

# Real Time Personalized Stress Detection for Risky Operations

Mr. A.V. Srinivas<sup>1</sup>, M. Appalarajumouli, G. Karthik<sup>2</sup>, Ch. Surendra<sup>2</sup>, E. Brahmanjali<sup>2</sup>, B. Sasank<sup>2</sup>

<sup>1</sup> Assistant Professor, Department of Information Technology, Vishnu Institute of Technology, Bhimavaram, Andhra Pradesh, 534202

<sup>2</sup> Department of Information Technology, Vishnu Institute of Technology, Bhimavaram, Andhra Pradesh, 534202

## Abstract

For the purpose of improving performance and reducing stress in risky operations, real-time stress detection is indispensable. Stress detection systems classify stress levels in unseen data by analyzing physiological signals such as respiration, heart rate, blood pressure, and electrodermal activity. These systems use machine learning. A personalized stress detection system that adjusts its feature selection based on individual characteristics was presented in a recent study. In order to assess the system for real-time deployment, a benchmark optimal probability classifier (Approximate Bayes; Naive Bayes) was used to compare traditional classifiers, including Naive Bayes, support vector machines, decision trees, and random forests. The goal of this customized model was to address the difficulties that generalized models encountered when attempting to handle the time-series nature of stress data. Tasks with different stress levels were given to healthy participants in the study, either in a virtual reality environment or a laboratory. Evaluation using holdout performance and cross-validation revealed differences between Naive Bayes and conventional classifiers, suggesting possible mistakes brought on by indirect approximations. Interestingly, the customized model changed which features it included depending on the tasks and window sizes, and one important indicator that stood out was blood pressure. Its superiority over generalized models was highlighted by its ability to account for individual differences, which led to higher classification accuracy for stress levels. This customized method has the potential to greatly improve stress detection and provide benefits to society by enhancing stress management in a variety of settings.

**Key Words:** Stress detection, machine learning, physiological sensors, Navie Bayes, support vector machine, decision tree, and random forest.

## 1. Introduction

Even with extensive emergency response training, a person's capacity to react appropriately in a real emergency can be compromised by situational stress. Stress can cause a number of physiological changes that can affect a person's ability to think clearly, perceive their surroundings, make decisions, and change their behavior. Inadequate stress management abilities can result in subpar work output and a higher chance of mishap, harm, or death. Therefore, improving training to strengthen one's resistance to this situational stress may yield better results. Thus, adjusting the stress level in training scenarios according to a person's real-time stress response monitoring could lead to a safer handling of hazardous operations in the real world.

Due to the temporal nature of physiological signals and individual variations in stress response, machine learning for stress detection faces substantial challenges. Conventional methods frequently generalize models without taking into account individual differences in stress perception. However, personalized models provide robustness because they take individual differences into account. Physiological data is time-series in nature, adding to the complexity, with correlations breaking independence assumptions. The Bayes theorem offers the best way to interpret model estimates against true conditional probabilities, although this is still a difficult task. While machine learning approximations aim to emulate Bayes, their inherent assumptions lead to problems with accuracy.

In order to address these issues, a research project seeks to assess the validity, reliability, and objectivity of a personalized stress detection methodology. The goal of objectivity assessment is to differentiate between different stress levels in individual features while taking physiological differences into account. Comparing performance across various tasks, window sizes, and classifier techniques are all part of the reliability evaluation process. The process of evaluating validity involves contrasting conventional supervised learning classifiers with an Approximate Bayes methodology that employs multivariate kernel density estimation to provide direct approximations. The project is in line with broader initiatives to create VR training scenarios that dynamically adapt to stress, which is essential for maximizing the performance of hazardous tasks and reducing stress.

### **Stress Detection:**

Continuous improvements in stress detection involve using machine learning to categorize physiological reactions into stress levels, potentially enabling real-time monitoring. Applications cover a broad spectrum of scenarios, such as virtual reality therapy, semi-urban driving, stress management, and workplace environments. Human-machine interfaces (HMIs) such as wearables, voice recognition, and facial expression analysis use stress detection as a technique to modify functionality based on the user's cognitive states. However, accuracy varies among individuals and technological systems. These systems gather data using sensors that measure physiological indicators like respiration, heart rate variability, and electrodermal activity. While heart rate variability is the main source of data used to compute stress indices, the time-series nature of physiological data is not taken into account when analyzing signal amplitude alone.

### **Time Series Classification:**

The time series nature of physiological signals can be handled in a number of ways for classification; these include feature extraction from intervals and Dynamic Time Warping (DTW) for whole series comparison. When used with a nearest-neighbor classifier, DTW is very successful for time series data, such as ECG patterns that repeat because of heart arrhythmias or sleep apnea. Because neural network frameworks like convolutional or recurrent neural networks are so accurate, they have become a popular choice for classifiers in interval methods. Unfortunately, the temporal and pattern variations of stress make it difficult to detect using these methods. HRV features are used in interval-based classification, which is popular in stress detection. The favour for their flexibility, neural networks are not always as interpretable as more conventional models such as decision trees and support vector machines.

Stress scale, which has a range of 0 to 100, to rate their subjective stress levels in order to assess different levels of stressors. The scale is designed to allow for a simultaneous comparative analysis of stress levels across all trials. Stress appraisal is continuous and relative.

## **2. Literature Survey**

Examine the literature that has already been written about the application of physiological signals, such as respiration, heart rate, blood pressure, and electrodermal activity, in stress detection systems [12]. Seek research on the role these signals play in accurately assessing and forecasting stress [3]. Stress Detection Machine Learning Algorithms: Examine how different machine learning algorithms might be used in stress detection systems [1]. Pay attention to both more recent strategies like customize models and more established classifiers like random forest, decision tree, support vector machine, and Naive Bayes.[10]

Real-time Deployment and Evaluation: Examine existing research on the difficulties and factors to be taken into account when implementing stress detection systems in hazardous real-time operations [5]. Examine evaluation techniques such as holdout performance, cross-validation, and comparison with reference classifiers such as Approximate Bayes (Naive Bayes) [17].

The main goal of our project is to investigate how temporal aspects of physiological signals can be addressed by applying time-series analysis techniques to stress data [2]. It seeks to explore techniques like feature extraction, windowing strategies, and different modelling approaches applied in time-series stress data analysis through a thorough review of the literature [8]. The present study to offer an understanding of the recent developments in customize stress detection systems and pinpoint possible avenues for future investigation [15].

A helpful method for analyze data is DTW analysis. The Patients' frequency domain measurements are used to identify mental stress and health conditions related to influenza in participants [11]. Simple measures are effective indicators. When used as binary classifiers, SVM and decision trees showed accuracy of 83% and 91% for stress classification and 85% and 72% for one type of classification for two test subjects.

Our machine learning pipeline, which includes data collection, preprocessing, feature extraction, and classification, was designed for stress detection. Real-time stress prediction was integrated with offline validation while preserving algorithm coherence. Continuous data streaming and parallel worker configurations were necessary for real-time processing. The online system demonstrated similar feature selection and classification accuracy to offline methods, even though retraining wasn't integrated for acute stress detection. Computational latency tests supported the validity and reliability of the system by ensuring timely stress predictions.

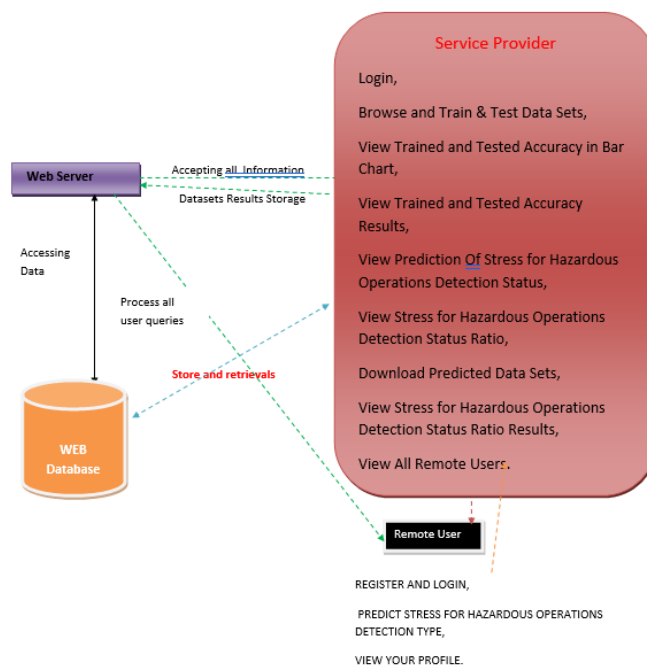
### 3. Methodology

#### 3.1 Dataset

For the purpose of this study, we used a dataset with multiple columns that represented variables for measuring stress using heart rate variability. Four of these were selected as inputs to be used in the machine learning model training process. There are labels for stress or no stress in the testing dataset. First, we obtained the required parameters from a freely accessible dataset and reprocessed them. A delimiter was then used to combine these parameters into a single column. The object type column in question was used to train the model. Stress and no-stress conditions are also included in the testing data. An 80:20 ratio was used to divide the data into training and testing sets. After that, we used five machine learning algorithms—Naive Bayes, SVM, Random Forest, and Decision Tree—to acquire more understanding of our workings.

The preprocessed dataset was transformed to enable model training by concatenating the chosen parameters into a single column format. The separation of the data into testing and training sets made it possible to assess the model's performance sufficiently. To ensure consistency across evaluations, standard settings were applied to each algorithm. Evaluation metrics were calculated to determine each algorithm.

#### 3.2 Methodology



### 3.3 Algorithms

#### A-Decision Tree

Because decision tree classifiers can extract descriptive decision-making insights from given data, they are widely used in many different domains. Training datasets are used to build these classifiers. The following describes the procedure for creating a decision tree given a set of objects ( $S$ ), each. The decision tree for  $S$  has a leaf node labelled with the class  $C_i$  if every object in  $S$  is a member. 2. If not, a test  $T$  with possible results  $O_1, O_2, \dots, O_n$  is selected.  $S$  is divided into subsets  $S_1, S_2, \dots, S_n$ , where each object in  $S_i$  produces an outcome ( $O_i$ ) for  $T$ . Each object in  $S$  corresponds to one outcome for  $T$ .  $T$  becomes the decision tree's root, and a subsidiary decision tree is created for each outcome  $O_i$  by repeatedly using the same process to set  $S_i$ . The given sets can be labelled through the given process of the Decision tree.

Because of their interpretability and simplicity of use, decision trees are flexible classifiers that are frequently used in a variety of domains. To classify instances, they make decisions at each node by recursively dividing the data into subsets based on the most important attributes. Pruning is one technique that helps mitigate the overfitting that decision trees can experience with complex datasets, ensuring robust and accurate classification.

#### b) Navie Bayes

The probabilistic machine learning algorithm Naive Bayes is well known for its effectiveness and ease of use in classification tasks, especially when dealing with high-dimensional datasets. Based on the Bayes theorem, it can handle both binary and multiclass classification tasks and computes conditional probabilities based on past knowledge. It stays computationally efficient even with large datasets, and its training process involves estimating probabilities from the data.

Because of its simplicity and speed, it is widely used in spam filtering, sentiment analysis, and document categorization. It performs well when handling a large number of features and is less likely to overfit. Although it makes the oversimplified assumption that features are independent, it produces reliable and effective results that are on par with other methods. But practitioners found it difficult to interpret, and this led to a new way of presenting the data that improved the classifier's understandability.

The applications in the real world by applying the Naive Bayes technique on a dataset with Tanagra, Weka and the Orange 2.0b, and RapidMiner 4.6.0, among other software tools. Our goal is to fully understand the results through in-depth analysis. Analyses are conducted against other linear techniques like logistic regression, linear discriminant analysis, and linear SVM

#### c) Random Forest

The Random forests, by building numerous decision trees during training, an ensemble learning technique are used for tasks like regression, classification, and other applications. Regression yields the average prediction of each individual tree, whereas classification yields the class selected by the majority of the trees. By addressing decision trees' propensity to overfit training data, these forests outperform decision trees used alone. However, depending on the features of the data, gradient boosted trees might outperform them in terms of accuracy.

Random decision forests were first introduced by Tin Kam Ho in 1995, using the random subspace method to implement stochastic discrimination. Leo Breima and Adele Cutler further refined this idea by combining bagging and random feature selection, and this innovation resulted in the trademarked term "Random Forests" in 2006. With their reputation for reliability and effectiveness, random forests are widely used "black box" models in a variety of industries.

#### d) SVM

Discriminant machine learning techniques aim to obtain a discriminant function from a training dataset that is identically distributed and independent (id). This allows for precise label prediction for newly acquired instances in classification tasks. Discriminant classification functions assign a data point  $x$  to one of the different classes in the task, while generative

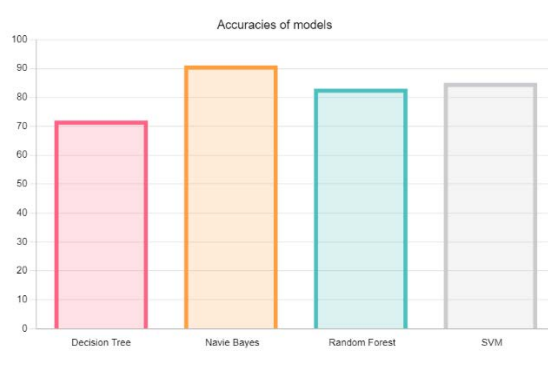
machine learning techniques require the computation of conditional probability distributions. Discriminant methods require less training data and less processing power than generative approaches, which are usually used for outlier detection. They are especially useful in multidimensional feature spaces and when only posterior probabilities are needed. Finding the equation for a multidimensional surface that successfully divides the various classes within the feature space is the first step in creating a classifier geometrically.

#### 4. Results

Following are the accuracies of following machine learning models in both tabular form and bar chart.

MODEL	ACCURACY
Decision Tree	72
Navie Bayes	91
Random Forest	85
SVM	85

**Fig 4.1** Accuracies of models



**Fig 4.2** Accuracies in bar chart

#### 5. Conclusion

The purpose of this study was to evaluate a live stress detection mechanism using a customized approach based on time-series intervals for fairness, accuracy, and consistency. This assessment aimed to address the wide range of individual responses to stressors and the sequential nature of physiological data. Different stress levels were elicited by using simple and complex tasks, which provided invaluable ground truth data for machine learning. Analyzing window sizes revealed which features and sensors worked best over different time periods. When compared to an optimal classifier, A Bayes, the personalized model performed better than a generalized model. Additionally, an investigation into the effects of indirect approximations on classifier performance revealed minor-to-moderate effects. These results demonstrate the potential of customize systems for multi-class stress detection, but they also emphasize how crucial it is to choose HMIs, sensors, and features carefully.

Additionally, compared to earlier studies on multi-class stress detection, this research shows promising performance, shedding light on the potential benefits of personalized stress detection systems. The study also emphasizes the need for caution when choosing sensors, human-machine interfaces (HMIs), and model development features because these components might not fully account for intra- and inter-individual variations in stress physiology. Further research will focus on improving personalized stress detection systems to take into consideration changes in an individual's stress response over time as well as physiological signals. Through the use of techniques that adjust dynamically to these shifts, these kinds of systems have the potential to improve stress detection efficiency and precision in practical situations.

## 6. Conclusion

The " REAL TIME PERSONALIZED STRESS DETECTION FOR RISKY OPERATIONS " project has a lot of potential for the future in a number of areas. First, improving the process to include personalized features based on each person's physiology for real-time stress detection will improve the accuracy and dependability of stress evaluation. This will make it possible to create closed-loop automation systems that can dynamically adjust their surroundings in order to minimize stress.

Furthermore, by investigating cutting-edge techniques like multivariate kernel density estimators and Bayesian classifiers, stress detection algorithms will be further improved, becoming more comprehensible and efficient. By creating immersive and adaptive environments that adjust to the trainee's physiological state, the integration of real-time stress detection systems with virtual reality (VR) training scenarios has the potential to completely transform training methodologies.

In general, the project's future trajectory entails improving and validating customized stress detection models, incorporating them into hazardous operations applications in real-time, and possibly expanding their use to more contexts outside of their original purview. The groundwork for a revolutionary strategy for stress management in high-stakes situations is laid by this research.

## 7. References

- [1] J. E. Driskell, E. Salas, J. H. Johnston, and T. N. Wollert, *Stress Exposure Training: An Event-Based Approach* (Performance Under Stress). London, U.K.: Ashgate, 2008, pp. 271–286.
- [2] I. Barshi and D. L. Dempsey, "Risk of performance errors due to training deficiencies: Evidence report," Nat. Aeronaut. Space Admin. (NASA), NASA Johnson Space Center, Houston, TX, USA, Tech. Rep., JSC-CN- 35755, 2016.
- [3] M. Gjoreski, M. Luštrek, M. Gams, and H. Gjoreski, "Monitoring stress with a wrist device using context," *J. Biomed. Inform.*, vol. 73, pp. 159–170, Sep. 2017, doi: 10.1016/j.jbi.2017.08.006.
- [4] M. Zahabi and A. M. A. Razak, "Adaptive virtual reality-based training: A systematic literature review and framework," *Virtual Reality*, vol. 24, no. 4, pp. 725–752, Dec. 2020, doi: 10.1007/s10055-020-00434-w.
- [5] Y. S. Can, B. Arnrich, and C. Ersoy, "Stress detection in daily life scenarios using smart phones and wearable sensors: A survey," *J. Biomed. Informat.*, vol. 92, Apr. 2019, Art. no. 103139, doi: 10.1016/j.jbi.2019.103139.
- [6] A. O. Akmandor and N. K. Jha, "Keep the stress away with SoDA: Stress detection and alleviation system," *IEEE Trans. Multi-Scale Comput. Syst.*, vol. 3, no. 4, pp. 269–282, Oct. 2017, doi: 10.1109/tmscs.2017.2703613.
- [7] M. Verleysen and D. Franais, "The curse of dimensionality in data mining and time series prediction," in *Proc. Int. Work-Conf. Artif. Neural Netw.* Berlin, Germany: Springer, 2005, pp. 758–770, doi: 10.1007/11494669\_93.
- [8] S. Tong and D. Koller, "Bayes optimal hyperplanes? Maximal margin hyperplanes," in *Proc. IJCAI*, 1999, pp. 1–5.
- [9] I. Rish, "An empirical study of the naive Bayes classifier," in *Proc. IJCAI Workshop Empirical Methods Artif. Intell.*, 2001, vol. 3, no. 22, pp. 41–46.