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Epileptic Seizure Detection by Cascading Isolation Forest-Based Anomaly Screening and Easy Ensemble

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A R T I C L E I N F O

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A B S T R A C T

Electroencephalogram (EEG) signal-based emotion recognition has attracted wide interests in recent years and has been broadly adopted in medical, affective computing, and other relevant fields. Depression has become a leading mental disorder worldwide. Evidence has shown that subjects with depression exhibit different spatial responses in neurophysiological signals from the healthy controls when they are exposed to positive and negative. We focus our analysis in the main aspects involved in the recognition process (e.g., subjects, features extracted, classifiers), and compare the works per them. We propose the emotional activation curve to demonstrate the activation process of emotions. The algorithm first extracts features from EEG signals and classifies emotions using machine learning techniques, in which different parts of a trial are used to train the proposed model and assess its impact on emotion recognition results. The primary objective of this project was to improve the performance of emotion recognition using brain signals by applying a novel and adaptive channel selection method that acknowledges that brain activity has a unique behavior that differs from one person to another and one emotional state to another. The result shows that our proposed method significantly improves the accuracy of classifying depression patients emotion as positive and negative

INTRODUCTION

Worldwide, depression is a common illness that affects people of all ages. It is categorized as a mood disorder and is defined as feelings of melancholy or rage that interfere with a person's day-to-day activities. The World Health Organization predicts that by 2030, it will probably overtake all other diseases worldwide. A medical condition known as depression disorder produces a wide range of symptoms that impair both mental and physical functioning. Cognitive deficits are frequently associated with it, and these can hasten cognitive decline and raise the risk of suicide and Alzheimer's disease. Depression is easier to treat the sooner it is identified. Electroencephalography is a low-cost, noninvasive acquisition method with good temporal resolution that is commonly utilized in rehabilitation engineering and brain systems. An offline and online system are the main components of the conventional computer-aided system for electroencephalogram (EEG)-based depression diagnosis that Acharya et al. proposed. The main topics of this article are the experimental paradigm, feature selection, machine learning, emotion feature extraction, and the training and testing dataset. The focus is on spatial information feature extraction and selection. This topic was selected because numerous studies have demonstrated that when depressed individuals are exposed to stimuli, their neurophysiological signals have distinct spatial responses than those of healthy controls.

Numerous researches have been done on depression; some have concentrated on jobs, while others have examined the condition when at rest. For instance, Li et al.'s investigation on the EEG-based brain electrical source of individuals with mild depression revealed that the dysregulation in temporal pole activity observed in sad people was likely caused by their increased seeing of negative emotional faces. Both studies produced results with a classification accuracy above 80%. Liao et al.

gathered 54 6-seconds resting-state EEG data from 12 depressed patients and 12 healthy controls. Yang et al. took 24 8-second resting-state EEG data from 17 patients with depression and 17 control participants. During a resting-state session and an emotion-induction session, Wu et al. recorded EEG data from 55 participants—24 of whom had major depressive disorder (MDD) and 31 of whom were healthy controls. They did this because they believed that resting-state EEG reaches a bottleneck when it comes to differentiating MDD from non-MDD, and emotion-induction EEG provides a higher accuracy of above 83%. 48 college students participated in an experiment by Li et al. on the facial expression viewing task (emotional and neutral blocks), 24 of whom were deemed depressed and 24 of whom were considered healthy. In our study conducted at the Shanghai Mental Health Center, we employed a convolutional neural network to discern between depressed and healthy students, achieving an accuracy rate of 85.62%. The experiment involved 16 participants diagnosed with depression (Dep) and 14 healthy controls (HC). The stimuli for the face-in-the-crowd task comprised six distinct human faces.

EEG signals, like many other physiological signals, are nonstationary and nonlinear. The power spectrum density, variance, mobility, Lempel-Ziv complexity, correlation dimension, Higuchi fractal, approximation entropy, fluctuations, permutation entropy, Lyapunov exponent, and Kolmogorov entropy are examples of linear and nonlinear properties that are commonly employed to study these signals. The classifiers could be misled by some dimension features, therefore choosing the best features was essential to conducting an efficient analysis of our hypothesis. Typical data mining search techniques include GreedyStepwise (GSW), BestFirst, RankSearch, and GeneticSearch, which are based on correlation feature selection. In the realm of class discrimination, various methods such as BayesNet, logistic regression (LR), support vector machine (SVM), k-nearest neighbor (KNN), linear discriminant analysis (LDA), and random forest are commonly employed. In a study by Hosseinifard et al., they utilized KNN, LDA, and other nonlinear feature selection techniques to extract four nonlinear features from EEG signals. Through the integration of correlation dimension and LR approaches, aided by a genetic algorithm for feature selection, they achieved the most accurate classification between depressed patients and controls. Similarly, Li et al. utilized GSW and KNN techniques on the beta frequency band to derive eight linear features and nine nonlinear features from theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz) waves, resulting in notably high accuracy. Notably, the channel dimension in EEG analysis encapsulates spatial information due to the distribution of electrode channels across the human head's surface. It is important to select the best spatial information while choosing EEG channels. Numerous innovative methods have been suggested in response to the fact that the common spatial pattern (CSP) is among the most successful algorithms for a brain-computer interface (BCI) for the optimization of the spatial-spectral filter. This study uses the task-related common spatial pattern (TCSP), a spatially-based kind of spatial information, to offer an efficient EEG-based detection technique for categorizing depression.

EEG classification techniques that are frequently employed include leave-one-subject-out (LOSO) CV and subject-independent k-fold cross-validation (CV). The k-fold technique is actually a specific example of the LOSO method when k = 1. When compared to the k-fold method, the LOSO methodology consistently yields better results since it has access to more training data and can modify the super-parameters for each patient. In order to maximize the utilization of the available data, we selected the LOSO technique to assess the model for identifying depression patients in this investigation when identifying a possible patient with depression.

LITERATURE SURVEY:

M. Bachmann et al.," "Methods for using nonlinear and linear signal analysis to classify depression in single-channel EEG", 2018, One of the main contributors to the load of disease in the modern world is depression, which is predicted to top the list globally in 2030. An affordable, patient-friendly approach based on readily quantifiable objective indications is necessary for the early identification of depression. The purpose of this study is to examine different single-channel electroencephalogram (EEG) tests that are used to diagnose depression. Thirteen drug-free depressed outpatients and thirteen age- and gender-matched controls participated in the EEG recordings. The 30-channel EEG signal that was recorded was analyzed utilizing nonlinear techniques such as Lempel-Ziv complexity, Higuchi's fractal dimension, and detrended fluctuation analysis, as well as linear techniques such as the alpha power variability, relative gamma power, and spectral asymmetry index. The classification accuracy between the control and depressed subjects was determined by the use of leave-one-out cross-validation in logistic regression analysis. Different calculations were made for every EEG channel. Every computed metric showed an increase in depression. For both linear and nonlinear measures, the maximum testing accuracy with a single measure was 81% & 77%, respectively. Two nonlinear measures and two linear measures combined yield an accuracy of 85% & 88%, respectively. Using a combined combination of three nonlinear and three linear metrics, a maximum classification accuracy of 92% was found. The preliminary study's findings validate that the combination of metrics used in single-channel EEG analysis can provide depression discrimination comparable to that of multichannel EEG analysis. The conducted study demonstrates that there isn't a single best way to identify depression.

J. Malik, et.al," According to " Gamma-wave brain wave frequency measurement for precise and timely depression detection ", 2019 there was a lot of fanfare when the Global System of Mobile Communication (GSM) made its debut in Nigeria in August 2001. The country was the last to join the League of GSM nations, following less prosperous African nations like Uganda, Botswana, Tanzania, and Mozambique. Fourteen years after the launch, questions have been raised about why customers of epileptic services are being shortchanged and defrauded of their money. This is the result of numerous issues, such as poor network delivery and congestion. The article addresses the development of GSM services in Nigeria, the scope of services offered, and the problems associated with their operation over the previous 14 years. Not to mention the positive impact it has had on the Nigerian economy. There are also recommendations on how Nigeria might increase the advantages of GSM communication. There is one suicide committed every 40 seconds, or 2,160 suicides per day on average, and over 8,00,000 suicides annually, according to a World Health Organization factsheet dated April 2016. Furthermore, suicide ranks as the third most common cause of death globally among those between the ages of 15 and 44. Studies have consistently demonstrated a substantial correlation between depression and suicide, with 90% of suicide deaths involving an underlying mental health condition. 95% of suicides are caused by depression. Depression claims the lives of roughly 3% of our population annually. This provides a comprehensive overview of the disease's severity and how it is displacing our species. Mental illness is causing us to lose workers and human resources. Frequently referred to as the "cold" of the brain, depression has its symptoms, causes, diagnosis, treatments, and problems much like any other illness. Despite being well aware of the treatments, 2,160 people commit suicide every day. The delay in diagnosis is one of the main causes of this. With time, sadness gets worse; mild depression develops into psychotic depression. Individuals who believe that their feelings are only a mild case of sadness frequently ignore the warning signs of minor depression. This "slight sadness" might occasionally last for a very long time.

A. R. Ozcan and S. Erturk," Using 3D convolutional neural networks and an image-based method for seizure prediction in scalp According to 2019, epileptic seizures arise from a process that takes place in epileptic networks over time and location. In this work, we assess the spatio-temporal correlation in the features derived from multichannel EEG recordings with the goal of creating a generalizable approach for seizure prediction tailored to each patient. The time domain and frequency characteristics of the EEG signals are revealed through the application of Hjorth parameters, spectral band power, and statistical moment. Based on the topology of the EEG channels, the features are converted into a series of multicolored pictures and fed into a convolutional neural network (CNN). To assess the spatial and temporal connection in training data collectively, the multi-frame 3D CNN model is suggested. The proposed 3D CNN model achieves a sensitivity of 85.7%, a false prediction rate of 0.096/h, and a proportion of time-in-warning of 10.5% in studies employing 16 patients from the CHB-MIT scalp EEG dataset. The findings demonstrate that, for 93.7% of the patients, the suggested method's advantage over a Poisson-based random predictor was statistically significant at the significance level of 0.05. Our trials with different temporal limitations demonstrate that the duration of the epileptic stage plays a important role in determining seizure performance. We describe a subject-specific seizure prediction algorithm that does not require subject-specific engineering and is robust for unbalanced data, applicable to any scalp EEG dataset.

PROPOSED SYSTEM:

METHODOLOGY:

The pre-processing stage, feature extraction, and classification main phases are depicted in the proposed model. to use spatial information to create an efficient EEG-based detection approach for depression classification. Using an EEG signal dataset, this method predicts the happy and negative emotions of patients with depression. The first step in doing such is pre-processing the collected EEG information to eliminate null and missing values. We must record EEG data from various subjects, process them to extract various attributes, and finally classify the various emotions. The features are used to create the data sets, which are subsequently classified. We suggest using deep learning (DL) (LSTM) and machine learning (ML) (KNN) algorithms in this procedure to categorize the depressed patient's emotions as positive or negative. Lastly, it increases the precision of dividing the emotions of depression patients into positive and negative categories.

BLOCK DIAGRAM:

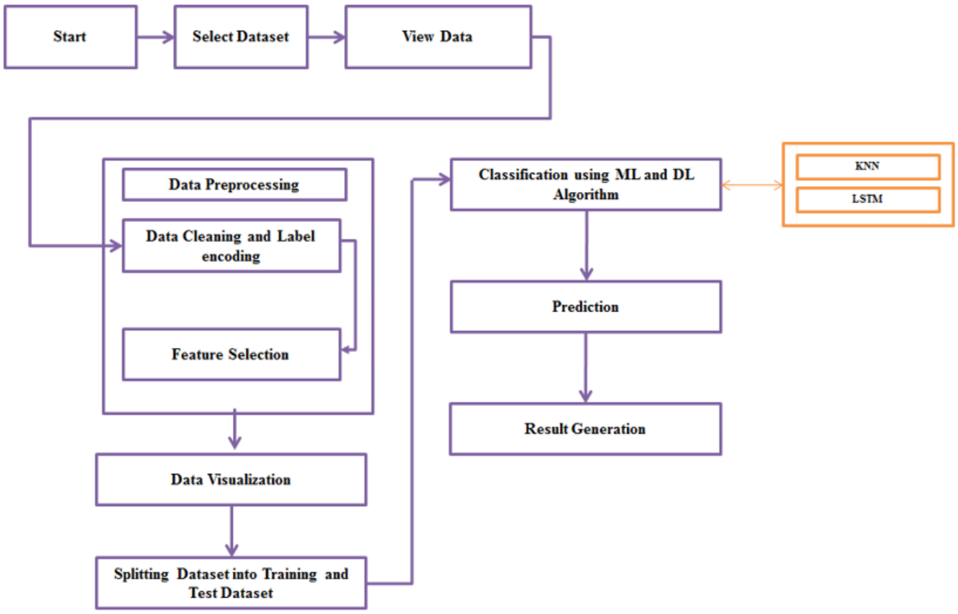

Fig:1 Block Diagram

DATA SELECTION AND LOADING

Data selection is the process of selecting information from the EEG emotion dataset to predict the mood of the depressed patient. We used our statistical extraction method to evaluate this set of EEG brainwave data. Three minutes were spent surveying two people, one male and one female, in each of the following states: positive, neutral, and negative. Using a Muse EEG headgear, we used dry electrodes to record the EEG sites for TP9, AF7, AF8, and TP10. After six minutes of resting in a neutral state, the stimuli utilized to produce the feelings are recorded as well.

df - DataFrame

Index	# mean_0_a	mean_1_a	mean_2_a	mean_3_a	mean_
0	4.62	30.3	-356	15.6	26.3
1	28.8	33.1	32	25.8	22.8
2	8.9	29.4	-416	16.7	23.7
3	14.9	31.6	-143	19.8	24.3
4	28.3	31.3	45.2	27.3	24.5
5	31	30.9	29.6	28.5	24
6	10.8	21	44.7	4.87	28.1
7	17.8	27.8	-102	16.9	26.9
8	11.5	29.7	34.9	10.2	26.9
9	8.91	29.2	-314	6.51	30.9
10	5.21	28.4	18.5	3.66	22.6
11	13.3	30.4	-149	11.8	28.3
12	30.1	32.7	29.4	28.3	24.3
13	19.3	31.7	-4.56	23.8	32.9

Format | Resize | Background color | Column min/max | Save and Close | Close

Table:1 Data Frame

DATA PREPROCESSING:

Data pre-processing is the process of removing the unwanted data from the dataset.

- ✓ Missing data removal
- ✓ Encoding Categorical data

Missing data removal: Using the imputer library, the null values, such as missing data, are eliminated in this procedure.

Encoding Categorical data: Categorical data comprises variables with a finite set of label values, while most machine learning methods require numerical input and output variables. To facilitate this transition, categorical data is typically converted into integer format through techniques such as integer encoding and one-hot encoding.

Pre-processing is the term used to describe the changes we make to our data before we feed it into the algorithm. Data preprocessing refers to the procedure of refining raw data into a polished dataset. To put it another way, when data is acquired in raw format from multiple sources, it is impractical for analysis.

Proper formatting of the data is necessary to achieve optimal outcomes from the applied model in machine learning projects. Certain data in a certain format is required for a certain machine learning model. The formatting of the data collection should also be such that many Machine Learning and Deep Learning algorithms are run on the same set of data, and the best algorithm is selected.

FEATURE SCALING:

Feature scaling is a method for bringing the independent features in the data within a predetermined range. Without feature scaling, a ML algorithm will often consider smaller values to be lower values and weigh larger values as higher, regardless of the unit of measurement.

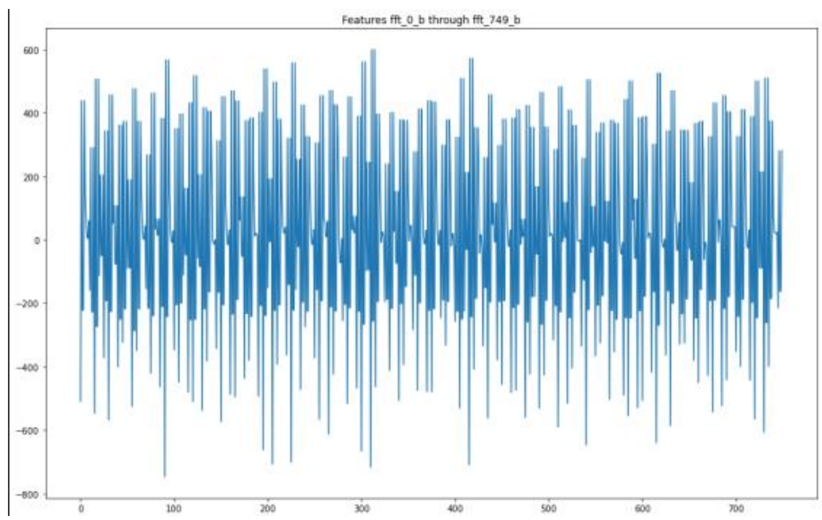

Fig 2 EEG Signal

SPLITTING DATASET INTO TRAIN AND TEST DATA:

Data splitting is the process of dividing up accessible data into two groups, usually for the use of cross-validators. In the development of a predictive model, one portion of the data is utilized for constructing the model, while another portion is reserved for evaluating its performance. A crucial step in evaluating data mining algorithms involves partitioning the dataset into training and testing sets. This segregation typically involves allocating the majority of the data for training purposes, with the remaining fraction dedicated to testing the model's performance.

The train-test split technique is a tool used to measure how well machine learning algorithms perform when they are applied to prediction on non-training data.

This procedure is expedient and straightforward, providing insights into the comparative effectiveness of machine learning algorithms within the context of your specific predictive modeling scenario. Even though the technique is easy to use and understand, there are scenarios in which it should not be used, such as when you have a tiny dataset, and others in which further configuration is necessary, like when the dataset is not balanced and the procedure is being used for classification.

CLASSIFICATION:

Classification is a procedure associated with categorization, which is the process of identifying, distinguishing, and comprehending concepts and things. In this project, data classification is performed using the K-Nearest Neighbor (KNN) and Long Short-Term Memory (LSTM) classification algorithms. KNN, a fundamental machine learning algorithm, operates under the supervised learning paradigm. It assigns a new case to the category most closely resembling existing categories, operating on the assumption that the new instance shares similarities with available examples. Classification of a new data point is determined based on its resemblance to existing data. This suggests that the K-NN algorithm can promptly assign newly encountered data to an appropriate category. DL uses artificial recurrent neural networks (RNNs) with long short-term memory (LSTM) architecture. LSTM has feedback connections, in contrast to conventional feedforward neural networks. It can handle whole data sequences as well as individual data pieces, like pictures. Data can be sequentially processed by the LSTM cell, which also maintains its hidden state overtime.

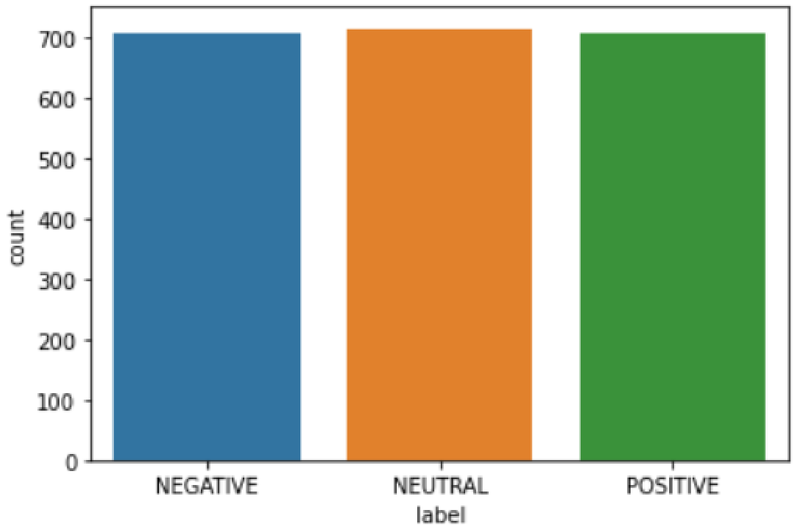

Fig 3.Bar Chart

RESULT GENERATION:

The comprehensive categorization and prediction will form the foundation for generating the Final Result. The efficacy of this proposed approach will be evaluated using various metrics like:

Accuracy

The accuracy of the classifier speaks about the classifier's capacity. It precisely forecasts the class label, while predictor accuracy evaluates the ability of a specific predictor to estimate the expected attribute value for a new dataset effectively.

$$AC= (TP+TN)/(TP+TN+FP+FN)$$

Precision

Precision is computed by dividing the total number of true positives by the sum of true positives and false positives.

$$Precision=TP/ (TP+FP)$$

Recall

A recall is calculated by dividing the total number of results by the number of correct results that should have been returned. In binary classification, recall is also known as sensitivity. It represents the probability that a query will retrieve a relevant document.

$$Recall=TP/(TP+FN)$$

F-Measure

F measure (F1 score or F score) is the weighted harmonic mean of the test's precision and recall, and it serves as a gauge of the test's accuracy.

$$F\text{-}measure=2TP/(2TP+FP+FN)$$

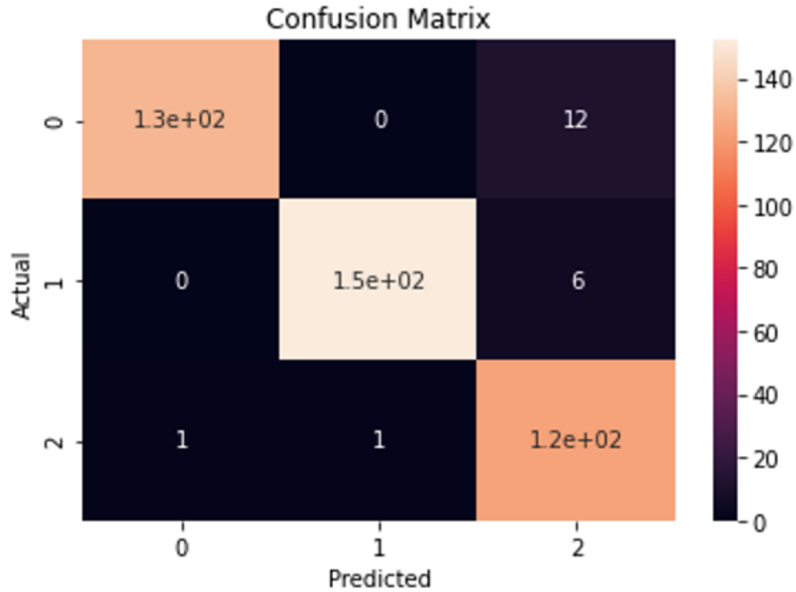

Fig.4 Prediction

CONCLUSION:

Depression, a mood disorder affecting an increasing number of individuals, prompted the development of an improved EEG-based feature classification technique. This method leverages spatial information to aid in the identification of depression patients. Utilizing a face-in-the-crowd task stimulus experiment, it incorporates frequency-based filtering, time-based feature extraction, and spatial information feature selection. Despite the need to consider limitations of the dataset, employing this method notably improved classification performance, indicating its potential to enhance spatial distinctions prior to feature extraction.

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