

A Comparative Analysis of Evaluating Emotion Recognition Using Arduino-Based Sensors and Consumer Wearable Devices

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ABSTRACT

The importance of physiological signals in affective computing research has showcased the use of wearable devices for emotion detection. This study presents a comparative examination of three core emotions: happy, fear, and sad. The two-phase methodology has been used for detection of emotions. At first, from the traditional methodology, non-invasive biomedical sensors along with Arduino UNO R3 were used to record the three physiological signals, such as oxygen saturation, skin conductance, and pulse rate. Phase 2 was developed as a comparative analysis, serve to determine the possibilities for the application of consumer-level smartwatches in obtaining physiological data regarding emotions. Supervised machine learning models such as k-nearest neighbor, support vector machine, and naïve bayes were utilized and gave 98%, 97%, and 96% accuracy, respectively, for phase 1. While phase 2 obtained a much lower percentage due to scattered results.

Keywords: Autism Spectrum Disorder (ASD), Affective Computing, Sensor-Based Intervention, Physiological Signals, Wearable Devices.

INTRODUCTION

The technical foundation of wearable technology in autism research rests on a variety of sensor modalities designed to capture the complex interplay between the autonomic nervous system and extrinsic behavior. According to the systematic review conducted by Cano et al. [1], the most common physiological signals that are utilized in stress detection in people with autism spectrum disorders include cardiac signals and electrodermal activity (EDA). Particularly, photoplethysmography (PPG) and electrocardiography (ECG) are commonly used to evaluate heart rate variability (HRV). HRV is considered a significant biomarker of emotional arousal and stress. These sensors allow for the non-invasive tracking of the sympathetic nervous system's response to environmental triggers, providing a window into the internal state of a child who may be non-verbal or unable to communicate distress through traditional means. Furthermore, the integration of these sensors into commercial and research-grade devices has expanded the scope of what can be measured in naturalistic settings. Hernández-Capistrán et al. [2] note that approximately 50% of analyzed wearable devices utilize a combination of ECG, EEG (electroencephalography), PPG, and EMG (electromyography) to facilitate real-time physiological monitoring. This multi-modal approach is essential because no single physiological parameter can fully encapsulate the autistic experience. For instance, while PPG might indicate a rising heart rate, the addition of EDA sensors can help

distinguish between physical exertion and emotional anxiety. The synthesis of these biometric data points allows for a more granular understanding of how autistic youth interact with their surroundings, though the authors emphasize that many of these devices still lack formal clinical validation or defined regulatory status, such as FDA clearance.

LITERATURE REVIEW

Although research on emotion recognition using wearables is on the rise, no prior study has directly compared proprietary biosensors and commercial smartwatches used for emotion recognition in young children aged around 6-10 years old. Prior research has largely focused on emotion recognition in adults using expensive wearables such as Empatica E4 or Polar H10, which cost roughly USD 1,500-2,500. Our research attempts to fill this void by exploring the use of low-cost Arduino sensors approximately \$15-30 and commercial smartwatches ranging from \$12-45.

Table 1 Literature Review

Year	Description	Device Type	Target Group	Physiological Signals / Other Parameters	Accuracy	Contributions
2024 [3]	Difference between persona and general ML models for 3-class emotion recognition	Wearable Stress and Affect Detection (WESAD)	Neurodivergent and Neurotypical	ECG, EDA, PPG and EMG	95.06%	To develop an approach towards personalized digital interventions for neuropsychiatry
2022 [4]	For detection of the abnormal RBD phenomenon in PD patients	ASUS Vivo Watch BP (HC-AO4)	Individuals with Parkinson's disease (PD)	PPG	Two-stage sleep-awake classifier 84.51% and Three-stage classification 64.02%	The utilization of smartwatch to monitor the sleep problems of PD patients in a convenient way
2022 [5]	A model of an AA-CBGRU network is	AA-CBGRU Network	General Public	CNN, BGR U network	71%	Neural network models for speech emotion recognition

	proposed for the speech emotion recognition					
2025 [6]	For the diagnosis of neurological diseases, especially those related to seizures in epilepsy patients	IoMT-based wearable device	Individuals with epilepsy	EEG, CT, MRI, SPECT, PET, MEG,	95%	Affirmation of feasibility and practicality of the proposed framework in continuous seizure monitoring for epilepsy patients
2020 [7]	A Heart Rate measuring device as a non-invasive and pain-free objective stress measure for preschool children with ASD	Heart rate device (electrode embedded belt with USB)	Individuals with ASD	ECG	autistic symptoms ($r = 0.415$; $p = 0.044$), (ADOS-2 free play; $r = 0.368$; $p = 0.077$ and ADOS-2 anticipation of a routine with objects; $r = 0.368$; $p = 0.076$	Provision of HR variability-based stress and ASD detection
2026 [8]	A smart emotion recognition system enabled through Internet of Things technology,	Smart emotion recognition system via IoT, using internal body parameters	General Public	Heart Rate, Muscle Signal, BP, Blood Glucose, Body Temperature, oxygen Concentration	94%	Physiological signal-based framework for emotion recognition

	utilizing internal body parameters					
2022 [9]	IoT-based smart emotion recognition system based on internal body parameters	Smart Belt	Students with anxiety	ECG and Heart rate	80%	Evidencing based MSY exercise for anxiety reduction
2021 [10]	Apple smart watchesbased movement disorder prediction methodology	Apple Watch 3 and Apple Watch 4	Normal and Individuals with Parkinson's disease	Seismometer, Fourier Transformation, Apple watch sensor and Euclidean Norm	Normal 90% Parkinson's disease 70%	Largest PD data set providing was done in this study
2023 [11]	Intelligent System to recognition of emotions through voice messages	Speech Emotion Recognition for Smart Assistance	General Public Emotion Recognition	Buzzer and light emitting diodes (LED) alert signals	81.02% for the RAVDEES dataset, 84.23% for the TIMIT dataset and 85.12%	Real time tracking and support to individuals and could also be used in the defense for security purpose.
2023 [12]	The study aims for the development of an intelligent system equipped with emotion prediction function.	Emotion Recognition-Based Smart Assistant System	General Public and Neurodivergent	Facial expression, voice, text and other information	Above 85% on average	To enhance intelligent assistant systems and provide better intelligent services for users

MATERIAL AND METHODS

We conducted a dual device experiment, both the phase captured physiological signals; pulse rate, oxygen saturation, and galvanic skin response. Phase 1 custom-built Arduino UNO R3 setup consisted of a pulse sensor, pulse oximeter sensor and galvanic skin response sensor. The phase 2 system collects the three vitals: by using two smartwatches: Orbit 2 and ZL99J for happy, sad, and fear emotions.

Emotion Induction Protocol

The procedure for emotion induction was carried out according to [13]. Data was collected in a secluded and controlled environment, where each child underwent a relaxation session for 2 minutes. After that, emotion-induction procedures were performed separately for each emotion. To induce fear, children watched a short video that included ghost appearance. To induce sadness, with the help of the school administration, children had to discuss the cessation of school off time activities. This procedure resulted in emotional reactions linked to the emotion of sadness. Children experienced happiness after taking part in a discussion of their favorite cartoon characters.

Table 2. Stimulus type for emotion induction for different

MATERIALS

Emotion	Stimulus Type	Specific Material	Duration
Happiness	Animated cartoon clip	A small conversation regarding happy moments, and a fruitful chat upon favorite cartoon character of the child.	3–5 minutes
Sadness	Illustrated emotional narrative	A conversation regarding school off-time cancelation.	3–5 minutes
Fear	Age-appropriate suspenseful visual clip	Mild suspense scenes from age-approved video (no violence)	3–5 minutes

Phase-1 Custom built Arduino UNO setup

The Phase I data acquisition system was built on top of an Arduino UNO R3 microcontroller, running at a clock speed of 16 MHz and employing a 10-bit analog-to-digital converter in conjunction with three peripheral sensors. A pulse oximeter sensor was used to monitor blood oxygen saturation levels, denoted by SpO₂, and pulse rate, in bpm, employing I²C communication. The pulse oximeter was placed on the end of the index finger of the left hand. A two-electrode galvanic skin response sensor was employed to monitor electrodermal activity, where the output was a linearly mapped integer value within the range of a 10-bit ADC, ranging from 0 to 667 microohms. The electrodes were attached to the fingertips of the index finger and the middle finger of the non-dominant hand. An additional pulse rate measuring optical pulse sensor was employed for cross-validation. Data was collected from

sensors manually and recorded on a CSV file. The Phase 1 approach was economically efficient but required a significant level of technical proficiency for sensor integration and data collection.

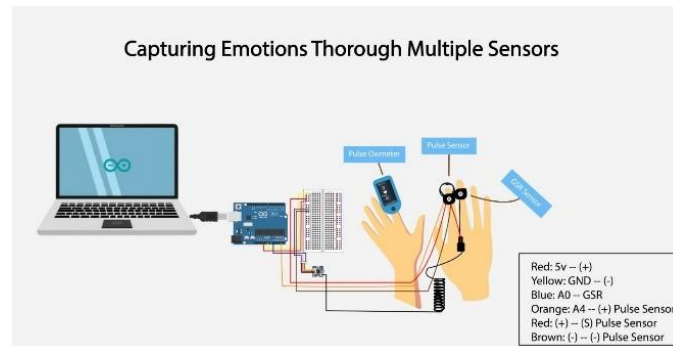


Fig 1 Vital Signs capturing infrastructure for Phase 1 [13].

The above image clearly demonstrates the positioning of all the sensors on both hands. The right-bottom box represents the summary of jumper wires connected to appropriate terminals. We utilized male-to-male, female-to-female, and male-to-female jumper wires in the connection of the sensors and the microcontroller to facilitate the transmission of physiological signals and communication data.

Arduino signals were recorded in comma-separated value (CSV) format, where each record includes information such as participant ID, time stamp for each session, SpO₂ (%), pulse rate (bpm), and analog GSR value (0-667 micro-ohms) for emotions.



Fig 2 Practical implementation for phase 1

Phase II: Consumer Smartwatch Devices

Phase II introduced two commercially available consumer smartwatches as data acquisition platforms. Both devices were selected based on their local availability in the Pakistani market, their stated health monitoring capabilities (heart rate, SpO₂, and stress/skin conductance monitoring), and their suitability for use on children's wrists. The technical specifications of both devices are presented in Table 1 below and discussed in the subsections that follow.

Table 3 Technical aspects of orbit 2 and zl99j

Specifications	Zero Lifestyle Orbit 2	ZL99J (ZHILIAN)
Brand	Zero Lifestyle; Pakistan	ZHILIAN / Amovan / Vestel Zazz — Chinese OEM
Display	1.38" Round TFT, 240×240 px	2.01" Square TFT, 240×296 px
Enclosure material	Zinc alloy frame + PC plastic back	PC plastic shell
Wireless connectivity	Bluetooth LE 5.3	Bluetooth LE 5.2
Processor Chipset /	Jl series (exact model disclosed by manufacturer)	L7012F6
GPS	Connected GPS via companion app	Connected GPS via companion app
Companion application	Zero Lifestyle App (Android / iOS)	H Band / Da Fit / YHWatch (Android / iOS)
OS compatibility	Android 5.0+ / iOS 9.0+	Android 5.0+ / iOS 9.0+

Smartwatch data was recorded manually from the device after each session. The data includes emotion labels, SpO₂ (%), pulse rate (bpm), and GSR equivalent stress output for analytical parity. The final smartwatch dataset includes 90 labeled data points, with 30 data points per emotion class.



Fig 3 Practical implementation for phase 2

Pre-Processing

Pre-processing for phase 1 includes handling inconsistent formatting, feature scaling, encoding categorical features, and combining data from multiple sources.

The Phase 2 smartwatch dataset was validated for normality, confirming that none of the three raw variables, oxygen saturation (SpO₂), heart rate, and GSR, are normally distributed ($p < 0.05$ for each). The pairwise Pearson test for correlations showed that the features exhibit minimal multicollinearity ($r < 0.21$), thereby supporting the independent discriminatory power of each sensor channel. Outliers were detected via the Z-score criteria ($|z| > 3$) for two borderline cases in SpO₂, which were preserved due to their physiological plausibility. Finally, five interaction features were generated by computing the ratio and product of the raw signals, leading to an increase in the dimensionality of the feature set to eight, all normalized via Z-score scaling based only on the training split. *E.*

Model Training

Classification process for emotion detection involved machine learning models; K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Naïve Bayes, based on the nature of their decision boundaries assumptions and their suitability for small sized multiclass datasets. The two datasets were then divided in the training and testing sets in the stratified manner of 80%: 20%, respectively, giving rise to 72 training samples and 18 testing samples while keeping the proportion of classes intact in both the sample sets. Tuning of hyperparameters was performed individually for the classifiers through Grid Search in conjunction with five-fold stratified cross validation.

Signal Analysis

The GSR response led to the most compelling differentiation between the two devices. The Arduino sensor array generated GSR in a range of 572 units (105 – 677), with an inter-class variance of 261 units (Happy vs. Fear) and 129 units (Sad vs. Fear) both well above their respective withinclass standard deviations, which proves high discriminability. The consumer smartwatch provided a mere 37-unit range (60 – 97) for all subjects and all

emotions, resulting in inter-class variances of just 3.1 units (Happy vs. Fear) and 4.6 units (Sad vs. Fear). These numbers are fully contained in the noise floor and cannot be differentiated from each other statistically.

The Arduino pulse rate established physiological autonomic arousal theories, generating an inter-class range of 26.5 bpm with Happy having the largest mean value at 106.1 bpm, Fear at the midpoint of 84.1 bpm, and Sad at the lowest mean value of 79.6 bpm – indicating an increase in sympathetic activity during positive autonomic arousal and an increase in parasympathetic activity during sadness. In contrast, the smartwatch pulse rate showed heavy compression of the same physiological signal, with Fear (86.4 bpm), Happy (86.6 bpm), and Sad (89.6 bpm) displaying a total inter-class range of just 3.2 bpm – which indicates firmware smoothing to produce consumer-friendly readings rather than physiological activity readings.

SpO₂ was found to be the least accurate parameter out of the three modalities used in both systems. For the Arduino-based device, the Coefficient of Variations for all emotional categories were from 27% to 32%. Physiologically unreasonable values such as SpO₂ levels of 14–15% owing to child movement during stimulus display have been observed; data with SpO₂ levels lower than 85% were regarded as artifacts and not considered during further analysis. The smartwatch showed greater SpO₂ reliability for Happy (CV = 3.1%) and Sad (CV = 1.2%), while higher variability (CV = 18.1%) could be associated with child movement during fear induction. Most importantly, mean values for SpO₂ of the smartwatch in each emotional category ranged from 96% to 97%, indicating that arterial oxygen saturation does not differ substantially in the timeframe of 3–5 minutes. Thus, SpO₂ can hardly serve as an effective indicator for short discrete emotion detection in healthy children.

Signal Acquisition for both watches

The Orbit 2 and ZL99J watches both use reflective optical PPG sensors to measure heart rate using a green LED (530–570 nm) shining into the wrist tissues, with an attached photodiode measuring light intensity fluctuations due to changes in the volume of blood in the capillary vessels during each heartbeat. The raw PPG signal undergoes processing via a low-pass moving average filter (window size 4–8 samples at 50–100 Hz) and subsequent second-order polynomial Savitzky-Golay filtering [14] to reduce noise. Following this, a double threshold cross-peak identification process is used to detect individual beats, whilst a debouncing process removes any false peaks resulting from the dicrotic notch. Heart rate is calculated using

$HR (bpm) = 60,000 \div \text{mean IBI (ms)}$ with IBI referring to the inter-beat interval calculated across a sliding window of 5–10 beats. Motion artifacts are filtered out by means of a normalized least mean square (NLMS) adaptive filter, which uses data from a triaxial accelerometer as the noise cancellation reference. Notably, whilst the sensor processes its measurements internally at a frequency of 25–100 Hz, only one processed BPM value is transmitted to the app once per second. The two units estimate SpO₂ based on ratio-of-ratios algorithm [15] from Beer-Lambert Law where red (660 nm) and infrared (940 nm) LEDs alternately illuminate wrist skin while making use of distinct absorption capabilities of oxygenated hemoglobin (HbO₂) and deoxygenated hemoglobin (Hb). Each PPG waveform is analyzed and separated into an arbitrary absorption AC part and static tissue absorption DC using highpass filtering and then calculating the ratio of $R = (AC_{red}/DC_{red}) \div (AC_{ir}/DC_{ir})$, which is used to calculate SpO₂ percentage using pre-calibrated formula

$SpO_2 \approx a - b \times R$, where $a \approx 110$ and $b \approx 25$ for generic OEM units. To make sure SpO₂ measurement is precise enough, at least 30 seconds of artifact-free signals with no flags raised are needed; nonetheless, many consumer-level budget products neglect this thresholding step and generate SpO₂ measurements that do not reflect actual physiological conditions, such as when the subject is moving. This issue was clear in the present analysis of the data where SpO₂ value of 58% was detected during fear induction stage because of weak signals at wrist PPG site compared with finger oximeter by 5–10 times and additional child movements during stimulus delivery.

From the two watches assessed, Orbit 2 is the one that possesses a stress measurement feature; the ZL99J watch, which uses the L7012F6 chipset, does not support stress or Electrodermal Activity functionality, and neither of its software apps, H Band or Da Fit, gives stress scores. To derive stress from HRV, Orbit 2 uses two approaches. The first method involves time-domain analysis, particularly the root mean square successive differences in IBI (RMSSD) [16], where low numbers are indicative of sympathetic dominance; the second method entails frequency

domain analysis using FFT to obtain the LF/HF ratio of power spectrum (LF range is 0.04 – 0.15 Hz while HF range is 0.15 – 0.4 Hz). All these factors, along with the average heart rate, are weighted using a proprietary algorithm by the manufacturer to yield a stress score in the 0 – 100 range.

Nevertheless, this method has four major drawbacks that become apparent when applied to our research.

- The sensor collects data on heart rate at around 1 Hz, which is not enough to calculate RMSSD (more than 4 Hz is required)
- Children naturally have high HRV, thus making general population norms meaningless.
- The time interval needed for calculation of HRV, 5 minutes, surpasses the duration of emotional stimulation, which lasts for only 3 to 5 minutes.
- Compressed output format eliminates class variation by 3 to 5 points, which is less than the statistical threshold.

DEVICE LIMITATIONS FINDING

The deterioration in performance in the smartwatch system could be attributed to a number of inherent causes related to the employment of consumer-level wearable technology. First, lack of access to raw signals makes it impossible to apply feature engineering that is vital for pattern extraction from physiological signals. First, the absence of raw signal access precludes the possibility of employing advanced feature engineering techniques, which are essential for the accurate extraction of physiological patterns. Second, the absence of the GSR sensor precludes the possibility of accurately detecting emotional arousal, thereby excluding the accurate detection of high-intensity emotions such as fear and stress. Third, the absence of raw signals in the smartwatch-based system, which typically only provide access to heart rate, SpO₂, and derived stress, results in low diversity in the feature extraction, which is inadequate for accurate emotion classification.

Finally, the use of black-box algorithms in the smartwatchbased system, in which the underlying filtering, calibration, and computation mechanisms are not available, precludes the possibility of transparency in the underlying mechanisms, thereby precluding the accurate control of the quality of the data being used in the system. Moreover, smartwatch sampling rate is too low and consumer smartwatches often only sample every 5 seconds, missing the micro-changes that Arduino captures.

Table 4. Technical compatibility of orbit 2 and zl99j in

Terms Of Signals

Criterion	Zero Orbit 2	ZL99J
HR sensor	Optical PPG (unspecified)	LC09A specified
Stress / GSR feature	Listed explicitly	Not listed
Sports modes	123	123

Raw signal access	No	No
Research suitability	Low — basic consumer device	Low — basic consumer device

RESULTS AND DISCUSSIONS

This section presents the experimental results that showed a significant performance variation in the results obtained for both phases of the experiment.

In Phase 1 of the experiment, the proposed Arduino-based multi-sensor platform, that showed highly promising results of K-Nearest Neighbors (KNN) classifier with an accuracy of 98%. This is because the proposed platform was able to collect raw physiological signals from the human body. While SVM, and Naïve Bayes got 97%, and 96% accuracy, respectively.

The overfitting was assessed by comparing the training and cross-validated accuracy results. For KNN, the overfitting is noticeable at 8.10% (100.00% for training vs. 91.90% for CV), which is normal for instance-based learning models. However, for SVM and Naïve Bayes, very low overfitting is observed, with gaps of 0.83% and 0.24%, respectively. While a single random split provided accuracies close to 98%, cross-validation revealed that the accurate ranking order was Naïve Bayes (96.19%) > SVM (93.81%) > KNN (91.90%). Such high accuracy scores are due to the strong separability of physiological signals in the Arduino data set. This can be seen from the inter-class signal-to-noise ratio for the GSR signal, which is equal to 4.82.

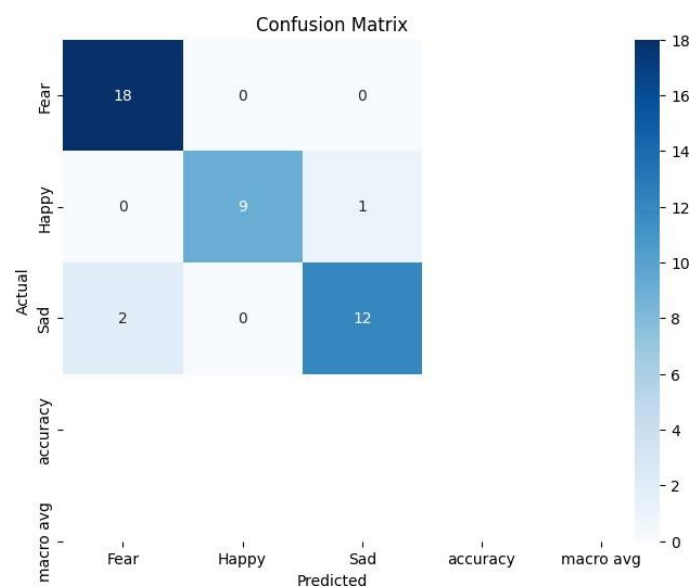


Fig 4 Confusion Matrix for best model KNN; Phase 1

The Phase 2 classification experiments revealed very distinct training and generalization behaviors. KNN ($k = 3$) had a training accuracy of 100%, with perfect memorization of the training data set, while the test accuracy was just 55.6% (CV: 66.57%, macro F1 = 0.54), revealing an accuracy gap of 44.4 percentage points, showing overfitting. SVM ($C = 1, \gamma = 1$, RBF kernel) performed the best among the three models about the balance between training and testing, with training accuracy of 83.3% and testing accuracy of 66.7% (CV: 66.67%, macro F1 = 0.66), having the smallest variance across the folds compared to the other two algorithms. GNB (var_smoothing = 1×10^{-12}) achieved a training accuracy of 63.9% and testing accuracy of 61.1% (CV: 55.52%, macro F1 = 0.60), although the highest cross-validation standard deviation indicated considerable instability across the folds.

Table 5 Cross-Validation Fold-Level Scores

Classifier	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean
KNN	66.7%	73.3%	57.1%	64.3%	71.4%	66.6%
SVM	66.7%	66.7%	57.1%	71.4%	71.4%	66.7%
Naïve Bayes	66.7%	46.7%	42.9%	50.0%	71.4%	55.5%

From the Phase 2 findings, SVM with $C=1$ and $\gamma=1$ and an RBF kernel is the most appropriate classifier for smartwatch emotion classification due to the minimal difference between the training accuracy rate (83.3%), test accuracy rate (66.7%), and mean cross-validation accuracy rate ($66.7\% \pm 5.22\%$). Conversely, the perfect training accuracy rate (100%) recorded by KNN compared to a test accuracy rate of 55.6% indicates serious overfitting caused by the small number of training samples ($N = 72$), while the Gaussian Naïve Bayes' large CV variance ($\pm 11.37\%$) highlights the sensitivity of Gaussian assumptions to abnormal physiological data.

Table 6 Model Comparisons

Models	KNN	SVM	Naïve Bayes
Phase 1	98%	97%	97%
Phase 2	55.6%	66.7%	61.1%

Comparative Analysis for Both Experimental Frameworks

In this research we conducted a comparative analysis among both the setups to analyze the performance and effectiveness.

Table 7 Feature comparison of phase 1 and phase 2 setups.

Features	Arduino Setup	Smartwatches
Cost	Low	High
Portability	Medium	High
Child Comfort	Low	High

Table 8 Performance of setups across all dimensions.

Criterion	Arduino UNO R3	Smartwatch	Better
Dataset size	n=210 (70/class)	n=90 (30/class)	Arduino
GSR dynamic range	105–677 (572 units)	60–97 (37 units)	Arduino
GSR inter-class separation	261 units (Happy vs Fear)	3 units (undetectable)	Arduino
Pulse rate separation	26 bpm (Happy vs Sad)	3 bpm (marginal)	Arduino
SpO2 consistency (Sad)	CV=32.1%	CV=1.2%	Smartwatch
GSR sampling resolution	Analog (0–1023)	Low-res proprietary	Arduino
Wearability / comfort	Wired, bulky	Non-invasive wristband	Smartwatch

Cost	Low (~\$15–30)	High (\$100–400)	Arduino
Setup complexity	Technical calibration requires	Plug and wear	Smartwatch
Suitability for children	Stressful attachment	Familiar, noninvasive	Smartwatch
Expected ML accuracy	High (clear class separation)	Near-chance (~33–45%)	Arduino

CONCLUSION

In this study, emotion recognition based on physiological signals was compared between two systems – an Arduino multi-sensor device and commercial smartwatches. In Phase I of the experiment, due to the integration of PPG, SpO₂, and GSR sensors, the acquisition of physiological signals was possible. It facilitated further preprocessing and analysis of extracted features leading to the highest classification accuracy of 98% obtained via the application of the K-Nearest Neighbors (KNN) classifier.

Meanwhile, the Phase 2 investigation was conducted as a pilot test of smartwatches as an alternative method of acquiring physiological signals for emotion recognition. It was found that smartwatches provide only discrete and process outputs, lack access to the raw signal, do not have GSR measurement capability, and provide limited features' diversity leading to their overlapping. As a result, the smartwatch data provided did not contain any distinguishable patterns of emotional states. Thus, it can be said that despite some benefits provided using smartwatches, they were not sufficient for conducting accurate emotion recognition. It is possible to conclude that at the current stage, the data acquired from such gadgets cannot be used for training models for this application successfully.

FUTURE WORK

Our future research agenda involves collecting a larger number of data samples using more diversified subjects, thus ensuring better generalization capability and robustness of the system. Finally, the system proposed in this paper can be utilized in clinical and healthcare settings, such as detection of neurodegenerative disorders like Alzheimer's disease, autism, epilepsy, and others.

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