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A Hybrid Filter-Wrapper Feature Selection Method for Stress Detection and Monitoring Among Employees at Workspaces

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Abstract— In this competitive world, employees often experience stress at work. Stress for a prolonged period of time is converted to chronic stress. This may lead to high blood pressure, damage to muscle tissue, inhibition of growth, suppression of the immune system and damage to mental health. Generally, stress management is subjective to the realization of the person. For a better mental health management, continuous monitoring and objective evaluation of stress is a need. Nowadays, various sensors are used for the same. This paper investigates how new context-aware pervasive systems can support knowledge workers to diminish stress. The focus is on developing an automatic classifier to infer working conditions and stress-related mental states from a multimodal set of sensor data (computer logging, facial expressions, posture, and physiology). Instead of using all the sensor data (149 features), the further focus is on selecting a subset of features, which are most effective in detecting stress using a hybrid filter-wrapper approach for feature selection. As a final note, implementing such a stress detection system in real-world settings brings additional challenges. Not only sensors have to be installed to collect data in the workplace, but also the signals need to be processed, features extracted and analyzed in real time yielding meaningful results. But selecting a set of features makes the task a lot easier and results in higher accuracy and fast processing. Different filter and wrapper methods and their hybrids were analyzed for the problem at hand. Finally, the hybrid of information gain and best first method resulted in a significant reduction in the number of features in the original feature set and an increase in accuracy.

Keywords— Machine learning, Stress, Feature selection, Hybrid method, Facial expression, Postures, Computer loggings, Physiological, Filter approach, Wrapper approach

I. INTRODUCTION

Stress at work is very common among employees these days, which can in the worst case lead to burn-out. Stress is primarily a physical response and in a broad concept, it refers to biological and psychological processes during emotional and cognitive demanding situations. Stress can be caused because of various factors like heavy task loads, lots of pressure for completing a task due to the deadline, interruptions in between the tasks etc. Employees can be stressed when they feel that they might not be able to handle the demands posed on them.

According to A. Fernandes [1] stress can be of three types:

[1] Acute stress which is short-term stress and does not cause extensive damage. It is easy to detect and treatable.
[2] Episodic acute stress which makes people anxious.
[3] Chronic stress which is long-term stress capable of extensive damage and difficult to be detected.

Questionnaires are one of the traditional methods that are used for stress detection. But questionnaires are not effective since they don't reveal the immediate effects of stress leading situations among employees. Sometimes employees having stress are unaware of that until it leads to some serious damage.

For handling stress, it is very necessary to first monitor it on time so that the person having stress can be easily deal with it before it starts affecting their performances. It became necessary to kept employees under continuous monitoring for stress detection. According to a worldwide survey reported by new business, half of the population have experienced rise in stress over the last two years. [2]

Stress can be detected using many sensors like heart rate, body postures, blood pressure, galvanic skin response etc. But, the accuracy of determination is limited by using individual parameters. Usage of multiple parameters aids in the better determination of stress. For example, a combination of features obtained from GSR and Blood Pressure increases the accuracy of detecting stress. So, the main aim is to identify all those parameters or features which combination gives the best accuracy for detecting stress. Feature selection in large dataset plays a vital role by increasing the efficiency of classification. Therefore, it is considered to use in pre-processing before applying algorithm on the dataset. [3]

This paper investigates which features or combination of features are more effective in detecting stress in workers at the workspace. The focus is on developing automatic classifier which without interfering working conditions detect stress and mental states of employees from a multimodal set of sensor data (computer logging, facial expressions, posture, and physiology)[2]. Instead of using all the sensor data (149 features), the further focus is on selecting a subset of features, which are most effective in detecting stress using a hybrid filter-wrapper approach for feature selection.

A. Contribution

The novelty and main contributions of this paper are to develop an optimized machine learning algorithm for continuous monitoring of stress levels in employees at workplaces with effective management of resources. This objective is further categorized into three major goals which are as follows:

- Develop an efficient method for continuous objective evaluation of stress levels.
- Identify suitable machine learning algorithm for effective evaluation of stress levels.
- Improve the performance of implemented machine learning algorithm by selecting an optimal feature set.

This paper is structured as follows: Section 2 explains the related work that has already been done in monitoring stress levels. Section 3 explains the implementation models for algorithm and feature selection. Section 4 gives a detailed experimental analysis of the proposed model. Section 5 concludes the paper by identifying remaining challenges and exposing our plans for future work.

II. PRELIMINARIES

There has been lots of work done previously by many researchers in determining stress in individuals by using only one or two sensors. But by using multiple sensors the accuracy of determination of stress increases that's why we are combining four sensors which are most efficient in the determination of stress.

In 2014 Saskia Koldijk [4] has published a series of papers on determining work stress in offices by combining unobtrusive sensors. According to their paper posture and facial expression yield the most valuable information in determining the stress level.

In 2009 Liza M. Vizer [5] published *Automated stress detection using keystroke and linguistic features*. This paper describes a way to classify cognitive and physical stress conditions relative to non-stress conditions based on keystroke and linguistic features with accuracy rates comparable to those obtained using affective computing method.

In 2014 Javier Hernandez [6] published *under pressure: sensing stress of computer users* which showed the possibility of using a pressure-sensitive keyboard and a capacitive mouse to discriminate between stressful and relaxed conditions. According to this study during the stressful conditions, the large majority of the participants showed significantly increased typing pressure (>79% of the participants) and more contact with the surface of the mouse (75% of the participants).

In 2014 Hua Gao [7] published *Detecting emotional stress from facial expressions for driving safety* which described a real-time non-intrusive monitoring system, which detects the emotional states of the driver by analyzing facial expressions. The system considered two negative basic emotions, anger, and disgust, as stress-related emotions.

In 2005 Dingers, David F. [8] and team published *Optical Computer Recognition of Facial Expressions Associated with Stress Induced by Performance Demands* which they applied optical computer recognition (OCR) algorithms for detecting facial changes during the performance while people experienced both low- and high-stressor performance demands.

In 2012 Feng Tso sun and team [9] published *Activity-Aware Mental Stress Detection Using Physiological Sensors* which showed continuous stress monitoring may help users better understand their stress patterns and provide physicians with more reliable data for interventions. They used Electrocardiogram (ECG), galvanic skin response (GSR) to gathered baseline physiological measurements and measurements while users were subjected to mental stressors. They achieved 92.4% accuracy.

In 2012 Dimitris Giakoumis and team [10] published *Using Activity-Related Behavioural Features towards More Effective Automatic Stress Detection* which showed activity-related behavioral features that can be automatically extracted from a computer system, with the aim to increase the effectiveness of automatic stress detection.

We can conclude that these four sensors give higher accuracy when used individually for determining stress. So, we can use the combination of these sensors to get more accuracy in determining stress.

Detecting stress using four sensors on continuous basis takes lots of time and resources. So the main aim of this paper is to select a set of features which are highly effective in detecting stress.

There are different types of feature selection approaches present in machine learning. The best feature subset selection algorithms are mainly categorized into two approaches **Filter approach** and **Wrapper approach.** [11]

Many researchers have used various feature selection methods for feature selection and classification. In previous studies, different kinds of feature selections were applied including filters and wrappers, as well as the combination of the two. Researchers[12] have applied the combination of four filter methods, namely; Information Gain, x2, Odds-Ratio, and Correlation Coefficient with Genetic Programming (GP), in order to gain the advantages provided by the different metrics.

Another approach in feature selection is wrapper methods. Wrappers, in contrast to filters, use learning algorithms to investigate the worthy of features [12]. The principal idea behind this approach is that the induction algorithm that eventually will use the selected features, can predict the accuracy of the selected features better than any other methods. Generally, wrappers produce better results than filters [12]; because they consider the relationship between the learning algorithm and the training data. From the other side, wrappers are slower than filters; because for every selected feature subset, the learning algorithm must be repeatedly executed.

This paper presents a two-phase approach for feature selection. In the first phase, a filter method is used as a statistical measure of similarity. This phase helps in improving the classification performance by removing redundant and unimportant features. A wrapper method is then used in the second phase. This phase helps in selecting relevant feature subset that produces maximum accuracy according to the underlying Random forest method.

III. IMPLEMENTATION OF PROPOSED MODEL

The implementation of the proposed model consists of two algorithm selection model and hybrid filter-wrapper approach of feature selection.

A. Machine learning algorithm selection

It is necessary to apply a machine learning algorithm for continuous monitoring of stress levels among employees efficiently. Different machine learning algorithms are compared to select an algorithm for developing an efficient method for continuous objective evaluation of stress levels. After comparing different algorithm we have selected an optimal algorithm which gives higher accuracy for further processing.

We have selected five different algorithms including Naïve Bayes, kNN, Bayes network, decision tree and random forest. The data in hand is divided into training and testing data in different partitions. After comparing the accuracy of different algorithms we have concluded that random forest has given higher accuracy. So, as a result, we have selected random forest as an optimal algorithm for continuous monitoring of stress. Thus, we chose Random forest since it was cost-effective and was easily implementable in general workspaces like colleges/offices.

The main idea is that instead of producing a single complicated and complex model which might have a high variance which will lead to overfitting or might be too simple and have a high bias which leads to underfitting, we will generate lots of Models by training on the Training set and at the end combine them. Such a technique is Random Forest which is a popular ensemble technique is used to improve the predictive performance of Decision Trees by reducing the variance in the trees by averaging them.

Table 1 Training & Validation Accuracy of Different ML Algorithms

ALGORITHMS	ACCURACY
Naive Bayes	51%
kNN	60%
Bayes Net	65%
Decision tree	76%
Random Forest	85%

In our model, we have provided the in general and unbiased solution and for getting this we have used k-fold cross-validation technique. The main objective is to choose different partitions of the training set and validation set, and then average the result so that the result will not be biased by any single partition. K is the number of partition which can be any integer.

B. Hybrid filter-wrapper approach for feature selection

Feature selection (also known as attribute selection or variable selection) is a technique to select an optimal features subset from the original input features according to some criterion. The criterion is often formulated as an objective function that finds which features are most appropriate for some task at hand. But the reason why we are interested in finding a subset of features is that it is always easier to solve a problem in the lower dimension. This helps us in understanding the nonlinear mapping between the input and the output variables [13]. Feature selection is the process of finding the most optimal subset of features of a certain size that leads to the largest possible generalization [14].

We have applied a hybrid filter-wrapper approach for feature selection. Firstly we applied a filter method and get a subset of most important features. On the obtained subset we then applied a wrapper method with the selected machine learning algorithm.

We have used different filter-wrapper methods present in FSelector package. The FSelector Package for R offers algorithms for filtering attributes (e.g. CFS, chi-squared, information gain, linear correlation) and algorithms for wrapping classifiers and search attribute subset space (e.g. best-first search, backward search, forward search, hill climbing search). The package also makes it possible to choose subsets of features based on attributes' weights by performing different ways of a cutoff.

The FSelector Package was created by **Piotr Romansk**, released on April 11, 2009.

IV. EXPERIMENTAL ANALYSIS

A.DATA SET

We have used dataset provided by SWELL knowledge work (SWELL-KW) [4] dataset for research and user modeling.

The dataset was collected in an experiment, where 25 people performed typical knowledge work (writing reports, making presentations, reading e-mail, searching for information). They manipulated their working conditions with the stressors: email interruptions and time pressure. A varied set of data was recorded: computer logging, facial expression from camera recordings, body postures from a Kinect 3D sensor and heart rate (variability) and skin conductance from body sensors.

We have used dataset provided by SWELL knowledge work (SWELL-KW) [4] dataset for this research. SWELL dataset consists of data captured broadly from the following four sensors:

- Computer interactions, via a computer logging tool
- Facial expressions, via a webcam
- Body postures, via a Kinect 3D camera
- Physiology (ECG and skin conductance), via body sensors

For more information on the dataset and its access can be found at this link:
http://persistent-identifier.nl/?identifier= urn: nbn:nl:ui:13-kwrv-3e

B. RESULT ANALYSIS

We have done the result analysis in two parts. In the first part we have analysed the individual and different combination of sensors and in the second part, we have analysed results obtained from different combinations of feature selection methods.

Table 2: SWELL-KW feature dataset. The dataset contains 149 features and 2688 instances. [4]

Feature types	Features
Computer interactions (18)	Mouse (7) Keyboard (9) Applications (2)
Facial expressions (40)	Head orientation (3) Facial movements (10) Action Units (19) Emotion (8)
Body postures (88)	Distance (1) Joint angles (10) Bone orientations (33) (as well as stdv of the above for amount of movement (44))
Physiology (3)	Heart rate (variability) (2) Skin conductance (1)

We have first calculated the accuracy in detecting stress by individual sensors. The results can be found in below tables. Further, we combined various sensors to determine which combination gives best results to determine stress. The results for various combinations of features can be found in the following tables.

C. Experimental results of feature selection

Machine learning works on the simple rule that if you want a valuable result you have to provide valuable data to a machine for learning. So it's very important that we should provide only relevant data to the machine. It becomes even more important when the number of features are very large. There is no need to use every feature for creating an algorithm.

We can assist the algorithm by feeding in only those features that are really important in detecting stress.

We have tried a combination of filter and wrapper methods present in **FSelector package** in R for selecting the best features.

Table 3: Results analysis of individual sensors

Sensor	Training Accuracy	Testing Accuracy
Computer interaction	47%	44%
Facial Expression	76%	77%
Body Posture	56%	56%
Physiology	51%	54%

Table 4: Results analysis of combining two sensors

Combination of sensor	Total features	Training Accuracy	Testing Accuracy
Computer & facial expression	58	78%	79.2%
Computer & physiology	21	57%	55%
Computer & posture	106	61%	61.3%
Physiology & facial	43	77%	78%
Physiology & posture	91	79%	78.4%
Posture & facial	128	84%	84.76%

Table 5: Results analysis of combining three sensors

Combination of sensor	Total features	Training Accuracy	Testing Accuracy
Computer & facial expression	58	78%	79.2%
Computer & physiology	21	57%	55%
Computer & posture	106	61%	61.3%
Physiology & facial	43	77%	78%
Physiology & posture	91	79%	78.4%
Posture & facial	128	84%	84.76%

Table 6: Results analysis of combining all sensors

Sensors	Total features	Training Accuracy	Testing Accuracy
Computer, facial, physiology, and Posture	149	82%	84%

The cases listed in Table 7 are a combination of filter and wrapper method. They mainly describing the sequence of applying feature selection methods.

By combining results from all the cases we have seen that a subset of 17 features is enough for detecting stress level with higher accuracy. The subset includes SCL, SAu06_CheekRaiser , SAu43_EyesClosed, SAu10_UpperLipRaiser,avgDepthstdv,SrightEyeClosed,Ssad,SleftEyeClosed,SAu24_LipPressor,ElbowLeft_WristLeft WristLeft_HandLeftavg,SgazeDirectionForward,Spine_ShoulderCenterShoulderCenter_Headavg,ShoulderCenter_ShoulderLeftShoulderLeft_ElbowLeftavg,WristRight_HandRightPlaneXYAxisYavg,ShoulderCenter_HeadPlaneYZAxisZstdv, HR,SnLeftClicked,SnErrorKey.

It consists of 2 physiological features, 2 computer interaction features, 7 facial expression features and 6 posture features. The subset obtained from all the cases have these features common. So we can conclude that these features set are most important features in stress detection. We have also seen that Case 7(combination of Information gain and best first method) has given the best result.

Table 7: Different cases by combining different methods

	Filter Method	Wrapper Method
Case 1	Chi-Squared	Best-First
Case 2	Chi-Squared	Greedy
Case 3	Chi-Squared	CFS
Case 4	Linear-Correlation	Best-First
Case 5	Linear-Correlation	Greedy
Case 6	Linear-Correlation	CFS
Case 7	Information-Gain	Best-First
Case 8	Information-Gain	Greedy
Case 9	Information-Gain	CFS

V. CONCLUSION

A comparison of several machine learning algorithms showed that for our dataset, neutral and stressful working conditions can be distinguished with 80% accuracy by means of the Random forest. Posture yields most valuable information, followed by facial expressions. Facial expressions give the most valuable information, followed by posture. Especially for estimating mental states it makes sense to focus on employee’s facial expressions or body postures.

We have also concluded that feature selection for supervised machine learning can be achieved by utilizing the efficiency of filters and the accuracy of wrappers. A hybrid filter-wrapper approach for feature selection algorithm has been implemented and empirically tested to support this claim.

The combined results from all the sensors are not cost effective and not feasible on daily basis. It can be made cost effective by selecting a combination of features rather than all of the feature types. By comparing Tables 4, 5 and 6 we can see that by combining facial and posture feature types the results are almost equivalent to that obtained from combining all the four feature types. And we have also selected set of 17 features which are best for stress detection.

Different filter and wrapper methods and their hybrids were analyzed for the problem at hand. Finally, the hybrid of information gain and best first method resulted in a reduction of 88.6% in the no. of features in the original feature set and increase in accuracy by 2%. The 17 features selected out of 149 features are enough for detecting stress at workspaces effectively and with 82% accuracy.

The future enhancement for this scheme is to provide analysis of other different machine learning algorithms and other different feature selection approaches. Various different other algorithms and approaches can be used for stress detection. We can even test the efficiency of the algorithm with a large amount of data and come up with more efficient and effective algorithms for stress detection. The only limitation of this algorithm is that we have analyzed a selected set of algorithms of different categories. We can thus be analyzed different algorithms and approach on large data sets so that a higher optimized accuracy can be achieved.

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