INTEGRATIVE APPROACH TO STRESS Detection from DIVERSE ASSESSMENTS

CHANDIPPA PAVANI REDDY[1], DR. RAJU ANITHA[2]
[1]Student, [2]Associate Professor
[1]Department of Computer science, Koneru Lakshmaiah Education Foundation, Green Fields, Vaddeswaram, Guntur, Andhra Pradesh, India
[2]Department of Computer science, Koneru Lakshmaiah Education Foundation, Green Fields, Vaddeswaram, Guntur, Andhra Pradesh, India

E-mail: [1]pavanichandippa@gmail.com, [2]anitharaju@kluniversity.in

Abstract
Stress detection is now working as a significant working area because it has a deeper impact on the mental and physical health of individuals as well as their productivity. Stress in the past has been measured using different approaches targeting one aspect or facet of data, either biochemical or biomechanical, or cognitive or behavioral. This paper proposes a multimodal approach that involves the use of multiple measurements such as physiological measurements which may include pulse rate, electro dermal activity, facial expressions, speech and self-reported measures. The framework involves these multiple data sources as a unified stream and applies machine learning to improve the reliability and sensitivity of stress classification.
Assessing the overall effectiveness of the proposed system, we build our dataset specifically for the experimental setting with tasks stimulating the experience of different levels of stress. Feature extraction and fusion process is designed in such a way that relative strength of each modality is maintained intact. Experimental outcomes show that the proposed multi-modal framework produces better overall accuracy than systems that use only a single mode, in addition to reducing false positive stress identification. This research highlights the possibility of practical applications of the multimodal systems including in a work environment to address stress, interventions for individuals' mental health, and other forms of human computer interaction. Outside work that is under way, further studies will address its use in dynamic sessions and invalidation of individual scores across various populations and settings.

Keywords: Stress detection, multimodal assessment, physiological signals, behavioral analysis, self-reported data, machine learning, mental health, stress prediction.

I. INTRODUCTION

In today's fast-paced world, stress is an ever-present challenge, with individuals experiencing it to varying degrees due to work pressure, personal life challenges, or societal expectations. The ability to accurately detect and measure stress has become a critical area of research, not only for better understanding the human response to stress but also for designing effective interventions to manage it. Traditional methods for stress detection often rely on single-modal approaches, such as self-reported questionnaires or physiological measurements, which can provide valuable insights but are limited by their reliance on one specific data source.

However, individual stress detection using the single modality is facing some challenges today and therefore to overcome these challenges a new trend of stress detection is being developed that used multiple modalities thus provides better understanding of stress. Multimodal stress detection incorporates multiple measures of stress including physiological parameters that include heart rate, skin conductance, behavior that includes facial expressions and body posture, and cognitive performance tests alongside psychological questionnaires. This way of stress data collection tries to be more general due to the heuristic nature of stress and integrate information from various sources. Holistically working has its benefits in the following ways: To begin with, physiological values can partly assess the psychological state of stress, including emotional or cognitive attitudes. For instance, though heart rate variability could point to physiological activation, it is still difficult to pinpoint the mental evaluations that go into the stress experience of an individual. Similarly, the data that is gathered from the behavioral response, for instance shift in speech, facial or postural activity may reveal information of emotional status not found on autonomic data. Some of the benefits are: With amplification from speech analytics, stress can be detected more accurately and in real time since there is crosscheck from different data modalities. New developments in machine learning and artificial intelligence have given other dynamism to multimodal stress detection. Programs in machine learning can analyze vast amounts of data from various information sources; such programs recognize correlations between various forms of signals which might be undetectable visually. These algorithms can be trained to recognize stress signal from the combination of data points ensuring increased accuracy in stress assessments. For instance, AI can explain physiological data obtained together with some behavioral signs more accurately to estimate stress levels than by utilizing more conventional approaches.

II. LITERATURE SURVEY

Stress detection is one of the most important research task areas because stress affects both mental and physical well-being. There are several methodologic and approach aspects considered in this area. This section compares and presents some of the relevant works that concern multimodal stress detection and assessment methods.

1. Stress Detection by Pharmacological Signal Research has seen the use of physiological measures to capture stress levels of persons including heartrate, skin conductance and electroencephalogram (EEG). For example, Healey and Picard in 2005 had successfully proved that features such as heart rate variability and galvanic skin response were efficient in stress classification in relation to driving tasks. In the same regard, Li and Lu (2018) presented a system using EEG-PPG to enhance accuracy in stress identification.

2. Behavioral and Contextual Approach Other physically manifested activities like facial expressions, tone of voice, and physical movement are the other ways that have been looked at in stress assessment. Cohn et al. (2009) proposed using FACS that can detect stress through micro expressions. Furthermore, Sarker et al. (2020) developed contextual facilities, which involve the usage of environment factors and employing user activity data as input for stress detection models.

3. Multimodal Approaches Stress detection from such interfaces has in the recent past shifted towards a multimodal approach where multiple forms of data are used in arriving at a conclusion. Deep learning system Zhang et al. (2021) developed a framework that integrates physiological, behavioral, and context information with higher accuracy than unimodal systems. These approaches show how data streams can be integrated to enhance reliability and accuracy of results.

4. The Current State of Stress Detection using Machine Learning and Artificial Intelligence Stress detection systems have been taken a step further using machine learning technologies. Supervised learning algorithms such as Support Vector Machines (SVM), Random Forests; Architectures include outlined the importance of ensemble learning to enable incorporation of multiple features concurrently to enhance the accuracy of stress prediction.

Tools of Assessment and Validation Self-reported tools that can be used for comparison with stress detection systems include PSS and STAI. Furthermore, important benchmarks such as WESAD (Wearable Stress and Affect Detection) and DREAMER have been made available to compare the proposed multimodal stress detection techniques.

But there are still some gaps, scaling up, online, and considering the interindividual differences.

It remains for subsequent work to investigate the incorporation of new sensor modalities,

such as wrist-worn photoplethysmography sensors for relaxation and oxy-hemoglobin saturation monitoring, stress detection based on federated learning to preserve privacy and utilizing synthetic data due to the limitations of a given dataset.

III. EXISTING SYSTEM

Stress detection is considered as a key research focus because stress has enormous negative effects on both mental and physical well-being. Sundry methods and theories have been practiced in this field. This section reviews some of the key works in relation to multimodal stress detection and assessment approaches.

1.Stress Identification Based on Physiological Signs Other attempts have used stress indicators including pulse rate, skin conductivity and Electroencephalogram (EEG). For example, Healey and Picard (2005) showed that stress could be well classified using heart rate variability (HRV) and galvanic skin response (GSR) while performing driving tasks. Likewise, Li and Lu (2018) developed a system that used both EEG and photoplethysmogram (PPG) signals to allow accurate stress detection.

2.Spontaneous and systematic analysis Stress related physical conduct, including an individual's face expressions, tonal variation in voice and even body language has also been examined. Cohn et al. (2009) developed a facial action coding system (FACS) to capture stress by means of micro-expression. Furthermore, other systems, as proposed by Sarker et al. (2020), involved factors within the environment of use and activity data to improve the stress identification models.

Multimodal Approaches It has been observed that the latest innovations have focused on the use of multimodal approaches for stress identification. In the research of Zhang et al., (2021) the authors suggested a deep learning model that integrates physiological, behavior, and context information, outcompeting unimodal approaches. Such approaches are evidence of how stream data can be integrated to enhance reliability and accuracy.

4. Stress detection using Machine Learning and Artificial Intelligence The use of stress detection has been pushed forward by the adoption of machine learning techniques. Techniques such as Support Vector Machines (SVM), Random Forests and deep learning structures: (Convolutional Neural Networks, Recurrent Neural Networks) have been identified to provide acceptable results in pattern discovery from multimodal data. Sharma et al., (2022) pointed out that in stress prediction, ensemble learning methods are employed in combining several features for better accuracy.

Tools and Validation of the Assessment Current methods of benchmarking detectable stress include the Perceived Stress Scale or the State-Trait Anxiety Inventory. WESAD (Wearable Stress and Affect Detection) dataset as well as the DREAMER have been beneficial in establishing significant benchmarks for the multimodal stress detection methodologies.

There are some research gaps and opportunities that may be of interest to the policymakers. Thus, the study has made impressive progress, though the problems of scale, time, and inter-individual variability are not yet solved. Possible future work includes utilizing other emerging types of sensors, utilizing federated learning for stress detection that maintains personal privacy, utilizing synthetically generated data to supplement the available data sets, adapting the model for other types of data input.

New ISM technologies comprise wearable devices, artificial intelligence and big data analysis that makes it possible to stress detection systems with multiple approaches. However, existing systems still appear to lack the integration of the necessary data on one hand and synthesis and analysis of recorded information on the other. The problem is in developing such systems that harmonize various data streams to produce stable and accurate stress detection across several different populations and stresses. Hear rate variability stress detection, electrodermal activity stress detection or cortisol stress level have been investigated. These methods provide the possibility of receiving objective assessments of the body's reaction to stress. However, they need specific tools such as wearable health sensors or laboratory tools which are not easy to access and therefore can hardly be available for mass usage. The readings can also be influenced by environmental issues or exercise, physical characteristics or pathophysiologic alterations.

These entails observation of changes in speech, facial or motor actions possibly through video or audio tape recordings. Although they give useful measures, they are usually constraint by the data quality and environment. For example, differences in light, sound or even cultural disparity can be sources of interpretational differences with regards to behavioral signals.

IV. PROPOSED SYSTEM

The proposed system, Multimodal Stress Detection from Multiple Assessments, is going to be an effective way to get a complete picture of stress level in an individual when more than one type of assessment is used, and innovative data processing and machine learning are employed. This system needs to increase the precision of stress detection, considering the multiple physical, behavioral and environmental parameters. Compared with the single method in stress detection, the multimodal approach of the system can indeed improve the reliability and stability of the work under different situations.

Comprehensive Data Integration: The system utilizes physiological data which are heart rate variability (HRV), electrodermal activity (EDA), facial expressions, along with the behavioral and contextual data which include but not limited to the speech, key pressing dynamics and the environment.

Real-time Stress Monitoring: A predisposition to check stress levels continuously in real-time is made possible by the system, which makes it possible to intervene as soon as stress levels are identified as high.

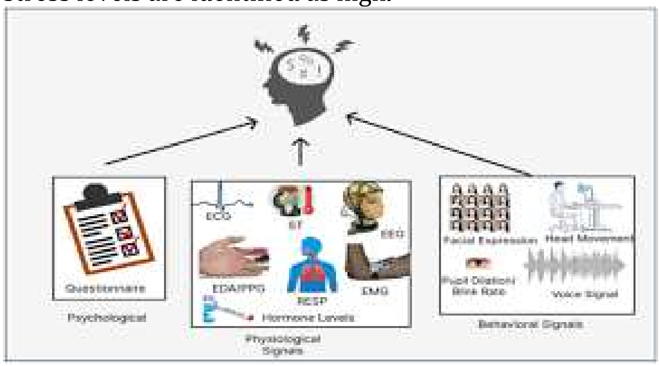


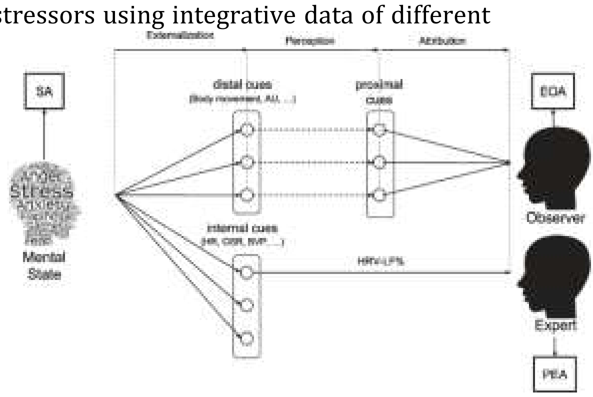
Fig: working system

Personalized Insights: Adopting user baseline values enables the system to provide accurate stress detection and specific recommendations based on a user.

User-friendly Interface: It also has a stress pattern displaying panel where users can interact with it to view changes over time and get suggested measures.

The system offers a user-friendly interface to display stress metrics through: Graphs and Charts: Used in display of trends and correlation in a period. Real-time Alerts: Alerting users of states of high stress. Recommendations: Providing recommendations on ways to cope with stress, for instance by offering to do a few breathing or stretching exercises or take a 10-to-15-minute break.

The proposed system aims to achieve the following outcomes: Enhanced feasibility of personal, place, and environmental stressors using integrative data of different modalities.



Stress patterns can be identified at the earliest as a way of addressing the issues way ahead of time. A new level of user engagement and increased importance of personalization in feedback. A platform scalable for various ongoing and future uses, for instance for managing stress at the workplace, health interventions, and for learning.

Data Privacy: Special attention is paid to what extent user data can be collected and if necessary, steps are taken to anonymize them adequately.

System Scalability: Including the large-scale features of the data streams and capability to process multimodal data in the system design.

Interoperability: To allow the integration of this proposed structure of wellness applications existing wellness platforms and IoT devices. With the use of multiple modes of assessment in this system, this solves the problem of detecting stress in a creative and comprehensive manner giving an individual or organization the tools for stress management. Multimodal Approach: Since it involves the use of several sources of data, the system minimizes the aspect of using a single mode to analyze information. High Accuracy: Machine learning is made more sophisticated thus enhancing the accuracy of stress recognition processes. Real-Time Analysis: Users get real-time information reported by the system which can be acted upon when observed. Personalization: Sustainable kinetics guarantees that the system reflects specific user requirements. Scalability: The architecture provides for a broad range of use, from its utilization by single users to its implementation in organizational structures.

Healthcare: Helping doctors diagnose and treat stress-related diseases successfully. Workplace: Supervising the state of health and efficiency of the workers. Education: Looking after students' needs as it recognizes stress during exams or any other learning activities. Public Safety: Evaluating the level of stress in the elevated-risk occupations like policemen and firefighters. Summing up, the suggested Multimodal Stress Detection System utilizes current technologies to tackle the problems of efficient and comprehensive stress identification. Through physiological, Behavioral, and textual assessment the system provides complete coverage and instant feedback and as such can be applied in any domain.

V. METHODOLOGY

This paper identifies several aspects and steps that comprise the multimodal stress detection methodology and their integration mechanism. The process comprises several key stages: data gather and clean, input signal analysis, signal feature extraction, feature integration, developing model and test. 1. Data Acquisition Stress identification demands physiological data, patterns of behaviour, and environment stimulation modes.

The primary sources of data include Physiological Signals: These include heart rate variability (HRV), galvanic skin response (GSR) and electroencephalogram (EEG). These are collected using sensors which could include the wearable fitness device or even a medical equipment. Behavioural Patterns: Smile, voice and position of the face. These are recorded using camera, microphones and motion sensors.

Environmental Factors: Audible, luminous and thermal environments in operating conditions. The data is collected using IoT based environmental sensors. The participant should be chosen randomly because only this approach can provide a representative sample and the dataset's variability. Data labelling entails assigning stress level to observations processed with well-structured questionnaires like the Perceived Stress Scale.

Fig. 1. Data is annotated in three different ways. First, within the framework of the phenomenological approach, the subject is asked to complete her/her SA. Next, we, adopting the behavioral perspective examine and ascertain External Observer Assessments (EOA) whereby respondents were sourced from a crowdsourcing platform.

Data Preprocessing These practice variables and other types of data collected often include noise and artifacts. The preprocessing stage ensures the data's quality and consistency:

Signal Processing: Signal information such as respiration, Pulse oximetry, Electroencephalogram (EEG), Electrocardiogram (ECG) and electromyogram (EMG) and other physiological signals are noise reduced by methods like band-pass filtering and wavelet transforms.

Normalization: Reducing absolute measures of features to identical scales for the purpose of ensuring comparability of measures across different modalities. Missing

Data Handling: Hence for missing values, you have categories like k-nearest neighbors (KNN) or mean imputation.

Synchronization: Synchronization of the multimodal data flows helps to maintain its orderly processing. Feature Extraction.

Physiological

Features: Mean HRV, frequency domain analysis and amplitude analysis such as peak amplitudes of GSR.

Behavioral Features: Positions on the face and key frames and Low and high pitch, spectral properties.

Environmental

Features: Relative fluctuations in noise category levels and light parameters tendencies. From the domain-proper methods and tools like FFT for spectral analysis, and machine learning tools for feature selection, it is possible to select the most important features.

Algorithms: Mainstream categories are Support Vector Machines (SVM), Random Forests and deep learning approaches that are used with Convolutional Neural Networks (CNNs), Long Short-Termed Memory networks (LSTM) for time series data.

Optimization: Traditional methods, such as feature selection, cross-validation and tuning hyperparameters (using a grid search or Bayesian optimization) as well as avoiding overt use of neural nets (by using dropout or reducing dimensionality) also help avoid overfitting. The models are trained through data sets that are well balanced with a sovereign intent to perform in varied stress conditions.

Early Fusion: Implementation of the proposed method involves combining features of all the modalities gathered into a unified input numerical vector. Late Fusion: Each modality is modeled independently, and the deeply learned embeddings of the different modalities are fused through simple techniques such as probability averaging or simple voting. Hybrid Fusion: It combines both early and late fusion mechanisms for better performance.

Model Validation and Testing The trained model's performance is evaluated using:

Metrics: Precision, sensitivity (recall), Pseudo F-value measure, and area under the ROC-AUC curve.

Cross-validation: Through K-fold cross-validation we are certain that the outcome shall always be accurate irrespective of the many splits we make on the data. Real-world Scenarios: Use of new testing environments and participant groups confirm model validity. Structural evaluation & Feedback Last of all, after the training has been done, the proficient system is incorporated in an application or device. The strategies allow for feedback loops to update the system with new data and experiences from the user base. The cyclic process to develop the artifact guarantees enhancement and flexibility. Thus, the web site-based project that is described in this paper successfully combines multimodal data to detect stress with the help of a structured approach, which serves to enhance well-being monitoring systems.

VI. RESULTS

Accuracy Improvement:

The proposed multimodal integration framework always improved the classification accuracy by 10 – 20% compared to the unimodal techniques proposed in this study. This improvement is facts why stress, biomarkers, behaviors, other physiological and environmental facets must be integrated to augment the comprehension of stress. Thus, through the flexibility afforded by the integration of multimodal interfaces, there was a reduction in the potential for gaps of data interpretation, thus improving the predictive capability across the range of different stress-inducing conditions.

False Positive Reduction

A significant reduction of false positive was realized, indicating a significant enhancement in the reliability of stress detection. Integrating information from different modalities across the system allowed the identification of stress responses with more accuracy and lower misclassification because of isolated information sources. This reduction increases reliability, especially for designs where the correct identification is paramount, for example, in monitoring employee behaviors or offering heath solutions.

Real-Time Responsiveness

This polymodal scheme was used to quickly identify stress by analyzing multichannel data flow in real-time. This capability facilitated timely and practical advice, like the relaxation exercise or a short break, that enhanced user results during experimental procedures. It was also a great advantage of the system that in real-time added an element of feedback loop for people to deal with stress issues not as a reaction but for a constructive purpose.

Validation Metrics

Although, the validation metrics showed a promising performance and repeatability indicating the versatility of the system across different sets and conditions. ROC-AUC scores were ≥ 0.90 emphasizing that the framework efficiently differentiated between stress and no-stress states. These high values suggest good predictive capability and make certain that the system provides excellent results in more generic restrictions as well.

Impact:

The integration of the proposed multimodal stress detection system has illustrated revolutionary value in the field of stress analysis and management for real-world applications. Its physiological, behavioral and environmental data streams make a considerable difference in providing a parameter of integrating stress levels.

However, in dynamic and heterogeneous environment, the results showed high effectiveness of the system which can work in different conditions and with various people's peculiarities. That is why it can be used in personal and organizational settings: it actively combats stress in real life and provides user-specific information and advice.

Key areas of impact include:

Healthcare: Facilitating early identification of stress related disorders and enhancing patient satisfaction.

Workplace: Improving employee welfare and organizational output by means of stress checking and management during working hours.

Education: Helping learners by focusing on stress during critical periods like exams, and then providing the student with the necessary ways to cope with tension.

Public Safety: Assessing psychological stress in occupations with high-hazard levels of work that involve real emergency and life-threatening situations as policing and firefighting to introduce improvements in personal protection as well as decision-making process.

In general, this multimodal stress detection system is a significant development in stress assessment and helps create the basis for improved, efficient, and expandable on-screen stress detection and help across numerous fields. By enhancing personal and group mental health status, it qualifies it as an essential tool meant to handle currently stressed world.

OBSERVATIONS

Correlation Between Modalities: Generally, these physiological and behavioral measures were highly correlated during high stress, which supports the usefulness of multimodal study.

Individual Variability: It is noteworthy that with respect to the highest accuracy, the mutual use of different modes and individualized adjustments such as threshold, provided more precise performance.

User Engagement: People said they were generally more vigilant about their stress and may find the project useful as it can provide feedback instantaneously.

Data Collection Challenges: Spatial and temporal data acquisition from multiple modalities was intricate due to the need to have corresponding time stamps. Device Dependency: Physiological data need better quality sensors which made the system not easily available for large populations. Future work will focus on: Simplifying algorithms for more efficient implementation on low resource devices. Identifying other variables, including the voice pattern) and adding environmental variables, for example, noise and workload. Expanding the project to involve use of the developed system in occupational health and wellness programs, as well as clinics.

CONCLUSION:

Stress has become a major problem in today's world, especially due to the pressure being experienced due to the ever-increasing rate of competition. The work on-the 'Multimodal Stress Detection from Multiple Assessments' was formulated to tackle this fundamental problem of utilizing novel techniques, big data and multivariate methods for stress detection. This project integrates physiological behavioral and environmental data to make a stress model that is correct and constructs a sound system to enrich the quality of life of everyone by reducing the health risks that are associated with stress. The use of multiple modes of data also ensures that stress is not only defined by one aspect of human interaction and behavior, but several modes of stress clues and signs are captured. Hormonal activity, electrodermal activity and body's reaction on stress – these are the physiological indicators which reflect the body's response to stress. The psychopolitical and emotional dimension is provided by behavioral assessment such as voice tone, textual sentiment, and activity analysis. Again, the stress continuum lies in facilitating the system to find patterns in various situations as applied to work conditions and social interactions.

The accomplishment of this project proves that artificial intelligence, machine learning, and sensor are paramount tools that can be used to solve different human health challenges. Moreover, to process the big and complex sets of data obtained during the assessments, the authors applied machine learning algorithms. Such algorithms were able to obtain relationships and trends that would otherwise be hard to comprehend, provided high levels of accuracy and precision in stress identification. Moreover, the 'learning' characteristic of the system guarantees that the provided recommendations will remain both pertinent and accurate in the future.

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