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A MODEL TO DETECT DROWSINESS USING MACHINE LEARNING AND DEEP LEARNING TECHNIQUES FOR BIO-MEDICAL SIGNALS

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Abstract - *Drowsiness refers to feeling sleepy or tired, or being unable to keep our eyes open. Feeling abnormally sleepy or tired during the day is commonly known as drowsiness. A variety of things may cause drowsiness. In this analytical model, we are identifying the drowsiness by using physiological signals. We have considered both EEG (Electro Encephalo Gram) and ECG (Electro Cardio Gram) values as Bio-medical Signals to detect drowsiness. Machine Learning and Deep Learning techniques are used to in our work with Naive Bayes algorithm 92.5%, ECLAT (Equivalence Class Clustering and Bottom up Lattice Traversal) algorithm 94.3%, SVM (Support Vector Machine) 93.2% and PCA (Principal Component Analysis) 94.3% and RNN (Recurrent Neural Network) 95.2%. Our model processes the loaded Bio-medical signals, detects the drowsy status of an individual by sleep pattern along with generating an alarm beep sound. Also we have compared all the Machine Learning and Deep Learning algorithms used for their performance time complexity.*

Key Words: Machine Learning (ML), Deep Learning (DL), Circadian Rhythm, Drowsy, EEG, ECG, Naïve Bayes, SVM, ECLAT, PCA, RNN

1. INTRODUCTION

Circadian rhythms influence important functions in our bodies, such as, hormone release, eating habits and digestion, body temperature and others. However, most people notice the effect of circadian rhythms on their sleep patterns. Disruptions to circadian rhythm can occur over the short-term or long-term. There are number of circadian rhythm sleep-wake disorders based on their characteristics and causes. A number of factors can contribute to drowsiness. Mental states and lifestyle choices, as well as serious medical conditions, are examples of these. Certain lifestyle factors, such as working very long hours or switching to a night shift, may cause increased drowsiness. Excessive drowsiness without a known cause may indicate a sleeping disorder.

In this analytical model, physiological signals are contributed for identifying the drowsiness. EEG and ECG data are used and applied ML and DL techniques. The model created to detect the drowsy status with sleep pattern and generates an alarm with beep sound and shows the accuracy over different algorithms applied. The time complexity these applied algorithms were compared through visual graphical result. The Fig-1 shows the DFD Level-0 of the proposed work.

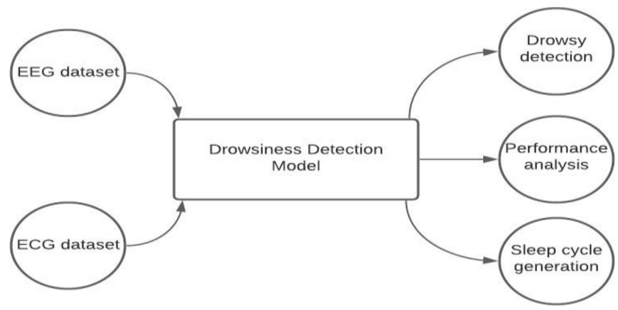

Fig-1: DFD Level-0 of the proposed model

2. PROPOSED WORK

Physiological signals are considered to give an accurate assessment of sleepiness because of their close connection with tiredness. Electro Encephalography (EEG) and Electro Cardiography (ECG) are the two most reliable methods for detecting drowsiness. The current study suggests a hybrid method for detecting drowsiness. Our proposed model loads with the data from the training-dataset, builds a model using machine learning and deep learning techniques (Naïve Bayes, SVM, ECLAT, PCA, RNN).

After creation, our model is tested with testing-dataset, which reads the patient-id referring to testing-dataset. Based on the patient-id, EEG and ECG data are used to detect the status of drowsiness. With EEG values, medically defined frequency thresholds were compared against drowsiness. All the variables of ECG are used compute and detect the defined sleep pattern.

If the tested data results in drowsiness, then a graph representing sleep pattern are generated for both EEG and ECG values of an individual to indicate individual is sleepy. The beep sound is generated as an alarm. The Fig-1 shows the architecture of the hybrid model created to detect drowsiness using EEG and ECG as bio-medical signals.

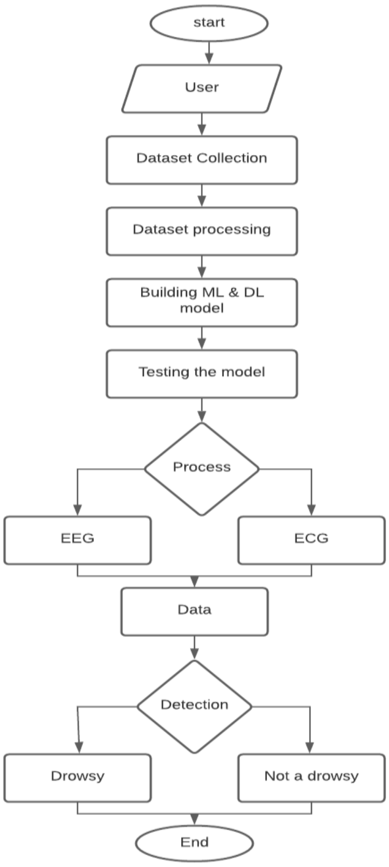

Fig-2: Architecture of the proposed model

3. METHEDOLOGY

The model is designed by ML and DL techniques, using EEG and ECG values to detect drowsiness.

3.1 Dataset and Data Preprocessing

The dataset used are the combined files of both normal and abnormal subjects. An EEG captures the electrical patterns in our brain. The billions of nerve cells in our brain produce extremely tiny electrical signals that combine to form brain wave patterns. During an EEG, little electrodes and cables are connected to your head. The electrodes detect our brain waves, which the EEG machine amplifies and records as a wave pattern. EEG data set consists of 161 rows and 6 columns. It contains total of 160 patient's data. The 6 columns represent the Alpha, Beta, Gamma, Delta, Theta and Concentrate values. Detection of the drowsiness is made using these values from EEG. Alpha: This attribute represents relaxation and attention. The frequency value ranges from 7 Hz to 13 Hz in this alpha wave. The frequency values are in between these ranges being considered as alpha wave. Beta: This attribute represents people who are in awake state. The frequency ranges from 14 Hz to 30 Hz. The values which are in these ranges are considered as Beta waves. Gamma: The frequency ranges from 30 Hz to 100 Hz. Delta: This wave is completely related to deep sleep. Frequency range is below 4 Hz. The values under this range are considered as Delta wave. Theta: This wave is also related to sleep. The value ranges from 4 Hz to 7 Hz. Concentrate: This attribute is considered as mean value of all 5 attributes.

Whereas ECG is an electrical and chemical signals are used by our nerve and muscle cells to communicate with one another. Our heartbeat is also controlled by regular electrical signals. The abnormal value of the heart beat does not lie between the ranges of 60 to 100 beats/ minutes. Slower rate than 60 beats/min represents a lower heart rate. The higher rate of the heart beat than 100 beats/ min is a fast heart rate. ECG data set consist 549 records from 290 subjects (aged 17 to 87, mean 57.2; 209 men, mean age 55.5, and 81 women, mean age 61.6; ages were not recorded for 1 female and 14 male subjects)

3.2 User Interface

The design of visual composition interface is to enhance the efficiency and ease of use of our model. It contains majorly three parts and is shown in the Fig-3 below:

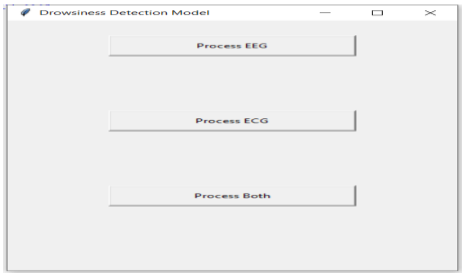

Fig-3: User Interface of the proposed model

The first *Process EEG* button allows to process EEG to detect drowsiness for the patient-id provided and generates the sleep pattern graph as show in Fig-4 and Fig-5.

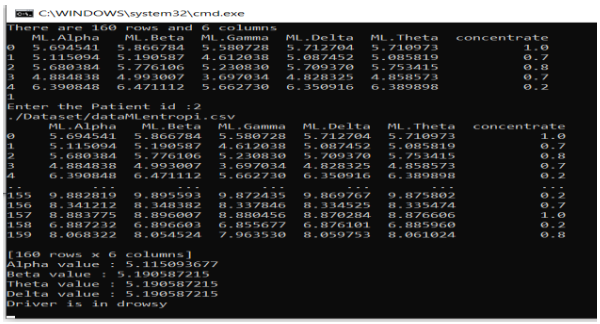

Fig-4: Drowsiness Detection-EEG

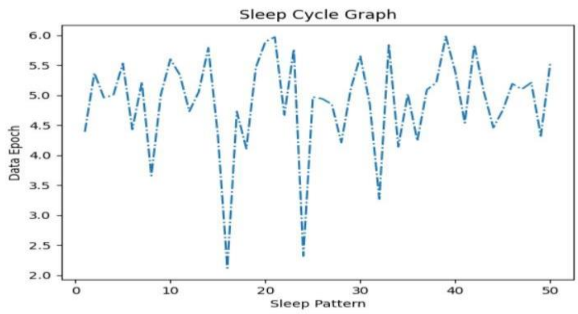

Fig-5: Sleep Pattern-EEG

The second *Process ECG* button allows us to process ECG for the given patient-id to detect drowsiness status and generates the sleep pattern graph as shown in Fig-6.

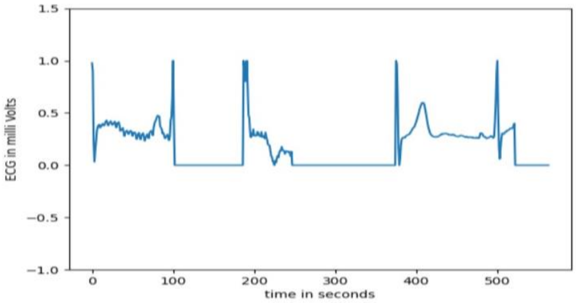

Fig-6: Sleep Pattern-ECG

And the last *Process Both* button allows to process both EEG and ECG at a time to detect drowsiness. On all these detection, a beep sound is generated as alarm to awake from drowsiness to alert state.

4. RESULT

At the end, our model gives the accuracy and the time complexity values of all ML and DL techniques used in our work in graphical mode as shown in Fig-7 and Fig-8 below:

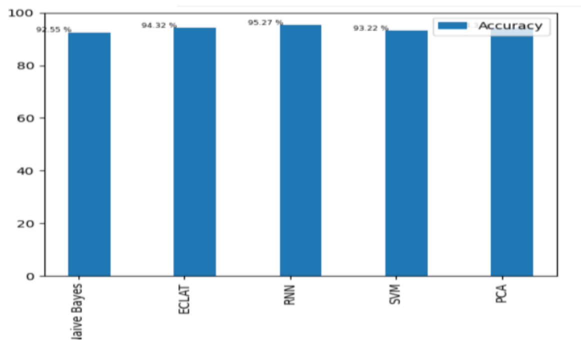

Fig-7: Accuracy comparison of algorithms

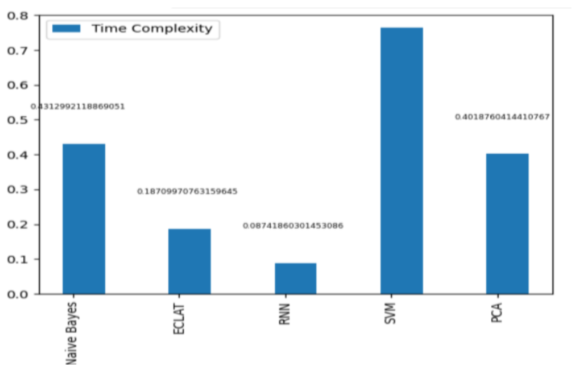

Fig-8: Time Complexity comparison of algorithms

5. CONCLUSIONS

Drowsiness cause many problems to a man kind. Disruption of sleep-awake cycle can cause fatal accidents, injury, and property damage. Our drowsiness detection model can be utilized to prevent all problems caused by drowsiness due to monotonous long hours work. Our tested drowsiness detection model could get the accuracy of ML algorithms as Naïve Bayes (92.55%), SVM (93.22%), ECLAT (94.32%), PCA (94.32%) and DL technique as RNN (95.27%). An adequate amount of sleep, make us to sync with circadian rhythm of the body, helping to sync with natural environmental clock, certainly making healthy society.

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