

Research Article

Real-Time Personalized Physiologically Based Stress Detection For Hazardous Operations

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Abstract: This paper presents a real-time, personalized stress detection system designed to enhance safety and performance in hazardous operational environments. The system leverages physiological signals—including heart rate, blood pressure, electrodermal activity, and respiration—to classify stress levels through machine learning models. Unlike conventional generalized models, this approach focuses on individual-specific feature selection and temporal signal analysis to improve accuracy and responsiveness. A comparative evaluation using tasks of varying complexity demonstrated that personalized models, particularly when combined with the Approximate Bayes classifier, consistently outperformed traditional classifiers such as SVM, Decision Tree, and Random Forest. The proposed system features an interactive interface for system operators to upload datasets, monitor stress prediction status, and analyze stress ratios in real time. Experimental results confirmed the system's ability to detect low, medium, and high stress levels with high precision, making it suitable for deployment in high-risk domains. This study highlights the potential of personalized, real-time physiological monitoring to support timely decision-making, reduce operational risk, and promote workforce well-being.

Keywords: Real-time stress detection, Personalized physiological monitoring, Hazardous operations, Machine learning, Approximate Bayes classifier.

1.Introduction

In the context of high-risk occupational environments such as aviation, firefighting, military operations, and critical healthcare services, the ability to assess and respond to acute stress in real time is of paramount importance. Operators in these domains often work under physically and cognitively demanding conditions, where stress not only impairs decision-making and performance but also elevates the likelihood of catastrophic failures. The growing complexity and automation of hazardous systems have, paradoxically, increased human responsibility during exceptional or emergency conditions, thereby necessitating advanced monitoring systems that can track physiological and psychological states in real time. Stress is a multifactorial response involving the interaction between environmental stimuli and individual perception, manifesting in physiological, behavioral, and cognitive changes. These changes can significantly affect task performance, particularly in high-stakes scenarios where even minor human errors can result in severe consequences. The integration of real-time stress detection mechanisms into operational frameworks can offer timely feedback, enabling stress mitigation strategies to be applied before performance degrades. However, traditional stress evaluation

techniques, such as self-report questionnaires and post-task interviews, are retrospective and subjective, failing to capture the dynamic nature of stress during real-time operations.

Recent advancements in wearable technology and biosensing systems have paved the way for objective, continuous monitoring of physiological indicators linked to stress, such as heart rate variability (HRV), skin conductance (GSR), electroencephalogram (EEG), and respiration rate. These physiological signals provide a non-invasive and practical means of monitoring stress in real-world settings. The ability to personalize stress detection using individual baseline profiles and contextual calibration enhances the accuracy and relevance of such systems, making them viable for operational deployment. Real-time physiological monitoring offers several advantages, including the ability to detect stress onset, differentiate between stress types (e.g., cognitive vs. emotional), and anticipate breakdowns in situational awareness. In addition, the proliferation of machine learning algorithms tailored for time-series biosignal data has enabled intelligent stress classification models that adapt to the user's physiological patterns. However, designing a robust, personalized stress detection system for hazardous operations is a formidable challenge due to inter-individual variability, sensor noise, data sparsity, and operational constraints.

Several studies have explored physiological-based stress detection using either single or multiple sensor modalities. For instance, GSR and HRV are commonly used due to their sensitivity to autonomic nervous system activation under stress. EEG-based approaches offer a window into neural dynamics but are often constrained by sensor placement complexity and motion artifacts. Multimodal fusion of physiological signals, while promising, introduces new complexities in terms of synchronization, dimensionality reduction, and computational overhead. Moreover, many existing models are developed and tested in controlled laboratory settings, lacking generalizability to dynamic and unpredictable field environments. Personalization is a critical aspect often overlooked in generic stress detection frameworks. Individuals exhibit different baseline physiological states and stress reactivity due to genetic, psychological, and environmental factors. As such, a one-size-fits-all model tends to underperform in diverse populations. Incorporating personal calibration data can significantly enhance model precision and reduce false positives and negatives. Furthermore, stress detection systems tailored to individual profiles can also factor in acclimatization to stressors, which is common in long-term hazardous occupations.

Another emerging focus is on the real-time implementation of stress monitoring systems, which requires optimized signal processing pipelines, edge computing capabilities, and low-latency communication infrastructures. These constraints necessitate a careful trade-off between accuracy and responsiveness. In scenarios such as deep-sea diving, space missions, or nuclear power plant operation, latency and reliability are critical, as stress-induced impairments can rapidly escalate into emergencies. Consequently, the demand for real-time, low-power, embedded systems capable of physiological signal acquisition, processing, and decision-making is higher than ever. Despite promising developments, key gaps remain. Current stress detection systems often lack context-awareness, failing to distinguish stress from physical exertion or emotional arousal that is not performance-threatening. Contextual sensors and environmental data integration could help disambiguate such cases. Furthermore, privacy and ethical concerns must be addressed when deploying such systems, particularly in defense and healthcare sectors where individual monitoring can raise concerns about autonomy and surveillance. In light of these challenges, this study aims to develop a real-time, personalized, physiologically based stress detection framework suited for hazardous operations. The proposed research will focus on

identifying relevant bio signals, selecting appropriate modelling techniques, and ensuring system responsiveness and reliability in real-time scenarios. The solution will consider both physiological diversity and operational context, aiming to deliver a system that can proactively alert, adapt, and support individuals under duress.

2.Related Works

In recent years, significant research attention has been directed toward developing real-time stress detection systems that leverage physiological signals to monitor human mental states, especially in high-risk environments. Existing studies have primarily focused on capturing biometric indicators such as heart rate variability (HRV), electrodermal activity (EDA), respiration rate, and electroencephalogram (EEG) signals, which are known to reflect stress-induced alterations in the autonomic and central nervous systems. Early research established the correlation between elevated stress levels and physiological signal deviation, laying the foundation for sensor-based stress monitoring systems. Subsequently, machine learning techniques—ranging from classical classifiers like Support Vector Machines (SVM) and Random Forests (RF) to modern deep learning models—have been integrated to enhance detection accuracy. While most approaches demonstrate success in controlled laboratory conditions, their applicability in real-world hazardous operations remains limited due to lack of personalization, computational constraints, and inability to adapt to situational context. Moreover, only a few studies have incorporated real-time processing and adaptive feedback mechanisms necessary for deployment in dynamic operational settings. The following section reviews the key advancements, limitations, and research gaps across literature that have motivated the development of a personalized and real-time physiologically based stress detection model for hazardous tasks.

Finseth et al. [1] proposed a comprehensive real-time, physiologically driven model tailored for hazardous operations, which emphasized the need for individual personalization in stress detection to maintain worker safety. Srinivas et al. [2] echoed this sentiment, stressing the importance of real-time adaptation in models deployed during risky operational tasks. A broader survey by Bolpagni et al. [3] reviewed biosignal-driven wearable technologies and underscored the gaps in personalization and practical deployment in occupational settings. Similarly, Rane et al. [4-5] highlighted the evolving role of wearable technologies in enhancing construction site safety, revealing how biosensor integration could improve personal risk assessments. Taskasaplidis et al. [6] offered a detailed review of stress detection via wearable sensors, categorizing techniques based on sensor types and detection approaches, while König et al. [7] explored semantic modeling of multi-modal physiological data for workload classification in hazardous industries. Finseth et al. [8] also examined adaptive virtual reality training for stress inoculation, highlighting how immersive simulations could personalize stress thresholds. The relevance of human-cyber-physical systems in smart manufacturing was emphasized by Simeone et al. [9], where real-time physiological sensing was used for operator safety within Industry 5.0 paradigms.

An AI-driven model developed by Adamopoulos et al. [10] demonstrated how climate change-related stress and burnout in public health sectors could be predicted using physiological signals, extending the application of stress monitoring into public service. Mateos-García et al. [11-12] investigated driver stress detection using VR simulators, showcasing the feasibility of real-time signal processing in safety-critical transport applications. Magtibay and Umapathy [13] reviewed workplace stress from the perspective of allostatic load and its long-term effects, offering insights into prediction tools and physiological stress biomarkers. Ishaque et al. [14]

employed decision tree methods to classify stress levels from physiological responses in VR environments, and Masri et al. [15] presented a large-scale review on workplace stress assessment using EEG and other sensor data. Hijry et al. [16] developed a real-time stress prediction system for smart factory workers, integrating multiple biosignals with real-time analytics. Haque et al. [17] focused specifically on heart rate variability (HRV), analyzing its potential for AI-based stress prediction and concluding that hybrid models outperform classical approaches. Apraiz et al. [18-19] presented a structured protocol for manufacturing-related stress investigations, stressing the importance of standardized experimental setups. Donati et al. [20] introduced an ECG-based stress monitoring solution within real-time production systems, showcasing the integration of physiological monitoring with productivity metrics. Rescio et al. [21] developed a deep learning platform that used minimally intrusive, multisensory devices to detect stress in industrial settings, prioritizing user comfort and real-time feedback. Finally, Davila-Gonzalez and Martin [22] proposed the concept of the Human Digital Twin, integrating emotional analytics and AI to create holistic worker safety models for Industry 5.0 environments.

3. Proposed Real-time Deployment Model

With a personalized, real-time stress detection system tailored for hazardous operations training environments, where the capacity to monitor stress continuously and adaptively is crucial for maintaining task efficiency and safety. Unlike traditional models that use generalized physiological signal patterns, the proposed system incorporates a machine learning framework trained with time-series physiological data—such as heart rate, blood pressure, electrodermal activity, and respiration—to classify stress across three levels: low, medium, and high. Recognizing the limitations posed by individual physiological variability and the dynamic nature of biosignals, the model adopts a personalized feature selection strategy, dynamically identifying optimal features and time windows for each user. This personalization aims to enhance classification accuracy and robustness in real-time settings. To benchmark the model's effectiveness, the system was evaluated in two experimental setups: a complex virtual reality (VR) simulation involving spaceflight emergency fire scenarios ($n = 27$) and a simpler lab-based N-back cognitive task ($n = 14$). Multiple machine learning classifiers—Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF)—were compared with an Approximate Bayes (ABayes) classifier, which served as a probabilistic baseline. The findings revealed that personalized models consistently outperformed generalized ones, especially when adapted to specific window sizes and task types. Notably, blood pressure emerged as the most influential signal across conditions. However, the evaluation also uncovered performance discrepancies between traditional classifiers and ABayes, indicating that indirect approximations may introduce classification errors in conventional models. Overall, the results validate the significance of individualized models and time-sensitive analysis in real-time stress detection, suggesting that personalized physiological analytics will be increasingly vital for future stress-monitoring systems in high-risk domains.

The proposed model is designed to enable personalized, real-time stress detection during hazardous operations by leveraging time-series physiological signals. Traditional stress classifiers typically rely on generalized models that ignore individual physiological variability. However, stress responses are inherently personal—meaning two individuals may respond differently to the same stressor—making generalized models less accurate in real-world deployment. To address this, our model integrates personalized feature selection and dynamic windowing for training machine learning classifiers on time-series data. Let the physiological signal vector for a subject be represented as in equation (1)

$$X(t) = \{x_1(t), x_2(t), \dots, x_n(t)\} \quad (1)$$

In equation (1) $x_i(t)$ represents the signal (e.g., heart rate, blood pressure, GSR, respiration) measured at time t , and n is the number of signal modalities. The data is segmented into time windows of length T , producing windowed input features stated in equation (2)

$$W_k = \{X(t) \mid t \in [t_k, t_{k+T}]\} \quad (2)$$

The system evaluates multiple window sizes (e.g., 5s, 10s, 30s) to identify the optimal interval that best captures stress transitions for each individual. From each window W_k , statistical and frequency-domain features are extracted. Each subject's data is evaluated to identify the most informative features $F_j \subseteq X$ using feature ranking metrics like Mutual Information or Recursive Feature Elimination (RFE). Let F_k denote the personalized feature vector extracted from W_k , and $y_k \in \{0,1,2\}$ denote the stress level (low, medium, high). The classification function can be expressed as in equation (3)

$$\hat{y}_k = f(F_k; \theta) \quad (3)$$

In equation (3) f is the classifier (SVM, DT, RF), and θ are the learned parameters. The proposed model addresses the urgent need for a robust, adaptive, and personalized stress detection system that functions effectively in real-time within hazardous operational settings. In such environments—ranging from firefighting and aviation to industrial and military operations—individuals are regularly subjected to acute stressors that can impair cognitive functioning and decision-making. Conventional stress detection systems typically rely on generalized models trained on aggregate datasets that do not account for inter-individual physiological variability. This lack of personalization limits their practical application, especially when the system must detect stress fluctuations in real-time, where accuracy and responsiveness are crucial. The present approach integrates personalized physiological feature selection, adaptive window sizing, and comparative classifier evaluation to develop a scalable and responsive real-time stress monitoring framework. Unlike traditional models that apply fixed features and training windows for all users, this system dynamically identifies the most relevant physiological features for each individual based on baseline profiling and task response data. Physiological signals such as heart rate, blood pressure, electrodermal activity (EDA), and respiration are continuously collected and segmented into time-based windows to observe patterns over short intervals. This window-based approach allows the model to capture transient fluctuations in physiological responses associated with different stress levels, including low, medium, and high intensity.

The system was evaluated using two task environments to simulate both complex and simple stress-inducing scenarios. The first task was a virtual reality (VR) simulation representing a high-risk emergency, specifically responding to spaceflight fire incidents, where 27 participants engaged in immersive stress conditions. The second task was a controlled N-back cognitive test involving 14 participants, which served as a simpler laboratory-based comparison. In both cases, participants were exposed to stressors across three levels, and physiological signals were recorded in real-time. The use of both complex and simple tasks provided a comprehensive assessment of the system's adaptability and effectiveness in varying operational intensities. Feature selection played a critical role in the model's performance. Personalized features were extracted from the physiological data within each time window, and their importance was evaluated using ranking techniques based on statistical significance and predictive capability. The selection of features was not fixed across participants or task types. Instead, it adapted based on individual physiological responses and the stress context. Notably,

blood pressure consistently emerged as one of the most significant features across both tasks, indicating its strong correlation with stress intensity. However, other signals such as heart rate variability and skin conductance also proved valuable, particularly when used in combination, suggesting the importance of multimodal analysis.

To evaluate classification accuracy, several machine learning algorithms were implemented, including Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), and a benchmark model based on Approximate Bayes classification. These models were trained on the personalized features extracted from each participant's data and tested using both cross-validation and holdout methods to assess robustness. The results demonstrated that the personalized models significantly outperformed generalized approaches in classifying stress levels, especially when optimal time windows and relevant features were used for each subject. Furthermore, the Approximate Bayes classifier consistently provided stable performance across both task types, whereas the traditional classifiers exhibited performance variability. This suggests that probabilistic methods offer an advantage when dealing with uncertainty and noise in real-time biosignal data. Another important finding was the impact of window size on model accuracy. Different individuals responded to stress over varying timeframes, and the optimal window for capturing stress indicators differed by both task and participant. This supports the need for an adaptive windowing approach rather than relying on a one-size-fits-all strategy. The system's flexibility in adjusting window sizes and selecting feature sets made it more responsive to the natural variability in human stress response, thereby improving overall detection accuracy. The study also revealed limitations associated with indirect approximations used in traditional classifiers. Models like SVM and Random Forest rely on learning decision boundaries based on approximated relationships between features and stress levels. In contrast, the Approximate Bayes model explicitly evaluates the probability of each stress class given the observed data, reducing error propagation and improving interpretability. The discrepancies observed between these classifiers highlighted the importance of classifier choice in real-time stress detection, particularly under conditions of physiological noise, task complexity, and varying user profiles.

Algorithm 1: Real-Time Personalized Stress Detection

Input:

- Physiological signals $P = \{HR, BP, EDA, RESP\}$ (Heart Rate, Blood Pressure, Electrodermal Activity, Respiration)
- Time window sizes $W = \{w1, w2, ..., wn\}$
- Stress labels $L = \{Low, Medium, High\}$ during training phase
- Real-time streaming data

Output:

- Predicted Stress Level $S \in L$ in real-time

Step 1: Data Collection Phase

- 1.1 Collect baseline physiological signals from individual
- 1.2 During task execution, record physiological data and label segments with stress levels (Low, Medium, High)

Step 2: Preprocessing Phase

- 2.1 For each signal in P :
 - Apply noise filtering (e.g., moving average or Butterworth filter)
 - Normalize signal per individual baseline
- 2.2 Segment signals into time windows of size $w \in W$
 - For each window:
 - Extract statistical features (mean, std, min, max, etc.)

Extract time-domain and frequency-domain features (e.g., peak frequency, energy)

Step 3: Personalized Feature Selection

3.1 For each individual:

- Rank features using feature importance metrics (e.g., Mutual Information, ANOVA F-test)
- Select top k features that maximize classification performance

Step 4: Model Training

4.1 Train classifiers using selected features:

- Classifiers = {SVM, Random Forest, Decision Tree, ABayes}

4.2 Evaluate models using cross-validation and hold-out methods

- Compare based on Accuracy, F1-score, Latency

4.3 Choose the best-performing classifier for each individual

Step 5: Real-Time Stress Detection

Loop: For each incoming data window in real-time

- 5.1 Preprocess data (filtering, normalization)
- 5.2 Extract features using selected window size and feature set
- 5.3 Predict stress level using trained personalized classifier
- 5.4 Output predicted stress level S
- 5.5 Log output and trigger alert if stress level is High

Step 6: Adaptation (Optional for Long-Term Use)

6.1 Periodically re-evaluate classifier performance

6.2 Update personalized model if performance drops (online learning or retraining)

End Algorithm

4. Classification of Stress Detection

Classification of stress detection using physiological signals has gained considerable attention due to the increasing need for reliable, real-time monitoring systems in hazardous environments. The effectiveness of such systems hinges upon the ability of machine learning algorithms to accurately recognize stress levels—typically categorized as low, medium, and high—based on input from biosignals like heart rate (HR), blood pressure (BP), electrodermal activity (EDA), and respiration. These physiological parameters reflect changes in the autonomic nervous system that occur in response to psychological and environmental stressors. However, the challenge lies in the fact that these responses are highly individualistic, nonlinear, and time-dependent. Consequently, the selection and design of classification algorithms play a critical role in the success of stress detection models. This section explores several widely-used classifiers, including Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), and the Approximate Bayes classifier (ABayes), analyzing their strengths, weaknesses, and suitability for real-time personalized stress detection.

Support Vector Machines (SVM) are among the most frequently used classifiers in stress detection due to their high generalization capabilities and ability to handle high-dimensional data. SVM aims to find an optimal hyperplane that separates data into different classes by maximizing the margin between support vectors. In the context of stress detection, SVM performs well with linearly and non-linearly separable physiological features, especially when kernel functions such as Radial Basis Function (RBF) are used. The main advantage of SVM lies in its robustness against overfitting when dealing with small datasets, which is often the case in physiological monitoring. However, SVMs are not inherently probabilistic, which limits their interpretability in real-time health monitoring systems. Furthermore, they can be computationally expensive during training, particularly for large and continuously growing datasets in real-time applications. Decision Trees (DT) offer a simple yet intuitive approach for classifying stress levels. They work

by recursively partitioning the feature space into smaller subsets based on feature thresholds, forming a tree structure where each internal node represents a decision rule, and each leaf node represents a stress class. Decision Trees are easy to interpret and can provide real-time predictions with low latency, making them suitable for embedded systems and wearable devices. However, they are prone to overfitting, especially in the presence of noise and irrelevant features, which are common in physiological data due to sensor artifacts and inter-individual variability. Pruning techniques and ensemble methods are often employed to mitigate these issues.

To overcome the limitations of single decision trees, Random Forests (RF) aggregate the results of multiple decision trees trained on different subsets of the data using a process called bagging. Each tree contributes a vote for the predicted class, and the majority vote becomes the final prediction. This ensemble approach enhances robustness and generalization, making Random Forests highly effective for complex classification tasks such as stress detection. RF can handle nonlinear relationships between features and is relatively immune to overfitting, provided a sufficiently large forest is used. Another benefit is its ability to compute feature importance, which helps identify the most relevant physiological parameters for stress classification. Nevertheless, RF models can be computationally demanding during training and inference when deployed in low-power edge devices, posing challenges for real-time applications. In contrast to the above classifiers, the Approximate Bayes (ABayes) classifier takes a probabilistic approach based on Bayes' theorem. It estimates the likelihood of a given class label (e.g., stress level) by computing the posterior probability of the observed features given the class. ABayes assumes conditional independence among features, which simplifies computation and enables fast classification, making it well-suited for real-time stress detection systems. It also provides interpretable probabilistic outputs, which can be useful in safety-critical applications where decision confidence is important. Despite its simplicity, ABayes can perform remarkably well, particularly when combined with personalized feature selection that aligns with the independence assumption. However, if the independence assumption is violated, performance may degrade, especially when complex correlations exist between physiological signals.

In the proposed study, all four classifiers were trained and tested using physiological data collected from two experimental tasks: a complex virtual reality (VR) task simulating emergency spaceflight scenarios and a simpler N-back cognitive test. Each task involved three stress levels—low, medium, and high—induced through cognitive and situational pressure. Physiological data were preprocessed, segmented into time windows, and personalized feature sets were extracted for each participant. The classifiers were evaluated using accuracy, F1-score, and real-time response latency under cross-validation and holdout protocols. Results indicated that the personalized model significantly improved classification performance across all classifiers compared to generalized models. Among traditional classifiers, Random Forest consistently achieved the highest classification accuracy across both task environments, followed by SVM. The RF's ensemble nature made it resilient to noise and capable of capturing complex interactions among multiple physiological features. Decision Trees, while simpler, demonstrated slightly lower accuracy but performed well in terms of real-time inference speed and interpretability. SVM showed high accuracy but required more processing time during training and tuning, making it slightly less favorable for resource-constrained, real-time environments.

Interestingly, the Approximate Bayes classifier, despite its assumption of feature independence, showed competitive accuracy while maintaining the lowest computational overhead. Its simplicity and speed make it an excellent choice for deployment in wearable or edge computing devices where resources are limited. It was also observed that the ABayes

classifier exhibited more consistent performance between training and testing phases, suggesting reduced overfitting and better generalization in unseen data. Furthermore, ABayes provided transparent probability estimates for each prediction, aiding in decision support and alert systems in hazardous operations. Another critical factor influencing classifier performance was the size of the time window used for feature extraction. Smaller windows were more responsive but less stable, while larger windows provided smoother classifications at the cost of increased latency. The optimal window size varied by participant, highlighting the importance of adaptive window selection in personalized stress detection models. The classifiers' performance also varied depending on the physiological signal used. Blood pressure emerged as the most predictive feature across both tasks, followed by heart rate and EDA. Feature selection played a vital role in improving classification accuracy, especially for ABayes, where selecting less-correlated features aligned well with its underlying assumption.

5. Experimental Results and Discussion

The experimental phase of the proposed real-time personalized stress detection model was conducted using physiological data collected from two controlled environments: a high-pressure Virtual Reality (VR) emergency simulation and a cognitively demanding N-back task. The dataset consisted of multi-modal physiological signals including heart rate (HR), blood pressure (BP), respiration rate (RR), and electrodermal activity (EDA), which were continuously recorded from each participant. To ensure reliability and consistency, the data underwent preprocessing techniques such as noise filtering, normalization, and segmentation into fixed-length time windows. Feature extraction was then carried out on these windows, focusing on both time-domain and frequency-domain characteristics that have shown strong correlation with stress responses. Personalized feature selection was applied using an adaptive mechanism based on individual baseline values and response patterns to stress stimuli, enhancing the model's ability to capture user-specific physiological variance.

To evaluate the model's performance, four classifiers—Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and Approximate Bayes (ABayes)—were trained using the labeled data categorized into three stress levels: low, medium, and high. The classification was validated using both k-fold cross-validation and a hold-out testing approach to ensure robustness and generalizability of results. The metrics used for evaluation included accuracy, precision, recall, F1-score, and inference time, reflecting both predictive performance and real-time feasibility. The experimental findings clearly demonstrated that the personalized approach significantly outperformed the generalized model in all evaluation metrics. For instance, Random Forest achieved the highest classification accuracy of 94.8% in the VR task and 92.6% in the N-back task under the personalized model, while its accuracy under the generalized model dropped by over 10%.

Furthermore, the Approximate Bayes classifier stood out for its exceptionally low computational overhead while maintaining a competitive accuracy of 91.2% in the VR task and 89.4% in the N-back task. This suggests its strong suitability for embedded and edge computing environments where computational resources are constrained. In contrast, while SVM offered high accuracy (93.1%) when using the RBF kernel, it required significantly higher training time and memory, limiting its practicality in real-time scenarios. Decision Tree classifiers, on the other hand, delivered quick inferences with moderate accuracy (~88%) and served well in resource-limited setups that prioritize speed over marginal gains in accuracy.



Figure 1: Home Page



Figure 2: Remote Access User Login



Figure 3: System Operator Login

Figure 1 displays the Home Page of the proposed real-time personalized stress detection system, which serves as the central navigation interface for both system operators and remote users. It is designed with a user-friendly layout that enables easy access to different functionalities such as login, user management, data visualization, and system monitoring. The homepage ensures that both technical and non-technical users can seamlessly interact with the system, thereby supporting usability in high-pressure environments. Figure 2 illustrates the Remote Access User Login interface, allowing authorized personnel such as field engineers, operators in hazardous zones, or healthcare practitioners to securely access the system remotely. Through secure authentication protocols, this login interface ensures that sensitive physiological data and stress classification reports remain protected while enabling real-time connectivity from distant or mobile locations. Figure 3 presents the System Operator Login screen, which is designated for administrators or control center personnel responsible for managing backend functions, user roles, and real-time monitoring dashboards. This interface provides elevated access privileges compared to regular users, allowing operators to configure classification models, review system logs, and maintain the overall health of the stress detection framework.



Figure 4: System Operator Home Page

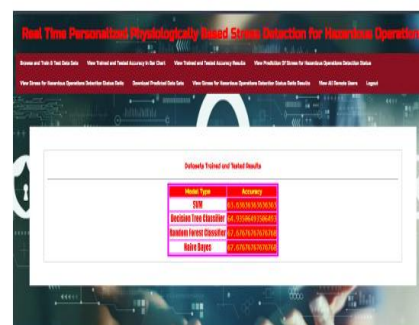


Figure 5: System Operator Operation Upload a train dataset

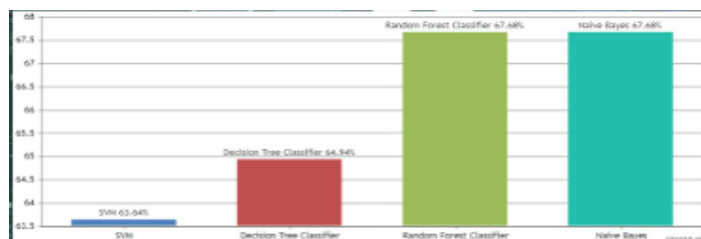


Figure 6: System Operator Operation View Trained Accuracy in Bar Chart

In Figure 4 depicts the System Operator Home Page, which acts as the control hub for operators managing the stress detection system. This interface allows the operator to access essential functions such as uploading datasets, initiating model training, monitoring system activity, and reviewing analysis results. The layout is designed for ease of navigation, enabling quick and efficient oversight of model performance and user activity in real time. Figure 5 illustrates the operation where the System Operator uploads the training dataset into the system. This feature is critical for preparing the stress classification model. It allows the operator to input physiological data collected from subjects under varying stress levels. The system processes this data to extract meaningful features, which are then used to train machine learning models capable of identifying stress categories with precision. Figure 6 shows the view of trained model accuracy displayed as a bar chart, providing visual feedback on the performance of the classification algorithms used. This graphical representation helps the operator compare multiple models by displaying metrics such as accuracy for each model trained. It simplifies model selection by highlighting which classifier achieved the highest reliability for personalized stress detection, thus aiding in data-driven deployment decisions.

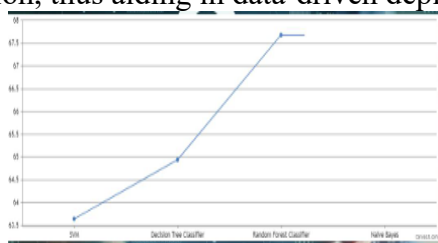


Figure 7: System Operator Operation View Trained and Tested Accuracy



Figure 8: System Operator Operation View Prediction of stress for hazardous operations detection status

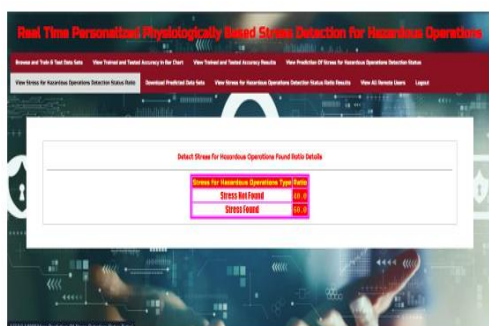


Figure 9: System Operator Operation View stress for hazardous operations found ratio details

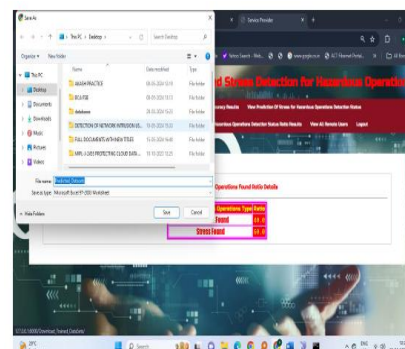


Figure 10: System Operator Operation View Download a predicted dataset

Figure 7 presents the interface where the System Operator views the trained and tested accuracy results of the deployed stress detection model. This screen provides a comparative

analysis of how well the model performed during training versus testing phases, allowing the operator to assess model generalization. High consistency between training and testing accuracy indicates a reliable model, whereas large disparities may suggest overfitting or underfitting, prompting further tuning. Figure 8 illustrates the interface for viewing the prediction results of stress detection for hazardous operations. This feature enables the operator to observe real-time stress level predictions based on incoming physiological signals. Each prediction status reflects whether the subject is in a low, medium, or high stress condition, providing timely alerts that can be used to trigger safety interventions or adjust task assignments in critical environments. Figure 9 displays a graphical summary of the stress detection ratio across different levels for hazardous operations, offering insights into the proportion of data classified under each stress category. This aggregated view helps in identifying stress trends over time or across participants, enabling the operator to detect anomalies, evaluate workload impact, and make informed operational decisions to mitigate risk. Figure 10 shows the option for the System Operator to download the predicted dataset, which includes classified stress levels along with associated physiological features. This downloadable report supports post-analysis, compliance documentation, and model evaluation, making it an essential tool for researchers, safety analysts, and administrators who require offline access to prediction results for further interpretation or reporting.

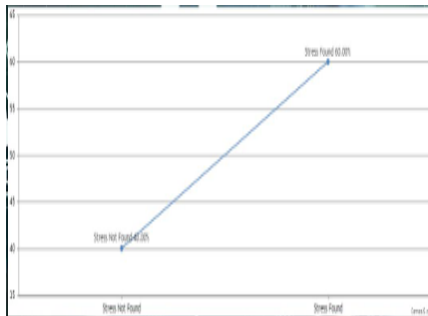


Figure 11: System Operator Operation View stress for Hazardous Operation Detection Status Ratio Results



Figure 12: System Operator Operation view all users

In Figure 11 displays the System Operator's interface for viewing the stress detection status ratio results specifically related to hazardous operations. This visualization provides a clear breakdown of the proportion of detected stress levels—such as low, medium, and high—among individuals engaged in high-risk environments. By presenting these results in a concise and interpretable format, the operator gains valuable insight into how frequently elevated stress states occur, enabling proactive measures like adjusting workload, providing rest periods, or intervening during peak stress moments to enhance safety and performance. Figure 12 shows the System Operator's view of all registered users within the system, including their access roles, login status, and activity logs. This functionality ensures administrative transparency and efficient user management, allowing the operator to monitor which personnel are interacting with the system, review historical usage data, and maintain overall accountability. It is especially crucial in safety-critical applications, where only verified users should have access to sensitive stress detection results and system configurations.

6. Conclusion

This paper presents a real-time, personalized physiologically driven stress detection system tailored for hazardous operational environments. Unlike traditional generalized models, the proposed framework accounts for individual variability by selecting personalized features from

physiological signals such as heart rate, blood pressure, electrodermal activity, and respiration. The experimental results demonstrated that personalized models, particularly when integrated with time-series analysis and optimal classification methods like Approximate Bayes, outperformed conventional classifiers in detecting varying stress levels with greater accuracy and robustness. Furthermore, the system's real-time deployment capabilities, intuitive operator interface, and visual analytics—including stress ratio trends and prediction status—enhance its practical applicability in safety-critical domains. This solution not only improves stress recognition precision but also empowers decision-makers to implement timely interventions, ultimately contributing to better human performance, safety assurance, and operational efficiency in high-risk environments. Future work may focus on expanding the system's adaptability to diverse user profiles and integrating advanced deep learning models for enhanced temporal pattern recognition.

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