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USING OPTIMIZED FEATURE SELECTION FOR CLASSIFICATION OF BRAIN MRI

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ABSTRACT

Several studies into the detection of brain anomalies have been carried out because of its considerably significant role in the identification of anatomical areas of interest for diagnosing diseases, treating illnesses or even the planning of surgeries. Alzheimer's disease (AD) is the most typical kind of dementia amongst elderly people across the world. Magnetic resonance imaging (MRI) is a method which yields images of excellent quality of the anatomical features of the human body, particularly in the brain and offers clinical data supporting diagnoses as well as for biomedical research. The current study is a features selection as well as classification study for normal brain subjects. During the features selection phase, features are chosen through Bacterial Foraging Optimization (BFO). Experimental evaluation was carried out for several other features selection techniques such as Information Gain (IG), Minimum Redundancy Maximum Relevance (mRMR) as well as classifiers such as Instance-based Learning (IBL), C4.5 as well as Fuzzy Classifiers.

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KEY WORDS

Image retrieval,Feature selection, Information Gain (IG), Bacterial Foraging Optimization (BFO), Fuzzy Classifier

INTRODUCTION

Humans have an extremely complex brain anatomy because of its complicated structure as well as functions. The brain is an integral part of the Central Nervous System (CNS) and is the center that controls the mental processes as well as physical actions of the human body. Brain abnormalities are symptoms wherein motor impairments or neuropsychological issues impact the CNS [1]. It is typically an anomalous growth of cells in the brain that may or may not be carcinogenic in nature. Several studies into the detection of brain anomalies have been carried out because of its considerably significant role in the identification of anatomical areas of interest for diagnosing diseases, treating illnesses or even the planning of surgeries.

Alzheimer's disease is a typical form of dementia and mostly presents itself in elderly people. Almost thirty million individuals in the world are afflicted with Alzheimer's and due to the rise in life expectancies the figure is expected to be tripled by the year 2050. Identifying efficient biomarkers is critical so as to diagnose as well as treat AD earlier in people who are most vulnerable to the illness. Mild Cognitive Impairment (MCI)is the stage of transition between age-related deterioration in cognition and Alzheimer's or between the earliest identifiable phase of progression toward dementia or Alzheimer's [2]. On the basis of earlier work, it is known that a considerable set of MCI afflicted individuals, around 10-15% will end up with Alzheimer's annually. Alzheimer's is recognized through the formation of intra-cellular neuro-fibrillary tangles as well as extra-cellular β-amyloid plaques and tremendous loss of synapses as well as neuronal deaths (atrophy) in the brain. The growth of the neuropathology in Alzheimer's may be noted for several years prior the appearance of the clinical symptoms of the illness.

In the current work, a new MRI-based method for detecting Alzheimer's conversion earlier on in MCI afflicted individuals is suggested through the usage of sophisticated machine learning protocols as well as combination of MRI information with standard neuropsychological test results. In further detail, the objective is the prediction of whether MCI afflicted individuals will develop Alzheimer's within a three year period through usage of baseline data. The information utilized in the current work is taken from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset that has MRIs as well as neuropsychological test results from standard Normal Controls (NC),

THE IIOAB JOURNAL ISSN: 0976-3104

Alzheimer's, and MCI cohorts. In recent studies, the focus has been on the prediction of transformation of MCI to Alzheimer's through the usage of MRI, Positron Emission Tomography (PET), Cerebro-Spinal Fluid (CSF) biomarkers as well as demographic/cognitive data.

Recently there has been a rise in the amount of software as well as hardware technology, several kinds of medical images like MRI, Computer Tomography (CT), X-Ray, ultrasound among others which are being produced in several medical centers. The medical scans provide significant anatomical as well as functional data regarding various body parts for detecting, diagnosing, treating diseases as well as for research and educational purposes [3]. Hence, the issue of efficient storage, processing as well as retrieval of medical image data is an important research area. An effective retrieval system is required for efficient organization as well as retrieval of medical images. Image retrieval is a model that is capable of browsing, searching as well as retrieving images from large datasets in an automated manner.

Image Retrieval refers to the job of looking for images from an image dataset. Queries to the dataset may be of any one of the several kinds given below:

- Query-by-text:Textual descriptions of image being searched for, is given as query.
- Query-by-sketch:Sketch of image being searched for is given as query.
- Query-by-example:Example image that is like the one being searched for is given as query.

In Image Retrieval, interactions are allowed with the users and these permit the users to manage their searches thereby providing assistance in the reaching of excellent results rapidly. One generally utilized method in information retrieval is relevance feedback. That is to say, after initial searches, users are given a list of results. It is quite obvious that certain results will match the queries while some do not. Users then mark the matching results as relevant while the remaining are deemed irrelevant. It is proven that relevance feedback is particularly helpful in information retrieval jobs which excellent results have been attained in image retrieval too.

Diagnostic MRIs are excellent clinical tools for visualization of organs as well as soft tissue in human skulls with no negative effects. It permits the healthcare professional to choose correct image plane for displaying pathological anatomies in an accurate fashion. The key points are that it is safe for handling, not radiological as well as non-invasive. Identification of brain diseases is the most accurate through these grey scale images. Conventionally, the determination of normal or anomalous depends on radiologist expertise [4]. The decisions are also highly reliant on their experience that might be related to particular features from their visual interpretations of the image or certain comparisons with other pathologies.

Images may be characterized in terms of basic attributes known as features, which can be categorized into two [5]: 1) Natural features which are delineated on the basis of visual appearance of the image and 2) Artificial features which are due to manipulation of images.

Features selection is extremely significant as all features are not useful in image retrieval systems. Certain features might interfere and reduce the success rates of the model. The primary goal of features selection therefore is the selection of a set of optimal features from a huge quantity of features. Accuracy is maximized while retrieval is simplified. Features selection may also be described as the choosing of amalgamations which best describe a features set. Features selection is a vast research area ever since the 1970s in the fields of pattern recognition, image retrieval as well as several other research domains.

Extra or repetitive features are discarded through the usage of dimensionality reduction methods and adequate quantity of useful features is extracted. Intrinsic dimensionality is needed for representing image feature values. Because of this reason there is a lot of interest in the reduction of dimensionality of descriptors through the stabilization of unique topologies of higher dimensional spaces. Dimensionality reduction methods in literature include Principal Component Analysis (PCA), Weighted Multi-Dimensional Scaling, Tabu Search (TS).

In recent years, Evolutionary Algorithms (EA) operate on the population of potential solutions through the relation of the presence of fittest yields best estimates to a solution. The primary benefit of usage of Evolutionary Algorithms is the searching of a set of potential solutions in a simultaneous manner for finding optimum features selection with less runs of the protocol. The most commonly utilized Evolutionary Algorithms for optimization of features are Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Gravitational Search Algorithm (GSA)

THE IIOAB JOURNAL ISSN: 0976-3104

Ant Colony Optimization (ACO). Generally, algorithms are sorted on the basis of the technique of evolution. For instance, GA evolves through every subsequent population of chromosomes while PSO as well as ACO update as per social behavior.

Classification as well as clustering are important components of image mining. Machine learning methods are utilized for reducing semantic gaps between low-level image features as well as high-level semantic features. Data classification is a two-stage procedure, comprising learning stage as well as classifications stage [6]. Classification algorithms are employed on image datasets wherein images are described for classification into classes. Classification is a problematic task in several fields such as biomedical imaging, video surveillances, vehicular navigation, remote sensing and so on and so forth. Image classification comprises three stages:

Feature extraction – Here, features are extricated from sample images which are pre-labeled and features descriptions for all images are established.

Training – Here, samples of all classes are trained and model descriptions for all classes are set up.

Classification – Model is utilized for classifying as well as indexing images which are not labeled.

Classifying pixels is useful in several areas within the domain of image processing. Particularly speaking, classification of pixels in image is helpful as a pre- or post-processing stage for the issue of image segmentation, that is, for facilitating segmentation or for refining the results. The usage of pixel classifications may also be employed for improving the performance of certain applications in the retrieval of images from the dataset.

In this paper Bacterial Foraging Optimization algorithm is proposed for feature selection and the experiment results compared with the other methods to evaluate the proposed method. The remaining sections organized as: Section 2 reviews the related work in literature. Section 3 explains the methods which are used in the proposed work. Section 4 discusses the experiment results and section 5 concludes the proposed work.

LITERATURE REVIEW

Veeramuthuet al., [7] utilized Spatial Gray Level Difference Method (SGLDM) features extraction protocol as well as Correlation based Feature Selection (CFS). Projected Classification protocol (PROCLASS) is suggested for brain image data. Experimental evaluation was carried out for comparison of the plug-in protocols with FAST, FCBF features selection protocols.

Spedding et al., [8] looked into the issue of features selection in neuroimaging features from structural MRI brain images for classifying subjects as healthy (controls), MCI-afflicted or AD afflicted. Genetic algorithm wrapper technique for features selection as utilized in conjunction with Support Vector Machine (SVM) classifier. Greatest accuracy attained was during the classification of test data (65.5%) through usage of genetic algorithms for features selection with three-class SVM classifier.

Padilla et al., [9] suggested a new computer-aided diagnosis (CAD) method for diagnosing Alzheimer's earlier on the basis of non-negative matrix factorization (NMF) as well as Support Vector Machine with bounds of confidence. Resultant NMF-transformed datasets contained lesser quantity of features and are sorted through usage of SVM-based classifier with bounds of confidence for decisions. The suggestedNMF-SVMtechnique provides 91% classification precision with extremely high sensitivity as well as specificity rates (greater than 90%). The NMF-SVM CAD tool is an accurate technique for SPECT as well as PET AD images classification.

A smart system was formulated bybyGopal&Karnan [10] for diagnosing brain tumors through usage of image processing clustering protocols like Fuzzy C Means alongside intelligent optimization techniques like GA as well as PSO. Detecting tumors happens in two stages which are pre-processing as well as improvement in the first and segmentation as well as classification in the second.

Sweety&Jiji [11] suggested Particle Swarm Optimization for reducing features as well as decision tree classifiers for classifications. Detecting Alzheimer's early happens in three stages: 1) features like Eigen vectors, Eigen brain, eman, variance, kurtosis and so on are extricated from MRIs and 2) Number of features are reduced through Particle Swarm Optimization and 3) Decision Tree classifiers are utilized for detecting if brain images are impacted by Alzheimer's or not.

Sasikala&Kumaravel [12] suggested as well as contrasted features selection protocols for detecting glioblastoma multiform in brain images. Textural attributes are extricated from normal as well as tumorous regions (RoI) through usage of spatial grey level dependence methods as well as wavelet transforms.Artificial neural networks are utilized for classification. PCA, traditional sequential techniques as well as floating search protocol are contrasted with genetic algorithms with regard to best recognition rates obtained as well as optimum quantity of features. Genetic algorithms achieve classification performance of 97.3% with optimum features when contrasted with sequential method as well as Principal Component Analysis.

THE IIOAB JOURNAL ISSN: 0976-3104

Brain atrophy with certain standard positions was valuated by Alam et al. [13] through usage of dimensionality reduction techniques. Comparisons were carried out between PCA as well as manifold learning through usage of LaplacianEigenmaps for quantifying brain atrophy. Additionally, a new technique has been suggested using both Principal Component Analysis as well as Manifold Learning that valuates brain atrophy with respective age groups. The suggested technique performs better than both dimensionality reduction technique with a score of (p<;0.0030). The discoveries indicate that multivariate network analyses of deformation maps identifies generic features of atrophy and offers an excellent tool for predicting brain atrophy with age.

METHOD

In this section we discussed different feature selection methods and classifiers used in the proposed work.

FEATURE SELECTION

Features selection is a global optimization issue in machine learning that decreases quantity of features, discards non-relevant, noise-filled as well as repetitive information and leads to adequate recognition accuracy. Though features selection is generally carried out for selecting relevant as well as useful features it also reduces computational overheads.

INFORMATION GAIN (IG)

The primary objective of IG criterion is the discovery of the quantity of unique data added by one feature to the entire features set. A feature's IGf may be calculated by F (S U f) − F (S), whereinF (.) refers to the evaluator criteria while S represents the chosen features subset. Features with more IG are favored.

IG is a metric based technique utilized for choosing best split features in decision tree classifiers as well as denotes the extent to which data's entropy is decreased. Furthermore, it detects values of every particular feature. All features basis obtain IF values that are utilized for deciding whether features are chosen or discarded. Therefore, threshold values for features selection are to be setup initially, features are selected when IG values are greater than threshold ones. Assume there is a set A comprising s samples and a set B comprising k classes. If P(Bi, A) is the fraction of samples in A which have class Bi, then, the anticipated information for class membership is expressed through [14]:

$$Info(A) = -\sum_{i=1}^{k} P(B_i, A) * \log(P(B_i, A))$$

The greater the IG, the greater the chance of obtaining pure classes in target class if splits are based on the parameter with the greatest gain.

MINIMUM REDUNDANCY-MAXIMUM RELEVANCE (MRMR)

Minimum Redundancy-Maximum Relevance (mRMR) refers to a mutual information based technique and it chooses features as per maximal statistical dependency criteria. Because of the challenges involved in the direct implementation of maximal dependency condition, mRMR is an approximation for maximization of dependency between joint distributions of chosen attributes as well as the classification parameter [15]. Minimization of redundancy for discrete attributes as well as continuous attributes is given by:

For Discrete attributes: minWI, $$W_I = \frac{1}{|S|^2} \sum_{i,j \in S} I(i,j)$$

For Continuous attributes: minWc, $$W_C = \frac{1}{|S|^2} \sum_{i,j \in S} |C(i,j)|$$

whereinI(i, j)as well asC(i, j)refer to mutual information as well as the correlation between fiandfj, correspondingly. Maximization of relevance for discrete as well as continuous attributes is given by:

For Discrete attributes: max VI, $$V_I = \frac{1}{|S|^2} \sum_{i \in S} I(h,i)$$

For Continuous attributes: max Vc, $$V_C = \frac{1}{|S|^2} \sum_{i} F(i,h)$$

whereinhrefers to the target class whileF(i, h)represents the F-statistic.

THE IIOAB JOURNAL ISSN: 0976-3104

PROPOSED BACTERIAL FORAGING OPTIMIZATION (BFO)

Features selection is a global optimization issue in machine learning which optimizes/reduces the quantity of repetitive as well as noise-filled attributes, discards inappropriate attributes resulting in adequate accuracy. Bacteria travel in an arbitrary fashion for finding greater amount of nutrients. Therefore the optimization method is helpful when gradients of cost functions are not made known. BFO, a non-gradient optimization method, is excellent due to its relative mathematical simplicity.

The notion of Bacterial Foraging Optimization has its basis in the fact that natural selection leads to the elimination of species with inadequate foraging schemes. After several generations, inadequate foragers are either wiped out or evolved into excellent ones. For instance, the E coli bacteria's foraging scheme is governed by four procedures which are chemotaxis, swarming, reproduction, as well as elimination and dispersal.

CHEMOTAXIS:

Chemotaxis is attained through swimming as well as tumbling. On the basis of flagella rotation in all bacteria, it is decided whether they should travel in a particular direction (which is known as swimming) or if they should travel in another direction (which is known as tumbling), for the duration of the bacteria's total lifetimes.

SWARMING:

Bacteria which have obtained optimal route of food attracts other bacteria for ensuring that they also arrive at that place in a fast manner.

REPRODUCTION:

Those bacteria that are not healthy die while healthy ones are divided into two and situated in one location so as to maintain constancy in the population of bacteria.

ELIMINATION AND DISPERSAL:

There is a possibility that in local environments, population lives change in a gradual manner through consumption of nutrients or because of arbitrary outside influences.

Extricated features are decreased through the usage of Bacterial Foraging Optimization for removing repetitive as well as non-relevant attributes and the resultant features subset is the most representative one. The positions of bacteria are either 0 or 1 on the basis of whether features are chosen or not in the search space. In the period of Chemotaxis, tumbling results in novel arbitrary positions which determine whether features are chosen or not in the subsequent iteration. Fitnesses are valuated for all bacteria and positions are updated if fitnesses are improved. Bacteria with the worst fitness are discarded while those with best fitness are split (reproduction). When the iterations are completed, positions of bacteria represent the most optimal features subset obtained **[Table-1]**.

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

CLASSIFIERS

Classification accuracy relies primarily on two elements: accurate features vectors which can identify uniquely the content of a single image; the image classification technique with excellent results which are similar to human beings' perceptions.

C4.5

C4.5 is a protocol that is utilized for generating decision trees and was formulated by Ross Quinlan. It is an extension of a previous ID3 protocol. Decision trees created by C4.5 may be utilized for classification and for this particular reason, c4.5 is typically known as a statistical classifier. C4.5 protocol utilizes IG as splitting criterion. It may input data with categorical or numerical values. For handling continuous values, it creates threshold and later splits features with values greater than threshold as well as values equal to or lesser than the threshold. C4.5 is capable of handling missing values [16] because missing feature values are not used in gain computations by C4.5.

C4.5 utilizes Gain Ratio as a features selection metric for building decision trees. It discards the bias of IG when there are several outcome values of a feature. Initially, the gain ratios of all attributes are computed. Root nodesare the attributes whose gain ratios are maximum. C4.5 utilizes pessimistic pruning for removing non-required branches in the decision tree for improving classification accuracy.

THE IIOAB JOURNAL ISSN: 0976-3104

INSTANCE-BASED LEARNING (IBL)

IBL is based in a set of machine learning protocols and it popular as memory-based learning as well as case-based learning. IBL protocols store the information and begin processing solely when predictions are demanded, which is why it is known as a lazy learning technique. IBL protocols do not generate extensional concept descriptions. As an alternate, concept descriptions may be determined by how IBL's chosen similarity as well as classification functions utilize the current set of saved distances. These functions are two of the three elements in the model given below which defines all IBL protocols:

Similarity Function:It computes similarity between training samples i as well as samples in the concept description. Similitude is a numeric value.

Classification Function:It acquires similitude function's outcomes as well as classification performance records of samples in the concept descriptions. It outputs classification for i.

Concept Description Updater:It maintains records on classification performances and determines the samples to be included in concept descriptions. Input involves i, classification outcomes, similitude outcomes as well as current concept description. Output is the altered concept description.

Instance-based Learningdecreases the quantity of training samples stashed to a minute set of representative ones. A further benefit of Instance-based learning is that it may be utilized in issues other than classification.

FUZZY CLASSIFIER

Certain problems occur because of the imbalanced classes as well as errors in object segmentation. This is the motivation for usage of fuzzy rule-based classifiers. Fuzzy sets are sets whose elements possess degrees of membership. Elements of fuzzy sets may be full members or partial members. This implies that membership values designated to elements are not constrained to merely two values (0 and 1). It may be 0, 1 or any value between the two. Mathematical functions that define the degree of membership of elements in fuzzy sets are termed membership functions. The linguistic description of the problems rather than precise numerical descriptions is the primary benefit of the fuzzy set theory.

Fuzzy inference refers to the procedure of formulating mapping from particular input to output through usage of fuzzy logic. Procedure of fuzzy inference includes: membership function, fuzzy logic operator as well as if-then rule. Fuzzy sets as well as fuzzy operators are the subjects as well as verbs of fuzzy logic. Typically the knowledge in fuzzy reasoning is described as a rule in the form given below:
If x is A Then y is B

wherein x as well as y refer to fuzzy parameters while A as well as B refer to fuzzy values. If-component of the rule "x is A" is known as the antecedent or premise and the then-component "y is B" is known as the consequent or conclusion. Statements in the premise or conclusion components of the rule may include fuzzy logical connectives like AND, OR and so on. In the if-then rule, the term 'is' is utilized in two completely distinct ways based on whether it is present in the premise or conclusion component.

RESULTS AND DISCUSSION

The experiments conducted for 3 different kinds of diseased images for the feature selection methods IG, MRMR and proposed BFO with the 3 classifiers, IBL, C4.5 and fuzzy classifier. **[Table-2]** shows the results from the experiments for different techniques.

Table: 2. Experiment Results

Techniques	IG-IBL	MRMR-IBL	BFO-IBL	IG-C4.5	MRMR-C4.5	BFO-C4.5	IG-Fuzzy classifier	MRMR-Fuzzy classifier	BFO-Fuzzy classifier
Classification accuracy	75.29	77.06	80.59	78.24	79.41	81.18	82.18	82.76	84.71
AD- Sensitivity	0.6909	0.7455	0.8	0.7636	0.8	0.8	0.7797	0.7797	0.8
MCI - Sensitivity	0.8462	0.8462	0.8615	0.8462	0.8462	0.8615	0.8615	0.8615	0.8769
CS-Sensitivity	0.7	0.7	0.74	0.72	0.72	0.76	0.82	0.84	0.86
AD- Specificity	0.8911	0.8911	0.9029	0.901	0.901	0.9038	0.9238	0.9245	0.9346
MCI -Specificity	0.8111	0.8261	0.871	0.8387	0.8602	0.8817	0.8878	0.898	0.9063
CS- Specificity	0.8692	0.8889	0.9009	0.8899	0.8919	0.9009	0.8947	0.8947	0.9099

THE IIOAB JOURNAL ISSN: 0976-3104

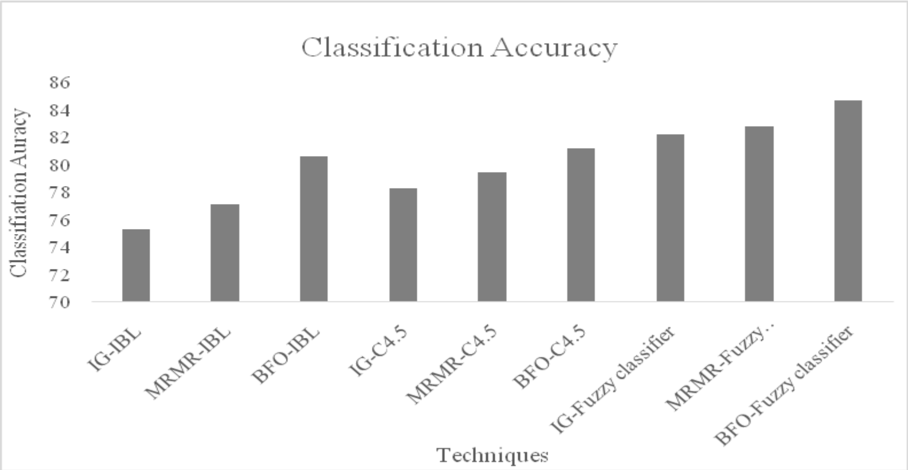

Fig:1. Classification Accuracy

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From **[Figure -1]**, it can be observed that the proposed BFO with fuzzy classifier improved accuracy by 4.98% when compared with BFO with IBL method and by 4.26% than BFO with C4.5 classifier.

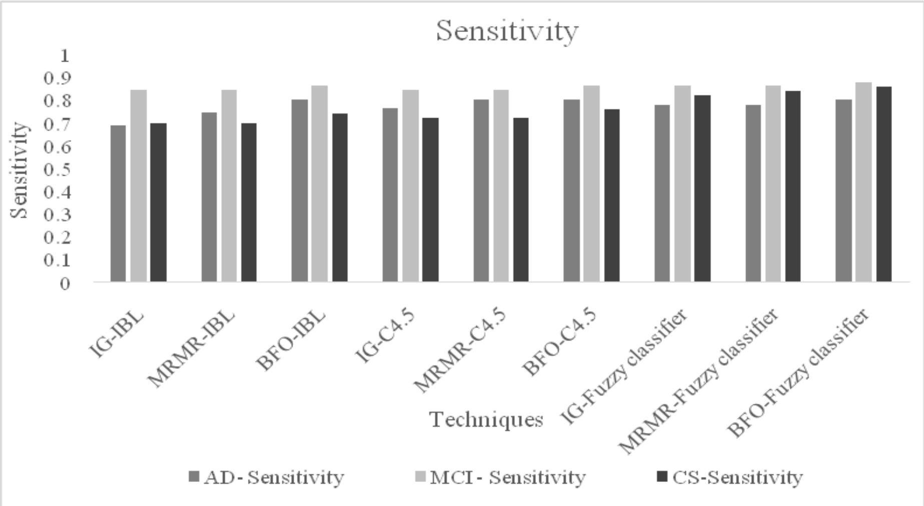

Fig: 2. Sensitivity

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It is observed from **[Figure -2]** that the proposed BFO with fuzzy classifier achieved sensitivity by 15% for CS and by 1.77% for MCI than BFO with IBL method.

COMPUTER SCIENCE

THE IIOAB JOURNAL ISSN: 0976-3104

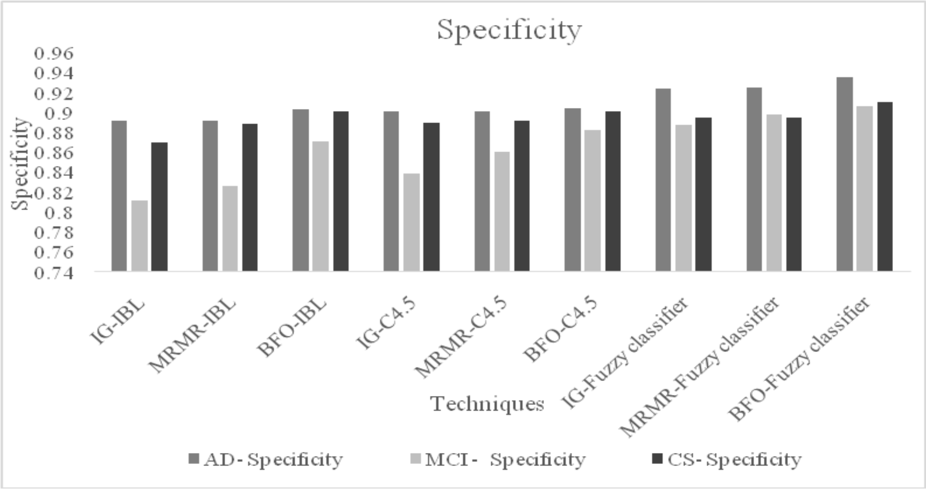

Fig:3. Specificity

It is observed from **[Figure -3]** that the proposed BFO with fuzzy classifier achieved specificity by 3.45%, 3.97 and 0.99% for AD, MCI and CSwhen compared withBFO with IBL method.

CONCLUSION

MRIs are typically the medical imaging technique used when soft tissue delineation is required. This is particularly true for attempt to sort brain tissue. Current work has proven that classifying human brains in MRIs is possible through supervised methods like ANNs as well as SVMs, and unsupervised classification methods like SOMs as well as Fuzzy C-Means merged with features extraction methods. In this work feature selection is done using bacterial foraging optimization. The experiment is conducted for 3 classifiers with IG, MRMR and the proposed BFO. The results indicated that the proposed feature selection outperformed than other methods.

CONFLICT OF INTEREST

The authors declare no conflict of interests.

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The authors report no financial interests or potential conflicts of interest.

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