RESEARCH ARTICLE

European Journal of Information Technologies and Computer Science
www.ej-compute.org

Predicting Psychiatric Disorder from the Classified Psychiatric Characteristics Using Machine Learning Algorithm

Md. Sydur Rahman and Boshir Ahmed

ABSTRACT

Psychiatry is an interdisciplinary field that focuses on a major public health concern. The following threats represent a significant risk to the mental health of anyone who is exposed to them. Various things might have an impact on both a person's physical and financial health. Psychiatric treatment can raise the likelihood of getting a mental disorder. Schizophrenia is a devastating mental condition that predominantly affects women. It is more prevalent in both male and female. Mentally sick individuals are more likely to engage in antisocial behavior which results in social behavioral distortion. As a direct result, societal concerns that were already evident have grown considerably more prevalent. According to global data, anxiety, drugs misuse, hazardous behavior, arrogance, suicidal thoughts, depression, disorientation, and consciousness are widespread among 20 to 30 years adults. These individuals are continuously searching for something new, which can be detrimental to their mental health because it makes them less stable.

A machine learning classifier has been predicted to classify the appropriate extracted features after applying Support Vector Machine (SVM) classifiers for various no-linear kernels, taking into account all the critical elements for psychiatry that have been stated. An unequal history of mental diseases has climbed from 10.5 percent in 1990 to 19.86 percent in 2022, according to Adult Prevalence of Mental Illness (AMI) 2022, and psychiatry currently accounts for 14.3 percent of yearly global mortality (approximately 8 million).

Keywords: Performance Analysis & Prediction, psychiatry, result comparison, SVM.

Published Online: August 29, 2022

ISSN: 2736-5492

DOI : 10.24018/ejcompute.2022.2.4.72

M. S. Rahman*
Rajshahi University of Engineering & Technology (RUET), Bangladesh.
(e-mail: sydur.ruet.113044@gmail.com)

B. Ahmed
Rajshahi University of Science & Technology (RUET), Bangladesh.
(e-mail: boshir78@gmail.com)

Corresponding Author

I. Introduction

Machine learning classification, in contrast to traditional classification techniques, is a hypothesis-free methodology in which algorithms are learned from training data and then applied to multi-modal data to determine the relative importance of various variables for categorization. A survey was carried out to investigate psychiatric features. A certain number of questionnaires were allotted to each group, and they were distributed on a regular basis. A data collection system and processing environment were implemented in response to the overwhelming quantity of affirmative survey replies.

This is because no machine learning classifier can presently reliably detect the relative psychiatric level when many psychiatric variables and healthy controls are combined. Several machine learning algorithms are used to classify a large sample of data that has been thoroughly examined in order to determine the relative importance of various symptoms, mental strength, and the ancient and current goals of psychiatry. We hypothesized that applying an SVM classifier to each predefined characteristic extracted from an adequate questionnaire survey would result in non-biased estimates of the most influential factors in classifying psychiatric disorders, which could then be used to inform classification strategies based on the extracted features.

The cerebral capacity, physical strength, and training of a person can be determined by their responses to critical questions. All participants with varied degrees of psychiatric illness were statistically examined. The secondary purpose of the study would be to examine the features of any healthy controls who were either diagnosed with or did not appear to have a mental condition during the experiment.

Geographically relevant age-based assessments of psychiatric patients would be made. Along with the analysis, after classifying all implemented data-sets of certain psychiatric features, it would be easier to predict one's mental strength and make a good recommendation to see a psychiatrist.

II. Background Study

The use of a machine learning classification approach for medical decision-making that involved complicated multilayer data, such as health evaluations, treatment decisions, and risk factor evaluation, was demonstrated in this study [1].

Several categories of psychiatric patients with differing mental health conditions have just been categorized based on machine learning approaches. Using proper transformation and transposition of numerous important parts, including as anxiety, drug abuse, large risk-taking, arrogance, suicidal attempts, depression, and confusion, a Support Vector Machine (SVM) classifier has been employed to categorize the level of psychiatry.

Generalized anxiety disorder (GAD) is one of the most widespread mental illnesses, despite the lack of a fast clinical diagnostic. This study aimed to construct a brief self-report measure that might be used to detect possible GAD cases, as well as to investigate the validity and reliability of the scale [2].

The DAST-10 is a self-report tool that can be used for population screening, clinical case finding, and treatment evaluation research. Adults and older children can also appreciate it. The DAST-10 is a ten-point scale that measures the severity of drug abuse-related outcomes [3]. The concept of arrogance is tackled from multiple disciplines. We present classifications for individual, comparative, and aggressive arrogance (each logically related to the next). From a false sense of self-worth comes a mistaken evaluation of one's abilities, a false sense of superiority over others, and ultimately disrespectful behavior [4]. Using a depression-anxiety self-assessment quiz, the severity of depression was evaluated [5]. When searching for confusion, the same examination methods must be utilized as when searching for other neurological or physical disorders. By conducting a comprehensive history, physical examination, and observation, the physician can increase the likelihood of a correct diagnosis and appropriate treatment [6].

Risk-taking has captivated both professionals and scientists for millennia. Numerous studies have demonstrated how insufficiently valid and predictive the current measurement technique is. In view of the recent calls for additional risk-taking concept measures, this paper will discuss six essential elements to consider when developing or implementing such measures. In addition, keep in mind that taking risks does not necessarily correlate to acting irresponsibly, reevaluate passive risk-taking measurement, and encourage more prudent risk-taking actions. In general, these concepts should aid researchers in making more accurate risk-taking decisions [7].

A neuro-scientific survey was utilized to investigate consciousness [8]. A machine learning classification system was utilized to assist in the making of medical decisions including complicated multi-layer data, such as health evaluations, treatment options, and risk factor evaluations.

III. Methodology

The goal of this thesis works to classify psychiatric characteristics using Support Vector Machine (SVM) and to show the statistical description of each criterion. And from the statistics, we can easily predict who are severely, moderately carrying psychiatry and who are free of any type of psychiatric disorder. For the concern, we have to follow some necessary steps:

A. Data Acquisition
B. Feature extraction and
C. Classification.

Data flow diagram of methodology has been stated in Fig. 1.

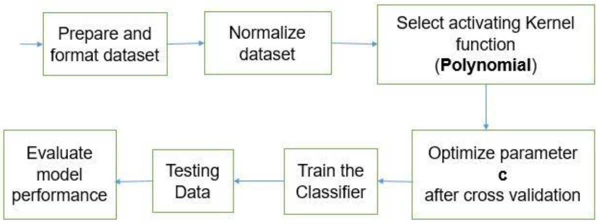

Fig. 1: Workflow diagram of proposed methodology.

A. Data Acquisition

The first step is to collect data with a survey for the following psychiatric characteristics: Anxiety, Drug -Abuse, Risk-taking Tendency, Arrogance, Confusion, and Depression with adequate questionnaires. The answer to each question has been ranked as values 0, 1, 2, 3 for proper measurement. Then tabular data has been generated from the responses of each individual. The total number of questions required a numeric categorical threshold of the factor which means its existence. Then sum up the total values of the specified characteristic to generate the score. A similar type of action has been performed for the stated psychiatric characteristics.

Generalized anxiety disorder (GAD) is characterized by excessive concern or anxiety that is all-pervasive and unfounded. The person is typically aware that their anxiousness is unjustified and that these emotions are uncontrollable. For instance, the mere prospect of performing mundane duties may induce anxiety. We intended to administer the GAD-7 test to anxious patients and compare the results to their survey responses.

Sample responses for Anxiety measurement has been stated in Table I.

TABLE I: Responses of Anxiety Questionnaires

Q-1	Q-2	Q-3	Q-4	….	Q-7
Acute	Yes	High	Low		Slightly
Acute	Yes	High	Not at all		Yes
Acute	At times	Medium	Low		Slightly
Acute	Yes	High	Not at all		Nope
Acute	At times	High	Medium		Yes

A self-report tool called the Drug Abuse Screen Test (DAST-10) can be used for drug addicted personnel screening, clinical case discovery, and treatment evaluation research. Both adults and older children can utilize it. The DAST-10 is a numerical scale that evaluates the gravity of effects brought on by drug abuse. The instrument, which can be completed as a self-report or interview, takes around five minutes to administer. The DAST can be applied in a number of circumstances to offer a quick evaluation of drug misuse issues.

Sample responses for Drug Abuse Range has been stated in Table II with their responses against the questionnaires.

TABLE II: Responses of Drug Abuse Range Questionnaires

Q-1	Q-2	Q-3	Q-4	….	Q-8
Maybe	At times	At times	No	….	Yes
Maybe	No	Yes	At times	….	Occasionally
No	No	Yes	At times	….	Occasionally
No	At times	No	No	….	Yes
No	No	Yes	At times	….	Occasionally

We tackled the topic of arrogance from a multidisciplinary standpoint. There are six stimulant factors that are logically related to one another. The elements range from an inaccurate understanding and a lack of skills to an unwarranted sense of superiority over others, an unwarranted evaluation of them, and the display of the associated contempt [9]. Although each component is likely to be present to some degree when the subsequent component operates, causality could flow in either direction between components.

Sample responses for Arrogance Level has been stated in Table III with their responses against the questionnaires.

TABLE III: RESPONSES OF ARROGANCE LEVEL CHECK QUESTIONNAIRES

Q-1	Q-2	Q-3	Q-4	….	Q-6
Yes	Yes	Yes	Maybe	….	Yes
Yes	Yes	Yes	Yes	….	Yes
No	No	Maybe	Maybe	….	Yes
Yes	No	No	Yes	….	Occasionally
No	Occasionally	Yes	Maybe	….	No

Major depressive disorder, clinical depression, uni-polar depression, or major depressive state are further names for depression. In addition to other symptoms, it can be identified by a depressed state of mind or a lack of interest in or enjoyment from routine activities [10]. Symptoms manifest daily and last for at least two weeks. Depression affects all element of a person's life, including employment and social relationships. Depression that is melancholic or psychotic might be mild, moderate, or severe.

Sample responses for Depression Level measurement has been stated in Table IV with their responses against the questionnaires.

TABLE IV: RESPONSES OF DEPRESSION LEVEL CHECK QUESTIONNAIRES

Q-1	Q-2	Q-3	Q-4	….	Q-7
Yes	Occasionally	Yes	Yes	….	Yes
Yes	Occasionally	Yes	Yes	….	Maybe
Occasionally	Yes	No	No	….	No
Yes	Yes	Yes	Yes	….	Occasionally
Yes	Yes	No	Yes	….	Yes

Risk-taking behavior is the propensity to engage in activities that have the potential to be damaging or dangerous. This includes alcohol abuse, binge drinking, and use of illegal substances, driving while inebriated, and unprotected sexual activity. According to the Centers for Disease Control and Prevention (CDC), these behaviors increase the likelihood of unintentional injury and violence.

Sample responses for Big Risk Taking Tendency has been stated in Table V with their responses against the questionnaires.

TABLE V: RESPONSES OF BIG RISK TAKING TENDENCY QUESTIONNAIRES

Q-1	Q-2	Q-3	Q-4	….	Q-9
Occasionally	Not at all	Partially	Maybe	….	Yes
Yes	Partially	Partially	Yes	….	Yes
No	Partially	Not at all	Yes	….	Yes
Yes	Fully	Partially	Yes	….	Yes
Yes	Not at all	Not at all	Maybe	….	Yes

Confusion refers to a reduction in cognitive aptitude, or our ability to think, learn, and comprehend. A decline in cognitive performance is frequently associated with dementia. Signs of confusion include problems with short-term memory, trouble completing tasks, a short attention span, inaccurate speech, and difficulties following a discussion. There may be confusion on occasion, but it will pass. Long-lasting chronic conditions have the potential to occasionally induce confusion.

Sample responses for Confusion Level measurement has been stated in Table VI with their responses against the questionnaires.

TABLE VI: RESPONSES OF CONFUSION LEVEL CHECK QUESTIONNAIRES

Q-1	Q-2	Q-3	Q-4	…	Q-7
Yes	No	Maybe	Yes	…	Yes
Yes	Yes	Yes	Yes	…	Yes
Yes	Yes	Maybe	No	…	Yes
Yes	Maybe	Yes	Yes	…	Yes
Yes	No	No	No	…	little bit

B. Feature Extraction

We must first extract the features from the dataset before we can apply machine learning algorithms to it. All responses from Table I, II, III, IV, V, and VI are replaced by 0, 1, 2, or 3 according to their type of answers. We have replaced the responses "No" and "Not at all" by 0 and "Low" is replaced by 1. Similarly "Moderate", "Medium", "Maybe", "At times", "Partially", and "Occasionally" are replaced by 2. And also "Yes", "High", "Acute", "Fully", and "Totally" are replaced by 3. And we sum up the numeric values of responses to generate the threshold for a specific feature. A sample data of six psychiatric factors namely Anxiety, Drug Abuse, Arrogance, Depression, Risk Taking Tendency and Confusion has been given in Table VII.

TABLE VII: A SAMPLE DATASET OF SIX PSYCHIATRIC FEATURES

Anxiety	Drug Abuse	Arrogance	Depression	Big Risk	Confusion
5	6	7	13	14	11
10	3	6	5	13	4
15	0	9	20	20	13
17	0	11	19	16	20
12	11	10	11	17	15
13	9	6	21	20	20

In addition to scaling the data for feature extraction, it is also divided into two feature sets, with the minimum feature set equal to zero and the maximum feature set equal to one. A compression technique reduces the amount of data to fit inside a certain range, which is often between 0 and 1. A scalar of characteristics alters data by re-scaling its attributes to a predetermined range. When used to compress a distribution of values into a defined range, it preserves the structure of the original distribution.

The Min-Max scaling is calculated using:

$$x\_std = (x - x_{min}(axis{=}0)) / (x_{max}(axis{=}0) - x_{min}(axis{=}0)) \quad (1)$$

$$x\_scaled = x\_std * (max - min) + min \quad (2)$$

where,

min, max = feature range

x_{min} (axis=0): Minimum feature value

x_{max} (axis=0): Maximum feature value

We have translated our dataset to a normalized form in where a sample is given in Table VIII.

TABLE VIII: SCALED DATASET OF SIX PSYCHIATRIC FEATURES

Anxiety	Drug Abuse	Arrogance	Depression	Risk Taking	Confusion
0.22	0.3	0.428	0.619	0.411	0.523
0.5	0.15	0.33	0.238	0.411	0.190
0.77	0	0.523	0.952	0.705	0.619
0.66	0.8	0.904	0.761	0.88	0.761
0.83	0.6	0.857	0.809	0.941	0.952
0.66	0.55	0.66	0.904	0.588	1

C. SVM Classifier

Strong binary classifier Support Vector Machine (SVM) is able to differentiate between two classes. SVM possesses both linear and nonlinear properties. The SVM kernel transforms low-dimensional input space into higher dimensional input space. It is most effective in non-linear separation problems. It transforms a problem that cannot be divided into one that can be. After conducting extremely complicated data transformations, the kernel decides how to split the data based on the labels or outputs specified.

Four non-linear SVM Kernels we have applied to our classifier are:

1) Linear Kernel

Linear Kernel is the most fundamental kind of kernel, typically just having one dimension. It turns out to be the best feature when there are many features. Since most of these problems can be linearly separated, the linear kernel is typically chosen for text classification issues. The speed of linear kernel functions is superior to other functions [11].

We can easily determine the linear hyper-plane with the following equation:

$$f(x) = < w.x > +b \tag{3}$$

Where x represents the observed data point, w the normal vector, and b a bias factor. We performed train-test-split for the derived dataset to apply the SVM classifier.

2) Polynomial Kernel

Polynomial Kernel is a general representation of kernels with a degree of more than one. It is a more extensive representation of the linear kernel [12], [14].

The following mathematical function represents Homogeneous Polynomial Kernel Function:

$$K(X_i, Y_j) = (X_i.Y_j)^n \tag{4}$$

Where '**.**' is the dot product of both the numbers and n is the degree of the polynomial.

The following mathematical function represents In-homogeneous Polynomial Kernel Function:

$$K(X_i, Y_j) = (X_i.Y_j + c)^n \tag{5}$$

Where c is a constant.

Applying SVM classifier, two different hyper-planes have been drawn to distinguish three different classes of psychiatric patients in Fig 2.

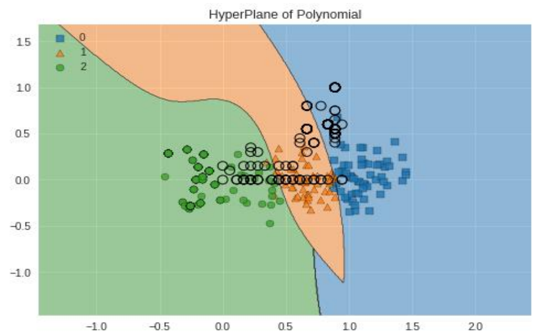

Fig 2: SVM classifier with hyper-plane.

3) RBF Kernel

Gaussian Radial Basis Kernel is one of the most popular and often employed kernel functions in SVM. Typically utilized for non-linear data. When there is no prior knowledge of the data, it aids in making the appropriate separation [15].

RBF Kernel Function is represented by the following mathematical function:

$$k(x_1, x_2) = exp\left(\frac{(||x_1-x_2||)^2}{2\sigma^2}\right) \tag{6}$$

Where $k(x_1, x_2)$ is the similarity of two points x_1 and x_2 and

σ is the variance and our hyper-parameter and $||x_1 - x_2||$ is the Euclidean (L_2-norm) Distance between two points x_1 and x_2.

4) Sigmoidal Kernel

For neural networks, it is mostly favored. This kernel function functions as an activation function for neurons and is comparable to a two-layer perceptron model of the neural network [15].

Sigmoidal Kernel Function is represented by the following mathematical function:

$$F(X_i, Y_j) = tanh(ax.by + c) \tag{7}$$

Our 67 percent of data is being used as training set. And on the other-hand 33 percent data of our data is used for testing set [13]. As the dataset contains three different classes of psychiatric patient's namely severe level, moderate level and normal patients. Different non-linear kernels of SVM say 'rbf', 'poly', and 'sigmoid' have been applied to categorize the performance of each.

IV. PERFORMANCE ANALYSIS

Performance evaluation is performed using the following statistical measurements. Using the known terminologies of performance analysis, a statistical description is stated.

True Positive (TP): Class level is induced by each characteristic and the classifier correctly determines its level.

False Positive (FP): The class level does not experience the characteristic but the classifier misinterprets the level as under the characteristics.

True Negative (TN): The class level is not induced by characteristic and the classifier correctly interprets that the class level is not under characteristic.

False Negative (FN): The class level is induced by features but the classifier misinterprets as the level is not under the characteristics.

European Journal of Information Technologies and Computer Science
www.ej-compute.org

Sensitivity: Refers to the ability of the classifier to correctly identify the class level under the following characteristics.

$$Sensitivity = TP/(TP+FN) \quad (8)$$

Specificity: Ability of the classifier to correctly identify the class level not under the characteristics.

$$Specificity = TN/(TN+FP) \quad (9)$$

Positive Predictive Value (PPV): The probability that the level is actually under the following characteristics when the classifier identifies that the class level is induced by the features.

$$PPV = TP / (TP+FP) \quad (10)$$

Negative Predictive Value (NPV): The probability that the class level is not under features, when the classifier identifies that the level is not induced by the following characteristics.

$$NPV = TN / (TN+FN) \quad (11)$$

Classification Accuracy of the Classifier: It is the ratio of the total number of correct assessments to the total number of assessments.

$$Accuracy = (TN+TP)/(TN+TP+FN+FP) \quad (12)$$

Here TP, TN, FP and FN are described earlier. Performance of each classifier has been plotted as performance chart considering 97% for linear, 99% for polynomial, 98% for radial basis and 79% for sigmoidal kernel. It has been represented by Fig. 3.

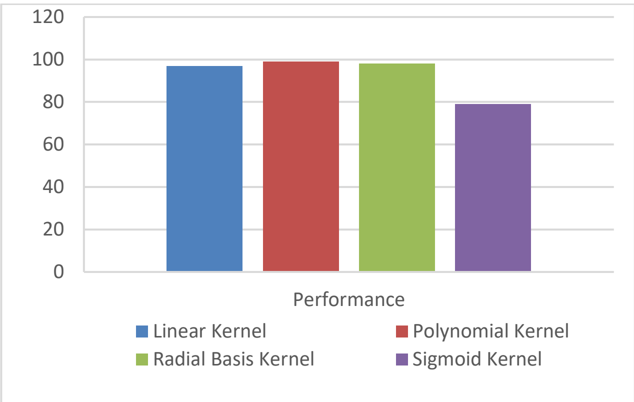

Fig. 3: Performance Chart of All Kernel SVM.

TABLE IX: ACCURACY REPORT OF CLASSIFIER

SVM Kernel	Accuracy
Linear Kernel	97%
Polynomial Kernel	99%
Radial Basis Kernel	98%
Sigmoid Kernel	79%

V. RESULT ANALYSIS

We can easily analysis the statistical findings applying SVM on different characteristics of Psychiatry.

Classification Reports of four non-linear kernel SVM have been stated in Table X, Table XI, Table XII, and Table XIII accordingly.

TABLE X: CLASSIFICATION REPORT OF LINEAR KERNEL SVM

Class	Precision	Recall	f1-score	Support
0	1.00	0.89	0.94	27
1	0.18	1.00	0.92	25
2	1.00	0.80	1.00	237
Accuracy			0.97	49
Macro avg	0.96	0.95	0.95	237
Weighted avg	0.97	0.97	0.97	237

TABLE XI: CLASSIFICATION REPORT OF POLYNOMIAL KERNEL SVM

Class	Precision	Recall	f1-score	Support
0	0.96	0.96	0.96	24
1	0.96	0.96	0.96	27
2	1.00	0.89	0.94	186
Accuracy			0.99	237
Macro avg	0.97	0.97	0.97	237
Weighted avg	0.99	0.99	0.99	237

TABLE XII: CLASSIFICATION REPORT OF RBF KERNEL SVM

Class	Precision	Recall	f1-score	Support
0	1.00	0.92	0.96	26
1	0.93	0.96	0.94	26
2	0.99	1.00	1.00	185
Accuracy			0.98	237
Macro avg	0.97	0.96	0.97	237
Weighted avg	0.99	0.98	0.99	237

TABLE XIII: CLASSIFICATION REPORT OF SIGMOIDAL KERNEL SVM

Class	Precision	Recall	f1-score	Support
0	0.00	0.00	0.00	0
1	0.00	0.00	0.00	0
2	1.00	0.78	0.88	237
Accuracy			0.79	237
Macro avg	0.33	0.26	0.29	237
Weighted avg	1.00	0.79	0.88	237

VI. PREDICTION

A prediction study for any individual has been created utilizing questionnaires for each characteristic and several support vector machine kernels (SVM). We have ultimately discovered that the accuracy of our suggested methodology of SVM for polynomial kernel keeps the highest accuracy of 99 percent when taking into account all classification reports, performance chart and ROC curves for each kernel.

VII. ROC AND AUC OF POLYNOMIAL KERNEL

Plotting all the classified features of psychiatry generated from train-test-splitting criterion we got a ROC for a single class for the polynomial kernel of applied SVM classifier which has been presented by Fig. 4.

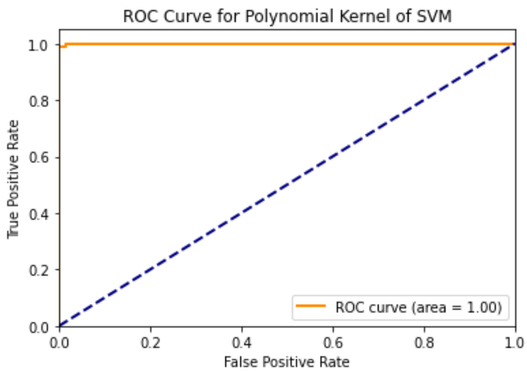

Fig. 4: ROC Curve of Polynomial Kernel (Single Class).

Finally, we got ROC curve for all the classified level of psychiatry for the dataset manipulated from the stated characteristics of psychiatry for the polynomial kernel of SVM in Fig. 5.

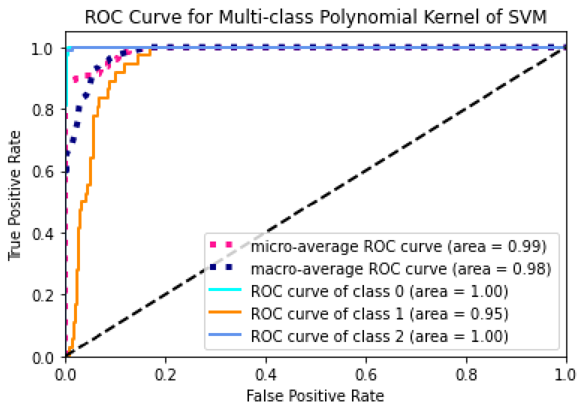

Fig. 5: ROC Curve of Polynomial Kernel (Multi-Class).

VIII. Conclusion

We have created a method for quickly identifying psychological issues in people. Using support vector machine (SVM) classifier with a non-linear polynomial kernel and following the right processes, we can quickly verify his mental strength after responding a survey of questionnaires on various psychiatric features that have been conducted with an easy approach. Region-based, age-based and occupation-based clustering of psychiatric patients may be a good point of view for our future work.

Acknowledgment

We would also like to show our gratitude to the authority and staff of Mental Hospital, Pabna, Bangladesh for sharing their documents of each psychiatric patient and pearls of wisdom with us to attain the goal of data collection during the course of this research, and we specially thank to Dr. Ratan Kumar Ray for his tremendous support and co-operation to collect data.

References

[1] Walsh-Messinger J, Jiang H, Lee H, Rothman K, Ahn H, Malaspina D. Relative importance of symptoms, cognition, and other multilevel variables for psychiatric disease classifications by machine learning. *J Psy Res*. 2019; 278: 27-34.

[2] Spitzer RL, Kroenke K, Williams JB, Löwe B. A brief measure for assessing generalized anxiety disorder: the GAD-7. *Arc Int Med*. 2006; 166(10): 1092-1097.

[3] French MT, Roebuck MC, McGeary KA, Chitwood DD, McCoy CB. Using the drug abuse screening test (DAST-10) to analyze health services utilization and cost for substance users in a community-based setting. *Sub Use Mis*. 2001; 36(6-7): 927-43.

[4] Cowan N, Adams EJ, Bhangal S, Corcoran M, Decker R, Dockter CE, et al. Foundations of arrogance: A broad survey and framework for research. *Rev Gen Psy*. 2019; 23(4): 425-43.

[5] Epstein-Lubow G, Gaudiano BA, Hinckley M, Salloway S, Miller IW. Evidence for the validity of the American medical association's caregiver self-assessment questionnaire as a screening measure for depression. *Am J Ger Soc*. 2010; 58(2): 387-388.

[6] Vink P, Tulek Z, Gillis K, Jönsson AC, Buhagiar J, Waterhouse C, et al. Consciousness assessment: A questionnaire of current neuroscience nursing practice in Europe. *J Clin Nurs*. 2018; 27(21-22): 3913-9.

[7] Bran A, Vaidis DC. Assessing risk-taking: what to measure and how to measure it. *J Risk Res*. 2020; 23(4): 490-503.

[8] Johnson MH. Assessing confused patients. *J N N Psy*. 2001; 71(suppl 1): i7-12.

[9] Gad MM. Classification of mental tasks using support vector machine based on linear predictive coding and new mother wavelet transform. *International Conference on Biomedical Engineering and Computational Technologies (SIBIRCON)*. 2015: 156-159.

[10] Ritter S, Barrett DG, Santoro A, Botvinick MM. Cognitive psychology for deep neural networks: A shape bias case study. *International Conference on Machine Learning*. 2017: 2940-2949.

[11] Ben-Hur A, Ong CS, Sonnenburg S, Schölkopf B, Rätsch G. Support vector machines and kernels for computational biology. *PLoS Com Bio. 2008*; 4(10): e1000173.

[12] Hsu CW, Lin CJ. A comparison of methods for multiclass support vector machines. *IEEE transactions NN*. 2002; 13(2): 415-25.

[13] Mayoraz E, Alpaydin E. Support vector machines for multi-class classification. *International Work-Conference on AN*. 1999: 833-842.

[14] Yaman S, Pelecanos J. Using polynomial kernel support vector machines for speaker verification. *IEEE Sig Proc Letters*. 2013; 20(9): 901-904.

[15] Han S, Qubo C, Meng H. Parameter selection in SVM with RBF kernel function. *World Automation Congress, IEEE*. 2012: 1-4.

M. S. Rahman is currently pursuing his M.Sc. Engineering degree in Computer Science and Engineering (CSE) from the Department of Computer Science and Engineering, Rajshahi University of Engineering Technology (RUET), Bangladesh. He obtained his B.Sc. Engineering degree in CSE from the Department of Computer Science and Engineering, Rajshahi University of Engineering Technology (RUET), Bangladesh in 2016. He is currently working as Lecturer in Department of Computer Science and Engineering, Bangladesh Army University of Science and Technology (BAUST), Saidpur, Bangladesh since 30th April, 2017 to date. His research focuses on neuroscience, psychiatric disorder, machine learning, remote sensing, digital image processing and data mining.

B. Ahmed is a Dhaka native and completed his Ph.D and M.Sc. Engineering degree in Computer Science & Engineering (CSE) from the Department of Computer Science & Engineering, Rajshahi University of Engineering & Technology (RUET), Bangladesh. He obtained his B.Sc. Engineering degree in CSE from the Department of Computer Science & Engineering, Dhaka University of Engineering & Technology (DUET), Bangladesh in 2001. He is working as a faculty member in the department of Computer Science & Engineering, Rajshahi University of Engineering & Technology since 24th June 2001. In addition to this role, he is professor of this Department, with research interests in image/video analysis and Computer vision. In this service period, he took active part in postgraduate & undergraduate academic programs of this department and also have got the opportunity to conduct and supervise different research projects.

His professional activities are listed down:

1) Organizing Member-Secretary, International Conference on Electrical, Computer and Telecommunication Engineering, ICECTE 2019.
2) Technical Co-Chair, International Conference on Electrical, Computer and Telecommunication Engineering, ICECTE 2016.
3) Technical Secretary, International Conference on Computer and Information Engineering, ICCIE 2015.
4) Organizing Secretary, National Collegiate Programming Contest (NCPC) 2015.
5) Career Asset Manager (CAM) of CISCO Systems, RUET local Academy
6) Member, IEEE, USA.
7) Fellow, Institute of Engineers Bangladesh (IEB).