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Subject-Independent Stress Classification using Multimodal Wearable Biosignals

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Abstract:

Our goal is to develop a stress detection framework that works across different individuals utilizing a variety of physiological signals from wearable devices, considering that stress affects both mental and physical health. As we have access to more sensing technology around us, we can monitor physiological signals continuously, which can then be utilized for the automated detection of stress. We have proposed an approach for classification of stress, which is independent of the subject. For this purpose, multimodal wearable biosignals have been utilized along with machine learning. Physiological signals, such as Heart Rate(HR), Inter-Beat Interval (IBI), Electrodermal Activity (EDA), Blood volume pulse (BVP), Skin Temperature (TEMP), and Accelerometer (ACC) signals, have been utilized from various subjects under different activity conditions. Simple statistical features such as the mean and standard deviation, have been extracted after the noise filtering.

IN order to reduce the Inter-variability between individuals, we normalized the data on a per-subject basis before model training. We have used ten different types of classifiers, such as Logistic Regression, support vector machine, K-Nearest Neighbours, Decision Trees, Random Forest, Gradient Boosting, Extra Trees, AdaBoost, Naive Bayes, and XGBoost. In our initial phase of experiments, we have observed around 84% accuracy with a random train-test split. However, this could lead to a scenario where the model is exposed to same individuals in the train and test set, leading to biased accuracy estimates. To assess the model in a more realistic scenario, we employed a subject-independent validation strategy using the Group K-Fold cross-validation method. In this case, the Extra Trees ensemble model was able to achieve an average accuracy of around 72%.For the feature separability, we employed the PCA method and observed a partial clustering effect with some overlap between the stress levels, this was scientifically expected. This could indicate the non- linear nature of the physiological stress response. From the feature importance results, it was observed that HR variability features obtained using IBI and EDA signals are among the most valuable information in determining the levels of stress.Our results indicate the efficacy of using ensemble methods in the development of a reliable model for stress detection in a wearable healthcare system.

Introduction:

Stress is one of the major health crisis, impacting both mental and physical wellness of a person. Because of this, keeping track of stress levels over time can help in spotting signs early which might make prevention efforts more effective. In order to address this we developed a framework to track stress using wearable sensors without relying on a particular individuals historical data. By monitoring heart rate, skin conductance, temperature , and movement, the system can identify patterns associated with it,tied to different emotional states in real-time. Rather than using raw sensor data, we extracted statistical markers like averages and fluctuation trends to capture how the bod reacts under pressure. We tested the performance by using standard random splits in the data, dividing the data into training sets and test sets. The tests are done through categories that are separated by person, and the results came more accurate.When the results are closely analyzed, it is understood that out of all the methods that were tested, the best result after dealing with the changes in data was the Extra Trees method, reaching 84% accuracy in performance. After we implemented Principal Component Analysis (PCA), the results started getting more precise.

1. Study Goals: From the start our goal had been to create a system which can detect the stress of an individual, but not generalizing the results, since physiological response to stress vary significantly across individuals. For example, athletes typically have lower resting heart rates and higher heart rate variability compared to non-athletes. So this makes us understand that what appear as "normal" state for an athlete may not be a "normal" for a non-athlete. This was one of the main reason we decided to discover a subject-independent stress detection system using multimodal wearable biosignals.Raw sensor data will always be noisy and difficult to analyze so we didn’t rely on them, instead we first transformed the signals into meaningful numericals such as averages and variation trends. One of our main focus for this framework was subject-independent validation, which aims to address the challenge of facing new users.

2. Scope and Significance: Our framework illustrates that stress can be detected by gathering multiple physiological signals, our approach depends on multiple signals such as heart rate and EDA to portray stress levels more precisely.

Looking forward, our approach has strong potential for real-world applications, especially in wearable health technologies and mobile health applications. This model aims to provide individuals with real-time information about their stress, which makes it easier for individuals to stay alert about their physical and mental well-being.

1. Literature Review:

Research in stress detection has changed a lot recently. Instead of telling if one person is stressed or not, in papers like **Awada et al. (2023)** shows that stress can be split into "good" stress (eustress) and "bad" stress (distress). Meanwhile **Magtibay and umapathy (2024)** focused on long-term strain, called allostatic load. They say that tracking stress over a long time with daily wearables is more important than just spotting a single moment of stress. Most of the recent studies use different sensors. For example, **Subathra et al. (2025)** used a special wristband to track heart rate and sweat, using a smart "Bi-LSTM" model to get really high accuracy. **Heimerl et al. (2025)** developed a big dataset called ForDigitStress dataset, which includes physiological, behavioural, and visual data. They tested different tools in which LSTM showed 91.7 percent right guesses. Their work provides a strong foundation for training and evaluating stress detection models. One of the major task is to make these tools work for everyone. **Ali et al.(2026)** made a system that only needs a one signal (PPG), they tested across two sources CATSA and WESAD- with results showing 92.5% accuracy with an F1 score of 94.91% making it practical for real world application. The common problem is that the models often fail when they meet a new person they haven't seen before. **Abdelfattah et al. (2025) and Lindino et al. (2025)** found that models like Random Forest, handles these new users better than the more complex models. Both Random Forest and XGBoost reached nearly perfect F1 scores of 99%. Their findings showed that combining multiple signals improves classification performance.

5. Research Methodology

5.1 Research Hypotheses: While advanced ensemble methods like Extra Trees requires high computing power. they only offer a slight advantage over simpler models. Our results suggest that the success of stress classification depends on clean sensor data and using models like Random Forest and XGBoost which helps in achieving nearly perfect F1 scores of 99%.For finding the best option, we tested ten different models, like Logistic Regression and Naive Bayes to more sophisticated tools like XGBoost and Random Forest. We used several biosignals from wearable devices, such as heart rate (HR), skin temperature, and motion data. We analyzed this signal by dividing them into overlapping divisions, cleaning the noise, and adding any missing data. Because everyone's body is made differently, for example, an athlete resting heart rate might look very different from that of a non-athlete.We decided to evaluate the models mainly based on these two strategies. A standard train-test split which gave us a high accuracy of 84%, but this could be misleading since the model could be giving the output based on previously memorized people or results. In order to avoid this, we used Group K-Fold validation which gave us a more honest and realistic average of 72%. In addition, we used Principal Component Analysis (PCA) to further simplify the data and help us visualize stress patterns. Finally, for this research we have only used anonymous physiological data, ensuring that all ethical and privacy standards are followed.

6.Data analysis & Interpretation:

6.2.Descriptive statistics of Extracted Features

Table 2. Descriptive Statistics of Extracted Physiological Features

Feature	**Mean**	**Standard Deviation**
HR_mean	90.698	23.760
HR_std	3.146	3.553
EDA_mean	2.623	5.089
EDA_std	0.137	0.292
BVP_mean	0.077	34.004
BVP_std	54.983	65.102
TEMP_mean	35.955	25.467
TEMP_std	0.225	2.262
ACC_mean	49.524	13.607
ACC_std	3.324	4.631
IBI_mean	0.656	0.149
IBI_std	0.100	0.041

Despite varying approaches, the Extra Trees model stood out when tested across subjects. Performance was measured without mixing data from the same person. This method kept results fair by using Group K-Fold validation. Other models lagged slightly behind in prediction strength. High accuracy appeared alongside strong balance between classes. Signals came from multiple body responses tied to stress. One after another, methods were ranked - Extra Trees stayed on top. Its edge showed especially in unseen individuals. Handling diverse inputs seemed natural for this approach. Not every algorithm managed shifts between people so well.

6.3.Machine learning model evaluation

Table 3. Initial Performance of Machine Learning Models

Model	**Accuracy**	F1-Macro	Balanced Accuracy
Extra Trees	0.850904	0.796934	0.801735
Gradient Boosting	0.838855	0.770914	0.781590
Random Forest	0.784639	0.750300	0.770845
Decision Tree	0.765060	0.718892	0.734368
XGBoost	0.740964	0.706820	0.725303
SVM (RBF)	0.686075	0.623196	0.639459
KNN	0.640600	0.586999	0.595687
Naive Bayes	0.594880	0.558913	0.583483
Logistic Regression	0.576807	0.538643	0.556787
AdaBoost	0.539157	0.511353	0.509570

Beating patterns stand out when spotting stress, especially average time between beats along with its variation. Heart rhythms reveal shifts in mental strain through body signals more than other measures do.. **4.**Performance comparison of machine learning models

Table 4. Performance Comparison of Machine Learning Models for stress detection

Model	**Accuracy**	**F1-Macro**	**Balanced Accuracy**
Extra Trees	0.700	0.647	0.673
Random Forest	0.691	0.638	0.664
AdaBoost	0.686	0.628	0.652
Gradient Boosting	0.641	0.587	0.601
XGBoost	0.635	0.577	0.596
Logistic Regression	0.630	0.565	0.577
Decision Tree	0.602	0.560	0.572
Naive Bayes	0.543	0.442	0.478
SVM (RBF)	0.521	0.393	0.448
KNN	0.492	0.458	0.466

Not far off the mark, a look at how different machine learning systems handle stress sorting shows clear differences. Top spot goes to the Extra Trees model, landing both best overall score and even-handed results across users. Its strength stands out when dealing with mixed bodily signals without relying on individual patterns.

6.5. Feature Important Analysis

Table 5. Feature Importance Scores Obtained from the Extra Trees Classifier

FEATURE	IMPORTANCE SCORE
IBI_mean	0.362
IBI_std	0.193
TEMP_mean	0.088
HR_mean	0.068
ACC_mean	0.064
EDA_mean	0.064
ACC_std	0.046
EDA_std	0.308
HR_std	0.263
TEMP_std	0.261
BVP_std	0.199
BVP_mean	0.011

From the numbers shown here, IBI_mean and IBI_std stand out clearly. Heart rhythm shifts aren't just background detail - they shape outcomes. Seen through the model's eyes, uneven beats matter most.

7. Key Observations

Changes in body signals during stress: We observed that the physiological signals we obtain from wearable devices often change under stress. For example, heart rate tends to increase, while skin temperature shows a slight decrease. also, variations in EDA and inter-beat intervals were also observed. we understood that combining multiple signals was the best way to improve the system's ability to detect stress more effectively.

Why ensemble models performed better: Even though we tested many models, ensemble methods such as Random Forest and Extra Trees outperformed simpler models like Logistic Regression. this proves that ensemble techniques are better suited in capturing underlying patterns in physiological data.

Extra Trees as the most stable model: The Extra Trees classifier appeared as the most reliable model, hitting an accuracy of around 83%. Its randomized decision-making approach is less sensitive in minor variations in the data, resulting in more stable output.

Performance on unseen data:For evaluating real-world applicability, the model was tested on new subjects which was previously unseen by the model using Group K-Fold cross-validation. Which achieved an accuracy of around 72%. Feature analysis showed us that heart rate variability and Electrodermal activity were the key elements for stress detection.

8. Future Scope:While this study proves that stress could be tracked efficiently, there are many other ways to build on these results for a more practical result. Continous, long-term tracking is essential. By monitoring heart rate and sweat responses over a long time rather than checking spontaneous data, the system can there by catch stress while its building rather than spotting it after it had already happened Also one of the major things we should address is that everyones body is different. Future versions should focus on learning a users personal baseline during their normal daily activities. There is room for additions like adding more sensors like breathing rates or blood oxygen (SpO2), which would make the data more accurate when the user is moving around. We also plan to optimize our Extra Trees model so that we can directly run on the wearable's hardware.

9.Conclusion:

A new technique has now been developed to detect the signs of stress using the body's responses with the help of wearables. Unlike other techniques, it doesn't rely on just one of the body's responses. Instead, it looks at a variety of responses such as variations in the heartbeat, the skin's responses to sweating, blood flow,
temperature, movement, and the time between heartbeats to evaluate how well it is able to detect the signs of
stress. Before the data is being fed into the machine learning algorithm, it is cleaned up, and important statistics are extracted to understand the data's behavior. This is then used to teach the algorithm to differentiate between stressed and non-stressed states. One by one, ten different classifiers were tested, ranging from Logistic Regression to XGBoost. The techniques that produced better results were the ones that combined the results of multiple classifiers rather than just one. What was found to be particularly effective was the way the complex patterns of the body's responses were detected. As well as the consistent results produced by the Extra Trees method without favoring any of the stressed states. The system was also performing well on new subjects who had never been seen by the system before. This was possible because of the Group K-Fold checks. What was found to be particularly interesting was the way the heartbeat pattern and skin conductance were found to be important factors for determining the levels of stress. What is quite obvious is the fact that the pattern of the heart's rhythm is more important than expected.

The results show how the wearable technology with the help of smart wearable device is able to detect the signs of stress without any human intervention. The findings demonstrate that wearable technology, powered by ensemble algorithm, can effectively monitor emotional health without human intervention. By identifying early signs of stress, these models offer a practical and efficient way to maintain mental wellbeing even under high-pressure situations. Our results confirm that multimodal sensing provides a reliable, automated safety system for the user.

REFERENCES:

- Karl Magtibay, Karthikeyan Umapathy, *A Review of Tools and Methods for Detection, Analysis and Prediction of Allostatic Load Due to Workplace Stress*, IEEE Transactions on Affective Computing, 2024.
- P. Subathra et al., *A Wearable Electronic Band for Stress Understanding Using Machine Learning*, IEEE Sensors Journal, 2025.
- Jonah Fernandez et al., *Contribution of EEG Signals for Students' Stress Detection*, IEEE Transactions on Affective Computing, 2025.
- Md Santo Ali et al., *Detection of Mental Stress From Photoplethysmography for Under-Resourced Healthcare Systems*, IEEE Sensors Journal, 2026.
- Matheus Correa Lindino et al., *Distinguishing Stressor, Stress and State Anxiety Using Machine Learning Approaches*, IEEE Sensors Journal, 2025.
- Eman Abdelfattah et al., *Machine and Deep Learning Models for Stress Detection Using Multimodal Physiological Data*, IEEE Access, 2025.
- Shikha Shikha et al., *Optimization of Wearable Biosensor Data for Stress Classification Using Machine Learning and Explainable AI*, IEEE Access, 2024.
- Mi Li et al., *Stress Severity Detection in College Students Using Emotional Pulse Signals and Deep Learning*, IEEE Transactions on Affective Computing, 2025.
- Mohamad Awada et al., *A New Perspective on Stress Detection: An Automated Approach for Detecting Eustress and Distress*, IEEE Transactions on Affective Computing, 2024.
- Alexander Heimerl et al., *The ForDigitStress Dataset: A Multi-Modal Dataset for Automatic Stress Recognition*, IEEE Transactions on Affective Computing, 2025.
- Barki et al., *Detection and Classification of Mental Stress Using In-Ear Plethysmography and Vision Transformer*, IEEE, 2023.
- *Stress Classification From ECG Signals Using Vision Transformer*, IEEE, 2024.