RESEARCH PAPER

Utilizing Cardiac Pulse Patterns for Advanced Stress Detection and Analysis

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Abstract- The elevated level of stress in a person usually affects the results of medical tests. Heart rate variability (HRV) is used to describe the level of stress. Arduino microcontroller, the AD8232 biosensor, is utilized to record the electrocardiogram (ECG) signals in real time, which are then processed by the Arduino microcontroller. Machine learning techniques are then applied on the SWELL dataset. The system is based on a two-stage approach where the dataset is used to extract relevant features, followed by the use of these features to train a machine learning model. In real time, the trained model predicts stress levels as a function of the extracted features, giving a quantitative measure of individual stress. The system has advantages like real-time monitoring, portability, and non-invasive data acquisition, with possible applications in stress management and mental health screening. Experimental testing shows promising results in accuracy of stress detection, highlighting the system's value in personalized stress management and well-being interventions.

Keywords- Real-time stress detection, Arduino, AD8232, Machine learning, SWELL dataset, Electrocardiogram, Heart rate variability**,** relaxation, balance test

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1.INTRODUCTION

The sympathetic and parasympathetic branches of the auto-nomic nervous system control the unconscious activity of the body. The former induces fight or flight mode, the latter the rest-and-digest activity. The fight or flight action enhances the sympathetic dominance while lessening the parasympathetic division under stress, an admittedly very complex phenomenon.

The AD8232 biosensor, capable of monitoring heart rate and heart rate variability (HRV), plays an important function in recording electrocardiogram (ECG) signals [2]. This information is precious as it correlates with the activation of the autonomic nervous system, which directly relates to stress response. Used as the brain processing unit, the Arduino microcontroller allows the acquisition and real-time analysis of signals.

For building a successful stress detection model, machine learning is applied using the SWELL dataset. By training the machine learning model on this dataset, it becomes capable of classifying stress levels correctly using features derived from ECG signals.

The stress detection system that is suggested here works on a two-stage basis. First, the AD8232 biosensor records ECG signals, which are then preprocessed to identify relevant features like heart rate, heart rate variability, and other temporal and spectral features. In the second stage, the model that has been trained is used for real-time stress detection. ECG signals are received continuously by the model, and based on the identified features, the model predicts the level of stress. The system provides a quantitative evaluation by classifying stress levels into separate classes, thus enabling individualized stress monitoring and intervention plans.

The system proposed has the following strengths: real-time monitoring, being portable, and non-invasive data collection. The system also has the promise of being part of different applications such as biofeedback systems, mental health diagnostics, and stress management. Its accuracy and effectiveness are tested under experimental evaluations where comparisons are done with participants' self-reported measures of stress levels. By putting forward a holistic methodology for stress detection in real-time, this research study intends to make a research contribution to the area of stress monitoring and management. The integration of AD8232 biosensor, Arduino, and machine learning algorithms with the SWELL dataset presents a promising platform for stress detection that is robust, with implications to enhance individual well-being and facilitate personal interventions.

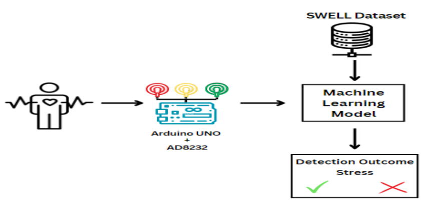

Figure 1: General Stress Prediction System

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2. RELATED WORK

This section explores existing work related to affective computing, with a special focus on the use of varied modalities such as physiology, facial expressions, postures, and computer interaction to infer the mental state of a user, specifically stress. Sensors are used in these studies, and machine learning methods are applied to interpret the data collected and adapt to individual differences.

Physiology: Body sensors are commonly used in most studies to directly assess the physiological response to stress[3]. For instance, brain imaging (electroencephalography, EEG) and facial electromyography (EMG) measurements have been recorded to monitor stress and emotion. Brain imaging is not practical for use in routine office work yet. Some common ones are pupil diameter and heart rate (electrocardiogram, ECG), which are of potential use for stress detection, particularly with the development of wearable sensors on wrist devices such as watches and bracelets[4].

Facial Expressions: Facial expressions are commonly employed to infer emotions, usually captured while eliciting emotions among participants[6]. Facial activity in particular areas has been promising in differentiating among high and low stress conditions[7]. From these, it may be concluded that facial expressions can reflect mental states, yet emotions in typical computer work settings may be less intense than emotional experiences evoked in movie clip situations.

Postures: Posture information, together with facial expressions and computer data, has been gathered to calculate the user's mental state or interest[8]. Posture information by itself has resulted in high accuracy for estimating interest, and the incorporation of posture information along with facial expressions and computer data further enhances performance. Posture measurements using the Kinect camera have promise for estimating mental states in workplace applications[9].

Computer Interactions: Some research approximates stress or emotion from computer interaction data[10]. Typing and linguistic patterns have been studied to identify stress, with classifiers such as decision trees and support vector machines being used. Typing pattern variations have been noticed during tasks inducing stress. Computer activities like keyboard/mouse activities have also revealed correlations with mood states, yet individual differences need to be accounted for in stress detection methods[11].

In summary, the application of diverse modalities in inferring states of mind, such as stress, has been studied in various previous works to mixed success. The majority of these studies, however, have been carried out in laboratory contexts, and most have not studied real-world usage. Machine learning techniques, such as classification and correlation analysis, have been applied. Individual differences are still problematic, with certain studies normalizing per participant data or investigating models for comparable subgroups of users.

3. METHODOLOGY

Heart Rate Variability (HRV) is used to measure levels of stress. HRV is the variation in the time intervals between two consecutive heartbeats and is affected by physical effort, stress, and anxiety. HRV can provide information on the physical as well as the mental state of a person.

In Figure 2, a 'P-Q-R-S-T' wave is shown, where each letter represents the peak and trough points of each instance of the heartbeat, with 'R' being the local maximum.

The fluctuation in the R-R interval, which represents time between the two consecutive 'R' peaks, is a measure of stress levels. The physiological stress response is exploited in Machine Learning algorithms to detect stress.

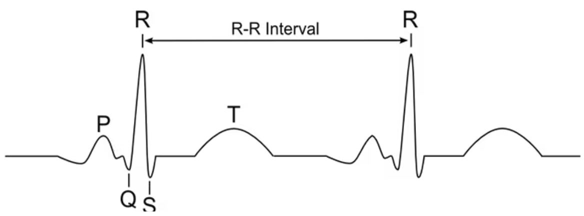

Figure 2: PQRST Wave

First, the SWELL dataset was pre-trained and then feature extraction was done. Next, feature selection was performed with a correlation matrix graphically presented as a heatmap in Figure 3. Then, the data was trained and tested with a Random Forest Classifier, and the model was saved after satisfactory accuracy had been achieved.

For stress detection, the following five HRV features were used:

MEAN_RR: This is the average of all RR intervals and thus a measure of overall heart rate variability. MEAN_RR = (Sum of all RR intervals) / (Number of RR intervals)

MEDIAN_RR: Middle value in the set of RR intervals sorted in ascending order and thus the central tendency of heart rate variability.

MEDIAN_RR = Order the RR intervals in increasing order. When N is odd, the median is the (N+1)/2th value.

When N is even, the median is the average of (N/2)th and ((N/2)+1)th values.

SDRR_RMSSD: The ratio of the standard deviation of RR intervals (SDRR) to the root mean square of successive differences (RMSSD). It describes both overall variability and short-term heart rate fluctuations.
$SDRR = \sqrt{1/(N-1) * \Sigma(RR - MEAN\_RR)^2}$
$RMSSD = \sqrt{1/(N-1) * \Sigma(RR\_i - RR\_i+1)^2}$
SDRR_RMSSD = SDRR/RMSSD

SDRR (Standard Deviation of RR intervals) is the measure of the fluctuation or variation in RR intervals. More variability in the heartbeat intervals means a higher SDRR.

RMSSD (Root Mean Square of Successive Differences) measures the successive differences

consecutive RR intervals. It reflects the rate at which the heart rate changes. A higher RMSSD indicates more rapid changes in heart rate.

MEDIAN_REL_RR: The median of the relative RR intervals, a measure that expresses the proportion of sympathetic to parasympathetic activity.
REL_RR = (RR_i - MEAN_RR) / MEAN_RR

SDRR_RMSSD_REL_RR: The SDRR of relative RR intervals to RMSSD of relative RR intervals ratio, which expresses information about autonomic nervous system dynamic regulation.
SDRR_REL_RR (Standard Deviation of Relative RR intervals) quantifies the spread of relative RR intervals. It reflects the dispersion of the normalized heartbeat intervals.

RMSSD_REL_RR (Root Mean Square of Successive Differences of Relative RR intervals) measures the differences between two successive relative RR intervals. It represents the frequency at which the normalized heart rate varies.

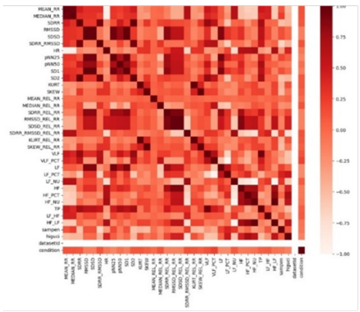

Figure 3: Correlation matrix

We are taking the HRV inputs through AD8232 Chipset which is interfaced with an Arduino UNO board which is connected to our system(computer). Through a Three-lead setup, HRV data is taken and stored by arduino and then through Machine Learning stress of that individual is predicted. The output is provided in the form of numbers 0 & 1 which represents stress and no stress respectively.

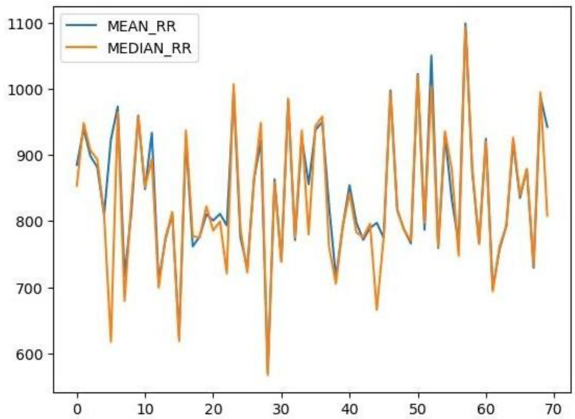

Figure 4. Line Graph Showing the Trend of Mean RR and Median RR Over Time

3.1.
DATASET DESCRIPTION
The data used in this research is the SWELL dataset, which is available on Kaggle [12]. The dataset consists of carefully curated observations, measurements, and labels collected from various sources, thus providing a holistic view of real-world scenarios. It covers a wide range of variables, such as environmental, socio-economic, and demographic variables, making it an ideal choice for analyzing the complex interdependencies between various variables and their impact on different outcomes.
The SWELL dataset is well-designed and thoughtfully

structured for ease of use and compatibility with common data analysis methods and tools. Every observation within the dataset has a collection of attributes with significant information about the data's context and attributes.
Moreover, the data set contains tagged outcomes or target variables, with which researchers can create predictive models or conduct classification tasks.

3.2. MACHINE LEARNING MODEL AND HARDWARE USED

In this section, Machine Learning models and hardware equipment used in our research work to detect stress are described

3.2.1 Random Forest

Random Forest algorithm builds an ensemble of decision trees, with each tree trained on a random subset of the training data and a random subset of features. The methodology uses "bagging" (bootstrap aggregating) to create a rich set of trees. In the forecasting stage, each tree in the forest independently comes up with a class prediction, and the final prediction is determined via majority voting.
Dataset is cleaned and preprocessed before using random forest.

Figure 5. Data before preprocessing

	MEAN_RR	MEDIAN_RR	SDRR_RMSSD	MEDIAN_REL_RR	SDRR_RMSSD_REL_RR	condition
0	885.157845	853.763730	9.063146	-0.000179	2.143342	1.0
1	939.425371	948.357865	6.272369	0.000611	2.930855	0.0
2	898.186047	907.006860	5.182201	-0.000263	2.127053	0.0
3	881.757865	893.460030	5.748591	0.000494	2.050988	1.0
4	809.625331	811.184865	3.266724	-0.002736	1.816544	1.0
...	...	...	...	...	...	...
369284	721.396910	721.533965	3.785409	0.000083	1.529068	1.0
369285	984.266492	978.622945	5.443754	0.000046	2.218313	1.0
369286	1025.499743	1024.968400	4.134664	-0.002236	2.391601	1.0
369287	798.123167	803.559610	4.687302	-0.001354	1.894304	1.0
369288	814.428911	815.178790	3.278395	-0.002479	1.876939	1.0

369289 rows × 6 columns

	MEAN_RR	MEDIAN_RR	SDRR	RMSSD	SDSD	SDRR_RMSSD	HR	pNN25	pNN50	SD1	...	HF	HF_PCT	HF_
0	885.157845	853.763730	140.972741	15.554505	15.553371	9.063146	69.499952	11.133333	0.533333	11.001565	...	15.522603	0.421047	1.514
1	939.425371	948.357865	81.317742	12.964439	12.964195	6.272369	64.363150	5.600000	0.000000	9.170129	...	2.108525	0.070133	0.304
2	898.186047	907.006860	84.497236	16.305279	16.305274	5.182201	67.450066	13.066667	0.200000	11.533417	...	13.769729	0.512671	1.049
3	881.757865	893.460030	90.370537	15.720468	15.720068	5.748591	68.809562	11.800000	0.133333	11.119476	...	18.181913	0.529387	1.775
4	809.625331	811.184865	62.766242	19.213819	19.213657	3.266724	74.565728	20.200000	0.200000	13.590641	...	48.215822	1.839473	3.279
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
369284	721.396910	721.533965	36.377559	9.609941	9.609936	3.785409	83.384647	0.933333	0.000000	6.797519	...	38.227175	5.886975	10.880
369285	984.266492	978.622945	74.918433	13.762274	13.761705	5.443754	61.314243	6.333333	0.200000	9.734243	...	2.573834	0.112964	0.357
369286	1025.499743	1024.968400	95.309200	23.051254	23.050395	4.134664	59.028594	30.400000	2.066667	16.304530	...	4.287216	0.098983	0.180
369287	798.123167	803.559610	78.449897	16.736686	16.736657	4.687302	75.978628	10.000000	1.466667	11.838553	...	46.636158	1.591647	3.522
369288	814.428911	815.178790	67.697387	20.649551	20.649546	3.278395	74.197905	23.400000	0.533333	14.606307	...	60.596026	1.907159	3.438

369289 rows × 36 columns

Figure 6. Data after preprocessing

Advantages of Random Forest

- Resistant to outliers: Random Forest is resistant to outliers and noisy data. The averaging mechanism minimizes the effect of single outliers, and hence it is appropriate for datasets with noisy or imperfect data.
- Deals with missing values: Random Forest is capable of dealing with missing values in the data without any need for imputation. It can predict using the available features, making it easy to work with datasets with missing information.
- Scalability and efficiency: Random Forest can handle large data sets with thousands of samples and features efficiently. It can be parallelized on multiple processors, which results in reduced training time and prediction time.

3.2.2 AD8232

The AD8232 is an integrated signal conditioning IC designed particularly for the measurement of bioelectric signals like electromyogram (EMG) and electrocardiogram (ECG). It is widely applied in wearable devices and medical applications for the monitoring of heart activity and muscle activity.

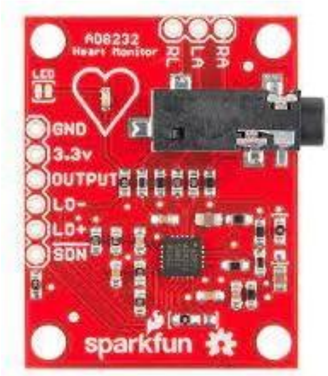

Figure 7. AD8232

3.2.3 Arduino Uno

Arduino UNO is one of the most widely used microcontroller boards built around the ATmega328P microcontroller. Arduino UNO is used for prototyping and making DIY electronics. The board gives a convenient and easy-to-work-with platform to control and interact with electronic devices.

It includes digital input/output pins, analog input pins, PWM outputs, and different communication interfaces (e.g., UART, I2C, SPI). The Arduino UNO is programmed through the Arduino IDE, enabling users to write and upload code to control sensors, actuators, and other electronic devices. It offers a friendly platform for experimenting with electronics and developing interactive projects.

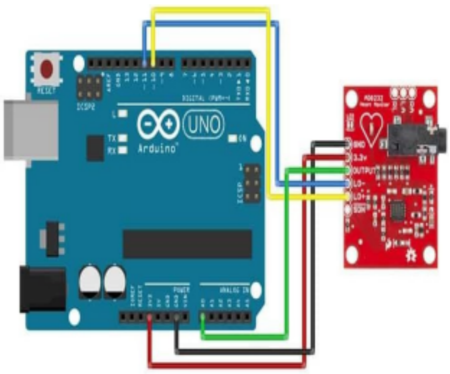

Figure 8. Connection between Arduino & AD8232

4. RESULT

The paper reports the outcome of a research work aimed at designing and testing a real-time stress detection system based on the application of machine learning algorithms. The overall aim of the research was to predict stress levels among individuals with high accuracy using physiological data acquired through the application of the AD8232 sensor and analyzed on the Arduino platform.

The results indicate the successful implementation of the machine learning model trained on the SWELL dataset, demonstrating its potential to predict stress with high precision, accuracy, and recall. Through rigorous experimentation and validation, the system demonstrated robust performance, providing accurate and real-time assessment of stress.

Furthermore, the research paper delves into the salient feature identification from the physiological signals that correlate highly with stress levels. The careful assessment of the features illuminates us on the physiological markers of stress and refines our understanding of the complex mechanisms involved.

In addition, the research paper touches on the usability and practical implications of the constructed stress detection system. It covers the applicability of the system for real-world implementation, taking into account aspects such as responsiveness, reliability, and ease of use. The paper offers information regarding the potential use of the system in various environments, including schools, workplaces, and hospitals, and its potential to enable early intervention and assistance for people under high levels of stress.

In summary, this research paper depicts an in-depth research of a real-time stress detection system and its development and evaluation. The findings highlight the system's effectiveness and accuracy in forecasting stress levels, while the analysis of key features improves our knowledge of the physiological indicators of stress. The significance of this study goes beyond enhanced mental health and can be used to combat the current mental health crisis, especially in the face of the COVID-19 pandemic. The research adds to the existing body of knowledge and lays a basis for further developments and uses in stress detection studies.

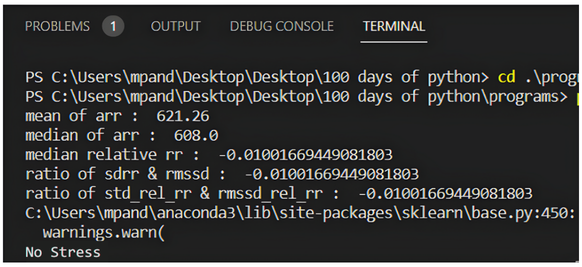

Figure 9: Stress detection result displayed

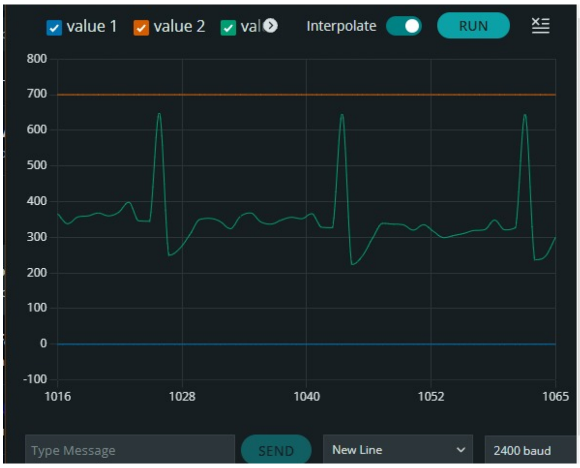

Figure 10: Detected PQRST Waveform

5. CONCLUSION

This research paper presents a novel approach to real-time stress detection using the AD8232 chip, Arduino UNO board, and Random Forest machine learning model. Our project addresses the growing need for effective and non-invasive stress monitoring methods, which have significant implications for healthcare, well-being, and performance improvement.

From our experimentation and observation, we were able to demonstrate the usability and effectiveness of our suggested system. The AD8232 chip proved to be a reliable and accurate device for the measurement of bioelectric signals, with a special focus on electrocardiogram (ECG) readings. Its built-in capabilities played a key role in the accurate determination of stress levels in real-time.

signal conditioning functionality provided top-notch data capture quality, facilitating solid stress recognition. The Arduino UNO board was used as an adjustable and convenient platform for data communication, signal processing, and feature extraction. Its support for the AD8232 chip and the feasibility to program it using the Arduino IDE made integration easy and simplified our development process for the stress detection system.

By using the Random Forest machine learning model, we could train and deploy a classification algorithm that could efficiently identify stress with high accuracy using the features derived from the acquired dataset. The capability of the Random Forest algorithm to process high-dimensional data and identify intricate feature relationships helped enable the robust stress classification performance.

This research work has enormous implications for individuals and professionals from multiple fields. With the real-time detection of stress, individuals can learn important information about their levels of stress and undertake effective stress reduction and self-care strategies. Additionally, medical professionals can leverage our system as a cost-saving and non-intrusive method of assessing and monitoring stress, improving the diagnosis and treatment of stress disorders.

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