 70% of lung cancers are discovered at an advanced stage, making cancer prognosis ineffective. As a result, early cancer detection is critical to a patient's survival chances.Lung cancer can be diagnosed using a variety of techniques [17], including X-rays, magnetic resonance imaging (MRI), positron emission tomography (PET), and computed tomography (CT) scans.

When lung cancer symptoms are noticed, a physician will recommend computed tomography, and a process biopsy (removing cancerous tissue for microscopic analysis) will be recommended only if there is strong confirmation or evidence of lung cancer [18]. Medical image processing has been a very effective method for cancer patient care and tumor detection [19]. Preprocessing, nodule segmentation, feature extraction, feature optimization, and identification of nodule abnormality using classification are included in the computer assisted diagnostic method.

Dimensionality reduction is a significant aspect in prediction and pattern recognition. The primary goal of this task is to obtain a minimal feature subset from a given dataset while increasing the accuracy rate over an original feature subset [16]. By reducing the number of attributes and eliminating unrelated and redundant attributes, dimensionality reduction improves the overall performance of classification algorithms.

The goal of this paper is to create an automatic Lung tumor diagnosis system that will assist physicians in segmenting the tumor and determining whether it is cancerous or not. This work's contribution is as follows:

(1) Creating an automatic lung nodulediagnosis system based on GWO-FRVM.

(2) Using the Grey Wolf Optimization algorithm for best feature subset selection that results in improved r and greater accuracy.

(3) Fuzzy Relevance Vector Machine classifier is applied for differentiating normal and abnormal CT scan lung images.

Related work

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Most of the researchers are highly motivated to develop automatic diagnosis systems because earlier cancer detection can increase patient survival rates. The number of publications in this research field is growing at an exponential rate, and significant progress toward the performance of a robust and efficient segmentation tool is still being made. This section presents the previous years' related research findings.

Armato et al. [4] proposed using computer-aided diagnosis to detect nodules in computed tomography lung images.The analysis is done on 43 CT images that have two-dimensional and three-dimensional details. For lung nodule identification segmentation, the morphological operation and gray level thresholdare used. This system had a sensitivity of 70% for detecting nodules overall.

The paper on detecting lung cancer using helical CT images was presented by Gurcan et al. [5]. The k-mean clustering technique is employed for identifying different lung regions. The knowledge rule-based classifier is used in conjunction with linear discriminant analysis and achieved 84% sensitivity at 1.74 FP/section. An automatic lung segmentation method described by Armato et al. [6] included pre-processing and lung nodule segmentation process. The thickness of tumor is assessed with a correlation of 0.97 is determined by a measurement.

Gomathi et al. [7] created a CAD system by combining various image processing techniques. Lung CT imageis then segmented by fuzzy possibility C-mean clustering (FPCM) algorithm and the support vector machine algorithm is used to classify it. Through image processing methods Gaikwad et al[17] developed in one of the papers through a novel approach using computed tomography of the lung. For lung nodule detection segmentation the controlled marker watershed algorithm is used, with an accuracy of 84.5%.

Gomathi [9] used support vector machine to classify benign and malign lung nodules in CT images. The features are then extracted from the segmented lung nodule. Based on the results of extracted features by the radial basis function support vector, the sensitivity of training data was determined to be 91.05% and the specificity of training data was determined to be 89.03%.

Using an optimization technique and a support vector machine classifier, Kohad et al. [10] described a method for detecting pulmonary nodules in lung CT images. The ant colony optimization method is used to determine the best feature subset andsupport vector machine is

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used to train the system for classification. Thomas et al. [11] proposed an automatic lung nodule detection paper in which three different classifiers are used for classification: k-nearest neighbor classifier, support vector machine, and minimum distance classifier. The performance of SVM is good than the other classifiers.

Parveen et al. [12] created a computer-aided diagnosis system by segmenting images with image processing techniques and categorizing them with support vector kernels. Three SVM kernels are employed, with sensitivity of 83%, 85%, and 91% obtained by implementing the linear kernel, radial bias functionkernel, and polynomial kernel.

Deshpande et al. [13] proposed a method for detecting lung cancer using CT-MRI image fusion and watershed segmentation after pre-processing to detect the tumor nodule and extract several features like eccentricity,area and perimeter.. A support vector machine classifier is used to determine classification.

Abdillah et al. [14] proposed a study in which the lung image is evaluated using three segmentation methods and the results are compared to determine whether the lung image is normal or abnormal using the binarization technique.. Kaur et al. [15] described a method for classifying lung disease CT images using an optimization algorithm. As a pre-processing technique, the guided filter and morphological filter are used. For feature selection, amix of two meta-heuristic techniques, particle swarm optimization and the genetic algorithm, is being considered.

Feature selection and segmentation play an important role in determining accurate classification and decision making is being concluded based on the literature review. A CAD system is proposed in this paper that extracts the lungs from chest CT scans automatically and these segments are processed to detect nodules.

This paper's major contributions are as follows:

• In most existing CAD-based nodule detectors, the lungs are manually marked by the radiologist, which is a tedious and time-consuming task. From CT images, the lungs are automatically segmented in the proposed algorithm, with no user intervention.

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• Nodules come in a variety of regular and irregular sizes and shapes. Many existing techniques detect nodules by using a few shape templates; however, the proposed algorithm is unaffected by shape or size of the nodule.

• The proposed system outperformed existing similar techniques in the terms of accuracy and sensitivity, in the experimental evaluation on a standard LIDC dataset.

Proposed Grey Wolf Optimization based classification of lung nodules

The main goal of this proposed work is to extract a minimal feature set from the CT images of lung cancer diagnosis. Image preprocessing, image segmentation, feature extraction, feature selection,and classification are the main stages of the proposed GWO-FRVM based CAD system for automated detection of irregular lung CT images. The complete methodology of the proposed scheme is depicted in Figure 1.

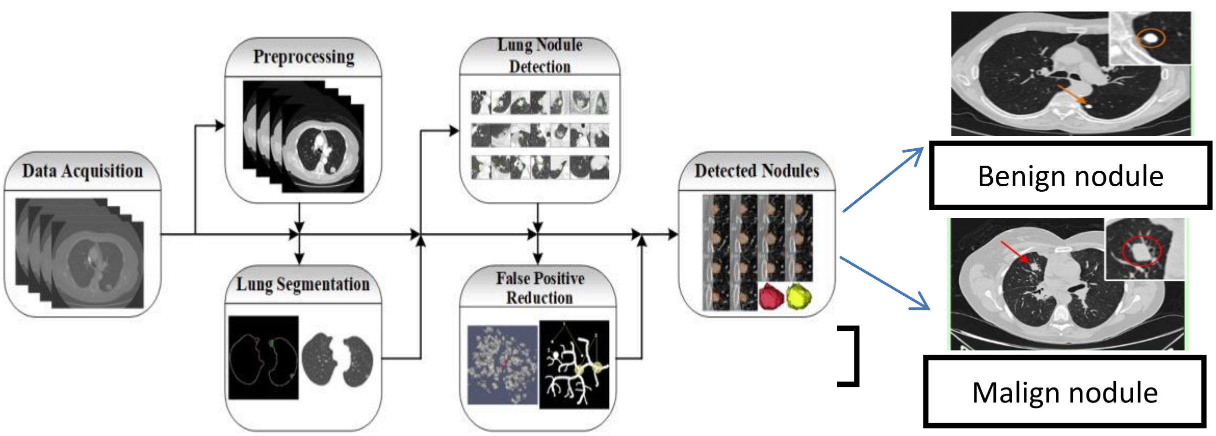

Figure1. Proposed system flow diagram

Every image used in this study is from a publicly available digital database of lung CT images [20]. The data used in the experiments for training and testing the lung image of the proposed hybrid algorithm was obtained from the Lung Image Database Consortium - Image Database Resource Initiative (LIDC-IDRI). The 1018 CT cases from the LIDC/IDRI dataset are evaluated. Four experienced thoracic radiologists examined each of the 1018 CT cases in the LIDC/IDRI

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dataset and classified lesions into one of three categories (“nodule > or = 3 mm,” “nodule 3 mm,” and “non-nodule > or = 3 mm”). Lesions with a diameter of 3 mm are more likely to be malignant than lesions in the other two categories.

Image Preprocessing

Preprocessing includes the removal of grains from the image. Noise, also known as grains, an unwanted information which contaminates an image. To remove the noisy pixels from the lung image [21,26] preprocessing is done. The goal of mammogram image preprocessing is to make cancer detection easier while preserving important features. Numerous issues, such as noises, artifacts, and patient information, can all have an impact on identification performance. In this study, the median filter is used to reduce noise in input CT images. It is a non-linear filter that is more robust than traditional linear filters due to its ability to provide excellent noise elimination with less obscuring and to preserve sharp edges. The median filter successfully reduces "impulse noise," "speckle noise," and "salt and pepper noise." To reduce the volume of noise prior to lung nodule segmentation, a median filter can be applied.

Image Segmentation

The process of dividing or segmenting a region into distinct parts [22] is called as Image segmentation. The proposed work uses global thresholding to segment the lung tumor region. Global thresholding is more computationally efficient and straightforward. The thresholding value will be determined by the grey level value of the image, which is a pixel property. Segmentation aids in separating the lung lobes from the rest of the chest parenchyma, improving prediction results.

Feature Extraction

It is critical to extract features from segmented images during this phase so that the system can accurately classify the masses as normal or abnormal [25]. To represent the appearances of the segmented masses, 31 features associated with the texture feature and intensity, shape based features are extracted from segmented images in this work [22,24]. The textural features of the segmented image are measured using the GLCM in various directions.The four GLCM distance

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matrices corresponding to directions of 0, 45, 90, and 135 are considered. Figure 2 shows the extracted features from segmented images.

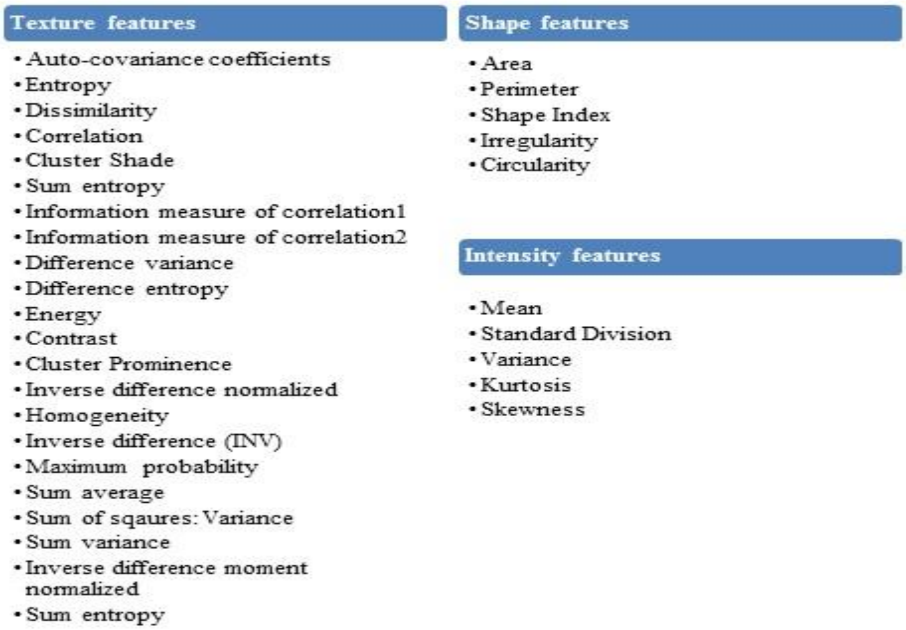

Figure 2. Extracted features from the segmented region

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Feature Selection

The GWO, a novel meta-heuristic technique based on the replication of grey wolf hunting behavior and community leadership [22,23]. Grey wolves are among the most well-known predators in the world. Grey wolves prefer to live in packs with an extremely strict socially dominant progressive system. They are distinguished by societal progression in the following areas:

i. The alpha wolf is generally in charge of creating decisions about sleeping,hunting, and other activities. The pack is subject to the alpha's decisions. Surprisingly, the alpha does not have to be the pack’s strongest member, but rather the most adept at dealing with the pack.
ii. The beta wolves are secondary level wolves in the progression, assisting the alpha in decision-making or other actions. Throughout the pack, the beta emphasizes the alpha's instructions and responds to the alpha.
iii. The grey wolf with the lowest positioning is omega. Omega can fulfill the entire pack while maintaining the pack's dominant design. They are in charge of providing accurate information to the other wolves in the pack.
iv. Delta refers to the remaining wolves. Delta wolves are in the same hierarchy as the alphas and betas, but they rule the Omega. Delta must keep an eye out for threats to the pack's security.

Alpha (α) is regarded as the best wolf in the mathematical construction of GWO. Beta (β) and delta (δ) are the second and third best wolves, respectively. Every other wolf is referred to as omega (ω). The wolf pack's first hunting task should be to encircle prey. The pack can update its location around the prey at any random location, as shown by the following equations. The numbers (1) to (4) are used.

$$\vec{A} = \left|\overrightarrow{H} \,.\, \overrightarrow{Y_p}(iter) - \overrightarrow{Y}\,(iter)\right| \tag{1}$$

$$\vec{Y}(iter+1) = \overrightarrow{Y_p}(iter) - \overrightarrow{F}\,.\vec{A} \tag{2}$$

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where $iter$ denotes the current iteration. $\overrightarrow{Y_p}$ shows the position vector of a grey wolf and $\overrightarrow{Y}$ is the position of the prey $\overrightarrow{F}$ and $\overrightarrow{H}$ are coefficient vectors and are measured with the following formulas,

$$\overrightarrow{F} = 2\overrightarrow{b} \,.\, \overrightarrow{rand_1} - \overrightarrow{b} \quad (3)$$

$$\overrightarrow{H} = 2 \,.\, \overrightarrow{rand_2} \quad (4)$$

Here, $\overrightarrow{rand_1}$ and $\overrightarrow{rand_2}$ are randomly produced vectors in [0, 1]. Components $\overrightarrow{b}$ are linearly diminished from 2 to 0 during the iterative process.

The grey wolves of the α, β and δ types in the pack have a better understanding of the likely location of prey. As a result, the first three best solutions obtained are retained, putting pressure on the other search agents for updating their positions in accordance with the best positions. In this case, the following formulas can be used.

$$\overrightarrow{A_\alpha} = \left|\overrightarrow{H_1} \,.\, \overrightarrow{Y_\alpha} - \overrightarrow{Y}\right| (5)$$

$$\overrightarrow{A_\beta} = \left|\overrightarrow{H_2} \,.\, \overrightarrow{Y_\beta} - \overrightarrow{Y}\right| (6)$$

$$\vec{A} = \left|\overrightarrow{H_3} \,.\, \overrightarrow{Y_\delta} - \overrightarrow{Y}\right| (7)$$

$$\overrightarrow{Y_1} = \overrightarrow{Y_\alpha} - \overrightarrow{F_1} \,.\, \left(\overrightarrow{A_\alpha}\right) (8)$$

$$\overrightarrow{Y_2} = \overrightarrow{Y_\beta} - \overrightarrow{F_2} \,.\, \left(\vec{A}\right) (9)$$

$$\overrightarrow{Y_3} = \overrightarrow{Y_\delta} - \overrightarrow{F_3} \,.\, \left(\overrightarrow{A_\delta}\right) (10)$$

$$\vec{Y}(iter + 1) = \frac{\overrightarrow{Y_1} + \overrightarrow{Y_2} + \overrightarrow{Y_3}}{3} (11)$$

where $\overrightarrow{Y_\alpha}$, $\overrightarrow{Y_\beta}$ and $\overrightarrow{Y_\delta}$ are the initial three best solution in the pack at a given iteration $iter$. In the last step, GWO is updating parameter $\overrightarrow{x}$ that manage the adjustment among exploration and exploitation. Each iteration, the parameter $\overrightarrow{b}$ is updated to range from 2 to 0 as per Eq. (12).

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$$\vec{x} = 2 - it\frac{2}{Maxit} \tag{12}$$

where it is the current iteration and $Maxit$ is the entire iteration allowed for optimization.

Algorithm 1: GWO Algorithm

```
Begin
Parameters popsize, ub, maxiter,and lb are initialized where
Popsize is the size of population,
Maxiter is theiterations maximum number,
ub is the variables upper bound,
lb is the variables lower bound;
Initial positions of grey wolves are generated with ub and lb;
Initialize a, A→, and C→;
Fitness of every grey wolf is calculated;
alpha is the grey wolf with the first maximum fitness;
beta is the grey wolf with the second maximum fitness;
delta is the grey wolf with the third maximum fitness;
while k<maxiter
    for i=1: popsize
      Update the current grey wolf's position by Eq. (11);
   end for
  Calculate the fitness of every grey wolf;
   Update alpha, beta, and delta;
k=k+1;
end while
Return alpha;
End
```

In Algorithm 1 the algorithm of the GWO algorithm is presented.

FRVM Classification

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In medical image diagnosis process techniques, classification is the final step. Based on its size and structure the tissue of tumor that has been finely segmented must be classified. Models based on Relevance Vector Machines (RVM) discover how to classify a given group of data using control algorithm instructions. The training data are labelled at the start, and the RVM classifies the data according to the labels. The disadvantages of the RVM classifier are that the cost of training is high., the resulting vector set is much smaller., and the criteria function optimization is not a quadratic problem further.

As a result, the rule-based fuzzy RVM classifier is used [21,24]. There are two possibilities for the fuzzy rule outcomes: malignant and benign. Fuzzy sets support varying set membership levels. A malignant membership is represented by a degree of one, while a benign membership is represented by a degree of zero. At that point, data is clustered and on the basis of this, fuzzy clustering is carried out.The membership function defines the grading of a given element's membership. This type of fuzziness is represented by the Fuzzy RVM, which is expressed as IF 1 THEN 0, in which 1 and 0 are the fuzzy sets.The purpose of the fuzzy-based RVM classifier is to improve classification accuracy as well as the execution time.In the following steps, the Fuzzy Relevance Vector Machine (FRVM) is used for classifying tumor tissues.

Algorithm 2 - Fuzzy Relevance Vector Machine (FRVM)

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Step 1: The output of RVM is illustrated as follows,

$$b(a) = \sum_{i=1}^{n} w_i f(a, a_i) + w_0$$

where, w – weight vector $\left(w = [w_0, \dots w_i]\right)$

$f(a, a_i)$ – kernel function

Step 2: Fuzzy RVM is given by

$$f(a, a_i) = \begin{cases} \exp\left[-\dfrac{\| a - a_i \|^2}{2\sigma^2}\right], & \text{if } M f > \sigma \\ \dfrac{\| a - a_i \|^2}{2\sigma^2}, & \text{Else} \end{cases}$$

Step 3: $p(b \mid w, \sigma^2) = (2\pi\sigma^2)^{-\frac{n}{2}} \exp\left[-\dfrac{1}{2\pi\sigma^2} \| b - \rho \|^2\right]$

where,

$$\rho(a_i) = [1, f(a_i, a_1), f(a_i, a_2), \dots, f(a_i, a_n)]'$$

Step 4: Probability Distribution over the weights

$$p(w \mid x) = \prod_{i=1}^{n} N\left(w_i \mid 0, x_i^{-1}\right)$$

where, x – Hyper – parameter vector

Step 5: Classifier function of relevance vector machine can be expressed by,

$$b(a) = \rho'(a)\left(\sum_{i=1}^{n} x_i \, \rho(a_i)\right)$$

Every feature vector is labelled as part of the classification process. The labels are predefined so that the classifier can classify the segmented image as benign or malignant as well as recognise them.The classification model is given a set of training features, where $a_i$represents their corresponding outputs from the feature extraction model and the input vector of feature data. The output of the RVM scheme is being displayed by step 1. In RVM the Gaussian kernel is used as the encountered kernel, and Fuzzy RVM is the condition to retrieve the kernel's parameter.The triangular membership function is used to frame the fuzzy rule in this work. Based on the value of the membership function and thedegree of the fuzzy setsas well as based on the given training set the fuzzy rule is being modified. Step 3 specifies the dataset's probability. The RVM model's capability is improved by using a probability distribution on the weights.So, the classifier function is finally developed to differentiate between benign and malignant tumor tissues.

Performance evaluation

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The optimization is the most important aspect of this proposed system. The GWO algorithm ignores irrelevant data from the features extracted and chooses only the finest features for better classification.

True Positive (TP) image results are those that detecting a disease when there is disease.

True Negative (TN) image results are those in which no nodule is detected as well as no disease is

diagnosed.

False Positive (FP) images are those that detect a disease even when it is not present.

False negatives (FN) are image results that detect a disease when it does not already exist.

Tables 1 and 2 compare the performance measures of conventional SVM, RVM, and the novel FRVM schemes without and with the use of the GWO algorithm respectively. Both tables show that the proposed FRVM with optimization scheme is far more accurate than traditional lung tissue classification schemes.

$$\text{Accuracy (\%)} = \frac{TP+TN}{TP+TN+FP+FN} x100 \qquad (1)$$

The percentage of nodules correctly predicted as cancerous is referred to as sensitivity.

$$\text{Sensitivity (\%)} = \frac{TP}{TP+FN} x100 \qquad (2)$$

The percentage of nodules correctly classified as noncancerous is referred to as specificity.

$$\text{Specificity (\%)} = \frac{TN}{TN+FP} x100 \qquad (3)$$

Table 1Performance measures comparison between SVM, RVM and FRVM without Optimization

Measures	SVM	RVM	FRVM
Sensitivity	65.43	83.31	90.43
Specificity	64.07	96.29	97.29
Precision	65.95	96.05	97.26
Recall	65.45	83.39	90.46
Accuracy	64.79	91.59	**94.77**

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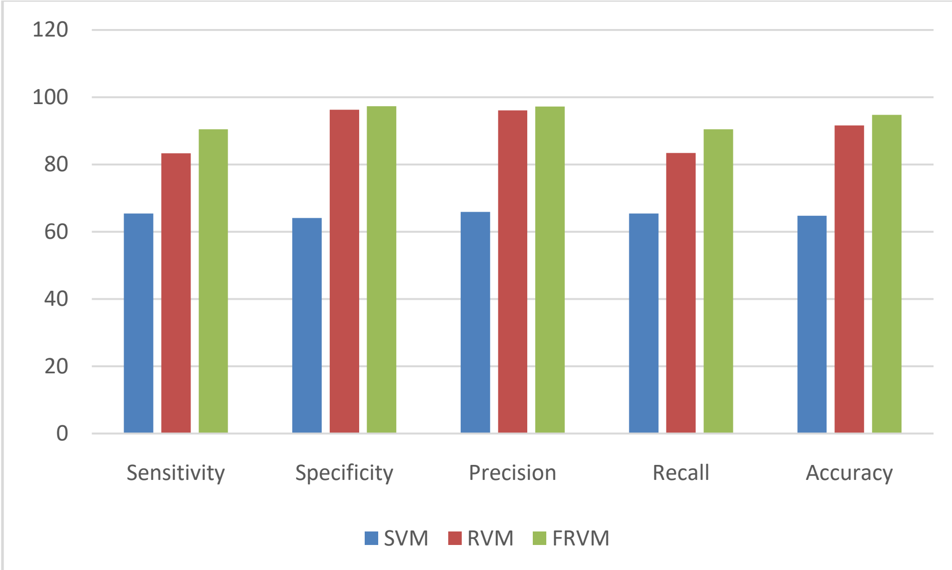

Figure 3 Performance measures without optimization

Table 2Performance measures comparison between SVM, RVM and FRVM with Optimization

Measures	SVM	RVM	FRVM
Sensitivity	43.48	89.83	92.12
Specificity	63.25	92.43	96.53
Precision	54	90.62	95.36
Recall	43.58	88.91	92.09
Accuracy	49.64	90.56	**96.54**

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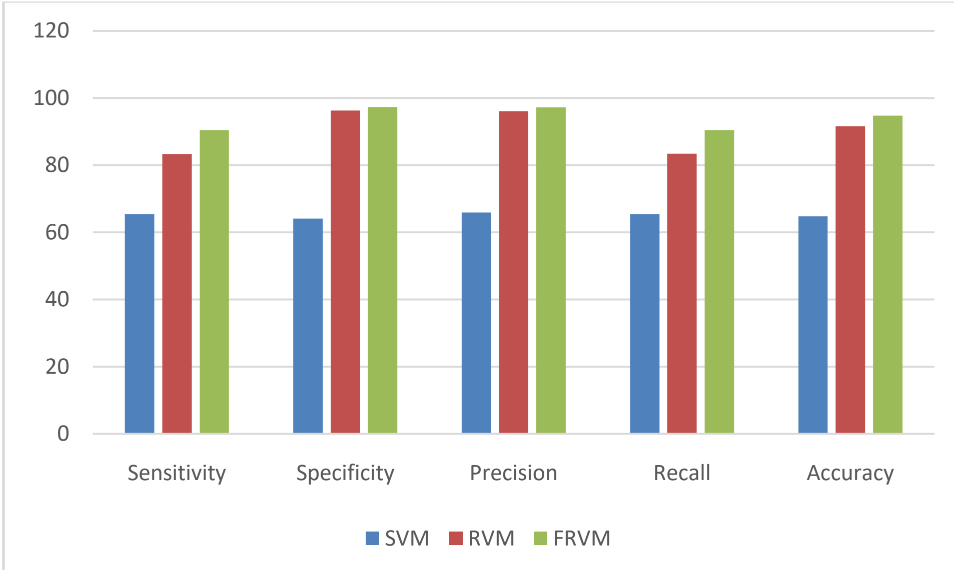

Figure 4 Performance measures with optimization

The assessment of the proposed algorithm and existing classification algorithms are shown in depicted in Figure 3 and Figure 4. It has been observed that FRVM with Grey Wolf Optimization has a better performance than other existing classifiers in general. In this system, it is realized that the performance of the classifiers gets improved by eliminating the redundant and irrelevant features. When too many features are selected, the uncorrelated factors will reduce the performance of the classifier.

Conclusion

Dimensionality reduction is a critical task in medical image processing. The primary objective of the proposed system is to design and develop a knowledge acquisition method for lung cancer diagnosis based on several classification techniques that appropriately and accurately mine the targeted information. Based on the grey wolf optimizer and FRVM, a novel CAD system for classification of lung nodules is proposed in this system. Image pre-processing, nodule segmentation, feature extraction, feature selection, and classification are all part of the proposed method. Thus, shape, texture, and intensity based features are extracted from segmented images and then redundancy features are eliminated by proposed GWO based feature selection algorithm. The GWO algorithm ignores irrelevant features and the best ones are selected from the segmented image. The Fuzzy Relevance Vector Machine (FRVM) algorithm assigns labels to the best features that are chosen. Labels are assigned to them and FRVM classifies the features, resulting in a more accurate classification of the tumor tissue. The analysis revealed that multiple features and the selection of the optimal feature set improve the tumor classification as benign or malignant. The planned GWOFRVM scheme has an accuracy of 94.14 %, which is higher than the conventional classifiers.

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