Automated Classification of Dementia Using PSO based Least Square Support Vector Machine

T. R. Sivapriya, A. R. Nadira Banu Kamal, and V. Thavavel

Abstract—**Machine learning techniques are widely used now for neuro-imaging based diagnosis. These methods yield fully automated clinical decisions, unbiased by variable radiological expertise. This research paper compares and evaluates the performance and reliability of conventional Least Square Support Vector Machine (LSSVM) with that of Particle Swarm Optimization (PSO) based LSSVM in the diagnosis of dementia. The manual interpretation of large volume of brain MRI and cognitive measures may lead to incomplete diagnosis. The PSO-LSSVM approach is trained with multiple biomarkers to facilitate effective, accurate classification which is a requirement of the hour. Wavelet based texture features and multiple biomarkers are fed as input to the classifier. PSO-LSSVM yields 98% accurate results and outperforms LSSVM classifier in terms of sensitivity, specificity and accuracy in this analysis**

Index Terms— **Classification, dementia, least square support vector machine, particle swarm optimization.**

I. INTRODUCTION

Medical data and neuroimaging has increasingly employed techniques from machine learning and computer aided diagnostics. For instance, a set of training input data is made to yield a desired output by means of a supervised machine learning algorithm that is "trained" for the purpose. Automated classification methods are commonly used for the analysis of neuroimaging studies. Several multi-resolution approaches have been proposed to detect significant changes in the brain volume using neighbourhood information. Various computer-aided techniques have been proposed in the past and include the study of texture changes in signal intensity[1], grey matter (GM) concentration differences [2], atrophy of sub-cortical limbic structures [3]-[5], and general cortical atrophy [6]-[8].

Brain image analyses have widely relied on univariate voxel-wise analyses, such as voxel-based morphometry (VBM) for structural MRI [9]. In such analyses, brain images are first spatially registered to a common stereotaxic space, and then mass univariate statistical tests are performed in each voxel to detect significant group differences. However, the sensitivity of these approaches is limited when the differences are spatially complex and involve a combination of different voxels or brain structures [10]. Recently, there has been a growing interest in support vector machines (SVM)

methods[11][12] to overcome the limits of these univariate analyses. There are some studies that involved neuropsychological measures for the diagnosis of dementia and the progression from MCI (Mild Cognitive Impairment) to Alzhemier Dementia. Reference [13] states that MMSE (Mini Mental State Examination) and CVLT-LDTR (California Verbal Learning Test Long Delayed Total Recall) were the only measures that arose from such multivariate analysis as independently associated with progression risk from MCI to early AD. According to their results, subjects scoring below 26/30 on MMSE and 4/16 on CVLT-LDTR constitute a MCI subgroup at high risk of progressing to early AD.

MMSE is one of the most used tests for screening of cognitive impairment worldwide, and it has been reported that decline in MMSE starts approximately three years before the diagnosis of dementia [14]. Other tests used to determine general cognitive status (ADAS-cog, Adden brooke's Cognitive Examination) have been reported as good predictors, independently or associated with other neuropsychological and neuroimaging measures [15][16]. Alzhemier's dementia(AD) is more prevalent today. The brain volume is significantly changed in Alzhemier's Dementia patients compared to healthy subjects of the same age group. Visual assessment of ventricle volume or shape change has shown to be quite reliable [17][18] in detecting AD. Fourier analysis applied for image features[19], [20], application of wavelets[21], Haralick components [22] are applied to extract features for brain MRI analysis.

Research papers with different approaches for image classification and segmentation are reported in the literature. This study sets out to investigate the reliability and efficiency of PSO based LSSVM techniques in detecting demented and non-demented patients combining MMSE and Clinical Dementia Ratio (CDR) with brain volume. To achieve a high degree of success in treatment, one requirement is to establish proper classification and diagnosis of patients with complex neurological diseases. Hence a central task is to discover most common features specific to each pathologic state (e.g. normal vs. demented) or differential profiles between experimental conditions from high dimensional data [23].

A. Related Work

There are several studies that demonstrate cross-sectional inter-group differences associated with Alzhemier's Dementia (AD). Fully automatic brain tissue classification from magnetic resonance images (MRI) is of great importance for research and clinical studies of the normal and diseased human brain. Several types of medical image segmentation methods can be applied to anatomical brain MRI. Previous work on MR image based detection of dementia, or more specifically Alzheimer's disease (AD), has

mainly focussed on the hippocampal shape. The work in [24] is most related to ours. They segment the MR brain images into grey matter, white matter, and cerebrospinal fluid. After registration to a population template, the (whole-brain) grey matter segmentations are used as feature vectors in a support vector machine (SVM). Leave-one-out validation on a group of 40 subjects suffering from mild to moderate dementia and 40 normal controls resulted in an accuracy of 92%. Automatically segmented hippocampi, which are registered to each other [25] is used in order to construct a dissimilarity matrix based on the deformation metric implied by their diffeomorphic registration approach. As in [26] a new method was proposed for abnormal MRI volume identification with slice segmentation using Fuzzy C-means (FCM) algorithm. Automated Segmentation and Classification of brain MRI [27] in which an SVM classifier was used for normal and abnormal slices classification with statistical features was proposed. The remainder of the paper is organized as follows: Section II focuses on SVM and LSSVM classifiers, Section III describes the proposed Methodology and the Data Set used for the study Section IV discusses the Results.

II. OVERVIEW OF CLASSIFIER

A. Support Vector Machines

Support Vector Machines are new learning techniques that were introduced in 1995 by Vapnik [28]. In terms of theory the SVMs are well founded and proved to be very efficient in classification tasks. Support Vector Machines (SVMs) are feed-forward networks with a single layer of nonlinear units.

Their design has good generalization performance as an objective and follows for that reason the principle of structural risk minimization that is rooted in VC dimension theory. Those training points for which the equality of the separating plan is satisfied (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 algorithm is firmly grounded in the framework of statistical learning theory – Vapnik Chervonenkis (VC) theory, which improves the generalization ability of learning machines to unseen data [29], [30]. In the last few years Support Vector Machines have shown excellent performance in many real-world applications including object recognition [31], and face detection, dementia diagnosis [32] in images.

B. LSSVM

The least squares support vector machine (LSSVM) is a least squares version of support vector machine (SVM). In this version one finds the solution by solving a set of linear equations instead of a convex quadratic programming (QP) for classical SVMs. Least Squares SVMs (LSSVMs) classifiers, was proposed by Suykens and Vandewalle. LSSVM is a class of kernel based learning method. Primary goals of the LSSVM models are regression and classification. LSSVM is a regularized supervised approximator, which has been proved to be efficient for function approximation. Only solving linear equation is needed in the optimization process, which not only simplifies the process, but also avoids the problem of local minima in SVM. In this section, a short summary of the LSSVM model is given. The LSSVM model [33] is defined in its primal weight space by,

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

where $\varphi(x)$ is a function which maps the input space into a higher dimensional feature space, x is the M-dimensional vector 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:

$$\min_{w,b,e} J(\omega, e) = \frac{1}{2}\omega^T\omega + \gamma\frac{1}{2}\sum_{i=1}^{N} e_i^2 \qquad (2)$$

subject to

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

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. Particle Swarm Optimisation

Particle Swarm Optimisers (PSO) is a new trend in evolutionary algorithms, being inspired in group dynamics and its synergy. In PSO individuals are called particles and the population is called a swarm. PSO are inspired in the intelligent behaviour of beings as part of an experience sharing community as opposed to an isolated individual reactive response to the environment. PSO algorithm is as follows:

1) Initialize a population size, positions and velocities of agents, and the number of weights and biases.
2) The current best fitness achieved by particle p is set as *pbest*. The pbest with best value is set as *gbest* and this value is stored.
3) Evaluate the desired optimization fitness function *fp* for each particle as the Mean Square Error (MSE) over a given data set.
4) Compare the evaluated fitness value *fp* of each particle with its *pbest* value. If *fp<pbest* then *pbest= fp* and *bestxp= xp*, *xp* is the current coordinates of particle *p*, and *bestxp* is the coordinates corresponding to particle *p's* best fitness so far.
5) The objective function value is calculated for new positions of each particle. If a better position is achieved by an agent, *pbest* value is replaced by the current value. If *fp<gbest* then *gbest= p*, where *gbest* is the particle having the overall best fitness over all particles in the swarm.
6) Change the velocity and location of the particle based on random number assigned.

$$vid = vid + \varphi 1 \times rnd() \times (pid\text{-}xid) + \varphi 2 \times rnd() \times (pgd\text{-}xid)$$
$$xid = xid + vid;$$

where i is the particle, $\varphi 1, \varphi 2$ are learning rates governing

the cognition and social components, *g* represents the index of the particle with the best p-fitness, and *d* is the dth dimension.

III. METHODOLOGY

A. Data Preprocessing

Data is pre-processed by applying z-score normalization. Normalization is a process where the attribute data are scaled so as to fall within a small specified range 0.0 to 1.0. In z-score normalization, the values for an attribute 'A' are normalized based on the mean and standard deviation of A. This method of normalization is useful when the actual minimum and maximum of attribute A are unknown, or when there are outliers that dominate the min-max normalization.

B. Feature Extraction

In this paper, the purpose is to individually classify AD patients and healthy elderly control subjects by using a whole-brain MR image analysis. A texture based analysis of the MR images employing wavelets along with Haralick methods is used to extract feature parameters. Thereby, focus is on characteristics of the distribution of the gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF), which intuitively makes sense when dealing with neurodegenerative diseases in general and AD in particular. Steps for feature extraction are as follows:

1) The voxel-wise texture features of image I are extracted at each slice of 3D ROI by convoluting with 2D Gabor filters [34] and averaging inside the ROI. Haralick features like inertia, entropy and correlation are calculated for each training image and the average is computed at different angles.
2) Compute the overall mean of each feature of the entire set of images considered for feature extraction.
3) Feature reduced vectors generated by wavelets is given as input vectors to the classifier.

C. LSSVM –PSO

For the standard SVMs and its reformulations, LSSVM, the regularization parameter and kernel parameters are called hyper-parameters, which play a crucial role to the performance of the SVMs. There exist different techniques for tuning the hyper-parameters related to the regularization constant and the parameter of kernel function. Analytical and algebraic methods can be used for tuning the parameters. Error measure is the central theme of analytical and algebraic techniques. However nowadays genetic algorithm and evolutionary strategy are employed for the hyper-parameters of SVMs. Grid search method involves a costly search procedure and gradient-based methods do not provide optimum performance measure. PSO is an evolutionary computation techniques based on swarm intelligence. It has many advantages over other heuristic techniques. This technique can exploit the distributed and parallel computing capabilities, to escape local optima and quick convergence.

D. Optimization of LSSVM Parameters

In the case of the algorithm LSSVM with radial kernel function [35], optimized parameters are: γ, which is the weight at which the testing errors will be treated in relation to the separation margin and parameter σ, which corresponds to the width of the kernel function. It is not known in advance what combination of these two parameters will achieve the best result of classification. It is impossible to complete the search space of models, therefore the choice of optimal set of parameters is a very complex problem, and the way its solution is a key element of the classification system. In order to find the best values several techniques like Grid-Search [36], K-fold Cross-Validation, Particle Swarm Optimization [37[-[42] are used. PSO provides better optimization than Grid-Search and K-fold method.

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) . For each subject, 3 or 4 individual T1-weighted MRI scans obtained within a single imaging session are included. Table I gives the list of MRI features considered for the study.

TABLE I: 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. 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 Alzhemier'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 II: DATA SET FOR CLASSIFICATION

Dataset	Longitudinal		Crosssectional	
	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.

IV. RESULT

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.

Sensitivity = TP/ (TP+FN) ×100%
Specificity = TN/ (TN+FP) ×100%
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 PSO-LSSVM method was tested on longitudinal data divided into two groups. Classification rates of 95% and 97% were achieved. An improved accuracy of 96% 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%. The experiment involved a training stage on the full set though. Table III and Table IV depict the result for the classification of longitudinal and cross-sectional data with SVM, LSSVM and hybrid PSO-LSSVM.

TABLE III: COMPARISON OF EFFICIENCY OF classifiers for LONGITUDINAL DATA SET

MEASURE	SVM	LSSVM	PSO-LSSVM
Sensitivity %	89	92	95
Accuracy %	90	90	96
Specificity %	89	93	97

TABLE IV: COMPARISON OF EFFICIENCY OF CLASSIFIERS FOR CROSS-SECTIONAL DATA SET

MEASURE	CLASSIFIER		
	SVM	LSSVM	PSO-LSSVM
Sensitivity %	92	94	98
Accuracy %	89	90	96
Specificity %	90	92	95

The results of Table V 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 V: COMPARISON OF EFFICIENCY OF CLASSIFIERS FOR LONGITUDINAL DATA SET WITH PSO-LSSVM WITH VARYING FEATURES

MEASURE OF PERFORMANCE	CLASSIFIER – PSO-LSSVM		
	Feature vectors		
	MRI-feature	MMSE	CDR
Sensitivity %	89	94	98
Accuracy %	93	92	96
Specificity %	90	91	95

V. CONCLUSION

In summary, the results are in line with those reported in the literature, taking into account that multiple biomarkers are included as inputs for the classifier. It can be said that PSO-LSSVM is a promising classifier to obtain a superior prediction performance for automated diagnosis of dementia. It is observed that significant improvements in the performance of the algorithm can be realised through optimisation by PSO.

Classification accuracy is improved when the neuro-imaging data is combined with MMSE and CDR values. The results do suggest though that it could be beneficial to additionally take into account all neuropsychological measures as input. This aspect can be investigated in future work, by testing the method for different combination of biomarkers that can improve the accuracy of the PSO-LSSVM classifier.

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