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Brain Activity Monitoring for Stress Analysis through EEG Dataset using Machine Learning

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Abstract—To determine the possible conditions of users during task execution, researchers employ psychological feedback tools such as skin conduction (S), electroencephalography (EEG), and electrocardiography (ECG). A set of protocols is developed via a series of cognitive studies in which participants complete a series of intellectually challenging activities. The high time resolution of electroencephalography (EEG) allows for continuous monitoring of brain conditions such as human mental effort, emotions, and stress levels. The main goal is to evaluate the efficiency of cognitive stress recognition systems. Lack of suitable EEG channels and bands selection for stress recognition system. Using brain interface for EEG with as few channels as possible. Quick Fourier Transform is a dimension reduction technique used to reduce the amount of data from the root. The acquired FFT and correlation-based feature subset selection methods were used to train three model taxonomic algorithms: SVM, K-Nearest Neighbor (KNN), Decision Tree (DT), and artificial Neural Networks (NN). We can expect brain monitoring such as stress to be cost effective and capable of reliable patient monitoring.

Keywords: *KNN, DT, ANN, Stress Analysis, EEG Signal Analysis*

1. Introduction

Depression effects all aspects of life and is associated with a variety of illnesses. More studies on stress analysis have been published in recent years. According to recent reports, depression has affected 75 percent of the population. It affects the physical health of people and society. Biological and physiological markers were used to assess stress. Several studies in neuroscience have linked stress levels to changes in brain activity in the limbic system and other areas using non-invasive methods such as functional magnetic resonance imaging (fMRI) and electroencephalography (EEG) Khorshidtalab (2011). [1]

EEG, on the other hand, can only calculate the activity of the cerebral cortex and respond to sound. As EEG is non- invasive and has the benefits of rapid signal detection and high-resolution resolution, according to. As the EEG receives signals from the head, combining it with a mask, which can be used to protect the wearer in the event of an industrial accident, makes it easy to install as wearable technology. Suggested bio-signal studies and EEG measurement work with a protective helmet. The dense structure of the EEG electrode on the human skin is believed to be essential for reliable pressure relief. Clinical EEG systems have multiple channels, which makes them difficult to use Madhuri et al. (2013) [2]. Used to make emotions stand out. Obtaining an electroencephalogram (EEG) is the first step. This includes placing electrodes in different positions of the skull to collect electrical signals that capture the thought or intent of the story. EEG trading equipment (such as Neurosky Mindwave mobile headsets) can be used to receive EEG signals. A computer system or digital signal processor that filters out DC noise and drifts. Decomposition techniques have also been used for various signal characteristics. -EEG alarm channels: Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz), and Gamma (above 30 Hz). As a result of post-human stress isolation, high beta and low gamma)) neural oscillations have been applied in a less suggested manner (FP1). A single- channel EEG headset is used in this examination to record brain activity. These EEG data are translated into wavelength sub bands, which are subsequently used to create working vectors. The suggested class management technique involves the elimination, selection, and classification of functions in the categories of objects and methods.

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2. Related Work

Stress testing has been conducted for many years. Scientists and researchers often refer to stress, and stress has many mean- ings. It is believed that stress is related to mental awareness and emotion when it exceeds one's ability. Researchers use a psychological feedback system. Recognize the user's emotional state during the task, such as B. skin conductance (SC), Electroencephalogram (EEG) and electrocardiogram (EKG). In the brain-computer interface, psychophysiological feedback has been proven to be effective in identifying the cognitive state

(BCI) of the user. Chi-Keong Alfred Lim and colleagues used the Fp1 channel to identify pressure. The data is linearly transformed from the spatial domain to the frequency domain using the Discrete Cosine Transform once the data is recorded in the time domain (DCT) Vaid (2015) [3]

. Furthermore, the close combination of features is employed to distinguish the sample groups. This is also an issue, particularly when the category difference is minimal. LDA is too close to the data in this example since it considers the mean to be the distinguishing element rather than the variance. By using KNNN, LDA and ANN with the nearest neighbors, the efficiency of this method can be improved. Sanay Muhammad Umar Said and his colleagues employed only one channel of signal capture and applied Fourier transforms (FFT) to the collected EEG signal to transform the data in the frequency domain. [4] These recorded EEG signals are sub-bands of the received signals. k use the SVM classifier to build the closest neighbor, pulse, and four support vector machines in order to determine the voltage level of each polynomial. Li Yuezhe and her colleagues achieved the greatest results by receiving EEG signals centered on theta and delta waves via a single channel Zheng and Subbulakshmimu- rugappan (2013) Hosseini (2010) [5] . Classifier for each situation (predicted state-speech meditation). AkaliyaDevi and his colleagues extracted the eeg signal from fp1 and used the FFT algorithm to divide it into sub band frequencies: Delta is 4 Hz, Theta is 4-7 Hz, Alpha is 8-13 Hz, Beta is 13-30 Hz, Gamma is greater than 30 Hz, and Mu is 8-12 Hz. Filters with infinite impulse response (IIR) and discrete wavelet decomposition are also employed. To lessen the computational burden, a low DWPT is recommended. To assess and compare performance, they utilized Support Vector Classifier (SVM) and Artificial Neural Network (ANN). Using support vector machines (SVM) and artificial neural networks (ANN), ac- cording to experiments, they show the highest classification accuracy. Nicholas Cimitt1 and his colleagues used a channel and considered the spectral characteristics [6] . Changing the number of bins allows the use of SVM ranges higher than 40 Hz. They discovered that increasing the number of compart- ments can enhance the accuracy of our SVM classifier by up to 80%. I'm putting in long hours. Researchers SalehaKhatun and his team used temporal domain and spectral domain data gathered from the Fpz channel [7].

Based on the existing work, it is clear that feature extraction has a significant role to play in the process of human stress recognition in any BCI applications. Most of the methods have used multiple EEG channels and bands for signal processing due to which the computational complexity is increased. No one has claimed about suitable channels and bands for stress recognition. Specifically, in the field on brain-computer interface, fully automated real-time stress recognition has not been implemented yet. Most of the feature extraction methods have used statistical property and spectral property features for classification rather than cepstral coefficient property features. Hence, an attempt is made to automate the process of feature extraction and classification which would be a further process stress recognition. Therefore, an automated framework is designed and implemented for human stress recognition based on different feature extraction and classification techniques. Also, EEG signal analysis serves as various purposes of making individuals life healthy through stress recognition.

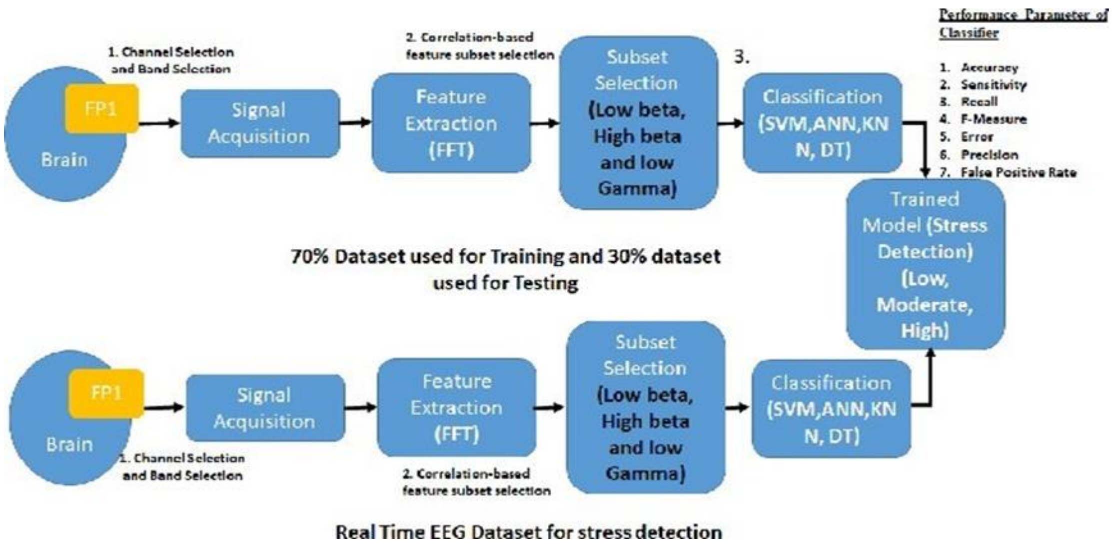

Fig. 1. Real Time EEG Dataset for stress detection

DATA ACCESS

With the invention of the EEG, the NeurosciMindwave mobile headset was used. The pocket contains a microphone, earpiece and sensor arm. The ear canal has reliable and grounded head electrodes, while the EEG electrode is located above the eye (FP1 position) on the forehead. The headset emits 12-bit raw-brains at a sample rate of 512 Hz (1–100Hz). The output of the EEG signal is affected by signals from other sources[31][32]. In biomedical measurement systems, name noise becomes an important part of signal analysis. The EEG signal is accompanied by a large amount of noise. It is surprisingly difficult to distinguish the required diagnostic features from the EEG signal without taking the audio signal. To eliminate distractions from EEG signals, different researchers have developed different methods to process the signals[36] Suryawanshi et al. (2022) [8], [9] .

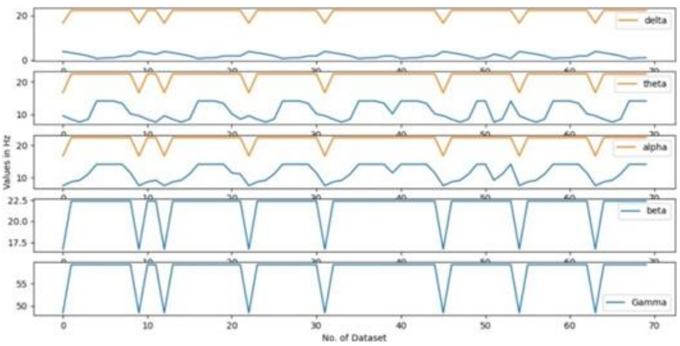

Fig. 2. No of Dataset

Features extraction and selection.

Choose a feature subset and score it using the objective function; the goodness of the feature subset will be used to determine which part of the search space to investigate next. And once we have finished this module, we will have a final function subset, which our machine learning or pattern recognition algorithm can use. So we will begin with an empty feature set and gradually add features. Then we have tried each of the remaining features and estimate the accuracy for each one. For each particular function, we estimated the classification or regression error. The validation collection, rather than the training set, used to assess which function offers the greater improvement. If there is no noticeable change, we have stopped processing. The data is converted into the standard domain by applying Fourier Transform (FFT) to the captured EEG signal. In addition, a band-pass filter is used to develop feature vectors based on neural wave forms to exclude sub-bands of sub- bands. ://Store.neurosky.com/products/myndplay-pro) and the third-party software MindplayPro, which was developed in co-operation with Neurosky headset. They are released according to frequency.The software creates CSV files for EEG subbands and records EEG data. The intensity Of these sub bands is only 0 to 1 beta (13-16.75Hz), beta(18- 29.75Hz). And gamma(31-39.75Hz)Vibration is selected as the key vibration that separates human stress, and this method is applied to the oscillator sub band. These sub-regions can increase the accuracy of the classifier, sensitivity results and reduce complexity Berbano et al. (2017) [10].

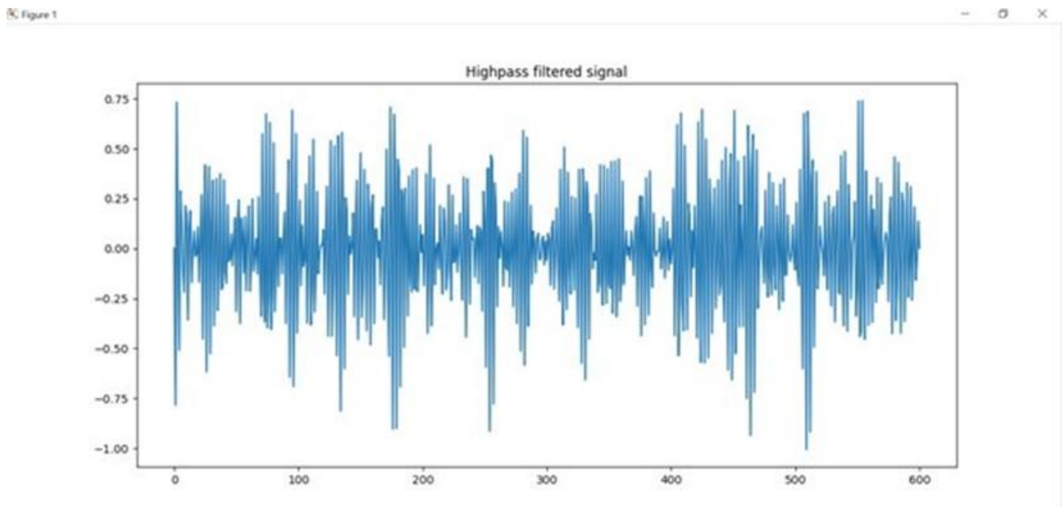

Fig. 3. Highpass filtered Data

Learning Dataset

The basic classifier used in most machines' learning problems were the most common divisions evaluated by BCI. Since then, researchers have concentrated their efforts on defining and improving classification methods for EEG-based BCIs. The poor signal quality and signal strength of the EEG, as well as its variability over time, are major challenges for BCI classification methods Liu et al. (2016b) Poomipatboonyaki- tanont et al [11] .

Also, between users, if the user's EEG signal changes during or during this process, the amount of training data that can usually be used to measure. Classifier will be limited, and the reliability and performance of the current BCI will be poor. After integrating EEG data, Fp1 is extracted and sent to various classifiers. They are Support Vector Machine (SVM), K-Neural Neighbors (KNN), DecisionTrees (DT) and Artificial Neural Networks (ANN).

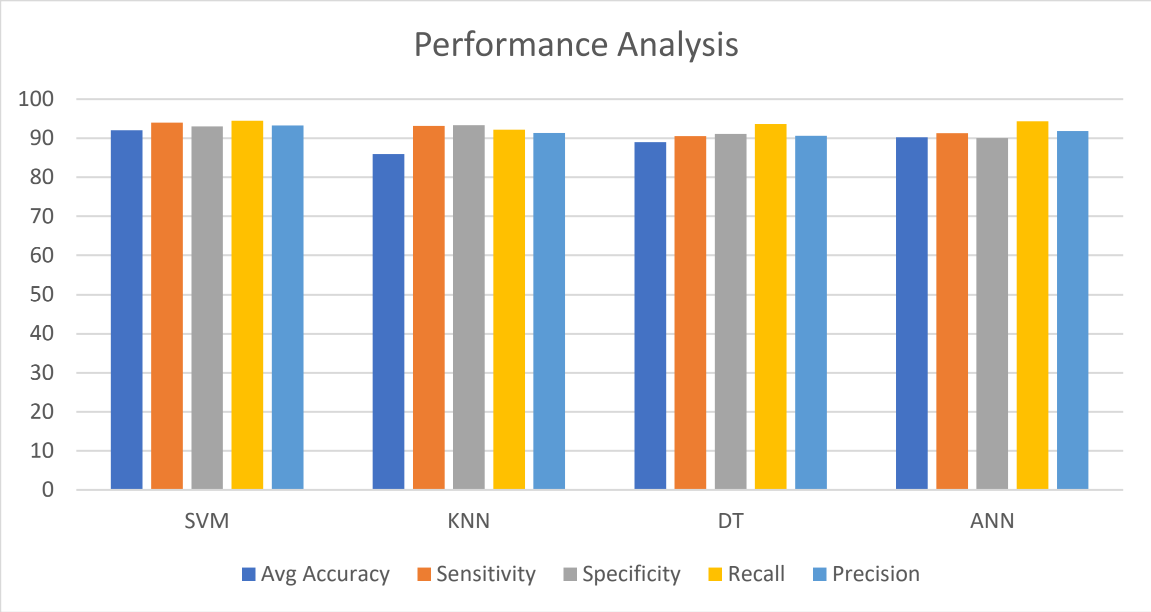

Fig. 4. Comparative Analysis

Standard classifier for a variety of machine learning situations. Since then, research has concentrated on identifying and developing specific categorization techniques based on EEG data. The primary issues encountered when using the classification approach are the poor signal-to-noise ratio of the EEG data, the instability over time within or between users, and when the EEG signal of the same person is even different between races Suryawanshi et al. (2020) [12]. When switching races, the amount of training data that can normally be utilized to calibrate the classifier is reduced, and the current BCI's reliability and overall performance are poor. Use 70% of the data for training and the remainder for analysis. 30% is utilized for testing. The operating parameters of the classifiers are accuracy, sensitivity, specificity, recovery rate, F measurement, error, accuracy, frequency of false positives. From above figure its shows that SVM showing good performance in terms of accuracy, sensitivity and recall. Which will definitely boost the performance of model.

3. Conclusion

Advances in signal processing and feature extraction tech-nologies, as well as the development of sensors and signal recorders, have improved the ability to capture signals from human organs, such as human organs. B. Signals from the brain or heart are used to detect a person's condition. To diagnose human psychological or pathological diseases. As a result, the signal classification problem has become important to improve the efficiency of signal-based case classification. The fewer EEG channels using BCI, the better. To lower the amount of data from the root, the Fast Fourier Transform (FFT) is utilized as a dimensionality reduction approach. Three classification model approaches are trained for trait subgroups using FFT and correlation-based selection methods: Support Vector Machine (SVM), K-nearest neighbour (KNN), Decision Tree (DT), and Artificial Neural Network (ANN) (ANN). The classifier's performance metrics reveal an improvement in accuracy, sensitivity, specificity, recovery rate, F measurement, error, accuracy, and false alarm rate.

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