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Effective Electroencephalogram-Based Detection Method For Depression Patients Using Spatial Data

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Abstract: **Background: Depression has become the number one mental disorder worldwide. It has been shown that subjects with depression exhibit different spatial responses to neurophysiological cues from healthy controls when exposed to positive and negative stimuli. Methods: We propose an efficient EEG-based detection method for classification of depression using spatial information. Thirty participants, including 16 depressed patients and 14 healthy controls, were given a face-to-face task that included positive and negative emotional facial expressions. Differential entropy and genetic algorithms are used for feature extraction and selection, and support vector machines are used for classification. A task-dependent common spatial pattern (TCSP) has been proposed to enhance the spatial disparity before feature extraction. Results and Discussion: We obtained TCSP positive and negative stimulus classification scores of 84% and 85.7%, respectively, which were statistically significantly higher than those obtained without TCSP of 81.7% and 83.2%, respectively ($p < 0.05$). We also evaluated the classification performance using individual frequency bands and found that the contribution of the gamma frequency band dominates. Furthermore, we evaluate various classifiers, including k-nearest neighbors and logistic regression, which show similar trends in classification improvement by using TCSP.**

***Index Terms* – KNN, SVM, LR, LOSO CV, LSTM.**

I. Introduction

Depression is classified as a standard global disorder as a mood disorder, described as feelings of sadness or anger that interfere with a person's daily life. According to the World Health Organization, it is likely to become a major disease in the world by 2030. Depression can be a pathological process that causes many symptoms and leads to decreased mental and physical functioning. It is often accompanied by cognitive impairment, which increases the risk of Alzheimer's and suicide, and accelerates cognitive decline. The earlier depression is detected, the better the treatment. As a low-cost, non-invasive, and high temporal resolution acquisition technology, EEG is widely used in nervous system and rehabilitation engineering. We propose a typical electroencephalography (EEG)-based computer system for the diagnosis of depression, which mainly includes an offline system and an online system. This focus was chosen because many studies have shown that subjects with depression exhibit different spatial responses to neurophysiological cues when stimulated compared to healthy controls. Many studies have been conducted on depression; some have focused on rest, while others have focused on tasks. For example, we conducted a study of EEG-based brain power in mildly depressed subjects, which showed that depressed subjects saw negative emotional faces for longer, leading to dysactivity of the temporal pole. We collected 54 resting-states, 6-second EEG signals from 12 depressed patients and 12 healthy controls, Yang et al. Twenty-four resting-state EEG signals for up to 8 seconds were extracted from 17 depressed patients and 17 controls; both studies achieved classification accuracy of over 80%. EEG signals are non-stationary and nonlinear, similar to many other physiological signals. Linear and nonlinear features are commonly used to examine these signals, such as B. power spectral density, Lempel-Ziv complexity, variance, liquidity, volatility, Higuchi fractal, approximate entropy, Kolmogorov entropy, correlation dimension, Lyapunov exponent, and permutation entropy. In order to effectively test our hypothesis, it is necessary to select optimal features, as some dimension features can mislead the classifier. BestFirst, GreedyStepwise (GSW), GeneticSearch and RankSearch methods with relevant feature selection assistance are typical data processing search methods, so BayesNet, Support Vector Machine (SVM), k-Nearest Neighbor (KNN), Logistic Regression (LR), Linear Discriminant analysis (LDA) and random forest methods are often used to distinguish classes. We extracted four non-linear features from the EEG signal and achieved the best classification accuracy for depressed patients and controls using correlation dimensions and LR approaches, among the KNN, LDA, and other nonlinear feature selection methods.

II. RESEARCH METHODOLOGY

The objective of our experiment was to develop an effective EEG-based detection method for depressed patients using spatial data:

A. PARTICIPANTS AND PROCEDURE:

The face-in-the-crowd undertaking stimuli consisted of six human faces, which had been chosen from the Ekman emotion database. There have been three sorts of expressions (positive, negative, and neutral) barring hair, glasses, beard, or different facial accessories. The test contained four blocks, two high quality and a couple of terrible goal blocks, and each and every block had one hundred forty four trials. During the nice blocks, seventy two positive, 36 negative, and 36 impartial stimuli have been introduced to the participants, and at some point of the poor blocks, seventy two negative, 36 positive, and 36 impartial stimuli have been introduced to them. Each trial was once displayed for 1500 ms towards a black background. THEN, an interstimulus interval of a thousand ms used to be presented, throughout which a fixation go regarded by myself inside the core of the display screen The contributors have been without problems seated eighty cm far flung from a 17-inch LCD-screen and had been requested to GAUGE whether or not the current photo contained the goal face for the duration of the stimulus onset asynchrony. During the tremendous block, the individuals have been requested to press button “1” if superb face stimuli have been found, and thru the terrible blocks, the members have been requested to press button “5” if terrible face stimuli had been found. There was once an chance length of 1 min between blocks, and the complete scan took about 30 min for each subject. The records have been segmented from 200 ms earlier than stimulus onset to one thousand ms publish stimulus. Segmentations with artifacts (> ±100 μv) or these main to wrong solutions have been excluded. During this study, we chosen the EEG sign 200 ms earlier than the stimulus onset due to the fact the baseline-EEG and consequently the EEG sign a thousand ms post-stimulus as the task-EEG.

B. TASK-RELATED COMMON SPATIAL PATTERN MATRIX

Research over the previous decade has proven that spatial facts can efficiently make contributions to the detection of Dep. When calculating the estimated covariance, the trials of topics that knock out the interested one are wont to calculate the estimated covariance. In our study, there have been two participant agencies (Dep and HC) and two venture stimuli (positive and poor emotions). For session 1 (positive stimuli blocks), we labeled the trials of Dep as classification 1 and consequently the trials of HC as category zero Additionally, we labeled the trials of Dep as category 1 and the trials of HC as type zero for session two (negative stimuli blocks). When calculating the estimated covariance, we used all the trials of the topics that leave out the interested/test one (Dep as classification 1 and fitness as category 0), which potential that the EEG trials of covariance 1 extend with depression, and the EEG trials of covariance zero make bigger with health. We bought the coaching dataset and take a look at dataset in accordance to the LOSO approach and calculated the TCSP projection matrix the usage of the education dataset. We then put the estimated TCSP projection matrix into the check dataset to differentiate Dep from HC. After frequency filtering, the EEG sign X of 1 trial consists of channels and time sampling points (N-channels ∗ T-samples). Supported the CSP, our goal was once to are looking for out the TCSP projection matrix, which may want to seriously change X inside the authentic sensor area into a new space, the place the statistic can incorporate extra discriminative information.

C. FEATURE EXTRACTION AND FEATURE SELECTION

As is well-known, entropy is frequently utilized to describe the diploma of sign irregularity in dynamical systems. Previous research have proven that modifications in entropy may also mirror adjustments in Genius activation when conducting cognitive tasks. DE has been verified to be an environment friendly characteristic in emotion recognition. During this study, delta

(1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–80 Hz) waves and wideband EEG (EEGW) have been extracted through wavelet packet decomposition. s three classification strategies: (a) a preferred strategy the use of all channels barring function selection, (b) a traditional method using a GA barring using the TCSP, and (c) our proposed approach using a GA with the TCSP. In techniques (a) and (b), DE is extracted from delta, theta, alpha, beta, and gamma additionally as EEGW. In approach (c), the TCSP is employed to beautify the function performance; thus, DE is extracted from the new delta, theta, alpha, beta, and gamma waves additionally as EEGW, as developed the use of the TCSP projection matrix. . The components for calculating DE can be expressed as DE = ∞ −∞ P (x)log (P (x))dx (9) Here, x denotes a range , and P(x) is that the likelihood density characteristic of x. We count on that the EEG indicators obey a Gaussian distribution: x ∼ N (μ, σ2). Then, the DE calculation are regularly simplified as DE = 12 log 2πeδ2 (10). For a section of EEG, the DE estimation is equal to the logarithm strength spectrum at some point of a precise frequency band. Additionally, the logarithm power spectrum can efficiently put off the remember of low-frequency power commonly having a comparatively greater magnitude than excessive frequency electricity in EEG. We initialized the populace dimension as Pn = 100, indicating that there have been one hundred random candidate chromosomes in the optimization problem. Furthermore, a health feature used to be used due to the fact the optimization objective. Here, we used the corresponding classifier due to the fact the health characteristic and the health price of each chromosome used to be the classification at some point of training. After calculating the health price of each and every candidate chromosomes, we used a wheel resolution algorithm to choose the possible beneficial chromosomes for recombination, with a range price of 0.5. We randomly (crossover price 0.7) selected the father or mother chromosomes amongst the possible beneficial chromosomes to make new chromosomes via recombination. According to the decision rate, we would have appreciated 50 youngster chromosomes. Then, the baby chromosomes mutated randomly with a mutation fee of 0.001, producing a substitute populace of a hundred chromosomes. The chromosome selection, crossover, mutation, and populace had been up to date and iterated till the feature no longer produced increased consequences when given a sure FS. Then, we received a probably top of the line subset of chromosomes.

D. **Machine Learning and Assessment Methods**

The SVM has been employed broadly in numerous classification and regression problems. The overall performance of the svm is affected with the aid of the kernel function, which can be a linear, radial basis, sigmoid, or polynomial function. A library for help vector machines used to be used for classification, the usage of the SVM-svc (support vector classification, svc) mannequin with a linear function, c-svc of price 1. Additionally, we used the KNN and LR approaches, which are broadly utilized in BCIS, to make our consequences greater robust. The overall performance accuracy (ACC), precision, recall, and f1 rating have been calculated throughout this study. Because the LOSO classification method was once used, ACC used to be enough to the recall, the precision used to be 1, and f1 used to be constantly large than acc. In addition, the WILCOXON signed-rank take a look at used to be wont to calculate the statistically extensive distinction of our test results, e.g., the statistical value of the accuracy enhancement the use of the TCSP.

III. RESULTS:

Based on the face-in-the-crowd mission stimuli, we recorded and preprocessed the EEG signals. We have chosen the EEG sign 200 ms earlier than the stimulus onset due to the fact the baseline-EEG and the EEG sign a thousand ms post-stimulus due to the fact the task-EEG. We evaluated the TCSP overall performance with the two EEG signals.

A. TCSP Performance underneath Task-EEG

To examine the overall performance enhancement with the TCSP, we utilized three classification strategies: (a) a preferred approach the usage of all channels except characteristic selection; (b) a normal technique the usage of characteristic resolution besides using the TCSP, the place we used a GA; and (c) our proposed approach the usage of a GA with the TCSP. Table I provides the consequences of the task-EEG beneath nice and bad stimuli, respectively. The common ACC and fashionable deviation (SD) are used here. We accomplished LOSO CV classification consequences of 84% and 85.7%

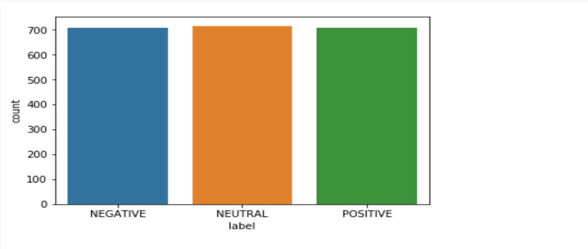
for tremendous and terrible stimuli, respectively, with the aid of the use of the TCSP, and a classification consequences of 81.7% and 83.2%, respectively, besides the use of the TCSP. When the use of all the channels barring characteristic selection, the classification consequences have been solely 66.5% and 68.6% for the fantastic and bad stimuli, respectively, which are appreciably much less than the values bought when the use of characteristic selection.

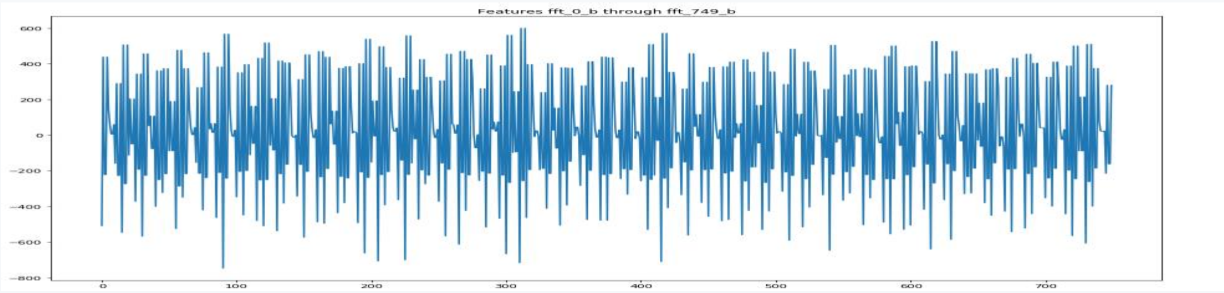
B. TCSP Performance underneath Baseline-EEG

When introduced with venture stimuli, members will reply stimuli,and consequently the intelligence activation will exchange with psychological and physiological activities. In Subsection III.A, we evaluated the TCSP overall performance beneath task-EEG. During this subsection, we are going to talk about the TCSP overall performance underneath the baseline-EEG. There are three classification strategies: (a) a trendy technique the use of all channels besides function selection, (b) a regular approach using a GA barring using the TCSP, and (c) our proposed approach using with the TCSP. The outcomes of the baseline-EEG beneath superb and terrible stimuli. We acquire classification outcomes of 72.8% and 73.6% for baseline-EEG below fantastic and terrible stimuli, respectively, the usage of the TCSP, and consequently the classification outcomes of 70.9% and 71.5%, respectively, barring the TCSP, inside the 6-Bands case. When the usage of all channels except function selection, we reap the classification consequences of 63.5% and 63.7% in 6-Bands, respectively, which are drastically decrease than the values received with characteristic selection, comparable to the task-EEG results. Further, the classification overall performance with the TCSP is nice than that besides the TCSP. The easiest ACC used to be additionally acquired inside the 6-Bands case, which used to be a mixture of all six common frequency bands, and the gamma waveband contributes greater to the classification performance, which is in accordance to the task-EEG consequences below high quality and bad stimuli.

C. Statistical Results and Significant Improvement

Statistical consequences for baseline-EEG and task-EEG beneath positive-stimuli, and negative-stimuli, respectively, for the 6-Bands frequency case. This area focuses on the distinction between the techniques and consequently the distinction between the task-EEG and baseline-EEG. For the three techniques of the use of all channels except characteristic selection, using a GA besides the TCSP, and using a GA with the TCSP, there are comparable statistical effects for the baseline-EEG and task EEG underneath advantageous and poor stimuli inside 6-Bands (using all channels besides characteristic determination vs. using a GA besides the TCSP, the usage of all channels besides characteristic resolution vs. using a GA with the TCSP, the usage of a GA barring the TCSP vs. using a GA with the TCSP). Based on the spatial information, there is a huge overall performance enhancement (using a GA barring the TCSP vs. the usage of all channels barring characteristic determination and using a GA with the TCSP vs. the use of all channels besides function selection), which indicates that spatial statistics contributes to the classification performance.





```
------K-Nearest Neighbor------

------Classification Report------
              precision    recall  f1-score   support

           0       0.98      0.94      0.96       139
           1       0.97      0.94      0.95       157
           2       0.87      0.95      0.91       131

   micro avg       0.94      0.94      0.94       427
   macro avg       0.94      0.94      0.94       427
weighted avg       0.94      0.94      0.94       427

------Accuracy------
KNN Accuracy: 0.9414519906323185
Confusion Matrix:
[[130   0   2]
 [  0 148   5]
 [  9   9 124]]
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```
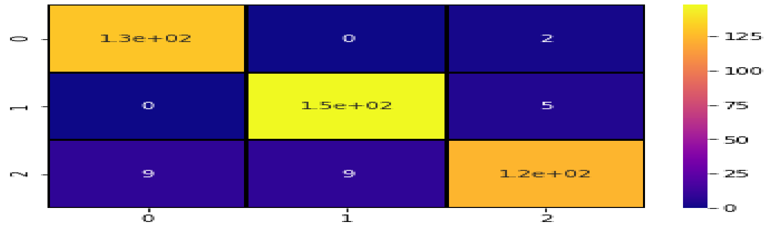
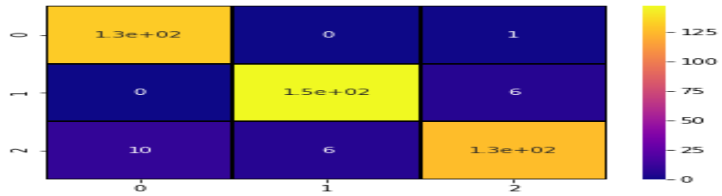
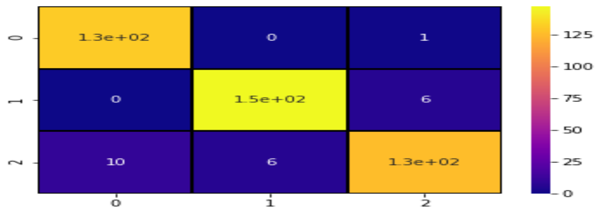



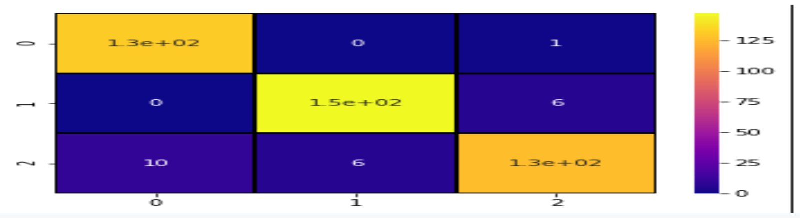

```
--------------------------------------------------------------------------------
SVM
Confusion Matrix:
[[131   0   1]
 [  0 147   6]
 [ 10   6 126]]
Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.99      0.96       132
           1       0.96      0.96      0.96       153
           2       0.95      0.89      0.92       142

   micro avg       0.95      0.95      0.95       427
   macro avg       0.95      0.95      0.95       427
weighted avg       0.95      0.95      0.95       427

Accuracy: 0.9461358313817331
Confusion Matrix:
[[131   0   1]
 [  0 147   6]
 [ 10   6 126]]
------------------------------------------------------------
```



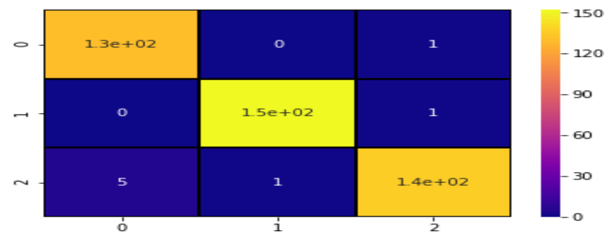

```
--------------------------------------------------------------------------------
------------------------------------------------------------
LogisticRegression
Confusion Matrix:
[[131   0   1]
 [  0 151   2]
 [  5   4 133]]
Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.99      0.98       132
           1       0.97      0.99      0.98       153
           2       0.98      0.94      0.96       142

   micro avg       0.97      0.97      0.97       427
   macro avg       0.97      0.97      0.97       427
weighted avg       0.97      0.97      0.97       427

Accuracy: 0.9461358313817331
Confusion Matrix:
[[131   0   1]
 [  0 147   6]
 [ 10   6 126]]
------------------------------------------------------------
```



```
------------------------------------------------------------------------------------
LOSO CV
              precision    recall  f1-score   support

           0       0.96      0.99      0.98       132
           1       0.99      0.99      0.99       153
           2       0.99      0.96      0.97       142

   micro avg       0.98      0.98      0.98       427
   macro avg       0.98      0.98      0.98       427
weighted avg       0.98      0.98      0.98       427

LOSO CV Accuracy is: 94.61358313817331 %
Confusion Matrix:
[[131   0   1]
 [  0 147   6]
 [ 10   6 126]]
-----------------------------------------------------------------
```




```
-----------------------------------------------------------------
LSTM
              precision    recall  f1-score   support

           0       0.96      0.99      0.98       132
           1       0.99      0.99      0.99       153
           2       0.99      0.96      0.97       142

   micro avg       0.98      0.98      0.98       427
   macro avg       0.98      0.98      0.98       427
weighted avg       0.98      0.98      0.98       427

LSTM Accuracy is: 97.18969555035129 %
Confusion Matrix:
[[131   0   1]
 [  0 152   1]
 [  5   1 136]]
-----------------------------------------------------
```



IV. CONCLUSION

As a temper disease, melancholy influences a growing wide variety of people. As a face-in-the-crowd mission stimulus scan supported frequency records filtering, time data function extraction, and spatial data characteristic selection, we developed an elevated EEG-based function classification approach using spatial information, which is advisable for the detection of sufferers with depression. By using the TCSP, the classification overall performance used to be significantly improved, which shows that the TCSP can decorate the spatial variations earlier than function extraction; however, we must continually be conscious of the problem of the datasets. inside the future, we will proceed to focal point on correlation research to achieve extra distinctive results.

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