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A New Cuckoo Algorithm Based Least Square Support Vector Machine for Classification of Alzheimer Disease from Human Brain MRI

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Abstract: Alzheimer's disease (AD) is a sort of brain condition that leads to the loss of daily functioning. Early diagnosis and classification of Alzheimer's disease remain unexplored due to the rapid progression of Alzheimer's patients and the absence of effective diagnostic instruments. The detection of early morphological changes in the brain and early diagnosis of Alzheimer's disease (AD) are important in the field of healthcare. It is possible to use high-resolution magnetic resonance imaging (MRI) to help diagnose and predict this disease. Machine learning techniques are widely used now for neuro-imaging based diagnosing. These strategies yield absolutely automatic clinical decisions, unbiased by variable radiological expertise. This analysis paper compares and evaluates the performance and effectiveness of standard Least Square Support Vector Machine (LSSVM) therewith of Cuckoo Search (CS) based LSSVM within the diagnosing of Alzheimer's disease (AD) diagnosing. The manual interpretation of enormous volume of brain imaging and cognitive measures could result in incomplete diagnosing. The CS-LSSVM approach is trained with multiple biomarkers to facilitate effective, accurate classification that could be a demand of the hour. Wavelet based texture features and multiple biomarkers are fed as input to the classifier. CS-LSSVM yields ninety eight correct results and beat than fuzzy c-means classifier in terms of sensitivity, specificity and accuracy during this analysis.

Keywords: Alzheimer's disease (AD), Classification, Dementia, Least Square Support Vector Machine, Particle Swarm Optimization.

1. INTRODUCTION

Medical data and Neuro-Imaging has more and more used techniques from machine learning and computer aided diagnostics. As an example, a group of training input data is formed to yield a desired output by suggests that of a supervised machine learning rule that's "trained" for the aim. Automatic classification strategies area unit ordinarily used for the analysis of neuro-imaging studies. Many multi-resolution approaches are projected to observe vital changes within the brain volume using neighbourhood data. Varied computer-aided techniques are projected within the past and embrace the study of texture changes in signal intensity [1], grey matter (GM) concentration variations, atrophy of sub-cortical limbic structures, and general cortical atrophy.

Brain image analyses have wide relied on univariate voxel-wise analyses, like voxel-based morphometry (VBM) for structural imaging [2]. In such analyses, brain pictures are 1st spatially registered to a standard stereotaxic house, then mass univariate statistical tests are performed in every voxel to observe vital cluster variations. However, the sensitivity of those approaches is restricted once the variations are spatially complicated and involve a mixture of various voxels or brain structures [3]. Recently, there has been a growing interest in support vector machines (SVM) methods [9, 10] to beat the boundaries of those univariate analyses. There are some studies that concerned psychology measures for the diagnosing of dementia and therefore the progression from MCI (Mild cognitive Impairment) to Alzheimer dementia. Reference [4] states that MMSE (Mini mental state Examination) and CVLT-LDTR (California Verbal Learning check Long Delayed Total Recall) were the sole measures which is raised from such multivariate analysis as severally related to progression risk from MCI to early AD. In step with their results, subjects marking below 26/30 on MMSE and 4/16 on CVLT-LDTR represent a MCI subgroup at high risk of getting to early AD.

MMSE is one of the most used tests for screening of psychological feature impairment worldwide, and it has been reported that decline in MMSE starts some three years before the diagnosing of dementedness. Different tests accustomed verify general psychological feature standing (ADAS-cog, Adden Brooke's psychological feature Examination) are reported nearly as good predictors, severally or related to different psychology and neuro-imaging measures [5]. Alzheimer's Dementia (AD) is additional current these days. The brain volume is considerably modified in Alzheimer's dementedness patients compared to healthy subjects of constant people. Visual assessment of ventricle volume or form amendment has shown to be quite reliable in detective work AD. Harmonic analysis applied for image features, application of wavelets, and Haralick's parts area unit applied to extract options for brain imaging analysis.

Research papers with completely different approaches for image classification and segmentation are reported within the literature. This study sets out to investigate the responsibleness and potency of cuckoo primarily based LSSVM techniques in detecting demented and non-demented patients combining MMSE and Clinical dementia ratio (CDR) with brain volume. To realize a high degree of success in treatment, one demand is to ascertain correct classification and diagnosing of patients with complicated neurologic diseases. Then a central task is to get most typical features specific to every pathologic state (e.g. Normal vs. Alzheimer's) or differential profiles between experimental conditions from high dimensional knowledge. The rest of the paper is organized as follows. Section 2 discussed the related work of existing Alzheimer's classification schemes of BAN. Section 3 discussed the background study of methodologies. Section 4 proposed methodology for brain MRI. Section 5 discusses the experiments and results. Finally Section 6 concludes the paper.

2. RELATED WORK

Different studies with completely different approaches are performed in reference to classification MRI images.

Soliman, S. A., et al., (2020) aims to study, analyzes, and tackles the recent published segmentation, feature extraction, feature selection, optimization, and classification algorithms and their state-of-the-art for the diagnosis of AD [6]. Some of these algorithms are based on histogram-based segmentation, region-based segmentation, edge-based segmentation, clustering segmentation, gray level co-occurrence matrix, linear discriminant analysis, deep learning, deep neural network, support vector machine, principal component analysis, and genetic algorithm. These algorithms and tools act as a way of understanding and studying the different relationships and associations of patterns hidden in the image data.

Revathi, M., & Singaravel, G. (2022) focus on being degenerative and progressive with brain cells that can be intervened by health professionals in case of early recognition [7]. Feature extraction is a technique employed for reduction of dimensionality. The features are generated for a image. The extraction of features has to be done accurately without any loss of information. The proposed work introduced a Cuckoo Search (CS) based Wavelet Filter Bank Selection algorithm for classification of Alzheimer's has been proposed. The Ada Boost classifier, Random Forest (RF), and Classification and Regression Tree (CART) were used for the identification of the affected patient with Magnetic Resonance Imaging (MRI). From results it can be found that proposed CS-based technique is used in classifying AD compared to conventional techniques.

Sathish, P., & Elango, N. M. (2019) Due to variance and complexity of tumors, the classification and segmentation of tumor are burdensome in MRI brain images [8]. This paper proposes a Radial Basis Neural Network (RBNN) based on exponential cuckoo search algorithm for the automatic classification of tumor in the brain. Initially, the fuzzy c-means clustering is employed to the segmentation for the detection of tumor region. Then, the features are extracted from the tumor and non-tumor regions that are concatenated to generate the feature vector. These features are applied to the proposed classifier RBNN. This classifier requires the optimal cluster centre which is iteratively evaluated by the newly proposed exponential cuckoo search algorithm. Thus, the classifier classifies the tumor and non-tumor images and also determines the severity of tumor. The proposed system is analyzed for the evaluation metrics, such as segmentation accuracy, MSE and accuracy. Thus, the proposed system attains the higher accuracy 89% which ensures, the better classification of MRI brain image.

Dar, S. A., & Imtiaz, N. (2023) used Particle swarm optimization (PSO). It is an algorithm that involves the optimization of Non-linear and Multidimensional problems to reach the best solutions with minimal parameterization [9]. This metaheuristics model has frequently been used in the Pathological domain. This optimization model has been used in diverse forms while predicting Alzheimer's disease. It is a robust algorithm that works on linear and multi-modal data while predicting Alzheimer's disease. Through this algorithm, the author providing an opportunity to other researchers to compare this algorithm with other state-of-the-art algorithms, while seeing the classification accuracy, with the aim of early prediction and progression of MCI into Alzheimer's disease.

Wang, S. H., et al., (2018) addressed the Detection of Alzheimer's disease (AD) from magnetic resonance images can help neuroradiologists to make decision rapidly and avoid missing slight lesions in the brain [10]. Currently, scholars have proposed several approaches to automatically detect AD. The proposed work aims to develop a novel AD detection system with better performance than existing systems. 28 ADs and 98 HCs were selected from OASIS dataset. The authors used inter-class variance criterion to select single slice from the 3D volumetric data. The proposed classification system is based on three successful components: wavelet entropy, multilayer perceptron, and biogeography-base optimization. The statistical results of our method obtained an accuracy of 92.40 ± 0.83%, a sensitivity of 92.14 ± 4.39%, a specificity of 92.47 ± 1.23%. After comparison, we observed that our pathological brain detection system is superior to latest 6 other approaches.

Fang, G., et al., (2023) founds that Alzheimer's disease is a progressive neurological disorder characterized by cognitive impairment and memory loss [11]. With the increasing aging population, the incidence of AD is continuously rising, making early diagnosis and intervention an urgent need. In recent years, a considerable number of teams have applied computer-aided diagnostic techniques to early classification research of AD. Most studies have utilized imaging modalities such as magnetic resonance imaging (MRI), positron emission tomography (PET), and electroencephalogram (EEG). However, there have also been studies that attempted to use other modalities as input features for the models, such as sound, posture, biomarkers, cognitive assessment scores, and their fusion. Experimental results have shown that the combination of multiple modalities often leads to better performance compared to a single modality.

3. BACKGROUND STUDY

In this section, the summary of classifier is explained. Additionally the fundamentals of cuckoo search rule also explained intimately.

A. Support Vector Machines

Support Vector Machines are very much useful in machine learning based disease prediction. In terms of theory the SVM are well based and tested to be terribly economical in classification tasks. Support Vector Machines (SVM) is feed-forward networks with one layer of nonlinear units.

Their style has sensible generalization performance as an objective and follows for that reason the principle of structural risk minimization that is unmoving in VC dimension theory. Those coaching points that the equality of the separating arrange is happy (i.e.) $y_i(x_i.w + b) \geq 0$ for all i, those which wind up lying on one of the hyperplanes H_1,H_2, and whose removal would change the solution found, are called Support Vectors (SVS). This rule is firmly grounded within the framework of applied mathematics learning theory – Vapnik Chervonenkis (VC) theory that improves the generalization ability of learning machines to unseen information [12]. Within the last few years Support Vector Machines have shown wonderful performance in several real-world applications as well as object recognition, and face detection, dementia identification in images.

B. LSSVM

The least squares support vector machine (LSSVM) could be a least squares version of support vector machine (SVM). During this version one finds the answer by resolution a collection of linear equations rather than a convex quadratic programming (QP) for classical SVMS. Statistical procedure SVMS (LSSVMS) classifiers, was projected by Suykens and Vandewalle. LSSVM could be a category of kernel based mostly learning technique. Primary goals of the LSSVM models are regression and classification [13]. LSSVM could be a regularized supervised approximate, that has been tested to be economical for operate approximation. Solely resolution equation is required within the improvement method, which not solely simplifies the method, however conjointly avoids the matter of native minima in SVM. During this section, a brief outline of the LSSVM model is given. The LSSVM model [35] is defined in its primal weight space by,

$$\hat{y}(x) = \omega^T \phi(x) + b \quad (1)$$

Where $\varphi(x)$a function is which maps the input space into a higher dimensional feature space, *x* is the *M*-dimensional vectors of inputs x_j, and ω and *b* the parameters of the model. Least Squares Support Vector Machines for function estimation formulate the following optimization:

$$min\, J(\omega, e) = \frac{1}{2}\omega^T\omega + \gamma\frac{1}{2}\sum_{i-1}^{N} e_i^2 \quad (2)$$

We subject to

$$y^i = \omega^T \phi(x^i) + b + e^i, i = 1, \ldots N$$

The parameter set θ consists of vector ω and scalar *b*. solving this optimization problem in dual space leads to finding the α_i and *b* coefficients in the following solution:

$$h(x) = \sum_{i-1}^{N} \alpha_i\, k(x, x_i) + b$$

Function $K(x, x_i)$ is the kernel defined as the dot product between the $\phi(x)T$ and $\phi(x)$ mappings. The meta-parameters of the LSSVM model are the width of the Gaussian kernels and γ the regularization factor.

C. Cuckoo search algorithm

Cuckoo search (CS) is an optimization algorithm developed by [14]. It was inspired by the obligate brood parasitism of some cuckoo species by laying their eggs in the nests of other host birds (of other species).

Some host birds can engage direct conflict with the intruding cuckoos. For example, if a host bird discovers the eggs are not their own, it will either throw these alien eggs away or simply abandon its nest and build a new nest elsewhere. Some cuckoo species such as the New World brood-parasitic Tapera have evolved in such a way that female parasitic cuckoos are often very specialized in the mimicry in colors and pattern of the eggs of a few chosen host species.

Cuckoo search idealized such breeding behavior, and thus can be applied for various optimization problems. It seems that it can outperform other meta-heuristic algorithms in applications. Cuckoo search (CS) uses the following representations:

Each egg in a nest represents a solution, and a cuckoo egg represents a new solution. The aim is to use the new and potentially better solutions (cuckoos) to replace a not-so-good solution in the nests. In the simplest form, each nest has one egg [15]. The algorithm can be extended to more complicated cases in which each nest has multiple eggs representing a set of solutions.

CS is based on three idealized rules:

1. Each cuckoo lays one egg at a time, and dumps its egg in a randomly chosen nest;
2. The best nests with high quality of eggs will carry over to the next generation;
3. The number of available hosts nests is fixed, and the egg laid by a cuckoo is discovered by the host bird with a probability p,a \in (0,1). Discovering operate on some set of worst nests, and discovered solutions dumped from farther calculations.

In addition, Yang and Deb discovered that the random-walk style search is better performed by Levy flights rather than simple random walk.

4. PROPOSED METHODOLOGY

A. Data Preprocessing

Data is pre-processed by applying z-score normalization. Normalization may be a method wherever the attribute knowledge is scaled therefore on fall at intervals a little such that vary zero.0 to 1.0. In z-score normalization, the values for associate attribute ‘A’ area unit normalized supported the mean and variance of A. This methodology of normalization is helpful once the particular minimum and most of attribute A are unknown, or once there are outliers that dominate the min-max normalization [16].

B. Feature Extraction

In this paper, the aim is to separately classify AD patients and healthy old management subjects by employing a whole-brain MRI image analysis. A texture based mostly analysis of the MRI images using wavelets at the side of Haralick strategies is employed to extract feature parameters. Thereby, focus is on characteristics of the distribution of the grey matter (GM), white matter (WM), and humor (CSF), that intuitively is sensible once handling neurodegenerative diseases normally and AD specifically. Steps for feature extraction are as follows:

1) The voxel-wise texture options of image I are extracted at every slice of 3D ROI by convoluting with second Gabor filters [17] and averaging within the ROI. Haralick options like inertia, entropy and correlation area unit calculated for every coaching image and also the average is computed at totally different angles.
2) Compute the mean of every feature of the complete set of images considered for feature extraction.
3) Feature reduced vectors generated by wavelets is given as input vectors to the classifier.

C. LSSVM –CS

For the quality SVMS and its reformulations, LSSVM, the regularization parameter and kernel parameters are known as hyper parameters that play an important role to the performance of the SVMS. There exist totally different techniques for calibration the hyper-parameters associated with the regularization constant and also the parameter of kernel operates. Analytical and algebraic strategies will be used for calibration the parameters [18]. Error measure is that the central theme of analytical and algebraically techniques. but these days genetic algorithm and organic process strategy area unit utilized for the hyper-parameters of SVMS.

Grid search methodology involves a pricey search procedure and gradient-based strategies do not give optimum performance measure. CS is evolutionary computation techniques supported swarm intelligence. It has several blessings over different heuristic techniques. This method will exploit the distributed and parallel computing capabilities, to escape local optima and fast convergence.

D. Optimization of LSSVM Parameters

In the case of the algorithm LSSVM with radial kernel function [19], optimized parameters are: γ, which is that the weight at that the testing errors are treated in reference to the separation margin and parameter σ, that corresponds to the breadth of the kernel operate. it is not noted beforehand what combination of those two parameters can accomplish the simplest results of classification. It is not possible to finish the search area of models, so the selection of best set of parameters may be a terribly advanced downside, and also the method its answer may be a key component of the system. so as to search out the simplest values many techniques like Grid-Search, K-fold Cross-Validation, and Particle Swarm optimization are used.

E. Data Set

OASIS provides brain imaging data that are freely available for distribution and data analysis. This data set consists of a cross-sectional collection of 416 subjects covering the adult life span aged 18 to 96 including individuals with early-stage Alzheimer's Disease (AD) and it classified image are shown in fig 1 . For each subject, 3 or 4 individual T1-weighted MRI scans obtained within a single imaging session are included. Table 4.1 gives the list of MRI features considered for the study.

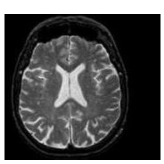

Figure 4.1.(a) Normal brain MRI images

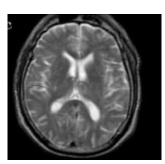

Figure 4.1.(b) Alzheimer's disease

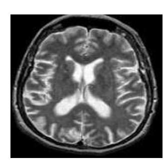

Figure 4.1.(c) Mild Cognitive Impairment

Table 4.1: Attributes Given As Input for Classification

Variable	Definition
X_1	Age

X_2	Education
X_3	Clinical Dementia Rating
X_4	Total intracranial volume
X_5	Whole brain volume
X_6	Mini Mental State Examination

1) Division of Data into Training and Testing

When a classification algorithm is developed, it is important to know that the classifier works well enough to be useful for the application [20]. It is easy to design an optimistically biased (low error, over-trained) algorithm. If, for example, the same data is used for model selection (i.e. Optimization of *C* and *γ* or *n* in our case), model training, and validation, an obvious risk is the creation of a machine which does not generalize. Such a model may be of limited effectiveness for classifying novel data. To eliminate such circular logic for this study, validation is performed on independent or unseen data.

The records of 370 patients with Alzheimer's disease (AD) Cognitively Normal (CN) datasets were randomly divided into two sets of 75 AD, 75 CN for training and 50AD, 50 CN for testing. The training datasets need not be exactly age and gender matched if age and gender are given as input to the SVM.

Table 4.2: Data Set For Classification

Data	Longitudinal		Cross sectional	
	Demented	**Cognitively Normal**	**Demented**	**Cognitively Normal**
Training	75	75	75	75
Testing	50	50	50	50

2) Cross validation of the Classifiers

Cross Validation is a statistical analysis method used to verify the performance of classifiers. The basic idea is that the original dataset is divided into training datasets which are used for training classifiers, and validation datasets for testing the trained models to obtain the classification accuracy as the evaluation performance of classifiers. This paper uses Leave-One-Out Cross Validation.

5. RESULTS & DISCUSSIONS

All classification results could have an error rate and on occasion will either fail to identify dementia or misclassify a normal patient as demented. It is common to describe this error rate by the terms true positive and false positive and true negative and false negative as follows:

- **True Positive (TP):** the classification result is positive in the presence of the clinical abnormality.
- **True Negative (TN):** the classification result is negative in the absence of the clinical abnormality.
- **False Positive (FP):** the classification result is positive in the absence of the clinical abnormality.
- **False Negative (FN):** the classification result is negative in the presence of the clinical abnormality.

1) Sensitivity = TP/ (TP+FN) ×100%
2) Specificity = TN/ (TN+FP) ×100%
3) Accuracy = (TP+TN)/ (TP+TN+FP+FN)×100 %

TP, TN, FP, FN, Sensitivity, Specificity and Accuracy are used to measure the performance of the classifiers. The CS-LSSVM method was tested on longitudinal data divided into two groups [21]. Classification rates of proposed system is 94% and 96.5% were achieved. An improved accuracy of 96.3% was obtained by taking into account only a volume of interest i.e. the grey matter. However the results are further enhanced only if multiple biomarkers including age, clinical dementia rating and MMSE are included.

A leave-one-out test on a set of 50 healthy controls and 50 patients with AD resulted in a classification accuracy of 96.5%. The experiment involved a training stage on the full set though. Table 4.3 and Table 4.4 depict the result for the classification of longitudinal and cross-sectional data with Fuzzy C-means and hybrid CS-LSSVM.

Table 4.3: Comparison of Efficiency of Classifiers for Longitudinal Data Set

MEASURE	Fuzzy C-means	CS-LSSVM
Sensitivity %	89	94
Accuracy %	90	96.5
Specificity %	89	96.3

Table 4.4: Comparison of Efficiency of Classifiers for Cross-Sectional Data Set

MEASURE	Fuzzy C-means	CS-LSSVM
Sensitivity %	94	97.25
Accuracy %	94.65	96.12
Specificity %	90	95.23

The results of Table 4.5 indicate that the classification accuracy increases as the cognitive measures are added. Although initially MMSE was used as a screening test for dementia, it can be effectively used as a feature for classification of dementia using machine learning methods.

Table 4.5: Comparison of Efficiency of Classifiers for Longitudinal Data Set with CS-LSSVM with Varying Features

MEASURE performance	CS-LSSVM		
	Feature vector		
	MRI-feature	MMSE	CDR
Sensitivity %	89	94	96
Accuracy %	93.52	92.58	94.58
Specificity %	90	91.25	95.63

Accuracy Comparison

The proposed CS-LSSVM classifier produces better accuracy rate shown in Fig. 4.2 which is much greater accuracy results than existing Fuzzy C-means classifier. When the number of images increases the accuracy of the result is increases. This approach produces high accuracy rate when compared to existing system.

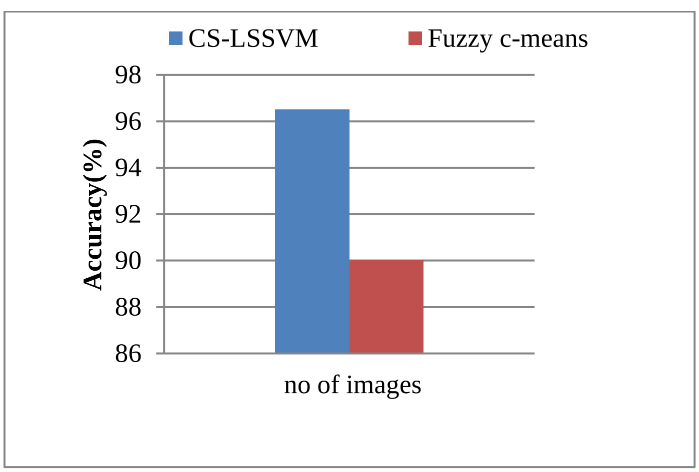

Fig. 4.2: Accuracy vs. no of images

Sensitivity Comparison

The proposed CS-LSSVM classifier produces high sensitivity shown in Fig..4.3 Which is much greater accuracy results than existing Fuzzy C-means classifier. When the number of images increases the sensitivity of the result is increases. This approach produces high sensitivity rate when compared to existing system.

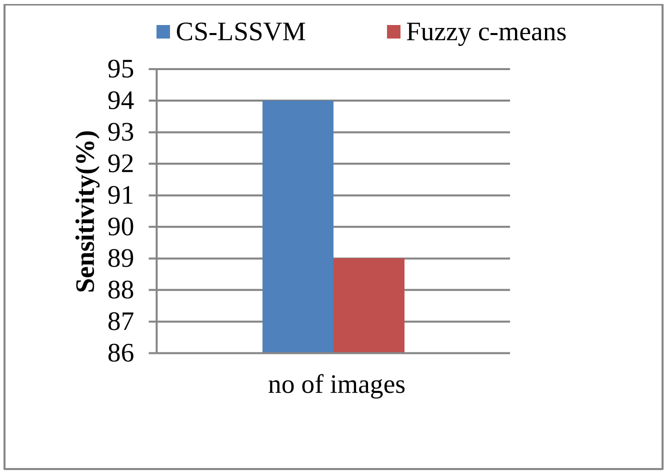

Fig. 4.3: Sensitivity vs. no of images

Specificity Comparison

The proposed DWT with FNN classifier produces high specificity shown in Fig.4.4 is higher than the existing DCT with ANN classifier and SVM classifier. When the number of features increases the specificity of the result is increases. This approach produces effective specificity rate when compared to existing system.

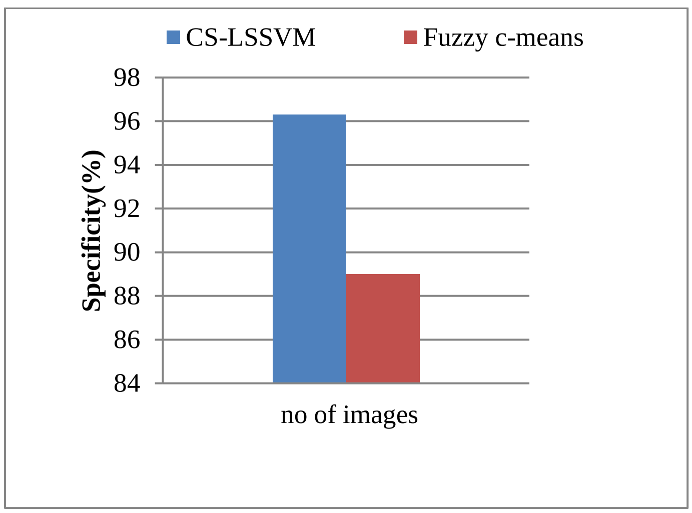

Fig. 4.4: Specificity vs. no of images

6. CONCLUSION

In summary, the results are in line with those reported within the literature, taking under consideration that multiple biomarkers are enclosed as inputs for the classifier. It is often aforementioned that CS-LSSVM may be a promising classifier to get a superior prediction performance for machine-driven identification of insanity. It’s determined that important enhancements within the performance of the algorithm are often completed through improvement by cs.

Classification accuracy is improved once the neuro-imaging knowledge is combined with MMSE and CDR values. The results do suggest although that it can be helpful to additionally take into consideration all psychology measures as input. This side is often investigated in future work, by testing the tactic for various combinations of biomarkers which will improve the accuracy of the CS-LSSVM classifier.

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