Analysis of Alzheimer's Disease Detection using GSVM Algorithm

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Abstract

We proposed an application to identify Alzheimer's illness in our research. The frontal section was utilized to extract the Hippocampus (H), the Sagittal section was used to analyze the Corpus Callosum (CC), and the axial section was used to work with the various aspects of the Cortex (C).Traditional machine learning approaches have relatively lower performance with larger amounts of input data. It can be challenging to detect brain abnormalities correctly and to find a solution for the automatic segmentation of brain structures. Such challenges mainly arise from the changes in settings for the acquisition of MRI scans, fluctuations in the appearance of pathology,normal anatomical variations in brain morphology,and imperfections in image acquisition. These limitations of traditional methods can be overcome by machinelearning-based methods. Moreover, machine learning can also be used to perform quantitative analysis of brain MRI through the self-learning of features, by which new features can be recognized. One of the procedures that are most commonly used in extracting features of Alzheimer's disease from a person's brain is called the Support Vector Machine-based Recursive Feature Elimination(SVMRFE) procedure.The specialty of SVMRFEis that it usesone slackvariable, whereas Universal Support Vector Machine (USVM) uses two slack variables.In the proposed method of classification, Global Support Vector Machine (GSVM), three slack variables are used. With the proposed method, theaccuracy is increased by 1.92%, sensitivityis increased by 10.24%in the diagnosis of Alzheimer's disease.

Key Words: GSVM, MRI, SVM,USVM, MORPHOMETRY,ALZHEIMER'S DISEASE.

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I. INTRODUCTION

Alzheimer's disease is a neurological disorder in which the person who is affected by this disease loses his/her cognitive ability slowly with the passage of time. Since it is one of the most common reasons for death in the world a lot of research has been done in this field to efficiently diagnose, verify and cure this disease[1]. One of the important procedures to detect this disease is using Magnetic Resonance Imaging (MRI). This is a procedure by which is non-invasive in nature and from the images that are obtained a large number of feature extraction procedures can be applied which will help to quickly determine the tissues in the brain that are affected by this disease. One of the procedures that are most commonly used in extracting features of Alzheimer's disease from a person's brain is called support vector machine-based recursive feature elimination also known as the SVM-RFE procedure[2][3]. The SVM-RFE procedure was first introduced by Guyon et al. (2002) to detect genes causing cancer and classify the discovered cancer. From this paper,many other SVM-based classification techniqueswere invented and utilized for the purpose of image processing and other research activities. One of the most commonly used techniques was the twin support vector machine classifier that was proposed on 2007 by Jayadeva, Khemchandani, and Chandra. By this technique, two planes that are not parallel to each other are generated in a manner that each plane is closer to one of the classes and is separated from each other by one distance. This thing is solved by solving two quadratic programming problems, also known as QPPs, each of which issmaller in size compared to one large QPP. That is required to be solved in case of most machine learning problems. As a result of this procedure the speed at which the problem can be solved increases vastly compared to those algorithms where we need to solve a single large QPP. This procedure also increases the accuracy of the results obtained at the end of the procedure. The results obtained from the experiments conducted by byJayadeva, Khemchandani, and Chandra showed that Twin support vector machine classifier also knows as TSVM technique vastly outperforms the standard SVM technique that was invented by Guyon et al. on 2007[4]. The TSVM technique invented by Jayadeva, Khemchandani and Chandra has been extended further in the research works of Shao and Deng (published on 2011), Khemchandani, Jayadeva and Chandra (published on 2009) and in the research works of Zhiquan Qi and Shi (published on 2012 and 2013). Based on this technique newer techniques have been invented called the Twin Support vector machine using Universal data. This seminal work was published by Zhiquan Qi, Y. Tian and Yong Shi on 2012 (Neural Networks, vol. 36 pp. 112-119)[5][6]. In this technique,the data from two classes are used along with the data from the two classes utilized along with the utilization of the Universal data also. In the case of our research, we obtained these data sets from the database on neurological and genetic databases of sources by ADNI (website id: *adni.loni.usc.edu*). We also obtained data from the AIBL(website id: *aibl.csiro.au*), and also from the databases of OASIS (website id: *www.oasis-brains.org*). From these databases, we have been able to obtain data on the tissue conditions of subjects who were at different stages of this dangerous Alzheimer's disease[7]. The subjects in the stages of this disease have been divided into three parts (1) subjects who are in normal conditions who are referred to as Control normal or CN in this document (2) subjects who are suffering from Mild Cognitive Impairment or MCI - and (3) subjects who are suffering from Alzheimer's Disease referred to as AD in this document. Incidentally,these methods of investigation have been adopted in a very recently published paper written by B. Richhariya, Tanveer, and Rashid on 2020. In this work,Richhariya et al. have identified regions in the human brain that are affected by the deadly Alzheimer's disease. To investigate their problem they utilized the SVM-RFE technique and also an new algorithm that they formulated called the USVMRFE algorithm[8][9]. In their research, they considered the same three types of subjects that we assumed for the purpose of our research, i.e., (1) subjects who are in Normal Condition(CN), (2) subjects who are suffering from Mild Cognitive Impairment(MCI), and (3) subjects who are suffering from Alzheimer's Disease as AD[10].In this research, they evaluated their technique with respect to the more established methods like Support Vector Machine – Recursive Feature Elimination or SVM-RFE. They compared their results for parameters like accuracy of diagnosis and sensitivity of their proposed algorithm. For the purpose of their research they consulted 150 images of MRI from the data base of Alzheimer's Disease Neuroimaging Initiative also known as ADNI (website id: *adni.loni.usc.edu*)[11]. The Alzheimer's Disease Neuroimaging Initiative was started on 2003 by the Principal Investigator of this project Michael W> Weiner, MD. It started as a public enterprises and private enterprises. The aim of the Alzheimer's Disease Neuroimaging Initiative as to get an idea by how effective the different neuroimaging techniques are by analyzing their effectiveness using real-time data. The different imaging techniques considered by the Alzheimer's Disease Neuroimaging Initiative are Magnetic Resonance Imaging technique (also known as MRI), Positron Emission Tomography technique (also known as PET)[12][13]. Apart from this, they utilized various other biological markers and they also gathers data on various clinical neurological tests where they investigated cases ofAlzheimer's disease from the starting of initial disease symptom conditions likeMCI.

For the purpose of our research we have consulted 150 MRI images that we obtained from the databases of the Alzheimer's disease Neuroimaging Initiative. We have considered data from subjects we were in the conditions of CN i.e. Control Normal, subjects who were in the conditions of Mild Cognitive Impairment and from subjects who are suffering from Alzheimer's disease[14][15]. The subjects whose neurological images were consideredof the age group between 50 to 90 years of age. And they had a mean age of 71.23 years with a standard deviation of 4.32years. Also, we have downloaded from ADNI images of 923 other subjects for the verification that the model that we designed are applicable in more general cases or not.

Since the work of Richhariya et al. has been published in 2020 in a highly acclaimed journal, we considered this work for the purpose of comparison with the Alzheimer's disease diagnosis algorithm that we developed in course of this work.The research objective's are as follows:

- To study the basic concept of Alzheimer's Disease.
- To study and realize the need and significance of Automatic Classifier techniques.
- Design of GSVM algorithm

II. METHODOLOGY

A. ***DataSets used and Methods Applied***:The data for this work has been obtained from the database of Alzheimer's Disease Neuro-imaging Initiative (website id: *adni.loni.usc.edu*). We collected 160 structural MRI images. While collecting the data we consciously collected 50 MRI images of subjects who are in CN condition, 50 images from subjects who are in MC Icondition, and 50 images on subjects who are in AD condition.

The chosen subjects were in the range of 50 to 90 years of age. The mean age of the considered subjects is 72.26 years and the standard deviation of the considered. Dataset of subjects in 4.332 years. We have done classification tasks on (1) Control Normal subject's vs Mild Cognitive Impairment subjects (2) Mild Cognitive Impairment subjects' vs Alzheimer's Disease subjects and (3) Control Normal Subjects vs Alzheimer's disease subjects. On the same data set of the same subjects we applied the algorithms of support vector machine-based recursive feature elimination (i.e., SVM-RFE) and Universum Support Vector Machine base Recursive Feature Elimination (USVM-RFE).

B. Analysis of Voxel Based Morphometry

In this work we performed Voxel Based morphometry analysis using the popular neuroimaging tool box called Statistical Parametric Mapping (SPM) version 11. The pre-processed images so obtained were used in the following binary classification jobs namely:

(1) Control Normal subjects vs Mild Cognitive Impairment subjects
(2) Mild Cognitive Impairment subjects vs Alzheimer's Disease subjects and
(3) Control Normal Subjects vs Alzheimer's disease subjects.

C. Analysis of Volume based Morphometry

For Volume-based Morphometry or VoIBManalysis we used the software Freesurfer's recon-all pipelineversion 5. This software has been sued by us on structural MRI images. Of all the images that we used, i.e. 150 MRI images, two (2) images on Mild Cognitive Impairment subjects have failed to be processed by Freesurfer. As a result the task of feature selection we executed on 148 MRI images. We obtained 32 volumes of subcortical tissues (also called SCV), 36 volumes of white matter (WM) tissues and 36 thicknesses of cortex measurements of each and every subject.

Finally in order to investigate the generality of our proposed algorithm we further acquired 820MRI images from the baseline dataset of ADNI. From these 820 MRI images that we downloaded, 5 images were not being able to be processed via the Freesufer pipeline.

The thickness feature of the cortex was formed by the addition of the Thickness measurements of the two brain hemispheres being added together. For the purpose of volumetric features a similar approach has been implemented. After this the volumetric features were divided by the total intercranial volume (or TIV value) to obtain the normalized value of volumetric features of the subjects.

The features are extracted from the masked images. After that the algorithms like Statistical Parametric Mapping or SPM, PCA and F-Score are applied on the obtained data to reduce the dimensionality and to select the correct features.

D. *Discussion of related Algorithms*:

In this sub-section, we give a brief overview of the algorithms that are used for the diagnostics of the Alzheimer's disease by the help of feature elimination method. The most important algorithms that we considered for our study are Support Vector Machine Recursive Feature Elimination (SVM-RFE) that have been proposed by Qi et al. in 2012 and the Universum Support Vector Machine based Recursive Feature Elimination (USVM-RFE) that has been proposed in 2020. We used both the algorithms on the data that we collected from ADNI to present comprehensive comparison about the effectiveness of our proposed algorithm and the effectiveness of the algorithms USVM-RFE(Richhariya et al, 2020) and SVM-RFE (Qi et al. , 2012).

E. Basic concept behind SVM-RFE

The support Vector machine or SVM is designed in the following manner:

$$\min_{x,y,s_1}\frac{1}{2}\|x\|^2+\rho_1\sum_{i=1}^{f}s_{1i}\quad(1)$$

Such that

$$c_i(x^T\phi(d_i)+y)\geq 1-s_{1i}\quad(2)$$

$$s_{1i}\geq 0,\forall\ \ i=1,2,\dots..,f$$

In which f represents the total number of points of data,ρ_1 is the penalty parameter, s_{1i} is the slack variable and c_i is the class label and $\phi: R^n\rightarrow R^p$ represents a function that is platting from to *p* dimensions from *n* dimensions and *p*>*n*.

Classifier in this case is represented as

$$f(x)=sign(x^Td+y\qquad(3)$$

F. Basic Concept of USVM or Universal Support Vector Machine

The Universal Support Vector Machine is formulated in the following manner:

$$\min_{x,y,s_1,s_2,s_3}\left[\frac{1}{2}x^2+\rho_1\sum_{i=1}^{f}s_{1i}+\rho_2\sum_{j=1}^{2a}s_{2j}\right](4)$$

Such that

$$c_i(x^T\phi(d_i)+b)\geq 1-s_{1i}(5)$$

$$c_j\left(\omega^T\phi\left(d_j\right)+b\right)\geq -\epsilon-s_{2j}(6)$$

$$s_{1i}>0,s_{2j}>0,$$

$$\forall\ \ i=1,2,\dots..,f$$

$$\forall j=1,2,\dots\dots\dots\dots.,2r$$

$$\forall k=1,2,\dots\dots\dots\dots n$$

where$f$ is the number of data points, $\rho_1>0,\rho_2>0$ are penalty parameters, $s_{1i},s_{2j}\ and\ s_{3k}$ are slack variables.$c_i,c_j\ and\ c_k$ are class label, ϕ:$R^n\rightarrow R^p$ is the function mapping from n to p dimensions where $p>n$, and r is the number of global samples.

G. Global support Vector Machine (GSVM)

Based on the findings of SVM and USVM we attempted to create a more generalized version of Support Vector Machines or SVM which will be used in this work to analyze the Magnetic Resonance Imaging Data that we obtained from the ADNI database of Alzheimer's disease patients.

We have formulated GSVM in the following manner

$$\min_{x,y,s_1,s_2,s_3}\left[\frac{1}{2}x^2+\rho_1\sum_{i=1}^{f}s_{1i}+\rho_2\sum_{j=1}^{2a}s_{2j}+\rho_3\sum_{k=1}^{b}s_{3k}\right]$$

(7)

Such that

$$c_i(x^T\phi(d_i)+b)\geq 1-s_{1i}(8)$$

$$c_j\left(\omega^T\phi\left(d_j\right)+b\right)\geq -\epsilon-s_{2j}(9)$$

$$c_k\left(\omega^T\phi\left(d_j\right)+b\right)\geq 1-s_{3k}(10)$$

$$s_{1i}>0,s_{2j}>0,s_{3k}>0,$$

$$\forall\ \ i=1,2,\dots..,f$$

$\forall j = 1,2, \ldots \ldots \ldots \ldots, 2r$
$\forall k = 1,2, \ldots \ldots \ldots \ldots n$
where f is the number of data points, $\rho_1 > 0, \rho_2 > 0$ and $\rho_3 > 0$ are penalty parameters, s_{1i}, s_{2j} and s_{3k} are slack variables. c_i, c_j and c_k are class label, $\phi: R^n \rightarrow R^p$ is the function mapping from n to p dimensions where $p > n$, and r is the number of global samples.

The speciality of this algorithm is that it utilizes three slack variables instead of two slack variable that are used in case of Universal Support Vector Machine (USVM) or just one slack variable as is used in case of Support Vector Machine (SVM). This allows us to include more information in our datasets for example inter-cranial blood circulation pressure and intercranial blood glucose levels and inter-cranial blood cholesterol levels. These data we are considering in addition to the data that the authors of USVM algorithm Richhariya et al. (2020) considered for their research like voxel based morphometry and volume based morphometry where they considered the intercranial volume one of the parameters inn their research.

Demonstrated below is the algorithm for the newly proposed GSVM or Global Support Vector Machine algorithm.

H. Proposed GSVM Algorithm

1. ***Inputs***:
2. Training Data
3. $X = [x_1, x_2, \ldots \ldots \ldots \ldots, x_l]^T$
4. Class labels
5. $C = [c_1, c_2, \ldots \ldots \ldots, c_l]^T$
6. Global Data
7. $U = [u_1, u_2, \ldots \ldots \ldots, u_r]^T$
8. ***Procedure***:
9. Find optimal parameters for recursive process using k-fold cross validation
10. Feature set
11. $S = [1,2, \ldots \ldots \ldots, n]$
12. Feature ranked list
13. $R = [\ ]$
14. Repeat until $S = [\quad]$
15. Feature selection
16. $X = X(:, S)$
17. $U = U(:, S)$
18. Train SVM classifier using parameters obtained in step 9
19. $\chi = GSVM_{train}(X, C, U)$
20. Compute the weight vector with dimension of length (S)
21. $\omega = \sum_{i=1}^{f+2r} \alpha_i c_i x_i$
22. Computing ranking criteria
23. $C_i = (\omega_i)^2, i = 1,2, \ldots., length(S)$
24. Find feature with smallest rank
25. $f = argmin(C)$
26. Update feature ranked list
27. $R = [S(f), R]$
28. Eliminate the feature with smallest rank
29. $S = [1: f - 1, f + 1: length(S)]$
30. ***Output***
31. Feature ranked list R

In this algorithm, we are considering three sets of data.

(1) AD vs CN

The comparison between subjects who are have normal neurological conditions which we refer to as Control Normal subjects or CN subjects and the other is the patients who are suffering from Alzheimer's disease which we refer to as AD subjects. For all these subjects we have downloaded data from the Alzheimer's Disease Neuroimaging Initiative database. We collected data which are neurological images from 50 subjects who were suffering from Alzheimer's disease and 50 subjects who had perfectly normal neurological conditions based on these data we performed experiments on the gathered source of information to generate s study. We applied the Universal Support Vector Machine – Recursive Feature Elimination Algorithm and the Support Vector Machine-Recursive Feature Elimination algorithm on both types of data i.e. data from the subjects with Alzheimer's disease and data from the subjects who have normal neurological conditions. After this we applied our self-developed GSVM-RFE or Global support Vector Machine – recursive feature elimination algorithm on the same data set. After the execution of these algorithms in MATLAB software, we obtained a result in which we evaluate the sensitivity of our algorithm to the obtained data set with respect to the Support Vector Machine Algorithm and the Universal Support Vector Machine algorithm. After this, we applied the Global Support Vector Machine Algorithm on the dataset and evaluated it for Accuracy of the generated results with respect to the Universal Support Machine algorithm and the Support Vector Machine Algorithm respectively. After this we also applied our self-developed GSVM or Global Support Vector Machine algorithm on the same dataset and we evaluated it for specificity and compared our obtained results with the results of the algorithms of Universal Support Machine and the results of the algorithm Support Vector Machine on the data set of neurological images of 50 AD or Alzheimer's disease affected subjects and on the neurological images of Control Normal subjects.

(2) MCI vs AD

In this case, we applied the self developed Global support Vector Machine algorithms on the data set of 50 subjects who are suffering from mid cognitive impairment and on the neurological MRI images of 50 patients who are deeply suffering from Alzheimer's disease. We performed our operations in MATLAB framework. These results we evaluated against the results that we obtained by applying the Support Vector Machine Agathism and the Universal Support Vector Machine algorithm or USVM-RFE algorithm. Which we applied on the same data set of 50 patients suffering from mild cognitive impairmentand on the imaging data of 50 patients suffering from severe version of Alzheimer's disease. After this we evaluated the data obtained from these programs with respect to each other. And we first evaluated this data to find out the accuracy of each algorithm in correctly identifying the person with normal neurological conditions with the person suffering from mild cognitive impairment with the person suffering from severe version of Alzheimer's disease. After this we evaluated the results obtained from our self-developed GSVM algorithm with respect to the results obtained from the USVM or Universal Support Vector Machine algorithms and the SVM or Support Vector Machine algorithm respectively for the parameter of Sensitivity. In this case we tried to find out which of the developed algorithms have more sensitivity to the datasets under evaluation with respect to the other similar algorithms. After this we evaluated our self-developed GSVM algorithms with respect of the USVM or Universal Support Vector Machine algorithms and the Support Vector Machine algorithms on the same neurological picture data set to evaluate the Specificity our the considered algorithms. From these results we got. Certainresults which we will demonstrate in the following parts of this chapter.

(3) CN vs MCI

In this algorithm, we applied our self-developed Global support vectorMachine algorithm with the Universal Support Vector Machine Algorithms with respect to the Support Vector Machine Algorithms on the data sets of 50 subjects s who are suffering from mild neurological disorders and neurological images of 50 subjects who are not suffering from any sort of neurological disorder. After evaluating these results, we have generated these types of studies based on our obtained results. First, we evaluated our results for the parameter of accuracy of prediction of possibility of the patient having mild neurological impairment which may lead to his or her progress towards the more imminent danger of Alzheimer's disease. Secondly, evaluated the results we obtained from for the parameter of sensitivity towards the detection of mild cognitive impairment with respect to the persons who are not suffering from any neurological disorders i.e. with Cognitive Normal persons. After this we evaluated these result for the parameter of specificity of the algorithms in detecting persons with mild cognitive impairment with people suffering from no neurological disorders. After evaluation of this result s the results have been planted in a graph and presented in the later sections of this chapter. From the results we will be able to establish the data for the fact that our self-developed GSVM algorithms performs much better than the USVM algorithm developed by Richhariya et al and the SVM algorithm developed by Qi et el. For similar kind of situations.

III.RESULTS AND DISCUSSION

Given below is the graphical representation of the results obtained for the self-developed GSVM algorithms as well as the results obtained by using the USVM algorithms and the SVM algorithm on the same data set.Accuracy of proposed GSVM algorithms against USVM and SVM algorithm for Control normal subjects and Mild Cognitive Impairment subjectsFrom the Results we concluded that with the proposed GSVM-RFE algorithm performs marginally better than the other two algorithms USVM-RFE [Richhariya et al, 2020] and SVM-RFE [Qi, et al. 2012] although Accuracy of SVM –RFE algorithm marginally increases above the proposed GSVM-RFE algorithm when we consider Tissue Features of 35% and 40%.Insight Figure 1 show that Comparison of performance for Accuracy of proposed GSVM-RFE algorithm against existing algorithms. USVM-RFE [Richhariya et al, 2020] and SVM-RFE [Qi et al, 2012]on dataset obtained from ADNI for Control Normal and Mild Cognitive Impairment Subjects

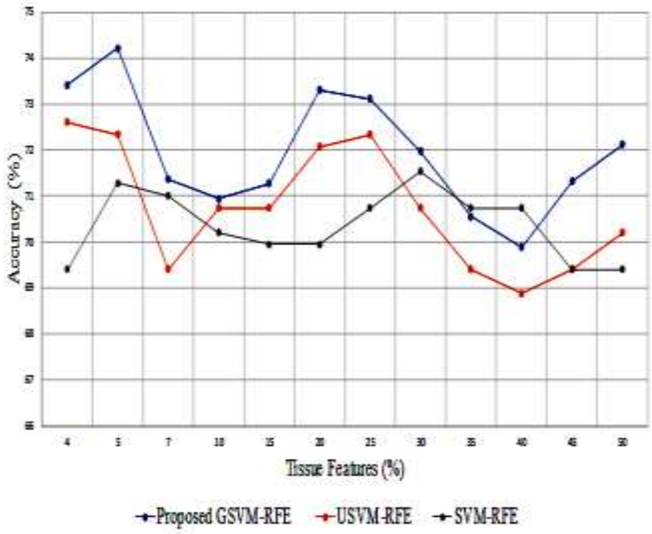

Figure 1.Comparison of performance for **Accuracy** of proposed GSVM-**RFE** algorithm against existing algorithms.

Table 1: Comparison of performance for **Accuracy** of proposed GSVM-RFE algorithm against existing algorithms

Tissue Features (%)	Accuracy (%)	Accuracy (%)	Accuracy (%)
Control Normal Subjects VsAlzheimer's Disease Subjects	Proposed GSVM-RFE	USVM-RFE	SVM-RFE
4	73.42	72.61	69.41

5	74.22	72.34	71.28
7	71.37	69.41	71.02
10	70.95	70.74	70.21
15	71.27	70.74	69.95
20	73.31	72.07	69.95
25	73.12	72.34	70.74
30	71.98	70.74	71.54
35	70.56	69.41	70.74
40	69.89	68.88	70.74
45	71.32	69.41	69.41
50	72.12	70.21	69.41

Given above is the graphical representation of the results of USVM-RFE [Richhariya et al, 2020] and SVM-RFE [Qi et al, 2012]ona dataset obtained from ADNI for Control Normal and Mild Cognitive Impairment Subjects
Accuracy of proposed GSVM algorithms against USVM and SVM algorithm for Control Normal subjects and Alzheimer's disease affected subjects based on the results obtained in Table 1. In Figure 2. And Table 2. it is demonstrated that when we are considering Tissue Features lower than 15%, the accuracy of SVM-RFE algorithm is higher than USVM-RFE and GSVM-RFE algorithms. For Most other Cases GSVM-RFE algorithm performs better than SVM-RFE and USVM-RFE.

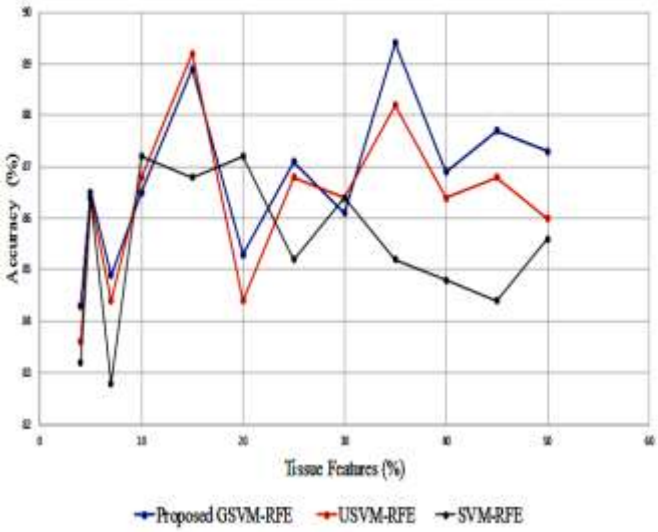

Figure 2. Comparison of performance for Accuracy of proposed GSVM-RFE algorithm against existing algorithms

Table 2: Comparison of performance for **Accuracy** of proposed GSVM-RFE algorithm against existing algorithms

Tissue Features (%)	Accuracy (%)	Accuracy (%)	Accuracy (%)
Control Normal Subjects Vs Mild Cognitive impairement Subjects	Proposed GSVM-RFE	USVM-RFE	SVM-RFE

4	84.31	83.67	82.98
5	85.26	85.34	84.87
7	82.45	81.67	81.67
10	81.76	80.56	79.45
15	84..53	85.65	82.56
20	86.21	85.43	84.43
25	85.26	85.19	84.13
30	88.67	87.56	86.77
35	87.98	87.45	86.48
40	86.76	86.23	85.89
45	85.29	84.26	83.76
50	85.92	84.18	83.93

Given above are the results of the evaluation of the GSVM protocol with respect to the USVM protocol and the SVM protocol on the dataset of subjects suffering from severe Alzheimer's disease and on the dataset of subjects suffering from no type of neurological disorder. USVM-RFE [Richhariya et al, 2020] and SVM-RFE [Qi et al, 2012] on a dataset obtained from ADNI for Control Normal and Alzheimer's Disease Subjects Accuracy of proposed GSVM algorithms against USVM and SVM algorithm for subjects suffering from Mild Cognitive Impairments and Alzheimer's Disease affected subjects.

Given below (in Fig. 3 and Table 3) are the results of the evaluation of the GSVM protocol with respect to the USVM protocol and the SVM protocol on the dataset of subjects suffering from severe Alzheimer's disease and on the dataset of subjects suffering from a mild type of Cognitive impairment.

Table 3: Comparison of performance for **Accuracy** of proposed GSVM-RFE algorithm against existing algorithms

Tissue Features (%)	Accuracy (%)	Accuracy (%)	Accuracy (%)
Mild Cognitive Impairement Subjects VsAlzheimer's Disease Subjects	Proposed GSVM-RFE	USVM-RFE	SVM-RFE
4	69.56	71.65	67.98
5	69.54	71.87	67.98
7	71.56	70.54	69.34
10	72.38	71.56	70.43
15	72.95	72.19	71.86
20	73.34	72.21	72.49
25	71.76	70.43	69.45
30	70,54	69.56	68.23
35	69.43	69.10	67.54
40	71.05	70.43	69.98
45	71.67	70.46	68.67

50	72.69	71.45	70.27

Figure 3. Comparison of performance for Accuracy of proposed GSVM-RFE algorithm against existing algorithms

From the results (demonstrated in detail in Figure 4. And Table 4) it can be concluded that when we are considering the data-sets for Control Normal subjects and Alzheimer’s disease affected patients, all three algorithms perform in close to a similar manner in terms of sensitivity. Although the proposed GSVM-RFE is found to be marginally better than USVM-RFE in some cases.

Table 4: Comparison of performance for Sensitivity of proposed GSVM-RFE algorithm against existing algorithms

Tissue Features (%)	Sensitivity (%)	Sensitivity (%)	Sensitivity (%)
Control Normal Subjects Vs Alzheimer’s Disease Subjects	Proposed GSVM-RFE	USVM-RFE	SVM-RFE
4	86.98	88.34	88.98
5	88.23	85.38	83.67
7	87.45	84.45	82.78
10	86.34	87.59	85.78
15	85.38	84.21	83.27
20	84.23	82.78	81.28
25	87.45	81.89	80.45
30	86.34	83.67	81.43
35	81.34	79.43	78.43
40	79.56	78.98	74.26
45	78.39	78.56	73.17
50	77.53	77.98	71.78

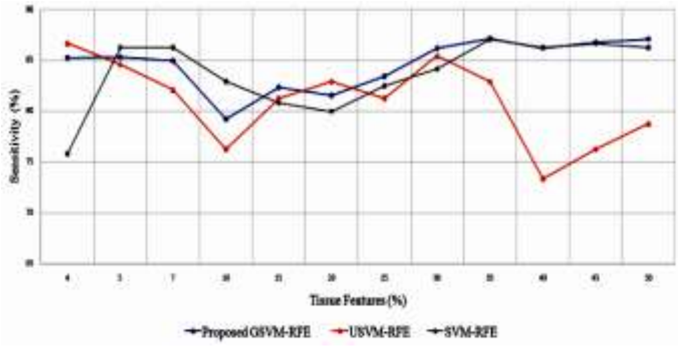

Figure 4. Comparison of performance for Sensitivity of proposed GSVM-RFE algorithm against existing algorithms

From the results (demonstrated in detail in Figure 5. And Table 5) it can be concluded that when we are considering the data-sets for Control Normal subjects and Mild Cognitive Impairment subjectaffected patients, all three algorithms perform in close to a similar manner in terms of sensitivity. Although the proposed GSVM-RFE is found to be marginally better than USVM-RFE in some cases

Table 5: Comparison of performance for Sensitivity of proposed GSVM-RFE algorithm against existing algorithms

Tissue Features (%)	Sensitivity (%)	Sensitivity (%)	Sensitivity (%)
Control Normal Subjects Vs Mild Cognitive Impairment Subjects	Proposed GSVM-RFE	USVM-RFE	SVM-RFE
4	85.23	86.67	75.83
5	85.28	84.58	86.25
7	84.95	82.08	86.25
10	79.23	76.25	82.92
15	82.34	81.25	80.83
20	81.56	82.92	80.00
25	83.45	81.25	82.5
30	86.19	85.42	84.17
35	87.12	82.92	87.08
40	86.21	73.33	86.25
45	86.76	76.25	86.67
50	87.08	78.75	86.25

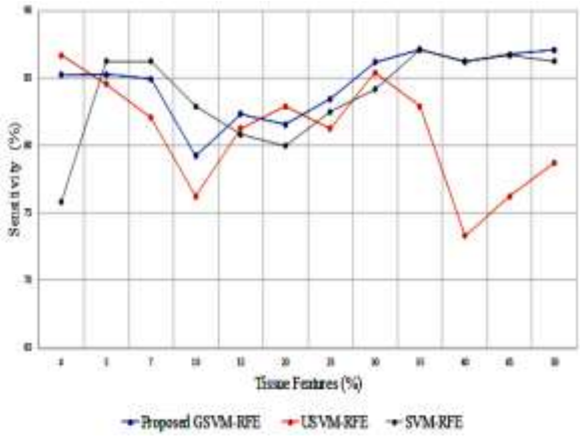

Figure 5. Comparison of performance for Sensitivity of proposed GSVM-RFE algorithm against existing algorithms

From the results (as demonstrated in Figure 6and Table 6) it can be concluded that when we are considering the data-sets for subjects suffering from Mild Cognitive Impairment and Alzheimer's Disease affected patients, the proposed GSVM-RFE algorithm is found to perform better than the other two algorithms in almost all cases. The results of the proposed GSVM-FE algorithm are found to closely follow the graph of USVM-RFE. Hence in terms of sensitivity, both GSVM-RFE and USVM-RFE give close to similar results, though GSVM-RFE performs marginally better in most cases.

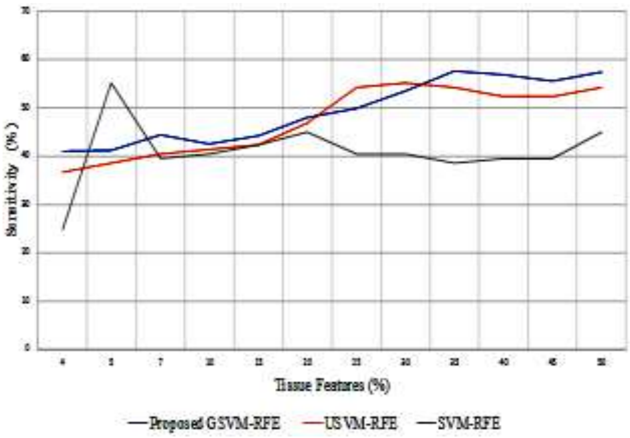

Figure 6. Comparison of performance for Sensitivity of proposed GSVM-RFE algorithm against existing algorithms

Table 6: Comparison of performance for Sensitivity of proposed GSVM-RFE algorithm against existing algorithms

Tissue Features (%)	Sensitivity (%)	Sensitivity (%)	Sensitivity (%)
Mild Cognitive Impairment Subjects VsAlzheimer's Disease Subjects	Proposed GSVM-RFE	USVM-RFE	SVM-RFE
4	40.89	36.7	24.77
5	41.07	38.53	55.05

7	44.33	40.37	39.45
10	42.56	41.28	40.37
15	44.26	42.2	42.2
20	47.89	46.79	44.95
25	49.88	54.13	40.37
30	53.44	55.05	40.37
35	57.56	54.13	38.53
40	56.89	52.29	39.45
45	55.42	52.29	39.45
50	57.31	54.13	44.95

IV .CONCLUSION

In AD analysis, a new CAD system situated on K-means and PSO segmentation, which intends to remove extremely envoy characteristics from every normal mind picture (NC, MCI, and AD), linked to the usual AD model, for categorizing and resolution maintain. The results of the proposed GSVM-FE algorithm are found to closely follow the graph of USVM-RFE. Hence in terms of sensitivity, both GSVM-RFE and USVM-RFE give close to similar results, though GSVM-RFE performs marginally better in most cases. The main objective of PSO segmentation is to detect a set of intracranial stenosis resources to present every AD phase. The resulting scheme executes consequently fine with segmented MRI information and expresses the capacity and strength in AD recognition as it givesa large precision value. We have developed a method to compare the performance of SVM, GSVM, and USVM classifiers for detecting AD. The accuracy increased by 1.92 %, and sensitivity increased by 10.24%, in the diagnosis of Alzheimer'sdisease.

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