Machine learning in medicine: Performance calculation of dementia prediction by support vector machines (SVM)

Gopi Battineni[a,*], Nalini Chintalapudi[b], Francesco Amenta[a,c]

[a] Center for Telemedicine and Tele Pharmacy, School of Pharmaceutical Sciences and Health Products, University of Camerino, Via Madonna Delle carceri 9, 62032, Camerino (MC), Italy
[b] Computer Science Department, MRIT, JNT University, India
[c] Studies and Research Department, International Medical Radio Center Foundation (C.I.R.M.), via dell'Architettura 61 Roma (RM), Italy

A B S T R A C T

Machine Learning (ML) is considered as one of the contemporary approaches in predicting, identifying, and making decisions without having human involvement. ML is quickly evolving in the medical industry ranging from diagnosis to visualization of diseases and the study of disease transmission. These algorithms were developed to identify the problems in medical image processing. Numerous studies previously attempted to apply these algorithms on MRI (Magnetic Resonance Image) data to predict AD (Alzheimer's disease) in advance. The present study aims to explore the usage of support vector machine (SVM) in the prediction of dementia and validate its performance through statistical analysis. Data is obtained from the Open Access Series of Imaging Studies (OASIS-2) longitudinal collection of 150 subjects of 373 MRI data. Results provide evidence that better performance values for dementia prediction are achieved by low gamma (1.0E-4) and high regularized (C = 100) values. The proposed approach is shown to achieve accuracy and precision of 68.75% and 64.18%.

1. Introduction

Machine learning (ML) was considered as an integral part of Artificial Intelligence (AI), also a data analysis technique that computerizes the explanatory model structure. In most scenarios, based on the learning method, two types of ML algorithms (supervised & unsupervised) were used [1]. At present, these algorithms are engaging in all the major industries like healthcare, banking, transport, social media, etc. [1,2]. Above all, the medical industry is advancing quickly with high volumes of information and increasing difficulties in inventory and patient outcomes. Economically developed nations such as USA, Japan, European countries are even facing the problems with the enormous collection of medical data [3]. However, by using conventional techniques, it is not possible to analyze this significant volume of information because of time consumption and efforts. Therefore, ML techniques are coming up with various algorithms and programs to avoid these issues. Besides that, the selection of proper algorithm is not an easy task since it depends on multiple factors such as data volume, information type, and outcomes related to industry requirements [1].

Nowadays, ML algorithms are progressively utilized in neuroimaging studies like a prediction of Alzheimer's disease (AD) from auxiliary MRI. Also, many studies attempted different ML strategies in predicting

AD and their causes [3,4]. In the study of AD prediction and retrieval, a multistage classifier utilizing ML, including Naive Bayes classifier, support vector machine (SVM), and K-nearest neighbor (KNN) was used to group Alzheimer's illness in the more acceptable and effective way [5]. Similarly, a study from Ref. [6], concluding that the utilization of locally linear embedding (LLE) kind of unsupervised learning was utilized to categorize AD based on fundamental MRI data. Besides, some preliminary studies with ML techniques concluded that these methods are valid and accomplish with high precision (up to 98%) in diagnosing clinical events with analysis of patient medical records [7].

Despite of it, AD is one of common type in dementia and associated mostly with older people [8]. In this paper, we explain how to predict dementia and calculate performance by using support vectors. Typically, SVM's are considered as supervised machine learning, which solves the data issues related to classification and regression analysis [9]. An SVMs give a compelling and adaptable structure for MRI, and that the proposed classifier perception technique has potential as a system for the assessment of characterization solutions [9,10]. This is also used to categorize dementia subjects and is similar to the research that use a uniform algorithm to differentiate 3 Primary progressive aphasia (PPA) subtypes in predicting PPA [11]. Distinguishing early morphological changes in the mind and making initial finding is

significant for dementia. High-resolution MRI data can be utilized to support finding and forecast of the disease [11]. To do this, we propose to find an optimal solution by experimenting with radial basis function (RBF) kernel in the SVM. The proposed method of calculation is inspired by a new approach of using an ensemble SVM for dementia classification [12], using MRI data and mini-mental state examination parameters (MMSE).

In contrast, we consider the attributes like MR delay; CDR, ASF, AGE, and GENDER included with MMSE that corresponds to subject ID. We strongly believe that it is the novel way of examining the importance of each parameter while forecasting dementia in older patients. Despite it, our work aims to predict dementia in elder individuals by SVM algorithms to accomplish promising outcomes. This paper is organized as follows; section 2 describes the SVM background with its key parameters; Section 3 will explain the data collection and methodology; section 4 will provide experimental results; Section 5 on proposed discussion and little conclusion in section 6.

2. Support vector machines (SVM)

2.1. Background

Support Vector Machines are a well-known ML technique for classification and other learning activities. SVM is a discriminative classifier and formally characterized by an optimal hyperplane. It produces an outcome of the optimal hyperplane, which classifies new examples and datasets that support hyperplane are called support vectors [13]. In two-dimensional (2D) region, this hyperplane is a line isolating into two segments wherein each segment lay in either side. For instance, multiple line data classification had done with two distinct datasets (i.e., squares and dots) and ready to propose an affirmative interpretation (Fig. 1). However, the selection of optimal hyperplane is not an easy job as it should not be noise sensitive, and generalization of data sets should be accurate [14]. Pertinently, SVM trying to find out optimized hyperplane that provides considerable minimum distance to the trained data set [13,14].

In mathematical notation, for 2D space, a line can distinguish the linearly separable data. The equation of the line is $y = ax + b$. By rename x with x_1 and y with x_2, the equation will change to $ax_1 - x_2 + b = 0$. If we specify $X = (x_1, x_2)$ and $w = (a, -1)$, we get w· x + b = 0, which is called the equation of the hyperplane.

2.1.1. Derivation of SVM optimization problem

To estimate w & b of the optimal hyperplane, it is mandatory to address a performance issue with the need of the geometric edge for every pattern must be more prominent to M [16].

$$\text{Max }_{w, b} \text{ M; Subject to } \gamma_i \geq M, i = 1 \ldots m \tag{1}$$

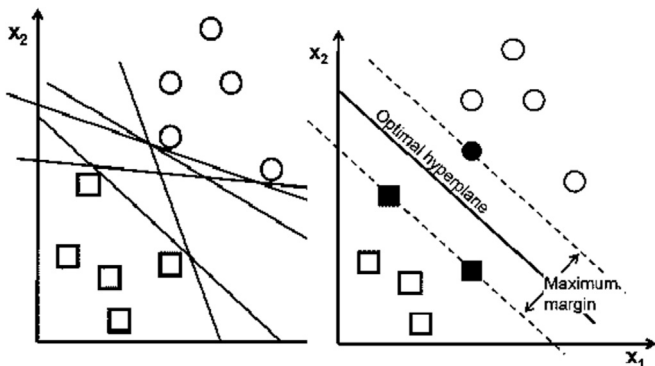If $M = \frac{F}{\|w\|}$ the above equation can be rewritten as:

Fig. 1. Data classification using multiple lines [On left] and data classification: optimal hyperplane [On Right] [15].

$$\text{Max }_{w, b} \text{ M; Subject to } fi \geq F, i = 1 \ldots m \tag{2}$$

The case that rescales w and b are yet boosting M, and the enhancement result will not change. Let us rescale w & b and make F = 1; the above equation shift to

$$Max_{w,b}\frac{1}{\|w\|}; subject \text{ to } fi \geq 1 , \text{ i= } 1\ldots m \tag{3}$$

This maximization issue is proportionate to the accompanying minimization issue written as

$$\text{Min }_{w, b}\|w\|; \text{ subject to } fi \geq 1, i = 1 \ldots m \tag{4}$$

This minimization issue is proportionate to the accompanying minimization issue written as

$$\min_{w,b}\frac{1}{2}\|w\|^2; \text{ subject to } y_1(wx + b) - 1 \geq 0, \text{ i= } 1\ldots m \tag{5}$$

The above statement refers to the SVM optimization problem.

2.1.2. SVM classifier

When we have the hyperplane, eventually we would be able to utilize the hyperplane to make predictions. The hypothesis function of H is

$$H(x_i) = \begin{cases} + 1 \text{ if } w.x \geq 0 \\ - 1 \text{ if } w.x < 0 \end{cases}$$

2.2. Tuning parameters

To comprehend the SVM working, it is critical to understand about some prerequisites like kernel, regularization, and gamma.

2.2.1. Kernel

In machine learning, the kernel is a technique that is used to solve the non-linear problem with the use of linear classifier and involved in exchanging linearly non-separable data into linearly separable data [17]. The idea behind this concept is linearly non-separated data in N-dimensional space might be linearly separate in high M-dimensional space. Mathematically, kernel indicated as K (a, b) = < F (a), F (b) > , Where K: kernel function and a, b are n-dimensional inputs. 'F' is mapping from N-dimensional to M-dimensional space (i.e., M > N). The mapping in the kernel is defined as K (a, b) = Ø (a). Ø (b).

Kernel Functions: There are several kernels functions some of them listed below here [18].

❖ Polynomial Type: is well known for nonlinear modeling and is represented as

$$K (a, b) = (a, b)^d \tag{6}$$

❖ Gaussian Radial Basis Type: Radial basis functions mostly with Gaussian form and represented by

$$k(a,b) = \exp(-\frac{\|a - b\|^2}{2\sigma^2}) \tag{7}$$

❖ Exponential Radial basis: function produces a bitwise linear solution that will be useful when discontinuities are satisfactory

$$k(a, b) = \exp(-\frac{\|a - b\|}{2\sigma^2}) \tag{8}$$

In addition to them, there are many more functions such as multi-layer perceptron, Fourier, additive, and tensor products type [18].

2.2.2. Regularization

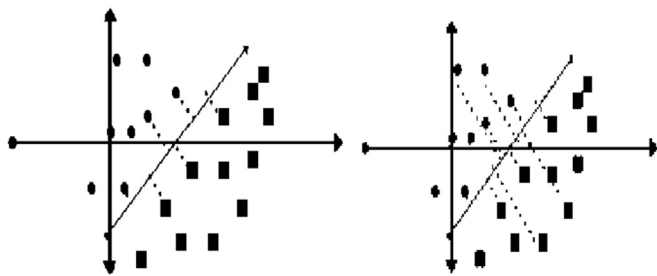The regularization parameter (C) explains the SVM optimization

Fig. 2. High Gamma Close points (left) and Low Gamma Far away points found (Right) [20].

and percentage of escaping the misclassified trained data [19]. For high C values, training data will categorize accurately by hyperplane; similarly, for low C, optimizer looks for higher margin separating hyperplane while it will misclassify the more data points.

2.2.3. Gamma

It describes the impact of specific training data [13,17,19]. The high gamma values (Fig. 2 left) results in consideration of datasets that are near to separation line. Similarly, for low gamma values (Fig. 2.Right) datasets that are away from the separation line, will also be taken into consideration while in the calculation of separation line (Chapter 2: SVM (Support Vector Machine) — Theory – Machine Learning 101 – Medium).

3. Data collection and methodology

3.1. Dataset

We consider a longitudinal collection of OASIS - MRI data set [21], comprising of demented and non-demented subjects with right-hand (R) type aging from 60 to 96. A sample size of 150 subjects, including men and woman, have attended scanning sessions more than two visits; sessions were separated by at least one year with 373 MR Sessions. The sample training data (Table 1) included with demographic values of Subject ID, MRI ID, Group, Visit, MR delay, Sex, Age, Social Economic Status (SES), Education level (EDUC), MMSE [22], Clinical Dementia Ratio (CDR) [23], estimated Total Intracranial Volume (e-TIV), normalized Whole Brain Volume (n-WBV) and Atlas Scaling Factor (ASF). Also, Fig. 3. Explaining the present MRI sessions categorization based on the current CDR (0–2) score and total sessions of non-demented (190), demented (146) and converted (37) were evaluated. In

particular, some subjects treated as demented at initial visit later transformed into the non-demented managed by converted type. If CDR value is equal to zero, the subjects were considered as mostly non-demented, simultaneously if CDR ≥ 1 the subjects will face the tendency to have dementia.

3.2. Methodology

The methodology layout that used and analyzed in the current study in explaining in Fig. 4.

❖ Data collection

The trained data set was collected from the Open Access Series of Imaging Studies (OASIS) included with longitudinal MRI data of 150 subjects.

❖ Data Preprocessing

Real world data is available more likely incomplete with missing entries. Therefore, data preprocessing is one of the data mining techniques to address this issue. Missing entries were filled-up by averaging of particular attribute values.

❖ Attribute Selection

Select a specific characteristics to predict the outcome to do mapping with input correspondence values. We choose the group column as output variable that corresponds to the dementia status based on other input variables.

❖ Input variable matching

Performance of any ML model largely depends on the number of input attributes taken into consideration. To maintain better performance, selection of the corresponding attributes, instead of selecting multiple ones is very important. Attributes like Subject ID, CDR, MMSE, Age, MR Delay, and n WBV chosen as input to SVM that were directly targeted to the dementia group attribute.

❖ Classifier

We consider three groups of dementia as demented, non-demented, and converted.

Table 1
Example of actual portion dataset of Longitudinal OASIS-2 MRI data.

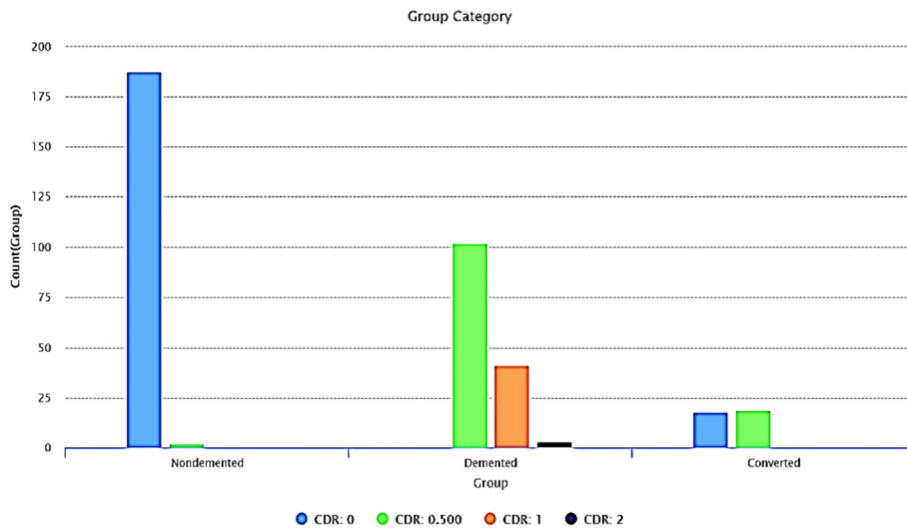| SUBJECT ID	MRI ID	GROUP	VISIT	MR Delay	M/F	Hand	Age	EDUC	SES	MMSE	CDR	E TIV	n-WBV	ASF
OAS2_0100	OAS2_0100_MR1	Non Demented	1	0	F	R	77	11	4	29	0	1583	0.777	1.108
OAS2_0100	OAS2_0100_MR2	Non Demented	2	1218	F	R	80	11	4	30	0	1586	0.757	1.107
OAS2_0100	OAS2_0100_MR3	Non Demented	3	1752	F	R	82	11	4	30	0	1590	0.760	1.104
OAS2_0101	OAS2_0101_MR1	Non Demented	1	0	F	R	71	18	2	30	0	1371	0.769	1.280
OAS2_0101	OAS2_0101_MR2	Non Demented	2	952	F	R	74	18	2	30	0	1400	0.752	1.254
OAS2_0101	OAS2_0101_MR3	Non Demented	3	1631	F	R	76	18	2	30	0	1379	0.757	1.273
OAS2_0102	OAS2_0102_MR1	Demented	1	0	M	R	82	15	3	29	0.5	1499	0.689	1.171
OAS2_0102	OAS2_0102_MR2	Demented	2	610	M	R	84	15	3	29	0.5	1497	0.686	1.172
OAS2_0102	OAS2_0102_MR3	Demented	3	1387	M	R	86	15	3	30	0.5	1498	0.681	1.171
OAS2_0103	OAS2_0103_MR1	Converted	1	0	F	R	69	16	1	30	0	1404	0.750	1.250
OAS2_0103	OAS2_0103_MR2	Converted	2	1554	F	R	74	16	1	30	0.5	1423	0.722	1.233
OAS2_0103	OAS2_0103_MR3	Converted	3	2002	F	R	75	16	1	30	0.5	1419	0.731	1.236
OAS2_0104	OAS2_0104_MR1	Demented	1	0	M	R	70	16	1	25	0.5	1568	0.696	1.119

Fig. 3. Categorization of dementia sessions based clinical dementia ratio (CDR).
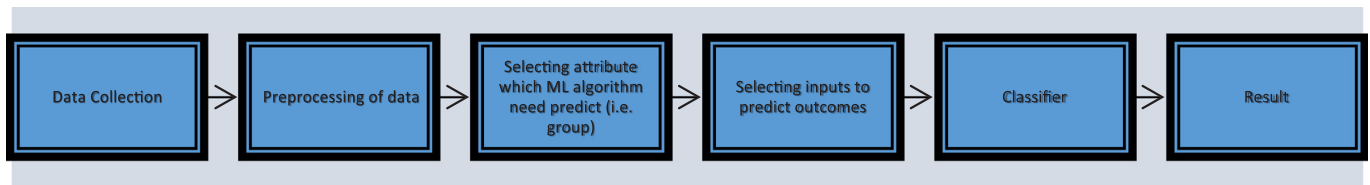

Fig. 4. Methodology layout.

❖ Results

Finally, the classification performance has achieved and analyzed. Performance value calculated as the percentage of correctly predicted outcomes divided by the total number of samples

$$i.\ e,\ peformance = \frac{\text{True predicted an outcomes}}{\text{Total number of samples}} \times 100$$

4. Results

Once the mapping has done by input attributes with targeted output group column, the machine will run the SVM algorithm automatically.

4.1. Kernel

The Kernel outcome model with 150 support vectors (Table 2) has generated, and three different categories of training data set are observed. As mentioned, kernel mapping with three input values formulated, as K (ND, D, C) = ø(79).ø(50).ø(21), where K is kernel function with three input class vectors such as non-demented (ND), Demented (D) and converted (C) and corresponding mapping values of 79, 50 and 21. Besides, bias value is equal to -0.3 (offset defines compensate the feature vectors that are not centered around the zero).

Table 2
Kernel outcome statistic values.

Total number of Support Vectors: 150
Bias (offset): 0.3 and Number of classes: three
Number of support vectors for class Non-demented - 79
Number of support vectors for class Demented- 50
Number of support vectors for class Converted - 21

4.2. Gamma VS. C

As discussed, Gamma and C values are obligatory to confirm optimal hyperplane. In further, Radial Basis Function (RBF) kernel is one of the novel kernel approaches that related to gamma. Hence, SVM anticipated with following performance conditions

$$if \begin{cases} RBF = 1.0E - 4\ ;\ C = 100 & p = 69.2\%; \\ RBF = 1.0E - 3\ ;\ C = 100 & p = 69.2\% \\ RBF = 1.0E - 1\ ;\ C = 10 & p = 57.1\% \end{cases}$$

Here, two conditions were supporting identical performance gain. However, as per condition of SVM it prefers to choose optimal hyperplane region with low RBF (1.0E-4), and High C (100) which represented by Yellow colored circle explained in Fig. 5.

4.3. Performance, precision, and recall

❖ Assessment of performance done by the percentage of true predicted subjects from the total subjects. From Table 3, sum of true predicted subjects were 105, therefore performance was calculated as 70% ($\frac{105}{150}$*100). This value is matching with the optimal system performance 69.2% by utilization of RBF and C values that proves the SVM hypothesis.

❖ Precision is define as percentage of positive predictive values for each subject category. For demented subjects precision validates as of 64.18% ($\frac{43}{43 + 14 + 10}$*100) and for demented 75%. On the counter note, no valid predicted values for converted category subjects. SVM algorithm predicted two subjects as a converted category, but in a real scenario, it belongs to non-demented ones.

❖ In the context of ML, recall is referred as sensitivity or true positive rate. Thus, recall for non-demented subjects validated with 81.13% ($\frac{43}{43 + 8 + 2}$*100), and demented 65.85%.
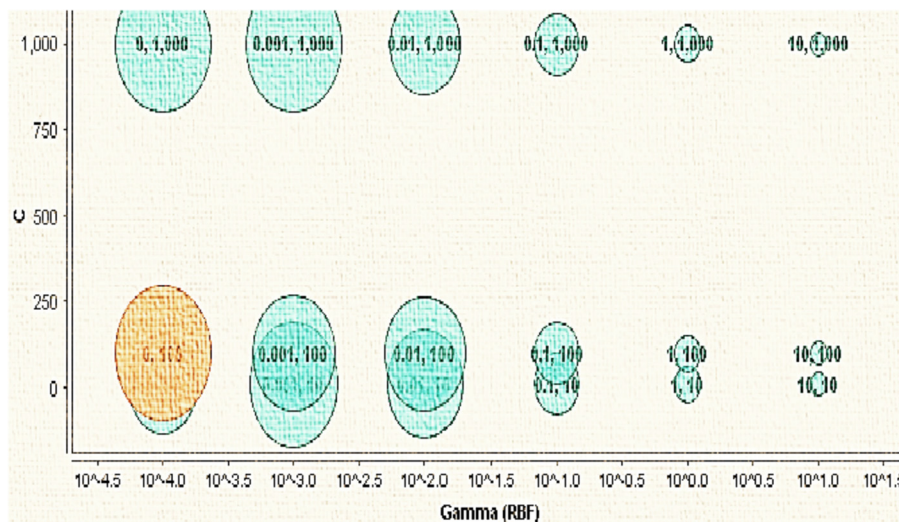
Fig. 5. Spatial distribution of Gamma (RBF) Vs. C values.

Table 3

Confusion Matrix of given subjects TND*: True Non-Demented; TD*: True Demented; TC*: True Converted; PND*: Predict Non-Demented; PD*: Predict Demented, and PC*: Predict Converted.

	TND	TD	TC	precision
PND	43	14	10	64.18%
PD	8	27	1	75.00%
PC	2	0	0	0.00%
Recall	81.13%	65.85%	0.00%	0.00%

5. Discussion

In present study, we considered longitudinal MRI subjects from OASIS datasets, and input information to machine chose as key attributes like MMSE, CDR, MR delay and n WBV. The forecasting of dementia depends on the scores of mentioned attributes. As best of our insight, this is the essential investigation for foreseeing dementia dependent on these scores by utilizing SVM calculations. Additionally, we locate an ideal hyperplane by using RBF and C esteems that is also used in the study of weather forecast datasets [24]. It helped us to make a correlation between hyperplane parameters to investigate better support vectors. We classified MRI sessions into three groups based on the CDR scale (0–2). Additionally, we conduct statistical analysis by bar charts to differentiate subject category. In next sections, we are going to introduce the outcomes of these group-level comparisons, after that, we discuss in more detail about how SVM produces optimized performance values to forecast dementia using kernel functions and study limitations when compared to other methods.

5.1. Dementia prediction by a selection of key attributes

As discussed, current MRI sessions division was done based on the current CDR value. Beyond that, our subject group classifications are in line with the study designed for investigating diagnostic agreements [25]. However, it is not feasible to predict dementia disease with single attribute or parameter. Thus, we examine with other key parameters such as MMSE, AGE, n WBV and MR delay that matched with targeted group column. At the same time we tried to exclude other demographic values like Gender, SES, EDU, and ASF since these parameters not good enough in dementia prediction, also by considering many attributes performance may get low [26]. In addition, outcomes mentioned that 100 subjects (Fig. 6) are predicted non-demented (actually these distributed as 63ND, 24D and 13C types), and 47 subjects predicted as
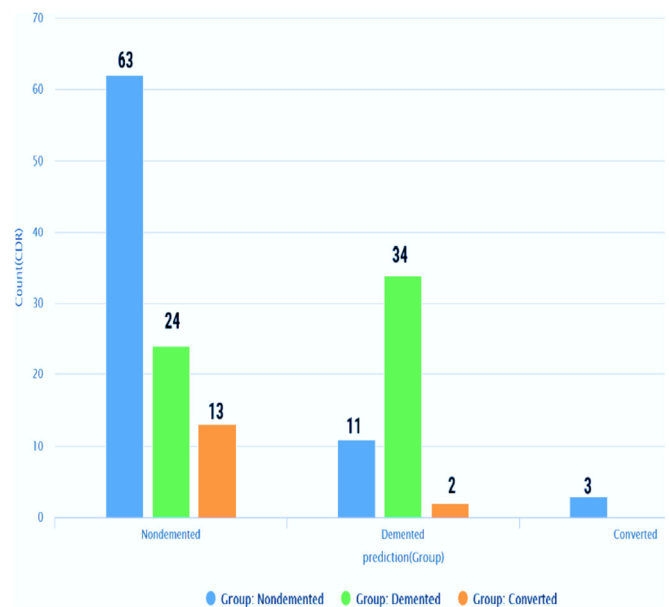
Fig. 6. Subject Classification between Predictions subject groups Vs Actual Subject Groups.

demented (but these distributed as 11ND, 34D and 2C types). Finally, 3 non-demented subjects forecasted as converted type.

The prediction was validated and done on the confidence values of the actual category of each subject (refer appendix). For example, in real time scenario Subject, ID-04 was non-demented based current CDR score (=0) but predicted as demented. This might be caused by the high age [27] or more significant delay in the MR value [28]. Therefore, this will change from subject to subject depending on the present reports.

5.2. Selection of optimal hyperplane

The performance for the given dataset by SVM algorithm producing about 70% and recall or sensitivity providing in the range of 65–82% that depended on the subject category. Until now, only single research tried to develop a new method for an ensemble of SVM for classification of dementia using systematic MRI and MMSE values [12]. The researchers performed ensemble SVM using RBF kernel or linear to achieve distinct class accuracies. In their results, accuracy was

increased from 55% to 59.1%. Our SVM approach by considering total brain value with MMSE and CDR, producing the accuracy nearly 70%. Additionally, we compared the statistical calculation of performance outcomes with optimal hyperplane coordinates to verify whether machine-generated results were performing similar SVM optimal performance (Fig. 5). In the end, outcomes generated by the ML system and Hyperplane are matched to prove the theory of support vector algorithms.

5.3. Limitations

The relatively lowest number of subjects may hamper the speculation of outcomes to the overall population of dementia patients. Despite that, our study closely related to Ref. [12], but we achieve better performance values by introducing an optimal hyperplane study. Classification and normalization of subject groups are not accurate in most cases, and it might tend to underestimation of dementia in older patients that result in getting low accuracies through SVM categorization. Nevertheless, approaching optimal hyperplanes, we tried to increase the performance by a selection of low RBF and high C values. Eventually, the order between sets of different subjects was an optimal hyperplane, which does not reflect the issue regarding accurate differential determination between a few neurological diseases. This issue should be addressed in future researches validating the use of SVM approaches consistently in real life.

6. Conclusion

Dementia is one of the significant health issues that has challenged health experts worldwide. In addition, it mostly happened in older people (age > 60). Unfortunately, there are no proper medicines for completely cure this disease, and sometimes it will directly affect person memory skills and reduce the human ability to perform daily activities. Many healthcare professionals and computer scientists were performing research activities on this problem from last two decades. Still, there is an extreme need for identification of relevant characteristics that can forecast the detection of dementia. We approached support vectors for classification and prediction purposes of dementia and achieved optimized results with efficient performance values.

Conflicts of interest

Authors do not have any conflict of interest.

Informed consent

Trained data gathered from OASIS longitudinal studies and access available from concerned authorities in participating in the mentioned study. Authors do not have permission for direct communication with a human participant in the study.

Author note and contributions

We are certifying that the manuscript is orginal and not published with any journal. All authors are strictly read and validated the final copy. GB: Made primary contributions of data collection,methodology developement,and conduct empirical analysis NC: Done contributions with literature review and discussion sections FA: Final check, approval and manuscript validation.

Appendix. Dementia predicted outcome dataset after SVM implementation

N	Age	CDR	MMSE	MR Delay	N WBV	Group	Conf (ND)	Conf (D)	Conf (Con)	Prediction
1	87	0.0	27	0	0.7	Nondemented	1	0	0	Nondemented
2	80	0.5	22	1895	0.7	Demented	1	0	0	Nondemented
3	88	0.0	28	0	0.7	Nondemented	1	0	0	Nondemented
4	90	0.0	27	538	0.7	Nondemented	0	1	0	Demented
5	85	0.0	30	1603	0.7	Nondemented	0	0	1	Converted
6	71	0.5	28	0	0.7	Demented	1	0	0	Nondemented
7	75	1.0	27	1281	0.7	Demented	1	0	0	Nondemented
8	68	0.5	27	0	0.8	Demented	0	1	0	Demented
9	66	0.5	30	0	0.8	Demented	1	0	0	Nondemented
10	68	0.5	29	854	0.8	Demented	1	0	0	Nondemented
11	78	0.0	29	0	0.7	Nondemented	1	0	0	Nondemented
12	80	0.0	29	730	0.7	Nondemented	1	0	0	Nondemented
13	85	0.0	29	1456	0.7	Nondemented	1	0	0	Nondemented
14	81	0.5	27	617	0.8	Nondemented	0	1	0	Demented
15	86	0.0	27	2400	0.8	Nondemented	1	0	0	Nondemented
16	87	0.0	30	0	0.7	Converted	1	0	0	Nondemented
17	88	0.0	29	489	0.7	Converted	1	0	0	Nondemented
18	92	0.5	27	1933	0.7	Converted	1	0	0	Nondemented
19	64	0.0	29	828	0.8	Nondemented	1	0	0	Nondemented
20	82	0.5	27	0	0.7	Demented	0	1	0	Demented
21	71	0.0	30	609	0.8	Nondemented	0	1	0	Demented
22	73	0.0	30	1234	0.8	Nondemented	1	0	0	Nondemented
23	77	0.0	29	0	0.7	Nondemented	1	0	0	Nondemented
24	60	0.0	30	0	0.8	Nondemented	1	0	0	Nondemented
25	86	0.0	30	0	0.7	Converted	1	0	0	Nondemented
26	90	0.5	21	0	0.7	Demented	0	1	0	Demented
27	88	0.0	30	0	0.7	Nondemented	1	0	0	Nondemented
28	89	0.0	27	405	0.7	Nondemented	1	0	0	Nondemented
29	75	0.0	29	2369	0.8	Nondemented	1	0	0	Nondemented
30	85	0.5	29	1123	0.7	Demented	1	0	0	Nondemented
31	89	0.5	26	2508	0.7	Demented	1	0	0	Nondemented
32	83	0.5	25	486	0.7	Demented	1	0	0	Nondemented

33	86	0.5	27	567	0.7	Demented	0	1	0	Demented
34	73	0.0	28	756	0.8	Converted	1	0	0	Nondemented
35	75	0.0	30	0	0.7	Nondemented	1	0	0	Nondemented
36	66	1.0	21	248	0.7	Demented	0	1	0	Demented
37	68	1.0	19	647	0.7	Demented	0	1	0	Demented
38	69	1.0	4	1233	0.7	Demented	0	1	0	Demented
39	78	0.0	30	1510	0.7	Nondemented	1	0	0	Nondemented
40	84	0.0	28	842	0.7	Nondemented	0	1	0	Demented
41	85	0.0	29	0	0.7	Converted	1	0	0	Nondemented
42	87	0.5	24	846	0.7	Converted	0	1	0	Demented
43	67	0.0	27	726	0.8	Nondemented	1	0	0	Nondemented
44	71	0.0	28	0	0.8	Nondemented	1	0	0	Nondemented
45	85	0.0	30	1340	0.7	Nondemented	1	0	0	Nondemented
46	79	0.5	26	212	0.7	Demented	0	1	0	Demented
47	70	0.0	30	873	0.7	Nondemented	1	0	0	Nondemented
48	72	0.0	30	1651	0.7	Nondemented	1	0	0	Nondemented
49	79	0.0	29	0	0.7	Nondemented	1	0	0	Nondemented
50	83	0.0	29	1351	0.7	Nondemented	1	0	0	Nondemented
51	81	0.5	27	490	0.7	Demented	1	0	0	Nondemented
52	81	0.5	26	830	0.7	Demented	0	1	0	Demented
53	82	0.5	18	1282	0.7	Demented	0	1	0	Demented
54	62	0.5	30	497	0.7	Demented	0	1	0	Demented
55	68	0.0	29	451	0.7	Nondemented	1	0	0	Nondemented
56	71	0.0	29	1438	0.7	Nondemented	0	1	0	Demented
57	73	0.0	28	2163	0.7	Nondemented	1	0	0	Nondemented
58	90	0.0	29	743	0.7	Nondemented	1	0	0	Nondemented
59	82	0.0	30	432	0.7	Nondemented	1	0	0	Nondemented
60	82	0.0	29	672	0.7	Nondemented	1	0	0	Nondemented
61	84	0.0	29	1415	0.7	Nondemented	1	0	0	Nondemented
62	86	0.0	30	2386	0.7	Nondemented	1	0	0	Nondemented
63	84	1.0	28	365	0.7	Demented	1	0	0	Nondemented
64	70	0.0	29	0	0.8	Nondemented	1	0	0	Nondemented
65	72	0.0	28	580	0.8	Nondemented	0	1	0	Demented
66	75	0.5	22	567	0.7	Demented	0	1	0	Demented
67	66	0.0	30	0	0.7	Nondemented	1	0	0	Nondemented
68	73	0.0	29	1393	0.7	Nondemented	1	0	0	Nondemented
69	89	0.0	28	0	0.7	Nondemented	1	0	0	Nondemented
70	71	1.0	16	584	0.7	Demented	0	1	0	Demented
71	66	0.5	25	0	0.7	Demented	0	1	0	Demented
72	68	0.5	30	580	0.7	Demented	0	1	0	Demented
73	69	0.5	28	1209	0.7	Demented	1	0	0	Nondemented
74	82	0.5	26	0	0.7	Demented	0	1	0	Demented
75	78	1.0	21	0	0.7	Demented	0	1	0	Demented
76	72	1.0	27	563	0.7	Demented	0	1	0	Demented
77	75	0.0	29	680	0.8	Nondemented	1	0	0	Nondemented
78	76	0.0	30	1345	0.8	Nondemented	1	0	0	Nondemented
79	61	0.0	30	0	0.8	Nondemented	1	0	0	Nondemented
80	67	0.5	28	661	0.8	Demented	1	0	0	Nondemented
81	80	0.5	27	0	0.8	Demented	0	1	0	Demented
82	77	0.0	29	0	0.8	Nondemented	1	0	0	Nondemented
83	76	0.0	30	1631	0.8	Nondemented	1	0	0	Nondemented
84	82	0.5	29	0	0.7	Demented	1	0	0	Nondemented
85	86	0.5	30	1387	0.7	Demented	1	0	0	Nondemented
86	75	0.5	30	2002	0.7	Converted	0	1	0	Demented
87	87	0.0	30	675	0.7	Nondemented	1	0	0	Nondemented
88	70	1.0	22	0	0.7	Demented	0	1	0	Demented
89	65	0.5	17	881	0.7	Demented	0	1	0	Demented
90	78	0.5	20	558	0.7	Demented	0	1	0	Demented
91	75	0.5	28	504	0.7	Demented	0	1	0	Demented
92	76	0.5	27	0	0.7	Demented	0	1	0	Demented
93	74	0.0	30	576	0.8	Nondemented	0	1	0	Demented
94	78	0.0	29	1927	0.7	Nondemented	1	0	0	Nondemented
95	81	0.0	28	0	0.8	Nondemented	1	0	0	Nondemented
96	74	0.0	30	647	0.7	Nondemented	1	0	0	Nondemented
97	86	0.0	30	0	0.7	Nondemented	1	0	0	Nondemented
98	88	0.0	30	597	0.7	Nondemented	0	1	0	Demented
99	71	0.5	27	472	0.7	Demented	1	0	0	Nondemented
100	79	0.0	29	0	0.7	Converted	1	0	0	Nondemented
101	81	0.5	29	1042	0.7	Converted	1	0	0	Nondemented
102	84	0.5	29	2153	0.7	Converted	1	0	0	Nondemented
103	86	0.5	30	2639	0.7	Converted	1	0	0	Nondemented
104	76	0.0	28	0	0.8	Nondemented	1	0	0	Nondemented
105	78	0.0	30	0	0.7	Nondemented	1	0	0	Nondemented
106	82	0.0	29	1591	0.6	Nondemented	0	0	1	Converted
107	65	0.5	30	0	0.8	Converted	1	0	0	Nondemented
108	74	0.0	30	0	0.7	Nondemented	1	0	0	Nondemented
109	78	0.0	27	1146	0.7	Nondemented	1	0	0	Nondemented
110	74	0.5	28	0	0.7	Demented	1	0	0	Nondemented
111	75	0.5	30	636	0.7	Demented	1	0	0	Nondemented
112	73	0.0	29	0	0.8	Nondemented	1	0	0	Nondemented

113	67	0.5	29	0	0.8	Demented	1	0	0	Nondemented
114	76	0.5	26	0	0.7	Demented	0	1	0	Demented
115	65	0.0	30	0	0.8	Nondemented	1	0	0	Nondemented
116	91	0.0	30	561	0.7	Nondemented	0	1	0	Demented
117	93	0.0	29	1553	0.7	Nondemented	0	0	1	Converted
118	68	0.0	30	0	0.8	Converted	1	0	0	Nondemented
119	82	0.0	30	1806	0.7	Nondemented	1	0	0	Nondemented
120	81	0.0	29	0	0.7	Nondemented	1	0	0	Nondemented
121	73	0.5	30	0	0.7	Demented	1	0	0	Nondemented
122	66	0.0	29	0	0.8	Nondemented	1	0	0	Nondemented
123	68	0.0	29	790	0.8	Nondemented	1	0	0	Nondemented
124	77	0.0	28	791	0.7	Nondemented	1	0	0	Nondemented
125	75	1.0	18	764	0.7	Demented	0	1	0	Demented
126	73	0.5	29	0	0.8	Demented	1	0	0	Nondemented
127	76	0.5	28	759	0.8	Demented	1	0	0	Nondemented
128	77	0.0	29	0	0.7	Nondemented	1	0	0	Nondemented
129	82	0.5	23	0	0.7	Demented	0	1	0	Demented
130	84	0.5	22	621	0.7	Demented	0	1	0	Demented
131	77	1.0	23	0	0.8	Demented	0	1	0	Demented
132	79	2.0	25	580	0.8	Demented	0	1	0	Demented
133	73	0.0	30	691	0.7	Nondemented	1	0	0	Nondemented
134	77	0.0	30	493	0.8	Nondemented	1	0	0	Nondemented
135	75	0.5	30	0	0.7	Demented	1	0	0	Nondemented
136	70	0.5	26	0	0.7	Demented	0	1	0	Demented
137	73	0.5	28	1343	0.7	Demented	1	0	0	Nondemented
138	87	0.0	30	774	0.7	Converted	1	0	0	Nondemented
139	68	0.0	26	0	0.8	Nondemented	0	1	0	Demented
140	70	0.0	28	665	0.8	Nondemented	1	0	0	Nondemented
141	89	0.0	29	0	0.8	Nondemented	1	0	0	Nondemented
142	90	0.0	28	600	0.7	Nondemented	0	1	0	Demented
143	79	0.5	26	0	0.7	Demented	0	1	0	Demented
144	74	0.5	26	0	0.7	Demented	0	1	0	Demented
145	73	0.5	23	0	0.7	Demented	0	1	0	Demented
146	66	0.0	30	182	0.7	Nondemented	1	0	0	Nondemented
147	86	0.5	26	2297	0.7	Demented	1	0	0	Nondemented
148	61	0.0	30	0	0.8	Nondemented	1	0	0	Nondemented
149	63	0.0	30	763	0.8	Nondemented	1	0	0	Nondemented
150	62	0.0	26	1180	0.7	Nondemented	1	0	0	Nondemented

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