Machine Learning Model for Stress and Anxiety Recognition Using Heart Activity Signals.

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Abstract - Numerous recent studies have focused on using physiological signals from body-worn sensors to detect negative emotional states like stress and worry. Many authors have achieved good accuracy findings using a variety of signals, such as cardiac, skin conductance, and skin temperature. Machine learning classifiers are typically used to features acquired from sensor data. However, it is rarely discussed how reliable these models are for field implementation. In this work, we assess the generalizability of models built from cardiac signals with an emphasis on stress and anxiety detection using publicly available data from two extensive experimental studies. Our findings also highlight how crucial it is to incorporate a variety of emotional states within the training set in order to reduce incorrect classification from hidden areas.

Key Words: Emotion recognition, generalizability, machine learning, physiological signals.

1. INTRODUCTION

The scientific community has become more interested in machine learning for emotion recognition since the early 2000s. Cowie presented their research on the application of emotion recognition in human-centered computing, describing the possibility of using artificial intelligence to recognize emotions from a variety of input sources. Machine learning methods that distinguish between positive and negative valence have been developed since 2001 through a number of studies. An axis of emotion in a circumplex model of affect is described by valence in connection to emotion. To illustrate emotions in relation to state, the scale plots emotions against arousal. Although significant advancements in positive and negative valence classification accuracy have been made, no study has been done on the generalizability of machine learning models for negative valence, such as stress and anxiety. The relevant machine learning models' generalizability increases impact and broadens the range of possible applications. Take into consideration the application of such machine learning algorithms in game-based solutions, where participants are required to adhere to stringent laboratory settings or remain motionless throughout data gathering. The generalizability of machine learning models for emotion recognition with physiological signal data and rigid experiment procedures is examined in this article. Specifically, blood volume pulse (BVP) and electrocardiogram (ECG) data are used to predict negative affect from various open emotion recognition datasets.
In this article, "rigid" experiments are defined as ones where participants must adhere to the data collection protocols. certain guidelines that, without prior supervision or training, are unlikely to be repeated outside of the experimental context. specifically utilizing electrocardiogram (ECG) and blood volume pulse (BVP) data to predict negative affect from various open emotion recognition datasets. In this article, "rigid" experiments are defined as those where participants must adhere to particular guidelines as part of the data collecting methods, which are unlikely to be repeated outside of the experimental context without previous supervision or training. For instance, must maintain a steady hand, refrain from sitting or standing, or concentrate on a particular visual signal throughout the trial. The generalizability of the rigidity of the experimental circumstances in this context raises concerns about the reproducibility of the accuracy claimed in the literature in nonrigid contexts, including employing these models in applications where users can participate from home. The following contributions are presented in this article.
1) To assess the generalizability of new machine learning models outside of their original experimental environment, we present a unique methodology based on testing plausible hypotheses using publicly available datasets.
2) Using publicly available datasets collected in various laboratory settings, we assess the generalizability of data generated from BVP and ECG, with an emphasis on prediction accuracy.
3) We demonstrate that high-quality data is necessary for the generalizability between cardiac signal sensor modalities (BVP and ECG), and that models will train on proxies inside the noise for lower quality data. In the area of generalizability, we find no significant increase in classification between the deep learning and machine learning techniques.

2. METHODOLGY

2.1 System Architecture

The Edge Sensing Layer and the Backend Analytics Layer are the two main layers of the suggested system design, as shown in Fig. 1. The ESP32 microcontroller is interfaced with several physiological sensors at the edge layer, such as the GSR sweat sensor, heartbeat sensor, temperature sensor, and SpO_2 sensor. The local data processing and transmission unit is the ESP32. After obtaining raw analog inputs from the sensors and performing preliminary signal processing and feature extraction, it shows the real-time values on the wearable LCD module. After being preprocessed, the sensor data is packetized and sent wirelessly to the cloud-based data ingestion service, like ThingSpeak IoT channels, over the onboard Wi-Fi interface.

Through a REST API, the incoming physiological data streams are received by the Backend Analytics Layer. To guarantee consistency and reduce noise, the data is further refined and normalized by a preprocessing module. The Stress and Anxiety Prediction Model, which is implemented as a cloud-based machine learning classification service, receives the processed data. To identify the user's current mental state category—normal, mild stress, or high stress—the model makes use of stored feature vectors, historical data, and training parameters from the model registry. This classifier's output is shown on a web dashboard so that medical experts or end users can view it remotely. Because of the smooth integration between edge-level real-time sensing and cloud-level intelligent analysis made possible by this layered architecture, precise and continuous mental health monitoring

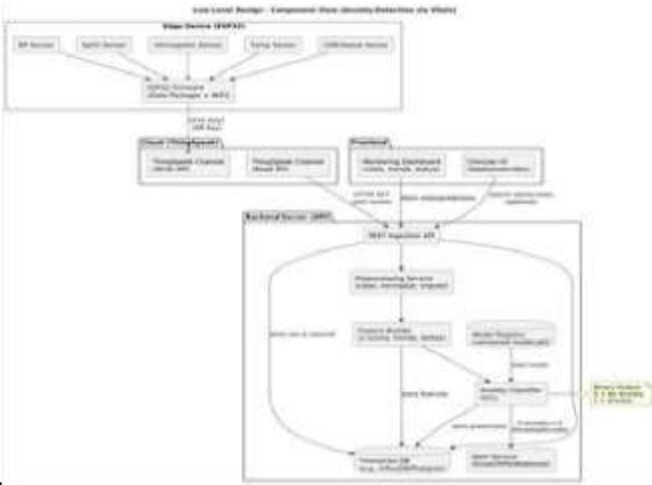
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Fig. 1 System Architecture

2.2 Hardware Implementation

Physiological data is gathered by sensors. Those signals are read by Arduino. Values are shown on the LCD by Arduino. For remote monitoring, the WiFi module transmits data to an app or cloud platform. As seen in Fig. 2, the system can use sensors like heartbeat, temperature, and GSR in conjunction with Arduino to monitor a person's health condition in real time if data surpass a certain threshold. In addition to being transferred to the cloud via a WiFi module for remote monitoring, the gathered data is shown on an LCD screen. It aids in the ongoing monitoring of vital signs and may be helpful in identifying fever, tension, or an irregular heartbeat. This makes it appropriate for applications such as emergency health alerts, fitness tracking, and patient care.

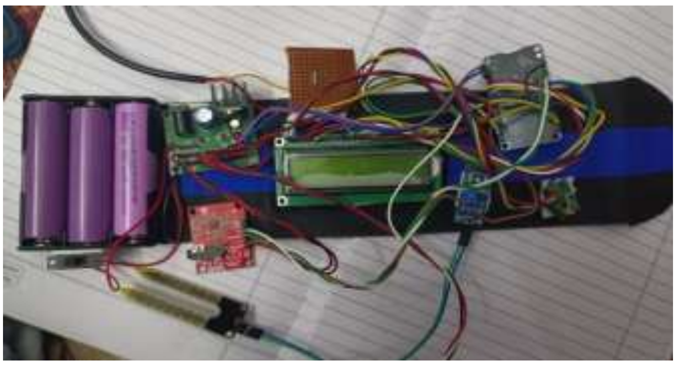

Fig. 2 Hardware Implementation

2.3 Working Module

A wearable health monitoring system that uses Arduino to measure the user's vital signs in real time. The wearable strap is equipped with a heartbeat sensor and GSR sensor to continuously measure skin conductance and pulse rate, which aids in stress detection. In Fig. 3, a temperature sensor takes the body's temperature and transmits the data to the Arduino for processing. The user may examine their condition right away thanks to the LCD display, which displays real-time health data. Additionally, a Wi-Fi module that may transmit the gathered sensor readings to a mobile application or web server for remote monitoring is included. Rechargeable Li-ion batteries power the entire arrangement, and a voltage regulator circuit ensures a steady power supply. This wearable technology is easy to use,portable, and useful for continuous health tracking and early detection of abnormal health conditions.

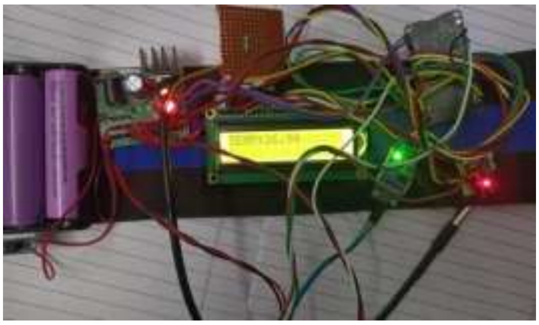

Fig. 3 Working Module

2.4 Monitoring System

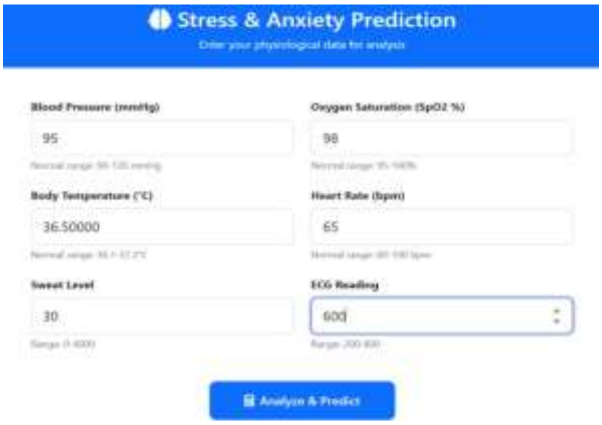

Fig. 4 Monitoring System

An interface called Stress and Anxiety Prediction was created to assess a person's emotional and physiological conditions. Users can view health metrics including blood pressure, oxygen saturation (SpO_2), body temperature, heart rate, sweat level, and ECG readings, all of which are directly related to the human body's reaction to stress. The data is processed through a trained prediction model using the "Analyze & Predict" button after the numbers are entered, as illustrated in Fig. 4. The system determines whether the user is in a relaxed, normal, or stressed state based on the input values. Students, patients under observation, and those who wish to keep an eye on their mental health can all benefit from this interface's simplicity, interactivity, and ease of use. Such tools are especially useful in early detection of stress-related health issues and support timely medical guidance or lifestyle adjustments

2.5 Key Components

2.5.1 Sensors and Hardware

The system continuously monitors physiological parameters using a heartbeat sensor, temperature sensor, GSR sweat sensor, and SpO_2 sensor. An ESP32/Arduino microcontroller, which manages signal acquisition and preliminary processing, interfaces with these sensors. The real-time readings are shown on a small LCD module, and portability is guaranteed by a rechargeable battery. As seen in Fig. 2, the hardware configuration permits continuous, real-time measurement.

2.5.2 Software and Algorithms

The microcontroller used for device control and data sampling is the ESP32. Wi-Fi is used to send the processed values to a cloud platform. Python-based machine learning algorithms classify stress levels on the backend by analyzing the received parameters. Preprocessing and prediction are supported by libraries like NumPy and Scikit-learn, which increase the precision of stress detection.

2.5.3 Data Processing

After being normalized at the device level, sensor data is wirelessly transferred to the server for additional classification. This guarantees constant synchronization between the wearable system and the analytical interface, allowing for timely notifications and real-time monitoring, as covered in fig .4.

2.6 Advantages

With little manual labor, the technology provides real-time stress and health monitoring. It promotes preventative healthcare and makes it possible to identify abnormal physiological patterns early. The system is scalable, energy-efficient, and appropriate for clinical and personal monitoring applications due to its modular design.

CONCLUSIONS

The suggested approach effectively offers an effective method for early stress detection and permits continuous monitoring of important physiological indicators. The system provides real-time insights into the user's health condition with little manual intervention by combining biomedical sensors with a microcontroller and using machine learning-based analysis. The system's cloud-based processing and wireless data transfer improve accessibility and make it appropriate for distant, clinical, and personal monitoring settings. All things considered, the design is scalable, affordable, and portable. It may be expanded with more sensors or sophisticated predictive algorithms to enable more extensive healthcare applications. With further improvements, the technology might function as a trustworthy wearable wellness tracker and make a substantial contribution to preventive and individualized healthcare. Additionally, its capacity to continuously assess physiological Users may be able to make healthier lifestyle choices and become more conscious of stressors thanks to trends. This illustrates the system's applicability in contemporary health monitoring systems where data-driven decision-making and early action are crucial.

ACKNOWLEDGEMENT

We would like to express our sincere gratitude to East West Institute Of Technology for providing the resources and conducive academic environment that enabled the completion of this research. We are profoundly grateful to our Principal, Dr. K Channakeshavalu, for their invaluable guidance, encouragement, and support throughout my academic endeavors. Our deepest appreciation extends to our parents, whose unwavering love, sacrifices, and belief in our potential have been a constant source of strength. We would also like to thank my professors and colleagues for their insightful feedback and assistance, which significantly contributed to the success of this work.

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