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HYBRID ARTIFICIAL IMMUNE SYSTEMS FOR CLASSIFICATION ON MRI BRAIN IMAGES

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ABSTRACT

Aim: *Dementia is a common neurodegenerative disease which propagates itself through minute symptoms and develops into a form of severe brain damage. Magnetic Resonance Imaging (MRIs) are currently the best medical imaging tools that permit cross-sectional views of the human body with excellent tissue contrasts. MRIs play a significant part in the appraisal of pathological features of brains and are effective in diagnosis of dementia. In this work, the brain MRI are classified as dementia and non-dementia. Features are extracted using Discrete Wavelet Transform (DWT) and feature selection is via proposed hybrid Artificial Immune System (AIS). Genetic Algorithms (GAs) are combined with AIS to optimize the feature subset selection. Naïve Bayes, C4.5 and K nearest neighbour then classifies the selected features as dementia or non-dementia. Experimental results show that the proposed method is effective in improving the efficiency of the classifiers*

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KEY WORDS

Magnetic Resonance Imaging (MRI), Dementia, Feature Selection, Artificial Immune System (AIS), Naïve Bayes, KNN, C4.5,Radial basis function (RBF).

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INTRODUCTION

Alzheimer's Disease (AD), an old age-related illness, characterized by progressively declining cognitive facilities. It is widely accepted that this is a disease that affects only the elderly, i.e. people who are sixty-five, and is a predictable onset of dementia. However, aless-known fact about AD’s and more importantly about Dementia is that this disease is not restricted to the elderly, and there are several variations of the illness [1]. Not all the variants of Dementia are age based, and vascular or multi-infarcted illnesses are an example of irreversible dementia. Apart from this, Alzheimer's is a kind of disease that progressively declined mental capacities, like cognition, memory and learning capabilities. AD is accepted as a predominant old age illness and cannot be associated with vascular dementia, as the latter could be an onset of motor disabilities and cognitive malfunctions. However, the presence of AD is quite subtle as the disease does not immediately present itself. It propagates itself through minute symptoms which can develop into a form of severe brain damage. It is, therefore, essential to recognize the onset of AD before it gradually takes over as a serious illness. Some common methods used for early diagnosis are Magnetic Resonance Imagers (MRI) and Computed tomographers (CT). These recommended techniques follow prescribed guidelines to capture the illness at any stage of its growth. It must be noted that only a rare percentage of dementia patients can be completely treated, and individuals with Dementia Lewy bodies (DLB), Front Temporal Dementia (FTD) and Vascular Dementia (VaD) are harder to treat [2].

The brain is the major organ which is affected by AD and it is through the loss of healthy cognitive functioning that Alzheimers can eventually result in loss of tissues and large-scale cerebral nerve cell damage. The operation of the brain, with age, deteriorates to the point where the slow loss of cognitive and intellectual functions leads to dementia. Here, it is observed that the brain can lose five to ten percent of its total volume during the transition to old age. Some of the leading causes of dementia, apart from Alzheimers, are caused due to organ failures, drug toxicity, and other similar reasons [3].

Recently, a new field of research is slowly gaining popularity, due to its likeness to the study of vertebrate immune systems. The study of this immune system could propagate a new terrain of study based on a bundant theories to generate resources for computer-based solutions. This growing field has is called the Artificial Immune System (AIS), and it utilizes notions from immunology to help build appropriate models which can perform tasks in engineering applications. Although this field might lack detailed resources for remote sensing, there is scope for developing this field within the paradigm of AIS study [4].

CT generated information provides relevant information for positron emission tomography (PET) and holistic care of the patients. There are numerous protocols undertaken by using PET/CT scans, commonly used for low -dosage attenuation corrections and anatomic localizations, in the situation where patients have an existent MR of their skull. If in the case where the MR IS contraindicated, a portion of the CT exam is an optimized performance with standard imaging parameters. It is important to review carefully CT images to minimize radiation dose to the lens [5].

An inherent initial stage in mining of huge databases is to calculate feature selections for classification of any pattern problem. Computational burdens are vastly decreased, by the reduction of data dimensionality. Feature selections algorithms constructed based on the following categories: exponential, randomized, and sequential, and the task of these algorithms is to search for best feature subsets which will reduce possible feature space with fewer losses in classification accuracy. The ideal goal here is to lower the number of features which are being analyzed, without the sacrificing of class discrimination, and eventually lead to classification accuracy [6].

This paper suggests a machine learning approach to help classify dementia and MRI medical images from each other, based on Discrete Wavelet Transform (DWT) to analyze features. It is proposed to use Artificial Immune System (AIS) as a feature selection methodology. The chosen features are categorized using Naïve Bayes, CART, C4.5 and K-Nearest Neighbour techniques. To evaluate the techniques, MRI image samplesare acquired from Open Access Series of Imaging Studies (OASIS) dataset. There maining paper is arranged thus: Section 2 reviews the essential iterature of the above problem. Section 3 & 4 provides a detailed methodology, and the experimental results, which is concluded in Section 5.

LITERATURE SURVEY

One of the methods to segment MRI brain images is presented by Adhikari et al., [7] who considers utilizing the intensity of non-uniformity (INU) and its spatial knowledge, with the help of a fuzzy C-mean clustering algorithm. The non-uniformity of brain images procured by MRI Scanners are repaired by Gaussian surface fusion cells. A single Gaussian surface calculated uniformly over various corresponding surfaces by investigatingits nucleus in the middle of a mass of other similar homogeneous region. Another aspect is the intensity of the inhomogeneity (IIH) where a repaired image is divided based on FCM algorithm probabilities, considering the spatial features of image pixels. The above method has proved to perform well, after utilizing 3D synthetic phantoms as well as actual patient MRIs of brains to conduct the above experiments.

Al-Badarneh [8] et al. proposed an automated classification model., to be utilizedfor MRI image tumor classifications. The results of this classification depicted how NNs as well asKNN models affect tumor classifications. The achievements of the experiments showedfull-fledged accuracies in ranking, using the KNN and 98.92% through NNs. Similarly, Jeena and Kumar [9] illustrated a comparative analysis for diagnosing strokes on CT and MRI images. Their proposed study proposed how to use digital images as a processing tools for identifying hemorrhaging in the cranium. They were able to perform these segmentation tasks using Gabor filtering as seeded region growth algorithms. Finally, the end product of this method was depicted using MRI brain images and CT scans, showing various levels of infarcts.

Extensive efforts to study the above experiment was also carried out by Hamdaoui et al., [10] which added a specific controlled unit that routine every task under various blocks of architecture. Hence, the newly obtained MRI images adhere to the synchronous art of image segmentation under the Particle Swarm Optimization method (PSO) which allows the researchers to cut short during the execution period, thus narrowly reducing the procedural search threshold to an optimal. Therefore, the performance of synchronous hardware infra strucutre is judged and verified based on a collection of medical MRIs. Another researcher Pinto [11]and his fellow colleagues, popularly known for introducing a fukky automatic segmentation algorithm, bases his work on a k-fold cross-validation approach under the Random Decision Forest Mechanism. The following features which were extracted, complemented itself with other intensity based appearances and context-based features. The researcher applied morphological filters for dealing with errors of misclassifications during the post-processing phase. Therefore, the above method achieved highly satisfactory results and wasable to detecta tumor and segment the possible variations of tumorous tissues in the glioma, A new approach was proposed by Rajini and Bhavani [12], who automated the diagnosis system based on MRI classification. Their proposed idea aggregates two different stages divided based on feature extraction and classification. The authors had procured the features related to MRI images in the firststep and using a discrete wavelet transformation (DWT) they extracted which features of MRIs had become diminished. By adopting this principle component analysis (PCA), the derived features will be conditioned to figure neural networks based a binary classifier. Therefore, this will automatically conclude if the image procured are of a healthy brain or a pathologically suffering lesioned brain. Ragini and Bhavani's research proved to have successful conclusions and can help further the MRI classifications. However, these are not the only successful studies available, as other successful stories are available from researchers like Rehman, Saraswathi, and Jang [13]. A Discrete Binary Particle Swarm Optimization (DBPSO) method for MRI feature selection was popularized by Rehman, who utilized it to classify the functioning of normal and abnormal brains, under the purview of Support Vector Machines and K-Nearest Neighbor experiments. The results of his experiment provided high accuracy possibilities and reduced other features which could hinder with performance.

However, a new technique for the detection of start of AD through MRIs was produced by Saraswathi et al., [14] who structured this classifying model into three groups: normal, extremely mild AD as well as moderate AD. The mechanized algorithm study she utilized was commonly known as the Extreme Learning Machine (ELM), which helped in optimizing performance by modifying the PSO as well as GA. Also for the study, a Voxel-Based Morphometry (VBM) method was carried out to extract features in the MRI developed images, and GA was adopted to diminish highly dimensioned features that needed classification.

Finally, Jang et al. [15] suggested a method to extract the cortex of inter-brain subjects, based on co-segmentation method. This method intends to divide binary images together. Jang emphasized the use of Markov Random Field (MRF) as a structure for creating basic functions and utilizing an optimal graph-cut algorithm for identifying identical voxel pairs, using a transformation matrix computed through the matching of 3D SIFT attributes. However to conduct experiments, the author suggests the use of pre-segmented cortex images and copies of segmented brain images, used as references.

METHOD

Since it is not an easy task to determine shapes utilizing feature extractions can be quite useful. The process of extracting features that are necessary for diagnosing the pattern of dementia. This is defined as an extraction process, containing specific characteristic attributes which help in the generation of collection of useful descriptors for images. The process is utilized to discover tissue sets which can precisely differentiate between dementia and non-dementia. However, the process of determining significantly extracted features is tricky as dementia cannot be assessed through a single feature. The various techniques used in feature extraction, feature selection, classification and the proposed technique is detailed in this section.

Dataset

Datasets comprising 436 neurological MRIs were made accessible by Open Access Series of Imaging Studies (OASIS) project. The ages of the subjects are between 18 and 96, with 100 individuals having clinical diagnoses from mild to moderate Alzheimer's disease. All scans comprise of 176x208x176 voxels that were pre-processed to remove the skulls, retaining merely brain matter in the images. All scans are linked to further data regarding the subjects, such as ages, sex, education levels, socio-economic status, intra-cranial volumes as well as normalized brain volumes and two metrics of dementia, which are clinical dementia ratings (CDR) as well as mini-mental state exams (MMSE).

Apart from pre-processing for removal of skulls scans are additionally processed under OASIS through k-means approach for binning pixel intensity as one among four colours that relate to the backgrounds (0), cerebrospinal fluids (1), grey matter (2) as well as white matter (3) [16].

Discrete Wavelet Transform (DWT)

Wavelet transform permits time-frequency localizations. Wavelets refer to small waves such that wavelet analyses refer to analyses of signals of short duration, finite energy function. It transforms signals which are being investigated to another abstraction that yields signals in better forms. In a mathematical manner, wavelets are given by:

$$\psi_{(a,b)}(t) = \frac{1}{\sqrt{|a|}}\psi\left((t-b)/a\right)$$

Wherein b refers to position variable a refers to scaling variable for given scaling variable a, translates wavelets through variation of variable b. Wavelet transforms are given

$$w(a,b) = \int_t f(t)\frac{1}{\sqrt{|a|}}\psi\left((t-b)/a\right)$$

Accordingly, for all (a, b), wavelet transform coefficients, denoting how much scaled wavelets is identical functions at position, t = b/a. Scales as well as positions are altered in a smooth manner, and later transforms are known as continuous wavelet transforms. When scales as well as positions are altered in a discrete manner, transforms are known as discrete wavelet transforms [17].

Feature selection

The removal of unnecessary features via the application of feature selection immediately impacts the speed of the classification process. Typically, a basic feature selection process has four relevant steps followed procedurally, namely:

1) Generating subsets
2) Evaluating subsets
3) Terminating criteria
4) Validating results

Apart from these basic steps, the above method can be represented by the following models. The first type of representation is known as the “Filter Model,” characterized by generic selection of data to access which features can provide an optimal subset(s), without applying learning algorithm, based on methods of correlation, entropy, mutual information, etc. The second model illustrated in this study is called the “Wrapper Model,” which adopts a learning algorithm to investigate features, and benefit its performance, based on the given algorithm. The space provided for the feature can be vast and complex, and therefore, it is essential to find the most efficient features through the selection and extraction process [18].

Proposed hybrid a is feature selection

In the proposed hybrid AIS feature selection, the Genetic Algorithm is incorporated with AIS. The AIS algorithm is summoned to assist GA in influencing the feasibility of units in populations. But rather than merely implanting an alternative GA to the primary search, the study can utilize a basic procedure which can is stimulated through the clonal selection principle. This relationship between AIS and GA is focused on a search outer loop among the current population for optimization constraints and is split into possible antigens and non-feasible antibodies after being investigated for any constraint. If it is found that there is no certainty for feasible individuals, then it is proposed to shift two infeasible individuals to antigen population and thus quantities of duplicates of better infeasible units is adjustable and may be proposed as the potential users.

In AIS a loop situated within alongside antibodies which are cloned and mutated. Following this, the distances are computed between antibodies and antigens and whichever bodies have a higher affinity distance (smaller sum of distances), are chosen to define new antibodies situated near the feasible regions. Thus, the cyclic procedure of the AIS system can be repetitive and some population of antibodies which survive, are passed through a pre-calculated GA system. Finally, this procedure is ended with a selection operation, to apply any recombinations and mutation operators among the parents chosen to reproduce a young population and thus to finish the outer loop of the GA.
Therefore, the GA selection procedure constitutes of binary tournaments in which the chosen candidates and its opponents are selected at random. The ground rules of this tournament are:

(i) The preference of feasible individuals over infeasible ones;
(ii) Healthier candidates will be chosen from a pair of infeasible candidates;
(iii) But it should be noted that individuals with lesser constraints are chosen between a pair of infeasible individuals, as this helps in computing the affinity factors from a genotypical distance, after adopting a Hamming Distance standard [23].
The feature set is encoded in binary form, where

K-Nearest neighbour classifier

KNNs are non-parametric or simple machine learning methods of classification. KNNs are among the most simple classification methods. Classifications are carried out through determination of k nearest training vectors as per adequate distance measure [19].Vector X is designated to the class to which most KNNs are a part of. KNN models are grounded in distance functions as well as voting functions in KNNs, the measure utilized is Euclidian distances. KNN classifiers are traditional non-parametric monitored classifiers which are supposed to provide excellent performances for best values of k. Like other monitored learning methods, KNN algorithms comprise training phases as well as testing phases. During the first one, data points are provided in n-dimensional spaces.
Training data points possess labels connected to them which assign their classes. During testing, unlabelled data are specified while algorithms generate lists of k nearest data points to unlabelled points. Algorithms later return classes of most of the list. Needed: distance functions on samples. Models are labelled training data (a1; c1); (aN; cN). Classification of fresh samples occurs thus:
Let (aj1 ; cj1); : : : ; (ajK; cjK) be K training samples whose features are nearest to a. Label a with class label which occurs mostly amongst cj1...... cjK., may provide greater weights to near neighbours weighted votes for labels.

$$v(c)=\sum_{x=1,cji=c}^{k}\frac{1}{d\left(a_{ji},a\right)}$$

Weighted votings are computed with c which have greatest v(c) values.
Algorithm of KNN:

1. Adequate distance measures are determined
2. During training stage: Stashes entire training data sets P as pairs (as per chosen attributes) P = (yi, ci), i=1. Wherein yi refers to training patterns in training datasets, ci refers to respective classes while n refers to quantity of training patterns.
3. During testing stage: Calculates distances between fresh features vectors as well as all stashed attributes, which is the training data.
4. KNN are selected and demanded to vote for classes of fresh samples. Accurate classifications provided in testing phases are utilized for measuring precision of the system. If it is not adequate, k values may be tuned till appropriate levels of precisions are attained [20].

Naïve bayes classifier

These are grounded in Bayesian theories and are simple yet effective probability classification techniques on the basis of monitored classification methods. For all class values, it predicts if specified sample is part of that class. Attribute items in a class are presumed as independent of others known as class conditional independences. These classifiers require limited quantity of training sets for estimation of variables for classifications. The classifier is denoted by Naïve Bayes (NB)

$$\mathrm{P}(\mathrm{A}|\mathrm{B})=\mathrm{P}(\mathrm{B}|\mathrm{A})*\mathrm{P}(\mathrm{A})/\mathrm{P}(\mathrm{B})$$

Wherein P (A) refers to the marginal probability of A, P (A|B) refers to the conditional probability of A, given B known as posterior probability, P (B|A) refers to the conditional probability of B given A while P(B) is the marginal probability of B that performs as normalizing constant. It gives the method through which conditional probabilities of occurrence A given B may be connected to the conditional probabilities of B given A, mathematically. Probability values of final classes dominate over the rest [21].

Radial basis function (RBF) networks

RBF networks perform identical function mapping with multi-layer NNs, though their structures as well as functions are distinct. RBFs are local networks which are trained in a monitored fashion. RBF carries out local mappings which imply that merely inputs close to receptive fields yield activation. Input layers of networks are sets of n components that accept components of n-dimensional input features vectors. n components of input vector x are inputs to hidden functions, outputs of hidden functions that are multiplied by weighting factors $w(i,j)$, are inputs to output layers of networks y(x). For all RBF units k, k = 1, 2,3,..., l centres are chosen as mean values of sample patterns which are a part of class k, that is

$$\mu_k = \frac{1}{N_k}\sum_{i=1}^{N_k} x_k^i \quad , \text{k=1,2,3,...,m}$$

Wherein x_k^i refers to eigen vectors of ith image in class k, while N_k refers to the overall quantity of trained images in class k.

As RBF NNs are a set of NNs, activation functions of hidden components are defined using distances between input vectors as well as prototype vectors. Generally, activation functions of RDF components (hidden layer component) are chosen as Gaussian functions iwht mean vectors μ_i as well as variance vectors σ_i thus

$$h_i(x) = \exp\left[-\frac{\|x-\mu_i\|^2}{\sigma_i^2}\right]$$

It is to be noted that x refers to n-dimensional input features vector while μ_i refers to n-dimensional vectors known as centre of RDF units, σ_i refers to widths of ith RBF component and 1 refers to number of RBF components. Responses of jth output units for inputs x are as follows:

$$y_j(x) = \sum_{i=1}^{l} h_i(x) w(i,j)$$

Wherein $w(i,j)$ refers to connection weights of ith RBF component to jth output nodes [22].

Algorithm

Specific algorithms were adopted by researchers, to compute the data received from the above tournaments. One such algorithm, known as the C4.5, created by Quinlan, as a basic software extension of the ID3 algorithms, was used to handle problems which have not been accessed by the ID3 algorithm. Ignoring the overriding of data, shortened pruning of errors and post-pruning issues, the mishandling of continuous data through missing variable attribute, these are the common problems faced when adopting the ID3 algorithm. Therefore, the C4.5 classification algorithm benefits users, as it reinforces tree splitting via entropy and information gain. When researchers adopted this method in their training phase as a test, the algorithm was useful in obtaining the rule set and through this testing phase, it was possible to classify the rules to the pre-processed data [24].

RESULTS AND DISCUSSION

Experimental evaluations are carried out through 436 neurological MRI scans from the OASIS project. The image is segmented using Multi-scale Image Segmentation. Features are extracted using DWT. The features are reduced using proposed AIS feature selection and classified using Naïve Bayes, RBF Classifier, C4.5 and KNN.

Table: 1. Classification Accuracy

Classifiers	GA	AIS	GA-AIS
KNN	92.66	94.95	96.79
Naïve Bayes	93.12	95.87	97.94

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C4.5	95.41	98.17	98.62
RBF Classifier	97.02	98.85	99.08

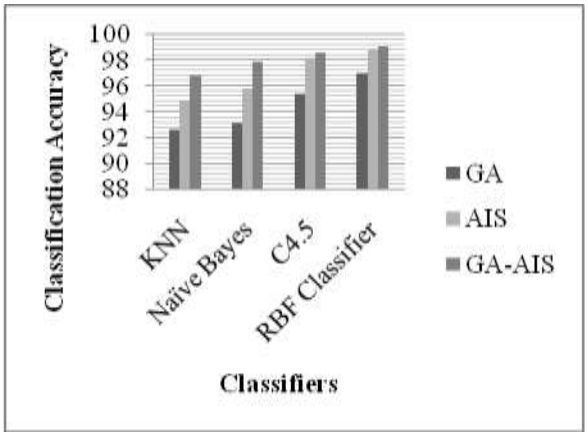

Fig: 1. Classification Accuracies

Observing **[Figure- 1]**, it is seen that proposed AIS technique increased classification accuracies for all the classifiers. RBF classifiers with the proposed hybrid GA-AIS achieve the best accuracy of 99.08%, and it improves accuracy by 2.1% compared to GA feature selection and by 023% when compared to AIS feature selection.

Table: 2. Sensitivity for Normal

Classifiers	GA	AIS	GA-AIS
KNN	0.9547	0.9756	0.9826
Naïve Bayes	0.9582	0.9756	0.9826
C4.5	0.9756	0.9895	0.993
RBF Classifier	0.9791	0.993	0.993

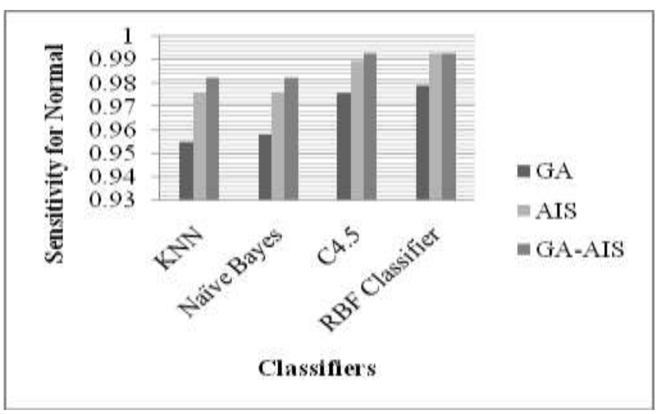

Fig: 2. Sensitivity for Normal

From the **[Figure- 2]**, it is seen that proposed AIS technique improved sensitivities for Normal by 0.71%, 0.71%, and 0.35% for GA-AIS when compared with AIS for KNN, Naïve Bayes, C4.5 classifiers.

Table: 3. Sensitivity for Dementia

Classifiers	GA	AIS	GA-AIS
KNN	0.87	0.89	0.94
Naïve Bayes	0.88	0.93	0.97
C4.5	0.91	0.97	0.97
RBF Classifier	0.95	0.98	0.99

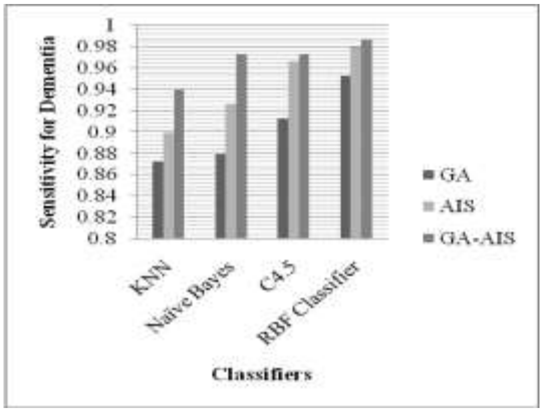

Fig: 3. Sensitivity for Dementia

From the **[Figure -3],** it is seen that presented GA-AIS technique improved Sensitivity for Dementia by 3.03%, 5.21%, 5.7% and 2.78% for GA feature selection compared with KNN, Naïve Bayes, C4.5, and RBF classifiers.

Table: 4. Specificity for Normal

Classifiers	GA	AIS	GA-AIS
KNN	0.87	0.89	0.94
Naïve Bayes	0.88	0.93	0.97
C4.5	0.91	0.97	0.97
RBF Classifier	0.95	0.98	0.99

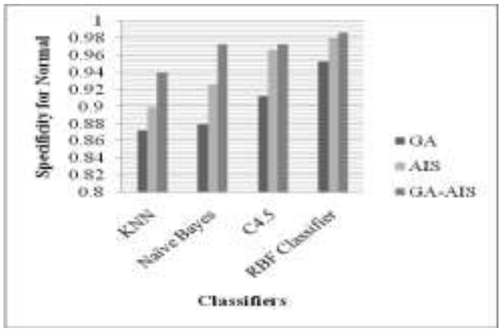

Fig: 4. Specificity for Normal

From the **[Figure- 4]**, it is seen that presented AIS technique improved Specificity for Normal by 4.38%, 4.95%, 0.7% and 0.68% for GA-AIS when compared with KNN, Naïve Bayes, C4.5, and RBF classifiers.

Table: 5. Specificity for Dementia

Classifiers	GA	AIS	GA-AIS
KNN	0.95	0.98	0.98
Naïve Bayes	0.96	0.98	0.98
C4.5	0.98	0.99	0.99
RBF Classifier	0.98	0.99	0.99

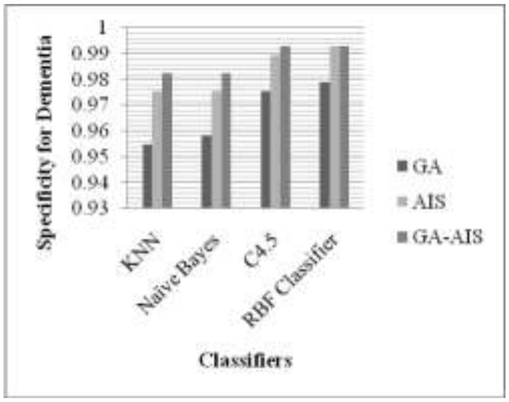

Fig: 5. Specificity for Dementia

From the **[Figure- 5]**, it is seen that presented AIS approach improved Specificity for Dementia by 2.17%, 1.8%, 1.41% and 1.41% for GA when compared with KNN, Naïve Bayes, C4.5, and RBF classifiers.

CONCLUSION

Neuroimaging is an important tool in the diagnostic work up of dementia.This paper presents an automatic MRI medical images classification process for classifying dementia. A feature selection based on AIS is proposed. These extracted features are classified with Naïve Bayes, C4.5 and K Nearest Neighbour. Comparative study with several alternate algorithms was carried out and AIS-GA yielded best outcomes in all categories. Results demonstrate that KNN with the proposed feature selection method achieves the best results and the proposed AIS feature selection improves the efficacy of the classifiers. Additional work is required to improve classification accuracy further through supervised learning.

CONFLICT OF INTEREST
The authors declare no conflict of interests.

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