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Deep Learning Techniques for Stress Detection

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Abstract

The Convolutional neural network (CNN) approach is utilised to recognise stress in this paper. Biosignals in the body of the person are used to identify stress in this case. Physionet's ("drivedb") database was used to create this model (www. Physionet.org). In today's world, stress is a major factor in the development of a wide range of disorders. In this case, stress may be recognised by analysing the body's biosignatures. Bio signals include EDA, sequential minimum optimization (SMO), heart rate visibility (HRV), galvanic skin reaction, and so on. Generally, we use these bio signals. QT and RR intervals may be extracted from the ECG database. Improved performance is achieved by using CNN, which uses biosignals to classify stress in the input data.

Keywords: An electroencephalogram (EEG), a galvanic skin response (GSR), a pulse of blood volume (BVP), etc.

INTRODUCTION

The importance of stress management systems in identifying the levels of stress that threaten our socioeconomic well-being cannot be overstated. Currently, Anxiety is brought on by too much work and family issues, as well as by the environment we live in as a whole. To help those who are dealing with stress, this anxiety psychotherapy will be offered. Stress cannot be avoided, but defensive actions may help alleviate it. A person's level of depression (stress) is now only determined by medical and physiological experts [1, 2 3]. Stress plays a role in some suicides. Depression, on the other hand, affects certain individuals. The risk of health problems and the improvement of safety are reduced by the automatic detection of stress. We'll be able to pinpoint the source of the problem thanks to the questionnaire approach. To determine whether a person is stressed or normal, this method relies on how tense they seem while answering the question. For example, a gadget that utilises physiological signals to recognise stress levels in people will be necessary.

As a significant social engagement that improves people's way of life, stress detection is studied in several literatures. Analysis of stress is done by analysing Respiratory, Heart rate, face EMG, Galvanic skin response (GSR) foot, and GSR hand data, with a conclusion that elements linked to respiration progression are significant in stress identification. This explains how to forecast mental stress using simply a GSR as a physiological sensor connected to a solo piece of stress detecting gear. Electrocardiogram (ECG) data will be used to determine stress levels in a new research (ECG).

The dependability of a multimodal system is examined using experimental data to quantify the level of stress felt by workers. Control information from sensors such as temperature distribution, HR, blood volume pulse (BVP), and electro dermal activity (EDA) may be accessed via this (EDA). A motion tracking device is often used to assess facial expressions in conjunction with stress variables such as word check memory tasks and pick-up-related data. Using a number of non-destructive sensors, the researchers capture bio-signals including ECG, GSR, Electroencephalography (EEG), EMG, and Peripheral Oxygen Saturation (POS) (SpO2). GSR, EMG, heart rate, and skin temperature are all used to derive constant stress levels from many sensors. Several pattern detection algorithms are capable of automatically recognising stress. Sensor data is compared to a stress index, which serves as a threshold for determining the amount of stress in the system. A Bayesian Network, Sequential Minimal Optimization (SMO) method was used to assess the data from 16 participants under four stressor situations. It has been utilised to manage stress rates by predicting the heart rate, GSR, blood pressure, and variance frequency domain characteristics (HRV), as well as ECG strength differential qualities.

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The most commonly utilised physiological signals, such as ECG, EMG, GSR, BVP, etc., are derived from these properties. Anxiety levels may be determined by calculating these using suitable sensors that pick up particular aspects and organise them into clusters. Because of this, the results of minor clusters are more stable in stress recognition when utilising the General Regression Neural Network (GRNN). It is necessary to take into account elements of the cardiac signal in the frequency domain such as LF/HF (the ratio of the LF/HF) and time domain features such as the mean, median, and standard deviation of the heart signal in order to detect stress in real time. Stress detection relies heavily on physiological sensor data. The ECG, on the other hand, is a primary tool for detecting both long-term and short-term stress. A person's heart rate (variability) may be inferred from their electrocardiogram (ECG) and used to quantify their cardiac electrical activity. When a person is in pain, GSR measures the skin's varied degrees of excitement. Sweating is released swiftly by the neurological system in response to stress. Fingers are used as resistance terminals for GSR electrodes, which are positioned beneath the fingertips.

RELATED WORK

The diagram below is indicative of the current system.

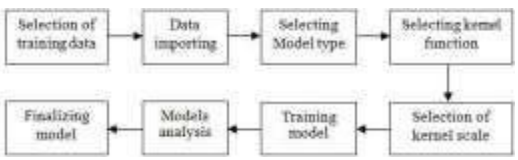


Fig 1: Block diagram for existing method.

Stress has been detected using Supervised Machine Learning. A number of ECG parameters have been shown to be useful in stress detection, including the QT, RR, and ECG-derived respiration intervals [5]. The model will determine whether or not the theme is strained or relaxed by studying them. We used a support vector machine (SVM) for the classification and stress analysis since our data had precisely two class labels (stressed and not stressed or relaxed).

Continuous and discrete datasets may be utilised with the Support Vector Machine (SVM). As a result of the Classification Technique, the majority of this information may be found in separate data sets There are n characteristics to plot on an n-dimensional plane with this approach. The hyper plane that divides the two groups is then used to put classification into action. SVMs of three kinds (Linear, Quadratic and Cubic) were trained using the default kernel functions and a cross validation technique was selected as the holdout validation with a degree of 50% in Classification Learner App. ECG Derived Respiration (EDR) was employed in addition to QT and RR intervals. The exact model may be determined by evaluating the scatter plots, confusion matrix, and ROC curves. Table 1 reports on the model precision for various SVM types. The model may be fine-tuned further to get more accurate results.

TABLE 1

MODEL ACCURACY FOR DIFFERENT TYPES OF SVM MODEL USING ALL THE FEATURES AND THE DEFAULT KERNEL FUNCTION INMATLAB.

Model name	Features used	Accuracy
Linear SVM	QT interval, RR interval, EDR	52.6%
Quadratic SVM		88.6%
Cubic SVM		97.2%

As a means of determining whether or not stress can be correctly detected, the model was first trained with just one feature. Table 2 shows that using just one attribute has a considerable impact on the model's accuracy. Training the model with only two features from "Feature Selection" option of Classification Learner results in a lower model accuracy than when training the model using all three features.

TABLE 2

MODEL ACCURACY BY USING ONLY ONE FEATURE.

Model name	QT interval	RR interval	EDR
Linear SVM	50.5%	61.3%	48.6%
Quadratic SVM	30.6%	40.8%	48.7%
Cubic SVM	61.5%	54.5%	49%

Nearly 95% of the time, the combination of the QT and RR intervals proved to be accurate. Other models that tried to use a mixture of two characteristics but failed to provide the same level of accuracy (Table 3). Stress detection approaches based on model-based models have often employed just one characteristic, such as the RR interval, to identify stress in the literature. Biomedical applications, on the other hand, are not satisfied with their performance (i.e. Accuracy level less than 95 percent). As a result, we trained the model using QT, RR, and ECG Derived Respiration (EDR) intervals independently in this research and analysed the evidence. Because EDR (ECG Derived Respiration) has comparable qualities and has been used effectively in many prior research, we have chosen it as an alternative to respiration signal for our study. In order to capture the respiration signal, no external sensors were utilised at all. It is to the best of our knowledge that no previous learning has used ECG-derived respiratory and QT interval information in stress identification using machine learning approaches.

TABLE 3

MODEL ACCURACY BY USING COMBINATION OF TWO FEATURES USED FOR MODELLING.

Model name	QT, RR	QT, EDR	RR, EDR
Linear SVM	50.6%	52.6%	61.5%
Quadratic SVM	83.5%	86.3%	51.2%
Cubic SVM	94.9%	89.2%	53.1%

Additionally, the model's "Kernel Function" may be tweaked to enhance performance. We used a variety of kernel functions to fine-tune the models. The results of linear and quadratic kernel functions were disappointing. Table 4 shows that only the Gaussian and Cubic kernel function types are capable of identifying stress using all three ECG characteristics.

TABLE 4

MODEL PERFORMANCE BY CHANGING KERNEL FUNCTIONS MODEL TYPE KERNEL FUNCTION ACCURACY

Model type	Kernel function	Accuracy
Linear SVM	Gaussian	98.6%
	Cubic	97.2%
Quadratic SVM	Gaussian	98.6%
	Cubic	97.1%
Cubic SVM	Gaussian	98.6%
	Cubic	97.2%

I. METHODOLOGY

The approach suggested explains stress detection through the use of convolutionary neural networks (CNN). The following displays the block diagram for the process suggested.

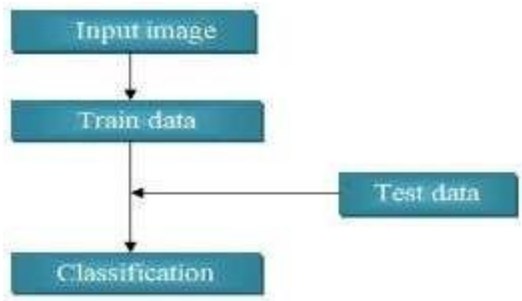


Fig 1: Block diagram of proposed method

There were some healthy participants' normal and stressed ECG data gathered for training the model in the Stress Recognition in Automobile Drivers database ("drivedb") at Physionet (www. Physionet.org). Physiological signals from healthy participants were used to identify stress caused by driving in high traffic conditions in this database.

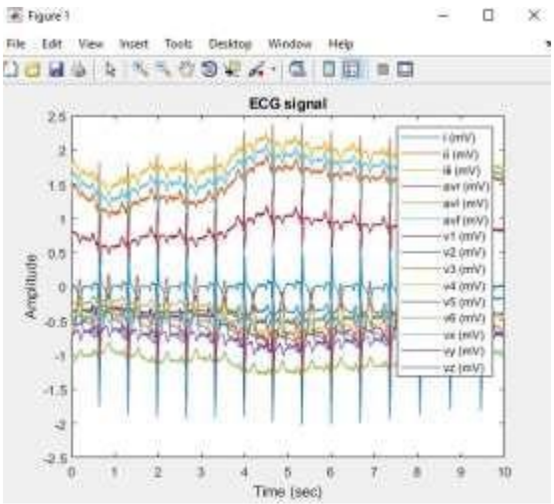
The convolutional neural network is a popular approach in deep learning. Computers use CNN to learn to classify photos, videos, audio, and text; it's a sort of machine learning. Automatic attribute extraction is no longer required, as it was in previous versions of CNN. It is CNN's personal goal to provide the most up-to-date recognition assessments possible. By retraining CNNs to do new reconnaissance tasks, you may build on existing networks of CNNs already in use.

Hundreds of layers in a convolutinal neural network may let it discern between different aspects of a picture. In each training database, sensors are added in various configurations, and the resolution of each processed picture is altered as a result.

Data from this layer is sent into the next. To enhance an object's uniqueness and uniqueness of characteristics by adding a level of nuance and complexity, filters may be as modest as brightness and edges.

A CNN has an input layer, an output layer, and a number of hidden layers in between. The objective of these layers is to learn information-specific properties by modifying data. The three primary layers are convolution, activation or reLU, and pooling. Use domain-specific learning features to transform data in these levels. The most popular layers are convolution, activation or reLU, and pooling.
Using a succession of convolutionary filters, the convolutional layer places the input pictures, each of which enables particular visual attributes. Faster and better learning may be achieved by converting negative values into zero while maintaining positive values in the rectified linear unit layer (ReLU). Because only the deactivated features are passed to the next layer, it is sometimes referred to as activation. The non-linear down sampling of the pooling layer improves the network's performance and reduces the number of variables that the network must learn.

This is performed across several levels, with each layer becoming better at identifying certain traits. Many layers of feature analysis precede the switch to grouping in a CNN. K-dimensional vectors are produced by the next to last completely linked layer, which is capable of simulating any number of classes. In this procedure, each degree of the picture is graded based on its probability. Uses such a layer as softmax to provide classifier output in final layer of Classification model



RESULTS AND DISCUSSION

Fig 3: Input ECG Signal

The above figure 3 is the graphical representation of input ECG signal. These input ECG signals is collected from the dataset and in the form of ".mat". The graph is plotted between amplitude & time in seconds and shows various forms of millivolts per Volt which is marked as in the form of coloured legends.

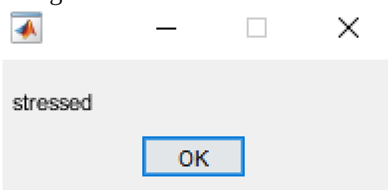


Fig 4: Output Dialog box

Input ECG signal is fed to neural network and output is classified as Stressed/Non-stressed with the help of trained dataset. Figure 4 classified the output as „stressed".

TABLE 5
COMPARISON TABLE

Parameters	Existing method	Proposed method
Accuracy	74 %	86%
F measure	83.92 %	95.96 %

When constructing a classification problem model, it is nearly always preferable to consider the model's accuracy in terms of the total number of accurate predictions. Our model performs better when it is more accurate. The pre-existing works yield 74% accuracy, whereas our suggested model gives 86%.

It is defined as the weighted harmonic mean of the precision and recall of a test and is known as the F1 score or F score. The higher the F-measure, the better the model. Nearly 84 percent of the F-measure is provided by the current model, whereas the suggested model provides 96 percent.

CONCLUSION

Convolutional neural networks were shown to be used by the algorithm created to detect stress. On addition, there's no need to hunt for features in this network since CNN already has them in its database. After evaluating features in several layers, the architecture of a CNN goes on to classification. These make it simple to identify stress, and the findings are more accurate and precise.

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