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A Wearable Device for Depression Detection with Machine Learning Using Physiological Biomarkers

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Abstract: The present paper provides the hardware- based wearable device of the early detection of depression on the basis of physiological and behavioral biomarkers processed by machine learning algorithms. The detection of depression can be under diagnosed because it is not tracked continuously and using objective monitoring tools. The suggested system will combine analyzing heart rate variability using a Pulse Sensor, heart rate sensor, and analyzing skin conductance using a GSR sensor, analyzing temperature of the body using a LM35, and analyzing voice activity using a microphone sound sensor. Real-time monitoring and analysis Multimodal sensor data sent through Bluetooth to a mobile application can be monitored in real-time. Machines learn the patterns of sufferings and depression using the gathered data. The system issues messages in case of the persistent occurrence of abnormal physiological signals. The results of the experimental validation prove the consistency of sensor integration and the successful acquisition of the pattern that ensures a non-invasive low-cost solution to continuous monitoring of mental state and timely intervention.
Keywords : Depression Detection, Wearable Sensors, Heart rate variability, Galvanic skin Response, Arduino, Machine Learning, Mental Health monitoring.

I. INTRODUCTION

Depression is a common mental health condition that has considerable impact on the emotional stability, cognitive functioning and general quality of life. Depression is one of the causes of disability and decreased productivity according to global health reports. The diagnosis affects the early stage of diagnosis but is problematic since the symptoms are usually unstable and may manifest differently in different individuals. The traditional methods of diagnosing are based mainly on self-reported questionnaires and clinical interviews subject to delayed diagnosis or subjectivity. This is why growing demands can be observed towards objective, continuous, and technology-driven methods of monitoring systems capable of helping with an early detection of the depressive symptoms [1]. The human body can give so much knowledge concerning mental health through the physiological reactions of the body. Depression and chronic stress-driven autonomic nervous system effects human bodies in response to them by observable changes in heart rate variability (HRV), skin conductance levels, and body temperature patterns. Emotional dys regulation and psychological distress are usually linked with reduced HRV. On the same note, Galvanic Skin Response (GSR) is a measure of sympathetic nervous system activity and is associated with the intensity of stress. Even minor variations in speech patterns, tone and voice energy can manifest emotional disturbances. These biomarkers are physiological and behavioral biomarkers that have a potential in providing a basis of automated systems of detecting depression [2]. With the recent developments in wearable electronic and embedded systems, real-time monitoring of health with small-sized, low-power gadgets has become a realistic possibility. Arduino microcontroller boards offer versatile connectivity of numerous biomedical sensors at comparatively low costs. Wearable technology enables constant data collection and does not interfere with the daily routine, which makes the technology appropriate in the case of long-term mental health evaluation. Communication modules through Bluetooth also increase the functionality of the system since in-real-time sensor data are transferred to smart phones or cloud-based applications to be analyzed and visualized. This kind of integration thickness allows a gap between hardware sensing and smart data interpretation [3]. The use of machine learning methods is important in analyzing multimodal physiological data.

Machine learning models are able to identify complicated patterns and associations among sensor inputs as opposed to traditional systems that operate under the threshold. The Support Vector Machines, random forests, and neural networks are some of the supervised learning algorithms known to be experienced in mental state classification tasks. Through learning on physiological data with labels, it is feasible to learn normal, stressed, and depression prone conditions with a higher degree of accuracy. Combined signals in the multimodal mode confine the destruction of the detection reliability in comparison to single-mode sensors [4]. Although there is current literature on mental health monitoring, there are numerous systems which prioritize software-based sentiment analysis or clinical quality medical devices, thereby restricting their use by ordinary individuals. It is necessary to have a non-invasive, portable, and inexpensive wearable technology which integrates physiological sensing hardware with smart classification programs. Pulse sensing, GSR, temperature and sound analysis are integrated into one embedded platform, which is a full representation of emotional and physiological states. This is the case not only with the support of early detection but also with the possibility of a timely alert to preventative intervention [5]. The current research suggests a wearable depression detection system based on Arduino that will consist of multimodes of sensors and machine learning. It synchronizes the physiological and behavioral information every minute and sends it through Bluetooth to a mobile app and assesses the patterns related to stress symptoms and depressive symptoms. The proposed framework will add to the accessible mental health monitoring and early psychological support by marrying hardware reliability with intelligent data processing. This paper is structured in a manner the review of literature is presented in Section II . Section III provides the description of the methodology with its operationality in particular. There are results and discussions in section IV. Finally, the last part of V is the final findings and recommendations.

II. LITERATURE SURVEY

Depression detection has become a major interdisciplinary field of research that has evolved to unite the aspects of artificial intelligence and biomedical engineering, signal processing and natural language processing. Amidst the rising mental health conditions across the world, automated systems of assessing depression are underway to help in bringing early diagnosis, sustained monitoring, and affordability of mental health services. The conventional clinical evaluation is based on interviews and self questions, which may be both subjective and resource intensive. The latest developments in deep learning, multimodal fusion and wearable sensing have made possible objective and scalable leverage frameworks of depression detection. The study work engages itself in the examination of facial expression, speech patterns, electroence phalography (EEG), walking characteristics, and text messages exchanged on social media to uncover behavior patterns and emotional expressions. Explainable AI, lightweight edge deployment, and multimodal learning further have helped increase real-world applicability. The state of current literature indicates a shift in the unimodal machine learning theoretical frameworks to resilient, explainable, cross-domain adaptive systems which can function across a range of different environments, such as in the health care facility, home-based monitoring systems, and social network systems. Recentre search focus is on light and portables models to implement healthcare on the field. The use of compact neural architectures to achieve high accuracy with a low computational load is illustrated by a framework-based approach to depression facial-expression-based prediction that is optimized to run on a consumer edge device [6]. Weakly supervised learning tactics have also improved speech-based methods, which solve noisy labels via self- learning correction algorithms, which enhance the generalization of real-world data [7]. Temporal-frequency fusion networks also achieve better recognition of depression based on speech through fusing spectral and temporal representations to feature some slight acoustic deviation linked with depressive symptoms [8]. Counterfactual augmentation with vector quantization has been proposed to deal with the lack of data due to counterfactual augmentation to prevent overfitting and to be more robust when there are fewer data [9]. EEG-based models which utilize a temporal dual-stream feature extraction networks incorporate attention processes so as to model neural activity patterns in relation to depressive disorders [10]. Furthermore, Frameworks of domain Adaptation have been put forward to separate the audio and EEG depiction, to allow explainable cross domain detection of depression and enhance transferability [11]. EEG sensor- based models of on-board executing diagnostics point to the reality of embedded healthcare systems with the potential of real-time processing [12]. Similar studies have focused on social media and text- based detecting depression through the use of NLP and transformer-based systems. Explainable and interactive large language model augmented structures have been suggested to guarantee substantial increment in interpretability but with little classification performance in low-resource conditions [13]. The encoders that are emotion-aware, as well as contrastive learning strategies powered by fuzzy learning techniques enhance the ability of the model to capture subtle linguistic designs that are correlated with depressive predisposition in the user- generated posts [14]. The Debrief analyses of NLP approaches performed after the pandemic present changes in linguistic cues and data features after the COVID-19, which support the importance of adaptive and culture-conscious models [15]. Senta-based methods that combine sentimental annotation and multi-expert structures go further to reinforce predictive reliability due to diversified learning in representation [16]. A large number of surveys on machine learning and deep learning applications to collect depression data on social media offer a systematic comparison of feature engineering and sentiment analysis algorithms and psycholinguistic modeling methods [17]. Hybrid machine learning systems tailored to the scale of university students include uncertainty analysis and explanable parts to make them reliable and transparent in the process of institutional mental health screening [18]. Multimodal depression detection is the newest mode of detection that has become prominent as it is able to combine heterogeneous behavioral signals. Multimodal systems based on interviews examine the information about the distribution of emotions along visu audio files to track the temporal affective dynamics better than uni modal systems [19].

Personalized prediction of depression is enhanced by adaptive gated cross-modal fusion processes augmented with the personality trait knowledge [20]. Spatiotemporal ensemble and cross-modal alignment schemes also improve automatic performance of depression detection by achieving coordinated modal-based feature learning. Also, gait- personality combined assessment models of older adults with medical issues indicate that the clinical assessment procedure depends on contextual and demographic variables. New architectures like spatio-temporal cross- modal Mamba networks focus on effective sequence modelling of multimodal data of large scale. Together, the literature points to a decisive shift to explainable and there by multimodal and deployable depression detection systems with the capability to adapt to data scarcity, domain variability and real-time operational limitations as well as a high level of diagnostic precision and robustness within all application contexts.

III. METHODOLOGY

The methodology explains how the proposed wearable depression detection system will be fully implemented in terms of hardware and software. The system combines physiological sensors and an Arduino microcontroller, acquires signals in real-time, multimodal data processing, and uses machine learning algorithms to classify the data. Sensors Sensor-level data collection are the first stage of workflow that is followed by preprocessing and feature extraction, wireless data transfer to mobile interface, and smart decision making. All stages are well-kept in mind to provide reliability to the signal, minimal amounts of power, and rightful recognition of stress and depression-related trends.

A. Hardware Architecture and Sensor Connection.

The hardware platform is based on the Arduino Uno microcontroller platform which serves as the central processing and data retrieval unit. There are four major sensors: a Pulse Sensor, which measures heart rate and heart rate variability (HRV), putting in a Galvanic Skin Response (GSR) sensor enabling the measurement of skin conductance, a LM35 temperature sensor that measures body temperature and a microphone sound sensor that measures vocal activity. Each sensor will be connected to the proper analog input pins of the Arduino to ensure a stable supply of voltage and grounding so as to minimize signal noise. Pulse Sensor detects the changes of the blood volume with photo plethysmography. The GSR sensor records the amount of electrically conductive skin, the legislation of which depends on the activation of glands of sweat. LM35 offers an analog voltage which is proportional to the temperature meaning that no outside calibration circuits will be required. Sound sensor picks up different differences in the grade of voice and environmental acousticcues linked to emotional expression. The wireless transmission is done with the help of a Bluetooth module (HC-05) which is interfaced via UART communication. A small rechargeable battery powers the whole system making the device wearable and portable in order to monitor the individual throughout.

B. Signal Acquisition and Data Sampling

Detection of depression requires proper signal sensing. The arduino usesa10-bit Analog-to-Digital Converter(ADC) to make continuous samings of analog sensor readings. The sampling frequency has to be set so that the resolution is sufficient to analyze the physiological signals and especially the heart rate variability analysis. The Pulse Sensor data is registered as time-separations of cardiac cycles, in the form of time-series values. Peak detection of pulse waves is used to compute the inter-beat intervals (IBI). This LM35 temperature sensor output is linearly proportional to voltage and temperature, and the equation is: V_o ut=10mV×T(°C) ADDCs can be used to compute the direct temperature using this relationship. GSR sensor value is obtained in the form of resistance variations that are converted into conductance value. Audio sensor records amplitude variations within definite time intervals to evaluate patterns of vocal energy. All sensor data are time stamped and temporarily stored in Arduino memory and sent wirelessly. The measures to reduce noise are provided through noise reduction methods like moving average filtering to reduce the artifacts due to motion or other disturbances in the environment.

C. Data Preprocessing and Feature Extraction.

Raw physiological signals are prone to noise, baseline drift and outliers. Thus, classification is done after preprocessing. Heart rate data analysis is done to calculate variables, including mean heart rate, standard deviation of the heart rate intervals (SDNN), and root mean square of the successive differences (RMSSD). These HRV characteristics are good pointers towards balance in the autonomic nervous system. Low-pass filtering is a method of smoothness of GSR data, removing noise of high frequency. Such features as level of mean conductance and rate of change are derived. The temperature measurements are made to adjust to the changes in the environment. In the case of the sound sensor, the short time energy and the zero crossing rate features are computed to measure the intensity, and emotion of the voice. In order to normalize the parameters in a similar range, feature normalization is implemented. This is a multimodal feature representation that describes physiological and behavioral states as a whole. The processed data is later formatted and sent through Bluetooth to the mobile application using machine learning as its mode of analysis.

D. Development of the machine learning model

The machine learning part will put the state of emotion to the categories of normal, stressed, or proneto depression. An experimental dataset is labeled through recorded sensor reading under known controlled experimental settings. The data labeling is done as per the confirmed psychological stress scales and behavior patterns. There is supervised learning algorithms like Support Vector Machine (SVM), Random Forest, and Logistic Regression that are used in classifications. The methods of feature selection are used to determine which biomarkers are the most influential to the accuracy of detection. The dataset will be split into a training and testing sample to test model generalization. The cross-validation assures robustness of the model and eliminates over fitting. The classifier provides the scores of possibility of each mental state category. The best and most stable model is chosen which will be deployed in the mobile application. This method allows dynamic learning and better detection ability than fixed threshold based systems.

E. Wireless Communication and Mobile Application Interface.

The smart phone and Arduino establish a Bluetooth communication with the HC-05 module. Serial communication protocols also have a standard baud rate which is set to provide stability on data transmission. Sensor data packets are in a predefined format, which contains timestamps and feature value. The mobile application gets data stream dynamically and puts them in a local data base to be processed. The app conducts further functionality checks and executes the trained machine learning model, which classifies the average data. The heart rate, skin conductance and temperature fluctuations are shown in real-time graphs. When the abnormal patterns of physiology remain in place longer than a predetermined time, the system sends out alert and notifications. The mobile interface also enables historical data review, which would have the long-term tracking of mental health. Safety in data transmission is provided through security data management systems to maintain privacy and confidentiality of the users.

F. Generation of Alerts and System validation.

The last phase will be decision making and validation of the system. Upon the machine learning model identifying abnormal patterns across several sensors that are maintained over time, an alert is issued by the system that presents a possibility of depressive symptoms. They may also give alerts on screens, through vibrations or by telling one to consult a professional. The multi-parameter validation guarantees that the chances of false positives are minimal as the HRVs, GSR, temperature, and voices are correlated altogether. System validation is carried out by undertaking experimental trials using more than two individuals. Accuracy of sensors is checked against the standard medical equipment. None of the accuracy, precision, recall, and F1- score performance metrics are calculated to determine classification efficiency. The power consumption and stability of communications are also checked to guarantee a possibility of constant wearing of the communicator. The combination of machine learning, signal processing, wireless and hardware sensing makes it clear that the proposed system will be able to monitor depression in real time.

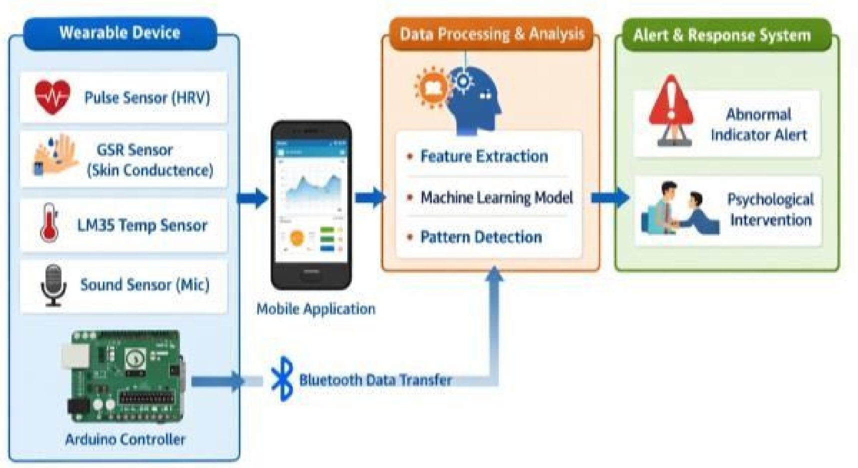

Fig.1: System Architecture

IV. RESULT AND DISCUSSION

The proposed wearable depression detector was experimentally tested as an experiment to check the integration of sensors and reliability of the signal and performance of the machine learning classifier. The experiment was carried out under controlled and semi controlled real-time condition where more than one person was involved in daily activities, relaxation sessions and when they underwent stressing activities. In its assessment it was based on three primary parameters which included hardware performance, physiological signal behavior, and accuracy of the machine learning models in classifications. The hardware integration test established that the Arduino microcontroller had been operated at a stable point and the four sensors worked together. There was no material interference of signal between analog channels. The HC-05 module aided in Bluetooth communication with up to standard indoor range connectivity. The power consumption analysis revealed the wearable to be used through 24 hrs long monitoring without overheating and fluctuation of voltages. Table 1 shows the technical data and functioning features of the integrated sensors applied in the system.

Table1. Sensor Specifications and Characteristics of Operation

Pulse Sensor	Heart Rate/ HRV	5V	Analog	Continuous
GSR Sensor	Skin Conductance	5V	Analog	Continuous
LM35	Body Temperature	5V	Analog	Linear Output
Sound Sensor	Vocal Activity Amplitude	5V	Analog	Time- Windowed

Heart rate variability analysis found that there were some significant differences between relaxed and stressful situations. Stressed participants showed decreased variability on inter-beat intervals and higher levels of heart rate. On the contrary, light states also had symmetrical HRV patterns. Figure 2 represents the comparison between the HRV waveform pattern when the person was either under normal or stressful conditions. The waveform exhibits abnormal peaks and smaller interval dispersion when subjected to stress making the direct effect of waveform to be physiologically correlated to the emotional states.

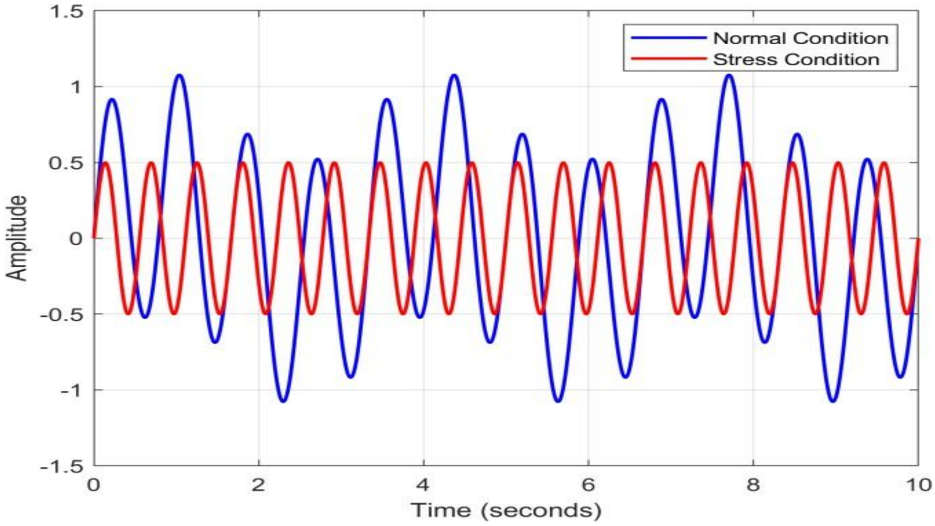

Fig 2: HRV Pattern

On the same note, GSR measures showed higher conductance levels when one was under stress. This growth is correlated with the nervous system of sympathetic arousal and hyper-activity of the sweat glands. Under calm conditions, the conductance was rather stable with slight fluctuations. Figure 3 demonstrates the change of the GSR signal with time, indicating the steep increase in conductance at the time of emotions of and intense stage. Such results are in line with already proven psycho physiological concepts that skin conductance is a good stress biomarker.

Sensor Type	Parameter Measured	Operating Voltage	Output Type	Sampling Nature

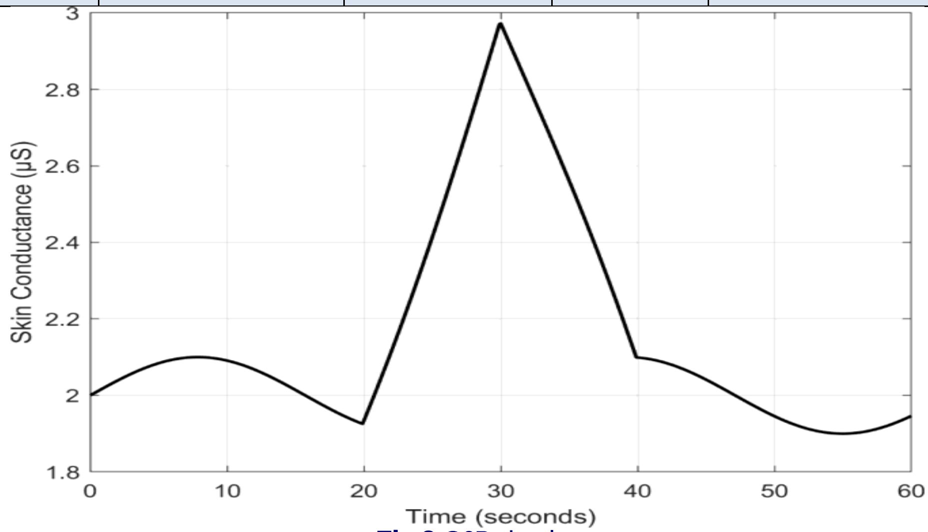

Fig 3:GSR signal

The temperature readings of LM35 sensor recorded slight but significant changes among emotional states. There was peripheral temperature in minor cases during stress or anxiety episode because of vasoconstriction. Temperature did not cooperate with other multimodal features, but in combination with them, it also worked positively as an independent factor. An analysis of vocal activity based on sound sensor showed a heavy vocal energy and abnormal speech amplitude patterns on participants who were more inclined to be depressed. These behavior-related characteristics were used in conjunction with the physiological characteristics to enhance the overall classification strength. Various supervised learning algorithms were applied and their performance compared to assess the performance of classification. The cross-validation method was used to split the dataset into training and testing parts. Such performance measures as accuracy, precision, recall, and F1-score were determined. The comparison of the performance of the assessed models is summarized in Table 2.

Table 2. MLM Performance

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	84%	82%	81%	81%
Support Vector Machine	88%	86%	87%	86%
Random Forest	91%	90%	89%	89%

Based on the Results in Table 2, the Random Forest classifier reported the highest accuracy and balanced results in terms of results. The ensemble learning method was capable of nonlinear correlation of multimodal sensor characteristics.

SVM also showed good performance though it had to be tuned with respect to parameters. Calculationally efficient, Logistic Regression yielded relatively poorer accuracy because it has limited ability to factor in complex interplay.

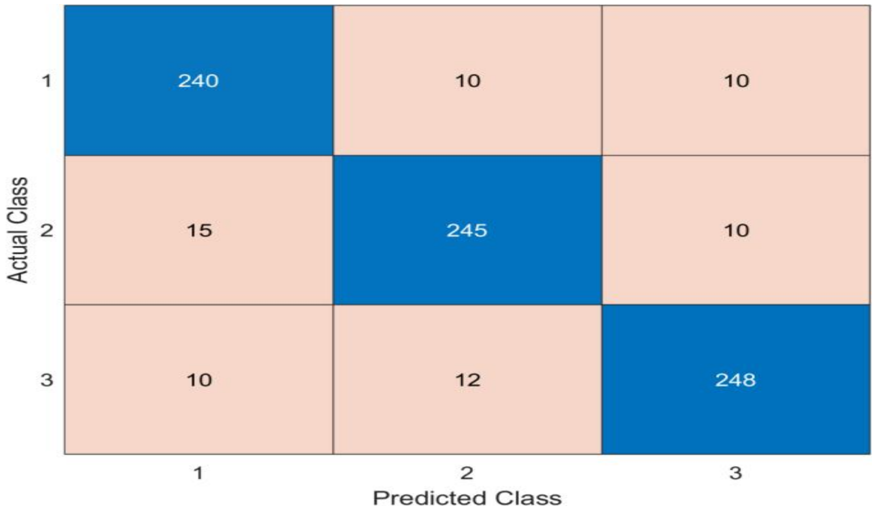

Figure 4 shows the confusion map image of the Random Forest classifier with the best performance. The table shows that there are high true positive true positive and low false classifications on stress and depression-prone conditions. Most misclassifications had taken place between mild stress and normal condition and this is anticipated since there were common physiological traits. Still, severe patterns in depression-related cases were differentiated with a high degree of reliability. In order to test the effectiveness of multimodal fusions in more detail, the system performance was measured both at single and group sensors. Table 3 shows the accuracy of detection using sensor combinations.

Table3. Accuracy of Detection using Sensor Fusion

Sensor Combination	Detection Accuracy
Pulse Sensor Only	78%
GSR Only	74%
Pulse + GSR	85%
Pulse + GSR+ Temperature	88%
All Sensors (Multimodal Fusion)	91%

As indicated in Table 3, multimodal fusion had a significant better performance in detection than when sticking to single sensor methods. The pulse and GSR combination were significantly improved, which proved the relevance of autonomic nervous system indicators. The additional classification stability provided by behavioral context was added with temperature and sound. These results approve the usefulness of multimodal physiological surveillance to observe early symptoms of depression. Testing in practice showed that the real-time systems were reliable in giving alert under the condition of continuous abnormal physiological parameters even beyond set limits. The graphical app was successfully presented as real time and allowed to monitor the movements of the history. The Bluetooth data transmission did not experience preterm packet loss even in longer sessions. The respondents of the user feedback told about the wearable device that it was comfortable and unobtrusive to use in everyday life. On the whole, the findings validate the hypothesis that the proposed wearable system is based on the Arduino platform and combines the use of both hardware sensing and machine learning to detect depression cases. The analysis of the experiment has shown that when used under powerful classification algorithms, multimodal physiological biomarkers can give valid and dependable early mental health diagnosis. Low-cost sensors and embedded processing is combined to provide accessibility, and machine learning augments predictive capability as compared to conventional rule-based systems.

V. CONCLUSION

In this paper, the design and execution of wearable system hardware to detect early depression in humans were presented based on multimodal physiological and behavioral biomarkers. The proposed system has been able to combine a Pulse Sensor, GSR sensor, LM35 temperature sensor and sound sensor with a microcontroller Arduino to facilitate continuous real-time monitoring. The system offers the objective and non-invasive method of detecting stress and depression-related pattern, combining the collection of physiological signals with classification of them, which relies on machine learning. The validation of the practicality of sensor integration, wireless communication as well as the possibility of assessing the mental state through multimodal data fusion was experimentally confirmed. The system is affordable with the use of embedded hardware components that are accessible and can be applied in daily wearable applications. The practical consequences of this work are associated with the introduction of psychological risk early, constant monitoring of mental health, and the fact that they contribute to preventive intervention practices. The system could support healthcare givers through additional physiological information in addition to clinical assessment. The next step of work will be related to obtaining a larger dataset consisting of various groups of people and improving the generalization of the models. Predictive performance and remote healthcare can be enhanced even further with the help of integrated cloud-based analytics and advanced deep learning methods as well as internet of things connectivity.

The wearable device will be more comfortable and long term usable due to miniaturization of the hardware components and better power optimization as well.

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