The Effect of Emotions and Parkinson's Disease Prediction Using Classification Learner Models with EEG Dataset Generation

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Abstract: Nearly all hazardous illnesses that affect humans are mostly brought on by emotion. Emotion influences blood pressure, heart rate, renal functionality as well as a few neurological issues. Parkinson's disease movement dysfunction is one of the neurological issues. This problem is caused by a decrease in dopamine secretion in our brains. Dopamine production abnormalities are associated with essential hypertension. Dopamine is important in anxiety modulation in various parts of the brain. Patients with PD frequently encounter that moments of acute stress make their motor symptoms, such as gait freezing, dyskinesia, and tremors, worse. We can say with absolute certainty that emotions play a crucial role in Parkinson's disease. The Classification Learner algorithms and the EEG dataset, which covers the clinical range of Parkinson's disease progression, were the main topics of this research study. We look at the supervised machine learning algorithms: Course Gaussian SVM, Medium Gaussian SVM, Quadratic SVM, and Linear SVM. This yields the accuracy required to detect Parkinson's disease early on with the aid of SVM algorithms and the EEG dataset. With MATLAB, we were able to predict the following: accuracy, sensitivity, specificity, precision, and error rate.

Keywords: Parkinson’s disease (PD). Electroencephalogram (EEG). MATLAB, Support Vector Machine (SVM).

1 INTRODUCTION

Parkinson's disease is a progressive neurological disorder affecting the nervous system's control over the anatomical systems as well as the nervous system of the

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brain. Over 10 million people worldwide have Parkinson's disease [1]. The onset of Parkinson's disease symptoms usually occurs after the age of 45[2]. The somewhat greater incidence and prevalence of Parkinson's disease (PD) in male subjects is one of the most well-documented disease characteristics that demonstrates a gender-specific effect. Furthermore, it seems that men are more susceptible to Parkinson's disease (PD) than women are, possibly because estrogen protects premenopausal women from the disease [3, 4].

A significant proportion of emotions, including excitement, rage, anxiety, and depression, have always been correlated with high hypertension [5]. Hypertension leads to depression. Multiple research studies have shown that stress has a significant role in aberrant psychology, notably the emergence of depression. [6]. Bipolar disorder is triggered by depression. Parkinson's disease manifests itself as soon as bipolar disorder first appears in adolescence. [7].

When they experience anxiety, people with Parkinson's disease will deteriorate more quickly. There is no doubt that anxiety-related symptoms are ubiquitous and may have clinical significance in PD [8]. Anxious depression and depression are the two clinical morphological characteristics of depression that can appear in PD patients [9]. Apathy is a potential Parkinson's disease (PD) non-motor sign, making it challenging to effectively manage the disease's symptoms. The possession of inadequate dopamine has been attributed to apathy.[10].

Along with irritability and anger, Parkinson's disease (PD) is accompanied by behavioral changes. To conclude caregivers should approach PD patients' symptoms positively and emotionally if they occur.

The confusion matrix and the ROC curve were the outcomes of using the four classification leaner models with the MATLAB tool. The performance of the classification model in terms of accuracy, sensitivity, specificity, and error rate was illustrated using the confusion matrix and ROC curve. The training and testing data were subjected to the Confusion Matrix technique. Our study shows that the Quadratic SVM predicts Parkinson's disease with the highest accuracy.

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2 LITERATURE REVIEW

In their research paper, "Machine Learning Approaches for Detecting Parkinson's Disease from EEG Analysis: A Systematic Review," Maitín et al. used a variety of PRISMA techniques and achieved 90% accuracy[11].

Koch et al, presented their work titled "Automated Machine Learning for EEG-based Classification of Parkinson's disease patients". They created a hand-crafted model with 91.0% accuracy by utilizing the knowledge acquired from our automated approach [12].

"Early diagnosis of Parkinson's disease using EEG, machine learning, and partial directed coherence" was the title of the research project that De Oliveira et al presented. They generated the best classification, which was carried out by random forest at an early stage of PD with 78% accuracy [13].

The research work by Betrouni et al. was presented under the title "Electroencephalography-based machine learning for cognitive profiling in Parkinson's disease: Preliminary results." Following a blind investigation, the models' overall classification accuracy for the KNN and SVM algorithms was 88% and 84%, respectively [14].

"Predicting Parkinson's disease using gradient boosting decision tree models with electroencephalography signals" was the title of the research paper that Seung-Bo et al presented. They had a high accuracy of 89.3% when using GBDT algorithms to separate PD patients from HCs [15].

3 IMPACT OF EMOTIONS IN PD

3.1 Depression in Parkinson's disease

There are many causes of depression, including sexual assault, living alone, gender, significant financial loss or the loss of loved ones, genetic issues, serious illnesses, and more. Parkinson's disease may affect more than 70% of depressed individuals, and more than 90% of depressed individuals will experience symptoms of PD [16].

Negative emotions are overemphasized in depression, and the reward that comes from pleasurable experiences is diminished. The development of depression may be significantly influenced by long-term stress.

We can lessen discriminability with PD EEG data using Dimensional emotion recognition experiments. Besides that, the results of categorical emotion recognition revealed that while sadness was well acknowledged, low recognition rates for disgust, fear, and surprise were affiliated with PD data [17].

3.2 Anxiety in Parkinson's disease

An anxiety disorder (PD) is a neurocognitive complication of Parkinson's disease [18]. The majority of emotional processing is done by the limbic system of the brain. Anxiety sufferers might exhibit increased activity in these regions. A neurotransmitter called dopamine (DA) controls how information is transmitted. Limbic DA participates actively in motivated behavior, whereas extrapyramidal DA is necessary for motor program execution, and its impairment leads to Parkinson's disease symptoms. Anxious depression and depression are the two clinical manifestations of depression that might appear in PD patients. However, a sizable portion of patients may also experience relatively minor anxiety [19].

According to Si-Chun et al. (2020), significant levels of XGBoost and logistic regression from the prospective PPMI study can be applied to predict the presence of nonmotor symptoms including anxiety and clinically significant depression in early PD [20].

Apathy: One of the feelings of Apathy is frequent in PD, though it can be difficult to distinguish it from motor and other neurobehavioral symptoms [21]. A unique PD phenotype is indicated by apathy. Since apathy is a crucial component of dopamine deprivation, we might anticipate it to appear in early, untreated PD [22]. Apathy levels might vary from patient to patient, making assessment difficult. It is linked to axial symptoms that manifest earlier, gait issues, motor issues, exhaustion, and cognitive impairment. The risk of developing these problems may be higher in patients with chronic apathy throughout follow-up than in those with incidental apathy [23].We could say Anxiety and indifference are two possible neuropsychiatric indicators of vulnerability in Parkinson's disease [24]. Apathy is a typical neuropsychiatric classic symptom of Parkinson's disease (PD). Apathy is a common symptom of depression, as has been demonstrated [25]. Apathy is one of the uncommon behavioral indicators used to identify PD patients [26]. Studies reveal that the progressive worsening of depressive symptoms in patients with Parkinson's disease (PD) may be a risk factor for growing apathy and the subsequent loss of some cognitive functions. [27].

3.3 Anger

Anger is triggered by the brain's amygdala, which activates the hypothalamus. Anger may also be influenced by prefrontal brain functions. Emotional regulation is often problematic for those who have damage to this region. There is compelling evidence that the development and expression of fear memories depend on the amygdala's release of dopamine. The majority of Parkinson's disease patients will exhibit higher levels of anger control and less outward display of rage [28].

3.4 Impact of Caretaker's Emotions

The non-motor symptoms of Parkinson's disease, which include depression, anxiety, fury, and irritability, can all significantly lower your quality of life and the lives of those surrounding you, even though not all patients experience them all. Patients with Parkinson's disease often lose their mobility. That could result in job loss and a struggle to survive financially. That has only made them angrier and more frustrated. Another factor is that PD patients require constant care from their careers, which makes them emotionally fragile. All of the carers in the home had to take care of the resident's physical, social, and emotional needs. The majority of the carers were female spouses. To care for their loved ones, some caregivers may forgo their jobs, pastimes, and social engagements. Because they are typically only concerned with the patient, healthcare professionals frequently fail to recognize the burdens and challenges faced by caregivers. They must increase their mental and physical stamina and share responsibility with the rest of the family. There are many medications available today to treat Parkinson's disease, allowing those taking them to live normal lives just like people without the condition.

4 METHODOLOGY

4.1 Proposed Architecture

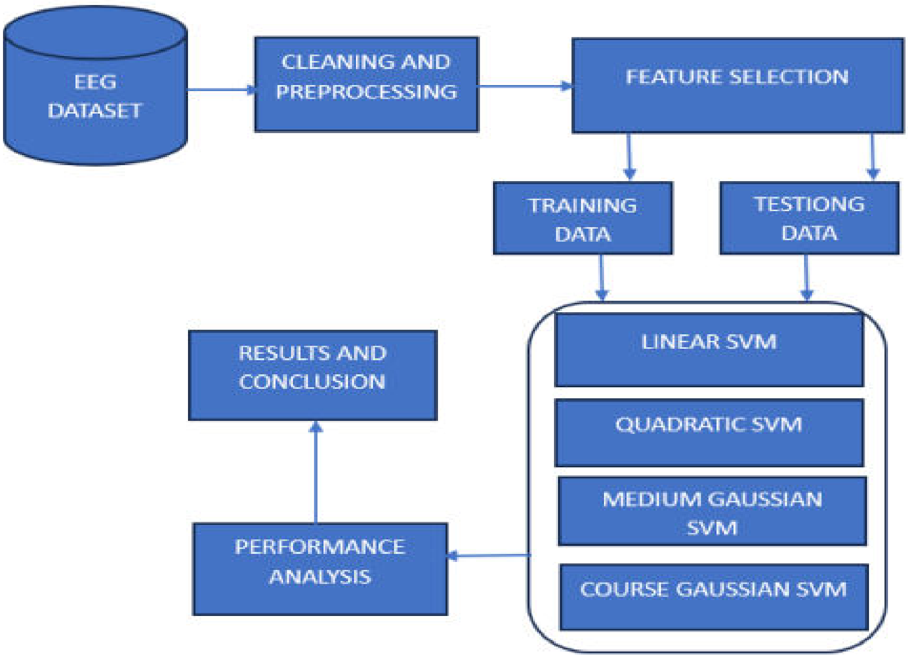

Fig 1 . Proposed Architecture

This study's suggested architecture depicts how EEG data flows through machine learning algorithms. Using ANOVA and Bayesian optimization, the top 50 highly ranked features out of 754 are taken into consideration as input. Additionally, 756 data sets were collected for preprocessing and cleaning, as shown in Figure 1. Twenty percent of the datasets have been tested and eighty percent of the datasets have been trained using different SVM algorithms, including LSVM, QSVM, CGSVM, and MGSVM. 50 attributes were looked at during the testing and training phases.

4.2 Training Results

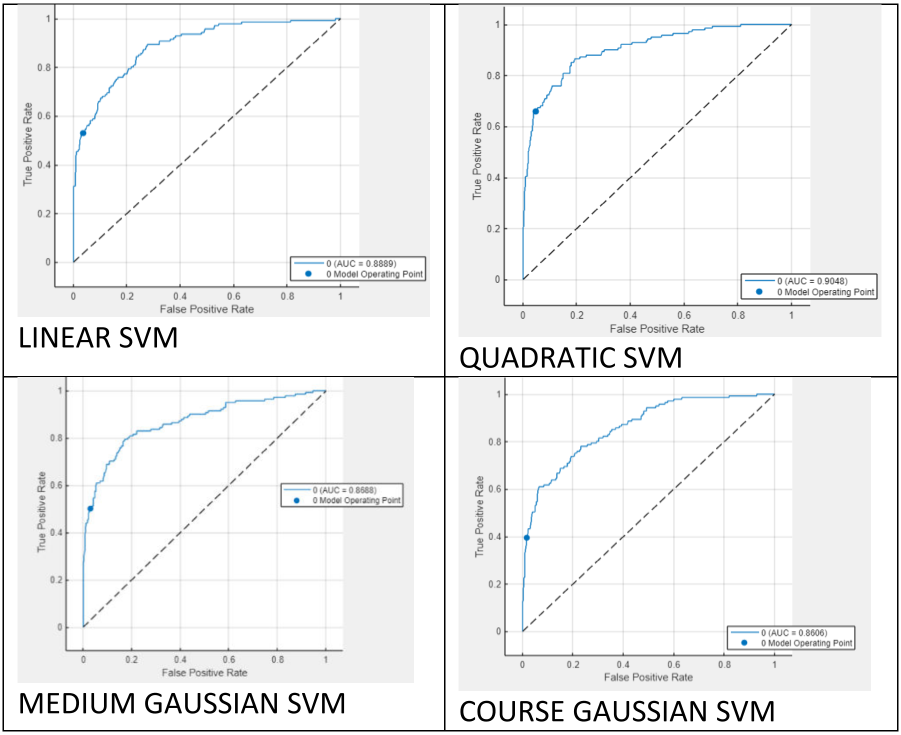

Fig. 2 ROC Curve Results of Training Datasets

The 605 trained datasets across four distinct SVM algorithms are displayed in the above figure as ROC curve results. First, after training for 13.382 seconds, the LSVM yielded an accuracy of 86%, a total validation cost of 83, and a model size of approximately 95kB. It also produced a prediction speed of about 1100 obs/sec. Second, the QSVM yielded an accuracy of 88%, a validation cost of 70 in total, a prediction speed of ~5800 obs/sec in 13.382 sec of training, and a model size of ~94kB. Third, the MGSVM yielded an accuracy of 86%, an overall validation cost of 84, a prediction speed of about 2700 objects per second in 25.335 seconds of training time, and a model size of about 116kB. Fourth, the CGSVM yielded an accuracy of 84.6% and a validation expense overall.

4.3 Testing Results

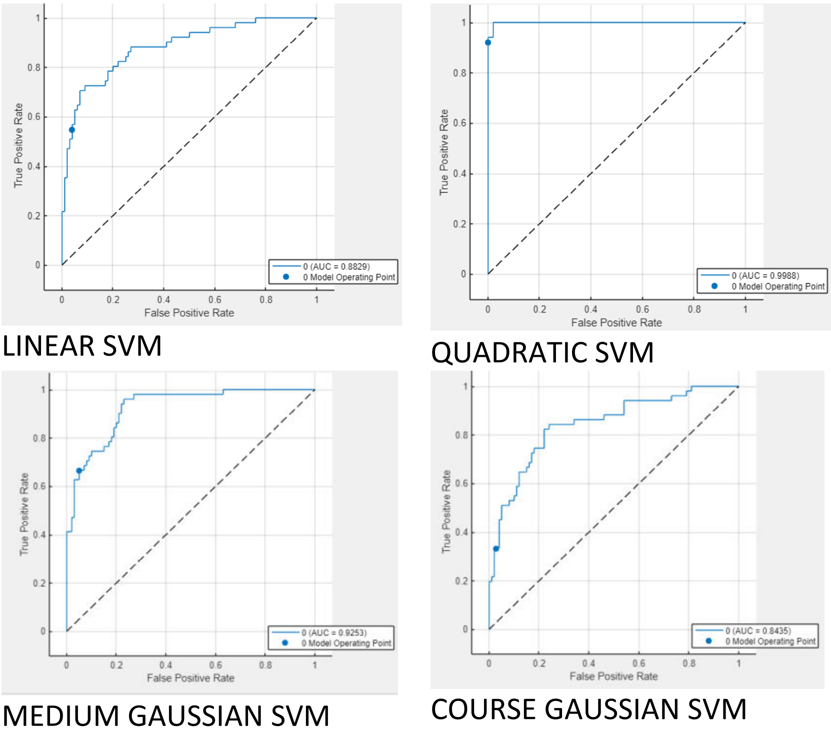

Fig. 3 ROC Curve Results of Testing Datasets

The ROC curve results for 151 tested datasets using four distinct SVM algorithms are displayed in the above figure. Initially, the LSVM yielded an 82% accuracy, a validation cost of 27, a prediction speed of approximately 710 objects per second in 28.843 seconds of training, and a model size of approximately 44kB. Second, the QSVM yielded a 97% accuracy rate, a total validation cost of 4, a prediction speed of about 1200 objects per second in 14.554 seconds of training, and a model size of about 40 kB. Third, the MGSVM yielded an accuracy of 85%, a total validation cost of 22, a prediction speed of approximately 1500 objects per second in 12.124 seconds of training, and a model size of approximately 49 kB. Fourth, a full validation with an accuracy of 75% was obtained from the CGSVM.

5 RESULTS AND CONCLUSION

The following is how we assessed the four SVM algorithms' performance: utilizing the confusion matrix of the training and testing data and determine accuracy, sensitivity, specificity, precision, and error rate. We can derive the Accurate positive prediction (TP), Incomplete positive prediction (FP), or false positive (TP) from the Confusion matrix. A true negative (TN) is an accurate negative prediction, whereas a false negative (FN) is an imprecise negative prediction.

- Accuracy = (TP+TN)/(TP+FP+FN+TN)
- Sensitivity = TP/(TP+FN)
- Specificity = TN/(TN+FP)
- Precision = TP/(TP+FP)
- Error rate = (FP+FN)/(TP+TN+FN+FP)

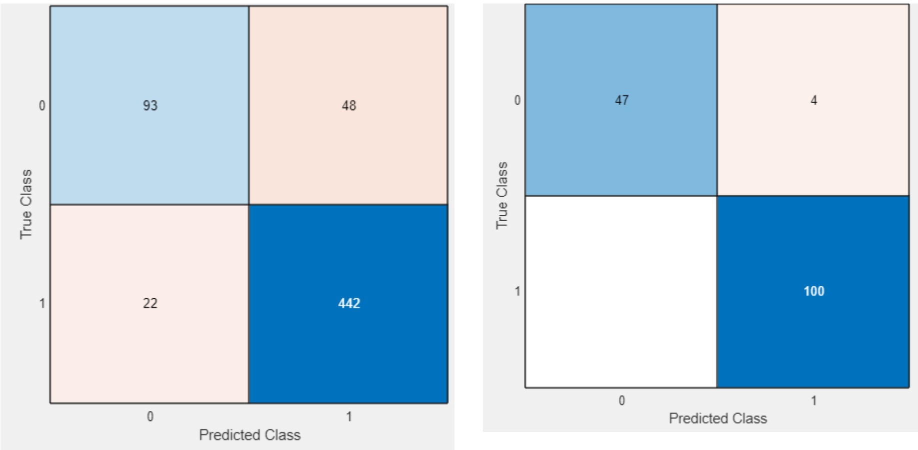

Fig.4. Confusion Matrix of QSVM's Training and Testing Results

Divide the total number of accurate predictions by the total number of datasets to determine accuracy. Sensitivity is calculated as the number of correct positive predictions divided by the total number of positives. Specificity is calculated as the number of correct negative predictions divided by the total number of negatives. By dividing the total number of positive predictions by the number of correct positive predictions, the precision formula can be calculated.

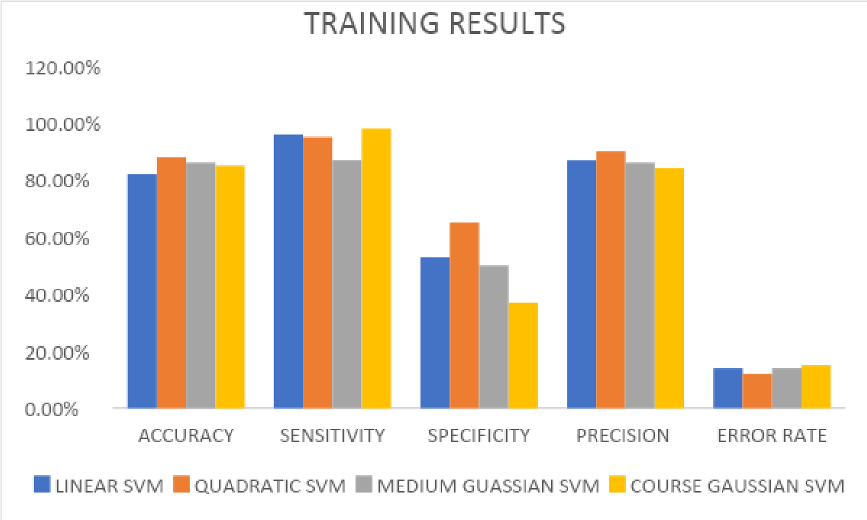

Fig.5. Training Results Chart

The trained performance of the four SVM algorithms is displayed in the above chart. The Linear SVM produced the worst result, 82%, and the Quadratic algorithm produced the best accuracy, 88%.

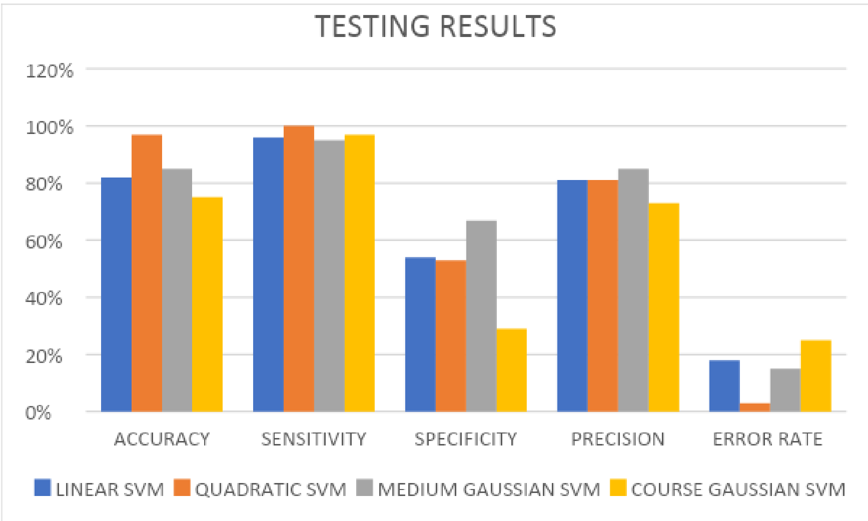

Fig.6. Testing Results Chart

We can observe the trained performance of the four SVM algorithms in the above chart. The Quadratic algorithm yielded the best accuracy of 97%, while the Course Gaussian SVM produced the worst results, at 75%.
All people have beautiful, natural emotions in their lives. They add color to our world, help us get by in life, and give us a glimpse into our minds. We experience a wide range of emotions in our lives, both good and bad. The negative emotions can include depression and anxiety as well as hallucinations, dementia and memory loss, anger, apathy, and other symptoms. Anxiety and depression are two of the most frequently encountered mental health problems among Parkinson's patients. According to the majority of studies, individuals who have PD frequently encounter mood swings and emotional dysfunctions, including depression, apathy, anxiety, and alexithymia. Patients with PD can control their emotions to prevent the majority of its negative effects. Although we can't completely control our emotions, we can manage them so that we maintain control over our lives. The caretaker's role is crucial in managing the emotion. because they have to take care of themselves as well as patients. Therefore, both PD patients and caretakers must learn to manage their emotions healthily. The self-control of one's emotions is what this is. Our mental health can significantly improve if we learn effective emotional regulation techniques. Our research used Matlab's SVM algorithms to show how valuable the features from the EEG datasets are for PD evaluation. We used the Kaggle dataset to classify the PD subjects. The Quadratic SVM predicts Parkinson's disease (PD) early on because of its high training and testing results in accuracy, sensitivity, specificity, precision, and error rate and there is no conflict of interest.

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