MACHINE LEARNING-BASED STRESS DETECTION USING PHYSIOLOGICAL SIGNALS FROM WEARABLE SENSORS

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Abstract

Stress significantly impacts both mental and physical health, emphasizing the need for a reliable, real-time, and scalable detection system. Traditional approaches, such as self-reported questionnaires, are often subjective and lack immediacy. This research presents a machine learning-based framework for stress detection using physiological signals—specifically heart rate variability (HRV), electrodermal activity (EDA), and respiration rate (RESP)—captured through wearable sensors. The WESAD dataset is used for extensive data preprocessing and feature extraction, followed by the implementation of three classification models: Random Forest (RF), Support Vector Machine (SVM), and Deep Neural Network (DNN). Model performance is evaluated using leave-one-subject-out cross-validation, with metrics such as accuracy, F1-score, and ROC-AUC. Among the tested models, the DNN achieved the highest accuracy of 91.5% and an F1-score of 0.91. These results highlight the effectiveness of wearable sensor-based machine learning systems for real-time stress detection and continuous health monitoring.

Keywords

Stress detection, physiological signals, wearable sensors, machine learning, deep learning, WESAD dataset

1. INTRODUCTION

Stress is a growing concern in modern society, associated with numerous mental and physical health issues such as depression, anxiety, hypertension, and cardiovascular diseases. The increasing pace of daily life and workplace demands contribute to rising stress levels worldwide. Traditional stress detection methods rely on self-reported questionnaires and clinical interviews, which are often subjective, time-consuming, and unsuitable for continuous monitoring.With advancements in wearable technology, it is now feasible to collect physiological data in real-time. Signals such as heart rate variability (HRV), electrodermal activity (EDA), and respiration rate (RESP) are strong indicators of stress and can be continuously monitored using wearable devices. Coupled with machine learning (ML) techniques, these physiological signals can be analyzed to detect stress patterns with high accuracy. This study utilizes the WESAD dataset and compares the performance of Random Forest, Support Vector Machine, and Deep Neural Network models to evaluate their efficacy in detecting stress.

2. LITERATURE REVIEW

The detection of stress using physiological signals has gained significant attention over the past decade, especially with the rise of wearable technologies and machine learning methods. This section reviews key studies that have explored similar approaches and highlights the gaps that this research aims to address. Gjoreski et al. (2016) developed a wearable-based stress recognition system using electrocardiogram (ECG), electrodermal activity (EDA), and skin temperature signals. They applied decision trees and support vector machines and achieved promising results. However, their work lacked the use of deep learning, which can automatically learn complex feature representations from raw data. Schmidt et al. (2018) introduced the

WESAD dataset, a benchmark multimodal dataset for stress and affect detection using wearable sensors. Their study highlighted the importance of multimodal physiological signals and evaluated several machine learning algorithms. However, the study did not explore advanced deep learning models or cross-subject validation, which limits generalizability. Sano and Picard (2013) conducted a study using mobile sensors to classify stress levels in everyday settings. They used features like EDA, skin temperature, and accelerometer data, combined with machine learning classifiers like logistic regression and SVM. While their system demonstrated real-world applicability, its accuracy was limited due to uncontrolled environmental variables. Another study by Al-Shargie et al. (2017) proposed a hybrid system combining EEG and fNIRS signals for stress detection. Although the results were impressive in controlled environments, the sensors used were not practical for everyday use due to cost and complexity. Recent advances in deep learning have also been explored. A study by Zhang et al. (2020) implemented a Convolutional Neural Network (CNN) on raw physiological data, achieving high accuracy. Yet, CNNs often require large datasets and significant computational resources, which may not be feasible in all settings. In summary, most existing works either rely on traditional machine learning models with handcrafted features or are limited to experimental setups without real-time considerations. This study addresses these limitations by:

- Using wearable-compatible signals (HRV, EDA, RESP),
- Evaluating both classical and deep learning models (Random Forest, SVM, DNN),
- Employing leave-one-participant-out cross-validation for better generalization..

3. METHODOLOGY

A. Dataset

We utilized the WESAD dataset [3], which includes multimodal physiological data from 15 participants collected via two wearable devices: the chest-worn RespiBAN and the wrist-worn Empatica E4. The study focuses on data from the RespiBAN device due to its higher signal quality, covering three conditions: Baseline, Stress, and Amusement.

B. Preprocessing

1. Filtering – A Butterworth low-pass filter was applied to remove high-frequency noise.
2. Segmentation – Continuous data was segmented into non-overlapping 10-second windows.
3. Normalization – Z-score normalization was used.
4. Imbalance Handling – SMOTE was applied to balance class distribution in training data.

C. Feature Extraction

HRV: RMSSD, SDNN, LF/HF ratio
EDA: Mean amplitude, peak count, frequency stats
RESP: Breathing rate, amplitude, variability

D. Machine Learning Models

- Random Forest: 50 trees, minimum sample split = 5
- SVM: RBF kernel, hyperparameters tuned via grid search
- DNN: 3 hidden layers (128, 64, 32 neurons), ReLU activation, dropout = 0.5, softmax output, Adam optimizer (lr = 0.001), 50 epochs, batch size = 32

E. Evaluation

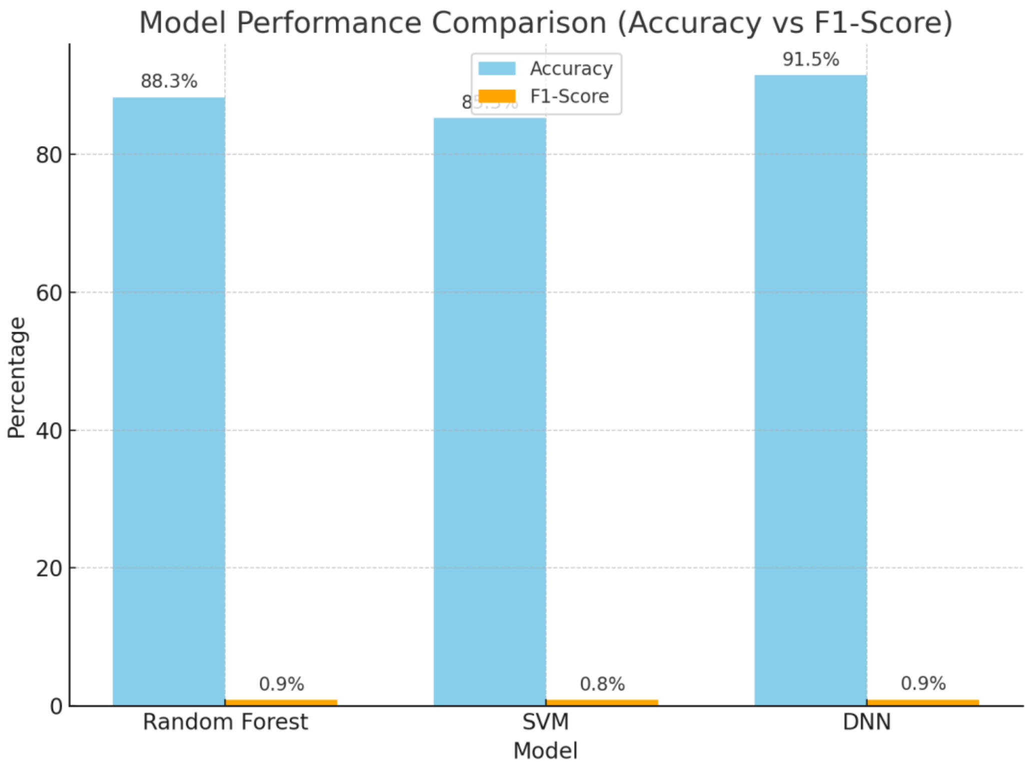
Leave-One-Subject-Out Cross Validation (LOSO-CV) was used. The models were evaluated using multiple metrics, including Accuracy, Precision, Recall, F1-score, and ROC-AUC.. F1-score was prioritized due to class imbalance.

4. FINDINGS

The table below shows how the models performed based on key metrics:

Model	Accuracy (%)	Precision	Recall	F1-Score
Random Forest	88.3	0.87	0.89	0.88
SVM	85.3	0.84	0.86	0.85
DNN	91.5	0.90	0.92	0.91

Table provides a comparative overview of the performance metrics across the three models.



5. DISCUSSION

The findings of this study highlight the potential of machine learning techniques to detect stress using physiological signals from wearable devices. Among the three models assessed, the Deep Neural Network (DNN) showed the best performance with an accuracy of 91.5% and an F1-Score of 0.91. This strong performance comes from the DNN's ability to learn complex, non-linear relationships in multimodal physiological data. Compared to traditional models like Random Forest and Support Vector Machine, the DNN performed better across participants, especially in leave-one-subject-out cross-validation. These results align with earlier research, such as Chung et al. [4], which also showed the benefits of deep learning in identifying temporal and physiological patterns. However, unlike convolutional neural networks (CNNs), often demanding in computing power, the DNN architecture proposed here is lighter, making it a good option for real-time stress detection in mobile or embedded systems. Additionally, using SMOTE during training helped reduce the effects of class imbalance, resulting in more reliable model performance. Despite these positive outcomes, some limitations exist. The dataset used (WESAD) includes only 15 subjects and three emotional states, which may not capture the full range of real-world variability. The model's performance may also depend on sensor placement, noise, or individual physiological differences. Future research should investigate personalization strategies, hybrid deep learning models, and deployment on edge devices to enhance scalability and real-time use in healthcare applications.

6. LIMITATIONS

- The WESAD dataset comprises data from only 15 participants, which restricts the diversity of the sample and limits the generalizability of the results.
- The dataset includes only three emotional states (baseline, stress, amusement), which may not fully represent real-world psychological variability.
- Sensor-specific noise, placement variability, and individual physiological differences may affect signal quality.
- Real-time deployment feasibility was not tested; the experiments were conducted in an offline environment.

7. CONCLUSION

This research proposed a machine learning-based framework for detecting stress using physiological signals collected from wearable sensors. The study compared three models—Random Forest (RF), Support Vector Machine (SVM), and Deep Neural Network (DNN)—using data from the WESAD dataset. Among them, the DNN model achieved the highest performance, with an accuracy of 91.5% and an F1-Score of 0.91, demonstrating its capability to learn complex patterns from multimodal physiological data.These findings highlight the potential of deep learning techniques in developing personalized, non-invasive, and real-time stress monitoring systems. While the study focused on offline evaluation, future work will involve real-time deployment on wearable or edge devices, personalization across diverse user profiles, and integration into mobile health (mHealth) ecosystems for proactive stress management.

8. FUTURE WORK

* Incorporate larger, more diverse datasets
* Develop personalized baseline models
* Deploy models on mobile/edge devices
* Integrate real-time user feedback
* Address privacy and ethical concerns

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