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A genetic optimized neural network for image retrieval in telemedicine

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Abstract

Telemedicine integrates information and communication technologies in providing clinical services to health professionals in different places. Medical images are required to be transmitted for diagnosis and opinion as part of the telemedicine process. Thus, telemedicine challenges include limited bandwidth and large amount of diagnostic data. Content-based image retrieval is used in retrieving relevant images from the database, and image compression addresses the problem of limited bandwidth. This paper proposes a novel method to enable telemedicine using soft computing approaches. In the present study, images are compressed to minimize bandwidth utilization, and compressed images similar to the query medical image are retrieved using a novel feature extraction and a genetic optimized classifier. The effectiveness of compressed image retrieval on magnetic resonance scan images of stroke patients is presented in this study.

Keywords: Telemedicine; Feature extraction; Image retrieval; Classification; Neural network

1. Introduction

Telemedicine integrates information and communication technologies in providing clinical services to health professionals in different places. It provides expert-based healthcare services to exchange information required for diagnosis, consultation, and referential purposes. Telemedicine not only includes diagnostic, remote monitoring, and interactive services but also drug evaluation, medical research, and training. People living in remote areas and isolated regions find telemedicine very helpful. It is also useful in critical care and emergency situations. The main challenges faced by telemedicine are limited bandwidth, large volume of data, and availability of expert opinion [1,2]. With the progress of medical technologies, obtaining digital images of human anatomy through X-rays, magnetic resonance imaging (MRI), electrocardiography (ECG), and computed tomography (CT) has become a norm. The digital images are stored in databases and can be easily accessed through internet for training and diagnostic purposes. The difficulty of getting an expert either online or offline to advice on diagnosis based on the medical image is addressed by the use of content-based image retrieval (CBIR). CBIR can be used to retrieve diagnostic cases similar to the query medical image from the medical database [3,4]. CBIR is of significance in medical image retrieval as the medical databases contain a huge amount of data in visual form, conventional method of retrieval based on semantics is not feasible, and image content is more versatile than the text. CBIR is increasingly applied in medical image applications; many CBIR algorithms, architectures, and systems are reviewed in the literature [5,6].

Though medical image retrieval has been successfully implemented in nontelemedicine applications, the limited bandwidth and large amount of diagnostic data required to be transmitted are two of the major issues that need to be addressed in using CBIR in telemedicine. Transmitting compressed medical images can be an option for physical diagnosis by an expert; however, automated retrieval of compressed medical images has not been extensively studied. Image compression reduces data required to represent an image; it reduces the storage and transmission requirements. Redundancies in the image are removed during the compression process to yield a compact representation of the image. Lossless

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compression techniques are used when the original image is to be perfectly recovered, and lossy compression techniques are used when a high compression rate is required with minor loss in details. Limited techniques for compressed medical image retrieval have been proposed in [7-9]. Compression techniques using lossless methods have been studied in [10,11] where attempts have been made to propose encoding techniques that showed improvements over existing techniques including Huffman coding. As image transmission is part of telemedicine, wavelet-based coding has been found to be robust for compressed image transmission and has proved to be efficient at low bit rates [12].

This work focuses on compressed medical image retrieval. CBIR has been successfully applied in classifying MRI brain images. Studies in [13-15] show feature extraction techniques and classification algorithm for stroke identification and classification in uncompressed images. Cocosco et al. [16] proposed techniques for feature extraction which showed robustness against variability in MRI image quality. Lahmiri and Boukadoum [17] proposed a feature extraction technique using discrete wavelet transform (DWT) and obtained good classification accuracies using a probabilistic neural network (PNN) algorithm. El-dahshan et al. [18] presented techniques for feature reduction using principal component analysis (PCA) of the features extracted using DWT. Using *k*-nearest neighbor (k-NN) and feedforward back propagation-artificial neural network (FP-ANN) classifications, accuracies of 95.6% and 98.6% were obtained. Bagher-Ebadian et al. [19] proposed a method to study ischemic stroke using ANN. The method identifies the extent of ischemic lesion recovery. Experiments using new datasets showed that the prediction made by ANN had an excellent overall performance and was very well correlated to the 3-month ischemic lesion on the T2-weighted image. Stroke classification using various feature techniques and classifiers has been proposed in [20-22].

Though good classification accuracy has been demonstrated in the literature, a detailed study of compressed MRI stroke image retrieval which is crucial for telemedicine has not been studied extensively to the best of our knowledge. This work focuses on compressed image retrieval for the classification of stroke and nonstroke MRI images. The proposed method is subdivided to the following techniques comprising compression, feature extraction, and classification. Haar wavelet for decomposition and Huffman encoding have been used to compress the images. The main contributions of this study are listed as

- A novel feature extraction technique using the proposed image retrieval-specific fast Fourier transform (IRS-FFT)
- An improved neural network classifier, genetic optimized parallel neural network (GOP-parallel NN).

2. Proposed feature extraction

The proposed IRS-FFT for feature extraction can be derived as given in [23-25]. Feature extraction was performed on diffusion weighted imaging (DWI) scan images showing stroke.

Fast Fourier transform has the tendency to produce large values which may introduce an artifact. In order to overcome the issue of artifact, a normalization procedure is proposed and integrated with Fast Fourier transform. The proposed normalization model is shown in Equations 1 and 2.

Consider a matrix U of dimension $N \times N$ with its (m, n)th element defined as in Equations 1 and 2:

$$u[m,n]u_N^{mn} = \left(e^{-j2\Pi/N}\right)^{mn} \tag{1}$$

where (m, n = 0, 1, 2,..., N − 1).

$$u_N \frac{1}{\sqrt{N}} e^{-j2\Pi/N}. \tag{2}$$

The IRS-FFT can be defined as in Equation 3:

$$X_{\mathrm{irs}}[n] = \int_{-\alpha}^{n} \frac{1}{\sqrt{2\Pi\sigma^2}} e^{-\frac{(n-\mu)^2}{2\sigma^2}} X[n], \tag{3}$$

where $X[n]$ and μ is given as in Equations 4 and 5:

$$X[n] = \begin{bmatrix} u[0,0] & u[0,1] & \dots & u[0,N-1] \\ u[1,0] & u[1,1] & \dots & u[1,N-1] \\ \dots & \dots & \dots & \dots \\ u[N-1,0] & u[N-1,1] & \dots & u[N-1,N-1] \end{bmatrix} \begin{bmatrix} x[0] \\ x[1] \\ \dots \\ x[N-1] \end{bmatrix} \tag{4}$$

and

$$\mu = \frac{1}{N} \sum_{0}^{n-1} X(n). \tag{5}$$

Sample images after feature extraction is given in Figure 1.

The proposed feature extraction technique produces a large number of feature vectors. Information gain (IG) is used to reduce the feature vectors by selecting the top ranked features. The information gain that has to be

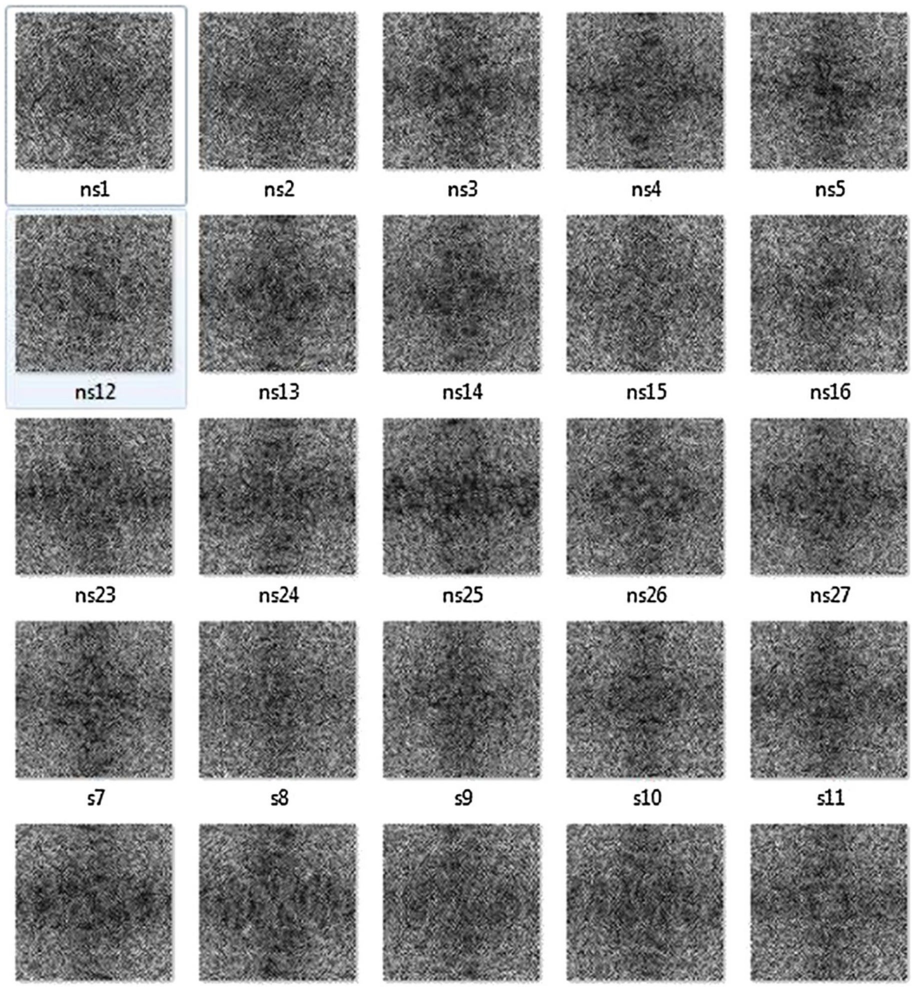

Figure 1 Sample Images after feature extraction.

computed for an attribute A whose class attribute B is given by the conditional entropy of B given A, $H(B|A)$ is

$$I(B;A) = H(B) - H(B|A).$$

The conditional entropy of B given A is

$$H(B|A) = -\sum_{i=1}^{j=1} P(A = a_j) H(B|A = a_j).$$

3. Proposed genetic optimized parallel MLP neural network

Neural network are modeled similar to the neurons in the brain. The proposed neural network genetic optimized parallel multilayer perceptron neural network (GOP-MLP NN) is an extension of the existing multilayer perceptron (MLP) model. Unlike the MLP, full interconnectivity between the layers is not achieved. The network processing the input signals uses several parallel MLPs as it reduces the number of weights required, and hence, the training time for the network is reduced over the traditional MLP network. The block diagram of the proposed GOP MLP neural network is shown in Figure 2.

It could be observed from Figure 2 that the proposed neural network consists of two parallel MLPs with each performing different subtasks. Each MLP consists of two layers. The first submodule MLP uses the first 50% of the attributes, and the remaining are used by the second submodule. The number of weights is reduced by 50% using this process.

A genetic optimization function is introduced in the second hidden layer of the proposed network to find the best learning rule and momentum. The GOP-MLP NN proposed in this paper uses the criteria specified in Table 1.

The learning capability and the generalization capability of the proposed neural network model are calculated

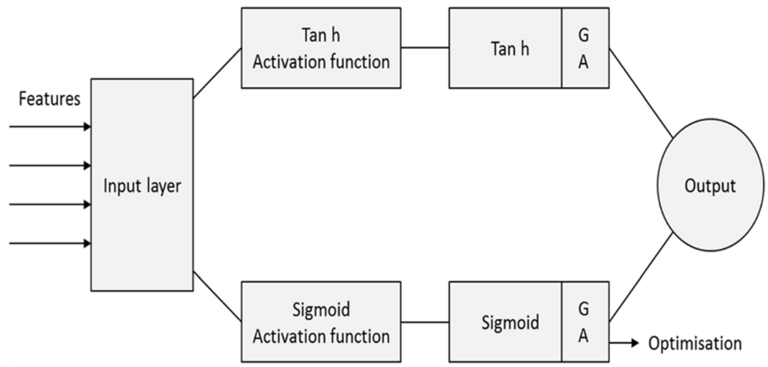

Figure 2 Block diagram of the proposed GOP MLP neural network.

using the performance measure of the mean square error (MSE). The MSE is given as

$$\mathrm{MSE} = \frac{\sum_{j=0}^{E}\sum_{i=0}^{N}\left(o_{ij}-y_{ij}\right)^2}{EN}, \tag{6}$$

where E is the number of processing elements, N is the number of exemplars, o is the desired output for exemplar i at processing element j, y is the obtained output for exemplar i at processing element j; tan h will squash the range of each neuron to between −1 and 1, and its activation function is given as

$$\tan \mathrm{h}(i) = \frac{e^{i}-e^{-i}}{e^{i}+e^{-i}}, \tag{7}$$

where i is the sum of the input patterns.

Table 1 Parameters for the proposed GOP-MLP NN

Parameter	Value/description
Output neuron	2
Number of hidden layer	2
Number of processing elements	
Upper	4
Lower	4
Transfer function of hidden layer	
Upper	tan h
Lower	Sigmoid
Learning rule of hidden layer	Momentum with genetic optimization
Step size	0.1
Momentum	0.7
Transfer function of output layer	tan h
Learning rule of output layer	Momentum
Step size	0.1
Momentum	0.7

Genetic optimization is used in the hidden layer of the network. Genetic algorithms (GA) are a class of optimization algorithms inspired by evolution. The steps in GA include reproduction, crossover, and mutation to evolve better solutions. Generally, the solutions available are evaluated using fitness function. Based on the fitness function, the evolutionary process is iterated till an ideal solution is reached or a specific number of generations has occurred. The proposed neural network architecture is optimized for ideal momentum value using GA with the following parameters specified in Table 2.

The flow diagram of the proposed GOP MLP neural network is presented in Figure 3.

The genetic algorithm iterates and evolves the population, forming a new population at each step. The genetic algorithm iteration consists of the following steps:

1. *Selection*. The first step consists of selecting individuals/chromosomes for reproduction. Fitness value plays an important role in this selection and is completed randomly. Individuals with better fitness

Table 2 Genetic optimization parameters

Parameter	Value/description
Number of iterations	500
Population size	10
Maximum generations	100
Momentum optimization lower bound value	0.05
Momentum optimization upper bound value	0.95
Encoder mechanism	Roulette
Crossover type	One point
Crossover probability	0.75
Mutation	Uniform
Mutation probability	0.02

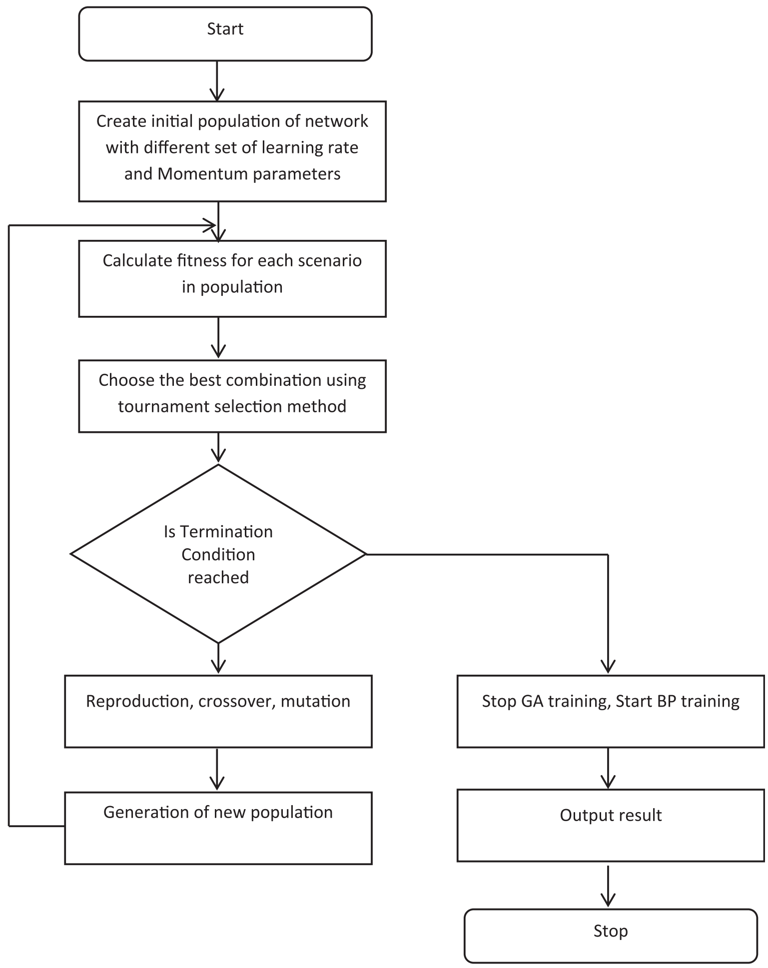

Figure 3 Flow diagram of the proposed GOP MLP neural network.

value are chosen more often for reproduction than poor ones.

2. *Reproduction*. Offspring are produced by the selected individuals. Both recombination and mutation techniques are used in generating new chromosomes.
3. *Evaluation*. The fitness of the new chromosomes is then evaluated.
4. *Replacement*. During the last step, individuals from the old population are removed and replaced by the new ones.

In the present design, the MSE is evaluated as the fitness function with a total of 100 generations. The MSE was found to decrease, and no significant change was observed as presented in Figure 4.

4. Experimental results and discussions

In order to test the effectiveness of our approach, a set of 52 DWI scan images consisting of 25 positive stroke patients was used. These images were provided by the MRI Department of Vijaya Health Centre in India. The MRI images were reviewed by an expert in the radiology department for a precise classification of patients with positive stroke. Figure 5 shows some of the stroke images used in the present study. Experiments were performed on the uncompressed and the compressed images to show the effectiveness of compressed images for image retrieval.

4.1 Experiment 1 for uncompressed images

The following are the steps in experiment 1 for uncompressed images:

1. Preprocessing of the image using a median filter for noise removal
2. Extracting of features using IRS-FFT
3. Feature reduction using Information gain
4. Classification using the proposed genetic optimized parallel neural network for 20, 40, 60, 80, and 100 features

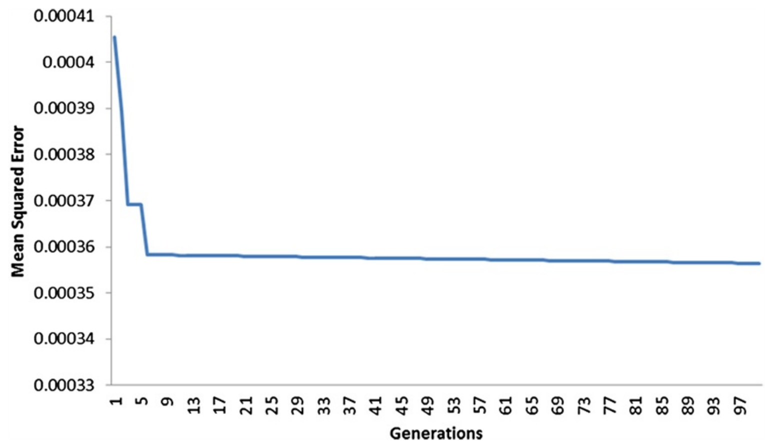

Figure 4 Best fitness versus generation obtained.

5. Performance evaluation of the proposed system with the MLP neural network.

4.2 Experiment 2 for compressed images

The following are the steps in experiment 2 for compressed images:

1. Preprocessing of the image using a median filter
2. Compression of images using Haar wavelet with Huffman encoding
3. Extracting of features using IRS-FFT
4. Feature reduction using information gain
5. Classification using the proposed genetic optimized parallel neural network for 20, 40, 60, 80, and 100 attributes
6. Performance evaluation of the proposed system with MLP neural network.

It is evident in Table 3 that the proposed GOP NN shows a higher degree of precision and classification accuracy compared to the MLP NN. It is observed that classification accuracy decreases when the number of features extracted is 60.

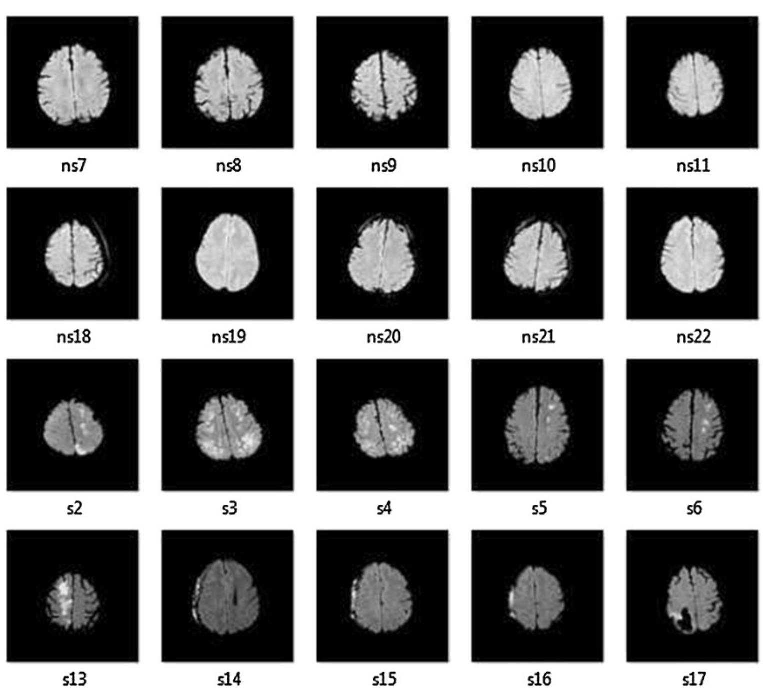

Figure 5 Sample DWI images of stroke patients.

Table 3 Classification parameters for uncompressed and compressed images

Number of features	Parameters	Classifiers	Uncompressed		Compressed	
			Feature extraction using FFT	Feature extraction using the proposed IRS-FFT	Feature extraction using FFT	Feature extraction using proposed IRS-FFT
20	Classification accuracy	MLP NN	88.46	92.31	90.38	92.31
		GOP NN	92.31	94.23	94.23	98.08
	Precision	MLP NN	0.92	0.96	0.86	1
		GOP NN	0.96	1	1	1
	Recall	MLP NN	0.85	0.89	1	0.86
		GOP NN	0.89	0.89	0.89	0.96
40	Classification accuracy	MLP NN	90.38	94.23	92.31	94.23
		GOP NN	94.23	96.15	94.23	98.08
	Precision	MLP NN	0.96	0.96	1	1
		GOP NN	1	1	1	1
	Recall	MLP NN	0.86	0.92	0.86	0.89
		GOP NN	0.89	0.93	0.89	0.96
60	Classification accuracy	MLP NN	88.46	90.38	92.31	94.23
		GOP NN	92.31	94.23	92.31	98.08
	Precision	MLP NN	0.92	0.96	1	1
		GOP NN	1	1	1	1
	Recall	MLP NN	0.85	0.86	0.86	0.89
		GOP NN	0.86	0.89	0.86	0.96
80	Classification accuracy	MLP NN	90.38	94.23	92.31	94.23
		GOP NN	94.23	96.15	98.08	98.08
	Precision	MLP NN	0.96	0.96	1	1
		GOP NN	1	1	1	1
	Recall	MLP NN	0.86	0.92	0.86	0.89
		GOP NN	0.89	0.93	0.96	0.96
100	Classification accuracy	MLP NN	90.38	94.23	92.31	94.23
		GOP NN	94.23	96.15	98.08	98.08
	Precision	MLP NN	0.96	0.96	1	1
		GOP NN	1	1	1	1
	Recall	MLP NN	0.86	0.92	0.86	0.89
		GOP NN	0.89	0.93	0.96	0.96

This seems to be a minor abnormality which could be associated with the data used as 40 and 80 features show linear approach. The classification accuracy, precision, and recall are computed as

$$\begin{aligned}
\text{Classification accuracy} &= \frac{\text{Number of correctly classified samples}}{\text{Total number of tested samples}} \times 100 \\
\text{Precision} &= \frac{\text{Number of relevent images retrived}}{\text{Total number of images retrieved}} \\
\text{Recall} &= \frac{\text{Number of relevent images retrived}}{\text{Total number of relevent images in the database}}.
\end{aligned}$$

Further, the accuracy of the proposed feature extraction technique is higher with a minimum of 40 feature vectors.

The graphs depicted in Figure 6 shows the classification accuracy of the proposed and existing MLP neural

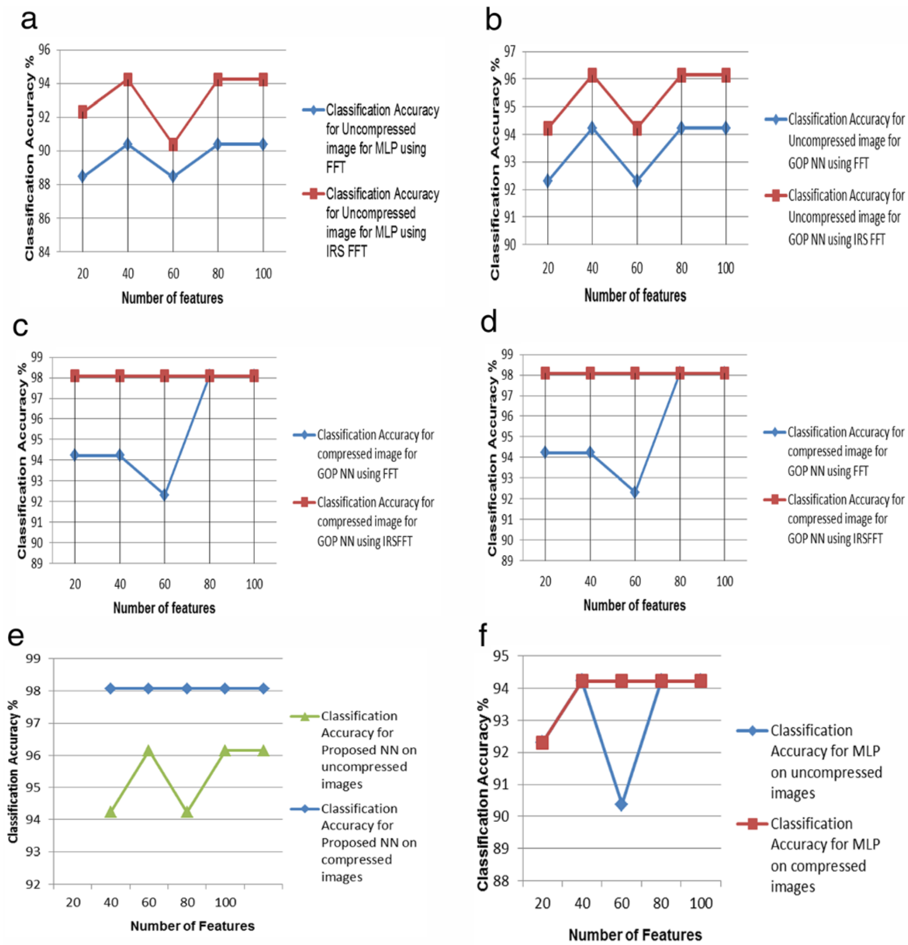

Figure 6 Classification accuracy. (a) Classification accuracy for MLP NN using FFT and IRS-FFT on uncompressed images. **(b)** Classification accuracy for GOP NN using FFT and IRS-FFT on uncompressed images. **(c)** Classification accuracy for MLP NN using FFT and IRS-FFT on compressed images. **(d)** Classification accuracy for GOP NN using FFT and IRS-FFT on compressed images. **(e)** Classification accuracy of the proposed GOP NN on uncompressed and compressed images. **(f)** Classification accuracy of the proposed MLP on uncompressed and compressed images.

network using conventional FFT and the proposed IRS-FFT for both compressed and uncompressed images. It is seen that the classification accuracy of the compressed images are better than that of the uncompressed images, thereby utilizing the bandwidth effectively and justifying its applicability in a telemedicine scenario.

5. Conclusions

In this paper, a modified IRS-FFT-based feature extraction technique was proposed. The basic idea of the proposed algorithm is to squash the values of FFT, thereby reducing noise and improving the classification accuracy. A novel neural network with parallel perceptrons to reduce the weights along with genetic optimization to find the ideal momentum was proposed. A two-class problem on MRI stroke images was used in evaluating the proposed feature extraction and classifier. Experiments were conducted using uncompressed and compressed images. IG was used to rank the extracted features, and the experiments were conducted with varying numbers of features. Multilayer perceptron neural network and the proposed NN architecture with genetic optimization classified the images based on the selected features. Results show the improvement in precision for the compressed images using the proposed system.

The proposed CBIR system achieves satisfactory retrieval accuracy for compressed medical images. An average compression ratio of 35.84 was achieved which translates to proportional savings in bandwidth critical for a telemedicine application. Compressing images for transmission in limited bandwidth is a norm in telemedicine. The proposed method efficiently extracts features and retrieves relevant images from compressed images which will be a good support for telemedicine applications. The proposed method can further be investigated for various types of medical images and also validated for a multiclass problem.

Competing interests
The authors declare that they have no competing interests.

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