Classifying MDD Patient Treatment Outcomes with EEG Signals

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1. Abstract

Major depressive disorder is a serious mental illness that plagues many, but the current methods that mental healthcare providers follow to treat this illness is less than optimal. Most of these providers use a trial-and-error methodology to treat their patients, which can lead to much longer recovery time and more strain on someone who is already struggling with depression. Electroencephalogram (EEG)-based predictions of antidepressant treatment outcomes is one possible solution to this problem. In this paper, we utilize data from a study performed by Wajid Mumtaz et al. to test and evaluate different machine learning models in order to determine which ones perform best for this case. Predictions extracted from these models may be able to predict antidepressant's treatment outcome for MDD patients.

2. Introduction

2.1. Background

Major depressive disorder (MDD) is a common, yet unpredictable mental illness that has become increasingly more prominent in the US. Patients who suffer from MDD and seek treatment usually face methods for approaching and treating their condition that can be subjective and is more of a trial-and-error approach rather than one backed by any data specific to that individual. The low efficacy rates of antidepressant treatment plans come largely from treatment failure, which is very common and almost always sets the patient back several weeks in their progress. MDD is an incredibly heterogenetic disease and being able to choose appropriate medications and treatment plans for patients in early stages of their treatment has the potential to improve the low treatment efficacy associated with antidepressant medications. Electroencephalogram (EEG)-based studies has given results that are promising for being able to utilize neural signals to successfully predict individuals responses for patients.

2.2. Motivation

MDD is a life-threatening mental illness and treatment of such an illness is taken very seriously. A low treatment efficacy leads to more harm, or even death, for those that suffer from depression. When treatments fail, the patient is often set back weeks or months in terms of their systems becoming accustomed to antidepressant medication. EEG-based research studies in adjacent fields have proven quite successful thus far while still being a very cost-effective and high resolution form of neural signal measurements [1]. Because of the recurrent nature of MDD, it is important for mental healthcare providers to be able to develope more personalized approaches to their patients' illness [2]. EEG biomarkers have shown promise in predicting treatment outcomes, but their results cannot be fully proven to be utilized by clinics [3]

3. Data

3.1. Participants

For this dataset, a sample of 34 MDD outpatients (17 males and 17 females, mean age = 40.3 ±12.9) were recruited to participate, along with 30 age-matched healthy controls s (21 males and 9 females, mean age = 38.3±15.6). An EEG cap with nineteen electro-gel sensors was used to collect experimental EEG data.

The EEG data was collected through the following process: Data was recorded for two conditions, eyes close and eyes open, each 5 minutes in length. Participants were instructed to sit in a semi-recumbent position with minimal eye blinks.

3.2. Data Preprocessing

In order to avoid erroneous analysis of the collected data, artifact corrections were performed to compensate for eye blinks, muscle activity, heart activity, etc. The artifact marking allows for further estimation of noise topographies found by brain electrical source analysis (BESA).

The datasets used in python are extracted from .csv files containing the EEG signals for 51 participants, each containing 38 features corresponding to the bands for the 19 EEG electrodes. The corresponding output variables are in a separate .csv file containing a list of 51 binary classifications corresponding to controls versus MDD patients. We then used an sklearn pipeline to standardize our EEG feature data using the Min-Max Scaler in order for our regression models to optimally model our data. This is because regression models are highly sensitive to large figures so standardizing our data is necessary.

4. Models

4.1. K-means Clustering

The aim of k-means clustering is to partition n observations into k clusters. The k-means algorithm does so by minimizing intra-cluster variance when looking at each observation. To determine the optimal number of clusters in this dataset, we ran our K-means clustering algorithm over a range [2,10] clusters and calculated several performance metrics to determine what the optimal cluster was.

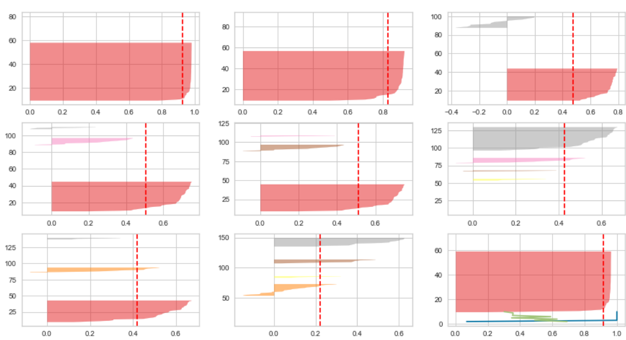

Figure 1: Silhouette visualization for a range of clusters.

The Silhouette score uses a combination of intra-cluster and inter-cluster euclidian distances to calculate a metric we can use to determine the optimal number of clusters. Figure 1 shows that our algorithm determined 2 clusters to be optimal, although there seemed to be noise as it also suggested several other k clusters for this data. To confirm our findings, we also used the SF and SI scores, the results of which are given in Figure 2.

These metrics confirm our findings, but also suggest other cluster sizes. Our actual data class size is binary so the optimal k clusters should be $k = 2$, and although this is the case, k-means is also finding correlations and is able to partition the data into more clusters than the number of classes given for our supervised ML model.

4.2. Logistic Regression

Linear regression functions are able to make predictions for classification problems by computing weights for all of the feature variables and using a built equation to make binary classification predictions. For our dataset, we used a barebones OLS regression algorithm, as well as lasso, ridge, and elastic-net regression. These are all regression models that utilize regularization, which minimizes or negates certain features depending on their correlation to the target variables. We used a grid search to check over a range of hyperparameters for these regularizers and then tested all of the models. The best performing regression model was the Elastic-net, and the confusion matrix and metrics for this model are seen in figure 4. The metrics used to measure performance of these models are f1 score, balanced accuracy, matthews correlation coefficient, and a confusion matrix.

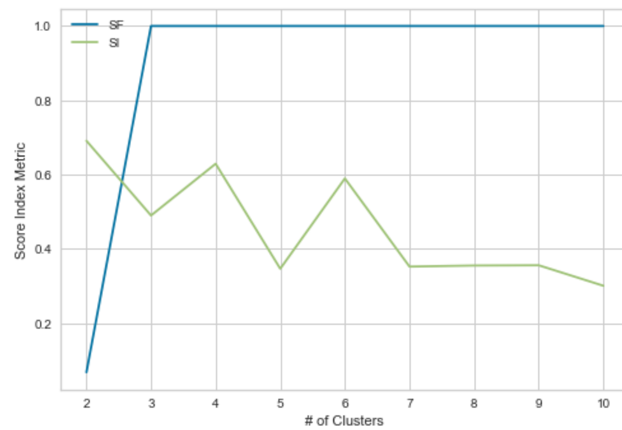

Figure 2: SF and SI metrics over a range of clusters.

The f1 scores represent a balanced mean of the precision and recall of the model. The balanced accuracy is defined as the mean recall obtained for each class. The matthews correlation coefficient is used in machine learning as a measure of the quality of binary classification models, and represents the correlation in the model. For binary classification, we can use a 2x2 confusion matrix, where we can represent the values for our models true positives, false positives, true negatives, and false negatives in order to evaluate the accuracy of our classification.

4.3. Support Vector Machines

Support vector machines, or SVMs, are a type of machine learning algorithm whose objective is to find a hyperplane in an n-dimensional space, where n is the number of features in our dataset, that distinctly classifies the data. We use SVMs often because they are much less computationally expensive to run while having high accuracy. For this dataset, we chose to use a linear SVM and had the most success with this type of model.

4.4. XGBoost

XGBoost is a type of regression model that is built on top of a gradient boosting framework and XGBoost specifically uses separate models grouped together, which are defined as ”weak learners”, to combine models and produce a ”strong

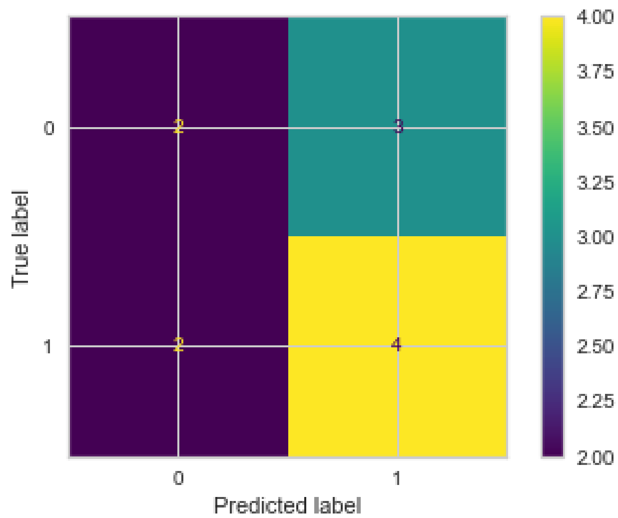

Figure 3: Confusion matrix for Elastic-Net Regression, the best performing model in the regression category.

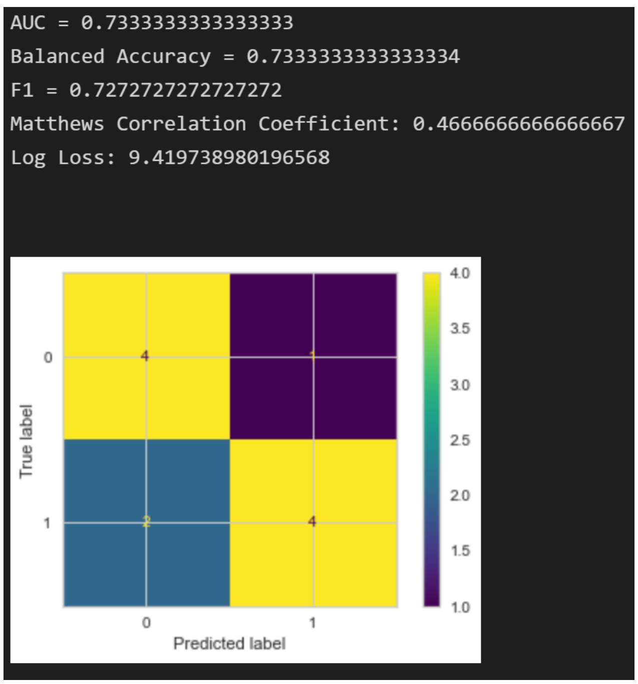

Figure 4: Performance metrics and confusion matrix for linear SVM.

learner" based off the earlier models. The loss function for XGBoost models is actually a function of functions, which works by using a sum of current and previous models as seen in figure 5.

Real value (label) known from the training data-set

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t-1)} + f_t(\mathbf{x}_i)) + \Omega(f_t)$$

Can be seen as f(x + Δx) where x = $\hat{y}_i^{(t-1)}$

Figure 5: Loss function for XGBoost Classification.

4.5. Principle Component Analysis

Principle component analysis, or PCA, is used to condense large feature sets while still explaining most, if not all, of the feature variance. For our purposes, we attempted to use PCA with our best performing model which was the linear SVM. When performing PCA on our data, we were able to plot the explained variance of our principle components to determine how many we would need in order to represent our data best.

Real value (label) known from the training data-set

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t-1)} + f_t(\mathbf{x}_i)) + \Omega(f_t)$$

Can be seen as f(x + Δx) where x = $\hat{y}_i^{(t-1)}$

Figure 6: Explained variance for a range of principle components.

In figure 6. we can see that the first PC explains almost 50% of variance in our data. We chose to use 6 principle components for our model, which explained about 95% of our data's variance. This model performed slightly worse than the original SVM, but we can see that our dataset was condensed to a much smaller and more efficient one for use in models.

5. Results

The following table shows our summarized results for each of the models we chose and their corresponding balanced accuracies and f1 scores.

6. Conclusion

From these experiments, we concluded that, although EEG signals may have great significance in MDD patient treatment outcomes, the models shown in this paper are not

	Balanced Accuracy	F1 Score
OLS Regression	0.451	0.50
Elastic Net Regression	0.533	0.615
SVM	0.733	0.727
SVM + PCA	0.616	0.714
XGBoost	0.616	0.714

accurate or consistent enough to be utilized clinically yet. The data we used for our models is very limited, and in order to build and optimize models that could be used by mental healthcare providers, more research and experimentation needs to be done in the field. MDD encompasses a wide range of mental illness and creating studies that have consistent subjects is difficult and, arguably, fairly subjective as well. To further the research on EEG signals and their correlation to MDD patient treatment outcomes, more resources need to be put towards more and larger studies in order to give more data to be used in model building. Only then would we be able to create models that would be accurate enough to have applications in mental healthcare.

References

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