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A REVIEW ON MACHINE LEARNING EEG SIGNAL PROCESSING IN A BIOENGINEERING

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Abstract: Electroencephalography (EEG) has been a staple method for identifying certain health conditions in patients since its discovery. Due to the many different types of classifiers available to use, the analysis methods are also equally numerous. In this review, we will be examining specifically machine learning methods that have been developed for EEG analysis with bioengineering applications. From this information, we are able to determine the overall effectiveness of each machine learning method as well as the key characteristics. We have found that all the primary methods used in machine learning have been applied in some form in EEG classification. This ranges from Naive-Bayes to Decision Tree/Random Forest, to Support Vector Machine (SVM). Supervised learning methods are on average of higher accuracy than their unsupervised counterparts. This includes SVM and KNN. While each of the methods individually is limited in their accuracy in their respective applications, there is hope that the combination of methods when implemented properly has a higher overall classification accuracy.

Keywords : EEG Analysis, EEG Signal ,SVM.

INTRODUCTION :

Electroencephalography (EEG) is a method of testing electrical signals in the brain. It is often applied as a technique for data analysis such as time and frequency series analysis. The brain's neurons contain ionic current, which creates voltage fluctuations that EEG can measure. This electrical activity is spontaneous and recorded over a period of time from many scalp electrodes to form an EEG signal. Traditionally, EEG signals are taken on the surface of the scalp, but there also exists EEG signals, which are taken inside the brain. In this paper, we will be focusing primarily on conventional scalp EEG signals. Conventionally, EEG recordings may be obtained by connecting electrodes to the scalp with the use of a conductive gel. A differential amplifier is then used to amplify each active electrode compared to the reference before it is sent through an anti-aliasing filter. Finally, this filtered signal is converted with an analog-to-digital converter. Clinically, EEG signals are used primarily to diagnose and treat various brain disorders such as epilepsy, tremor, concussions, strokes, and sleep disorders. More recent applications of EEG include using machine learning as a method of analysis. In particular, there is much research on epileptic seizure detection and sleep disorder research in combination with machine learning. Additionally, there is also a growing interest in studying EEG signals for gaming to control and manipulate objects using brainwaves due to EEG monitoring for brain activity during tasks . EEG signals were first discovered in 1875 by Richard Caton, a physician who was studying electrical brain activity in rabbits and monkeys.

EXISTING SYSTEM :

As existing approaches to extract stress prediction suffer from scalability, it is imperative to address the scalability issue. Connections in stress prediction are not homogeneous.CNN algorithm was used in the existing systemThis relation-type information, however, is often not readily available in stress prediction. A direct application of collective inference or label propagation would treat connections in a stress network as if they were homogeneous.As existing approaches to extract stress prediction suffer from scalability, it is imperative to address the scalability issue. Connections in stress prediction are not homogeneous. This relation-type information, however, is often not readily available in stress prediction. A direct application of collective inference or label propagation would treat connections in a stress network as if they were homogeneous

PROPOSED SYSTEM:

The proposed framework based on stress prediction is shown to be effective in addressing this prediction.The framework suggests a novel way of ECG (Normal/Abnormal) classification: first, capture the latent affiliations of actors by extracting stress prediction based on network connectivity, and next apply extant. Data mining techniques to classification based on the extracted prediction. In the initial study, modularity maximization was employed to extract stress prediction.The

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superiority of this framework over other representative relational learning methods has been verified with stress prediction stress data .we proposes an effective edge-centric approach to extract sparse stress prediction.It show through comprehensive experimental evaluation the effectiveness and the robustness of our proposed search log-based method, especially when combined with approaches using other signals such as text similarity. It will focus on evaluating the effectiveness of the proposed algorithms in capturing test data relevance. Relevance Measure. Best in signal data grouping process.

ARCHITECTURAL FRAMEWORK OF THE SYSTEM:

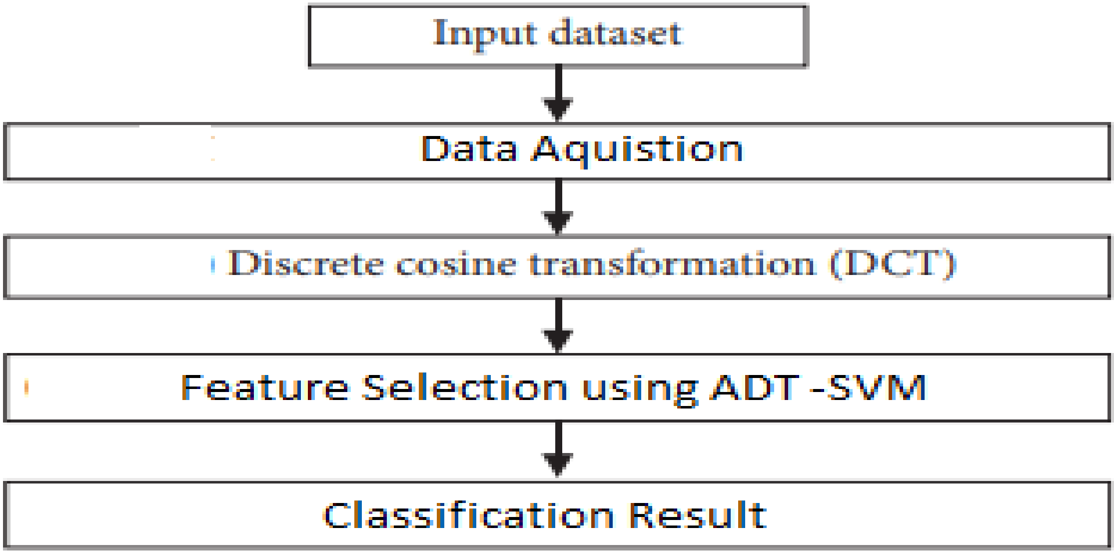

Fig: Architecture of the Proposed EEG signal

MODULES :
Data Acquisition
Feature Selection and Signal analysis
Classification of Scoring

DATA ACQUISITION:

The dataset used in the work was taken from. Around 14 human subjects with normal signal value of an average age of 26 years (ranging between 22 and 46) volunteered for the study.The subjects sat in a dimly lit room, at a distance of 110 cm from a signal having a block of 100 numerical data. Subjects were also holding a touch-sensitive button. (e 32 electrodes mounted on the ECG data attributes.) The Load method provides a technique for filling a single DataTable with data, retrieved from an IDataReader instance. This method provides the same functionality, but allows you to load multiple result sets from an IDataReader into multiple tables within a DataSet It also gives an overview of each of the methods and general applications that each is best suited to EEG recordings may be obtained by connecting electrodes to the scalp with the use of a conductive gel. The beta band is above 14Hz and is correlated with general motor behavior

FEATURE SELECTION AND SIGNAL ANALYSIS:

Feature selection, also known as variable selection, attribute selection or variable subset selection, is the process of selecting a subset of relevant feaures (variables, predictors) for use in model construction.The central premise when using a feature selection technique is that the data contains some features that are either redundant or irrelevant, and can thus be removed without incurring much loss of informationIt is typically non-invasive, with the electrodes placed along the scalp. Electrocorticography, involving invasive electrodes, is sometimes called intracranial EEG. EEG measure voltage fluctuations resulting from ionic current within the neurons of the brain Redundant and irrelevant are two distinct notions, since one relevant feature may be redundant in the presence of another relevant feature with which it is strongly correlated.

CONCLUSION:

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EEG is a noninvasive electrophysiological device that records the electrical activity of the brain by placing electrodes around the scalp. Based on this activity and oscillating electric potentials, EEG can be used to diagnose neurological disorders, such as epilepsy, or for emotion recognition. Of methods for emotion recognition, EEG is one of the most reliable because its signals are highly accurate and more objective than other external appearance approaches. The art of machine learning has led to the development and application of different techniques, which has made it possible for the computer to analyze and learn information from a given set of data, and make the desired prediction accordingly.

RESULT :

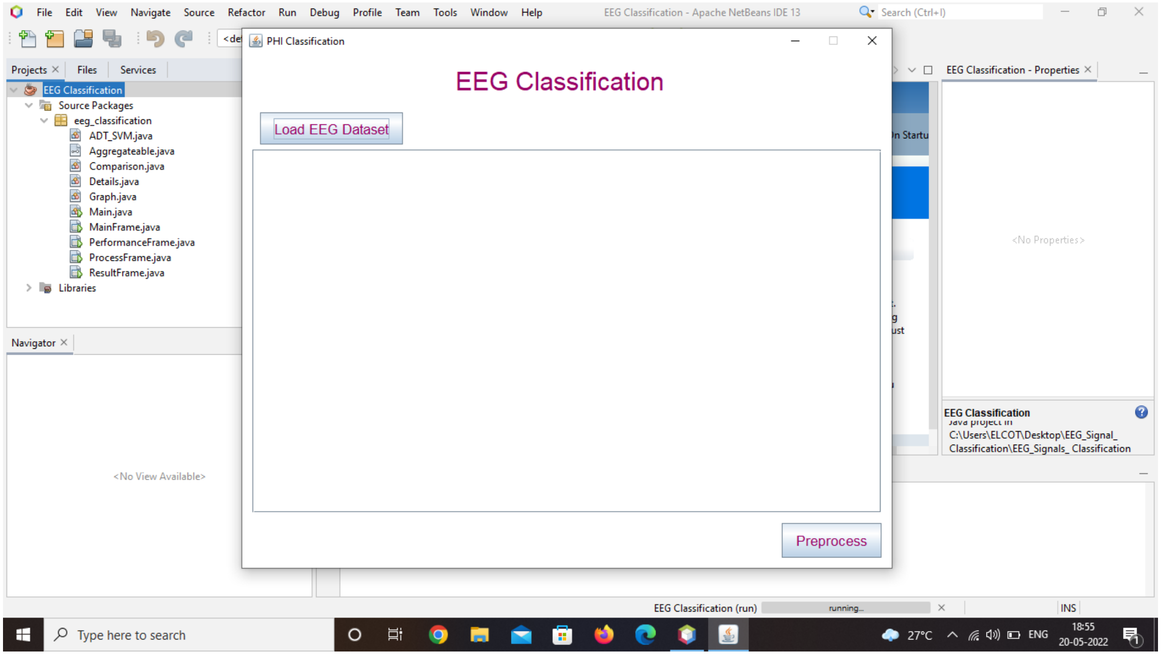
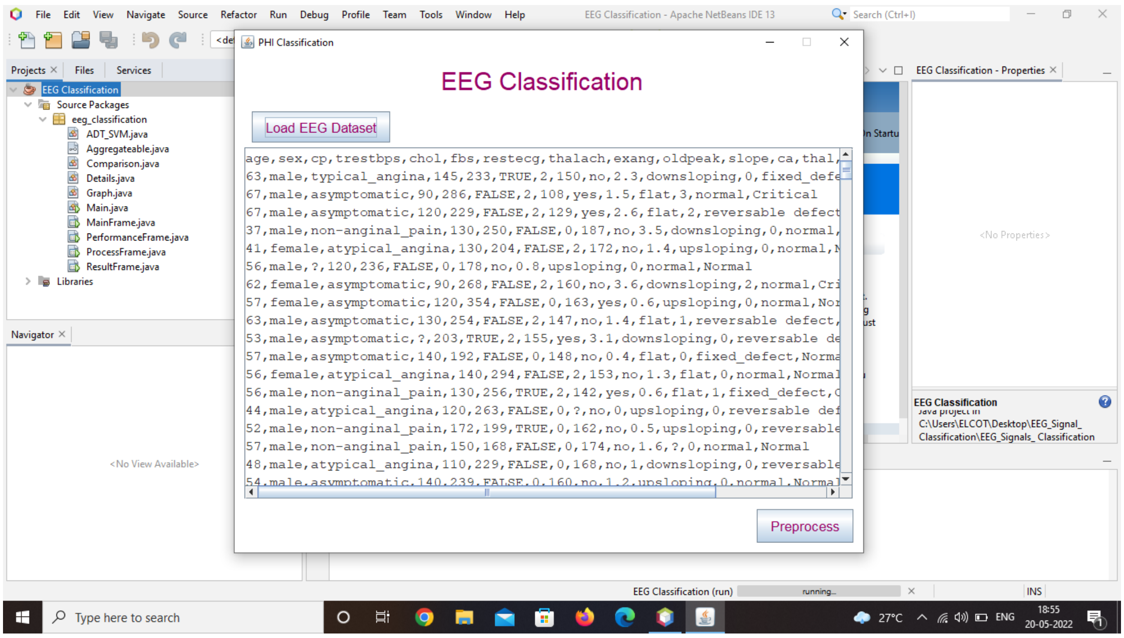


FIG:EEG Classification



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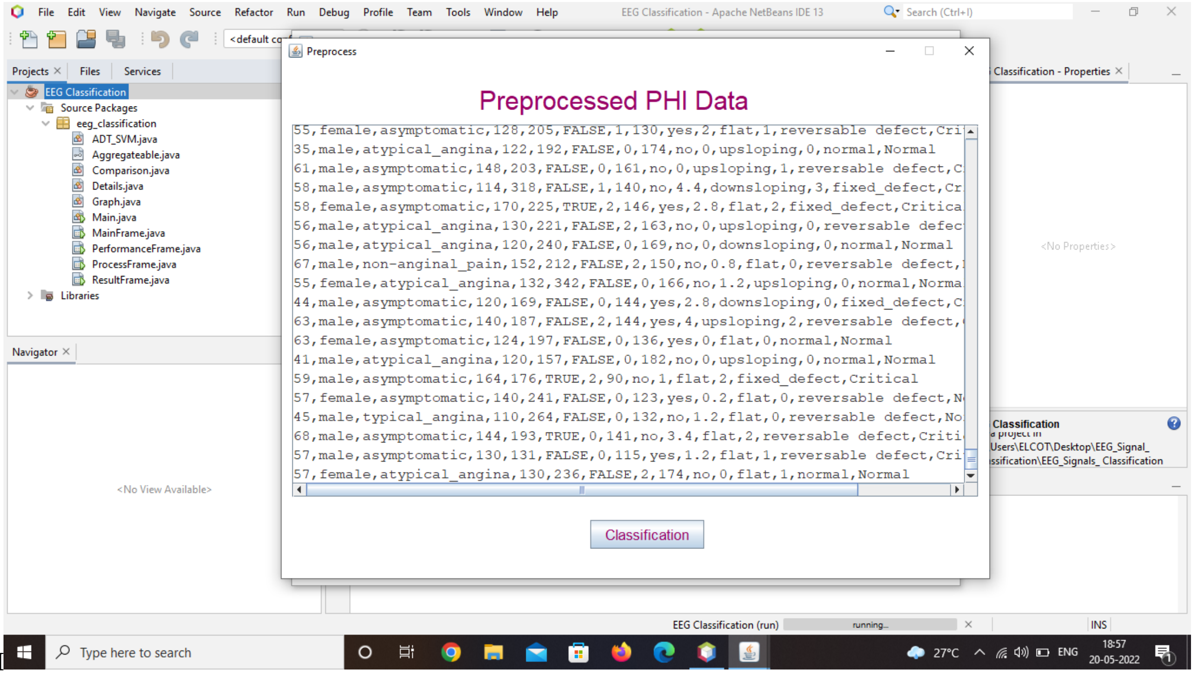
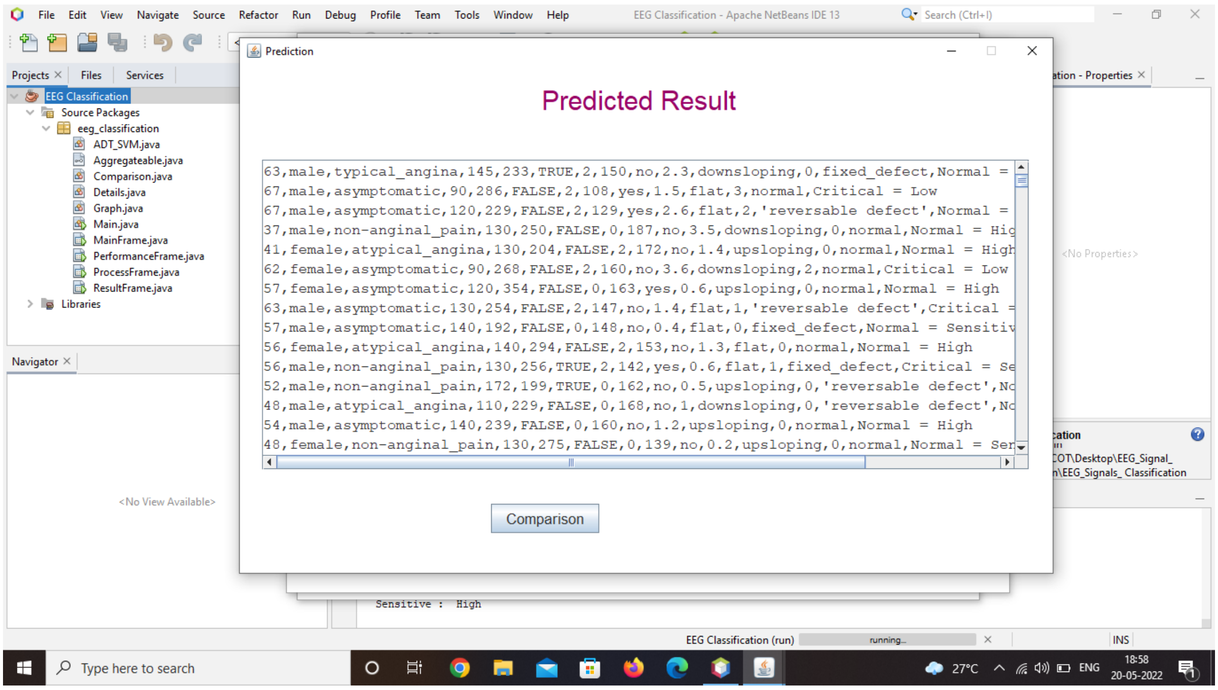


FIG:Preprocessed PHI Data



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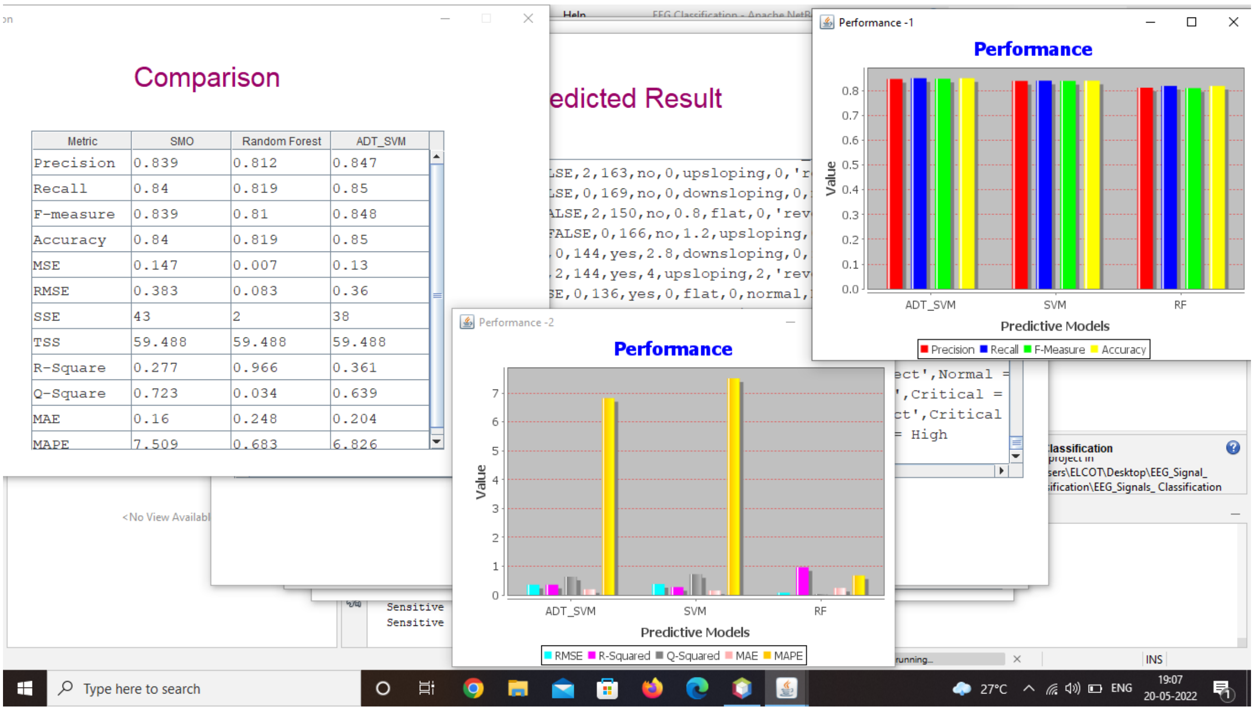

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