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ALZHEIMER'S DISEASE DETECTION USING KRILL HERD FEATURE SELECTION WITH NB, KNN AND CART CLASSIFIER

S Sumanth
Assistant Professor, Department of Computer Science,
Smt. V.H.D. Central Institute of Home Science (A), Bengaluru, India

Dr A Suresh
Head, Department of Computer Science, Sona College of Arts and Science,
Salem, Tamilnadu, India

ABSTRACT

Alzheimer's disease (AD) is the most common type of dementia and a major cause of disability worldwide. It is a progressive and degenerative disease that affects brain cells and its early diagnosis has been essential for appropriate intervention by health professionals. Magnetic Resonance Imaging (MRI) is a non-invasive medical imaging technique used in radiology to visualize detailed internal structure and limited functions of the body. Feature selection is one of the best optimization problems in human recognition, which reduces the number of features, removes noise and redundant data in images, and results in high rate of recognition. In this work, Krill Herd (KH) based feature selection methods are proposed. The NB, KNN and CART classifier is used. Experiments show the effectiveness of the proposed technique.

Key words: Alzheimer's disease (AD), Magnetic Resonance Imaging (MRI), Feature Selection, Krill Herd (KH) and Naive Bayes (NB), k-Nearest Neighbors(KNN), Classification And Regression Trees (CART).

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1. INTRODUCTION

Alzheimer's disease (AD) is an irreversible, progressive disease which in its early stages, memory loss is mild, but in the late-stages, patients lose the ability to carry on a conversation or respond to their environment as a result of the degeneration in the normal brain tissues. An accurate and early diagnosis of AD and identification of the risk of progression with awareness of the condition's severity allow the patients to take preventative measures, such as making lifestyle changes and taking medications that can slow down the symptoms of the disease. However, early detection of AD is still challenging process. The diagnosis of AD includes mental status, physical exam and neurological exam through analysing the different imaging techniques such as Magnetic Resonance Imaging (MRI) which are very useful in evaluating the anatomical degeneration using volumetric measures and analysing the structural changes. Therefore, brain MRI analysis is a very important factor in AD diagnosing and identifies its progression overtime [1].

MRI is an advanced technique used for medical imaging and clinical medicine and an effective tool to investigate the various states of human brain. MRI images provide the rich information of various states of brain which can be used to investigate, diagnose and carry out unparalleled clinical analysis of brain to find out if the brain is normal or abnormal. However, the data extracted from the images is very large and it is hard to make a conclusive diagnosis based on such raw data. In such cases, it need to use various image analysis tools to analyze the MRI images and to extract conclusive information to classify into normal or abnormalities of brain. The level of detail in MRI images is increasing rapidly with availability of 2-D and 3-D images of various organs inside the body [2].

Features, characteristics of the objects of interest, if selected carefully are representative of the maximum relevant information that the image has to offer for a complete characterization a lesion. Feature extraction methodologies analyze objects and images to extract the most prominent features that are representative of the various classes of objects. Features are used as inputs to classifiers that assign them to the class that they represent. Feature selection helps to reduce the feature space which improves the prediction accuracy and minimizes the computation time. This is achieved by removing irrelevant, redundant and noisy features .i.e., it selects the subset of features that can achieve the best performance in terms of accuracy and computation time [3].The classification of MRI brain image data as normal and abnormal are vital to analysis for the normal patient and to consider only those who have the chance of having abnormalities. Diagnosis of abnormalities can be done automatic with more accuracy in feature selection and classification of disease. The system is trained using some attributes (features) along with their label, these attributes are used by classifier to guess the unknown objects [4].

In this work, to overcome filters. The remaining part of the investigation is organized into the following sections. Section two explains Literature Review. Section three discusses methodology, section four gives experimental results and section five concludes the work.

2. LITERATURE REVIEW

Roman & Pascual [5] made an analysis of the recent findings that are relevant to the neuroimaging contribution to that of the diagnosis Alzheimer's Dementia (AD) and the Vascular Dementia (VaD). A Computerized Tomography (CT) or a Magnetic Resonance Imaging (MRI) will be provided as an accurate demonstration of the changes that affect the brain in the AD and also the different types of the vascular lesions that are observed in case of mixed dementias and also in the pure VaD. The cortical thickness and its quantification have permitted an early diagnosis and also a rate of progression from the MCI to the dementia. The White matter (WM) and its involvement may also be quantified using the Diffusion Tensor Imaging (DTI) and also the functional MRI (fMRI), the functional connectivity, and finally the Magnetic Resonance Spectroscopy (MRS).

Akbarpour et al., [6] made a proposal for a new method for the extraction of such regions that are affected by the AD from the medical images that are multispectral. Here the initial two MRI models are fused for achieving an image that has a high content of information. The statistical features are grouped into three different clusters using an unsupervised algorithm for performing the initial segmentation. The Labelling members of the clusters and the rearranging of images will yield a final image. The results of the quantitative analysis proved a good combination of fusion as well as segmentation that result in an image having a higher value of such quantitative metrics and a better visual outcome.

Zheng et al., [7] made a presentation of any summary of the current automatic protocols of dementia detection from the actual perspective of patterns and their classification. As in most such cases the protocols will contain features extraction, they will offer three types of techniques that are the voxel, the vertex including the RoI-based ones and four groups of classifiers being Linear Discriminant Analysis (LDA), the Bayes classifier, the Support Vector Machine (SVM) and the Artificial Neural Networks (ANN). The performance of classifiers proves several protocols can distinguish the AD from the Head Circumference (HC)s along with accuracies even though they differentiate the HCs from the ones suffering from MCI being a challenging task.

Chu et al., [8] further proposed four other common methods which are 1) the pre-selected Region of Interests (ROIs) which are on the basis of the prior knowledge. 2) the Univariate t-test filtering. (3) the Recursive Feature Elimination (RFE) and finally 4) the t-test filtering that is constrained by the ROIs. Such accuracies that are achieved from the various sizes of samples either with or without feature selection that had been compared statistically. For demonstrating this, the Grey Matter (GM) that was segmented from a T1-weighted scan of anatomy were collected by Alzheimer's Disease Neuroimaging Initiative (ADNI) being the input features of a linear SVM classifier. The different between patients of AD and the Cognitively normal (CN) subjects are characterized with the difference of the MCI patients as the input features to a linear SVM classifier. The objective was to be characterized the patterns of difference between the patients with MCI and the normal subjects.

Liu et al., [9] made a proposal of another novel method of multi-task feature selection. It is treated as the method of feature selection for preserving of the inter-modality relationship and also enforces their sparseness of the features chosen from every modality. Once the feature selection is made, an SVM that is multi-kernel is used for being integrating the features that were chosen from the modality of classification and this method had been evaluated by making use of the baseline Positron Emission Tomography (PET) and the MRI images of the subjects that are obtained from an ADNI database.

Liu et al., [10] made a proposal of another linear sparse SVM for building the classifiers for the purpose of distinguishing the AD and also the MCI subjects from that of the CN that is based on various combinations of the regional measures that have been extracted using the imaging data that included the perfusion and also the amyloid deposition information that was extracted from that of the early and the late frames of the 11C-PIB with the volumetric information of the GM that was extracted from that of the structural MRI. The results of the experiment showed that this classifier that was built based on the imaging measures and their combination that have been extracted from the early and the late frames of the 11C-PIB and the MRI that achieved a very high accuracy of classification for the studies of classification of the AD (100%) and the MCI (85%), that indicates the information of multimodality which can help in diagnosing AD and the MCI.

Dyrba et al., [11] made a proposal of a SVM classifier for the DTI and a volumetric MRI data from about 35 amyloid-ß42 negative MCI subjects (the MCI-Aß42-), the 35 positive MCI subjects (the MCI-Aß42+), and 25 of the HCs that are retrieved from that of the European DTI Study about Dementia. This SVM had been applied to that of the DTI derived fractional anisotropy, the Mean Diffusivity (MD), and the Mode of Anisotropy (MOA) maps. To compare this a classification based on the GM and the WM volume was studied. The results showed that the DTI data gave a better accuracy than that of the volume in a pre-dementia AD.

A review for the detection of the differential diagnosis and the early detection of AD using the MRI data after undergoing pre-processing, feature extraction and selection of MRI was made by Salvatore et al., [12]. The extracted MRI biomarkers were classified, validated using SVM. The results that were obtained by means of the studies reported based on their performance in classification and outcomes of the biomarker for shedding light on the parameters to accompany the normal and also the pathological ageing.

3. METHODOLOGY

Krill Herd feature selection method along with various classifiers NB, KNN and CART are investigated.

3.1. Feature Selection Utilizing Krill Herd Algorithm

KH is a novel kind of optimization strategy capable of solving complex problems. KH is also a member of swarm intelligence algorithms family that takes advantage of the evolving behaviors of krill individuals. It is based on the idealization of the krill swarms when hunting for food and communicating with each other. The KH method repeats the implementation of the three movements and takes search directions that proceed to the best solution. The position of a krill is idealized into three actions as [13]:

- Movement influenced by other krill;
- Foraging action;
- Physical diffusion.

In standard KH, the solutions are updated in the search space towards continuous-valued positions. However, in the proposed Binary Krill Herd (BKH) [14] the search space is modeled a n-dimensional Boolean lattice, in which the solutions are updated across the corners of a hypercube. In addition, as the problem is to select or not a given feature, a solution binary vector is employed, where 1 corresponds whether a feature will be selected to compose the new dataset, and 0 otherwise. In order to build this binary vector, it has employed the Equation (1 & 2), which can restrict the new solutions to only binary values:

$$S\left(x_i^j(t)\right) = \frac{1}{1+e^{-x_i^j(t)}} \quad (1)$$

$$x_i^j(t+1) = \begin{cases} 1 & if \;\; S(x_i^j(t)) > \sigma, \\ 0 & otherwise \end{cases} \quad (2)$$

In which σ ~ U(0, 1) and $x_i^j(t)$ denotes the new position at time step t.

3.2. Classification Algorithm

The Three Classifiers are used namely NB, KNN and CART.

3.2.1. NB

The Naïve Bayes algorithm is used to calculate the set of probabilities by counting the value and frequency of values in a given set of data [15]. It uses Bayes Theorem.

$$P(h1|dx) = \frac{P(xi|h1)P(h1)}{P(xi|h1)P(h1) + P(xi|h2)P(h2)} \quad (1)$$

$$P(h1|xi) = \frac{P(xi|h1)P(h1)}{P(xi)} \quad (2)$$

$$P(h1|xi) = \sum_{j=1}^{n} P(xi|hj)P(hj) \quad (3)$$

3.2.2. KNN

K Nearest Neighbor (KNN): K-Nearest neighbor classifies tests according to k neighbor of the test sample. This is an unsupervised learning strategy which decides the class of an example with the help of separation measures, for example, Euclidean separation. It works by reviewing the focuses from the training set which are sufficiently comparative to be considered, when picking the class to anticipate for another perception, is to pick the 'k-nearest data focus to the new perception. It has two to three defaulting steps, for example:

An authentic integer k is settled in view of the class

Selection of k sections in the current study database, which is nearest to the example image.

The most ordinarily happening classification is selected for these K cases.

The Euclidian separation is located based on occurrence

$$E_D = \sqrt{\sum_{i=0}^{n} (E_{oi} - E_{ti})^2} \quad (4)$$

3.2.3. CART

CART, an abbreviation of Classification And Regression Trees, was first introduced by Bremain (year) which is a binary tree using GINI Index as its splitting criteria. CART can handle both nominal and continuous attributes to construct a decision tree. Also, it can handle missing values by surrogating tests to approximate outcomes. In the pruning phase, CART uses prepruning technique called Cost – Complexity pruning to remove redundant braches from the decision tree to improve the accuracy. In Breiman's explanation, the Cost-Complexity pruning "proceeds in two stages. In the first stage, a sequence of increasingly smaller trees is built on the training data. In the second stage, one of these tree is chosen as the pruned tree, based on its classification accuracy on a pruning set. Pruning set is a portion of the training data that is set aside exclusively for pruning alone". In other words, CART adopts a cross –validated method in its pruning technique.

4. RESULTS AND DISCUSSION

The data that is used for evaluating the algorithms has been got from an Alzheimer's disease Neuroimaging Initiative (ADNI) database (www.loni.ucla.edu/ADNI). Table 1 and figure 1 shows the results evaluated for classification accuracy for KH feature selection – NB classifier, KH feature selection -KNN, KH feature selection CART.

Table 1 Classification Accuracy for KH feature selection – NB, KNN, CART

Techniques Used	Classification Accuracy
FS Krill Herd - NB	80.13
FS Krill Herd - KNN	78.83
FS Krill Herd - CART	83.06

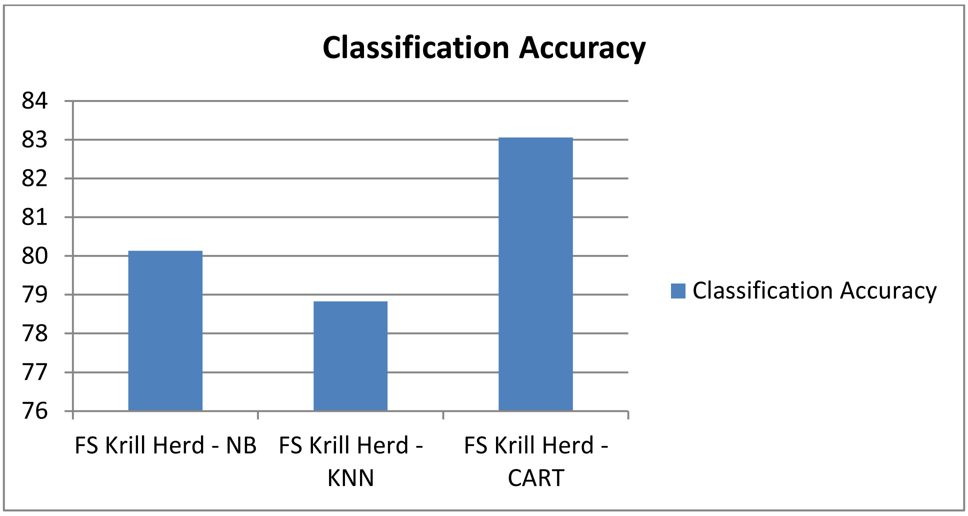

Figure 1 Classification Accuracy for Feature KH feature selection – NB, KNN, CART

It is observed from Table 1 and Fig 1 that the classification accuracy in Feature Selection Krill Herd – CART Classifier performs better by 3.6% and by 5.2% than KH feature selection – NB classifier and KH feature selection –KNN classifier.

Table 2 Sensitivity for KH feature selection – NB, KNN, CART

Techniques Used	Sensitivity for normal	Sensitivity for AD
FS Krill Herd - NB	0.8449	0.629
FS Krill Herd - KNN	0.8327	0.6129
FS Krill Herd - CART	0.8653	0.6935

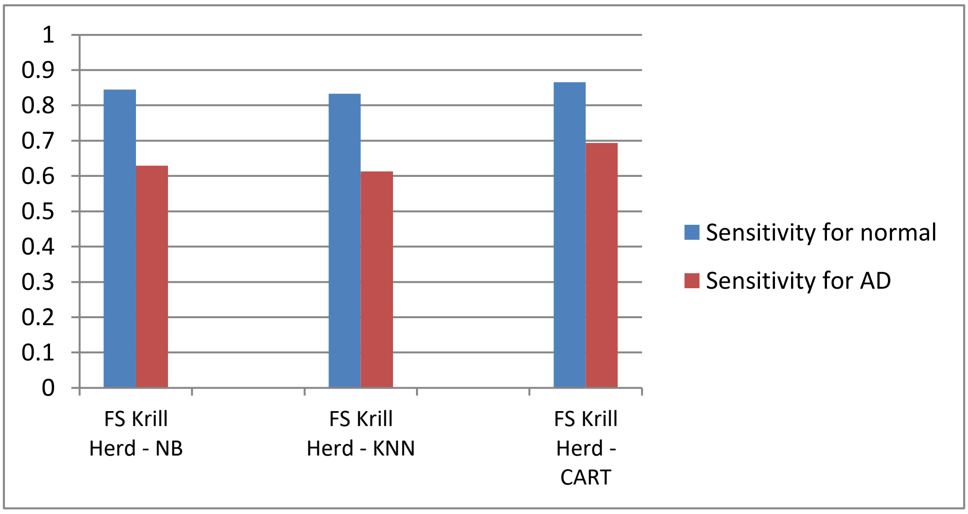

Figure 2 Sensitivity for KH feature selection – NB, KNN, CART

It is observed from Table 2 and Fig 2 that the sensitivity for the Normal case in Feature Selection Krill Herd - CART performs better by 2.38% and by 3.83% KH feature selection – NB classifier and KH feature selection –KNN classifier. Similarly, the sensitivity of AD for Feature Selection Krill Herd – CART performs better by 9.75%, and by 12.3% KH feature selection – NB classifier and KH feature selection –KNN classifier.

Table 3 Specificity for KH feature selection – NB, KNN, CART

Techniques Used	Specificity for normal	Specificity for AD
FS Krill Herd - NB	0.9	0.5065
FS Krill Herd - KNN	0.8947	0.481
FS Krill Herd - CART	0.9177	0.5658

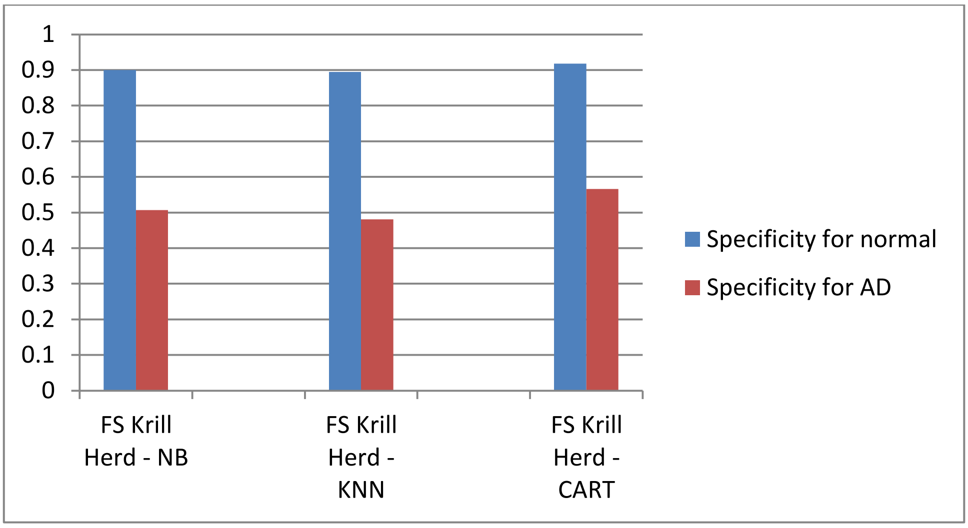

Figure 3 Specificity for KH feature selection – NB, KNN, CART

It is observed from Table 3 and Fig 3 that the specificity for the Normal case in Feature Selection Krill Herd - CART performs better by 1.94% and by 2.53% KH feature selection – NB classifier and KH feature selection –KNN classifier. Similarly, the specificity of AD for Feature Selection Krill Herd – CART performs better by 11.06%, and by 16.20% KH feature selection – NB classifier and KH feature selection –KNN classifier.

5. CONCLUSION

The work presents the Krill Herd algorithm that was based on a feature selection and various classifiers such as NB, KNN and CART to classify the MRI images better. The results have proved that the accuracy of classification of the Feature Selection Krill Herd – CART classifier has performed better by about 3.6% and 5.2% compared to the KH feature selection – NB classifier, and KH feature selection –KNN Classifier.

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