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Emotion Tracking Using Wristband

Mrs. Swati Aswale[1], Vishvajeet A. Jadhav[2], Aditya R. Jagtap[3], Gaurav G. Gaikwad[4]
[1,2,3,4] D.Y. Patil College of Engineering, Akurdi, Pune
Vishvajeetjadhav333@gmail.com

Abstract

Real-time emotion tracking is essential for supporting mental health, enhancing education and better customer service. In this paper, we have developed an "Emotion Tracking Wristband" which is equipped with sensors, including Heart rate sensor, Galvanic Skin Response (GSR) sensors, and Skin Temperature sensor, to extract human emotions effectively. Wristband captures and analyzes the physiological data associated with diverse emotional states such as Happy, Angry, Sad, Neutral, Fear, Surprise and Disgust. Our approach involved inducing emotions in participants through video stimuli within real-life settings while concurrently collecting physiological data. Subsequently, we extracted a wide array of features from these signals, encompassing time, frequency, and nonlinear characteristics. These physiological signals are subsequently processed through SVM, KNN, Decision Tree and Random Forest machine learning algorithms, which have been meticulously trained on an extensive dataset of emotional patterns. This training empowers the system to accurately classify emotions, such as happy, angry, sad, neutral, fear, surprise and disgust. Ultimately, the "Emotion Tracking Wristband" bridges the gap between technology and emotion, opening up new avenues for understanding and managing our intricate emotional landscapes. Our system achieved an impressive overall accuracy rate of 83% across 30 participants, underscoring its efficacy in recognizing human emotions.

Keywords—
Wearable wristband, heartbeat, blood pressure, skin temperature, electrodermal activity, and emotion recognition etc.

1. INTRODUCTION

1.1 Objectives of Project

Emotions are the outcome of individual internal and external influences, and they have a significant impact on human decision-making. Emotions are shaped by a complex interplay of internal and external factors, manifesting uniquely in each individual and wielding substantial influence over human decision-making processes. Emotion detection constitutes a significant area of research, with the potential to preemptively address a multitude of issues. The capacity to identify and predict emotions based on data can serve as a proactive measure, mitigating potential problems at an early stage. Emotion recognition holds promise in elucidating the mental states of individuals who may struggle to articulate their feelings and providing clarity to those unaware of the underlying causes of their ailments. Diverse methodologies exist for detecting a person's emotional state, encompassing facial recognition, speech analysis, and the utilization of physiological signals.

The "Emotion Tracking Wristband" initiative stands as a pioneering endeavor at the nexus of technology and emotional understanding. This pioneering system harnesses sophisticated sensors and machine learning algorithms to monitor and decode human emotional states through physiological indicators.

By seamlessly incorporating wearable technology in the form of a wristband, the system aspires to furnish real-time insights into individual's emotional well-being, offering potential contributions to fields such as mental health monitoring and personalized self-care. Moreover, it seeks to enhance comprehension regarding the embodiment of emotions.

Adverse emotional states not only jeopardize personal well-being but can also serve as early indicators or causative factors of severe mental health conditions. This holds particular significance for specialized groups, such as drivers, pilots, and engineers, where emotional stability significantly impacts public safety.

However, conventional audio and visual emotion channels often prove insufficient for precise emotion classification due to human's nature at concealing their true emotions behind social facades.

The significance of the proposed system is underscored by its potential applications, spanning personal well-being monitoring, mental health tracking, and the optimization of human-computer interactions, ultimately fostering emotional awareness. To address the aforementioned challenges, this initiative aims to create a technology for detecting emotions based on a wearable bracelet with additional sensors.

2. LITERATURE SURVEY

Wearable multi-sensor gadget Empatica E3 that collects data and offers real-time feedback. The PPG, EDA, 3- axis accelerometer, and temperature are among its four integrated sensors. The device offers high-resolution data, supports heart rate variability analysis, and provides flexibility with both real-time streaming and recording modes. They employed a ResNet-based Convolutional Neural Network (CNN). The emotions recognized were fear, anger, fearlessness, neutral, and happiness. Based on the ECG results, an accuracy of 78.42% for emotion identification was attained. . The system used to gather many modes of physiological signals, the system made use of a smartwatch with additional sensors. Developed fine-grained characteristics to identify various emotions. Proposed a paradigm for adaptive emotion identification that takes into account how activities affect physiological signals. Created a mechanism for identifying activity scenes using accelerometer data.

IoT-enabled emotion recognition framework using LSTM-based deep learning models and physiological sensors to interpret human emotions. The system achieved a high F-score of 95% for emotion recognition when using a combination of ECG, BVP, GSR, SKT sensors. The paper's main topic was the identification of emotions using physiological markers like ECG and heart rate variability. Early and late fusion-based temporal multimodal deep learning models are employed to improve emotion recognition using EEG and BVP. Information from tiny wearable physiological sensors. The models achieved promising results on a dataset of 17 participants watching video clips, outperforming non-temporal multimodal models. Employing physiological inputs like EEG, ECG and temperature for multimodal emotion recognition. It focuses on feature selection and discovers that features connected to the EEG have the best ability to discriminate. While valuable for improving emotion recognition, it also includes dataset specificity and potential feature bias.

[1] (2023): Data collected from Empatica E4 smartwatch. : SVM ML Algorithm accuracy of 74.3%

[2] (2020): Information on the skin temperature (ST), blood pressure (BP), respiration, electrocardiogram (ECG), and galvanic skin reaction (GSR) for 25 people. : (SVM) and neural network Precision - 0.84 F1 Score - 0.65

[3] (2021): Data was recorded from 30 participants: (LSTM), IoT┐ based data communication framework F-score of 95%

[4] (2021): Emotion Analysis Using Physiological Signals Database (DEAP) : (CNN) with ResNet Architecture Accuracy of 78.42%

3. BLOCK DIAGRAM

In order to track emotions using wearable technology, this paper suggests creating an intelligent system that uses a wristband and physiological signals. The System includes designing the wristband system, including the selection of appropriate sensors for measuring physiological signals related to emotions.

Block Diagram

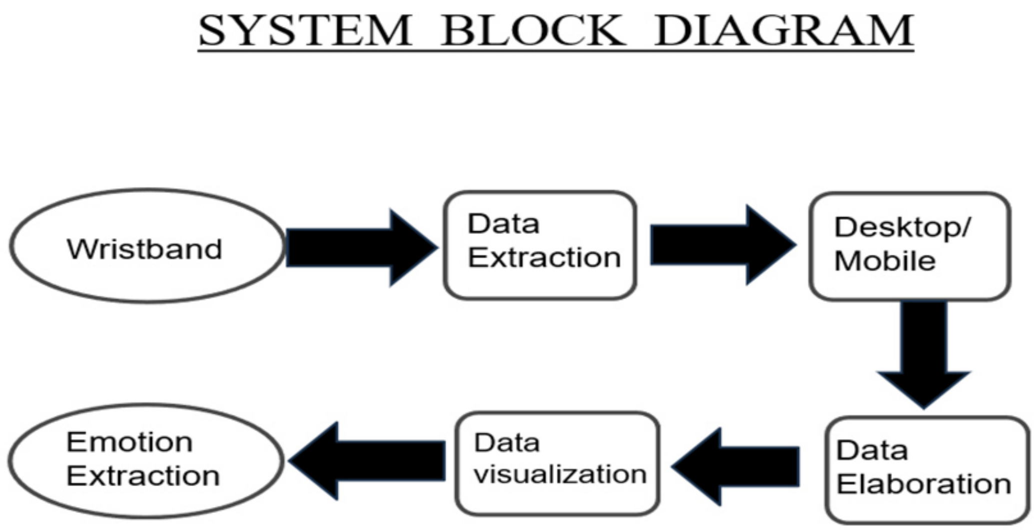

Fig1. Systematic Block Diagram of Emotion Tracking

4. SYSTEM SPECIFICATIONS

4.1 Sensors Used:

Skin Temperature (SKT)

It can be utilized to assess an individual's level of comfort. Dilated blood vessels cause the fingertip to become warmer when one is relaxed and colder when one is tense or anxious. The skt to become an electrical signal for feature extraction. The arousal was measured and converted into emotions using five categories. Positive feelings are simpler to identify than negative ones, according to the study. A different study distinguished between happy and melancholy and by studying SKT they were able to achieve 89.29% classification accuracy.

Galvanic Skin Response (GSR)

The fluctuation in Skin Conductance (SC) in response to sweat excretion activity is measured by GSR. This measurement, which is an essential factor in determining emotional arousal, cannot be consciously altered. The amount of excitation has a major impact on the conductance of the skin; as the level of excitation rises, so the conductance of the skin rises. Two electrodes are placed on the finger to measure skin conductance. In order to at least cover the fingertips, this calls for the use of sensors that might be included into a glove for on-the-go monitoring. It is known that the eccrine glands in the palm are more sensitive and involved in emotional activity in contrast to other sweat glands.

Heart Rate Sensor

We use a heart rate sensor to record insightful physiological data. This sensor continuously records changes in heart rate, providing a window into emotional reactions. We can better comprehend and be aware of emotional states and their effects by looking at heart rate patterns. We can create useful strategies for improving well-being and managing emotions according to this data-driven approach. Heart rate monitoring plays an important role in our project's inclusive strategy for tracking emotions.

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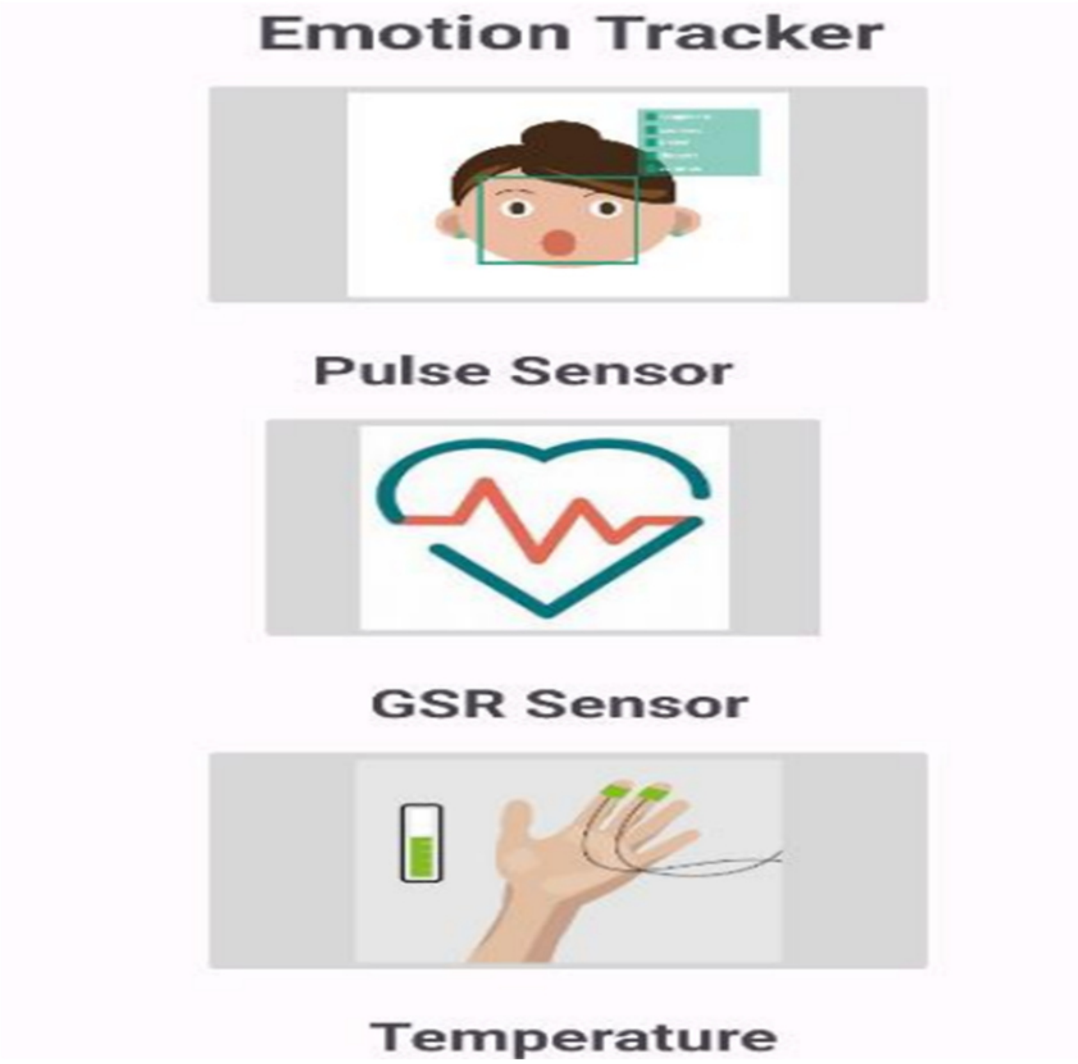

Fig 2. Emotion Tracker

Emotion Recognition:

Once the data has been collected, a machine learning algorithm must be put into place in order to recognize human emotions. Subprocesses have been created within the process to do this. To determine the qualitative value (the name of the emotion) of the emotions stored in the used dataset, the first method uses the SVM algorithm. The second procedure uses a KNN algorithm to categorize fresh wristband bio signal inputs into emotional values. Moreover, we applied the Random Forest and Decision Tree algorithms. These algorithms enable us to dissect and analyze complex emotional data, providing a precise understanding of human emotions. Decision Trees offer transparency and interpretability in emotional classification, while Random Forest leverages ensemble learning for improved robustness and generalization.

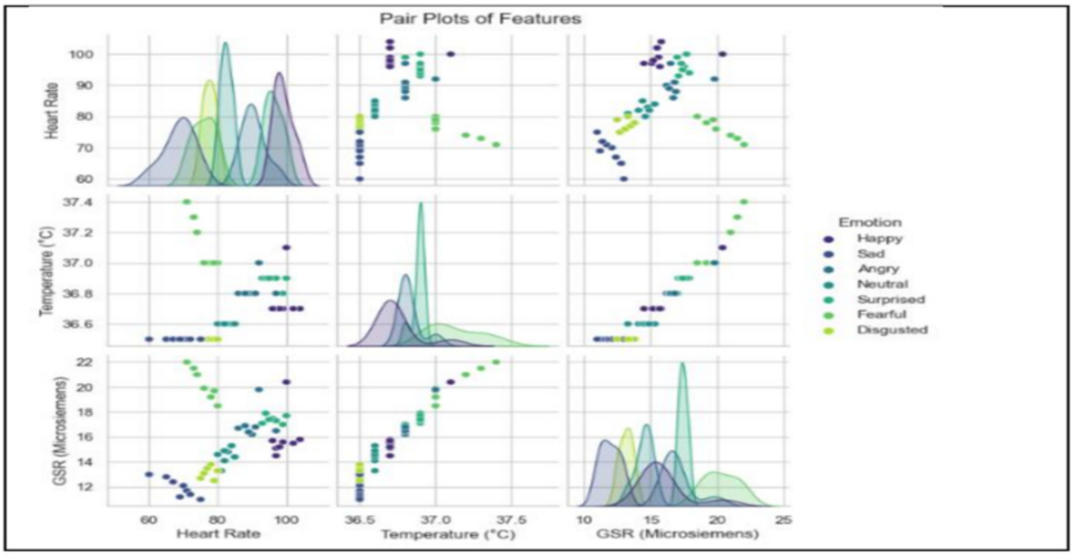

Fig 3. Physiological Correlation Pair plot

For precise emotion prediction, the machine learning models are hyperparameter-tuned using Grid Search CV. A classification report, a confusion matrix, and other important metrics are then used to assess the top-performing model, which has been trained on the training data.

The algorithms also offer useful data visualizations, such as a scatter plot, bar graph and histogram showing emotion distribution in a condensed feature space and a bar graph showing the distribution of emotions throughout the dataset as shown in Fig6.The performance and interpretability of the machine learning models are improved by this technique, making it a useful tool for comprehending and forecasting emotional states based on physiological inputs.

For monitoring this system, a user-friendly app is developed that displays real-time and historical emotional data along with insights, that provides visualizations that help users understand their emotional patterns over time. Also allows users to set goals for emotional well-being and receive recommendations based on their data.

5. RESULTS

The proposed methodology involves the development of an intelligent system for tracking emotions using wearable technology, particularly a wristband with sensors measuring physiological signals. The chosen sensors include Skin Temperature (SKT), Galvanic Skin Response (GSR), and a Heart Rate Sensor, which collectively provide comprehensive insights into emotional states.

Numerous research have examined how computers can understand our feelings, and they've made great progress. In this part, we'll talk about these studies in three ways. The first way is sorting emotions into categories. It's tough because people show emotions differently.

Researchers have come up with two common ways to do this. Using particular words like joy, fear, sadness, rage, and other emotions is one technique. Ekman and Friesen, for instance, claimed that there are six fundamental emotions. Another way is using scales, like how happy or sad someone is and how much energy their emotion has. We'll use this way in our study . The second way is using body signals to recognize emotions. Researchers have looked at things like brain signals, heartbeats, muscle activity, and more. They found that these signals can help tell how someone feels. But sometimes, using these signals in everyday life isn't easy . The third way is about using skin response to tell stress and workload apart. This has worked quite well, but it's tricky because everyone reacts differently to tasks . These studies have done well in understanding emotions, but they need a lot of data and good training to work in real situations.

6. APPLICATION

- Helps in Evaluating Condition of a Person.
- Medical Field & Medical Diagnosis.
- Education.
- Employee Safety

7. FUTURE SCOPE

1. Developing wristbands that provide real-time feedback or interventions to manage emotions based on the detected emotional state.
2. Integrating wristband data with artificial intelligence for more sophisticated analysis, possibly predicting emotional states or patterns based on daily activities and interactions.
3. Combining data from wristbands with other sources like smartphone apps, social media, or environmental factors for a more comprehensive understanding of emotions.
4. Improvements in sensor technology within wristbands to capture a wider range of physiological signals, leading to more accurate emotion detection.

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