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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; ABayes). Healthy participants completed a task with three levels of stressors (low, medium, high), either a complex task in virtual reality (responding to spaceflight emergency fires, n =27) or a simple laboratory-based task (N-back, n =14). Heart rate, blood pressure, electrodermal activity, and respiration were assessed. Personalized features and window sizes were compared. Classification performance was compared for ABayes, support vector machine, decision tree, and random forest. The results demonstrate that a personalized model with time series intervals can classify three stress levels with higher accuracy than a generalized model. However, cross-validation and holdout performance varied for traditional classifiers vs. ABayes, suggesting error from indirect approximations. The selected features changed with window size and tasks, but found blood pressure was most prominent.

The capability to account for individual difference is an advantage of personalized models and will likely have a growing presence in future detection systems.

1.INTRODUCTION

Despite extensive training in responding to an emergency, a person's response to an actual emergency can be negatively affected by the stressfulness of the situation. Stress can result in a cascade of physiological changes that may alter. Behavioral patterns, situational awareness, decision making, and cognitive resources [1].An inability to cope with the stress of a high-stress condition cande crease task performance and thereby risk mission failure, injury, or death [2]. Consequently, developing resiliency to this situational stress through improved training may lead to better outcomes. To that end, using real-time monitoring of a person's stress responses to customize the stressfulness of training scenarios may, in turn, lead to more appropriate handling of actual hazardous operation [3], [4].

Stress detection using machine learning has been challenging for several reasons. First, there are individual differences in the appraisal of, and physiological responses to, stressful situations. Numerous stress detection approaches have attempted to reduce technical complexity by generalizing their models to a broad population, or the ''average'' response [3]. However, the stress response to a unique situation is largely subjective, and personalized stress detection models may be more robust to individual differences [5], [6].

The second challenge is that the time series nature of physiological signals can be problematic. The physiological stress response has temporal and feature correlations. These correlations may violate the machine learning assumption that the data are independently and identically distributed, thereby leading to biased results [7]. An additional challenge is interpreting how well model estimations match the true conditional probabilities of a subject's stress levels. Stress detection models rely on traditional machine learning algorithms that make data-driven approximations to estimate the chance that the individual is experiencing a state of stress given their physiological responses. However, these estimations are often indirect and without a

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benchmark for comparison. From classical statistics research, the Bayes theorem is theoretically the optimal solution and a classifier given the same parameters as Bayes theorem will have the lowest probability of error [8]. The Bayes theorem uses an empirical density distribution as a true prior probability, which can be used to calculate the conditional probability of each class. The classifier selects the class with the greatest posterior probability of occurrence, also known as maximum a posteriori. Machine-learning algorithms attempt to approximate the density distributions. If the density estimates of the classifier converge to the true densities, then the estimated probability represents the true probability of occurrence and a classifier that approximates Bayes becomes an Optimal Bayes classifier. However, these approximations can have varying accuracy due to assumptions made by the algorithm, such as independence of predictors [9]. Thus, it can be difficult to interpret the model's logic. Physiological systems are known to have a high degree of dependence with regard to a stress response, because they are often initiated by the same neuro endocrine axis [10]. Some researchers have shown that classifiers may account for dependencies using multivariate kernel density estimators [11]. Therefore, it may be beneficial to evaluate supervised machine learning classifiers against a benchmark optimal classifier that approximates Bayes using a density distribution estimated through multivariate kernel density estimation for stress detection. To achieve real-time and continuous monitoring of stress levels, new approaches are needed to analyze time series for physiologically-based stress detection [12]. Real-time stress detection can enable closed-loop automation to either modify the training environments to better match the trainee's responses or better assess individual stress during staged or real operations [13]. In datasets with repeated measurements at multiple times that present uncertainty from randomness or incompleteness, such as multiple measures of physiological data, multivariate kernel density estimators may help increase detection accuracy [11]. To address these challenges, the goal of this research is to assess the objectivity, reliability, and validity of a personalized model methodology. The first research question focuses on objectivity, and whether the

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stressor levels can show distinct levels in personalized features used for the classification model while accounting for individual differences in physiology. This will provide confidence that the model is designed for the appropriate context and that the training data reflect distinct ground truth levels. The second research question focuses on the system's reliability by evaluating the performance of the time-series interval approach using a post-hoc model comparing between a standard laboratory cognitive task and a complex job-specific task, window sizes, classifier validation techniques, and features selected for each individual. The third research question focuses on the validity of the system by seeking to understand whether indirect approximations influence traditional supervised machine learning classifiers compared to a Bayes classifier, known as Approximate Bayes (A Bayes), which uses direct approximations of optimal stress classes through multivariate kernel density estimation. This research is part of a larger development effort to design VR training scenarios that can dynamically adapt a virtual environment using real-time stress detection [14], [15], [16]. To answer these research questions within the constraints of the larger system, the experiment will assess a time-series interval approach to stress detection for a post-hoc model of physiological response data, its accuracy in detecting participant stress using a collected during stressful tasks, and provide the architecture for a real-time stress detection system that uses this classification methodology. Validating a machine learning pipeline post-hoc allows for translation to real-time stress detection and applications for stress monitoring.

2.LITERATURE SURVEY

Decision tree classifiers

Decision tree classifiers are used successfully in many diverse areas. Their most important feature is the capability of capturing descriptive decision making knowledge from the supplied data. Decision tree can be generated from training sets. The procedure for such generation based on the set of objects (S), each belonging to one of the classes C1, C2, …, Ck is as follows:

Step 1.If all the objects in S belong to the same class, for example Ci, the decision tree for S consists of a leaf labeled with this class

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Step 2.Otherwise, let T be some test with possible outcomes O1, O2,…, On. Each object in S has one outcome for T so the test partitions S into subsets S1, S2,…Sn where each object in Si has outcome Oi for T. T becomes the root of the decision tree and for each outcome Oi we build a subsidiary decision tree by invoking the same procedure recursively on the set Si.

Gradient boosting

Gradient boosting is a machine learning technique used in regression and classification tasks, among others. It gives a prediction model in the form of an ensemble of weak prediction models, which are typically decision trees.[1][2] When a decision tree is the weak learner, the resulting algorithm is called gradient-boosted trees; it usually outperforms random forest.A gradient-boosted trees model is built in a stage-wise fashion as in other boosting methods, but it generalizes the other methods by allowing optimization of an arbitrary differentiable loss function.

K-Nearest Neighbors (KNN)

- Simple, but a very powerful classification algorithm
- Classifies based on a similarity measure
- Non-parametric
- Lazy learning
- Does not "learn" until the test example is given

- Whenever we have a new data to classify, we find its K-nearest neighbors from the training data

Example

- Training dataset consists of k-closest examples in feature space
- Feature space means, space with categorization variables (non-metric variables)
- Learning based on instances, and thus also works lazily because instance close to the input vector for test or prediction may take time to occur in the training dataset

Logistic regression Classifiers

Logistic regression analysis studies the association between a categorical dependent variable and a set of independent (explanatory) variables. The name *logistic regression* is used when the dependent variable has only two values, such as 0 and 1 or Yes and No. The name *multinomial logistic regression* is usually reserved for the case when the dependent variable has three

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or more unique values, such as Married, Single, Divorced, or Widowed. Although the type of data used for the dependent variable is different from that of multiple regression, the practical use of the procedure is similar.

Logistic regression competes with discriminant analysis as a method for analyzing categorical-response variables. Many statisticians feel that logistic regression is more versatile and better suited for modeling most situations than is discriminant analysis. This is because logistic regression does not assume that the independent variables are normally distributed, as discriminant analysis does.

This program computes binary logistic regression and multinomial logistic regression on both numeric and categorical independent variables. It reports on the regression equation as well as the goodness of fit, odds ratios, confidence limits, likelihood, and deviance. It performs a comprehensive residual analysis including diagnostic residual reports and plots. It can perform an independent variable subset selection search, looking for the best regression model with the fewest independent variables. It provides confidence intervals on predicted values and provides ROC curves to help determine the best cutoff point for classification. It allows you to validate your results by automatically classifying rows that are not used during the analysis.

Naïve Bayes

The naive bayes approach is a supervised learning method which is based on a simplistic hypothesis: it assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature .

Yet, despite this, it appears robust and efficient. Its performance is comparable to other supervised learning techniques. Various reasons have been advanced in the literature. In this tutorial, we highlight an explanation based on the representation bias. The naive bayes classifier is a linear classifier, as well as linear discriminant analysis, logistic regression or linear SVM (support vector machine). The difference lies on the method of estimating the parameters of the classifier (the learning bias).

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While the Naive Bayes classifier is widely used in the research world, it is not widespread among practitioners which want to obtain usable results. On the one hand, the researchers found especially it is very easy to program and implement it, its parameters are easy to estimate, learning is very fast even on very large databases, its accuracy is reasonably good in comparison to the other approaches. On the other hand, the final users do not obtain a model easy to interpret and deploy, they does not understand the interest of such a technique.

Thus, we introduce in a new presentation of the results of the learning process. The classifier is easier to understand, and its deployment is also made easier. In the first part of this tutorial, we present some theoretical aspects of the naive bayes classifier. Then, we implement the approach on a dataset with Tanagra. We compare the obtained results (the parameters of the model) to those obtained with other linear approaches such as the logistic regression, the linear discriminant analysis and the linear SVM. We note that the results are highly consistent. This largely explains the good performance of the method in comparison to others. In the second part, we use various tools on the same dataset (Weka 3.6.0, R 2.9.2, Knime 2.1.1, Orange 2.0b and RapidMiner 4.6.0). We try above all to understand the obtained results.

Random Forest

Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. For classification tasks, the output of the random forest is the class selected by most trees. For regression tasks, the mean or average prediction of the individual trees is returned. Random decision forests correct for decision trees' habit of overfitting to their training set. Random forests generally outperform decision trees, but their accuracy is lower than gradient boosted trees. However, data characteristics can affect their performance.

The first algorithm for random decision forests was created in 1995 by Tin Kam Ho[1] using the random subspace method, which, in Ho's formulation, is a way to implement the "stochastic discrimination" approach to classification proposed by Eugene Kleinberg.

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An extension of the algorithm was developed by Leo Breiman and Adele Cutler, who registered "Random Forests" as a trademark in 2006 (as of 2019, owned by Minitab, Inc.).The extension combines Breiman's "bagging" idea and random selection of features, introduced first by Ho[1] and later independently by Amit and Geman[13] in order to construct a collection of decision trees with controlled variance.

Random forests are frequently used as "blackbox" models in businesses, as they generate reasonable predictions across a wide range of data while requiring little configuration.

SVM

In classification tasks a discriminant machine learning technique aims at finding, based on an *independent and identically distributed* (*iid*) training dataset, a discriminant function that can correctly predict labels fornewly acquired instances. Unlike generative machine learning approaches, which require computations ofconditional probability distributions, a discriminant classification function takes a data point *x* and assignsit to one of the different classes that are a part of the classification task. Less powerful than generativeapproaches, which are mostly used when prediction involves outlier detection, discriminant approachesrequire fewer computational resources and less training data, especially for a multidimensional featurespace and when only posterior probabilities are needed. From a geometric perspective, learning a classifieris equivalent to finding the equation for a multidimensional surface that best separates the different classesin the feature space.

SVM is a discriminant technique, and, because it solves the convex optimization problem analytically, it always returns the same optimal hyperplane parameter—in contrast to *genetic algorithms* (*GAs*) or *perceptrons*, both of which are widely used for classification in machine learning. For perceptrons, solutions are highly dependent on the initialization and termination criteria. For a specific kernel that transforms the data from the input space to the feature space, training returns uniquely defined SVM model parameters for a given training set, whereas the perceptron and GA classifier models are different each time training is initialized. The aim of GAs and perceptrons is only to minimize error during training,

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which will translate into several hyperplanes' meeting this requirement.

3. EXISTING SYSTEM

The physiological stress response involves the interaction between the nervous system and the endocrine system that aims to maintain physiological integrity under changing environmental demands. The time course of the physiologic responses to stress varies by system and by the intensity andduration of the stressor; they are neither physiologically independentnor statistically orthogonal. After the psychologicalappraisal of a stressor, neural ganglia pathways are activatedalmost instantaneously to evoke very rapid responses via local neurotransmitters. For example, disinhibition of heartrate via vagal withdrawal occurs within milliseconds while asympathetically-mediated increase in heart occurs after a fewseconds (5-10 s) [10]. Sympathetic and sudomotor activity results in the opening of eccrine sweat glands on handsand feet, which occur about 1-5 seconds after stimuli [17].On the other hand, the physiologic responses due to circulatingchemicals take longer to manifest. Epinephrine is secretedfrom the adrenal medulla and range from milliseconds to minutesto exert their cardiovascular effects. Whereas, cortisol isinitiated by the adrenal cortex 5–10 min after stressor onsetand peak between 20 and 30 min [18]. These processes canact exclusively or in conjunction on target organs to potentiate(e.g., memory, muscle activation) or attenuate organ function(e.g., digestion, reproduction).

Stress detection, by means of classifying these physiological responses into levels of stress via machine learning, continues to evolve and is motivated by the potential utility of continuously monitoring stress levels in real-time [12], [21]. Stress detection systems have been developed for drivers in semi-urban scenarios [22], [23], patients undergoing virtual reality therapy [24], individuals in working environments [25], and people that need help managing daily stress [21], [26], [27], [28], [29], [30]. Stress detection can also be applied to a variety of human-machine interfaces (HMIs) which may monitor stress, but also infer the cognitive state of the user to adapt system functionality [31]. Examples of HMIs that may use stress detection include wearable

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devices, voice recognition systems, eye tracking systems, facial expression analysis, and brain/body computer interfaces [12], [32]. However, these HMIs may not be able to accurately detect stress in all individuals, and the accuracy of stress detection may vary depending on the specific technology and approach used [33].

These detection systems collect information about stress responses from either objective physiological sensors or subjective psychological metrics, in the form of independent variables called features, which are then used to classify the stress level. Commonly used sensors include electrodermal activity (EDA), electrocardiogram (ECG), respiration (RSP), electroencephalogram (EEG), skin temperature (ST), and blood volume pulse (BVP) [33]. For an ECG signal, stress indices have been primarily inferred from changes in the time intervals between heartbeats, which measure Heart Rate Variability (HRV) using time-domain, frequency-domain, or nonlinear analysis. HRV metrics have been associated with sympathetic and parasympathetic activation. However, attempting to detect stress levels from signal amplitude alone neglects the time series nature of physiological data. Physiological systems may be simultaneous and coupled (e.g., breathing can modulate heart rate), contain both deterministic and stochastic components, and may be correlated when measured over long periods of time [34]. Stress sensor signals are continuous ordered attributes; therefore, they are best characterized by features that quantify the distribution of data points, variation, correlation properties, stationarity, entropy, and nonlinear properties [35]

Disadvantages

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

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

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

Proposed System

This paper describes the development of a personalized physiological-based stress detection system to classify acute stress using feature selection on intervals of the time-series data. To train the machine learning model, participant physiological signals were collected for three stressor levels during either a spaceflight emergency fire procedure on a VR International Space Station (VR-ISS) [46], [47] or a well-validated and less-complex N-back mental workload task [48].

Several previous studies have detected stress induced by N-back tasks via machine learning methods, both alone [48], [50] and with another job-specific task [51]. Therefore, comparing a jobs pecific VR-ISS task to the N-back using the same personalized approach is a way to assess the system's reliability can work for multiple stress detection tasks. Each participant had features selected at different interval window sizes, then those personalized features trained the classifier model, and subsequently tested the classifier's predictive accuracy. Since the stress response is complex and often unique, the analysis will explore which features are selected most for individuals depending on window size, and how this changes classification

performance. Classifier performance was assessed using both holdout and cross-validation validation techniques to simulate how the model may perform on unseen data as an analog for deployment in real-time.

Advantages

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

4. OUTPUTSCREENS

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

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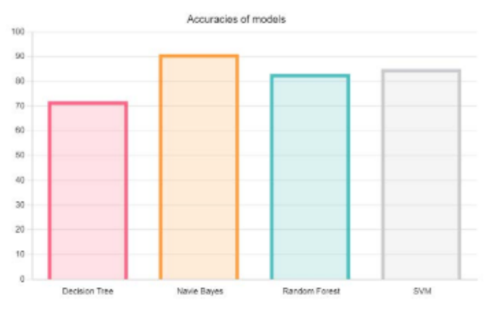

5. CONCLUSION

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

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