A Convolutional Neural Network model for stress classification based on electrocardiogram data

Rodrigo Alexandre dos Santos[1]

[1]*Department of Software Development, CPQD Foundation, Campinas, SP, Brazil*

---***---

Abstract - Several studies have been published in recent years addressing the use of technologies for monitoring and diagnosing mental health. Stress disorders have aroused great interest among researchers and have been widely addressed in several studies due to the negative impacts they can cause to people's quality of life and the possibility of triggering serious illnesses that can seriously compromise physical health. Machine Learning techniques have proven to be a promising alternative to provide technology that can help to deal with challenges in the medical field and Deep Learning models particularly have provided excellent performance when dealing with complex problem domains, such as the classification of types and levels of stress. This study proposes a Convolutional Neural Network (CNN) model for classification of stress through the analysis of electrocardiogram data. The model was trained with a dataset generated from an experiment where individuals were monitored by electrocardiogram while performing stress-inducing tasks. The model achieved an accuracy rate of 91.14% in predictions and presented an adequate balance between performance and computational costs. The results obtained demonstrate the potential of Machine Learning techniques as tools to aid in monitoring and diagnosing mental health.

Key Words: machine learning, deep learning, mental stress, electrocardiogram

1. INTRODUCTION

Several studies have been published in recent years addressing the use of technologies for monitoring and diagnosing mental health. According to Kang and Chai [1], the factors that justify the increase in investments in these studies are the large number of people around the world who suffer from mental health problems and the prospect of increasing financial costs associated with these diseases in the coming years.

According to Hickey et al. [2], the mental disorders that have been most addressed in studies about mental health are: stress, anxiety, depression, schizophrenia, and sleep disorders. Among these disorders, stress has received a lot of attention from researchers because, according to Hickey et al. [2] and Long et al. [3], stress causes negative impacts on the individual's quality of life and can trigger serious illnesses that can seriously compromise physical health. Another justification for the concern about stress disorders is that, according to Benchekroun et al. [4], stress is considered one of the most prevalent mental health problems worldwide and the estimated expenditure on stress treatments is around 300 billion dollars per year in Europe.

The evolution of wearable biosensors that occurred in recent years has created new possibilities for medical care by allowing physiological signals to be captured even in environments outside the laboratories during the daily activities of individuals and to be used in the creation of datasets that can be processed by computational tools for stress diagnosis. Computational tools based on Machine Learning have achieved positive results in dealing with such datasets and have been considered a promising alternative to aid decision-making in the medical field. According to Benchekroun et al. [5] and Rafie et al. [6], these advances can contribute to reducing financial costs and optimizing medical care services by enabling remote monitoring of patients to anticipate the diagnosis of mental disorders and carry out their early treatment.

This study aims to propose a Deep Learning model for stress classification through the analysis of electrocardiogram data. The study aims to present a model that provides a performance that proves its ability to efficiently address the problem under study.

2. BACKGROUND

Stress can be defined as a process generated by the 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 the 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 because it enables adaptation and reaction to different everyday situations.

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 [7], while acute stress is desirable for the individual's adaptability to the external

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 11 | November - 2023 SJIF Rating: 8.176 ISSN: 2582-3930

environment to occur; chronic stress is highly harmful to the individual because exposure to stressors for a long period of time can cause imbalances in the body that can lead to various pathologies such as high blood pressure, heart attack and stroke.

Stress can also be classified according to the type of stressor that triggers it. According to Falk et al. [8] and Birjandtalab et al. [9], from this perspective, stress can be classified into three categories: cognitive stress (also called mental stress), emotional stress (also called affective stress) and physical stress. Cognitive stress is usually associated with situations of reasoning and mental effort. Emotional stress is usually associated with feelings of anxiety, fear, or discomfort. Physical stress is usually associated with activities that generate physical exertion.

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 iMotions [10] and Shahsavarani et al. [11], the SNS comes into action when the body is stimulated by some stressor element and starts to release hormones that cause physiological changes in the body for its adaptation to the external environment (increase in heart rate, for example), and the PNS enters in action after the occurrence of the stressful event to inhibit the effects of the SNS and take the organism back to the 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 analysis of the functioning of the cardiovascular system to detect stress levels has been widely addressed in research due to the relationship between the brain and the heart. SNS and PNS activities directly influence rhythm and heart rate pattern; therefore, the heart rate analysis can provide information about the behavior of the nervous system and enable the detection of stress levels. According to iMotions [10], the analysis of the frequency and strength of cardiac contraction allows understanding how the heart is being affected by sympathetic activity and verifying whether the activity in the prefrontal cortex is flowing regularly or is deregulated. A dysregulated ANS activity could be an indication of chronic stress.

The electrocardiogram (ECG) is the equipment that performs the test that evaluates the electrical activity of the heart through electrodes attached to the skin. The electrodes capture the electrical activity (in microvolts) generated by the depolarizations and repolarizations of the heart muscle. According to iMotions [10], the ECG has become popular and widely used in cardiac exams because it is a non-invasive and low-cost technique; in addition to offering an excellent time resolution that makes it possible to record information in the interval of up to milliseconds. According to Rafie et al. [6], the ECG has become such a widespread and important tool for medicine due to its ability to enable the diagnosis of various pathologies such as cardiac arrhythmias, pericardial and myocardial disease, electrolyte disturbances and pulmonary disease.

The ECG records the phases of the cardiac cycle, that is, the process of depolarization and repolarization of myocardial cells that generates the action potential that stimulates contraction (systole) and relaxation (diastole) events of the heart. The record obtained by the ECG can be viewed as a trace (Fig. 1) where the vertical axis shows the recorded voltage and the horizontal axis shows the temporal sequence of occurrence of electrical potentials. The phases recorded by the ECG are: P wave (atrial muscle depolarization), QRS complex (ventricular muscle depolarization) and T wave (ventricular muscle repolarization and return to the baseline state). Fig. 2 shows a representation of the phase sequence of a normal cardiac cycle. According to Becker [12], abnormalities detected in the phase sequence or in the time interval between phases may be indicators of certain disorders such as atrial fibrillation, atrial flutter, and atrioventricular block; and all these disorders cause cardiac arrhythmias and their consequences.

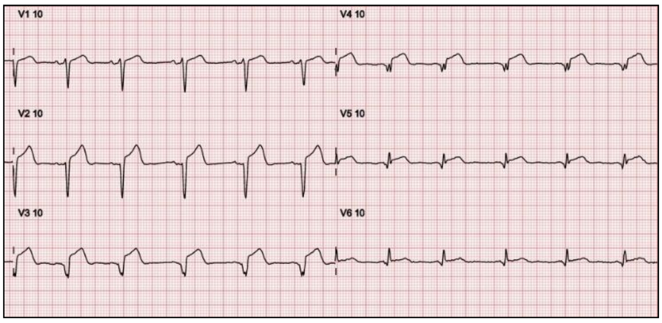

Figure 1 - Example of an ECG exam.

According to Benchekroun et al. [4] and Arquilla et al. [13], the detection of stress in ECG records is usually performed through the analysis of Heart Rate Variability (HRV). The HRV is the measure of the time interval between successive R peaks (highest wave of the QRS complex) and is a metric that reflects the balance between the SNS and PNS systems. According to Benchekroun et al. [4], a decrease in HRV indicates an increase in SNS activity and consequent increase in stress, and an increase in HRV indicates an increase in SNP activity and a consequent reduction in stress. Fig. 3 shows an exemplification of the HRV in the sequence of cardiac cycles.

Several studies have proposed the use of Machine Learning techniques to classify stress levels through the analysis of data from physiological tests. According to Li and Liu [14], models based on Artificial Neural Networks (ANN) have achieved high accuracy rates in predicting stress levels due to their high capacity to model complex systems and extract patterns from data.

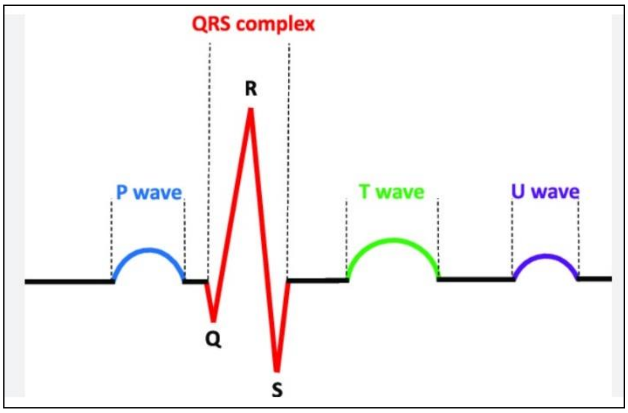

Figure 2 - Phases of the cardiac cycle recorded by the ECG.

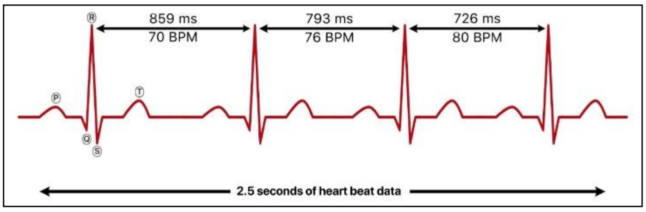

Figure 3 - Phases of the cardiac cycle recorded by the ECG.

Recent studies have explored the use of Convolutional Neural Networks (CNN) to deal with problems in which data can be analyzed as time series and the data recorded in ECG exams fit into this scenario. Although CNNs have become popular in the context of computer vision and image processing, recent work has shown that CNNs also have the ability to efficiently deal with time series analysis problems as demonstrated in the work presented by Wibawa et al. [15] in which the use of a CNN model achieved better results than other models like Multilayer Perceptron (MLP) and Long Short-Term Memory (LSTM). According to Tzevelekakis et al. [16], CNNs have shown promising results in this scenario by enabling the implementation of models that require a smaller number of parameters and lower computational costs for model training compared to other ANN architectures.

3. METHODS

3.1. Dataset Description

The dataset used in this study is called Non-EEG. This dataset was derived from research carried out by Birjandtalab et al. [9] and was publicly available by Goldberger et al. [17]. The dataset contains a set of physiological records collected in an experiment in which 20 individuals aged between 19 and 33 years were monitored while performing stress-inducing tasks.

The sequence of tasks performed in the experiment was: relaxation with music for meditation (for 5 minutes), running on a treadmill to generate physical stress (for 5 minutes), relaxation with music for meditation (for 5 minutes), arithmetic test and Stroop test to generate cognitive stress (for 5 minutes), relaxation with music for meditation (for 5 minutes), watching a horror movie to generate emotional stress (for 5 minutes).

The physiological signals collected in the experiment were: electrocardiography (heart rate), temperature, 3D acceleration, electrodermal activity (EDA) and oxygen saturation (Sp02). The dataset is called Non-EEG because the researchers intended to analyze various physiological signals except for electroencephalogram signals that they considered difficult to monitor in day-to-day activities. For this study, only heart rate data were used since its focus is on the use of ECG to classify types of stress.

The sampling frequency used in the equipment was 1 Hz (1 record per second); which made it possible to generate a dataset with a total of 42,000 samples. Each sample was classified into one of 4 classes: 0 – relaxation, 1 – physical stress, 2 – cognitive stress, 3 – emotional stress.

3.2. Preprocessing

An exploratory analysis of the data was carried out in which it was possible to verify that the dataset does not have problems of data inconsistencies such as duplicated samples or data with noise; which dispensed with the need to perform some treatment for these types of problems. The visual analysis of the data showed that the dataset has an asymmetrical distribution; which pointed to the need to perform a normalization on the data in order to make the distribution more suitable to achieve better performance in model training.

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 dealing with datasets with this characteristic in studies carried out in recent years. The analysis of data as a time series also aims to explore the hypothesis that the identification of types or levels of stress can be more accurate if patterns in Heart Rate Variability (HRV) are analyzed. "Time windows" containing 30 samples each were generated. Each "time window" represents 30 seconds of ECG signal measurements. The dataset contained 1,400 samples after being reorganized into "time windows".

It was verified that the dataset was unbalanced, and an oversampling process was performed to increase the number of samples of each class to the same number of samples of the majority class in the training set. The Synthetic Minority Over-sampling technique (SMOTE) was applied to the training set to balance the data.

3.3. Model Training

The architecture of the CNN model proposed in this study is shown in Fig. 4. The architecture is composed of 3 Convolutional layers, 1 Max Pooling layer, 1 Flatten layer, 3 Fully Connected layers and 1 output layer. Table 1 shows the definition of hyperparameters for each network layer.

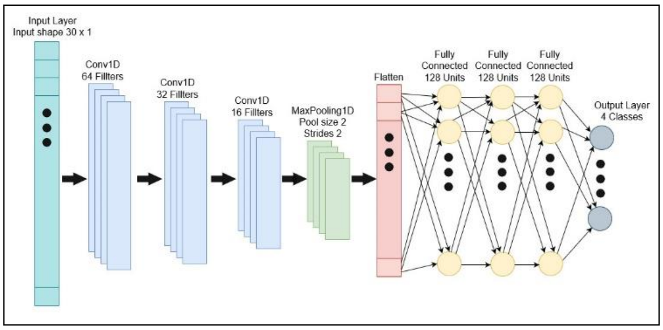

Figure 4 - CNN model architecture.

Table 1 – Hyperparameters setup.

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	MaxPooling	-	-	-	-
Layer 5	Flatten	-	-	-	-
Layer 6	Dense	-	-	reLU	128
Layer 7	Dense	-	-	reLU	128
Layer 8	Dense	-	-	reLU	128
Layer 9	Dense	-	-	Softmax	4

An oversampling process was necessary to improve model training performance. After applying the SMOTE technique, the number of samples in the training set increased from 1,400 to 2,880.

The model was implemented with the Tensorflow framework using the Keras library. The training was performed with a limit of 300 epochs using the AdamW optimizer and a batch size of 32. The cross-validation technique (10 Folds) was used for training in order to reduce bias and variance, avoid underfitting and overfitting, and, to obtain a set of metrics that would allow evaluating the consistency of the model.

4. RESULTS AND DISCUSSION

The CNN model achieved an average accuracy of 91.14% in the test set. The model's performance was consistent during the execution of the 10 folds. It can be said that correctly predicting the type of stress for 91.14% of the "time windows" is equivalent to saying, for example, that the model was able to correctly predict the types of stress in 54 minutes out of a total of 60 minutes monitored by ECG.

Table 2 presents the detailed metrics (precision, recall and F1-Score) obtained from the training. The high rates achieved for these metrics are an indication that the model handled well with the prediction of all dataset classes and did not have its performance compromised by false positives or false negatives.

Fig. 5 and 6 show the history of accuracy and loss recorded during the execution of each fold. It can be verified that the model converged quickly, reaching high accuracy rates, and reaching stability in about 120 training epochs. It was observed that the use of smaller values for the batch size (32 in this case) provided better accuracy and generalization ability with the use of a smaller number of samples.

Table 2 - Metrics of CNN model training.

Class	Precision	Recall	F1-Score
0	0.93	0.94	0.94
1	0.92	0.90	0.91
2	0.86	0.86	0.86
3	0.88	0.84	0.86

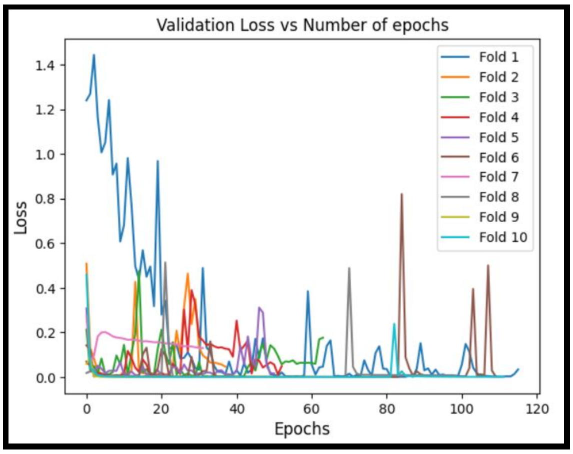

Figure 5 - History of accuracy in the 10 folds**.**

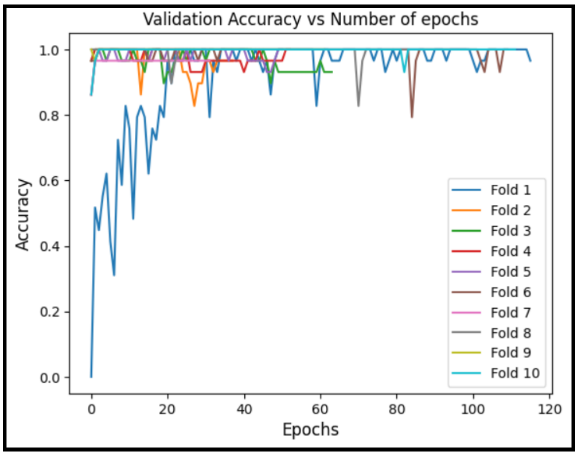

Figure 6. History of loss in the 10 folds.

The proposed CNN architecture uses 66,228 trainable parameters. This reduced number of parameters made it possible to train the model using less computational resources. This feature is desirable to enable the execution of the model on lower capacity hardware or on cloud infrastructures in which it is essential to consume less computational resources to reduce costs.

This study, however, is subject to some limitations. Difficulties related to the interpretability of ANN models can make it difficult to understand how the model performed its predictions. This characteristic can make it difficult to accept the results obtained by the model in problem domains in which the explainability of the model is crucial for its results to be considered in decision making. Future works that make it possible to obtain better interpretability of the model's conclusions could contribute with more insights to the understanding of the various issues related to stress.

5. CONCLUSIONS

The use of Machine Learning to help monitor and diagnose health problems is considered a promising alternative to help promote people's well-being and quality of life. Healthcare professionals can benefit from the help of this technology to perform their analyzes faster and more comprehensively, in addition to obtaining more accurate results. The availability of technologies that can be used in everyday situations can create alternatives to try to overcome certain limitations that make it difficult for the individual to obtain better health care services.

Understanding aspects related to negative stress and discovering new insights about this disorder is considered a challenging issue given the complexity involved in the various subjective and objective aspects related to the topic. The recognition of negative stress as a major factor affecting the quality of life of the population and generating high financial costs tends to generate more and more interest and investments in the development of research and practical applications aimed at dealing with these issues.

ANN models have a great ability to identify patterns in data that have complex relationships, which makes them an interesting alternative to deal with problem domains in which data analysis is considered challenging. ANN models make it possible to achieve high rates of accuracy in predictions, which can be a desired characteristic in scenarios that demand high precision in the results, as in medical analyses. Convolutional Neural Networks (CNN) make it possible to achieve a balance between high prediction capabilities and lower consumption of computational resources, which makes them an interesting alternative for the treatment of several problems in scenarios that demand a better management of the use of computational resources.

REFERENCES

1. Kang, M., Chai, K. (2022). Wearable sensing systems for monitoring mental health. Sensors, 22(3), pp. 994. doi: 10.3390/s22030994
2. Hickey, B. A. et al. (2021). Smart devices and wearable technologies to detect and monitor mental health conditions and stress: a systematic review. Sensors, 21(10), pp. 3461. doi: 10.3390/s21103461
3. Long N. et al. (2022). A scoping review on monitoring mental health using smart wearable devices. Mathematical Biosciences and Engineering, 19(8), pp. 7899-7919. doi: 10.3934/mbe.2022369
4. Benchekroun M. et al. (2023). Cross Dataset Analysis for Generalizability of HRV-Based Stress Detection Models. Sensors, 23(4), pp. 1807. doi: 10.3390/s23041807
5. Benchekroun M. et al. (2022). Mmsd: A Multi-modal Dataset for Real-time, Continuous Stress Detection from Physiological Signals. Proceedings of the 15th International Conference on Health Informatics, Lisbon, Portugal, 2022, p. 240-248. doi: 10.5220/0010985400003123
6. Rafie N. et al. (2021). ECG Interpretation: Clinical Relevance, Challenges, and Advances. Hearts, 2(4), pp. 505-513. doi: 10.3390/hearts2040039
7. McEwen B. S., Akil, H. (2020). Revisiting the stress concept: implications for affective disorders. Journal of Neuroscience, 40(1), pp. 12-21. doi: 10.1523/JNEUROSCI.0733-19.2019
8. Falk T. et al. (2020). PASS: a multimodal database of physical activity and stress for mobile passive body/brain-computer interface research. Frontiers in Neuroscience, 14(1), pp. 542934. doi: 10.3389/fnins.2020.542934
9. Birjandtalab J. et al. (2016). A Non-EEG biosignals dataset for assessment and visualization of neurological status. 2016 IEEE International Workshop on Signal Processing Systems (SiPS), Dallas, TX, USA, 2016, pp. 110-114, doi: 10.1109/SiPS.2016.27
10. iMotions. (2023). Electrocardiography (ECG): the complete pocket guide. Available: https://imotions.com/guides/ [Accessed 8th march 2023].
11. Shahsavarani, A. M. et al. (2015). Stress: facts and theories through literature review. International Journal of Medical Reviews, 2(2), pp. 230-241.
12. Becker, D. E. (2006). Fundamentals of Electrocardiography Interpretation. Anesth Prog, 53(2), pp. 53-64. doi: 10.2344/0003-3006(2006)53[53:FOEI]2.0.CO;2
13. Arquilla, K. et al. (2022). Utility of the Full ECG Waveform for Stress Classification. Sensors, 22(18), pp. 7034. doi: 10.3390/s22187034
14. Li, R., Liu, Z. (2020). Stress detection using deep neural networks. BMC Medical Informatics and Decision Making, 20(11), pp. 285. doi: 10.1186/s12911-020-01299-4
15. Wibawa, A. P. et al. (2022). Time-series analysis with smoothed Convolutional Neural Network. Journal of Big Data, 9(44). doi: 10.1186/s40537-022-00599-y
16. Tzevelekakis, K. et al. (2021). Real-Time Stress Level Feedback from Raw Ecg Signals for Personalised, Context-Aware Applications Using Lightweight Convolutional Neural Network Architectures. Sensors, 21(23), pp. 7802. doi: 10.3390/s21237802
17. Goldberger, A. et al. (2017). PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals. PhysioNet, 101(23), pp. e215–e220. doi: 10.13026/C26Q2Z