Developing A System For Detecting Of Tension And Anxiety Levels Through Cardiac Signal Rhythm Analysis

Mr. Bhagavath Singh Asso. Prof, Dept of ISE

Kavya Pai 1RN20IS074 Rajvir Singh 1RN20IS116 Shreshta M 1RN20IS151 Shresth S 1RN20IS152

Abstract:

Recent research in affective computing, intersecting computer science, psychology, and cognitive science, focuses on detecting negative emotional states like stress and worry using body-worn sensors. These studies apply machine learning classifiers to features extracted from physiological signals such as heart rate, cutaneous conductance, and body temperature. Despite achieving high accuracy in various studies, the real-world applicability of these models needs further exploration. Leveraging publicly available data from extensive experimental studies, this work aims to evaluate the generalizability of these models in detecting stress and anxiety through cardiac signals. It provides an overview of emotional computing, outlines key theoretical concepts, describes state-of- the-art advancements in emotion recognition, and draws conclusions and future directions for developing innovative machine learning algorithms tailored to physiological signals used in emotion detection.

Literature Survey:

A project report's literature survey or review, which takes into consideration the many project elements and the project's scope, highlights the many studies and research projects conducted in the area of interest as well as the results already published. The primary purpose of a literature review is to examine the project's past, which aids in identifying the system's flaws and provides guidance on which outstanding problems should be remedied. Therefore, in addition to providing a history of the project, the following subjects also highlight its shortcomings and issues, which provided motivation for the development of its remedies.

In The Early Developments in Stress and Anxiety Detection: Initial research focused on identifying physiological markers associated with stress and anxiety, such as heart rate variability (HRV), skin conductance levels (SCL), and cortisol levels. Studies like Thayer et al. (2012) emphasized the role of HRV in detecting stress, laying the groundwork for future machine learning applications.

Machine Learning in Physiological Data Analysis: Advancements in machine learning led to more sophisticated analyses of physiological data. Researchers began to use algorithms like Support Vector Machines (SVM) and Neural Networks to classify stress and anxiety states. A notable study by Healey and Picard (2005) demonstrated the effectiveness of SVM in differentiating between stress and relaxed states using physiological data. For instance, wearable devices such as "Garmin" and "Samsung Galaxy Watch" employ AI algorithms to analyze HRV, detecting stress patterns and providing users with insights. They offer remote monitoring and guidance for stress reduction techniques. the limitations seen in certain systems, these wearables for sale could depend on ongoing connectivity and device compatibility, which would impact their use and ability to monitor continuously.

Applications for cardiac signal-based AI/ML-driven stress detection systems are found in a variety of fields. These techniques allow for the early diagnosis of stress in the hospital setting, facilitatingtailored therapy.

The pivotal role of emotions in human behaviour extends to influencing vital mechanisms like perception, attention and learning. Therefore, comprehending emotional states becomes fundamental in understanding human behaviour, cognition, and intelligence (2019). Within the realm of affective computing, various applications emerge across diverse domains. For instance, in the context of automated driver assistance, the system tailors recommendations based on users' preferences and pre-established emotional responses (2019). Studies such as Smets et al. (2018) highlighted the difficulty in generalizing models due to individual physiological differences

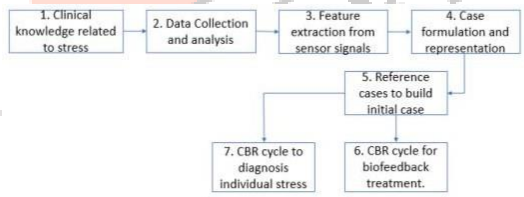
1. Introduction

This paper delves into the realm of emotion recognition through machine learning, with a specific focus on identifying stress and anxiety. The field has seen a surge in interest since the early 2000s, with numerous studies leveraging artificial intelligence to discern human emotions from a variety of data sources. While progress has been made in classifying emotions as positive or negative, the application of these findings in real-world, uncontrolled environments remains a relatively unexplored area, especially for detecting negative emotions.

The core of this research is to test the adaptability and accuracy of these emotion recognition models beyond the confines of the laboratory. It primarily uses data from blood volume pulse (BVP) and electrocardiogram (ECG) to determine the presence of stress and anxiety. Traditional research settings often require strict compliance with experimental protocols, which may not be feasible in less controlled, everyday environments. This study aims to understand if these models, successful in lab settings, can also provide reliable results in more dynamic and unstructured scenarios like a person's home, where conditions are not as rigid and participants are not continuously monitored.

In essence, this study seeks to bridge the gap between laboratory accuracy and practical application in everyday life, examining whether tools designed for emotional detection in controlled settings can be effectively translated to casual, everyday use.

2. System Overview :



Here we follow these steps :

1. Clinical knowledge related to stress:Inorder to work on this topic, it is

important for us to have the knowledge about stress.

2. Data collection and its analysis: Once the data is collected , the datais further analysed .
3. Feature extraction from sensor signals: To assess stress and anxiety levels, extract features from cardiac sensor outputs such as statistical measures (mean, median), time- domain descriptors (heart rate, RR intervals), and frequency-domain characteristics (power spectraldensity).
4. Case Formulation and representation : Create a case formulation and representation technique that integrates critical data retrieved from sensor signals to identify stress and anxiety levels using cardiac signal rhythm analysis. This entails developing an organized framework that takes into account the correlation between recognized characteristics and affective states, improving the system's precision in assessing stress and anxiety based on cardiac signals.
5. Reference cases to build initial cases : Make reference to past research or situations where the detection of tension and anxiety was accomplished through the use of cardiac signal rhythm analysis. With the help of these reference examples, establish a framework for the first model development, learning about feature selection, algorithm design, and technique related to the detection of tension and anxiety levels.
6. CBR cycle to determine individual stress: Employ a Case-Based Reasoning (CBR) cycle to assess and stress levels in real-time through the monitoring of cardiac signal rhythms for the detection of tension and anxiety.
7. CBR cycle for biofeedback treatment: Apply cycle in biofeedback therapy to measure anxiety and tension levels by analysing cardiac signal rhythms. Make use of the cycle to continually modify and improve interventions based on prior experiences, offering individualized and successful tactics for people who are tense or anxious.

3. System Study :

Machine Learning Models for Developing a System for Detecting of Tension and Anxiety Levels through Cardiac Signal Rhythm Analysis This part offers the fundamental theoretical foundation for the ideas required to create cutting-edge emotion recognition algorithms. We begin by outlining the idea of emotion.

A)EMOTIONS

Determining what an emotion is should be the first step towards recognizing it. Emotions: People from various fields, including computer science, philosophy, neuroscience, and phenomenology, have attempted to address this inquiry and establish a common understanding of emotion. There isn't a single, generally accepted definition, though, due to disagreement. Understanding emotion is crucial in machine learning since it's essential to define the success conditions that need to be met. Two models suggest that a typical strategy to lessen this issue is to not be emotional .

B. ANALOGICAL INDIVIDUALS

As we know, there are observable physiological reactions of the ANS to emotional states. Physiological sensors that are worn on the body, including as the ECG, EEG, EDA, and BVP, which are briefly discussed below, can read these responses.

(A) Electrocardiography (ECG): this is a numerical recording of the possible variations that are sent to the skin's surface as a result of the heart's electrical activity (which results from the cardiac muscle's contraction and relaxation in response to electrical stimulation). Three primary factors determine the heart's rate of contraction and relaxation:

(B) Galvanic skin Response (GSR): measures the skin's resistance by applying a small amount of voltageor current.

(C) Blood Volume Pulse (BVP) : a photodiode detects the quantity of light that a skin voxel scatters back. The quantity of light that returns or goes through the other to a BVP sensor is therefore proportionate to the tissue's blood volume in a BVP signal.As a result, the pulse local maximum can be used to detect heartbeats by measuring blood flow;this allows for the determination of the HR by showing each cardiaccycle.

(D) Respiration (RESP): this technique measures a subject's respiration pattern, how quickly and deeply they are breathing, and is typically applied as a chest belt around the abdomen. To identify the emotion, a high level of arousal, such as that ofwrath, fear, or joy, can be indicated by a respiration rate that is rapid and deep. Quick shallow breathing may be a sign of nervous anticipation. A relaxed resting state is indicated by slow, deep breathing.

C. DATASETS

There are numerous publicly accessible datasets that use physiological markers to identify emotions in movies. These make it possible to benchmark emotion identification algorithms, which makes it easier to compare the outcomes of various approaches directly:

(a) DEAP: has data from 32 volunteers who watched 40 one-minute music videos. It captured frontal face videos of 22 of the individuals. Following each movie, the volunteers self-annotated the dataset with regard to dominance, like-dislike, familiarity, and arousal valence.

(b) MAHNOB-HCI :this dataset includes audio, eye gaze, ECG, EEG, SKT, and GSR data in addition to facial video recordings from 30 participants who saw 20-lm clips ranging in duration from 35 to 117 seconds.

(c) ASCERTAIN:58 volunteers watched 36 movie clips ranging in length from 51 to 127 seconds while EEG, ECG, GSR, and video face activity data were collected. Every video clip had self-annotations in the form of evaluations for engagement, liking,arousal, and familiarity.

(d) Eight-Emotion : this set of data includes one subject's BVP, EMG, and EDA information, evoking eight different states: neutral, anger, hate, grief, love, passionate love, joy, and reverence.

(f) AMIGOS: includes depth and full-body movies, as well as EEG, ECG, and GSR data from 37 people watching four long videos and 40 individuals watching 16 short videos. Self-assessment of affective levels (valence-arousal, 141000 control, familiarity, like-dislike, and selection of basic emotions) as well as external evaluation of participants' valence levels were used to annotate the dataset. In addition, the participants were requested to fill out forms with Personality Traits and PANAS questionnaires in order to explore how the participants' feelings related to their personality and mood.

(g) DECAF: This resource includes near-infrared (NIR) facial films, peripheral physiological responses , sensor data, and information on 30 participants' emotional reactions to 40 one-minute music video segments and 36 movie clips.

METHODS :

A. PRE-PROCESSING SIGNALS

Numerous things could go wrong during the data acquisition protocol that would lead to noise and external interference degrading the sensor signal, such as subject movement, electrodes disconnecting, changes in humidity and temperature outside the subject's body, electrostatic artifacts, and other unrelated user movements.

B. REPRESENTATION OF DATA

There are two distinct approaches that can be used to identify emotional states: Deep learning approaches are an example of a feature-independent machine learning technique.

C. CLASSIFICATION OF DATA

There are three categories of traditional model-based machine learning methodologies: semi-supervised, unsupervised, and supervised. A model is built from a training set in supervised learning (SL) that associates the properties of the physiological signal with its labels.

D. ACCREDITATION

The final step in an ML framework is the validation of the model in order to obtain an overall view of how the model will perform on never-before-seen data, outside of laboratory constraints. The model must be able to generalize into new unseen data and avoid over-training on the training set data. This is achieved once the classifier has beendesigned and trained

4. Conclusion

a. Experimental Design: Whether in a lab setting with restrictions or in an unrestricted daily environment, the experimental setup for eliciting emotions can be designed to be both really generated or obtained.

b. Verify Signal Quality Before Data Collection: It makes sense to verify the data's quality before obtaining any information. According to this study, ensuring the quality of the data prior to collection can improve the performance of these systems in various scenarios.

c. Application in Multiconditional Settings: Recognizing the significance of real-world applicability, the study promotes expanding applications and methods from fixed-experiment circumstances to extensively used, multiconditional settings.

d. Experiment with Different Approaches to Develop Emotion Programs: A variety of computer approaches can be used to develop emotion-reading programs that function well under a variety of conditions. For instance, analyzing emotion trends may aid in the development of more efficient and effective online emotion-reading software.

References :

- https://medium.com/@Sammyst_The_Analyst/machine-learning-project-on-stress-detection-214e526aeb83
- https://www.youtube.com/watch?v=NUZ1_LKUM7E&ab_channel=AISciences
- https://www.sciencedirect.com/science/article/pii/S2667096822000532
- https://www.researchgate.net/publication/362928201_How_can_machine_learning_be_used_in_stress_management_A_systematic_literature_review_of_applications_in_workplaces_and_education