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A Convolutional Neural Network Model to Detect Stress Levels in Electroencephalogram Signals

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Abstract - Chronic stress is recognized as a major contributing factor to the impairment of people's health and quality of life due to the negative impacts it causes both in personal and professional life. There is a tendency for the increasing of concerns about mental health and investments in healthcare in the coming years and this fact has motivated the conduction of several studies that aim to develop technological solutions that can be applied for monitoring of people's mental state to early detection and treatment of stress. Machine Learning and Deep Learning techniques have proven to be a promising alternative to provide technology to help solve the challenges in the medical field. This study presents a Convolutional Neural Network (CNN) model for classifying stress levels in data from electroencephalogram signals. The model was trained with a dataset generated from an experiment in which individuals were monitored by electroencephalogram while performing stress-inducing tasks. The model achieved an accuracy of 87.29% in predictions and presented an adequate balance between performance and computational costs. The results obtained demonstrate the potential of Deep Learning techniques as tools to aid in the health monitoring and diagnosis.

***Key Words*:** machine learning, deep learning, mental stress, electroencephalogram

1. INTRODUCTION

Chronic stress has become a common element in people's daily lives largely due to changes in the population's lifestyle in recent decades. Chronic stress can have a variety of emotional and physical consequences. Some examples of problems caused by stress are: irritability, depression, impaired decision-making, sleep disorders, high blood pressure, tachycardia, burnout syndrome, risk of heart attack and stroke.

According to The Lancet Global Health [1] and Kang and Chai [2], concern about mental health problems (including stress) has increased in recent years due to the large number of people affected by such disorders worldwide and the high financial costs estimated for the management and treatment of these disorders. The need for creating mechanisms that help reduce these problems and improve people's quality of life has motivated the conduction of several studies that aim to develop technological solutions that can be applied for monitoring people's mental state for early detection and treatment of stress.

According to Can et al. [3], Hickey et al. [4] and Long et al. [5], monitoring people's mental state and making decisions in real time based on verified information poses several challenges due to the dynamic characteristics of the environment and the complexities inherent in the stress detection process itself, and Machine Learning and Deep Learning techniques have been explored in several related studies and have been considered as a promising alternative to provide effective technological solutions to address these challenges.

This study aims to present a Deep Learning model that can classify stress levels in electroencephalogram data with a high level of accuracy and can be considered an adequate solution for treating the problem under study. The goal is to present a model that can be trained consuming less computational resources and can achieve good performance.

2. BACKGROUND

Stress can be defined as a process generated by body to respond to external stimuli (also called stressors) that are perceived as demands or threats from the external environment. This process is initiated by brain and causes the secretion of certain hormones that can cause emotional, behavioral, and physical changes in the individual. Stress is a necessary mechanism for the survival of human beings, as it enables them to adapt and react to different situations to which they are subjected daily. Stress is usually classified into two categories according to the amount of time the body is exposed to a given stressor: acute stress (short term) or chronic stress (long term). According to McEwen and Akil [6], while acute stress is desirable for the individual's adaptability to the external environment to occur; chronic stress is highly harmful to individual because exposure to stressors for a long period of time can cause imbalances in the body which can lead to various pathologies such as high blood pressure, heart attack and stroke.

The brain communicates with other organs in the body through the Autonomic Nervous System (ANS). The ANS is divided into two parts: Sympathetic Nervous System (SNS) and Parasympathetic Nervous System (PNS). According to Shahsavarani et al. [7], de Looff et al. [8] and Weissman and Mendes [9], the SNS comes into action when the body is stimulated by some stressor element and starts to release

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hormones that cause physiological changes in the body for its adaptation to the environment (e.g. increased heart rate), and the PNS comes into action after the occurrence of the stressful event to inhibit the effects of the SNS and bring the organism back to a state of homeostasis. An analysis of the joint activity of the two systems makes it possible to verify how the body is behaving to respond to stressors. The two systems operate harmoniously when acute stress occurs and, normally, operate in a deregulated manner when chronic stress occurs.

The Electroencephalogram (EEG) is the device that makes it possible to record the brain's electrical activity through the use of electrodes connected to the scalp. The EEG measures electrical voltage fluctuations resulting from ionic current flowing within neurons. The signal obtained by the EEG at a certain instant of time represents the amplitude of the voltage recorded in a certain position of the scalp and it is measured in microvolts (μV). The set of measurements recorded in a given time interval (usually called a brain wave) represents the frequency of oscillations occurring in the amplitude of the signal and it is measured in Herts (Hz). According to Can et al. [3], Hickey et al. [4], Long et al. [5] and Kang and Chai [2], the EEG has been widely accepted and used as a tool for analyzing stress levels through the analysis of the joint operation of the SNS and PNS systems.

According to iMotions [10] and TMSi [11], the EEG has become a widely used tool both for research related to the understanding of brain functioning and the analysis of diseases in medical practice due to its ease of use, and because it is considered a low-cost and non-invasive tool compared to other tools for brain imaging. Another characteristic that has favored the use of EEG for brain activity analysis is its high time resolution, which makes it possible to record hundreds of snapshots of electrical activity in a single second and makes it possible to analyze events at the precise moment of their occurrence.

The EEG is a flexible device that allows the definition of different configurations for the number of electrodes and their positioning on the scalp. The most widely used electrode configuration pattern is the so-called 10-20 System, which was proposed in 1957 by Heber Jasper. The 10-20 System defines 21 electrodes that are identified according to their location on the scalp and their relationship to the underlying area of the cerebral cortex. According to TMSi [11], the numbers "10" and "20" in the system name refer to the distances between adjacent electrodes that may represent 10% or 20% of the total distance of the skull. Fig. 1 shows a diagram of electrode positioning considering the spatial distances between adjacent electrodes.

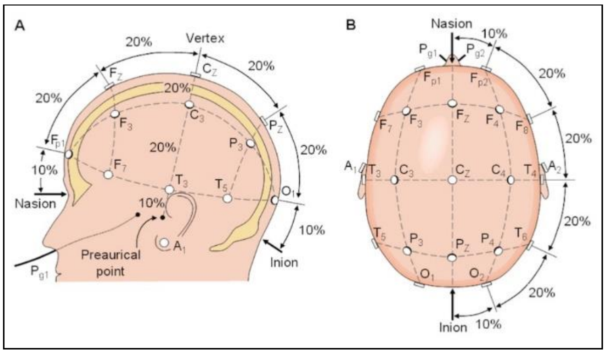

Figure 1 - Distance of the electrodes in the 10-20 System.

Each electrode is identified by one or two letters that represent the brain region to which it is associated. The letters used are: Fp (pre-frontal or frontal pole), F (frontal), C (central line of the brain), T (temporal), P (parietal) and O (occipital). The identification also receives a number that represents the distance of the electrode in relation to the midline of the brain. The electrodes located in the midline receive the letter "z" to indicate the number zero and the other electrodes receive numbers that increase as their location moves away from the midline. Odd numbers are associated with the left hemisphere and even numbers are associated with the right hemisphere. Fig. 2 shows a representation of the 10-20 System indicating the association of each electrode with the associated brain region.

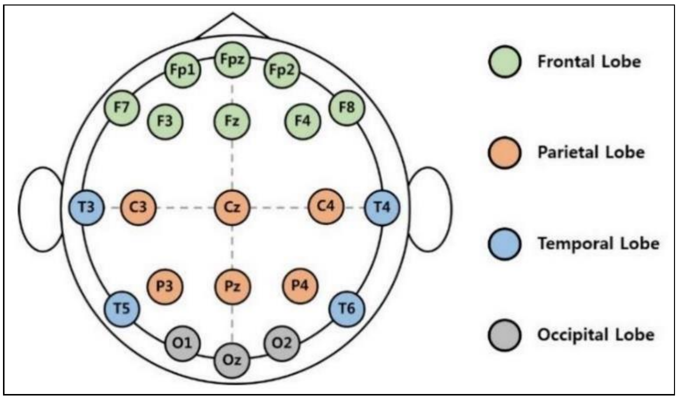

Figure 2 - Identification of electrodes in the 10-20 System.

In 1994 an extension to the original 10-20 System called the 10-10 System was accepted as a standard by the American Electroencephalographic Society. This system had been proposed in 1985 by researchers at the University of Washington. This standard allows the use of up to 74 electrodes and enables high resolution measurements to be performed. This pattern defines 10% of the total distance from the skull to all adjacent electrodes, as exemplified by Fig. 3.

The EEG is a device that has high sensitivity and its measurements are subject to the presence of artifacts which are unwanted signals that alter the signals of interest. Basically, there are two types of artifacts: physiological signals coming from other parts of the body outside the brain and non-physiological signals coming from the environment outside the body. According to TMSi [11], the main generators of physiological artifacts are eye movement, the movement of facial muscles and cardiac activity, and the main generators of non-physiological artifacts are electromagnetic interference from the network, electrode snapping, cable movement and the poor connection of measurement channel. Proper treatment of artifacts is considered a critical task in the analysis of EEG signals because the presence of artifacts can cause errors in the interpretation of the results obtained. According to TMSi [11] and Kumar and Bhuvaneswari [12], there are several techniques to prevent the capture of artifact-generating signals and techniques to remove unwanted signals during subsequent data processing.

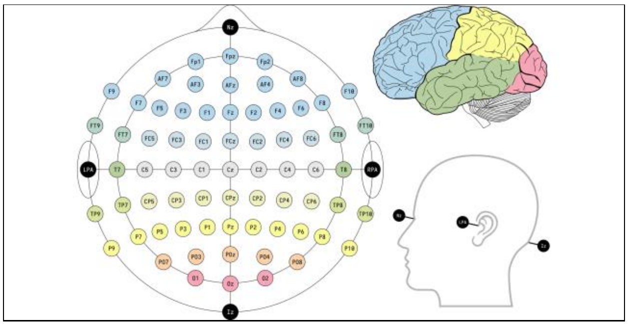

Figure 3 - The 10-10 System.

Several studies have proposed the use of Machine Learning techniques to classify stress levels through the analysis of data from physiological exams. The use of Deep Learning models has been considered an effective alternative to perform this task due to the recognized Artificial Neural Networks (ANN) ability to model complex systems and extract patterns from data. Several studies have demonstrated the potential of Deep Learning models for detecting stress levels, presenting results that are considered promising due to the high accuracy achieved by the models in the predictions, as can be seen in the results presented by Dham et al. [13], Zainudin et al. [14] and Li and Liu [15].

The Deep Learning models most explored in studies on classification of stress levels have been: Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN). According to Wibawa et al. [16] and Li and Liu [15], comparative analyzes between the models have shown that CNN models can achieve better results by allowing high accuracy rates to be achieved with the use of fewer parameters and lower computational costs for the model training.

3. METHODS

3.1. Dataset Description

The dataset used in this study is called SAM 40. This dataset was derived from the research developed by Ghosh et al. [17] at BCI Lab GU (Guwahati, India). The dataset has a set of records of EEG signals collected in an experiment in which 40 individuals aged between 18 and 25 years were monitored while performing stress-inducing tasks. The tasks performed were: listening to relaxing music (for 25 seconds), performing the Stroop test (for 25 seconds), solving arithmetic questions (for 25 seconds) and identifying symmetric mirror images (for 25 seconds). Each individual performed the sequence of tasks in 3 trials. The individuals assigned a stress level rating to each task performed. The assigned rating is on a scale of 0 to 10, where 0 means no stress and 10 means the highest level of stress.

The equipment used in the experiment was configured according to the 10-10 pattern of electrode placement with 32-channel recording. The electrodes used were: CZ, FZ, Fp1, F7, F3, FC1, C3, FC5, FT9, T7, CP5, CP1, P3, P7, PO9, O1, PZ, OZ, O2, PO10, P8, P4, CP2, CP6, T8, FT10, FC6, C4, FC2, F4, F8 and Fp2. The sampling frequency used in the equipment was 128 Hz; which made it possible to generate a dataset with a total of 1,536,000 samples with 32 features, where each feature represents the recording of brain activity (in microvolts) obtained by each of the electrodes used in the experiment.

The original dataset went through a pre-processing step before being made publicly available. According to Ghosh et al. [17], filtering techniques were used to remove artifacts present in the data that may have been caused by the influence that muscle movement and eye movement exert on the EEG signals.

3.2. Preprocessing

An exploratory analysis of the data was carried out, in which it was verified that the dataset does not have problems of data inconsistencies such as missing data, zero values, duplicated samples or noisy data; which dispensed with the need to perform some treatment for these types of problems. The exploratory analysis also provided a better understanding of the characteristics and patterns of the data present in each feature, and it was verified that the dataset has a symmetrical normal distribution; which is an indication that the data distribution is in line with what is normally expected by Machine Learning algorithms to achieve better performance in their learning.

The correlation analysis between each of the 32 features and the dataset target showed that none of the features has a different correlation with the target compared to the other features and for this reason it was decided to keep the 32

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features in the dataset considering that all of them may have the same importance for predicting the target.

The dataset was organized to be treated as a time series because, according to Wibawa et al. [16], CNN models have been shown to be effective in treating datasets with this characteristic in studies carried out in recent years. "Time windows" containing 3,200 samples each were generated. Each "time window" represents 25 seconds of EEG signal measurements (1 task performed). The resulting dataset contains 480 samples after being reorganized into "time windows". The “time window” structure is shown in Fig. 4

The dataset was stratified into 90% of samples for training and 10% for testing. The dataset was quite unbalanced, and it was necessary to use oversampling techniques to increase the number of samples in the training set and balance the class distribution. Initially, a resampling technique was applied to increase the number of samples, and then the Synthetic Minority Over-sampling Technique (SMOTE) was applied to balance the training set by creating synthetic instances. After oversampling was applied, the number of samples in the training set increased to 2,640.

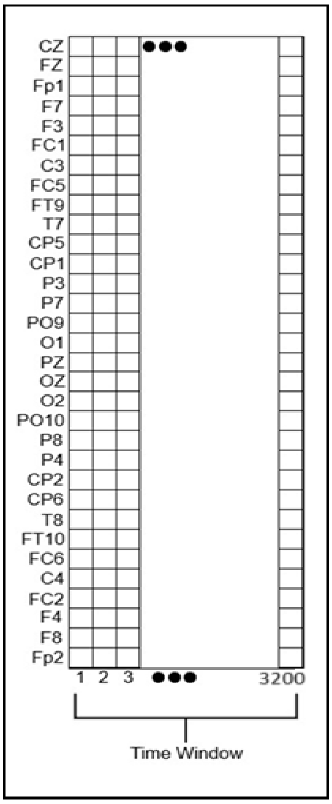

Figure 4 - “Time window” for each sample.

3.3. Model Training

The architecture of the CNN model proposed in this study is shown in Fig. 5. The architecture has 3 Convolutional layers, 1 Max Pooling layer, 1 Flatten layer, 1 Fully Connected layer using Dropout (0.2), and 1 output layer. Table 1 presents the configuration hyperparameters for each layer.

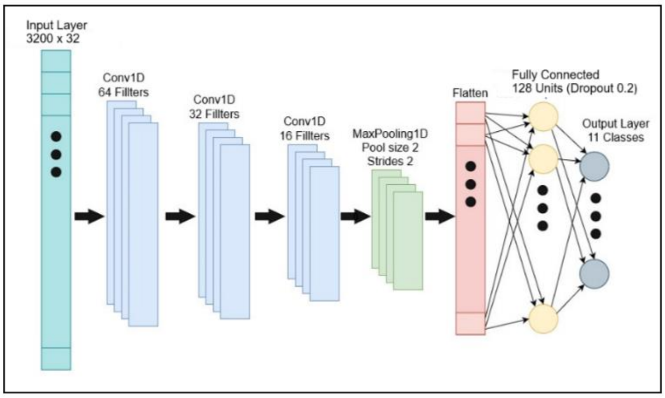

Figure 5 - CNN model architecture.

Table 1 – Layers configuration hyperparameters.

Layer	Layer type	Filters	Kernel size	Activation	Units
Layer 1	Conv1D	64	3	reLU	-
Layer 2	Conv1D	32	3	reLU	-
Layer 3	Conv1D	16	3	reLU	-
Layer 4	MaxPooling1D	-	-	-	-
Layer 5	Flatten	-	-	-	-
Layer 6	Dense	-	-	reLU	128
Layer 7	Dense	-	-	Softmax	11

The model was implemented using the Tensorflow framework with the Keras library. Training was performed with a limit of 300 epochs using the AdamW optimizer with a learning rate of 0.001 and a batch size of 32. The cross-validation technique (10 Folds) was used for training.

4. RESULTS AND DISCUSSION

The CNN model achieved an average accuracy of 87.29% in the test set. It can be said that correctly predicting the stress level for 87.29% of the samples is equivalent to saying, for example, that the model was able to correctly predict the stress levels in 52 minutes out of a total of 60 minutes monitored by EEG. Table 2 presents the detailed metrics (precision, recall and F1-Score) of the training. The high rates achieved for these metrics indicate that the model handled well with all classes and its performance was little impacted by false positives or false negatives.

Fig. 6 and 7 show the historical accuracy and loss registered during the execution of each fold. It can be verified that the model converged quickly, reaching high accuracy rates, and reaching stability with less than 40 epochs of training.

Table 2 - CNN model training metrics.

Class	Precision	Recall	F1-Score
0	0.91	0.87	0.89
1	1.00	0.79	0.88
2	1.00	0.88	0.94
3	0.91	0.84	0.88
4	0.72	0.89	0.79
5	0.83	0.91	0.87
6	0.85	0.88	0.86
7	0.88	0.91	0.89
8	1.00	0.83	0.91
9	1.00	0.90	0.95
10	1.00	0.75	0.86

Fig. 6 and 7 show the historical accuracy and loss registered during the execution of each fold. It can be verified that the model converged quickly, reaching high accuracy rates, and reaching stability with less than 40 epochs of training.

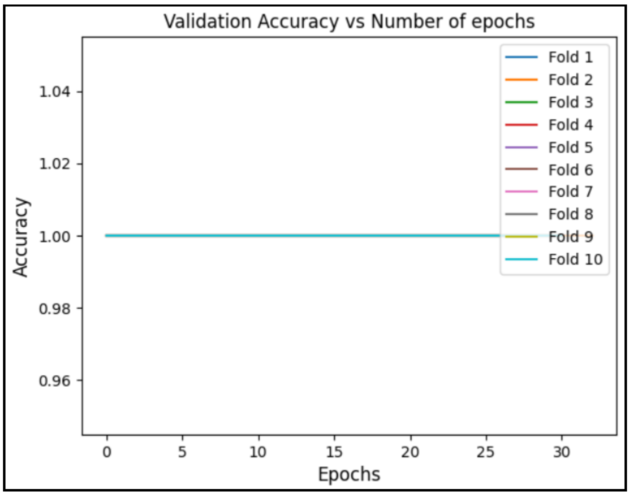

Figure 6 - History of accuracy in the 10 folds.

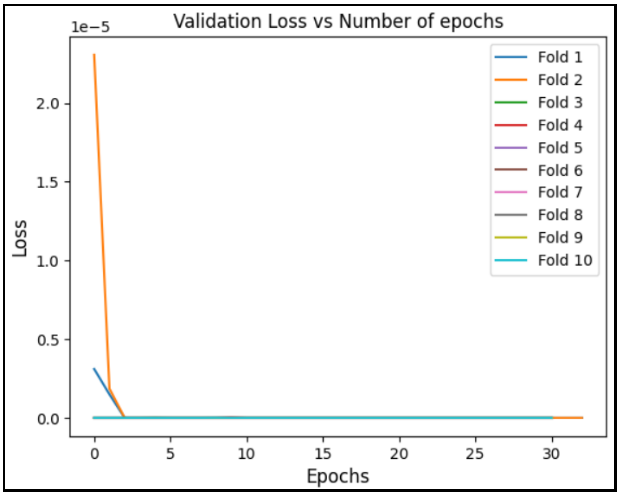

Figure 7 - History of loss in the 10 folds.

5. CONCLUSIONS

There is a tendency for the increasing of concerns about mental health and investments in healthcare in the coming years. Machine Learning and Deep Learning techniques have proven to be a promising alternative to provide technology that helps in the treatment of challenges in the medical field and in promoting the improvement of people's quality of life. Deep Learning models have proven to be efficient in identifying patterns in complex data such as those available in electroencephalogram exams. Solutions based on Deep Learning can create a range of possibilities for healthcare monitoring and real-time decision making when combined with other cutting-edge technologies such as biosensors, mobile devices, and cloud computing.

Developing technological solutions that provide excellent performance using less computational resources is a very important issue, especially because nowadays there is a tendency to handle ever larger amounts of data in less time. CNN models have been shown to be suitable for implementing approaches of data analysis that make it possible to achieve a better balance between performance and computational costs. The results achieved in this study demonstrate that CNN models can provide satisfactory results in the treatment of data organized in time series, which makes it possible to apply them to the treatment of a wide variety of problems.

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