BFO – AIS: A FRAME WORK FOR MEDICAL IMAGE CLASSIFICATION USING SOFT COMPUTING TECHNIQUES

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ABSTRACT

Medical images provide diagnostic evidence/information about anatomical pathology. The growth in database is enormous as medical digital image equipment's like Magnetic Resonance Images (MRI), Computed Tomography (CT), and Positron Emission Tomography CT (PET-CT) are part of clinical work. CT images distinguish various tissues according to gray levels to help medical diagnosis. Ct is more reliable for early tumours and haemorrhages detection as it provides anatomical information to plan radio therapy. Medical information systems goals are to deliver information to right persons at the right time and place to improve care process quality and efficiency. This paper proposes an Artificial Immune System (AIS) classifier and proposed feature selection based on hybrid Bacterial Foraging Optimization (BFO) with Local Search (LS) for medical image classification.

KEYWORDS

Computed Tomography (CT), Feature Selection, Artificial immune classifier, Correlation based Feature Selection (CFS), Bacterial Foraging Optimization (BFO), Local Search (LS)

1. INTRODUCTION

Medical images classification is fundamental in different applications in medical image retrieval systems [1]. Due to medical image data's high variability it is important to use correct models in classification. Various medical image classification methods are discussed in literature. Voluminous medical images generated daily have valuable information useful for medical diagnosis, treatment, research, and education. Automatic image annotation extracts symbolic knowledge from images to facilitate text-based retrieval of relevant images having specific disease abnormalities. Image based Computer Aided Diagnosis (CAD) uses images and serves as a second source of opinion for clinicians on abnormality detection and pathological classification [2].The task of automated knowledge extraction from medical image databases remains a big technological challenge.

CAD systems assist radiologists and increase diagnosis accuracy. Medical images are from varied modalities like Magnetic Resonance Images (MRI), Computed Tomography (CT), and Positron Emission Tomography CT (PET-CT) and Ultrasound. CT is a reliable technique for detection of abnormalities like tumours and haemorrhages [3] providing anatomical information to plan radio

therapy. For such reasons, this research presents an abnormality detection method and classification for CT brain images.

Medical images classification is a manual process [4]. The voluminous amount of medical images produced and limitations of current healthcare technologies in using an automatic classification method highlights the need for consistency in classification. This helps process a huge amount of images easily as this is costly when done manually.

Generally, images have color, shape, texture, edge, shadows, and temporal features. Most promising features are color, texture and edge for the following reasons [5]:

Color: Egeria occurs in two colors – black and pink (rusty rose)

Texture: Texture is a neighbourhood feature; a region or block. Each pixels variation regarding its neighbouring pixels defines texture.

Edge: Edge is a large frequency change.

Feature extraction in image processing is a dimensionality reduction form. When an algorithm's input data is too large to be processed and is supposed to be notoriously redundant (much data, but not information) then input data is transformed to a reduced representation features set (named feature vector).Transforming input data to a feature set is feature extraction. If extracted features are carefully chosen it is expected that features set will extract relevant information from input data to perform the desired task using less representation instead of full-size input. Image texture is an image area with repeated pixel intensities patterns arranged in some structural way. Textures are prominent in natural images (grasslands, brick walls, fabrics) and properties for interpretation and image description are revealed through texture observation and analysis like granularity, periodicity, coarseness, geometric structure, smoothness and orientation [6, 7].

Feature selection has two approaches. One is forward selection where a process begins with no attributes/features which are added one by one. At every step, feature which decreases most error is added and process continues till features addition does not decrease the error [8]. The Second approach is backward selection where the idea is to start with all attributes/features and remove them one by one. The feature removed at every step is that which decreases error the most. The process continues till any further removal increases error greatly.

Feature selection methods are classified into filter, wrapper, and hybrid approaches. A filter approach is applied to data before classification where features are evaluated by heuristics based on general data characteristics. In a wrapper approach, features are evaluated using classification algorithms. Features in a Hybrid approach are evaluated using filter and wrapper approaches [9].

Feature selection seeks an optimal set of d features out of m. Many methods were previously used for feature selection on training/testing data. Among various methods proposed for FS, population-based optimization algorithms like Genetic Algorithm (GA) and Ant Colony Optimization (ACO) attracted attention. In the new feature reduction system, an evolutionary hybrid feature selection algorithm based on swarm intelligence called Bacteria Foraging Optimization [10] is used.

In the study, CT images classification based on feature extraction using Gaussian wavelet and Gray Level Co-occurrence Matrix (GLCM) is used. Feature selection is by wrapper technique using Correlation based Feature Selection (CFS) and hybrid Bacterial Foraging Algorithm. Section 2 reviews related work, section 3 describes methodology, section 4 discusses experimental results and section 5 concludes the work.

2. RELATED WORK

Efficient implementations of curve let transform for denoising and medical image segmentation was presented by Al Zubiet al., [11]. A comparison study was carried out between different transforms revealing that curvelet transform showed optimal region of interest (ROI) representation with better accuracy and less noise.

An adaptive fusion algorithm of CT and MRI medical images based on NSCT was presented by Dai et al., [12]. Source images were decomposed multi-directionally using non-sub sampled pyramids (NSP) and non-sub sampled directional filter banks (NSDFBs). Combining adjustable parameter and adaptive fusion rules objective evaluation index were used for low-frequency sub-band fusion. The experiment verified the method's feasibility regarding visual quality and objective evaluation criteria, standard deviation, entropy, space-frequency, and mutual-information.

A low-dose scan protocol and an associated reconstruction algorithm allowing triple phase-correlated in vivo imaging of perfusion and associated processes was proposed by Sawallet al., [13]. The new reconstruction method keeps administered radiation dose as low as 500 mGy reducing metabolic inference to an animal ensuring longitudinal studies. It provided the first approach to phase-correlated perfusion CT imaging in mice, boosting preclinical research with new possibilities.

A method called Feature Selection based on the Compactness Measure from Scatter plots (FSCoMS) to select best features from medical images to improve CBIR effectiveness was proposed by Humpire-Mamaniet al., [14]. The algorithm has a scatter plots compactness analysis to locate most relevant features with high separability abilities. A scatterplot's high relevance value means better predictability among classes based on two features. This information generates a feature ranking for usefulness. This method was compared to 2 known feature selection methods using 3 real medical datasets. All were compared regarding final feature vector and retrieval effectiveness dimensionality measured by precision and recall graphs. Experiments show that the new method not only got the highest retrieval performance but also achieved smallest number of demanded features (dimensionality) than other analyzed methods.

A method, to choose an optimal subset of statistical texture descriptors inefficient representation and ultrasound medical images retrieval, was presented by Sohail et al., [15]. The new feature selection based approach of image annotation and retrieval was tested with a database of 679 ultrasound ovarian images. Retrieval performance achieved was satisfactory. Also, ultrasound medical image retrieval performance with/without applying feature selection based image annotation technique was compared.

A colon biopsy image classification technique, where 2 novel structural feature types: white run-length features and percentage cluster area features were introduced and proposed by Rathore et

al., [16] were calculated for each colon biopsy image. Features were reduced using PCA. The new technique was evaluated on 174 colon biopsy images, and promising performance was observed regarding various well-known performance measures like accuracy, sensitivity and specificity. The new technique also proved to be better compared to earlier published techniques in the experimental section. Further, classifiers performance was evaluated using ROC curves, and area under the curve (AUC). Rotation boost classifier with PCA based feature selection showed better classification results compared to other classifiers.

The ability to decompose 5 materials using energy discriminating detectors and multiple discriminant analysis (MDA) was investigated by Leeet al., [17]. A small field-of-view multi-energy CT system was built. Linear attenuation coefficient was considered a feature of multi-energy CT. MDA decomposes 5 materials with 6 measurements of energy dependent linear attenuation coefficients. The results showed that a CdTe detectors based CT system with MDA can decompose 5 materials.

A new method for lung-motion tracking from 4-dimensional X-ray computed tomographic (4D-CT) images proposed by Kubota et al., [18] uses an enhanced 3D-KLT tracker. The feature point extraction algorithm is image gradients based. The new method adopted pyramidal image structure based hierarchical tracking. The proposed method's performance for artificial 4D-CT images described quantification results of real 4D-CT images. Results showed that lung movement is not modelled by simple translation but by oval pattern.

A new algorithm for medical image segmentation with reference to abdominal aortic aneurysm and degraded human brain imaging was presented by Pham et al., [19]. The new algorithm's development was based on theoretic distance matrix implementation with spatial semi-variances.
An alternative, approach to use energy sensitive CT imaging techniques, was proposed by Ghadiriet al., [20]. To accurately validate the new method, a new bone model based on cortical and marrow mixtures was proposed. A two-step energy mapping algorithm was implemented. Phantom tomographic projections in 5 energy bins were acquired and reconstructed for validation. The new energy mapping technique estimated LAC of different bone tissues at 511 keV. The results had 1.1% error maximum compared to true values. To test precision, 10% variation's effect on effective energy was investigated.

Medical image fusion for merging complementary diagnostic content using PCA and Wavelets was carried out by Krishnet al., [21]. The new fusion approach involved sub-band decomposition using 2D-Discrete Wavelet Transform (DWT) to preserve spectral and spatial information. Also, PCA was applied on decomposed coefficients to maximize spatial resolution. An optimal variant of daubechies wavelet family was selected for better results. Simulation showed improved visual quality in the fused image compared to other state-of-art fusion approaches.

An automated tibial eminence extraction in MDCT image using shape matching was proposed by Uozumi et al., [22]. The new method evaluated 6 patients (Age 27 ± 7, four males / two females). Hence, the new method automatically extracted an eminence shape for all patients.

3. METHODOLOGY

This study uses classification process for CT images based on feature extraction using Gaussian wavelet and GLCM. The features extracted are reduced using Information Gain and CFS [32].

The Hybrid bacterial foraging optimization (HBFO) is proposed in this paper for feature selection and the selected features are classified using artificial immune classifier. The proposed HBFO for feature selection and artificial immune classifier are discussed in this section.

3.1 Proposed hybrid Bacterial Foraging Optimization (BFO)

Global optimization combines a fast local optimization method with an initial search phase, showing improved robustness compared to local search strategies [26]. It uses randomization and local search to solve an optimization problem. Different meta-heuristic approaches solve the same optimization problem differently [27]. BFO algorithm is a new evolutionary computation algorithm based on Escherichia coli (E. coli) bacteria's foraging behaviour in the human intestine. The BFO algorithm is a biologically inspired computing technique mimicking E.coli bacteria's foraging behaviour [28].Natural selection removes animals with poor foraging strategies favouring the circulation of genes of animals with successful foraging strategies, as they are more likely to enjoy reproductive success. After generations, poor foraging strategies are removed or shaped into good ones. Foraging is used in optimization which is explained below:

Chemotaxis: This simulates movement of an E.coli cell by swimming and tumbling via flagella. Biologically, an E.coli bacterium moves in two ways. It can swim in the same direction or tumble, or alternate between these two modes for an entire lifetime.

Swarming: Interesting group behaviour was observed in many mobile bacteria species including E.coli and S. typhimurium, where stable spatio-temporal patterns (swarms) are formed in a semisolid nutrient medium [29].

Reproduction: least healthy bacteria eventually die while healthier bacteria (those yielding higher fitness function values) asexually split into two bacteria in the same location keeping the swarm size constant.

Elimination and dispersal: Gradual / sudden changes in environment where a bacterium population lives occurs for various reasons; e.g. significant rise in local temperature may kill a group of bacteria that are in a region with a high nutrient gradients concentration. Events take place so that all bacteria in a region are killed, or a group disperses to new locations. To simulate this, some bacteria are liquidated at random with very small probability while new replacements randomly initialize over search space.

Chemotaxis is the basis for local search, and reproduction speeds up convergence simulated by a classical BFO. To a large extent, Chemotaxis and reproduction are not enough for global optima searching. As bacteria may get stuck in initial positions or local optima, it is possible for BFO diversity to change gradually or suddenly to eliminate being trapped in local optima [30]. Dispersion in BFO happens after certain reproduction processes. Then some bacteria are chosen, according to a preset probability Ped, to be killed and moved to another position in the environment.

The algorithm's steps are as follows [31]:

Step 1. Initialize parameters n, S, NC, NS , Nre, Ned ,

Ped, C(i), (i = 1,2,..., S),θi

where

n : dimension of the search space,

S : the number of bacteria in the colony,

NC : chemotactic steps,

NS : swim steps,

Nre: reproductive steps,

Ned : elimination and dispersal steps,

Ped: probability of elimination,

C(i) : the run-length unit (i.e., the size of the step taken in each run or tumble).

Step 2. Elimination-dispersal loop: l = l +1 .

Step 3. Reproduction loop: k = k +1.

Step 4. Chemotaxis loop: j = j +1 .

Sub step 4.1. For i =1,2,..., S , take a chemotactic step for bacterium i as follows.

Sub step 4.2. Compute fitness function, J (i, j,k,l) .

Sub step 4.3. Let J last= J (i, j,k,l) to save this value since we may find better value via a run.

Sub step 4.4. Tumble. Generate a random vector Γ(i)∈ Rn with each element i m n Γm(i), = 1,2,..., ,

a random number on [1 −1].

Sub step 4.5. Move, let

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\frac{\Gamma(i)}{\sqrt{\Gamma^T(i)\Gamma(i)}}$$

This results in a step of sizeC(i) in the direction of thetumble for bacterium i.

Sub step 4.6. Compute J (i, j +1,k,l) with θ i (j +1,k,l) .

- If J (i, j +1, k, l) <J last , let J last= J (i, j +1,k,l) , then another step of size C(i) in the same direction will be taken as (2.2) and use the new generated
- θi (j +1,k,l) to compute the new J (i, j +1,k,l) .
- Else let m = Ns.

Sub step 4.7. Swimming.

I: Let m = 0 (counter for swim length).

II: While m < Ns (if has not climbed down too long), the following hold.

- Let m = m +1.
- If J (i, j +1, k, l) <J last , let J last= J (i, j +1,k,l) , then another step of size C(i) in this same direction will be taken as (2.2) and use the new generated
- θi (j +1,k,l) to compute the new J (i, j +1,k,l) .
- Else let m = Ns.

Sub step 4.8. Go to next bacterium (i+1).If i ≠ S ,go to Substep4.2 to process the next bacterium.

Step 5. If $j < N_C$, go to Step 3. In this case, continue Chemotaxis since the life of the bacteria is not over

Step 6. Reproduction

Sub step 6.1. For the given k and l ,and for each i = 1,2,..., S let

$$J_{health}^{i} = \sum_{j=1}^{N_c+1} J(i,j,k,l)$$

be the health of the bacteria. Sort bacteria in ascending order of J health values

Sub step 6.2. The Sr bacteria with the highest J health values die and the other Sr bacteria with the best values split and the copies that are made are placed at the same location as their parent.

Step 7. If $k < N_{re}$, which results in keeping the number of bacteria in the population constant to do this, if a bacterium is go to Step2. In this case the number of specified reproduction steps is not reached and start the next generation in the chemotactic loop.

Step 8. Elimination-dispersal: for i =1,2,...,S with probability P_{ed} eliminate and disperse each bacterium, eliminated, simply disperse one to a random location on the optimization domain. If l <Ned , then go to Step2; otherwise end.

BFO reduces extracted features to remove redundancy and irrelevant features and the resulting feature subset (through BFO) is a representative subset. BFO parameters are listed in the table below:

Table 1 BFO Parameters

Parameter Name	**Description**
J_{cc}	Cost function value
J^{i}_{Health}	Health of bacterium i
L	Counter for elimination- dispersal step
P_{ed}	Probability of occurrence of elimination-dispersal events
S	Population of the E. coli bacteria
$\omega_{attract}$	Width of attractant
$\omega_{repellant}$	Width of repellent

The BFO algorithm has some drawbacks concerning complexity, possibility of being locked up by a local solution. These are overcome by Local search. It is an iterative algorithm moving from one solution S to another S' according to a neighbourhood structure. Local search procedure has the following steps.

1. Initialization. Choose initial schedule S to be current solution and compute value of the objective function F(S).
2. Neighbour Generation. Select a neighbour S' of current solution S and compute F(S').
3. Acceptance Test. Test whether to accept move from S to S'. If accepted, then S' replaces S as current solution; otherwise S is the current solution.
4. Termination Test. Test whether algorithm should terminate. If so, output best solution generated; otherwise, return to neighbour generation step.

3.2 Artificial Immune System (AIS)

Artificial immune system (AIS) information is introduced to explain the design and implementation of an immune algorithm and Background information on immune system metaphors to understand AIS classifiers concepts. AIS are a new computational intelligence process inspired by a biology immune system. Immune systems regulate defence mechanism of innate and adaptive immune response. The latter is more important as it has metaphors like diversity, recognition, memory acquisition and self-regulation [23]. Of various mechanisms in a biological immune system that are explored, clonal selection, negative election and immune network model are most discussed.AIS' key features like feature extraction, recognition, and learning are used in classification and clustering tasks. AIS's advantage is that it requires positive examples and patterns, it has learnt, are explicitly examined. Also as it is self-organizing, no effort is needed to optimize system parameters.

AIRS is a popular immune classification system whose aim is to develop a set of memory cells to classify data. Memory cells are evolved from an artificial recognition balls (ARBs) population. An ARB represents many identical ARB cells and reduces duplication. It dictates survival in a population [24]. The AIRS maintain a memory cells population and ARBs for each class of antigen (AG).The algorithm's first stage is determining the affinity (based on Euclidean distance) of memory cells to each AG of a specific class. The next stage is identifying strongest ARBs, based on affinity to a training instance. They create an established memory set for classification. This is achieved through a resource allocation mechanism.

An important problem of most current artificial immune classifiers is the antibody population, which is the classifier, is generated randomly. Clonal selection classification algorithm (CSCA) uses antibody pruning to remove bad antibodies with low fitness scores, to improve classification performance [25]. But, there are high affinity antibodies in the antibody population in CSCA, which decreases fitness scores of high quality antibodies and results in high quality antibodies being pruned. Also, there are no mechanisms to guide antibody generation, which may affect classification performance negatively.

4. EXPERIMENTAL RESULTS

In this investigation, Wavelet and GLCM are used for feature extraction after. Features are selected by Correlation Feature Selection (CFS), Information Gain (IG), proposed BFO and hybrid BFO.

Table 2 Classification Accuracy

Techniques	AIS classifier	Ripper	OneR	Proposed AIS classifier
Feature selection using CFS	89.2	84.53	85.47	93.13
Feature selection using IG	94.13	86.87	87.6	94.87
Feature selection using proposed CFS -BFO	95.13	87.87	89.2	96.07
Feature selection using proposed CFS -HBFO	95.93	89.13	91.13	97.07

The experimental results with the different classifiers and various feature selection methods are obtained as above.

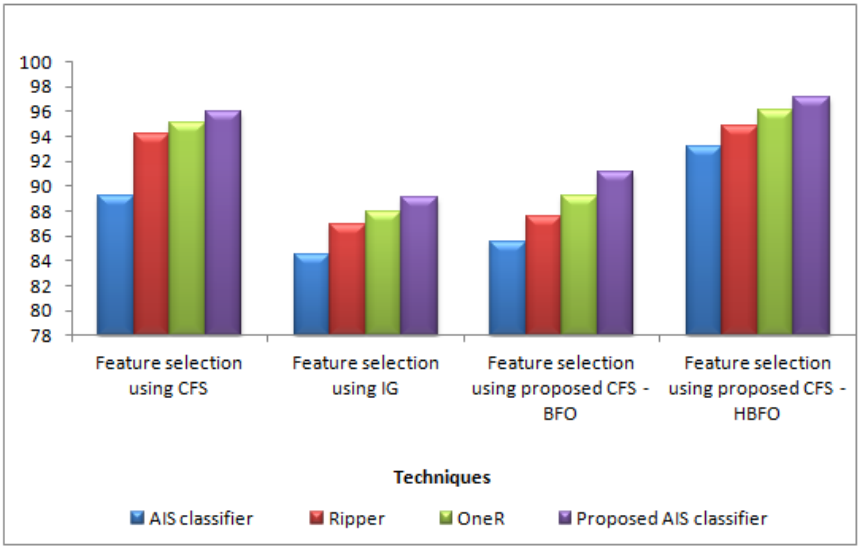

Figure 1 Classification Accuracy

The Ripper classifier with HBFO improved the classification accuracy by 5.2977% when compared with the Ripper with using CFS method. The proposed AIS classifier with HBFO improved the classification accuracy by 4.143% when compared with the proposed AIS classifier with using CFS method.

Table 3 Precision

Techniques	**AIS classifier**	**Ripper**	**OneR**	**Proposed AIS classifier**
Feature selection using CFS	0.8918	0.8455	0.8556	0.9316
Feature selection using IG	0.9414	0.8728	0.8799	0.9488
Feature selection using proposed CFS -BFO	0.9517	0.8824	0.8918	0.9609
Feature selection using proposed CFS -HBFO	0.9596	0.893	0.9119	0.971

Precision is a measure of classifiers exactness. It is the number of positive predictions divided by the total number of positive class values predicted. The precision for the different techniques used is depicted in the above table.

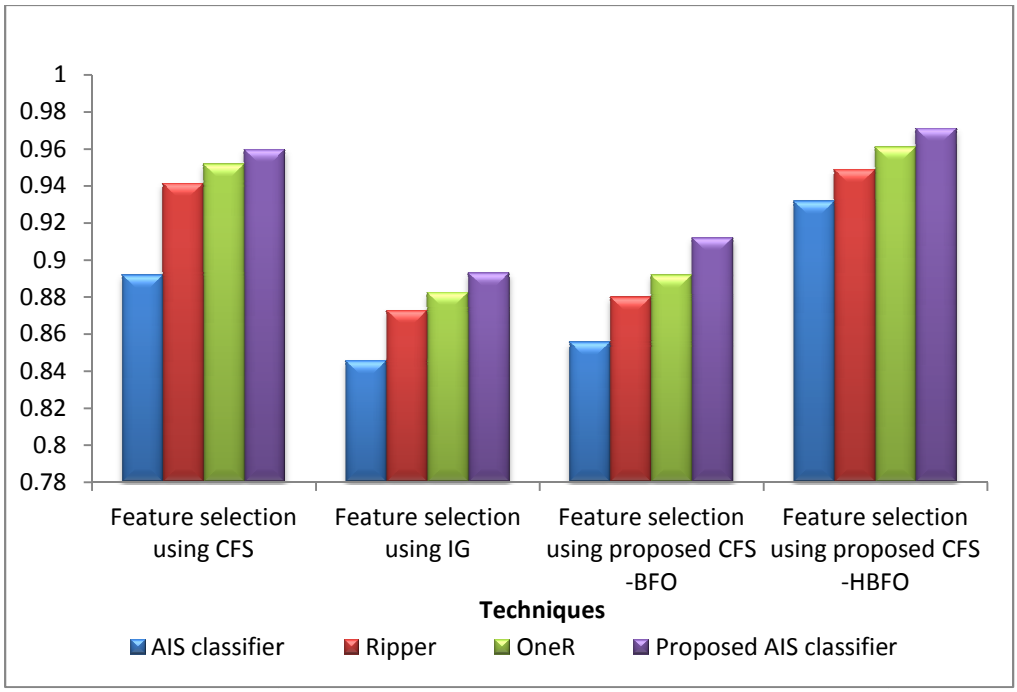

Figure 2 Precision

The Ripper with HBFO improved the precision by 5.4645% when compared with the Ripper with using CFS method. The proposed AIS classifier with HBFO improved the precision by 4.1417% when compared with the proposed AIS classifier with using CFS method.

Table 4 Recall

Techniques	**AIS classifier**	**Ripper**	**OneR**	**Proposed AIS classifier**
Feature selection using CFS	0.8918	0.8455	0.8556	0.9316
Feature selection using IG	0.9414	0.8728	0.8799	0.9488
Feature selection using proposed CFS -BFO	0.9517	0.8824	0.8918	0.9609
Feature selection using proposed CFS -HBFO	0.9596	0.893	0.9119	0.971

Recall is the measure of classifiers completeness. It is the number of True Positives divided by the number of True Positives and the number of False Negatives. The table above depicts the recall values obtained for the different techniques applied in this research.

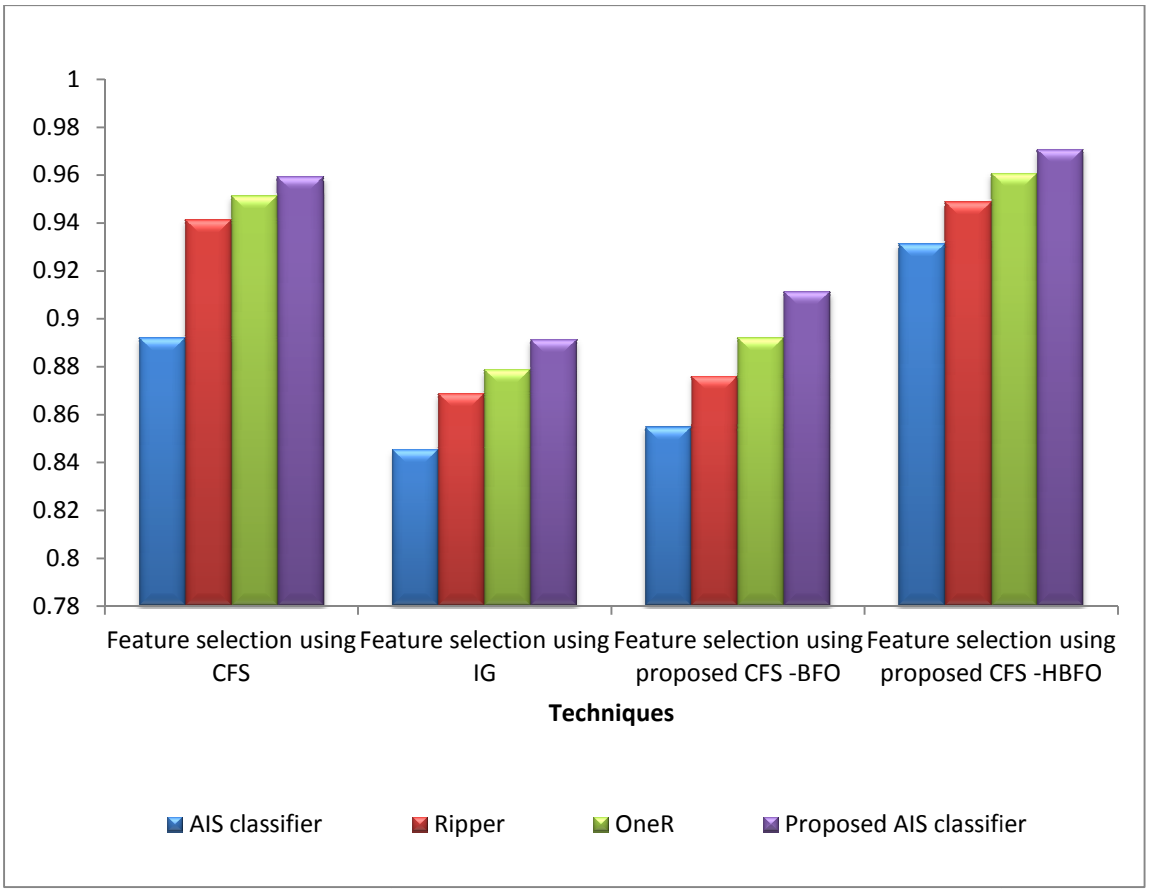

Figure 3 Recall

The Ripper with HBFO improved the recall by 5.2977% when compared with the Ripper with using CFS method. The proposed AIS classifier with HBFO improved the recall by 4.143% when compared with the proposed AIS classifier with using CFS method.

Table 5 F Measure

Techniques	AIS classifier	Ripper	OneR	Proposed AIS classifier
Feature selection using CFS	0.8919	0.8454	0.8551	0.9314
Feature selection using IG	0.9413	0.8707	0.8779	0.9487
Feature selection using proposed CFS -BFO	0.9515	0.8805	0.8919	0.9608
Feature selection using proposed CFS -HBFO	0.9594	0.8921	0.9116	0.9708

F-measure is the measure of a test's accuracy. It is interpreted as the average mean of Precision and Recall. F-measure reaches its best value at 1 and worst at 0. Here, the highest F-measure is obtained with the proposed AIS classifier.

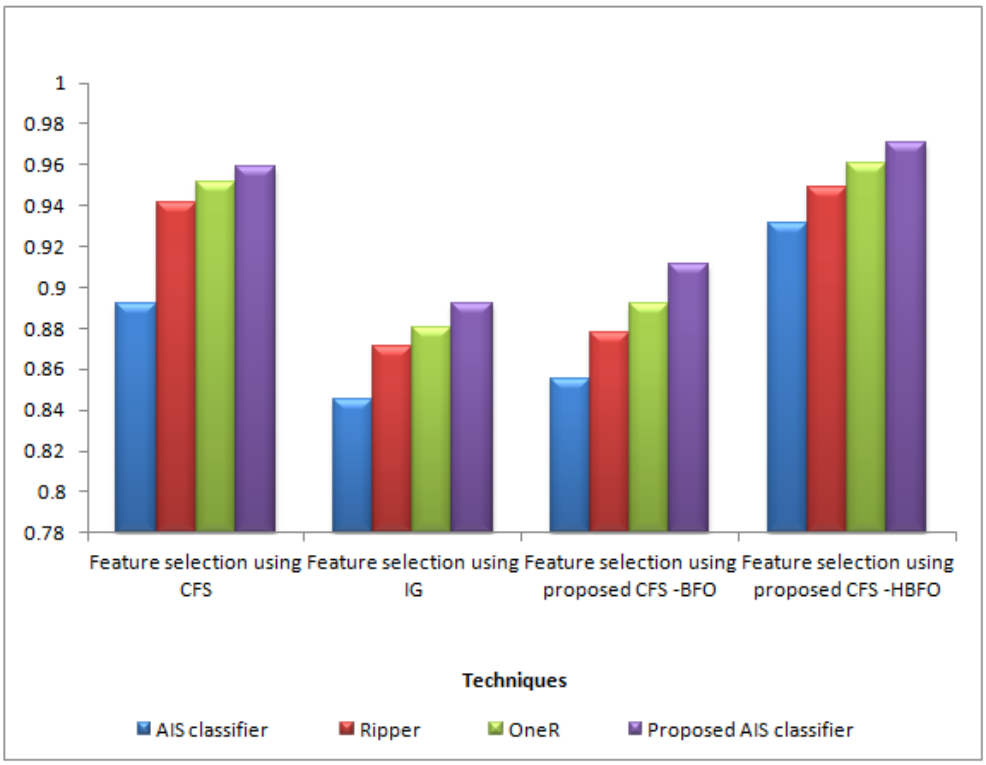

Figure 4 F Measure

The Ripper with HBFO improved the f measure by 5.3755% when compared with the Ripper with using CFS method. The proposed AIS classifier with HBFO improved the f measure by 4.1426% when compared with the proposed AIS classifier with using CFS method.

5. CONCLUSION

Medical images classification in different applications is basic in medical image retrieval systems. Bio-medical devices use imaging techniques like Computed Tomography (CT), and Magnetic Resonance Imaging (MRI), which are important diagnostic factors. Due to medical image data's high variability, correct classification models must be used. CT modality is applied to clinical diagnosis to help radiologists detect/locate pathological changes accurately. This paper used an AIS classifier with hybrid BFO for medical images classification. Results proved that the new method improved performance over other classifiers and feature selection methods.

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