Multimodal Stress Detection Using Bio signals And Wireless Signals

Mrs.Vidhya A[1], Dr.M. Rajaram[2], Mrs.C. Preethibha[3], Dr.V. Shanthi[4], Gopinath M[5], Hiruthika V[6] Nithya B[7], Subashini K[8]

[1]Assistant Professor, Department of Electronics and Communication Engineering, Park College of Engineering and Technology

[2]Dean, Department of Electronics and Communication Engineering, Park College of Engineering and Technology, Coimbatore, India

[3,4]Associate Professor, Department of Electronics and Communication Engineering, Park College of Engineering and Technology, Coimbatore, India

[5,6,7,8]Students, Department of Bio Medical Engineering, Park College of Engineering and Technology, Coimbatore, India

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Abstract—**Stress is a significant cause of numerous physical and psychological disorders, and there is a need to have dependable and constant monitoring systems. The conventional ways of detecting stress primarily use wearable biosensors or questionnaires that either create discomfort or are subjective in nature and do not have real-time flexibility. In this paper, a new multimodal stress detection model will be suggested, which uses physiological biosignals together with non-invasive monitoring of wireless signal distortion. Galvanic Skin Response (GSR) and Photoplethysmography (PPG) sensors are utilized in order to record the changes in heart rate and skin conductance, whereas WiFi-based Received Signal Strength Indicator (RSSI) and Channel State Information (CSI) measurements are utilized in order to detect the micro-movements due to the stress-induced changes in the wireless channel. The obtained signals are preprocessed and feature extracted and normalized, and then multi-modal data fusion methods are used. To classify the stress levels in real time, a Support Vector Machine (SVM) classifier is used to classify the data in real-time into low, medium, and high. The presented system is more robust and more accurate because it ties together contact-based and contactless sensing modalities. The experimental validation has shown a better reliability, less user discomfort, and efficient monitoring that is found within a 5–10-meter range of wireless sensing, which is also applicable in smart healthcare.**

Index Terms—**Multimodal Stress Detection, Biosignals, GSR, PPG, RSSI, CSI, Wireless Sensing, Data Fusion, Support Vector Machine, Non-Intrusive Monitoring.**

I. INTRODUCTION

Stress is a major determinant of human health, as it can lead to cardiovascular diseases, mental illness, poor working efficiency, and general life degradation. Stress level should be monitored continuously to prevent stress and provide healthcare management at an early stage. The conventional methods of assessment of stress use wearable biosensors like GSR and PPG, or questionnaire-based self-reporting. The recent developments in the field of wireless sensing have demonstrated that subtle physiological movements can be detected by signal distortion in WiFi channels, including RSSI and CSI. The combination of physiological and wireless sensing modalities offers an avenue of hope to non-obtrusive stress detection frameworks that are accurate.

Even though there are several studies on wearable biosignal-based stress detection, it is commonly necessary to maintain physical contact continuously, and it can be uncomfortable to users. On the same note, emotion recognition methods based on the camera are sensitive to damage by lighting conditions and privacy. RSSI or CSI methods of wireless sensing have been independently investigated, although their individual operation might not be very reliable, since they are affected by the environment.

There are very few studies that have involved the combination of biosignals with wireless channel distortion on multimodal stress detection. Moreover, online classification and powerful fusion schemes have not been fully investigated, which underscores the importance of providing a comprehensive, dynamic, and nonintrusive stress detection system.

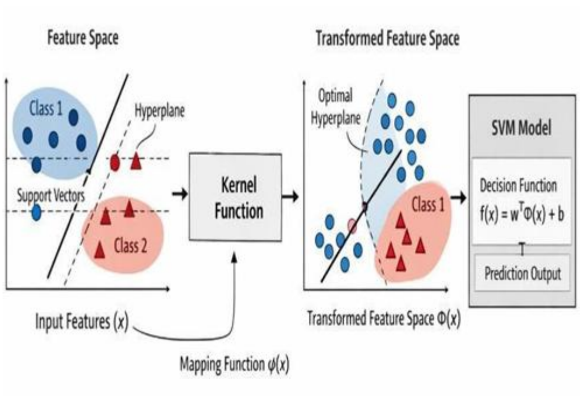

Fig 1. SVM Architecture

The rising incidence of stress-related disorders in the workplace, educational facilities, and healthcare environments creates a need to develop effective and sustained monitoring systems. The current systems either diminish the comfort of the user or do not possess the strength in dynamic environments. The rationale of this project is to come up with a hybrid stress detection system, which is a blend of contact-based biosignals and contactless wireless sensing in order to enhance the accuracy and reliability. Using variations in WiFi signals combined with physiological aspects, the system will promote a better detection rate and decrease the reliance of the system on intrusive wearable devices. The style allows the monitoring to be implemented smoothly without any drastic changes in user behavior and complex set-up processes.

The creation of a multimodal stress detector has a number of technical issues. Motion artifact and environmental noise can affect the biosignal acquisition and preprocessing methods need to be effective to address these issues. RSSI and CSI measurements of wireless signal distortion are affected by multipath fading, interference, and surrounding movements. It is not an easy task to synchronize heterogeneous sources and make correct multi-modal fusion. Also, to estimate the best features and create a stable model of classification in the context of real-time stress, it is necessary to optimize the choice carefully. The implementation of embedded hardware that ensures low latency, high accuracy, and energy conservation also imparts complexity to the system and necessitates efficient algorithm design.

The design and implementation of a multimodal stress-detecting device based on GSR and PPG biosignals in combination with WiFi-based RSSI and CSI measurements are within the scope of the proposed project. This system assumes preprocessing of signals, feature extraction, normalization, and multi-modal data fusion followed by the use of a Support Vector Machine (SVM) classifier to predict the level of stress. It facilitates real-time detection of low, medium, and high stress levels at a range of 5 to 10 meters. Smart healthcare, workplace surveillance, remote patient observation, and IoT-based health surveillance applications can be scaled to the proposed framework in the future with scalability improvements.

II. RELATEDWORKS

The effects of stress on physical and mental health have made the identification of stress an area of significance in research. Recent development has concentrated on multimodal techniques which incorporate biosignals and wireless sensing devices in order to enhance accuracy, strength, and real-world usability. A stress detection model based on bio-signal processing combined with IoT and machine learning approaches was proposed by Ahuja et al. [1], specifically in the case of elderly residents in old-age homes. They used physiological measurements like heart rate and Galvanic Skin Response (GSR) to show how remote stress monitoring can be possible with wearable sensors linked to cloud applications. This paper highlighted real-time data collection and long-range medical assistance.

A multimodal deep learning model is presented by Xiang et al. [2], which combines both time-domain and frequency-domain features of physiological signals. They demonstrated that multi-domain analysis, which incorporates heterogeneous features, can improve classification performance compared to single-domain analysis. On the same note, Ramasubba

Reddy et al. [3] enhanced the accuracy of stress detection on the WESAD data and utilized SMOTE to address the issue of class imbalance. Their machine learning model demonstrated that balanced datasets are highly beneficial in enhancing model generalization.

A different IEEE conference study [4] investigated stress detection through wearable devices that record multimodal physiological measurements such as ECG, EMG, and skin temperature. Their comparative study of classifiers showed that ensemble models are superior to classical machine learning schemes. Similarly, M. B. et al. [5] emphasized in their scoping review that personalization is significant in wearable-based stress detection systems, since physiological variations among individuals require adaptive algorithms.

Non-invasive alternatives have recently emerged through wireless sensing technologies. Dang et al. [6] integrated facial expression recognition and wireless sensing technology to achieve multimodal emotion recognition. Their findings showed that combining wireless signals with visual cues improves emotional state recognition accuracy. Bobade [7] demonstrated that combining physiological modalities with machine learning and deep learning methods can effectively support hybrid approaches.

WiFi Channel State Information (CSI)-based contactless sensing has attracted significant attention. Sai et al. [8] reviewed WiFi CSI-based recognition systems, focusing on feature extraction methods and classification models. Alzaabi et al. [9] assessed unobtrusive vital sign monitoring based on WiFi CSI and validated heart rate and respiration signal measurements through volunteer experiments. Sharma et al. [10] proposed the Wi-Gitation dataset for physical agitation recognition, which can also be useful in stress and behavioral studies.

Datasets play an essential role in multimodal research. Bussolan et al. [11] introduced MultiPhysio-HRC, a multimodal physiological dataset for human-robot collaboration in industrial environments, enabling stress and workload studies in workplace settings. Shen et al. [12] conducted a scoping review focusing on passive sensing for mental health monitoring using wearables and smartphones, with particular emphasis on long-term behavioral analysis.

Stress detection based on EEG signals has also shown considerable advancement. Kim et al. [13] proposed a wearable EEG signal-processing-based stress detection system, which achieved high classification accuracy under controlled conditions. Kumar et al. [14] applied fatigue and stress analysis in construction workers, highlighting practical occupational health applications. Patil and Paithane [15] compared AI-based multimodal stress detectors and showed that deep learning models outperform conventional algorithms when multiple sensing modalities are combined.

The fusion of facial and biometric techniques has also shown promising outcomes. Hosseini et al. [16] developed a multimodal system using facial landmarks and biometric cues for stress recognition. Their architecture improved robustness under changing environmental conditions through fusion techniques. Oliver and Dakshift [17] analyzed WESAD data across modalities and revealed that combining multiple sensing modalities provides greater classification reliability compared to unimodal approaches.

Recent studies have further expanded the use of wireless sensing technologies. Qu et al. [18] proposed MultiFormer, an attention-based CSI model for multi-person pose estimation, demonstrating the broad applicability of CSI. Krishnaa and Hailes [19] discussed robustness issues in WiFi sensing systems and evaluated the reliability of deep learning models under adversarial and environmental perturbations. Liu [20] proposed STAR, a privacy-preserving and energy-efficient edge AI platform for WiFi CSI-based human activity recognition, offering secure and scalable deployment possibilities.

Overall, the literature clearly demonstrates the evolution of stress detection systems from biosignal-based methods to multimodal frameworks integrating physiological responses, facial expressions, and wireless CSI measurements. Biosignal methods provide high measurement accuracy, although wearable sensors may create user discomfort. In contrast, wireless sensing offers unobtrusive monitoring but may suffer from environmental sensitivity. Combining biosignals with wireless sensing appears to be a promising direction toward developing accurate, continuous, and privacy-sensitive stress monitoring systems applicable in healthcare, workplace safety, and smart living environments. The concept of multimodal stress detection using biosignals and wireless signals represents a major advancement in intelligent health monitoring. Future research should focus on adaptive personalization, resistance to environmental variations, privacy-preserving edge computing, and large-scale real-world testing to enable practical deployment.

III. PROBLEM STATEMENT

Stress has become a major health concern in modern society, leading to various physical and mental disorders. However, existing stress detection methods are intrusive, unreliable, or unsuitable for continuous real-time monitoring. Wearable biosignal systems require constant physical contact with users, resulting in discomfort and reduced user compliance, whereas camera-based and questionnaire-based methods are limited by privacy concerns and subjective bias. RSSI- or CSI-based wireless sensing methods have shown potential but often lack robustness due to environmental interference and noise. Moreover, most existing systems lack the capability to combine multiple sensing modalities to improve accuracy and flexibility. Therefore, there is a need for a non-intrusive, real-time, and robust multimodal stress detection system that integrates physiological biosignals and wireless signal distortion analysis to improve reliability, user comfort, and monitoring performance in dynamic real-world environments.

IV. EXISTING SYSTEM

Current stress detection systems are mainly based on single-modality approaches such as wearable biosensors, camera-based emotion detection, or questionnaire-based self-reporting. Wearable systems utilize physiological parameters such as Galvanic Skin Response (GSR), heart rate, and electrocardiogram signals to estimate stress levels, requiring continuous physical contact with the user. Camera-based systems analyze facial expressions and eye movements, but they are highly sensitive to lighting conditions and raise privacy concerns. Questionnaire-based assessments depend on user opinions and cannot provide real-time monitoring. In addition, several studies investigate wireless signal parameters such as RSSI or CSI independently, but these approaches are highly affected by environmental noise and interference. Overall, current systems lack robustness, flexibility, and integration capability for reliable continuous stress prediction in real-world environments.

V. METHODOLOGY

A. Data Acquisition Module

This module will gather the data of physiological and wireless signals of the observed subject. Galvanic Skin Response (GSR) sensors are used to record changes in the skin conductance as a result of the activity of the sweat glands, whereas Photoplethy smography (PPG) sensors record the pulse of the heart rate and blood volume. At the same time, wireless transceivers measure Received Signal Strength Indicator (RSSI) and Channel State Information (CSI) of WiF isignals. They are signals of micro-movements and physiological changes that are a result of stress. The received multimodal data are integrated in to time and sent to the processing unit where they are analyzed further.

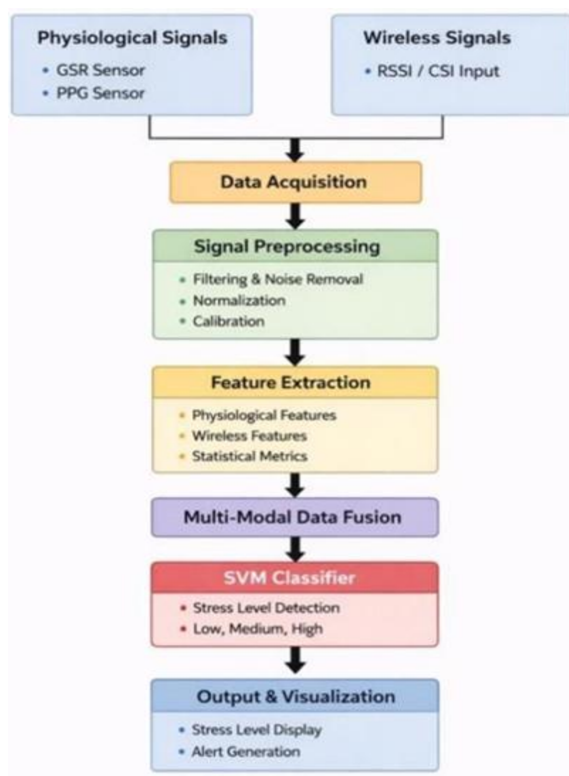

Fig2. Flow Chart

B. Signal Preprocessing Module

Raw signals detected by sensors and wireless channels usually possess noise, motion artifact, and other environmental interference. This module uses filtering, which is a noise removal technique that applies low-pass and band-pass filters. Baseline adjustment and normalization are used to standardize signal amplitudes. In the case of wireless signals, the multipath fading and the interference effects are reduced by the use of smoothing and calibration methods. Preprocessing guarantees better signal quality, stability, and reliability before features are extracted.

C. Feature Extraction Module
In this module, physiological and wireless characteristics of stress are significantly obtained. HRV features and heart rate are calculated based on PPG signals. Out of GSR signal, skin conductance level (SCL) and skin conductance response (SCR) are obtained. RSSI variance, CSI amplitude variations, and CSI phase shifts are some of the wireless features. Mean, standard deviation, variance, and entropy are the statistical parameters calculated. Such characteristics are the quantifiable signs of the physiological alterations that are stress-induced.

D. Multi-Modal Data Fusion Module
In this module, the biosignals and wireless sensing features are incorporated in order to enhance the accuracy of detection. The feature-level fusion is done by pooling the normalized feature vectors to form one composite feature set. Dimensionality reduction methods and correlation analysis can be used to eliminate redundant information. The merged data increases the robustness of the sensing data by overcoming the drawbacks of the individual sensing modalities and improving the accuracy of stress classification.

E. Classification Module
The combined set of features is inputted to a Support Vector Machine (SVM) classifier to predict the level of stress. The SVM model is trained with labeled datasets of various stress conditions. It determines maximum hyperplanes in order to segregate stress classifications according to discovered features. The classifier is determined according to three levels of stress, namely Low, Medium, and High. The reason why SVM is selected is because it is effective in dealing with high-dimensional data and also provides high classification accuracy.

F. Output Visualization Module
The last module shows the classified stress level on a user interface such as a mobile application or PC dashboard. Graphs of variations in heart rate, skin conductance, and wireless signals are displayed in real time to monitor variations. The system can also send alerts in case of high levels of stress. The module is user-friendly according to visualization and constant monitoring.

VI. PROPOSED MODEL

The suggested system presents a multimodal stress warning system that incorporates physiological biosignals and wireless signal distortion analysis to accomplish precise and non-invasive monitoring. The system records GSR and PPG measurements as indicators of heart rate and skin conductance changes during stress. At the same time, wireless signals performed over WiFi are interrogated through RSSI and CSI to measure the micro-movements and micro-physiological alterations due to stress without being in contact.

The obtained signals are preprocessed, filtered, normalized, and features are extracted followed by the application of multi-modal data fusion procedures. The classification of stress level into Low, Medium, and High is done in real time using an SVM classifier. This unified solution increases accuracy, durability, and user comfort, as well as allows continuous monitoring within a workable wireless sensing distance.

VII. RESULT AND DISCUSSION

An integrated biosignal sensors (GSR and PPG) and a WiFi based wireless signal monitoring (extraction of RSSI and CSI) were used to implement the proposed multimodal stress detector system. Hardware architecture involved biosignal acquisition modules having connections with a microcontroller where data were collected synchronously. Wireless transceivers were programmed to track signal strength/change in channel state continuously in a 5-10 meters indoor setup.

To eliminate motion artifacts and environmental noise, signal preprocessing was conducted with the help of the digital filtering methods. The algorithm off eature extraction was performed in Python/MATLAB to calculate the heart rate, heart rate variability, skin conductance level, RSSI variance and CSI amplitude and change of phase.Combining normalized feature vectors into a single dataset was also used as feature-level fusion.

SVM classifier was trained with labeled datasets of stresses that were conducted under controlled low, medium and high stress conditions. The data was separated into training and test sets in order to assess the performance of the system.

Depending on the experimental assessment, the multimodal approach proved to be much more effective in terms of accuracy in detecting stress than single-modality systems. SVM classifier showed high-level classification in a range of three stress levels.

The confusion matrix revealed that there was good separation between the classes of low, medium and high levels of stress. Biosignal characteristics were useful in the physiological stress detection, whereas the wireless signal characteristics enhanced the stability of detection when the body moved about slightly.

These findings support the notion that integration of physiological biosignals with wireless signal distortion offers a more credible mechanism of detecting stress compared to when a single sensor is used in the traditional methods. Biosignals are only sensitive to the motion artifacts, and wireless sensing is only affected by the environmental interference. To overcome these limitations, the multimodal fusion provides enhanced robustness and adaptability.

The SVM classifier showed good segregation of stress groups with equal accuracy and recall rates. Nonetheless, its performance could change based on the environmental factors, user variability, and signal synchronization accuracy.

Table1.Comparison Between Existing and Proposed Systems

Aspect	Existing System	Proposed System
Approach	Single-modality stress detection	Multimodal stress detection
Input	GSR,ECG,facial images, questionnaires	GSR,PPG,WiFi RSSI, CSI
Monitoring	Limited/non-continuous	Continuous real-time monitoring
Stress Classification	Basic/manual analysis	SVM-based (Low, Medium, High)
Accuracy	Moderate and noise sensitive	Higher accuracy with data fusion

The suggested system presents a scalable, non-invasive, and real-time solution applicable to the smart health monitoring tasks, stress management in the workplace, and the health surveillance applications based on IoT.

VIII. CONCLUSION

The suggested multimodal stress detector system manages to combine physiological biosignals and wireless signal distortion analysis to obtain proper and non-invasive stress detection. The system is stronger as it integrates GSR and PPG response with WiFi-based RSSI and CSI variations to improve the reliability of the classification and enhance the strength of the system as shown by the single-modality methods. The feature-level fusion and classification using the SVM allows real-time stress level classification into low, medium, and high with better stability in dynamic indoor conditions. The implementation shows that there is less user discomfort, less latency, and that it can be used to monitor with a practical sensing range.

The system can be further improved in the future by the addition of deep learning algorithms for adaptive classification and enhanced scalability. Remote health monitoring and massive data analysis can be achieved by integrating it with IoT cloud platforms. The diversification of the dataset in terms of age groups and real-life conditions will also contribute to the enhanced generalization of the models and their efficient implementation in smart health and workplace settings.

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