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IMPROVING GABOR FILTER BANK DESIGN AND SVM OPTIMIZATION THROUGH STOCHASTIC DIFFUSION SEARCH FOR MILD COGNITIVE IMPAIRMENT CLASSIFICATION

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ABSTRACT

Mild Cognitive Impairment (MCI) is considered a precursor to Dementia in most cases, manifesting as one of the first symptoms to appear in an individual. Alzheimer's disease (AD) is the topmost reason behind dementia among elderly patients. Advanced neuroimaging methods are exhaustively utilized for diagnosing primary Alzheimer's disease as well as Mild Cognitive Impairment affected individuals with amnesia. In the current study, automatic labelling method which effectively classifies Magnetic Resonance Images (MRIs) as normal or anomalous is suggested through the use of machine learning methods. Textural attributes of MRIs are extricated through Gabor filters because of their excellent performance and textural analyses capacity for analysing spatial frequencies. Choosing best filters is crucial to enhancing performances of machine learning methods and it is NP-hard. The current study suggests a systematic Gabor filter optimization method which produced better as well as problem-specific filter sets utilizing Stochastic Diffusion Searches (SDSs), which are able to discover the location of predetermined patterns or in event that they do not exist, their most optimal instantiation within the search space. This is attained through parallel explorations of entire search spaces by groups of agents exploring in competitive yet cooperative fashion. The filters are valuated though Support Vector Machine (SVM)-based application-oriented fitness criteria. Outcomes revealed that better performance of the suggested Gabor filter as well as SDS optimized SVM.

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KEY WORDS

Magnetic Resonance Imaging (MRI), Mild Cognitive Impairment (MCI), Alzheimer's Disease (AD), Gabor Filters, Support Vector Machine (SVM), Stochastic Diffusion Search (SDS)

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INTRODUCTION

Alzheimer's disease is a neurodegenerative disorder that progresses for a long time before the manifestation of clinical symptoms. Even though there has been extensive research on AD, there is still some degree of uncertainty with respect to is prodromal stages. The symptoms of Mild Cognitive Impairment, on the other hand, may be identified several years prior to the actual diagnosis. This implies that there is a prolonged preclinical phase which precedes the clinical manifestation of AD. Timely treatment and precocious diagnosis is crucial here, since the progression of the disease may be slowed down and the development of new symptoms delayed [1].

For the early detection of Alzheimer's as well as the prodromal state of dementia, MCI holds great clinical importance. MCI is a heterogeneous syndrome which is often undiagnosed since it is challenging for clinicians to detect cognitive impairment be it at any stage. In later stage dementia up to 50% may escape recognition. The screening tests prevalently used including the Mini-Mental State Examination (MMSE) fail to reliably recognize subtle cognitive impairments in patients in the early stages. Word list, narrative recall and other linguistic memory tests exhibit greater efficacy in the detecting MCI, but they run the risk of yielding false positive diagnosis, which is undesirable [2].

The three phases of Alzheimer's disease are preclinical, MCI and dementia. The starting stage is the preclinical stage, MCI is characterized by mild changes in memory and dementia indicates severe affectation
of the disease. AD patients may exhibit symptoms that vary from person to person. Following are few of the common symptoms:

- Loss of memory that inhibits the performance of day-to-day chores.
- Difficulty in problem-solving or planning.

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- Time and place disorientation.
- Challenges in comprehending visual content and spatial relationships.
- Impaired judgment.
- Withdrawal from and loss of interest in work and other social interactions.

Initially, cross-sectional studies employed structural MRI to distinguish individuals with MCI from healthy subjects. A majority of the previous MR neuroimaging research concentrated on investigating the grey matter utilizing voxel-based morphometry in identifying MCI. There were significant volume differences distributed primarily within the precuneus and cingulate gyrus between patients afflicted with MCI and those in the control groups, as revealed by a series of such studies. New contributions towards research on neurodegenerative diseases suggest that using DTI to assess the changes in WM microstructure might be a more reliable parameter as compared to grey matter data. This approach is more sensitive to mild structural changes that may take place during the initial stages of degenerative process.

Greater accuracy in structural neuroimaging analysis can be gained by using high tissue contrast yielded by T1-weighted (T1w) MRI as a potential surrogate biomarker that can be used in the diagnosis and prediction of AD. Image processing techniques so far have failed to predict with accuracy the probability of contracting AD in the future for patients who have MCI. In the investigation of various diseases and disorders including dementia, OCD and schizophrenia, by examining cortical structural changes and differences, measurements of cortical thickness gained from MRI is used which exhibits high sensitivity to even minor structure modifications over the cortex.

Results derived from previous studies, however, indicate that the performance of using cortical thickness measurements is poorer than other methods in predicting Alzheimer's disease in patients with MCI, getting accuracy rates of 56% to 70% based on the technique. Since the measurement of cortical thickness is at a great resolution (ranging up to tens of thousands of points on the cerebral cortex), prediction in a discriminatory model utilizing such a vast number of measurements may run the risk of over-fitting.

The aim of feature extraction stage is the extraction of important image-based attributes from MRIs for all subjects in references as well as study group. Firstly, raw scans are adjusted for intensity non-homogeneities apart from noise being removed through non-local means methods. The scans are scaled in a linear fashion in grey-level intensity over all subjects for matching mean levels of reference images, set in standardized target template spaces optimizing global as well as local alignments between reference as well as subjects through consequent modifications [3].

Selecting features is automated features selections mostly, with relevance to predictive modelling problems. It incorporates the selecting of features subsets which have relevance, and are utilized for constructing models. Selecting features is different from reducing dimensionalities. Both decrease features in datasets, but reducing dimensionalities is done through the creation of novel features combination while selecting features involves the inclusion or exclusion of data features with no changes. Selecting features is the identification of non-relevant or repetitive features from data which offer nothing to the predictive method's precision or actually reduces the method's precision and discard them. Three classes of features selection methods are present which are filters, wrappers as well as embedded techniques. Filter approaches utilize statistical metrics to rank attributes and on the basis of the ranks, attributes are retained or discarded from datasets. With wrappers, selecting features sets are regarded as search issues where predictive models valuate attribute subset. The embedded approach learns which attributes offer most to the method's precision during the construction of the models.

Latest classification techniques were built so that they permit individual classes estimations. Amongst them, machine learning methods are suggested for distinguishing MRIs from two sets of subjects that is healthy versus sick individuals. All the methods need training set that is already classified subjects such as healthy individuals as well as individuals with confirmed diagnoses for the categorizing of fresh subjects who are part of the test populations, into any of the classes which subjects of training sets are part of. One or more attribute variables are needed for the differentiating of the two sets which are being studied.

Particularly, SVMs are being used in recent times for assisting in the distinguishing of Alzheimer's disease afflicted individuals from control subjects through the use of anatomical MRIs. Classification techniques are employed for classifying MCI afflicted individuals in contrast to control individuals or in assisting in the differentiation of Alzheimer's disease from fronto-temporal lobar degradation. Although attribute variables may

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be delineated from the entire brain, the variables might not possess related physio-pathological interpretations or merely partial sets of most discriminatory voxels or areas are gradually utilized for the classification of subjects [4].

In the current work, a MCI classification using Gabor filters, SDS and SVM methods. The paper's structure is thus: Section 2 reviews relevant literature. Section 3 elaborates on methods employed; Section 4 exposes outcomes from experiments and Section 5 provides the conclusion.

RELATED WORKS

Roman and Pascual [5] surveyed the latest discoveries within the field of neuroimaging related to diagnosing Alzheimer's disease as well as Vascular Dementia (VaD). MRIs as well as Computerized Tomographies (CT) have been offered precise demonstrations of locations as well as degree of advancement of atrophic alterations impacting brains due to Alzheimer's disease as well as the several kinds of vascular lesions noted in mixed dementias as well as in pure vascular dementias. Quantifying cortical thicknesses permits earlier diagnoses as wel as rates of advancement from MCIs to dementias. Quantification of white matter may be carried out by Diffusion Tensor Imagings (DTI) and functional MRIs (fMRI), functional connectivities, and MR Spectroscopies (MRS).

Zhou et al., [6] suggested CAD based technique on the basis of wavelet-entropies of attribute space method as well as a Naïve Bayes classification technique for the enhancement of brain diagnoses' precision through NMR scans. The attribute that was relevant the most was taken as wavelet entropies that was utilized to for training Naïve Bayes classifiers. Outcomes revealed that the suggested classifier identified anomalous from normal control brains excellently and was on par with recent techniques.

Zhuang et al., [7] utilized DTIs for detecting white matter structure modifications in MCIs as well as its sub-kinds and focused on the examination of whether DTIs may be utilized as possible imaging markers of MCIs. Ability of DTI in discerning MCIs from CNs was tested through binary logistic regression models.

Liu et al., [8] suggested a new multi-task features selection technique for preserving complementary inter-modality data. Particularly, it considered features selection from all modalities as distinct tasks and moreover imposed constraints for the preservation of inter-modality relations, apart from ensuring sparsity of chosen attributes from all modalities. Once features are selected, multi-kernel SVMs were utilized for the integration of chosen attributes from all modalities for classifications. The technique was tested through baseline PET scans as well as MRIs of subjects got from the Alzheimer's disease Neuroimaging Initiative (ADNI) database.

Zhang et al., [9] suggested a new hybrid method for the classification of provided MRIs as normal or anomalous. The suggested technique initially utilized DWT for extracting features and later PCA for reducing features space. Later, Kernel Support Vector Machines (KSVM) with RBF kernels, utilizing Particle Swarm Optimization (PSO) for optimizations was built. Five-fold cross-validations were used for obviating over-fitting.

METHODOLOGY

Textural attributes of MRIs brain images are extricated through Gabor filters. In this section, the Gabor filter, SDS proposed optimization of the Gabor filter and SVM methods are described.

Gabor filters

Gabor filters are band-pass filters that possess both orientation-selective as well as frequency-selective characteristics as well as best joint resolutions in spatial as well as frequency fields. Through the application of adequately tuned Gabor filters to signature images, textural data may be created. The accentuated textural data may be utilized for the generation of features vectors. Gabor filters are utilized with great success in segmenting fingerprints as well as palm prints, apart from their detection [10].

1D Gabor filters are given as the product of cosine/sine (even/odd) waves with Gaussian windows thus,

$$g_e(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{x^2}{2\sigma^2}} Cos(2\pi w_o x) \quad (1)$$

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$$g_o(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{x^2}{2\sigma^2}} Sin(2\pi w_o x) \quad (2)$$

Wherein w_o is center frequency (frequency wherein filters yield best response) and σ refers to the spread of Gaussian windows [11].

Gabor filters are obtained through the modulation of sinusoids with Gaussians. For 1D signals, 1D sinusoids are modulated with Gaussians. Filters respond to certain frequencies, though merely in signals' localized parts. Let g(x, y, θ, φ) be function delineating Gabor filter centred at origin with θ as spatial frequency as well as φ as orientation. Gabor filter is given by

$$g(x, y, \theta, \phi) = \exp(-\frac{x^2 + y^2}{\sigma^2}) \exp(2\pi\theta i(x \cos\phi + y \sin\phi))) \quad (3)$$

It is revealed that standard deviation of Gaussian kernels relies on spatial frequencies assessed that is θ.
2d Gabor functions comprise of sinusoidal plane waves of certain frequencies as well as orientations, with modulation by 2D Gaussian envelopes. 'Canonical' Gabor filters in spatial domains are as follows:

$$h(x, y) = \exp\left\{-\frac{1}{2}\left[\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right]\right\} \cos(2\pi\mu_0 x + \phi) \quad (4)$$

Wherein μ_0 and ϕ are frequencies as well as phases of sinusoidal plane waves along z-axes while σ_x and σ_y are space constants of Gaussian envelopes along x-axes and y-axes, correspondingly. Gabor filters with random orientations θ_0 may be got through rigid rotations of x-y coordinate systems. The 2D functions are revealed to be excellent fits with corresponding field profiles of generic cells in striate cortices.

Frequency-selective as well as orientation-selective characteristics of Gabor filters are more direct in their frequency domains' representations. When $\phi = 0$, Fourier transforms of Gabor functions in (5) are real-valued and become

$$H(u, v) = A(\exp\{-\frac{1}{2}[\frac{u - u_0}{\sigma_u^2} + \frac{v^2}{\sigma_v^2}]\} + \exp\{-\frac{1}{2}[\frac{u + u_0}{\sigma_u^2} + \frac{v^2}{\sigma_v^2}]\}) \quad (5)$$

Wherein

$$\sigma_u = 1/2\pi\sigma_x, \ \sigma_v = 1/2\pi\sigma_y, \ and \ A = 2\pi\sigma_x\sigma_y \quad (6)$$

Fourier domains' representations in (6) specify the quantity by which filters modify or modulate all frequency components of inputted images. These representations are known as Modulation Transfer Functions (MTF). Choosing best filters is crucial to enhancing performances of machine learning methods and it is NP-hard.

Stochastic Diffusion Search (SDS)

The current study suggests a systematic Gabor filter optimization method which produced better as well as problem-specific filter sets utilizing Stochastic Diffusion Searches (SDSs), which are able to discover the location of predetermined patterns or in event that they do not exist, their most optimal instantiation within the search space. SDS may be utilized for pattern searches as well as matchings. These issues may be considered with regard to optimizations through the definition of objective functions F(x), for hypotheses x regarding locations of solutions, because similarities between target patterns as well as respective regions at x in search spaces as well as discovering x so that F(x) is maximum. Generally, SDS may be employed with ease to several optimization issues wherein objective functions are capable of being divided into units which may be valuated in an independent fashion:

$$F(x) = \sum_{i=1}^{n} F_i(x) \quad (7)$$

Wherein $F_i(x)$ is given as the i[th] partial evaluation of F(x).

For locating optimum of specified objective functions, SDS uses populations of k agents, all of which maintain hypotheses regarding optimum. During operations, the model entails iterations of Test as well as Diffusion stages till agents perform convergence on best hypothesis.

SDS Algorithm comprises [12]:

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Initialising agents()
while(terminating criterion is not fulfilled)
Testing hypothesis()
Diffusion hypothesis()
Stop

Initialisation: Generally, first hypotheses of all agents are chosen evenly arbitrarily across search spaces. If data regarding potential solutions are accessible in an a priori fashion, it may be utilized for biasing original choosing of hypotheses.

Test Function: Boolean test functions reveal if arbitrarily chosen partial valuation of objective functions denote 'good' hypothesis or not.

Test Phase: All agents employ test functions to their current hypotheses. When test functions return true, agents are active, else they are inactive. **Diffusion Phase**: All inactive agents (A) choose one more agent (B) arbitrarily. If they are active, then their hypotheses are duplicated by A. If they are inactive, then A chooses one more arbitrarily across search space. **Convergence**: With the advancement of iterations, clusters or agents with identical hypotheses are generated. When converged, biggest cluster of units gives the best solution.

SDS efficiently carried out most optimal match among already present objects in search spaces as well as descriptions of targets. It is given that SDS will be capable of discovering targets if they exist in the search space else they identify objects with most identical descriptions of targets. Spaces as well as objects are delineated with regard to Atomic Data Units (ADUs) that comprise set of fundamental attributes. All objects in search spaces as well as targets are defined with regard to ADU and are not capable of possessing attributes ADUs may be regarded as single pixel intensities when search spaces are bitmap images or may comprise few higher level characteristics such as vertical or horizontal lines, angles or even semicircles. When search spaces as well as targets are delineated with regard to these characteristics or they may be letters or nodes in graphs.

All agents act in an autonomous manner as well as in parallel with others attempt to identify the location of targets in search spaces. The location of targets are denotes as coordinates of predetermined reference points in targets' descriptions. Transmissions or dispersal of data ensures that units are able to interact with one another and allot operational resources in a dynamic fashion on the basis of results of searches. On the basis of the performance in searches, agents may become active if they reveal possibly accurate locations in search spaces else, they are inactive. Every agent has access to search spaces as well as descriptions of targets [13].

Originally every agent is arbitrarily initialized to a reference point in search space. Additionally, they are first set as inactive. All agents, independent of one another perform probabilistic checks of data at reference points through comparison of arbitrary ADU from targets with respective ADU in search spaces. If tests are successful, agents become active else, they are inactive.

In conclusion, activities of agents indicate the probability that they point to accurate location. But because of partial testing, probability of false positives is not discarded and neither is the likelihood of false negatives. In this manner, SDS may obviate local minimum through correspondence to objects which have partial matches to descriptions of targets. Consequently during diffusion, all inactive agents arbitrarily choose one more agent to interact with. On the basis of whether the selected unit is active or not, the selecting agent points to the same point as the one that is active else arbitrarily resets its position, if it is also inactive. Active units do not perform sampling of other agents for transmissions but they go through fresh testing stage and on the basis of it, maintain active status or become inactive.

The procedure continues till statistical equilibrium is attained. Terminating criteria utilized and supervised the most quantity of agents showing same location in search space. When quantity of agents in the cluster is greater than a specified threshold and it within particular boundaries for a set of iterations, it is described as SDS reaching equilibrium while process is stopped. Although agents perform in an autonomous manner and merely weak forms of probabilistic couplings exist, it ensures that agents build cooperative nature.

Support Vector Machine (SVM)

SVM is a group of monitored learning mechanisms utilized in classifications as well as regressions. It belongs to a set of generic linear classifications. Specific characteristic of SVMs are that they concurrently reduce empirical classification errors to a minimum while bringing to a maximum the geometric margin. Hence, SVMs are known as maximum margin classifiers. SVMs are grounded in Structural Risk Minimization (SRM). SVM maps input vectors to high dimensional spaces wherein maximal separating hyperplanes are created. Two parallel hyperplanes are created on both sides of hyperplanes which keep information separate. Separating hyperplanes are those which make the distance between two parallel hyperplanes maximum. A presumption that is made is that the greater the margin between parallel hyperplanes, the more improved the generalization error of classifiers [14].

It regards data points in the format

$$\{(x_1, y_1), (x_2, y_2), (x_3, y_3), (x_4, y_4).....,(x_n, y_n)\} \quad (8)$$

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Wherein $y_n = 1/-1$, a constant representing class to which point xn is a part of. n = number of sample. Every x_n is a p-dimensional real vector. Scaling is significant in guarding against variables with greater variance. The training data may be viewed through separating hyperplanes that take

$$w \,.\, x \;+\; b \;=\; o \tag{9}$$

Wherein b is scalar and w is p-dimensional Vector. Vector w is perpendicular to the separating hyperplane. Appending offset variable b permits the expansion of margins. Absent of b, hyperplane is made to pass through origin, limiting solution. Parallel hyperplanes may be given as

$$w.x \;+\; b \;=\; 1$$
$$w.x \;+\; b \;=\; -1 \tag{10}$$

If training data is linearly separable, it is capable of selecting hyperplanes such that there are no points between them and later attempts the maximization of distances. Geometrically, it discovers the distance between hyperplanes as 2/|w|. Hence, |w| is to be minimized. For excitation of data points, it is required to be ensured that for every I either

$$w.\,x_i \;.\, b \;.\, 1 \; or \; w.\,x_i \;.\, b \;.\; -1 \tag{11}$$

This may be given as

$$y_i \;(\; w.\,x_i \;.\, b) \geq 1\,, \quad 1 \leq i \leq n \tag{12}$$

Samples along hyperplanes are known as Support Vectors (SVs). Separating hyperplanes with biggest margin delineated by M = 2 / |w| which defines supports support vectors implying training data points nearest to it. This has to fulfil:

$$y_j[w^T.x_j + b] = 1 \qquad ,i = 1 \tag{13}$$

Optimal Canonical Hyperplanes (OCH) are canonical hyperplanes possessing most margin. OCHs ought to fulfil the restrictions given below:

$$y_i[w^T.x_i + b] \geq 1 \qquad ;i = 1,2.....1 \tag{14}$$

Wherein l is Number of Training data point. For discovering best separating hyperplanes possessing most margins, learning machines ought to make minimum the $\|w\|^2$

The issue was resolved by saddle points of Lagrange's Function:

$$L_p = L_{(w,b,\alpha)} = \tfrac{1}{2} \| w \| 2 - \sum_{i=1}^{1} \alpha_i (y_i (w^T x_i + b) - 1)$$

$$= \tfrac{1}{2} w^T w - \sum_{i=1}^{1} \alpha_i (y_i (w^T x_i + b) - 1) \tag{16}$$

Wherein α_i is a Lagranges multiplier. Searching for best saddle points (w_0, b_0, α_0) is required as Lagranges should be made minimum in terms of w and b and should be made maximum in terms of nonnegative α_i ($\alpha_i \geq 0$). The issue may be resolved n primal or dual forms. The two formulae are convex and KKT conditions that are required as well as adequate criteria for maximums of equations. Partially differentiated equations in terms of saddle points (w_0, b_0, α_0) [15]:

$$\partial L / \partial w_0 = 0 \tag{17}$$

$$w_0 = \sum_{i=1}^{1} \alpha_i \; y_i \; x_i \tag{18}$$

$$\partial L / \partial b_0 = 0 \tag{19}$$

$$\sum_{i=1}^{1} \alpha_i \; y_i = 0 \tag{20}$$

Replacing above equation, it changes primal to dual form.

$$L_d(\alpha) = \sum \alpha_i - 1/2 \sum_{i=1}^{1} \alpha_i \alpha_j y_i y_j x_i^T x_j \tag{21}$$

To discover optimal hyperplanes, dual Lagrangians (L_d) have to be made maximum in terms of nonnegative α_i (i .e. α_i should be in nonnegative quadrant) as well as in terms of equality restrictions as given:

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$$\alpha_i \geq 0 \qquad ,i=1,2.....1$$

$$\sum_{i=1}^{1} \alpha_i y_i = 0 \qquad (22)$$

It is to be noted that dual Lagrangians $L_d(\alpha)$ are given with regard to training data as well as depending solely on scalar products of input pattern $(x_i^T x_j)$.

Several kernel functions assist SVM in obtaining best solutions. RBF is employed often because it is capable of classifying multi-dimensional data. With RBF kernels, two variables C that represent costs of penalties as well as Υ impact splitting result in features space ought to be set adequately.

RESULTS AND DISCUSSION

Performance efficacy of suggested methods for the classification of MRIs as MCI is tested through 135 images taken from individuals between 20 and 65 years of age, with around 84 anomalous scans revealing MCI. Feature extraction is carried out on the MRIs through Gabor filters as well as the suggested optimization technique. The outcomes got through Gabor filters with no optimization but filter banks with orientations of 0, 45, 90 and 135 degrees on 13 by 13 windows. **[Table 1 - 5]** and **[Figure 1 - 5]** as shown below:

Table: 1. Classification Accuracy

Techniques used	Classification Accuracy (%)
CSGabor - SVM(Poly)	89.95
CSGabor - SVM(RBF)	93.15
SDSGabor- SVM(Poly)	88.13
SDSGabor- SVM(RBF)	92.69
CSSDS- SVM(Poly)	94.93
SCSDS- SVM(RBF)	95.85

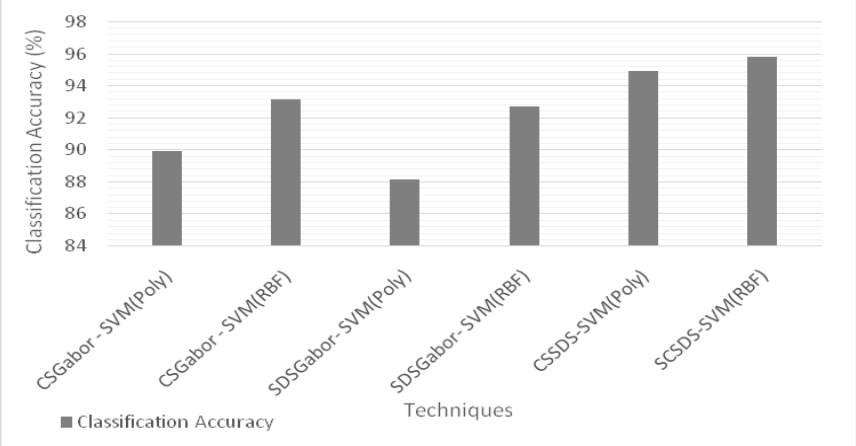

Fig: 1. Classification Accuracies

From the **[Figure- 1]**, it is seen that the SCSDS-SVM (RBF) technique increased classification accuracies by 195.78%, 195.92%, 8.39%, 3.35% & 0.96% when compared with various number of CSGabor – SVM (Poly), CSGabor – SVM (RBF), SDSGabor- SVM (Poly), SDSGabor- SVM (RBF) and CSSDS-SVM (Poly) methods.

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Table: 2. Sensitivity for normal

Techniques used	Sensitivity for normal
CSGabor - SVM(Poly)	0.9111
CSGabor - SVM(RBF)	0.9556
SDSGabor- SVM(Poly)	0.8741
SDSGabor- SVM(RBF)	0.9333
CSSDS- SVM(Poly)	0.9699
SCSDS- SVM(RBF)	0.9699

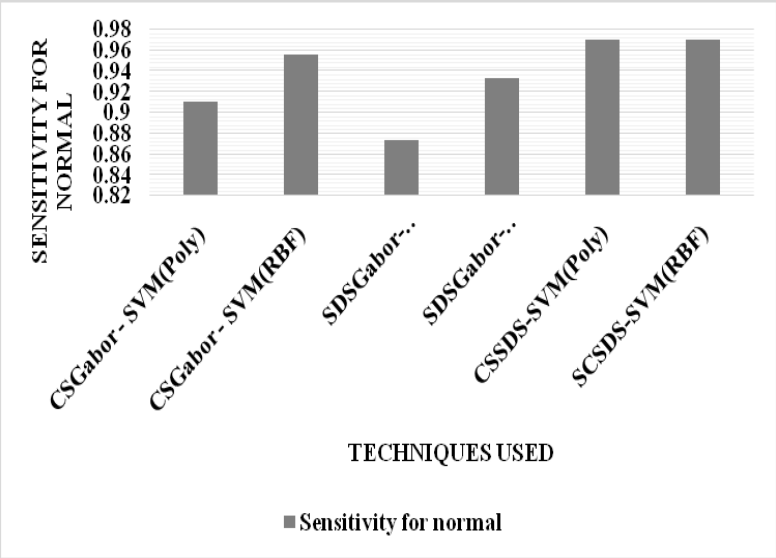

Fig: 2. Sensitivity for normal

From the **[Figure- 2]**, it is seen that the SCSDS-SVM (RBF) technique improved sensitivities for normal by 6.25%, 1.48%, 10.39%, 3.84% & 0% when compared with various number of CSGabor – SVM (Poly), CSGabor – SVM (RBF), SDSGabor- SVM (Poly), SDSGabor- SVM (RBF) and CSSDS-SVM (Poly) methods.

Table: 3. Sensitivity for abnormal

Techniques used	Sensitivity for abnormal
CSGabor - SVM(Poly)	0.881
CSGabor - SVM(RBF)	0.8929
SDSGabor- SVM(Poly)	0.8929
SDSGabor- SVM(RBF)	0.9167
CSSDS- SVM(Poly)	0.9167
SCSDS- SVM(RBF)	0.9405

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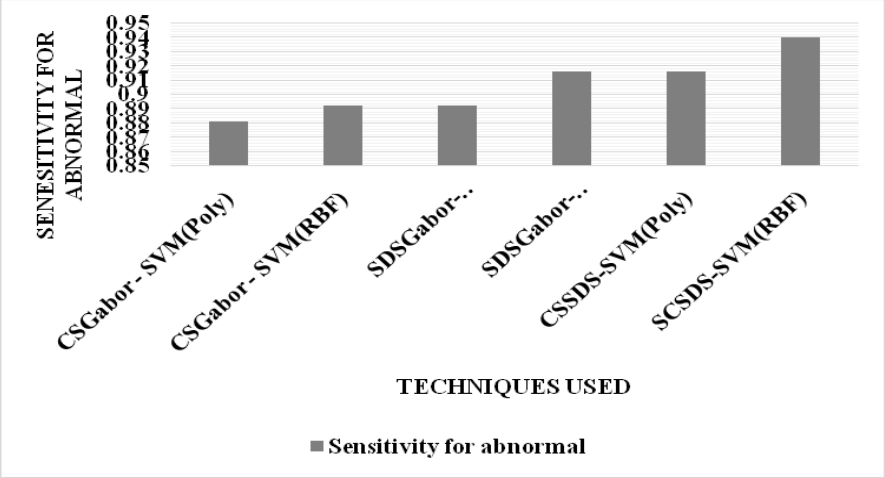

Fig: 3. Sensitivity for abnormal

From the **[Figure- 3]**, it is seen that SCSDS-SVM (RBF) technique improved sensitivities for abnormal by 6.53%, 5.19%, 5.19%, 2.56% & 2.56% when compared with various number of CSGabor – SVM (Poly), CSGabor – SVM (RBF), SDSGabor- SVM (Poly), SDSGabor- SVM (RBF) and CSSDS-SVM (Poly) methods.

Table: 1. Specificity for normal

Techniques used	Specificity for normal
CSGabor - SVM(Poly)	0.881
CSGabor - SVM(RBF)	0.8929
SDSGabor-SVM(Poly)	0.8929
SDSGabor-SVM(RBF)	0.9167
CSSDS-SVM(Poly)	0.9167
SCSDS-SVM(RBF)	0.9405

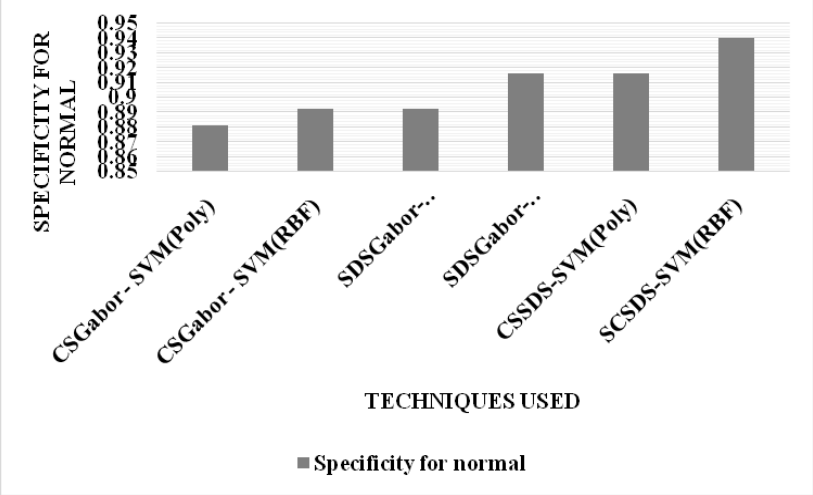

Fig:1. Specificity for normal

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From the **[Figure 4]**, it can be observed that the SCSDS-SVM (RBF) method increased Specificity for normal by 6.53%, 5.19%, 5.19%, 2.56% & 2.56% when compared with various number of CSGabor – SVM (Poly), CSGabor – SVM (RBF), SDSGabor- SVM (Poly), SDSGabor- SVM (RBF) and CSSDS-SVM (Poly) methods.

Table: 2. Specificity for abnormal

Techniques used	Specificity for abnormal
CSGabor - SVM(Poly)	0.9111
CSGabor - SVM(RBF)	0.9556
SDSGabor- SVM(Poly)	0.8741
SDSGabor- SVM(RBF)	0.9333
CSSDS- SVM(Poly)	0.9699
SCSDS- SVM(RBF)	0.9699

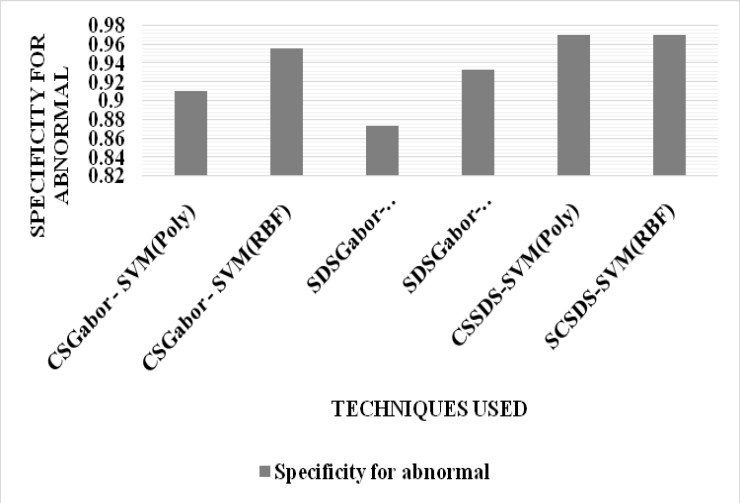

Fig:2. Specificity for abnormal

From the **[Figure- 5],**it can be observed that the SCSDS-SVM (RBF) method increased Specificity for abnormal by 6.25%, 1.48%, 10.39%, 3.84% & 0% when compared with various number of CSGabor – SVM (Poly), CSGabor – SVM (RBF), SDSGabor- SVM (Poly), SDSGabor- SVM (RBF) and CSSDS-SVM (Poly) methods.

CONCLUSION

To optimize variables, several search as well as optimizing methods are utilized because it is NP-hard. The current work utilized SDS for selecting variables in SVM and for optimizing variable selections for Gabor filters. Gabor filter banks are also built through SDS with the goal of most textural attributes discriminations. Gabor filters as well as histogram extricate attributes from MRIs and the attributes are sorted through SVM RBF and SVM with suggested kernel optimizations. Outcomes reveal that the suggested method increases classification accuracies in a significant manner. The SCSDS-SVM (RBF) method increased classification accuracy by 195.78%, 195.92%, 8.39%, 3.35% & 0.96% when compared with various number of CSGabor – SVM (Poly), CSGabor – SVM

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(RBF), SDSGabor- SVM (Poly), SDSGabor- SVM (RBF) and CSSDS-SVM (Poly) methods. Discovering most optimal C and variables are NP-hard.

CONFLICT OF INTEREST

The authors declare no conflict of interests.

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