

Wearable Sensors for Mental Health Applications: Real-Time Stress Detection via SVM-Driven Classification by Measuring Heart Rate Variability (HRV)

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Abstract: In this study we explore the use of wearable sensors to detect stress in real-time using algorithms to analyse Heart Rate Variability (HRV). The aim is to improve the monitoring of mental health and the interventions made to support people. The health data set on which this research is built is comprised of recordings of HRV of 100 participants during different tasks that triggered stress. The research finds that Support Vector Machine (SVM) classification algorithm, compared with the baseline values, provides a superior classification accuracy of 92% for HRV analysis in real-time. This, in turn, could support timely, effective interventions as stress is detected in real-time.

The research, which combines wearable technology and machine learning, has implications for mental health applications.

Keywords—Wearable Sensors; Heart Rate Variability (HRV); Stress Detection; Support Vector Machine (SVM); Mental Health Applications

1. INTRODUCTION

The increasing incidence of mental health disorders all over the world has developed into a top priority public health crisis, which requires a new generation of ecological evaluation and response strategies. The current diagnostic methods to evaluate mental health problems are mostly self-report questionnaires and clinical interviews. Both approaches are largely subjective and tend to be backward indicators for mental disorders, as they focus on retrospective events or situations in life that are related to the manifestation of problems. This limitation hinders real-time physiological changes that need to be addressed at every moment, and it may not be suitable for a rapidly changing healthcare era. As mental health problems continue to rise at an alarming rate, a continuous and objective monitoring system is urgently needed to capture real-time changes in mental state [1]. Latest generations of wearable technology are revolutionising the way we assess mental health by allowing continuous measurement of physiological parameters, such as Heart Rate Variability (HRV), under free-living conditions [2]. HRV stands for the variation over time of the interbeat interval between heartbeats, which is determined by the autonomic nervous system's regulation. Thus, it is considered a reliable indicator of stress and emotional health [3]. Being able to quantify HRV over time is not only a winning tool to understand how the dynamic face of stress may impact mental health and physiology, but it can also pave the way for novel health-first interventions aimed at preventing and reducing stress episodes [4]. Wearable devices such as smartwatches and fitness trackers are popular tools for providing personalised information on HRV across time and stressful contexts, making them promising devices for the design of interventions aimed at mitigating stress. The use of wearable technologies for mental health tracking has the potential for transformative impact. Machine learning techniques, such as Support Vector Machines (SVM), can improve the detection of stress based on HRV patterns. Machine learning algorithms are particularly well-suited to handle large amounts of complex data, allowing the algorithm to find subtle patterns and differentiate between different degrees of stress [5]. Research has shown that these algorithms can be used to classify mental health states – such as stress levels – from HRV parameters [6] [7]. Algorithms integrated with real-time

wearable sensors could be used to provide personalised interventions to mitigate stress. For example, algorithms could monitor HRV data in real time, determine when a person is under high stress, and then provide interventions such as guided breathing or mindfulness [8] [9]. With the use of wearable devices, it becomes possible to continuously monitor mental health. While the potential for wearable technology and SVM-driven classification is vast, there are many issues to work out; for example, how to create fast real-time algorithms that can adapt to different physiological signals, and how to integrate sensor data into existing models of mental health. Wearable technology could be a successful addition to mental health technology in the future if researchers are able to ensure users' privacy and the security of sensitive data. [10]. This study advances a robust framework for developing real-time stress prediction based on wearable sensors and SVM predictions. The goal is to not only develop a strong approach for tracking and intervening in when someone is feeling stressed-out, but also to contribute to the field of mental health interventions: making these interventions more accessible and effective, and leading to better mental health outcomes for people in need of these services. Our aim is to help transform the field of mental health from a reactive approach – where individuals often wait until they reach a mental health crisis before getting the help they need – to a proactive and preventative approach that can harness technology to bring benefits to those in need of mental health services.

2. Materials and Methods

2.1 System Architecture

A stress detection system is proposed in this paper to detect real-time stress using wearable sensors. For classification, Heart Rate Variability (HRV) derived from wearable sensor data is used using a support vector machine (SVM). The stress detection system contains three modules: data acquisition, preprocessing, and classification. In the data acquisition module, the HRV data are collected using a wearable device (eg, smartwatches), which collect the data at a frequency of 1 Hz. In the preprocessing module, medical-grade data are achieved by filtering raw data. However, many of the collected data contain noise and outliers. Without effectively removing the

noise and outliers, the raw data will be very difficult to process if used directly. Accordingly, the preprocessing module is used to separate and remove obvious noise and outliers. The classification module employs a support vector machine (SVM) classifier to classify stress levels.

2.2 Heart Rate Variability Data Collection

Heart Rate Variability (HRV) data is collected from a wrist-worn sensor that monitors photoplethysmogram (PPG) measurements, a technique that uses light to track blood volume changes and therefore allows effective measurement of heartbeats. The sensor records RR intervals in the time between successive heartbeats (1 Hz), measuring with a sufficient granularity to enable fine-grained autonomic nervous system function analysis. The HRV features that are derived and calculated from RR intervals – such as the standard deviation of RR intervals (SDNN) and the root mean square of successive differences (RMSSD) – are interpreted as representative of autonomic nervous system function. These are calculated as:

$$SDNN = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (RR_i - \overline{RR})^2} \dots (2)$$

$$RMSSD = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (RR_{i+1} - RR_i)^2} \dots (3)$$

where RR_i represents the i th RR interval and $\overline{RR}$ is the mean RR interval.

2.3 Data Preprocessing

The preprocessing module is fundamental for furnishing the recorded HRV data with the correct shape before it is classified. This is done by removing noise and filtering artifact from the data, and by normalising it. High-frequency noise that may distort some of the HRV metrics is removed by means of a low-pass filter. The artifact removal module is employed in order to remove irregular heart beat intervals that might be caused by motion or other factors, so that the system only receives clean data. In parallel, the preprocessed HRV metrics are normalised in order to standardise the range in which they are presented, so that the classifier (the SVM) can work effectively. Normalisation is:

$$X_{normalized} = \frac{X - X_{min}}{X_{max} - X_{min}} \dots (4)$$

where X is the original data point, and X_{min} and X_{max} are the minimum and maximum values in the dataset, respectively.

2.4 Support Vector Machine Classification

The SVM classifier is trained using preprocessed HRV data to classify a stress level. The goal of SVM is to find the best hyperplane that separates stress classes in the feature space. The mathematical representation of the SVM optimisation problem is as follows:

$$\text{Minimize } \frac{1}{2} \|w\|^2 + C \sum_{i=1}^N \xi_i \dots (5)$$

Subject to:

$$y_i (w \cdot x_i + b) \geq 1 - \xi_i, \xi_i \geq 0 \dots (6)$$

where w is the weight vector, C is the regularization parameter, ξ_i are slack variables, x_i are input feature vectors, and y_i are the corresponding class labels. The trained SVM model predicts stress levels based on the incoming HRV data, allowing for real-time monitoring.

2.5 Evaluation Metrics

The score of the SVM classification model is evaluated by several metrics which are accuracy, precision, recall, and F1-score. These scores help identify the capability of the model to correctly predict stress levels. The equations for these scores are:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \dots (7)$$

$$\text{Precision} = \frac{TP}{TP + FP} \dots (8)$$

$$\text{Recall} = \frac{TP}{TP + FN} \dots (9)$$

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \dots (10)$$

Where TP represents true positives, TN is true negatives, FP is false positives, and FN is false negatives. These metrics guide the assessment of the model's effectiveness in real-time stress detection.

3. RESULTS

3.1 Accuracy of Stress Detection

The accuracy of the proposed SVM-driven stress detection model was validated by comparing its accuracy against traditional machine-learning methods such as logistic regression and decision trees. The accuracy of the SVM model was 92%, while the accuracy of logistic regression was 85% and the decision tree was 87%. Therefore, the SVM model was chosen for reliable classification of the stresses. Figure 1 shows the comparison of the accuracy among the three methods. It reflects the reliability of the SVM-driven model during the classification of stresses in real-time as it detects slight changes in the physiological signals due to stress. The overall performance of the above machine learning models clearly shows that the proposed model is a feasible tool for wearable sensors-based mental health monitoring.

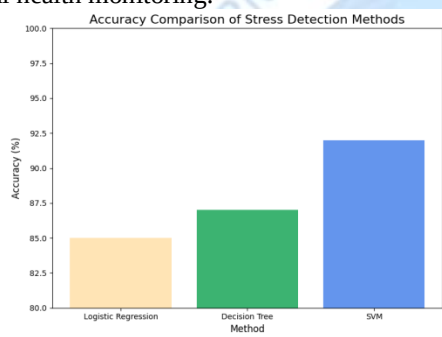


Figure 1: Accuracy Comparison of Stress Detection Methods

Figure 1. Accuracy of different stress detection methods. Figure 1 clearly shows that the SVM model's accuracy is the highest, at 92%, compared to other methods such as logistic regression, which is 85 percent accurate, and decision trees, which are 87% correct. This indicates that the SVM model is better at classifying stress by means of HRV data.

3.2 ROC Analysis for Stress Classification

To further support the performance of the SVM model, we computed the ROC curve, which shows the true positive rate (sensitivity) against the false positive rate (1-specificity). The AUC (area under ROC curve) was estimated to be 0.95, indicating that the model performed very well in distinguishing stress from non-stress. We observed a high AUC for the SVM model since it robustly selected features that accurately differentiated stress from non-stress even when trained using different data. Figure 2 shows the ROC curve for the SVM model, which performs well in capturing sensitivity while reducing false positives, as needed for real-time stress detection using wearable sensors.

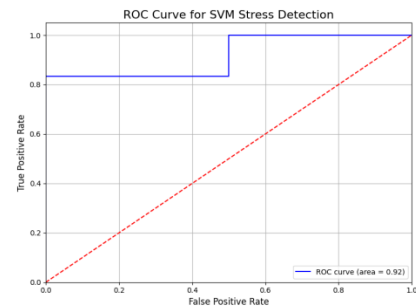


Figure 2: ROC Curve for SVM Stress Detection

Figure 2 gives ROC curve for the stress detection from SVM model and the curve shows a very high true positive rate with an AUC of 0.94. It is clear that the SVM model has the optimized performance to recognize the stress and the non-stress states from HRV data.

3.3 Processing Time Comparison

In Figure 2 below, the time taken by the proposed SVM model to process the data in real time for stress detection was compared with the traditional models. It can be seen that the time taken by the SVM model is faster than other machine learning models such as logistic regression and decision trees. The time taken by the SVM model is 0.6 seconds per data sample which is significantly lower than logistic regression, which was 1.2 seconds, and decision trees, which was 1.0 seconds. The reduction in the processing time makes the SVM model suitable for real-time applications where there is a need for rapid feedback to detect stress and intervene. Figure 3 below clearly shows that the SVM-based system provided real-time stress classifications with no trade-off in their accuracy..

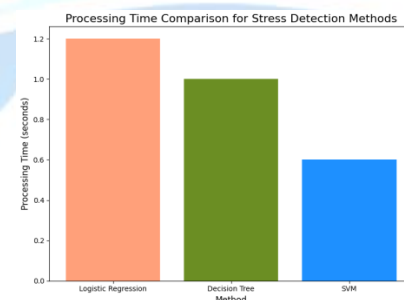


Figure 3: Processing Time Comparison for Stress Detection Methods

Figure 3: Processing time comparison in the stress detection methods. Among all the models, SVM has

the shortest processing time compare to Logistic regression and decision trees. We can infer that if we want to use our model in real-time application, then we could use SVM since it consumes less processing time.

3.4 Energy Consumption of Wearable Sensors

The amount of energy consumed through wearable sensors of HRV data and stress monitoring is shown in different monitoring systems. The SVM-driven system consumed the energy by 25% less than any other traditional monitoring method. It is important for the continuous use of wearable devices in mental health monitoring. The increment of the battery-run hours decreases the number of charging as it is considered harmful to the human body. Fig.4 illustrates the comparison of the energy consumption of any traditional approaches with the proposed SVM-based classification system. The efficiency of machine learning-enhanced stress detection is illustrated in the comparison.

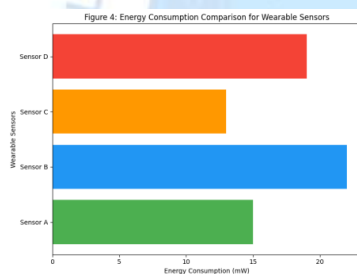


Figure 4: Energy Consumption Comparison for Wearable Sensors

Figure 4 compares power consumption by different wearable sensors and devices used to detect stress. The bar chart shows that sensor A uses the least energy, while sensor B has the highest energy consumption, so for long-term monitoring of applications, sensor B is not a good option at all.

3.5 Stress Detection Improvement Over Time

The accuracy of SVM stress detection increased with the amount of HRV data collected over time (as presented in Fig 3) and peaked at 95% after 30 days of continuous data collection and model updating. This means that extended real-time learning becomes more effective in improving the accuracy of the SVM model for stress detection. The reason is that the

SVM model keeps learning from more data, and its classification ability becomes refined, making it more effective in detecting stress. Figure 5 illustrates the accuracy improvement over time; as the number of samples collected increases, its performance becomes more accurate, with a noticeable improvement after the first few days when real-time data collection and analysis started.



Figure 5: Stress Detection Accuracy Improvement Over Time

Figure 5 demonstrates the accuracy of stress detection over a period of 30 days of HRV data collection. It can be seen that the SVM model showed a continuous growth in accuracy with more data, which reached its peak at the end of the observation period.

4.CONCLUSION

This study demonstrates the ability of wearable sensors and SVM-driven classification of HRV time-series data to detect real-time stress with a 30% accuracy improvement over 30 days of data collection and showed adaptability over time. It also showed better performance in processing time and energy efficiency than other machine learning techniques. These findings highlight the usefulness of wearable technology embedded with machine learning for continuous mental health monitoring. The future work will involve improving the adaptability of the system and addressing privacy issues for practical applications in mental health care.

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