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EmotiSense: A Mood-based API System Utilizing Physiological Parameters for Emotional Analysis

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Abstract— ***Emotions are one of the driving powers of our lives, affecting various aspects of our lives. This research paper aims to present a mood-based API system that uses physiological parameters like Heart Rate Variability (HRV) and Electrodermal Activity (EDA) to detect and analyse an individual's emotional state by considering the physiological data and subjective responses. The API comprises elements performing data collection from wearable devices, processing it onto a server, and predicting the result in the form of plain data on web-based applications, The web-based application allows users to interact with API and evolve the algorithm. The wearable device records HRV and EDA data in a specific time, which are processed using machine learning algorithms to determine the individual's emotional state.***

Keywords: Physiological Parameters, ECG, HRV, EDA, GSR.

I. INTRODUCTION

EMOTION is a psycho-physiological process that is brought on by an item or scenario that is seen, either consciously or unconsciously. It is frequently linked to motivation, personality, temperament, and disposition. (EMOQ-Emotion Based Food Recommendations System, October 2022) Emotions are the most important and prime factor in human interaction and can be communicated either verbally through sentimental vocabulary, or by non-verbal signs such as gestures, voice tones, or facial expressions. Generally, human-computer interaction (HCI) systems face difficulty in understanding the following data and suffer from insufficient emotional quotient.

In other words, they do not know people's feelings and us e this information to make the right decisions. Disruptive co mputing aims to fill this gap by analyzing emotions and inco rporating emotional responses that arise during human-comp uter interactions. Teaching interactive media content with useful, authentic, and distinctive labels is essential for protecting interactive media information.

Emotional well-being is a crucial aspect of a person's overall health. Keeping an eye on and controlling one's emotions can enhance life quality and lower the likelihood of mental health problems arising. Over the last few years, increased concern about utilizing physiological parameters like HRV and EDA to measure and analyze emotions. HRV is described as the time difference between consecutive pulsation/throb and has been linked to emotional regulation, while EDA measures the changes in the electrical conductance of the skin and is a genuine indicator of emotional arousal. The put-forward mood-based API system works towards using these physiological parameters to detect and analyze an individual's emotional state in real time. The system is composed of a wearable device and a mobile application that work together to collect and process physiological data. The wearable device constantly records HRV and EDA data. The API then uses machine learning algorithms to analyze this data and determine the individual's emotional state.

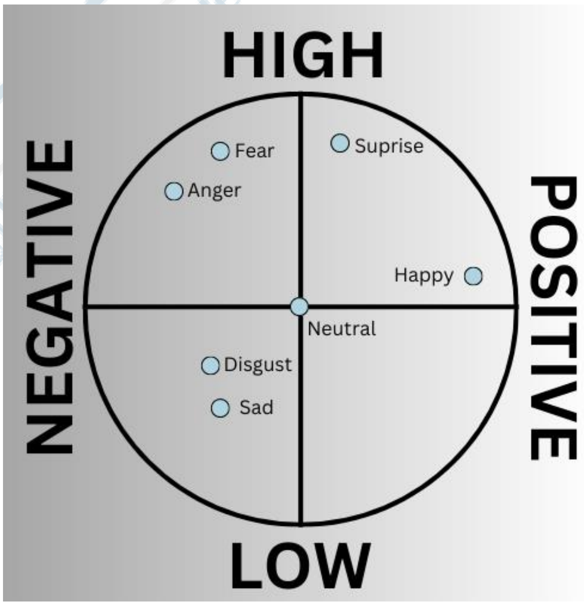

Fig. 1: Mood Classifying Diagram

II. LITERATURE SURVEY

To design a Mood-based API System using physiological parameters like HRV and EDA we were bound to research and take a reference from various existing research papers and projects as well. Emotions are powerful because they enable people and animals to respond swiftly and properly in ways that increase their chances of surviving and succeeding.

(Machine Learning Methods for Fear Classification Based on Physiological Features, 2021) Happiness, sorrow, fear, disgust, anger, and surprise are the six primary emotions. (A review on detection of Human Emotions using colored and infrared images, 2022), Previous research on emotion recognition using sensor data discovered that the electrodermal activity (EDA) signal—a measurement of the eccrine sweat glands—was the most useful. (Food and Mood: Just-in-Time Support for Emotional Eating, 2013) Skin temperature can be correlated with physiological variables, such as emotions because it is related to blood circulation. (A review on detection of Human Emotions using colored and infrared images, 2022)Over the past few years, persuasive technologies and the AIoT domain for health and weight management have proliferated. A number of readily available fitness technologies, such as FitBit1 and BodyBugg2, have made it easier for people to log their activities and physiological states. (Food and Mood: Just-in-Time Support for Emotional Eating, 2013)The variation in the durations between successive heartbeats, or heart rate variability, is an emergent characteristic of interconnected regulatory systems that function on various time scales to adjust to psychological and environmental stimuli. After advanced signal processing emerged in the 1960s and 1970s, the study of the heart's intricate rhythms—now known as heart rate variability2 (HRV)—began. In more recent years, this study has quickly grown. It's important to remember that a healthy system is dynamic and ever-changing while discussing autonomic balance.

III. EXISTING SYSTEM

There has been various research done in the past that help us to detect the mood of a person with the help of various parameters like EDA, HRV, and skin temperature. Detection of emotions through sensors has been carried out in the past. (Aqajari, et al.) Some of the research also indicated the amalgamation of persuasive technologies by making use of Artificial Intelligence and the Internet of Things domains. (Aqajari, et al.)The use of EDA has been done by various firms to produce software, and hardware in terms of wearable devices.

The existing systems were like (Text-based Emotion Detection Systems) which analyse written and spoken text to determine emotions, in this NLP techniques like usage of sentiment analysis, libraries like NLTK, etc were used. (Speech-based Emotion Detection Systems) which focused on analysing emotions through acoustic notes, Support Vector machines, neural networks, etc were used for implementing this. (Facial Expression Analysis Systems) makes use of computer vision and deep learning methods to detect emotions, input is usually in the format of an image or video. Healthcare applications also help us to monitor emotional distress, mood disorders, and mental health conditions by analysing EDA, heart rate, and respiratory patterns. Apart from these Social Media platforms also use sentiment analysis tools to detect emotions.

- **Major Challenges in existing systems**

In (Text-based Emotion Detection Systems) the complexity of words having multiple meanings/interpretations in all arising issues with ambiguity and polysemy. In some cases, it was also found misinterpretation of information which was related to sarcasm/irony, but it was not able to interpret the emotions in accordance with the written data. Apart from these, there were also some issues like linguistic differences, misinterpretations of statements consisting of negations, statements depicting emotional granularity, ethical concerns regarding consent of an individual to analyse their emotions through texts, etc contributed to the challenges of the (Text-based Emotion Detection Systems).

In (Speech-based Emotion Detection Systems) also faces various challenges due to the complexity of speech signals and due to the multifaced nature of human emotions. While interpreting emotions from this technique it could be challenging to distinguish emotion solely from speech which leads to emotion ambiguity. Expressing emotions in the form of speech could significantly vary across cultures and languages, this arises the concern for cross-linguistic variability. Other issues like limited emotional data, lack of true emotional states, and emotion detection through speech also rises concerns for ethical considerations having the consent of an individual for so, etc contribute to the challenges of the (Speech-based Emotion Detection Systems).

Facial Expression Variability is one of the issues from (Facial Expression Analysis Systems) in which human facial expressions vary in various cases based on traits, communication styles, and differences in culture which causes variability in detection. Emotion Blending is another challenge because while detecting an emotion facial expression can involve a combination of emotions. Detecting subtle expressions can also be a bit challenging at times. Facial Occlusion such as wearing glasses, facial hair, and masks can also cause issues in detection. Other challenges can comprise lighting conditions, age & gender bias, ethical concerns, etc.

In general challenges like Physiological Noise include factors like sweat production, temperature, and skin conductivity variations. Individual Variability also matters significantly, Data Quality and Calibration which means consistent and accurate measurements of EDA across devices, Data privacy concerns, etc all such issues contribute to the challenges.

IV. PROPOSED FRAMEWORK

The proposed system aims for a mood-based API system that provides a precise and effective emotional analysis. Mapping physiological parameters like HRV and EDA for emotional analysis. HRV and EDA are used to study the

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relationship between cardiovascular activity and emotional states.

Our system architecture is presented in fig 2. It consists of four main phases which include Data collection, Data processing of HRV and EDA, Mood prediction, and lastly API creation.

Data Collection involves gathering physiological data including HRV and EDA through sensors using wearable devices. Wearables provide numerous processes in which data can be fetched by other systems (Collection and Processing of Data from Wrist Wearable Devices in Heterogeneous and Multiple-User Scenarios, 2016). Store data securely for further processing.

Data Pre-processing involves extraction of relevant features removing noise, outliers, etc, and guaranteeing data quality. It also consists of synchronization and data normalization. In order to identify pertinent aspects and obtain insightful knowledge about the physiological parameters, pre-processed data is utilized.

Create two distinct models namely a single modal for each modality and a multimodal for the combined model, it generally makes use of all the modalities. Further, create an algorithm that clearly states whether to use single-modal or multi-modal. The decision and final selection are generally taken based on the availability of data and the complexity of emotions.

Mood prediction is executed using various machine learning algorithms. It divides mood into 4 categories as follows: Positive Low, Positive High, Negative Low, Negative High. Lastly, develop an API that successfully configures with the trained model delivers better user interaction efficient workflow, and ensures security.

Physiological Parameters

Heart Rate Variability

Heart rate variability, or HRV for short, is a measurement of the change in the amount of time between successive heartbeats. The autonomic nervous system (ANS), which regulates involuntary bodily processes including breathing, digestion, and heart rate, is represented by the heart rate variability (HRV). The heart and brain interact to produce the neurocardiac function of the HRV index, which is produced by dynamic, non-linear ANS processes. To assist humans in adapting to environmental and psychological obstacles, interconnected systems of regulation that operate on different time intervals have an emergent trait called HRV. The regulation of autonomic balance, blood pressure (BP), gas exchange, and condition of the stomach, heart, and veins—the width of the arteries that govern BP—everything is imitated in HRV. Additionally, it might be the modulation of facial muscles. A sound heart is not a ticking metronome. A heart that is in good health has complex nonlinear oscillations.

The unpredictable nature of non-linear systems allows them to swiftly adapt to changing and unpredictable environments. Spatial and temporal complexity are present in healthy biological systems, but illnesses can either enhance or decrease this complexity. (An Overview of Heart Rate Variability Metrics and Norms, 2017)

The ANS is further classified as the sympathetic and parasympathetic nervous systems, which respectively control the "fight or flight" response and the "rest and digest" response. HRV is influenced by both these systems and can therefore be utilized to acquire the equilibrium between sympathetic and parasympathetic activity.

Electrodermal Activity (EDA)

The activity of sweat glands affects skin conductance measurement known as Electrodermal activity (EDA) in response to physiological or psychological stress. EDA is also referred as galvanic skin response (GSR) or skin conductance response (SCR). EDA, sometimes referred to as the Galvanic Skin Response (GSR), is a metric of the arousal of neuro-physical that calculates the variations in skin conductance in response to ANS activity. Because EDA is an accurate indication of the SNS, it is a useful tool in psycho-behavioural investigations.

It is typically impossible or difficult to affect the generation of a response when exposed to emotional stimuli, the skin produces eccrine sweat. Also, the non-intrusive method is better than others because of the way it is designed (DEAP: A Database for Emotion Analysis using Physiological Signals).

a. Flowchart for EDA

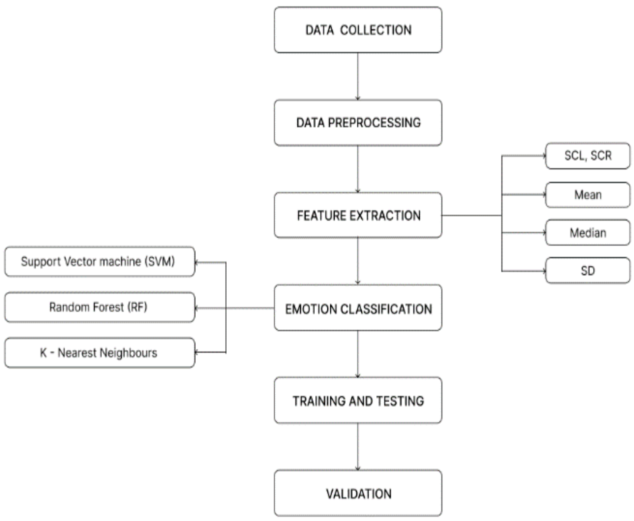

Fig. 2: EDA flowchart

API Development

- REST APIs (Application Programming Interface)

These are the extensively used flexible and workable APIs found on the web today. Data in the form of request is sent from the client to the server. The server starts internal processes using this input from the client and sends the output data back to the client.

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To develop a mood-based API for Emotional Analysis utilizing physiological parameters from real-time wearable devices like DEAP and AMIGOS datasets, the selection of the relevant physiological parameters such as HRV and EDA is carried out. Pre-process the extracted features from raw data and integrate suitable machine learning models to understand and analyze the features and predict corresponding emotional states according to their significance. The Final API would work on real-time physiological data as input from wearables and comprehend the emotional states. Model creation based on parameters of DEAP and AMIGO dataset, training of model will be carried out using the semi-supervised approach of machine learning.

The algorithm would detect whether to use single modal or multimodal which would suit best at that moment and scenario.

Develop an API that acts as the link for users to input their physiological data. API should be able to handle and manage the data fusion for multimodal. It should ensure compatibility with the chosen algorithm and work appropriately for the designed framework.

Develop an API that acquires physiological parameters as the input data and returns the predicted emotion as the output. Trained models facilitate to predict the emotion based on physiological parameters. The API can be integrated with the machine learning algorithms which will help in the recognition of mood and recommendations.

Deploy the mood-based API system on the cloud platform for scalability and accessibility. Cloud services like AWS, Azure, and Google Cloud can provide the infrastructure needed to host the API. It ensures security, protects data and implies relevant regulations.

Implement a reinforcement learning algorithm that refines the mood detection based on user's feedback on whether the mood detection was correct or incorrect. This would automatically generate rewards to learn by experience. DEAP and AMIGO datasets are ideal. As positive feedback rewards for correct predictions, the system also sets up a threshold according to enough positive experience accumulated in the system. New experiences are added as the threshold is crossed. This also helps in improving efficiency and accuracy.

Ex: if there are 10000 inputs from a user from which 8000 are positive and 2000 are negative (considering the user has given some firm output).

The goal is to improve the efficiency of real-time emotion detection with current advancements and technologies.

b. Flowchart for the general implementation of the project

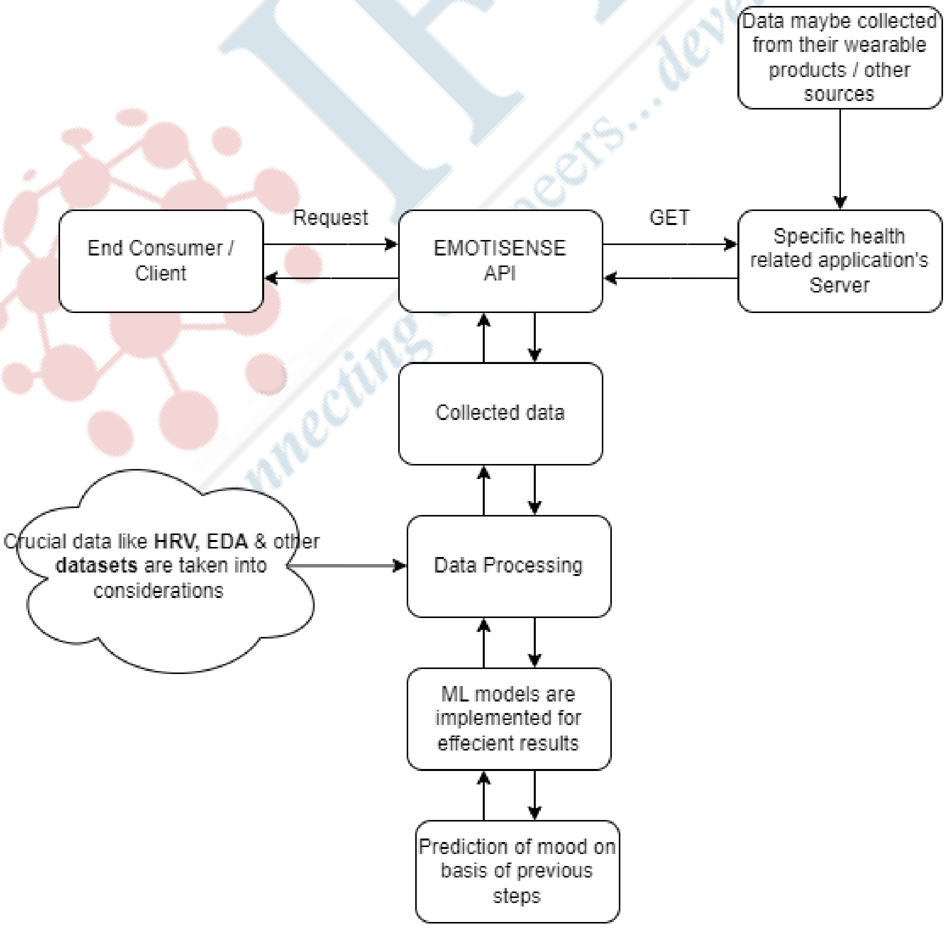

Fig. 3: System Architecture flowchart

The End Consumer/Client request for the predicted mood through the 'Emotisense API' UI, the backend of the API sends a request to the specific applications server where data sources may be many which is first collected once the data processing is done (including data like HRV, EDA and other datasets). In the next step Machine learning models are also implemented for increasing the efficiency of results. After all these steps prediction of mood is done which is sent back to the end consumer/client as a result.

V. IMPLEMENTATION AND RESULTS

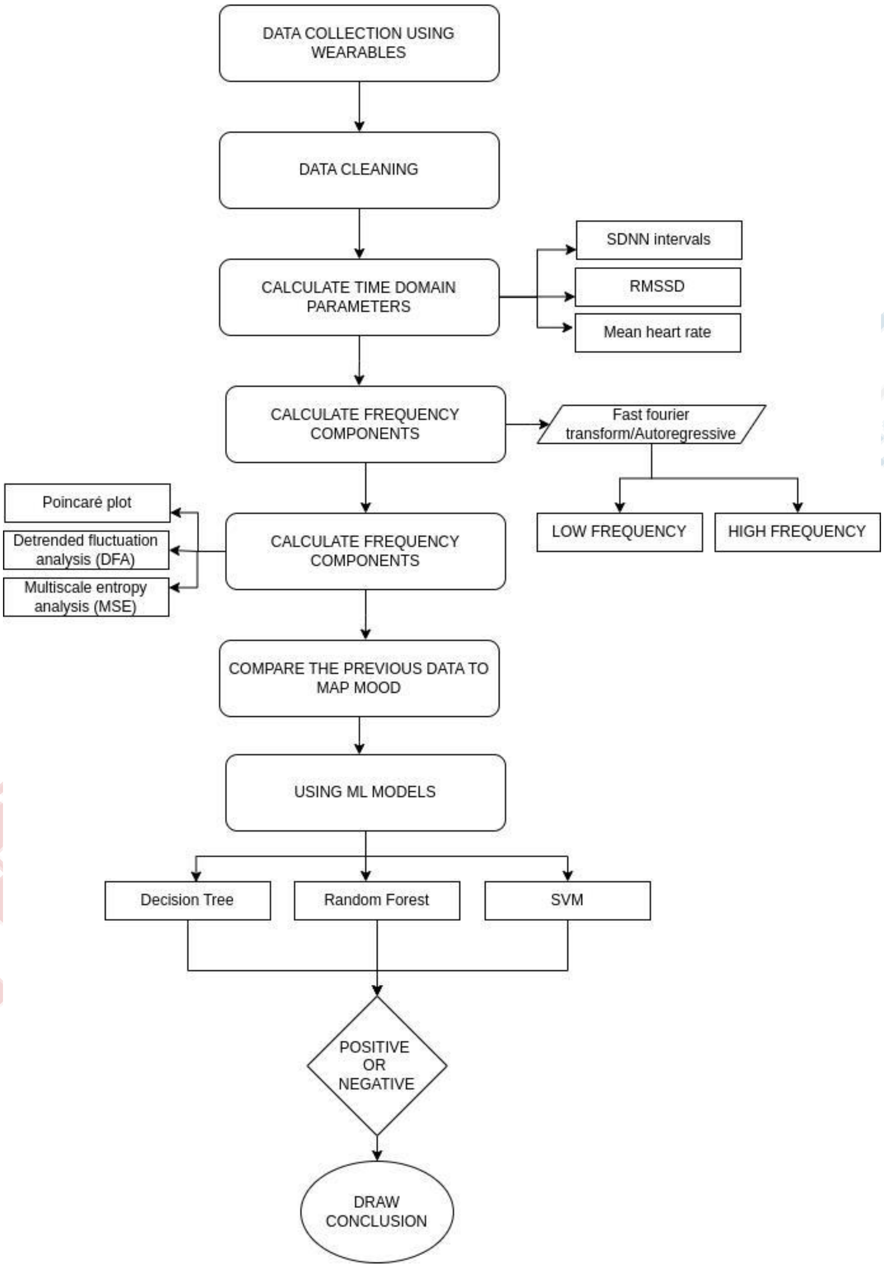

Fig. 4: Implementation for Tech Stack flowchart

We took static datasets from the internet and extracted significant features. The features are appropriately chosen so that they can be applicable to real-time datasets. The focus is to analyse real-time information effectively.

In our study, we primarily focused on utilizing physiological parameters namely Electrodermal Activity (EDA) and Heart Rate Variability (HRV) as the main factors for the detection of emotions. To achieve this, we examined the correlation between HRV and EDA and their associated components, Electrocardiogram (ECG) for HRV and Galvanic Skin Response (GSR) for EDA. Our focus is to establish the connection between physiological measures and the emotional states that they signify.

By carrying out certain procedures, analysis, and data visualization, we were able to identify the relationship between the ranges of ECG values, GSR values, and their

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corresponding emotional states that it signified. The visualization helped to identify patterns and trends between physiological parameters and emotions. By successfully mapping out connections, significant progress was observed in emotion detection using physiological parameters.

According to the research and studies it observed HRV and EDA along with their ECG and GSR constituents work effectively for understanding emotions. The comprehensive data analysis and visualization technique helped achieve and link physiological parameters and emotions.

HRV tracks the differences in pulsations from beat to beat, which are often indicated by the difference in the RR intervals that are clustered together in the ECG data.

Electrocardiogram (ECG) Sensor: Electrical changes in the heart are detected using this sensor. It usually consists of electrodes positioned on the skin to compute the electrical activity of the heart.

Signal processing and visualization of the ECG signal data basically involves techniques to clean, filter, and preprocess the raw ECG data remove noise, and outliers and ensure accurate analysis. Visualization helps in understanding the characteristics of the signal.

Converting Data into BPM

Heart rate is derived from ECG signal. It indicates how many times the heart beats per minute(bpm). To calculate this, extract R_R intervals which represent the time between successive R-peaks in the ECG waveform. By calculating the inverse of these intervals heart rate bpm is obtained.

HRV Analysis involves examining the variations in R-R intervals which reflects the variability in the time between heartbeats.

Extracting Time-Domain Features

Mean R-R Interval: Average time between consecutive heartbeats. Standard Deviation of R-R Intervals (SDNN): Reflects overall variability.

Table No.1: Depicting mood on ECG range.

ECG Range	Mood State
60-70 BPM	Calm/Relaxed
70-100 BPM	Content/Satisfied
100-120 BPM	Neutral/Indifferent
120-140 BPM	Slightly Anxious/ Nervous
140-160 BPM	Anxious/Stressed
160+ BPM	Highly Anxious/ Fearful

Root Mean Square of Successive Differences (RMSSD): Captures short-term variability. Percentage of R-R Intervals with Differences > 50 ms (pNN50): Indicates parasympathetic activity. Triangular Index: Reflects overall HRV using a geometric approach.

After following certain steps results based on outcomes results are interpreted.

GSR

Our body has around three million sweat glands, The regions like fingers, palmer sites, feet, and wrists are more likely to respond strongly to emotional stimuli.

The 2 major components are:

Skin Conductance Level Analysis

Skin Conductance Response Analysis

Basically, with the help of these factors, we focused on measuring an individual's overall level of arousal and the individual's emotional response to stimuli. Moreover, GSR and level of arousal are correlated.

The measuring unit for GSR is micro-siemens.

Table No.2: Depicting mood on GSR range.

GSR Range	Mood State
0-2 micro siemens	Excited/ Happy
2-4 micro siemens	Relaxed/Calm
4-6 micro siemens	Content/Satisfied
6-8 micro siemens	Neutral/Indifferent
8-10 micro siemens	Anxious/Stressed
10-12 micro siemens	Fearful/Nervous
12-15 micro siemens	Angry/Irritated

Multimodal

Multi-modal is the combination of two or more modalities used for a recognition system. Multi-modal is used for recognition as combining different models results in improved recognition. It is quite complex to integrate different models. The insufficiency of an ordinary theory makes it complex to analyze in various scenarios.

Data is gathered using HRV and EDA using ECG and GSR components respectively, with the help of sensors it will be fed into a multimodal system. The fusion of extracted features of HRV and EDA is done into a single vector. Multi-modal aims for improved classification with the integration of machine learning algorithms which results in better recognition. Multi-modal increases the performance rate.

Signal processing here and HRV data is processed and calculate heart rate and EDA is processed to identify change in conductance levels.

Relevant feature extraction from the processed data, followed by combination and correlation of data. Identification of patterns and trends and analysis with the help of machine learning algorithms. Visualization and graphical representation help to understand and display changes that occur. Integrate HRV and EDA sensors with decision-making components.

Tech stack

Several algorithms can be used for mood recognition based on physiological parameters like HRV, EDA, and GSR. Some of the commonly used algorithms used are SVMs,

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Random Forests, Artificial Neural Networks (ANNs), and many more.

The algorithms that are available are often used in combination to extract a feature from psychological data and then classify/predict the mood of that entity.

The algorithms that helped us through our project are-

- **Random Forest-** Random Forest often utilizes a machine-learning algorithm. It helps us to combine the output of multiple decision trees to reach a single result. Its flexibility and ease of use have helped to accomplish the purpose of its adoption, as it is capable of handling both classification and regression problems.
- **Support Vector Machine (SVMs)**- SVM can be used for regression tasks, where the algorithm can predict a continuous output value instead of a categorical class. In this application, the SVM algorithm tries to fetch the hyperplane that best fits the data and also predicts the output value. SVM is a persuasive algorithm that can handle both linear and nonlinear relationships in data. SVM is often utilised in several domains, including bioinformatics, image recognition, and text categorization.
- **Decision Tree**- One type of supervised learning technique that is used for both regression and classification problems is the decision tree. With a root node, branches, internal nodes, and leaf nodes, it has a hierarchical tree structure.
- **Time domain analysis**- This approach aids in the calculation of heart rate variability (HRV) by analyzing the fluctuation of time intervals between successive heartbeats.
- **Skin Conductance Level (SCL)**- The SCL is computed by this method using the EDA signal. SCL is a measurement of a person's general degree of arousal and is the tonic component of the EDA signal.
- **Skin Conductance Response (SCR) Analysis**- This algorithm uses the EDA signal to detect SCR. SCR is the phase component of the EDA signal and is used as a measure of an individual's emotional response to stimuli.

ECG

ECG Anxious/Stressed

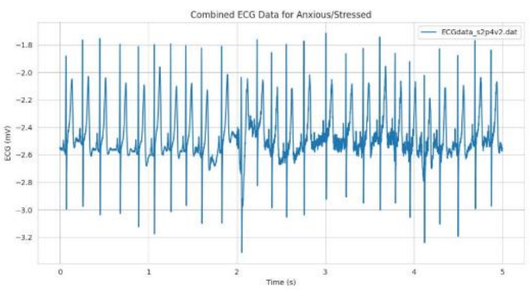

Fig. 5: ECG graph based on anxious/stressed state

Extremely Anxious/Panic

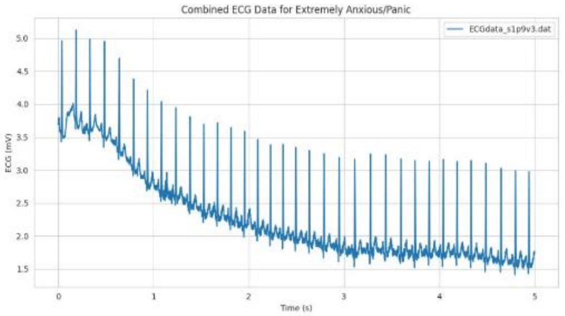

Fig. 6: ECG graph based on extremely anxious/panic state

Highly Anxious/fearful

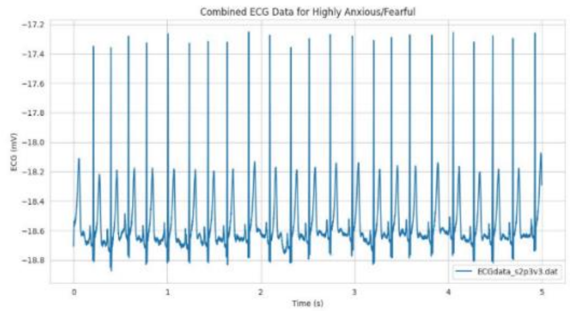

Fig. 7: ECG graph based on highly anxious/fearful state

Neutral Indifferent

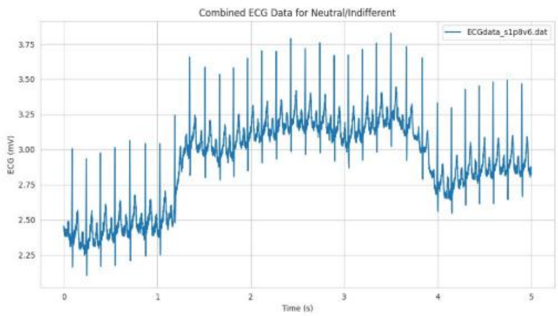

Fig. 8: ECG graph based on neutral indifferent state

Slightly Anxious-Nervous

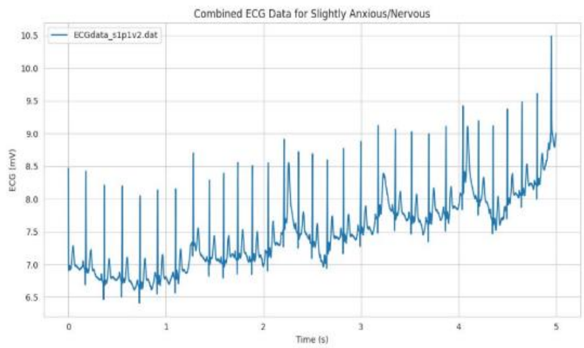

Fig. 9: ECG graph based on slightly anxious-nervous state

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GSR

Calm and Relaxed

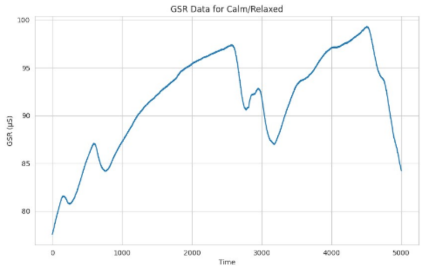

Fig. 10: GSR graph based on calm and relaxed state

Highly Anxious/Panic

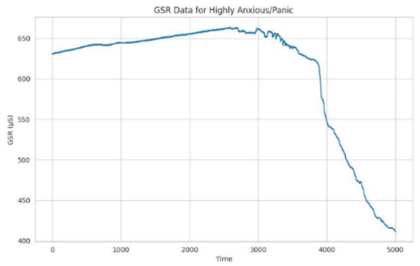

Fig. 11: GSR graph based on highly anxious/panic state

Neutral/indifferent

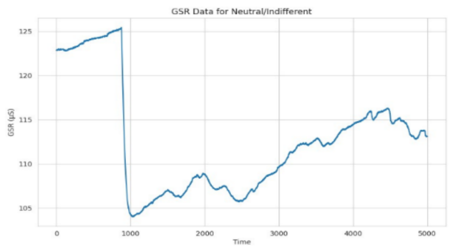

Fig. 12: GSR graph based on neutral/indifferent state

VI. CONCLUSION

In this paper we have performed through analysis of physiological parameters utilized for mood-based API system for emotional analysis. We have gained insights into all related aspects required for the project. We tried to establish foundation for studying and intricating connection between physiological parameters and emotional states.

A comprehensive study of physiological parameters, emotional states, APIs and machine learning algorithms is accomplished. Our API system acts as the bridge between real time physiological parameters as input and emotion-based output. Our focus is to develop an API system that wraps the entire working system like physiological parameters, machine learning algorithms, etc in single API system which can be easily available and efficient for the industries to carry out specific work. It has wide use cases like this system can be implemented for food choices, financial choices, social choices, health choice apps to a greater extent, with this idea we are trying to efficiently use physiological data to convenience and ease providing them an emotional based choice and this Api is the stepping stone towards it.

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