EmoGo: A Smart Wearable IoT System for Human Emotion Detection

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***Abstract*—The emotional well-being influences the thoughts and behavior of people. A person can experience different types of emotions throughout the day. These emotions significantly compel the decisions that affect their lives. Therefore, emotional awareness allows people to recognize the role and effects of their emotions. In addition, negative emotions that are repressed can harm the human body in multiple ways like chronic stress and damaging the immune system. Depression can cause feelings of sadness and a loss of enjoyment throughout the daily life. While these negative emotions can also decrease the human ability to function; in contrast, positive emotions boost a persons morale and increase their cognitive processing. These good emotions affect cognitive processing areas such as attention and learning. Therefore, classifying emotions in different spectrum is important to help people with mental health struggles. Our solution proposes an innovative wearable device that tracks and classifies different types of emotions. Our research aims to investigate physiological changes associated with relieved experiences of happiness, sadness, anger, fear, and disgust. Tracking these changes allows for an accurate representation of peoples emotions. In the psychiatric field, patients tend to exaggerate or downplay their emotions; this creates issues during therapy.**

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

It is safe to say that mental health affects how we think, feel, and behave toward life. The recognition of peoples emotions is a topic that is not really talked about nowadays. Making people aware of their emotions can help remove the barrier between family members and friends [1]. For instance, a person who experiences depression is not aware of their emotions until someone points it out. Therefore, having a device that can detect peoples emotions beforehand can help them deal with their emotions much sooner. After all, emotion recognition technologies have advanced like wildfire and facial recognition technologies have been on the forefront of emotion recognition. However, it doesnt accurately depict a persons emotions. Falsifying ones emotions by faking a laugh can negatively deter that person from getting the treatment they need. For people who cannot facially express their emotions, the use of facial recognition to detect emotion may as well be as useful as floppy disks nowadays. The detection and tracking of emotions early on can prevent mental health struggles [2], [3].

Studies on emotion recognition classifiers are on the rise due to the benefits on the understanding of human emotion has on various fields [4], [5]. Different emotional models exist that are extracted by applying various stimuli to the subjects and recording their physiological signals. Researchers from MIT have applied music as a stimuli and classified the signals into four emotions Joy, Anger, Sad, and Pleasure [9]. Although the number of subjects in the study is low (3) the results are found to be accurate to up to 70% and 90% depending on the subject. They used a statistical approach on the matter by applying linear discriminant analysis to compose their results. Another study by YP Lin and CH Wang [8] also applied music as a stimuli with a larger sample size of (26) to collect data from the brain using an EEG signal to classify emotion. These methods have some disadvantages that occur when the stimuli is applied. Music taste is subjective and although the subjects were considered to be non-musicians, the effect of the presented music might not be as accurate [6], [7].

Research done by Haag, A. and Goronzy, S [9]. appears to have the highest accuracy of emotional detection using five different physiological signals that are fed to a neural network to finally reach the accuracy of 96.58% [9]. The classifier used recognizes different levels of arousal from low, medium, and high. The stimuli they used in the research was a picture system to stimulate the emotion of the subject. In this project, we aim to create an emotional model based on combining existing models while also trying to increase the accuracy of the system. Different classifier techniques will be explored to achieve the highest accuracy possible for the system. The system will take the input as a physiological signal and process the signal by extracting the feature then it will be fed to our smart learning algorithm to classify and record emotion experienced. A web application will be built to record and monitor the recordings of the emotion. Tracking user's emotional development is vital information for psychologists and other health experts. This information will allow a better understanding of the patient. We plan to have multiple features in our web application such as a mood tracker, a safety protocol, and coping strategies [10], [11].

II. Problem Formulation

Mental health is stigmatized by culture and society. This creates the assumption that people who visit therapists are seen as weak or unable to handle their own emotions. In fact, according to the mental health foundation, 9 out of 10 people who tackle mental health struggles feel that discrimination and stigma negatively impacts their lives. This in turn leads to harmful effects like avoiding treatment [1]. While raising mental health awareness is our project's goal, it is our mission to provide an action plan for users to follow through. Analyzing the input data from the user's body allows for classification of the users emotional state. This means that if our system detects frequent changes in the mood of the user, certain recommendations will pop up to console that person. For example, if the user has done something that makes them happy like dancing over a period of time, our web application will suggest they continue doing that. In terms of the scalability of our product, Emogo products will be provided to the general public. This provides convenience to individuals who live a busy life, since a wearable device can be worn on the go. Emogo will target a broad range of industries who seek their employees' well-being or rehabilitation centers who want to closely monitor their patients' weekly mood changes [12], [13].

III. EmoGo System Architecture

The section showcase the design specifications of *Emogo* and provide features that will be included in the overall system design. In addition, a block diagram of *Emogo* system is illustrated to demonstrate the functioning and integration between the software and hardware components in Figure 1.

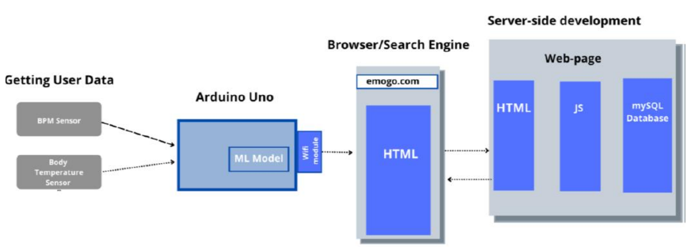

Fig. 1. Data flow Model illustration of EmoGo wearable System

Emogo provides a wearable device that users can wear to classify their emotions. After syncing the wearable device with our web application, users can track their emotional state on the go. Our application syncs the user with licensed therapists if the user consents to it. This option is provided to all users; however it is encouraged for users that show serious mental health struggles like depression. Our product can be used in health care establishments, workplace areas, or even for the everyday Joe. The wearable device uses eco-friendly materials to ensure a greener lifestyle. The Figure 1 illustrate the the integration between the wearable device and data analysis application. The system measures the BPM *Beats per minutes* and temperature data and process it via a microcontroller platform, where the machine learning algorithms are present. The digital system process the data received using ML models and sends the output. An ESP8266 WiFi module annexed in the system transfer the predicted results to the web application for storage and clinical applications. To predict emotional states, the system measures the BPM and temperature data. The K-nearest neighbour (KNN) algorithm used to classify emotional states. The results shows KNN is better in predicting emotional states accurately using BPM and temperature data [15].

Algorithm 1 KNN Algorithm for Emotional states prediction

$LoadrealtimeBPMandTemperatureData$
$InitializeK : \underline{withNneighbours} \gg 0$
$d(X_p, Y) = \sqrt{\sum_{i=1}^{N} (X_{pi} - Y_i)^2}$
$Calculate\ d(X_p, Y)\ between\ query\ and\ current\ data$
$Distance\ d(X_p, Y)+,\ Index\ i$
$RUN:\ Sort(Ordered\ Collection\ of\ Distances)$
$Select: First\ K\ form\ Sorted\ collection$
$Labels: Get\ labels\ of\ the\ selected\ K\ entries$
$Classification: Return\ the\ mode\ of\ the\ K\ Labels$

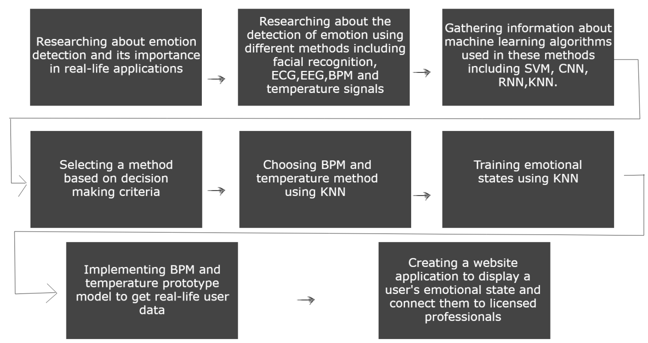

Fig. 2. EmoGo Data Analysis model

The KNN algorithem implemented in our system design and the accuracy of the emotional state prediction is around 85% to 90%. The KNN algoritm works by finding the distance between between a query and all the examples in the data, selecting the specified number examples (K) closest to the query, then votes for the most frequent label So in our study, KNN calculates the distance between the vector to be classified and feature vectors from the reference signals as illustrated in Algorithm 1. The signal to be classified is then assigned to the majority class among the k closest classes. The distance between the vectors is calculated by using the Euclidean distance shown in Equation 1

$$d(X_p, Y) = \sqrt{\sum_{i=1}^{N} (X_{pi} - Y_i)^2} \tag{1}$$

Where *Xp* is the feature vector to be classified, *Y* is the reference base and *N* is the number of features in this vector. In the KNN method, the coefficients are determined as follows in Equation 2.

$$\alpha_1 = \frac{k_i}{k} \tag{2}$$

$$\sum_{i=1}^{N} \alpha_1 = 1 \quad (3)$$

where k_i is the number of the *i*nearest neighbors found and M is the number of the emotional class. The KNN algorithm is simple but the difficulty is in finding the value for K. The higher the K value is, the model suffers from the risk of over-learning. We are still experimenting with different K values to find a higher emotion recognition rate. The data analysis model introduced in EmoGo using KNN algorithm is illustrated in Figure 2.

IV. Hardware Implementation

A micro-controller based digital hardware developed using Arduino board, LM35 temperature sensor and Hart rate sensor. The design also include a small LCD screen to display the predicted emotional state. The continuous stream of body temperature and heart rate will fed to micro-controller board for analysis using the machine learning algorithm (KNN). The predicted emotional state will send to the on-board LCD display and also data stored in a cloud web server. The data can accessed via the web application. A model of the hardwae implementation experimental model is illustrated in Figure 4.

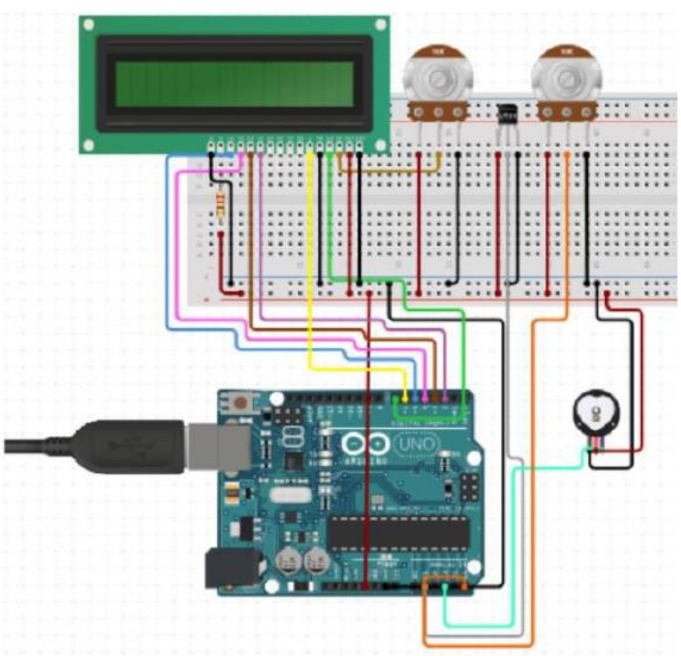

Fig. 3. EmoGo Hardware implementation

V. Classification of Emotions

The KNN based classification algorithm is trained using standard set of data and multiple subjects selected from different age groups of people. The majority of subjects were under the age group of 20 to 30 years old. The classification of emotions using BPM and Temperature is been reference using the data shown Table I. The data entries coming from the table is based on previous findings and studies done on healthy adults from the age group of 20-30 years old. This data entry will give us an idea of the emotional state of the person [14].

TABLE I
KNN Traning Data

Serial No	Classification of Emotional State		
	Emotional State	*Pulse Rate(BPM)*	*Temprature*
1	Normal	50 -80	36.5 - 37.5
1	Happy	80 - 100	37.5 - 38.0
1	Anger	95 - 120	37 - 38.5
1	Fear	110 - 150	36.0 - 37.0
1	Sad	80 - 100	35.0 - 36.0

The EmoGo website application allows users to view their BPM, Temperature, and Emotional state. JavaScript (JS) programming language is used to program the behavior of the web pages. It gives our web pages interactive elements that engage the user. In Emogos website, once users try booking an appointment with a licensed therapist, JS is used for validating the information the users included in the booking form. It also comes in use with saving the users information. Since JS is integrated with HTML, it becomes easy to implement. JS manipulates HTML pages; these eases the insertion and deletion of HTML tags. MySQL is an open-source database management system that stores and manages data. The data is managed one table with four columns. The four columns are: Time, BPM, Temperature, and Emotional Class. A sample website application data log from one of our experiment is shown in Table II.

TABLE II
KNN Traning Data

Time	Classification of Emotional State		
	Pulse Rate(BPM)	*Temprature*	*Emotional State*
6:17:29 AM	68	35.75	Normal
6:20:21 AM	81	37.6	Happy
6:40:20 AM	92	35.4	Sad
8:32:41 AM	120	36.5	Fear
9:41:50 AM	110	37.8	Anger

The PHP scripting language is used for managing the data coming from the Arduino board and storing that data into our HTML code. This data is the emotional state of the user, which will be showcased in the web application. The PHP programming-language is used for server-side programming, which interacts with databases to retrieve information, storing, email sending and provides content to HML pages to display on the web screen. The use of PHP allows for the generation of dynamic web pages, which allows for the display of different content for different users. The EmoGo website application provides numerous interesting features to its users. Few important features mentioned here.

- A user-log-in for existing users
- A sign-up option for new users
- Display of user BPM values where the user can determine if their BPM is low, normal, or high
- Display of user Temperature values where the user can determine if their temperature is low, normal, or high

- Display of users emotional state with a recommendation of booking a session with a therapist
- The option of choosing between licensed therapist when booking a therapy session
- A review section to allow users to give feedback on their experience using our device and website application.
- An appointment form where users can enter their information to book an appointment

VI. MVP: Minimum Viable Prototype Demonstration

Fig. 4. EmoGo Hardware implementation

VII. Conclusion

The aim of EMOGO project is to have awareness spread for mental health issues, and to have a prototype that can successfully and accurately detect a person's emotions using several sensors and mechanisms. This is achieved by integrating a body temperature sensor and a BPM sensor. The emotions of the user will be analyzed and interpreted by reading the users heart rate and classifying it using ML algorithms. The entire analysis and information will be displayed on a website application. Informing the user and the supervised therapist about the user's current and past emotions and experience will give both parties an idea of the emotion experienced and possible treatment options. In the future given more time, space. and budget for this project there are many external factors which can be integrated to widen the range of emotions detected and increase comfort for the user simultaneously. After interviewing a psychiatric specialist, he stated that we can add a breathing rate monitor into our design, this can help detect if the user is experiencing anxiety. Other sensors we should add based on the specialist are blood pressure monitor, oxygen monitor, and sweating rate which can be integrated with Emogos system. The final addition he would like is that we can successfully detect emotions in special needs patients like autistic children and adults, as well as detecting children's emotions especially at a young age since communication is limited. Lastly, since gender does slightly affect the classification of emotion, training our data set by adding more samples from different genders will significantly increase the accuracy rate of our system.

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