AStERisk* : Automatic Mental Stress Detection based on Electrocardiogram for Real Time Heart Risk Prediction using 1-D CNN

Alluri L S V Siddhartha Varma [1] **Aakash Agarwal** [1] **Amulya Varshney** [1] **Debanjan Das** [1]

Abstract

Mental health is highly affected by stress. Sometimes mental stress is the primary cause of serious cardiac problems. An electrocardiogram is widely used for monitoring the activity of the heart. The effect of mental stress on the heart is reflected in the ECG, which makes ECG vulnerable information to detect mental stress. This paper suggests an ECG-based Mental Stress Detection system and extending it for heart risk prediction. We used a 1-D convolution neural network model trained and evaluated on the ECG data present in the WESAD data set. The proposed 1-D CNN model achieved an area under the ROC curve of 0.9636. Our work is currently in progress. We are working on a heart risk prediction model and deployment of developed models in IoT devices powered by differential privacy for real-time monitoring and to keep users' medical data private.

1. Introduction

The world is growing at a very high pace. People are running in this world and neglect taking care of their mental health. Mental stress is the most common condition experienced by all kinds of humans. According to a study done in the United Kingdom in 2017 (1), 74% of the whole population reported that they are under stress. According to the report of the American Psychological Association in 2017, every three out of 4 is suffering from at least one of the symptoms of stress, which they mentioned in their report (2). Moreover, the report stated that around 45% of people could not sleep, whereas around 35% of people suffer from anxiety, anger, or fatigue. The scenario is even worse in India, with around 89% of the population suffering from stress-related issues.(3).

Mental stress not only leads to an ailing lifestyle but also has many adverse effects on health (4). A person experiencing mental stress for an extended period is prone to psychological problems like depression, personality disorders, and anxiety. It also leads to hormone-related problems, menstrual problems in women. However, the dangerous and terrible effects of stress are on the Cardiovascular System, causing Myocardial Infarction (heart attack), Increased blood pressure, Arrhythmia, and many other cardiac risks. All of these problems are caused mainly due to the long-term exposure to the stress (5). Small amounts of stress are considered healthy and lead to productivity. Hence there is a need for continuous monitoring to detect long-term stress.

In earlier days, doctors used to detect stress in patients based on questionnaire (6). But with the development of advanced sensors and measurement systems, we can measure many possible features related to stress. According to literature, Mental Stress can be detected based on many stress markers like ECG, Galvanic skin response (GSR), Acceleration, Respiration Activity, Heartbeat, Temperature, etc. But many of these features have their limitations. The values of many signals alter due to nature influence, and physical activity (7). GSR changes with temperature and excessive physical activity. Majorly many of them change with physical activity. Therefore, stress markers must be chosen with utmost care. We mainly focused on the relationship between stress and the cardiac system in this work. Hence we are only using the ECG signal as the stress marker in this study. The detailed biological relation between mental stress and ECG is explained in Section-3 (8)

With the great advent of Deep, Learning (9) (10) (11), many fields, including Image Recognition, Speech Recognition, etc., experienced great changes, and many real-life applications came into existence. One of the techniques in deep learning is 1-D convolutional neural networks (1-D CNN) (14), which does a great deal on time-series data. The performance of 1-D CNN on ECG data is state of the art according to past works (6)(7)(12)(13)(14). In this study, we used 1-D convolution for the detection of stress. A model is trained on ECG data that is present in the WESAD data-set (16). The representation of the proposed framework is shown in Figure-1.

We have created a 1D CNN model for the detection of stress using an ECG, as discussed in the following sections. Our

[1]IIIT Naya Raipur, India. Correspondence to: Alluri L S V Siddhartha Varma <siddhartha18101@iiitnr.edu.in>.

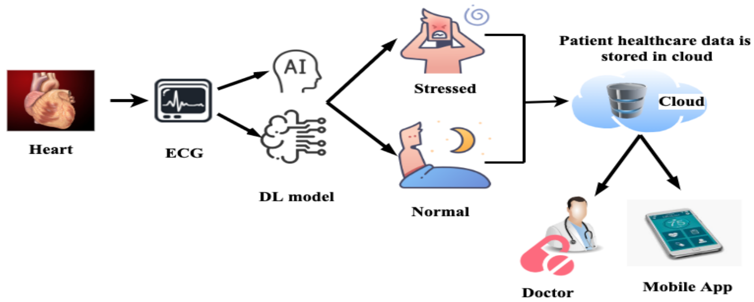

Figure 1. **Overview of the proposed system**

work is still in progress, and we plan to deploy our model on a hardware system to detect stress in real-time and take necessary actions. Also, medical data is sensitive, so to keep the medical data of the user private, we are adding the capabilities of differential privacy to the system. We will discuss more details about the current progress in further sections.

2. Existing Stress Detection Approaches

Various machine learning techniques require features extracted from ECG signals to classify them in many studies [7] [8]. The major drawback with them is the computational cost of hand-engineered features. Cardiologist performance is achieved in [12] using a complex architecture of 1-D CNN for classifying 12 rhythm classes. They achieved a ROC of 0.97 in their work. Hence, substantial evidence in the literature proves that end-to-end deep learning is an efficient way to classify ECG signals.

In recent years, many works have been based on different stress-markers and combinations of different stress-markers [15] [16]. In [19], using a smartphone-based app, they were classifying stress based on acceleration. They achieved an accuracy of 71% on a user-specific model, whereas they achieved an accuracy of 60% on the usage of a standard model. These works clearly show the urge for a more accurate model. In [21], ambulatory and laboratory stress is detected using a 1-D CNN technique on raw ECG signals for applications in real life. They developed a model with an accuracy of 90%. They proved that 1-D CNN is more reliable for real-time applications. In [6], the authors used a combination of 1-D CNN and recurrent neural network (RNN) for the detection. They achieved the highest accuracy of 87.39% on a test case with 13 subjects. Hence it is proved that ECG is an efficient stress-marker, and 1-D CNN is a good technique for the classification of ECG signals. We developed a 1-D CNN model, trained and evaluated using the data from WESAD.

3. Relation between Mental Stress and ECG

Mental stress is a response to the situation in life. In biological terminology, stress can be defined as the disruption of the homeostasis in the body of a human (28). In general, during conditions like the death of loved ones, finance-related problems are the prevalent causes of stress (29). Stress causes emotional, behavioral, and bodily changes (30).

According to the medical literature, (32), in the patients suffering from problems like hypertension, etc., stress biomarkers are present. Mental stress has a direct relation with the Autonomous Nervous System. When a person is under stress, it leads to an imbalance between the Sympathetic and Para-sympathetic branches of the Autonomous Nervous System, which directly affects the human cardiac system, which is reflected in ECG signals.

An electrocardiogram is a signal measuring the electrical activity of the heart. It is represented graphically. Today it is the most common and fundamental tool used in the cardiological sciences. In many cases of Myocardial Infarction, the patient was suffering from chronic stress. This shows that there is a relation existing between the heart and mental stress. The Sympathetic Nervous System, which causes stress, is observed to be persistently active in patients with hypertension. This clearly shows the relation between stress and the heart. ECG is a reliable stress marker since it is the best tool available to monitor the heart's activity.

4. Stress Detecting Model

4.1. Data Set

In this study, we used the WESAD data set (16). It is a publicly available data set addressed for the detection of wearable stress and affect detection; It is a multi-modal data set, containing both physiological and movement data collected from two devices placed at the chest and wrist. The data set contains, electrocardiogram, electrodermal activity, blood volume pulse, respiration, body temperature, electromyogram, and acceleration. It contains three labels, which are neutral, stress, and amusement. The ECG data

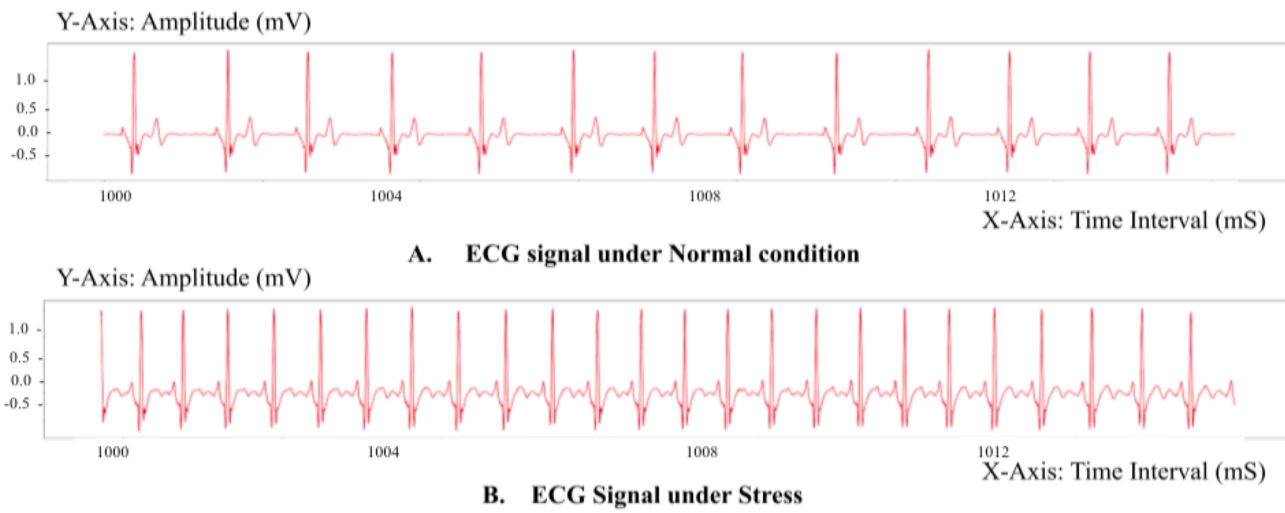

Figure 2. **Samples of stressed and normal ECG signal**

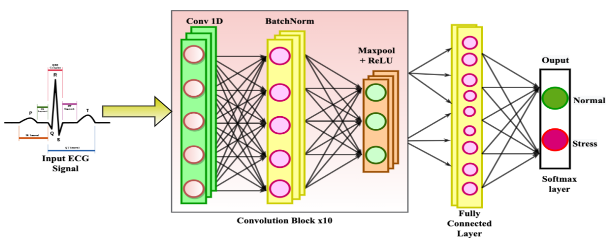

Figure 3. **Proposed Model Architecture for stress detection**

is collected with a special device called RespiBAN at a sampling frequency of 700Hz

Out of all the different modalities provided in the data set, we extracted only the ECG data. The data is provided in pickle format in the data set. The data collected from 15 subjects in laboratory environment. They created different activities and environments for collecting data in the stress, normal, and amusement conditions. In this study, we mainly focused on mental stress. Hence we only considered the data for stress and neutral conditions.

4.2. Data Preparation

The data provided in the data set is corrupted with many artifacts like baseline wander, respiration activity, etc. Hence we cleaned the ECG signal using the Moving Median technique. Both stressed and standard signals of the same subject are shown in figure-3. Difference between the rhythms can be observed.

The data is given in the data set as a whole for each subject for the purpose of training the model. We experimented with different lengths of signals. And, finally, we segmented the data and produced signals, each with a duration of 7.14 seconds. After generating the completed data set, it is split into training and testing sets. The training set contains 1000 signals, and the testing set contains 440 signals. Signals are randomly shuffled to ensure better performance.

4.3. Model Architecture

The architecture used in this work is built based on the convolution block 1-D Convolution layer followed by Max pooling, Batch Normalization, and Activation function. The convolution block is followed by fully connected dense layers and drop-out layers. The convolution block is repeated ten times with increasing no. of channels and decreasing filter size. The basic block of architecture is shown in the figure.

The model is built using the PyTorch Framework. The model is trained using the following parameters:

Loss Function: Binary Cross Entropy Loss

Optimizer: Adam's optimizer

Learning Rate: 0.0001

No. of Epochs: 35

5. Results

The proposed model is evaluated on the test set generated. We evaluated different metrics like Accuracy, Precision, Recall, F1-score. Furthermore, we evaluated the confusion matrix and the Area under the ROC curve. The evaluated metrics are tabulated in Table-2

Table 1. **Comparison with Existing works**

Paper	**Stress Marker**	**Method**	**Accuracy**
Wijsman, Jacqueline, et al. (22)	ECG, EMG, GSR	Machine Learning	80%
Garcia-Ceja et al.(25)	Acceleration	Machine Learning	60%
Zenonos, Alexandros, et al. (26)	Physiological features	Machine Learning	70.6%
Rachakonda, Laavanya, et al. (15)	Temperature, Acceleration and Humidity	Deep Neural Network	99.7%
Hwang, Bosun, et al. (6)	ECG	1-D CNN	87.39%
Sun, Feng-Tso, et al. (7)	ECG, GSR and Acceleration	Decision Tree	92.4%
Cho, Hyun-Myung, et al.(27)	ECG	1-D CNN	90%
Present Work	ECG	1-D CNN	96%

The model has achieved a performance, where Area under the ROC curve is 0.9636, and the metrics evaluated in Table-2 prove the fact that the model is performing well. For a better understanding of performance, the confusion matrix is provided in Table-3. Here, 0 refers to normal condition, and 1 refers to the stressed condition.

We compared the performance of various methods involving different stress markers in Table-1. Our current work has shown improvement over some previous works. It is a piece of clear evidence for the advantages of end-to-end deep learning.

6. Conclusion and Future works

We mainly addressed the adverse effects caused by mental stress and proposed a solution for the detection of mental stress. Preventing stress in the long term is the main goal that can be achieved through the proposed model. Additionally, with the help of 1-D convolution neural networks, which do not require much signal processing or hand-engineered features for classification, a robust, less time-complex classifier can be implemented in real-time devices for continuous monitoring of mental stress. The proposed model performs classification with an accuracy of 96%, specificity of 99%, and sensitivity of 93%.

The ECG-based stress detector model can be developed further to predict heart diseases caused due to stress like heart attacks, arrhythmia, high BP, etc. With the help of this, any person can get treatment earlier or get help in some other way if he/ she can analyze their condition before sudden outbursts of heart disease. This helps to save many lives from being victims of heart diseases. In our upcoming part of this work, we will implement the current model in hardware to detect and monitor the stress in real-time along with heart risk prediction. Using, Internet of Things (IoT), a cloud-based user application will be developed in which each person can verify their stress levels, which at the same time can be helped as a good source for a physician to analyze patient condition based on his history of stress levels without having any effect to the privacy.

Table 2. **Performance of the Model**

Metric	**Performance**
Accuracy	0.963
Precision	0.99
Recall	0.93
F-1 Score	0.962

Table 3. **Confusion matrix**

ID	0	1
0	**218**	2
1	14	**206**

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