MACHINE LEARNING APPROACH FOR STRESS DETECTION FOR HAZARDOUS OPERATIONS

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Abstract: When training for hazardous operations, real-time stress detection is an asset for optimizing task performance and reducing stress. Stress detection systems train a machine-learning model with physiological signals to classify stress levels of unseen data. Unfortunately, individual differences and the time-series nature of physiological signals limit the effectiveness of generalized models and hinder both post-hoc stress detection and real-time monitoring. This study evaluated a personalized stress detection system that selects a personalized subset of features for model training. The system was evaluated post-hoc for real-time deployment. Further, traditional classifiers were assessed for error caused by indirect approximations against a benchmark, optimal probability classifier (Approximate Bayes; ABayes). Healthy participants completed a task with three levels of stressors (low, medium, high), either a complex task in virtual reality (responding to spaceflight emergency fires, n =27) or a simple laboratory-based task (N-back, n =14). Heart rate, blood pressure, electrodermal activity, and respiration were assessed. Personalized features and window sizes were compared. Classification performance was compared for ABayes, support vector machine, decision tree, and random forest. The results demonstrate that a personalized model with time series intervals can classify three stress levels with higher accuracy than a generalized model. However, cross-validation and holdout performance varied for traditional classifiers vs. ABayes, suggesting error from indirect approximations. The selected features changed with window size and tasks, but found blood pressure was most prominent. The capability to account for individual difference is an advantage of personalized models and will likely have a growing presence in future detection systems.

1. INTRODUCTION

Despite extensive training in responding to an emergency, a person's response to an actual emergency can be negatively affected by the stressfulness of the situation. Stress can result in a cascade of physiological changes that may alter. Behavioral patterns, situational awareness, decision making, and cognitive resources [1].An inability to cope with the stress of a high-stress condition cande crease task performance and thereby risk mission failure, injury, or death [2]. Consequently, developing resiliency to this situational stress through improved training may lead to better outcomes. To that end, using real-time monitoring of a person's stress responses to customize the stressfulness of training scenarios may, in turn, lead to more appropriate handling of actual hazardous operation [3], [4]. Stress detection using machine learning has been challenging for several reasons. First, there are individual differences in the appraisal of, and physiological responses to, stressful situations. Numerous stress detection approaches have attempted to reduce technical complexity by generalizing their models to a broad population, or the ''average'' response [3]. However, the stress response to a unique situation is largely subjective, and personalized stress detection models may be more robust to individual differences [5], [6].The second challenge is that the time series nature of physiological signals can be problematic. The physiological stress response has temporal and feature correlations. These correlations may violate the machine learning assumption that the data are independently and identically distributed, thereby leading to biased results [7]. An additional challenge is interpreting how well model estimations match the true conditional probabilities of a subject's stress levels. Stress detection models rely on traditional machine learning algorithms that make data-driven approximations to estimate the chance that the individual is experiencing a state of stress given their physiological responses. However, these estimations are often indirect and without a benchmark for comparison. From classical statistics research, the Bayes theorem is theoretically the optimal solution and a classifier given the same parameters as Bayes theorem will have the lowest probability of error [8]. The Bayes theorem uses an empirical density distribution as a true prior probability, which can be used to calculate the conditional probability of each class. The classifier selects the class with the greatest posterior probability of occurrence, also known as maximum a posteriori. Machine-learning algorithms attempt to approximate the density distributions. If the density estimates of the classifier converge to the true densities, then the estimated probability represents the true probability of occurrence and a classifier that approximates Bayes becomes an Optimal Bayes classifier. However, these approximations can have varying accuracy due to assumptions made by the algorithm, such as independence of predictors [9]. Thus, it can be difficult to interpret the model's logic. Physiological systems are known to have a high degree of dependence with regard to a stress response, because they are often initiated by the same neuro endocrine axis [10]. Some researchers have shown that classifiers may account for dependencies using multivariate kernel density estimators [11]. Therefore, it may be beneficial to evaluate supervised machine learning classifiers against a benchmark optimal classifier that approximates Bayes using a density distribution estimated through multivariate kernel density estimation for stress detection. To achieve real-time and continuous monitoring of stress levels, new approaches are needed to analyze time series for physiologically-based stress detection [12]. Real-time stress detection can enable closed-loop automation to either modify the training environments to better match the trainee's responses or better assess individual stress during staged or real operations [13]. In datasets with repeated measurements at multiple times that present uncertainty from randomness or incompleteness, such as multiple measures of physiological data, multivariate kernel density estimators may help increase detection accuracy [11]. To address these challenges, the goal of this research is to assess the objectivity, reliability, and validity of a personalized model methodology. The first research question focuses on objectivity, and whether the stressor levels can show distinct levels in personalized features used for the classification model while accounting for individual differences in physiology. This will provide confidence that the model is designed for the appropriate context and that the training data reflect distinct ground truth levels. The second research question focuses on the system's reliability by evaluating the performance of the time-series interval approach using a post-hoc model comparing between a standard laboratory cognitive task and a complex job-specific task, window sizes, classifier validation techniques, and features selected for each individual. The third research question focuses on the validity of the system by seeking to understand whether indirect approximations influence traditional supervised machine learning classifiers compared to a Bayes classifier, known as Approximate Bayes (A Bayes), which uses direct approximations of optimal stress classes through multivariate kernel density estimation. This research is part of a larger development effort to design VR training scenarios that can dynamically adapt a virtual environment using real-time stress detection [14], [15], [16]. To answer these research questions within the constraints of the larger system, the experiment will assess a time-series interval approach to stress detection for a post-hoc model of physiological response data, its accuracy in detecting participant stress using a collected during stressful tasks, and provide the architecture for a real-time stress detection system that uses this classification methodology. Validating a machine learning pipeline post-hoc allows for translation to real-time stress detection and applications for stress monitoring.

2. LITERATURE SURVEY

1) Real-World Driver Stress Recognition and Diagnosis Based on Multimodal Deep Learning and Fuzzy EDAS Approaches

Abstract: Mental stress is known as a prime factor in road crashes. The devastation of these crashes often results in damage to humans, vehicles, and infrastructure. Likewise, persistent mental stress could lead to the development of mental, cardiovascular, and abdominal disorders. Preceding research in this domain mostly focuses on feature engineering and conventional machine learning approaches. These approaches recognize different levels of stress based on handcrafted features extracted from various modalities including physiological, physical, and contextual data. Acquiring good quality features from these modalities using feature engineering is often a difficult job. Recent developments in the form of deep learning (DL) algorithms have relieved feature engineering by automatically extracting and learning resilient features. This paper proposes different CNN and CNN-LSTSM-based fusion models using physiological signals (SRAD dataset) and multimodal data (AffectiveROAD dataset) for the driver's two and three stress levels. The fuzzy EDAS (evaluation based on distance from average solution) approach is used to evaluate the performance of the proposed models based on different classification metrics (accuracy, recall, precision, F-score, and specificity). Fuzzy EDAS performance estimation shows that the proposed CNN and hybrid CNN-LSTM models achieved the first ranks based on the fusion of BH, E4-Left (E4-L), and E4-Right (E4-R). Results showed the significance of multimodal data for designing an accurate and trustworthy stress recognition diagnosing model for real-world driving conditions. The proposed model can also be used for the diagnosis of the stress level of a subject during other daily life activities.

2) Stress detection in daily life scenarios using smart phones and wearable sensors: A survey

Abstract: Stress has become a significant cause for many diseases in the modern society. Recently, smartphones, smartwatches and smart wrist-bands have become an integral part of our lives and have reached a widespread usage. This raised the question of whether we can detect and prevent stress with smartphones and wearable sensors. In this survey, we will examine the recent works on stress detection in daily life which are using smartphones and wearable devices. Although there are a number of works related to stress detection in controlled laboratory conditions, the number of studies examining stress detection in daily life is limited. We will divide and investigate the works according to used physiological modality and their targeted environment such as office, campus, car and unrestricted daily life conditions. We will also discuss promising techniques, alleviation methods and research challenges.

3) A Review on Mental Stress Assessment Methods Using EEG Signals

Abstract: Mental stress is one of the serious factors that lead to many health problems. Scientists and physicians have developed various tools to assess the level of mental stress in its early stages. Several neuroimaging tools have been proposed in the literature to assess mental stress in the workplace. Electroencephalogram (EEG) signal is one important candidate because it contains rich information about mental states and condition. In this paper, we review the existing EEG signal analysis methods on the assessment of mental stress. The review highlights the critical differences between the research findings and argues that variations of the data analysis methods contribute to several contradictory results. The variations in results could be due to various factors including lack of standardized protocol, the brain region of interest, stressor type, experiment duration, proper EEG processing, feature extraction mechanism, and type of classifier. Therefore, the significant part related to mental stress recognition is choosing the most appropriate features. In particular, a complex and diverse range of EEG features, including time-varying, functional, and dynamic brain connections, requires integration of various methods to understand their associations with mental stress. Accordingly, the review suggests fusing the cortical activations with the connectivity network measures and deep learning approaches to improve the accuracy of mental stress level assessment.

4) Stress Monitoring Using Machine Learning, IoT and Wearable Sensors

Abstract: The Internet of Things (IoT) has emerged as a fundamental framework for interconnected device communication, representing a relatively new paradigm and the evolution of the Internet into its next phase. Its significance is pronounced in diverse fields, especially healthcare, where it finds applications in scenarios such as medical service tracking. By analyzing patterns in observed parameters, the anticipation of disease types becomes feasible. Stress monitoring with wearable sensors and the Internet of Things (IoT) is a potential application that can enhance wellness and preventative health management. Healthcare professionals have harnessed robust systems incorporating battery-based wearable technology and wireless communication channels to enable cost-effective healthcare monitoring for various medical conditions. Network-connected sensors, whether within living spaces or worn on the body, accumulate data crucial for evaluating patients' health. The integration of machine learning and cutting-edge technology has sparked research interest in addressing stress levels. Psychological stress significantly impacts a person's physiological parameters. Stress can have negative impacts over time, prompting sometimes costly therapies. Acute stress levels can even constitute a life-threatening risk, especially in people who have previously been diagnosed with borderline personality disorder or schizophrenia. To offer a proactive solution within the realm of smart healthcare, this article introduces a novel machine learning-based system termed "Stress-Track". The device is intended to track a person's stress levels by examining their body temperature, sweat, and motion rate during physical activity. The proposed model achieves an impressive accuracy rate of 99.5%, showcasing its potential impact on stress management and healthcare enhancement.

3. EXISTING SYSTEM

The physiological stress response involves the interaction between the nervous system and the endocrine system that aims to maintain physiological integrity under changing environmental demands. The time course of the physiologic responses to stress varies by system and by the intensity and duration of the stressor; they are neither physiologically independent nor statistically orthogonal. After the psychological appraisal of a stressor, neural ganglia pathways are activated almost instantaneously to evoke very rapid responses via local neurotransmitters. For example, disinhibition of heart rate via vagal withdrawal occurs within milliseconds while a sympathetically-mediated increase in heart occurs after a few seconds (5-10 s) [10]. Sympathetic and sudomotor activity results in the opening of eccrine sweat glands on hands and feet, which occur about 1-5 seconds after stimuli [17]. On the other hand, the physiologic responses due to circulating chemicals take longer to manifest. Epinephrine is secreted from the adrenal medulla and range from milliseconds to minutes to exert their cardiovascular effects. Whereas, cortisol is initiated by the adrenal cortex 5–10 min after stressor onset and peak between 20 and 30 min [18]. These processes can act exclusively or in conjunction on target organs to potentiate (e.g., memory, muscle activation) or attenuate organ function (e.g., digestion, reproduction). Stress detection, by means of classifying these physiological responses into levels of stress via machine learning, continues to evolve and is motivated by the potential utility of continuously monitoring stress levels in real-time [12], [21]. Stress detection systems have been developed for drivers in semi-urban scenarios [22], [23], patients undergoing virtual reality therapy [24], individuals in working environments [25], and people that need help managing daily stress [21], [26], [27], [28], [29], [30]. Stress detection can also be applied to a variety of human-machine interfaces (HMIs) which may monitor stress, but also infer the cognitive state of the user to adapt system functionality [31]. Examples of HMIs that may use stress detection include wearable devices, voice recognition systems, eye tracking systems, facial expression analysis, and brain/body computer interfaces [12], [32]. However, these HMIs may not be able to accurately detect stress in all individuals, and the accuracy of stress detection may vary depending on the specific technology and approach used [33].

DISADVANTAGES:

The complexity of data: Most of the existing machine learning models must be able to accurately interpret large and complex datasets to find Stress Detection.

• Data availability: Most machine learning models require large amounts of data to create accurate predictions. If data is unavailable in sufficient quantities, then model accuracy may suffer.

• Incorrect labeling: The existing machine learning models are only as accurate as the data trained using the input dataset. If the data has been incorrectly labeled, the model cannot make accurate predictions.

4. PROPOSED SYSTEM

This paper describes the development of a personalized physiological-based stress detection system to classify acute stress using feature selection on intervals of the time-series data. To train the machine learning model, participant physiological signals were collected for three stressor levels during either a spaceflight emergency fire procedure on a VR International Space Station (VR-ISS) [46], [47] or a well-validated and less-complex N-back mental workload task [48]. Several previous studies have detected stress induced by N-back tasks via machine learning methods, both alone [48], [50] and with another job-specific task [51]. Therefore, comparing a jobs pecific VR-ISS task to the N-back using the same personalized approach is a way to assess the system's reliability can work for multiple stress detection tasks. Each participant had features selected at different interval window sizes, then those personalized features trained the classifier model, and subsequently tested the classifier's predictive accuracy. Since the stress response is complex and often unique, the analysis will explore which features are selected most for individuals depending on window size, and how this changes classification performance. Classifier performance was assessed using both holdout and cross-validation validation techniques to simulate how the model may perform on unseen data as an analog for deployment in real-time.

ADVANTAGES

The novelty and contribution of this research is to show that stress detection may benefit from using personalized time series approaches to quantify temporal patterns in physiological signals, to assess whether traditional classifiers are limited in approximating the optimal Bayes solution, that certain features may be better at different windows sizes, and that this approach has a suitable performance for detecting stress for a VR spaceflight emergency training procedure.

SYSTEM ARCHITECTURE

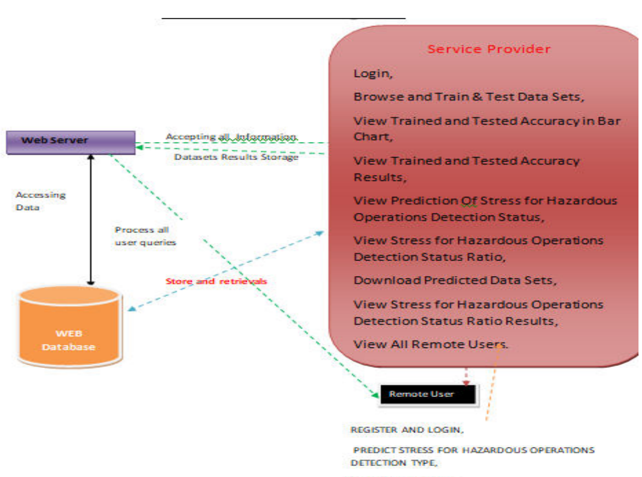

Fig 1: System Architecture

5. UML DIAGRAMS

1. CLASS DIAGRAM

The cornerstone of event-driven data exploration is the class outline. Both broad practical verification of the application's precision and fine-grained demonstration of the model translation into software code rely on its availability. Class graphs are another data visualisation option.

The core components, application involvement, and class changes are all represented by comparable classes in the class diagram. Classes with three-participant boxes are referred to be "incorporated into the framework," and each class has three different locations:

• The techniques or actions that the class may use or reject are depicted at the bottom.

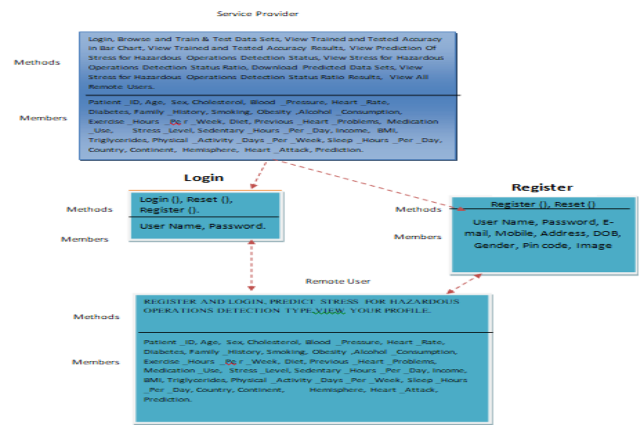

Fig 5.1 shows the class diagram of the project

2. USECASE DIAGRAM:

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

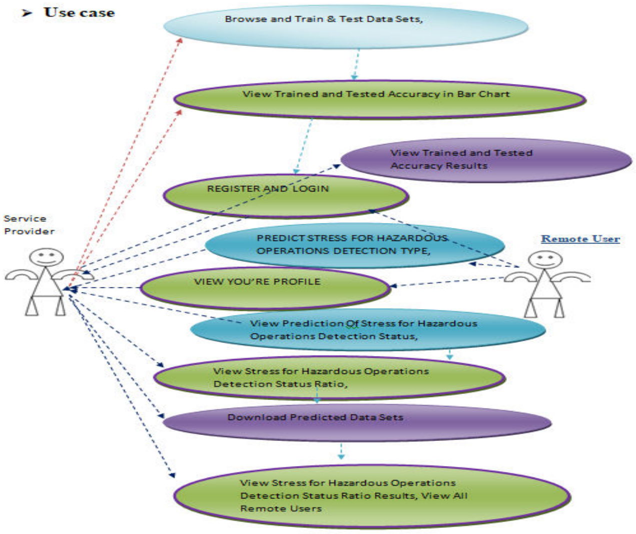

Fig 5.2 Shows the Use case Diagram

3. SEQUENCE DIAGRAM:

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.

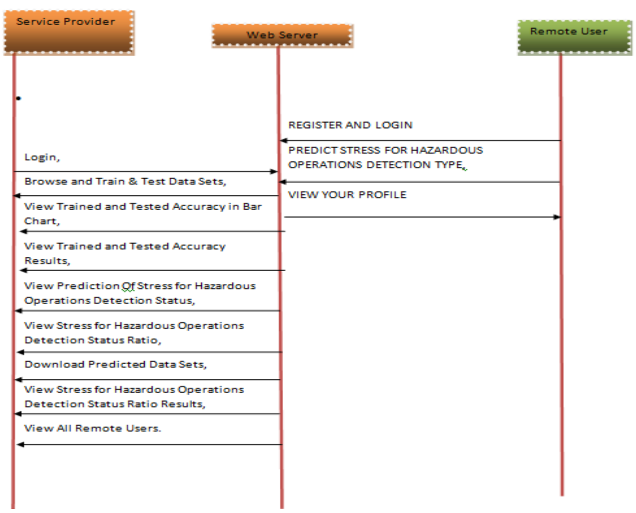

Fig 5.3 Shows the Sequence Diagram

6. RESULTS

6.1 Output Screens

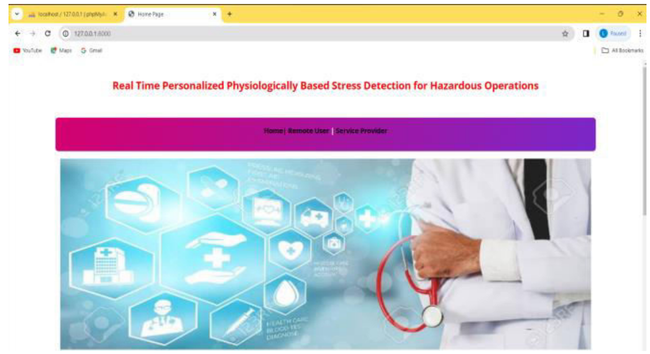

Fig 6.1 Home Page

In above screen is the home page

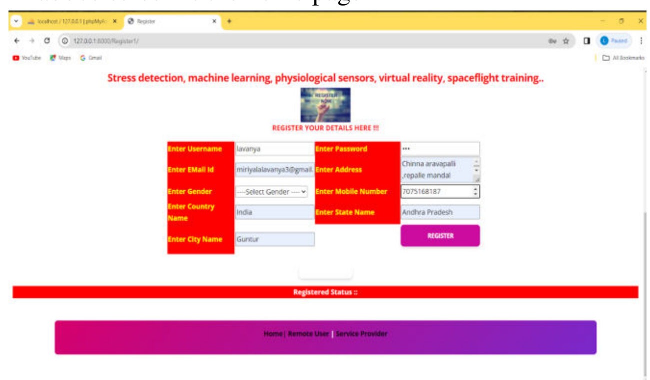

Fig 6.2 Remote User Registration page

In above screen we can enter the remote user login details

Fig 6.3 Service Provider Login Page

In above screen shows the service provider login page.

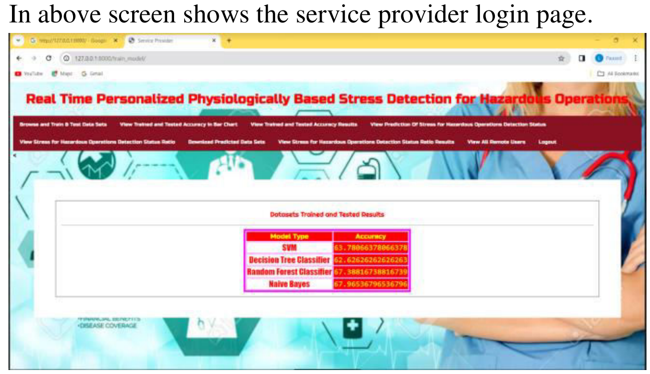

Fig 6.4 Accuracy for the ml algorithms

In above screen shows the different machine learning algorithms accuracy.

Fig 6.5 Accuracy in Bar Charts

In above screen shows algorithms accuracy in bar charts.

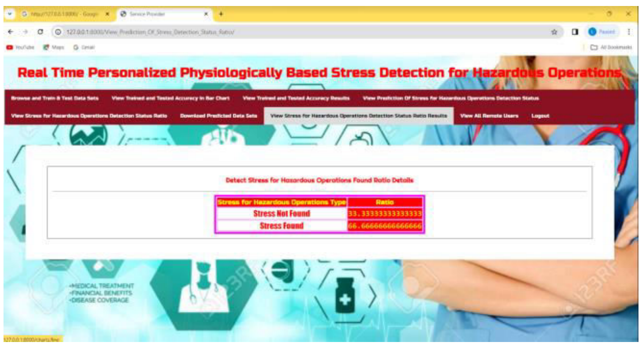

Fig 6.6 Stress detection Ratio

In above screen shows the stress detection ration

Fig 6.7 Stress Detection Status

In above screen shows the results.

7. CONCLUSION

To address the challenges of vast differences between individual stress responses, the time-series nature of physiological signals, this research evaluated the objectivity, reliability, and validity of a real-time stress detection system using a personalized time-series interval approach. The simple and complex tasks were able to achieve distinct levels of stress enabling their use as machine learning ground truth. Analysis of the window sizes provided insight into which sensors/features were useful for varying time-intervals. The personalized model was found to have better performance than a generalized model. Furthermore, it evaluated the effect of indirect approximations by supervised machine learning classifiers evaluated against a benchmark optimal classifier, A Bayes. It was found that indirect approximations can have a minor-to moderate effect on classifier performance (-11% to +14% of A Bayes). The current findings suggest that a personalized system provides promising performance when compared to past research on multi-class stress detection. Researchers should be careful about the selection of HMIs, sensors, and features for models, as they may not account for inter and intra- individual differences in stress physiology. Future work will further investigate these personalized stress detection systems with the aim of implementing approaches that account for temporal changes in the individual stress response and physiological signals.

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