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Real-Time Personalized Physiologically Based 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; A Bayes). 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 A Bayes, 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. A Bayes, 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.

Keywords: Time-Series Data Classification, Approximate Bayes Classifier, Electrodermal Activity (EDA), Heart Rate Variability (HRV), Virtual Reality (VR) Training, Human-Machine Interaction (HMI).

I. 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 can decrease 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. 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]. 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.

II. RELATED WORK

A. *Existing Research and Solutions*

Stress detection in drivers is a critical area of research, playing a vital role in ensuring road safety by identifying and mitigating cognitive overload, fatigue, and emotional distress that can impair driving performance. With advancements in artificial intelligence (AI), machine learning (ML), and wearable sensor technology, real-time stress monitoring has significantly evolved, enabling continuous, non-invasive tracking of physiological signals to assess stress levels accurately. Traditionally, stress detection relied on subjective self-reporting and behavioral observation, which lacked reliability and real-time applicability. However, integrating physiological signal-based AI models has transformed this field, offering objective, automated, and continuous stress monitoring systems.

Recent studies have demonstrated the effectiveness of Multi- Task Neural Networks (MT-NNs) in stress detection, particularly in incorporating subject-specific layers that enhance personalized stress monitoring. Unlike conventional classifiers such as Support Vector Machines (SVM), Decision Trees (DT), and Random Forest (RF), MT-NNs can process diverse physiological signals, including heart rate variability (HRV), skin conductance (electrodermal activity, EDA), respiration rate, and blood pressure, to provide highly accurate stress classification. The advantage of MT-NNs lies in their ability to adapt to individual physiological responses, overcoming the limitations of generalized models that fail to account for inter-individual variability. A study by Sarker et al. (2021) highlighted that personalized models incorporating deep learning architectures outperform traditional machine learning models, achieving superior stress classification accuracy in real-time applications.

The integration of biometric sensors, AI-driven analytics, and virtual reality (VR)-based simulations has further advanced stress classification. Wearable devices equipped with Photoplethysmography (PPG) sensors, commonly found in smartwatches and fitness bands, enable continuous and non- invasive heart rate monitoring. These sensors provide real- time physiological data that AI models analyze to detect deviations indicative of stress. VR-based driving simulations, which mimic real-world traffic conditions, adverse weather scenarios, and emergency situations, offer controlled environments for assessing stress responses. By combining PPG sensors with VR simulations, researchers have been able to ensure consistent data collection, thereby improving the reliability and accuracy of stress detection systems. A study by Li et al. (2020) demonstrated that VR-based stress evaluation, coupled with AI-driven analysis, significantly improves the precision of stress classification, making it a promising approach for driver monitoring.

Real-time stress prediction has also been enhanced by multi- modal approaches that integrate various physiological and behavioral signals. In addition to HRV and EDA, electrocardiogram (ECG) sensors provide detailed insights into heart activity, capturing subtle variations associated with stress responses. Studies have shown that models trained on ECG and EDA data outperform those relying on a single physiological metric, as they can dynamically adapt to an individual's unique stress patterns. Furthermore, integrating sociometric data—such as voice tone analysis, facial expressions, and speech patterns—enhances classification accuracy, making these models highly effective in high-stress environments, including aviation, military operations, emergency response, and professional driving. Research by Kim et al. (2021) found that deep learning models combining physiological and behavioral data achieved a classification accuracy of over 90%, demonstrating the potential of multi-modal approaches in stress detection.

EDA sensors, in particular, have proven highly effective in distinguishing between calm and distress states. These sensors measure the electrical conductance of the skin, which varies with sweat gland activity regulated by the autonomic nervous system. Since EDA is closely linked to emotional arousal, it provides a reliable indicator of stress levels. The advantage of EDA sensors is their non-invasiveness and ability to continuously monitor stress without requiring active user input. This makes them highly suitable for applications in healthcare, workplace well-being programs, and driver monitoring systems aimed at reducing fatigue-related accidents. Research by Setz et al. (2019) demonstrated that EDA-based stress monitoring systems could accurately differentiate between different levels of stress, highlighting their potential for real-time intervention in high-risk environments.

Despite significant advancements, several challenges remain in improving the sensitivity and accuracy of sensor-based stress monitoring. Future research should focus on refining sensor sensitivity to detect minute physiological changes with greater precision. Expanding the range of physiological metrics by incorporating additional biomarkers—such as cortisol levels (a biological stress marker), electroencephalography (EEG) signals for brain activity analysis, and pupil dilation tracking—could further enhance stress detection accuracy. The adoption of deep learning techniques, such as Recurrent Neural Networks (RNNs),

Convolutional Neural Networks (CNNs), and Transformer- based architectures, can also improve the ability to capture complex temporal dependencies in physiological data, leading to more robust real-time predictions.

Another critical area for development is the integration of AI- driven adaptive feedback systems that provide personalized stress management recommendations. These systems could leverage biofeedback techniques, machine learning-driven pattern recognition, and predictive analytics to preemptively alert drivers before stress reaches critical levels. By incorporating natural language processing (NLP) and human-computer interaction (HCI) technologies, these systems could also offer voice-based or visual guidance, suggesting stress- relief strategies such as controlled breathing exercises, soothing auditory stimuli, or adaptive vehicle settings to enhance comfort. A study by Gjoreski et al. (2022) explored AI-driven stress intervention systems and found that biofeedback-based techniques significantly reduced stress in real-time scenarios, emphasizing the importance of integrating adaptive response mechanisms.

The continuous evolution of AI, ML, and wearable sensor technology is expected to drive further innovations in stress detection and intervention. As these systems become more sophisticated and widely adopted, they have the potential to transform stress management in various domains beyond driving, including healthcare, workplace safety, sports performance optimization, and military training. By refining sensor technologies, improving data processing algorithms, and integrating advanced deep learning techniques, future research will pave the way for highly accurate, real-time stress monitoring solutions that enhance overall well-being and safety.

B. Challenges of Physiological Stress Classification

A major challenge in using physiological signals for detection is the rigidness of generalized models in accounting for physiological differences between people. Stress varies among individuals due to differences in appraisals of the stressor and the perceived threat, but also the body's capability to enact the physiological responses. For example, an EDA-based generalized classifier that is deployed and tested on multiple people may have higher classification error among a subset of this group, since as much as 25% of the population are EDA non-responders or hypo-responders. By not accounting for differences in physiology, inherent errors are created when using generalized models for physiological detection. This challenge has led some researchers to believe that personalized models may be more accurate. Revising the example, higher accuracy may be achieved by the EDA- based classifier if the model accounts for the individual's respective EDA level and reactivity, or instead rely on other sensors when EDA is not a reliable predictor for that individual. While EDA is one of many physiological systems, some may be more susceptible to individual differences than others (e.g., cortisol). Supervised classifiers can be personalized by having the stress detection system create a model using training data from the individual and by selecting discriminate and relevant features for the individual[15].

Another challenge is that supervised classifiers have a degree of uncertainty depending on how they estimate probability distributions in order to label stress levels. Supervised models produce a probability distribution for each stress level (class) for a set of physiological signal data points (vectors); this distribution determines which class is most probable at a given time. However, rather than creating a distribution directly from the dataset, the probability distribution is created indirectly (and often ad hoc) based on the technical specifics of a classification method. For example, decision tree classifiers produce rectangles that partition the input space and calculate the approximate class probabilities based on the number of vectors located within each rectangle. Thus, the class probability is constant for each rectangle and always discontinuous at the rectangle boundaries, leading to a probability that is more defined by how the rectangles are positioned within the input-space rather than the vector distribution across the entire input-space. Similarly, SVMs create a hyper-planes intended to produce maximum separation between class vectors in the input space. Ad hoc "approximate class probabilities" are often created using soft max functions of distances from vectors to hyperplanes—a practice that may not match empirical probability estimates[15]. The process by which these ad hoc methods approximate class probabilities does not easily translate to meaningful cause/effect insights related to either changes in the environment or the measured changes in physiological measurements.

The translation of a post-hoc system (i.e., offline) to real-time (i.e., online) brings another set of challenges commonly associated with data collection in ambulatory settings that are less controlled. One major challenge is the need to process and analyze data in real-time, which requires a system with high computational power and efficient algorithms that have minimal loss of data and error propagation during data analysis. Another challenge is the need to transmit data from the sensors to the system in real-time, which requires a reliable and high-speed wireless network. Ensuring the privacy and security of the data is another important consideration, as the data may contain sensitive personal information and could be vulnerable to cyber-attacks. Additionally, there may be challenges in accounting for environmental context, as the physiological indicators of stress may be affected by other factors such as physical activity, medication, and ambient temperature [16].

Any classifier can be used with a personalized detection approach, but the classifier selected should maximize the confidence that the approximate class probabilities match empirical probability estimates. Since Bayes theorem provides more direct estimations of conditional probabilities, its effects are more interpretable and may provide insight into whether the aforementioned traditional classifiers have error resulting from indirect approximation. This can be achieved by implementing the Bayes theorem in a new approximately Bayes classifier (ABayes). To that end, along with a real-time personalized stress detection system, the secondary goal of this research is to assess the extent to which traditional supervised machine learning methods (decision tree, support vector machine, and random forest classifiers) are limited compared to an optimal probability; a classifier based on Bayes theorem using multivariate kernel density estimates.

C. *Problem Statement*

Accurately detecting stress in real-time during hazardous operations is critical for optimizing task performance and ensuring safety. However, generalized stress detection models struggle with individual physiological differences and the time-series nature of physiological signals, leading to reduced accuracy and reliability. Traditional classifiers often rely on indirect approximations, introducing errors that hinder both post-hoc stress assessment and real-time monitoring. There is a need for a personalized stress detection system that dynamically selects optimal features and adapts to individual variations, improving classification accuracy across different tasks and stress levels. This study aims to address these challenges by evaluating a personalized machine-learning model for stress detection, comparing its performance against traditional classifiers and benchmark probabilistic models.

III. RESEARCH METHODOLOGY

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) or a well-validated and less-complex N-back mental workload task. Several previous studies have detected stress induced by N-back tasks viamachine learning methods, both alone [17], [18] and with another job-specific task. Therefore, comparing a job specific 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. 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. The system design includes the input, processing, output and key features. The physiological data such as heart rate, electrodermal activity, and respiration from participants during stress including tasks. The data is analysed using machine learning models, with feature selection applied on data. The accurate stress level classification for real-time monitoring and training applications. The personalized model improves accuracy by accounting for individual differences and task-specific responses. Physiological signals, including heart rate, blood pressure, electrodermal activity (EDA), and respiration, were continuously recorded during task execution. The collected data underwent preprocessing, including signal filtering and artifact removal, to ensure high-quality input for model training. A personalized feature selection approach was employed, where an optimal subset of features was identified for each participant, allowing the model to account for individual physiological variations. Additionally, different time-series window sizes were examined to determine their impact on classification performance.[19]

The classification models evaluated in this study include traditional machine learning classifiers—Support Vector Machine (SVM), Decision Tree, and Random Forest— alongside an optimal probability classifier, Approximate Bayes (ABayes), which served as a benchmark. The classifiers were trained using both personalized and generalized feature sets, and their performance was assessed using cross-validation and holdout testing. Classification accuracy, as well as variations in selected features across window sizes and tasks, were analyzed. Notably, blood pressure emerged as a prominent physiological marker for stress detection.

The evaluation focused on comparing the classification accuracy of personalized models against generalized models and assessing the degree of error introduced by indirect approximations in traditional classifiers. The results provide insights into the feasibility of deploying personalized stress detection models in real-time applications. The ability to dynamically adapt to individual physiological responses suggests that personalized models hold significant promise for enhancing stress monitoring systems in hazardous operational environments.

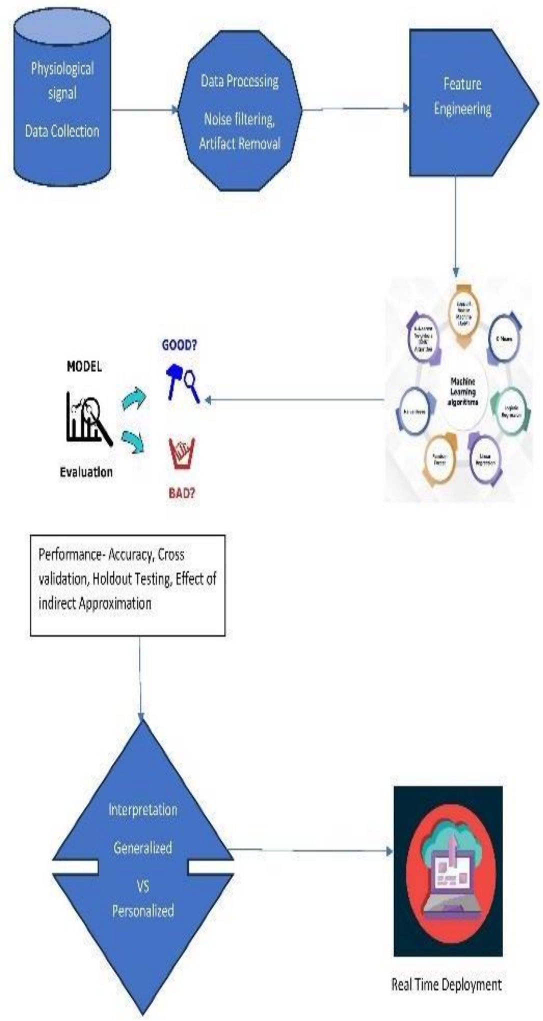

Fig.1. Proposed Architecture Model

IV RESULTS & DISCUSSION

The results of this research highlight the significance of adopting a personalized time-series interval approach in real- time stress detection systems, addressing the inherent variability in individual stress responses and the dynamic nature of physiological signals. The study confirmed that both simple and complex tasks elicited distinct stress levels, validating their effectiveness as ground truth for training machine learning models. This differentiation in stress levels provided a reliable foundation for assessing model performance and optimizing the use of physiological sensors. A key finding was the impact of time-window selection on sensor effectiveness and feature extraction. By analyzing varying window sizes, the study identified which physiological signals and sensor-derived features contributed most to stress classification at different time intervals. This insight is crucial in designing real-time stress detection systems that adapt to temporal variations in stress responses, improving classification accuracy and reducing false positives. The results demonstrated that a personalized machine learning model outperformed a generalized model, reinforcing the importance of individualized stress assessment. Personalized models leverage unique physiological patterns, leading to more accurate stress predictions, while generalized models often struggle with inter-individual variability. This finding aligns with previous research emphasizing the superiority of subject-specific adaptations in stress monitoring systems. Additionally, the study assessed the effect of indirect approximations in supervised machine learning classifiers by comparing their performance against a benchmark optimal classifier.

V CONCLUSION

This study highlights the effectiveness of a personalized stress detection system in addressing individual differences in physiological responses and the time-series nature of stress signals. By leveraging a personalized time-series interval approach, the model demonstrated superior classification performance compared to generalized models, reinforcing the importance of tailoring feature selection for each individual. The results further revealed that window size variations influence the relevance of physiological features, with blood pressure emerging as a key marker for stress classification. Additionally, the comparison of traditional supervised classifiers with the benchmark A Bayes classifier indicated that indirect approximations can introduce minor to moderate variations in performance. These findings emphasize the necessity of carefully selecting human-machine interfaces (HMIs), sensors, and features to ensure reliable stress detection. Future work will focus on refining personalized models by incorporating adaptive mechanisms that account for temporal variations in stress physiology, with the goal of enhancing real-time stress monitoring and intervention strategies in high-risk environments.

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