



Stroke Risk Prediction through Non-linear Support Vector Classification Models

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Abstract: The aim of this study is to find the possible risk of Cerebro Vascular Accident (CVA) or Stroke by subjecting the risk factors to Support Vector Machines (SVM). The prediction of the attack of the disease is highly dependent on the quantification of risks contributed by each factor. Therefore an assessment of relative intensity of risk contributed by the factors is imperative for early prediction and preventable measures. The classification accuracies are achieved through the efficient kernel functions of Radial Basis Function (RBF=98%) and Polynomial (Poly=92%) and finally these results are compared with benchmarking evaluation methods like classification accuracy, sensitivity, specificity and confusion matrix. The proposed stroke risk prediction models are obtained with satisfactory accuracy and it would be promising models in the classification of stroke risk prediction process.

Keywords: Support Vector Machines, Cerebrovascular Accident, Stroke Risk factors, Classification, Kernel Functions.

I. INTRODUCTION

Stroke is defined by the National Institute of Neurological Disorders and Stroke (NINDS), USA as a sudden loss of brain function resulting from an interference with blood supply to the brain. The brain receives about 25% of the body's oxygen, but it cannot store it. Brain cells require a constant supply of oxygen to stay healthy and function properly. From 1995-2005 the stroke death rate fell approximately 30%. However it is reported that 80% of strokes are preventable. Medical diagnosis systems and disease prediction tools using different machine learning approaches have shown great potential. In the last two decades, the uses of machine learning tools have become widely accepted in medical applications to support patients in effective management of disease and also in preventive measurements. The aim and use of Support Vector Machine (SVM) is to devise a computationally efficient way of learning in classification. Hence, relative risk on stroke and risk factors reduction is an important step in preventing stroke and also this study would assist the primary and secondary treatment interventions. The proposed stroke risk prediction of mathematical models based on non-linear Support Vector Classification (SVC) would be a promising tool in the classification of stroke risk prediction process.

II. RELATED WORKS

Application of various machine learning approaches such as Decision Trees (DTs), Artificial Neural Networks (ANN), Bayesian Networks (BN), and Support Vector Machines (SVMs) have been actively tried to meeting clinical support requirements. In SVM technique, structural risk minimization is used whereas in ANN technique empirical risk minimization is used. By the strength of the statistical learning theory [26], SVMs are not only popular

in the machine learning and mathematics community also. Research efforts have reported with increasing confirmation that the SVM has greater accurate diagnosis ability. Different aspects of research in stroke have been studied by various researchers by their different approaches [2], [3], [7],[10], [15], [16], [17], [18], [20], [21], [23], and [24]. The interpreted results in these existing approaches having the different properties and also merits and demerits in its accuracy produced. The use of classifier systems in medical diagnosis is increasing gradually [12]. SVM has been used as a classification tool with a great deal of success in a variety of areas ranging from Cardiovascular disease prediction [22], a DSS based on SVM for diagnosis of the heart valve diseases [8], an application to hypertension diagnosis [4], classification of diabetes disease [12], prediction model building in breast cancer diagnosis [5]. Current treatments for patients with established stroke are relatively ineffective and risk factor interventions are real hope in reducing morbidity and mortality in populations [9] and [1].

III. MATERIALS AND METHODS

A. Proposed Modeling

Risk factors for stroke are well documented. Prediction [13] about the course of risk factors of the stroke is a key component of healthcare decision-making process.

Table 1 Classification of stroke risk factors

Type of Risk Factors	Modifiable / Controllable / Treatable	Non-Modifiable Uncontrollable / Non-Treatable
Demographic	-	Age, Sex

		and Race
Lifestyle	Cigarette Smoking, Alcohol use and Obesity / Excessive weight.	-
Medical / Clinical	Hypertension, Diabetes Mellitus, Atrial fibrillation, Lipid profiles: Total cholesterol, HDL, LDL and Triglycerides.	Previous history of stroke or TIA, Family History of stroke and heart disease.
Functional	Physical Activity / Exercise	-

Major risk factors for stroke might be considered as main targets for primary and secondary prevention of stroke. More individual risk factors may help to improve the individual risk assessment [19]. In this line of research, we proposed the SVC stroke risk prediction models from its risk factors, is experimented through the effective kernel functions of RBF and Polynomial kernels. Its parameters are described in Table 2. Many risk factors can be changed or managed, while others cannot be changed. There are two clusters of stroke risk factors which are explained in Table 1.

B. Support vector machines methodology:

Support Vector Machines (SVM) recognized in the theory of Statistical Learning Theory (SLT) and a newly proposed method of Machine Learning has some outstanding advantages and it can be used for Support Vector Classification (SVC) and Support Vector Regression (SVR). It is suitable for both linear and nonlinear data processing; it has special generalization ability, especially for problems of small size. SVMs make predictions by automated learning from existing knowledge [26]. This type of learning requires training data where the answer is known so that rules or other functions that fit the data can be generated. The aim of SVM is to devise a computationally efficient way of learning in classification. It can separate the classes with a particular hyper plane which maximizes a quantity called ‘margin’. The margin is the distance from a hyper plane separating the classes to the nearest point in the dataset. In binary classification, we are given a set of input vectors $\{x_i\}$, $x \in \mathfrak{R}^n$ together with the corresponding class labels $\{y_i\}$ where $y_i \in \{1,-1\}$. The goal is to infer an information $f(y)$ based on the training set. This can be done by choosing a learning model $f(\cdot)$ which is controlled by some unknown parameters x , and “learning” these parameters from the given training set. SVMs [6], are one of the most popular methods and make predictions based on the classification decision function; i.e., Structural Risk Minimization (SRM) principle,

$$f(y) = \text{sgn} \left[\sum_{i=1}^{\text{Bsv}} \alpha_i y_i k(x_i, y) + b \right] \quad (1)$$

where y_i are the labels, α_i are the Lagrange multipliers (it is a systematic way of generating the necessary conditions for a stationary point), x_i is the support vectors previously identified through the training process, and y is the test data

vector. Here, $\alpha_i \geq 0, i = 1, 2, \dots, n$ (where ‘n’ is the number of support vectors) are non-negative Lagrange Multipliers that satisfy $\sum_{i=1}^n \alpha_i y_i = 0$. In equation (1), kernel function and

weight vector ‘x’ are the parameters of the model. The success of SVM is attributed to the margin maximization theory [26]. $k(x_i, y)$ for $i=1, 2, \dots, n$ represents a symmetric positive definite kernel functions that defines an inner product in the feature space. In a typical classification task, only a small subset of the Lagrange multipliers α_i usually tends to be >0 . The respective training vectors having non-zero which are closest to the optimal hyper plane (α_i) are called support vectors or latency vectors. These support vectors will be formed into a model by the SVM. For training, SVMs use a quadratic optimization problem [25]. The construction of a hyper plane $w^T x + b = 0$ (w is the vector of hyper plane co-efficient [Input vectors], b is a bias term and x is an adaptive weight vector).

C. Setting support vector classification model parameters through its kernel function

SVM can present mathematical models with better prediction ability. Support Vector Classification (SVC) has been used as a mathematical modeling in this work for both SVM_{RBF} and SVM_{Poly} machines. The performance of SVC modeling is dependent on the combination of several factors, including the parameter C, the kernel type and its corresponding parameters. The kernel functions Gaussian RBF and Polynomial have been selected in this investigation to generate the stroke risk prediction through the task of SVC. No specific kernel functions have the best generalization performance for all kind of problem domains. The decision on selecting appropriate values of d is basically by trial and error. SVM maps the training samples from the input space into a higher dimensional feature space via a mapping function ϕ . The kernel function $k(x_i, x_j)$ defines an inner product as $k(x_i, x_j) = \phi(x_i) \cdot \phi(x_j)$. Usually the inner products are replaced by kernel function in the dual Lagrange. The following different kernel functions are used in our SVC stroke risk prediction modeling.

1. Polynomial kernel:
 $K(x, x') = (x \cdot x' + 1)^d$;
 where d is the degree of kernel and positive integer number.
2. Gaussian (RBF) kernel :
 $K(x, x') = \exp(-\|x - x'\|^2 / \sigma^2)$;
 where σ is a positive real number.

IV. EXPERIMENTAL RESULTS

In order to improve and achieve our goal towards model building using support vector classification accuracy and the Table 2 depicts the mentioned kernel parameters are set in our experiment. It produced above 90% accuracy in its prediction.

Table 2 SVM kernels and their corresponding kernel specific parameters

Hypersurface kernel type	Kernel specific parameters	Parameters Value
Polynomial	Even degree (d)	2
Gaussian (RBF)	Kernel width (γ)	0.01

Performance analysis data have been classified by SVC and are listed in Table 6 by using Gaussian RBF and Polynomial kernels. The rate of correctness of prediction by RBF is 98% and by Polynomial is 92%. It proves that the application of SVC models can be used for the processing of stroke related risk factors data. Also, it implies that our models have good generalization ability. In this research work, we used the SVM^{Light} software for implementation.

A. RBF modeling

Using the RBF kernel function with capacity parameter $C=100$, the following criterion for the stroke risk prediction has been obtained through classification decision function.

$$f(x) = \sum_{i \in SV} \alpha_i y_i \exp(-\|x - x_i\|^2 / \sigma^2) - 0.3113364 \quad (2)$$

where $b = -0.3113364$, $\sigma = 0.01$, α_i (listed in Table 3) are corresponding to the Lagrange multipliers of support vectors. $y_i = 1$ corresponds to the samples of class 1; while $y_i = -1$ corresponds to the samples of class 2. x is a vector (pattern of sample) with unknown activity to be discriminated; x_i is one of the support vectors. $f(x) \geq 0$ corresponds to class 1. In this stroke risk prediction models using the RBF kernel function with the aforesaid parameters are used for mathematical model building (see equation 2).

Table 3: The sample number of support vectors and their corresponding coefficients for the kernel of Gaussian RBF kernel

Sample No.	α_i						
1	0.59325	18	0.59325	37	-0.59325	56	-0.59325
2	-0.59325	19	0.59325	38	-0.59325	57	0.59325
3	0.59325	20	-0.46380	39	-0.59325	58	0.59325
4	0.59325	22	-0.59325	41	0.59325	60	-0.59325
5	0.59325	24	0.59325	43	-0.59325	62	0.59325
6	-0.59325	25	0.59325	45	0.59325	63	-0.59325
7	-0.59325	26	-0.47678	46	-0.59325	65	0.59325
8	-0.59325	28	0.59325	48	0.59325	67	-0.59325
11	0.59325	29	-0.59325	49	0.59325	68	-0.17322
12	-0.50880	30	-0.59325	50	-0.59325	69	-0.59325
13	-0.59325	32	0.59325	51	0.59325	71	0.59325
15	0.59325	33	-0.59325	52	-0.59325	72	-0.12727
16	-0.59325	35	0.59325	54	0.59325	73	-0.59325
17	0.17323	36	0.59325	55	0.34573	75	0.00891

B. Polynomial modeling

With the evident of experimental results, the polynomial kernel function (even degree $d=2$) with $c=100$ has been used for modeling by SVC. The mathematical model (see equation 3) obtained can be expressed as follows.

$$P_{75} = \sum \beta_i [(x_i \cdot x) + 1]^2 + (-2.8246306) \quad (3)$$

where β_i (listed in Table 4) is the Lagrange coefficients corresponding to support vectors. x is a vector with unknown activity. x_i is one of the support vectors. All support vectors obtained are presented in Table 4. The results of stroke risk prediction of the mathematical model built by SVC are more reliable. Hence SVM has been

considered as a new powerful tool for the prediction of stroke risk.

C. Real data set of stroke

The real life data set of stroke is used in this investigation, data extracted from cohort of population set of various Hospitals situated at Tiruchirappalli city, Tamilnadu, India. From the data set, 100 Patients Medical Records Information (PMRI) were taken into analysis. The binary response variable takes the values '+1' or '-1', where '+1' means a positive test (Stroke disease) for stroke and '-1' (Non-disease) for negative test for stroke (Refer Table 5). Each of the patient record includes eight attributes (inputs) used for the prediction of stroke risk from highly influenced stroke risk factors are explained below;

1. Hypertension 2. Diabetes Mellitus 3. Obesity 4. Cigarette Smoking 5. Heart Disease 6. Prior Stroke /TIA 7. High Cholesterol and 8. Physical Activity/ Exercise. These eight attributes (variables) for each patient’s data are pre-processed by means of positive real values; finally this forms a training set and test set. The details are;

Total no. of Input attributes : 08
 Total no. of Output attribute : 01 (Training set)
 Total no. of Class Labels : 02 (Class 1[+1] and Class 2 [-1])
 Total no. of Training samples : 75
 Total no. of Testing samples : 25
 Regularization Parameter value (C) : 100 (for both RBF and Polynomial kernels)

Table 4: The sample no. of support vectors and their corresponding coefficients for the kernel of polynomial

Sample No.	β_i						
1	0.13253	20	-0.13253	38	-0.13253	57	0.13253
2	-0.13253	21	0.13253	39	-0.13253	58	0.13253
4	0.13253	22	-0.13253	41	-0.13253	59	-0.13253
5	0.13253	24	0.13253	42	-0.13253	60	-0.13253
6	-0.13253	25	0.13253	43	-0.13253	62	0.13253
7	-0.13253	26	-0.13253	45	0.13253	63	-0.13253
8	-0.13253	27	0.13253	46	-0.13253	65	0.13253
10	0.13253	28	0.13253	48	0.13253	66	0.13253
11	0.13253	29	-0.13253	49	0.13253	67	-0.13253
12	-0.13253	30	-0.13253	50	-0.13253	68	-0.13253
13	-0.13253	32	0.13253	51	0.13253	69	-0.13253
15	0.13253	33	-0.13253	52	-0.13253	71	0.13253
16	-0.13253	35	0.13253	54	0.13253	72	-0.13253
18	0.13253	36	0.13253	55	0.13253	73	-0.13253
19	0.13253	37	-0.13253	56	-0.13253	75	0.13253

Table 5: Class labeling of stroke patient’s data set

Sample No.	Class						
1	C2	26	C1	51	C2	76	C1
2	C1	27	C2	52	C1	77	C2
3	C1	28	C1	53	C1	78	C1
4	C1	29	C1	54	C2	79	C1
5	C2	30	C1	55	C2	80	C1
6	C1	31	C2	56	C1	81	C2
7	C2	32	C2	57	C1	82	C1
8	C2	33	C2	58	C2	83	C1
9	C1	34	C1	59	C1	84	C2
10	C1	35	C1	60	C1	85	C2
11	C1	36	C1	61	C1	86	C1
12	C2	37	C2	62	C2	87	C1
13	C2	38	C2	63	C2	88	C2
14	C1	39	C1	64	C2	89	C1
15	C1	40	C1	65	C1	90	C1
16	C2	41	C2	66	C1	91	C1
17	C1	42	C1	67	C2	92	C2
18	C1	43	C1	68	C2	93	C2
19	C1	44	C1	69	C1	94	C2
20	C2	45	C2	70	C1	95	C1
21	C1	46	C1	71	C2	96	C1
22	C1	47	C2	72	C1	97	C2
23	C2	48	C1	73	C1	98	C2
24	C2	49	C1	74	C1	99	C1
25	C1	50	C1	75	C2	100	C1

*"Class 1 (C1)" denotes the samples of stroke disease patients and "Class 2 (C2)" denotes those of prone risk patients.

D. Performance metrics

We have used four methods for performance evaluation of stroke risk prediction. These are classification accuracy, two epidemiological indices (i.e., sensitivity analysis, specificity analysis) and confusion matrix. Table 6 shows the classification accuracy predicted by our SVC models

through test data set. Computing formula for Sensitivity and Specificity analysis is as below.

Sensitivity (True positive achieved) =

$$\frac{TP}{TP+FN} \%$$

Specificity (True negatives achieved) =

$$\frac{TN}{FP+TN} \%$$

Table 6: The obtained classification accuracy, values of sensitivity and specificity by SVC models for the classification of stroke risk prediction

Statistical Measures	SVM	SVM
	RBF	Poly
Total Classification Acc (%) in test set	98 %	92 %
Sensitivity	93 %	100%
Specificity	100 %	80%

E. Confusion matrix

A confusion matrix is a method of finding an error measure and it contains information about actual and predicted classifications done by a classification system. Performance of a system is commonly evaluated using the data in the matrix. Table 7 shows the confusion matrix for a two class classifier. The entries in the confusion matrix are;

1. a is the number of correct predictions that an instance is negative,
2. b is the number of incorrect predictions that an instance is positive,
3. c is the number of incorrect predictions that an instance is negative and
4. d is the number of correct predictions that an instance is positive.

Table 7: Representation of Confusion Matrix

Actual	Predicted	
	False	True
False	FN ^c	FP ^b
True	TN ^a	TP ^d

where TP, TN, FP and FN denotes true positives, true negatives, false positives and false negatives respectively.

Table 8: SVM_{RBF} data placed in the confusion matrix

Actual	Predicted	
	False	True
False	01	00
True	10	14

Table 9: SVM_{Poly} data placed in the confusion matrix

Actual	Predicted	
	False	True
False	00	02
True	08	15

Table 10: Performance analysis of SVM_{RBF} and SVM_{Poly} classifier

Kernel function used	No. of support vectors	% Accuracy (Test Set)
RBF	56	98
Polynomial	60	92

F. Evaluation of error prediction of mathematical models

Results of the prediction of mathematical models are validated and compared with accuracy metrics. The evaluation metrics are Mean Absolute Error (MAE), Upside Mean Absolute Error (UMAE) and Downside Mean

Absolute Error (DMAE) is computed with the respective formulas (see equation 4 to 6) and the values are tabulated in Table 11. These metrics are used to evaluate the prediction performance. Mean Absolute Error is used to find a measure of the discrepancy between the actual and predicted values.

$$MAE = 1/m * \sum_{i=1}^m |xi - pi| \tag{4}$$

$$UMAE = 1/m * \sum_{i=1, xi \geq pi}^m (xi - pi) \tag{5}$$

$$DMAE = 1/m * \sum_{i=1, xi < pi}^m (pi - xi) \tag{6}$$

(where ‘xi’ and ‘pi’ are the actual and predicted values. ‘m’ is the number of testing data).

Table 11: Error of prediction of mathematical models obtained by SVM_{RBF} and SVM_{Poly}

Method of classification	MAE	UMAE	DMAE
SVM _{RBF}	0.275215	-0.085039	0.085039
SVM _{Poly}	0.402814	-0.187087	0.187087

Table 12: Stroke data set statistical analysis

Name of the Attribute	Mean Value	Standard Deviation
Hypertension	0.6116	0.1131
Diabetes	0.3924	0.1997
Obesity	0.4383	0.1454
Cigarette smoking	0.4585	0.1715
Heart Disease	0.1585	0.1953
TIA	0.0585	0.1040
High Cholesterol	0.6787	0.0320
Physical Activity	0.6045	0.0772

The Table 12 shows the statistical analysis of stroke data (i.e., Mean and Standard Deviation values) samples taken for the process of support vector classification of stroke risk prediction task.

V. DISCUSSIONS

To evaluate the effectiveness of the proposed stroke risk prediction models, the results are evaluated through confusion matrix and are tabulated in Table 8 and in Table 9. The results reported that the performance of the SVM_{RBF} kernel method has performed well (98%) when compared with SVM_{Poly} (92%). Polynomial kernels are suited for problems where all the training data in normalized. Based on study [11], it was analyzed by using polynomial kernel d=2 with a constant parameter c=10 proved its cystine connectivity prediction with high accuracy. It was shown

that SVM with polynomial kernel provides a good performance for prediction and classification [27]. Another study indicates that SVM with RBF kernel has stronger ability [14]. The classification accuracy results of test set of stroke risk prediction by SVM_{RBF} and SVM_{Poly} are shown in Table 10. It is also observed that the samples 1 and 16 are only misclassified (misclassification error is 0.08%) by using SVM_{Poly} model, whereas in SVM_{RBF} model, all samples (except the sample 22) of test set are correctly classified (misclassification error is 0.02%) is shown in Figure 1. The proposed models are well fit-in in the stroke risk prediction. The study proved and confirmed the validity of SVM kernels like RBF, and Poly. It also provided the good performance accuracy. It is believed that the SVC models have been suited for stroke risk prediction.

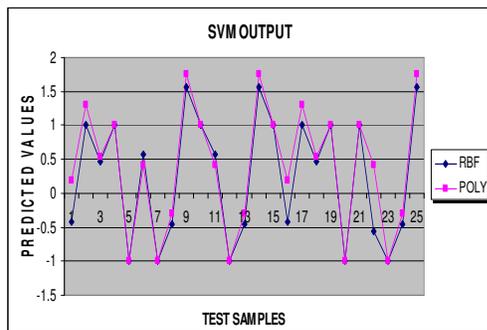


Figure 1. Two-class classification accuracies by SVM_{RBF} and SVM_{Poly} machines

VI. CONCLUSION

In this study, the classification models are evaluated through SVM_{RBF} and SVM_{Poly}. The results strongly suggest that these models can assist the medical practitioners for planning the proper treatment strategies in the stroke risk prediction. We hope that more interesting results would be possible through further exploration of huge population data set. Authors conclude that the proposed prediction models would assist in the reduction of mortality and morbidity rate of stroke populations.

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