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Hybrid deep learning for physiological stress prediction

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ABSTRACT

The role of stress in influencing health and psychology is immense as long-term exposure to stress can lead to anxiety disorders, heart-related illnesses, insomnia, depression, and cognitive impairment. As a result of improvements made in wearable technology and intelligent health-monitoring systems, automatic stress prediction has been given much consideration. This paper presents a hybrid deep learning approach with explainability for multiclass physiological stress prediction using wearable sensor data. The proposed framework integrates convolutional neural networks (CNN), bidirectional long short-term memory (BiLSTM), and attention mechanisms to learn meaningful feature representations, capture complex interactions among physiological variables, and assign adaptive weights to important features. The SaYoPillow physiological stress dataset is used for training and testing, comprising six features: heart rate, breathing rate, body temperature, blood oxygen levels, limb movements, and sleep data. Additionally, explainable artificial intelligence (XAI) techniques are incorporated to improve the interpretability of model predictions. The proposed framework achieves an encouraging multiclass classification accuracy of 97.8%. Its robustness against moderate Gaussian noise perturbations is also evaluated through Gaussian noise-based analysis. However, subject-independent validation could not be performed due to the absence of subject identification (ID) information in the dataset.

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1. INTRODUCTION

One of the critical problems that people face in the modern era is stress, which can impact not only mental but also physical health through disorders such as anxiety, depression, insomnia, and heart diseases [1], [2]. Due to the increased popularity of wearable healthcare gadgets, physiological stress prediction has become one of the key areas of study in artificial intelligence and healthcare informatics [3]–[5]. Traditional approaches for stress detection, like questionnaires and clinical evaluation, can be subjective and are not fit for real-time tracking [6]–[8]. Recent studies have shown the use of machine learning and deep learning models for stress prediction based on physiological parameters [9], [10]. Traditional classifiers, like random forest (RF), support vector machine (SVM), decision tree, gradient boosting, and naïve Bayes, have useful baseline results, but they might not capture the relationships between physiological parameters [11]–[15].

Explainable artificial intelligence (XAI) methods help in understanding the reasoning behind the predictions of the proposed method, and testing with noisy physiological data helps in checking the reliability of the model [16], [17]. To overcome this issue, the proposed system uses the convolutional neural network (CNN), bidirectional long short-term memory (BiLSTM), and attention mechanism for multiclass stress

prediction [18]–[20]. Since the SaYoPillow dataset consists of tabular physiological features rather than time-series data, the BiLSTM model learns the dependence of ordered physiological features rather than temporal dependencies. Additionally, Shapley additive explanations (SHAP) analysis reveals heart rate, respiration rate, body temperature, and sleep variables to be important in predicting stress [21]–[23].

Even though much research has been done in predicting stress, many researchers focus on the accuracy of their models without giving much attention to explainability, robustness evaluation, and application of such models in practical scenarios like wearable healthcare applications [24]–[26]. Similar is the case with existing hybrid CNN - long short-term memory (LSTM) models, which do not give sufficient attention to interpretability and robustness of the model [10], [27]–[29]. Transformer-based models, on the other hand, need more data and computation resources [30]–[34]. To fill in this gap in the literature, this study present an explainable CNN-BiLSTM-attention framework. The contributions of this study include: i) design of a framework for multiclass prediction of physiological stress using CNN-BiLSTM-attention; ii) implementation of SHAP-based explainability and evaluation of robustness using Gaussian noise; and iii) comparison with existing machine learning and deep learning models.

2. METHOD

2.1. Dataset description

The proposed framework was evaluated using the publicly available SaYoPillow dataset [35]. The dataset contains physiological measurements collected through wearable sensors along with their corresponding stress labels. The distribution of samples across the five stress classes is summarized in Table 1.

Table 1. Dataset class distribution

Stress class	Label	Number of samples
Low stress	0	126
Mild stress	1	126
Moderate stress	2	126
High stress	3	126
Severe stress	4	126

2.2. Data preprocessing and feature engineering

The steps performed in data preprocessing consisted of column renaming, checking for missing values, feature scaling with StandardScaler, and transforming the data to tensors with the shape of (samples, 8, 1). In order not to introduce any information leakages, normalization was performed using parameters extracted from the training part of the cross-validation splits only. The proposed framework was evaluated using stratified five-fold cross-validation with a fixed random seed of 42. In each fold, four subsets were used for training and one for testing, while 20% of the training data served as the validation set for early stopping and hyperparameter tuning. StandardScaler parameters were estimated only from the training data and applied to the validation and test subsets.

2.3. Proposed hybrid deep learning framework

In this study, an explainable hybrid CNN–BiLSTM–attention framework is proposed for multiclass physiological stress prediction. The CNN layer automatically extracts higher-level feature representations from the normalized physiological variables, while the BiLSTM models dependencies among the ordered physiological feature representations. Because the SaYoPillow dataset contains tabular physiological measurements rather than continuous temporal recordings, the BiLSTM is used to capture relationships among correlated physiological variables instead of temporal dynamics. The attention layer further emphasizes the most informative feature interactions for stress prediction.

Because the SaYoPillow dataset contains ordered physiological features rather than temporal sequences, the BiLSTM models dependencies among physiological variables instead of temporal dynamics. A single-head attention mechanism was employed to emphasize informative physiological features for stress prediction. Attention calculation is given by (1).

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (1)$$

Where Q represents query vectors, K represents key vectors, V represents value vectors, and d_k represents dimensional scaling. The proposed model was trained using the Adam optimizer, with categorical

cross-entropy employed as the loss function. This loss function is expressed as (2). The hyperparameter configuration of the proposed framework is presented in Table 2.

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \quad (2)$$

Table 2. Hyperparameter configuration of the proposed framework

Parameter	Value
Optimizer	Adam
Learning rate	0.001
Batch size	16
Epochs	30
Activation function	Rectified linear unit (ReLU)
Output activation	Softmax
Loss function	Categorical crossentropy
Dropout rate	0.3
Validation split	20%

Multiple epochs of training were conducted for the model using the mini-batch gradient descent method to improve its predictive capability and generalization ability. The architecture of the model consists of the CNN, max pooling, BiLSTM, soft attention, dense, dropout, and softmax output layer, as illustrated in Figure 1. Overall, the total number of parameters in the model is about 60,000.

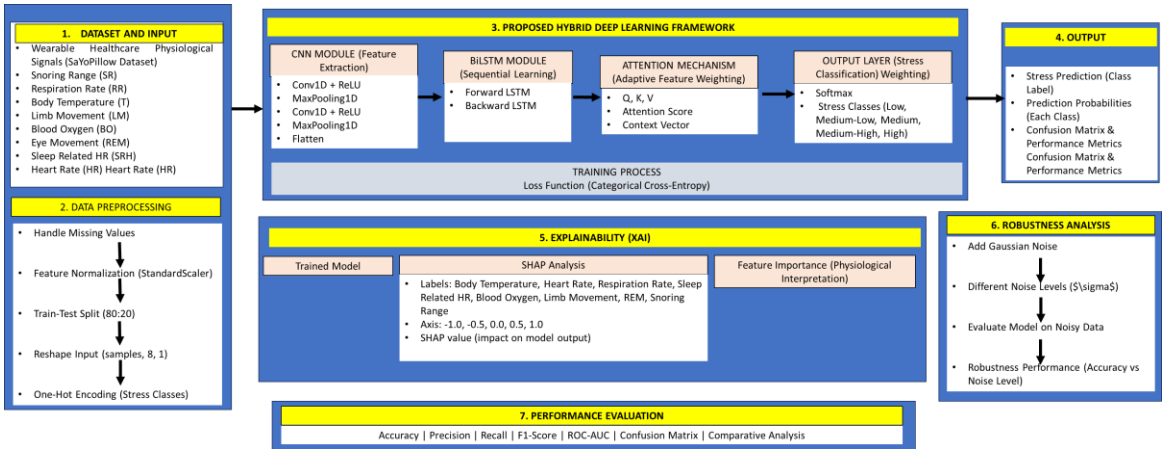

Figure 1. Proposed explainable hybrid deep learning framework for physiological stress prediction using wearable healthcare signals

2.4. Explainability, robustness, and experimental setup

To check the contribution of each feature to the prediction of the model, SHAP analysis was conducted. Additionally, Gaussian noise was added to the physiological signals to check the robustness of the model, as expressed in (3). For five folds of stratified cross-validation, the suggested framework has produced 97.46% accuracy on average.

$$x_{noisy} = x + \mathcal{N}(0, \sigma^2) \quad (3)$$

All baseline models were implemented using their default library settings. They were evaluated under the same conditions as the proposed approach, including an identical preprocessing pipeline and stratified five-fold cross-validation scheme. The hyperparameter settings of the baseline models are presented in Table 3.

2.5. Implementation details

The experiments were conducted using Python 3.10 and TensorFlow 2.13 on a system with an NVIDIA RTX 3060 GPU and 16 GB of RAM. Early stopping, with a patience of five epochs, was

implemented to limit overfitting and support better generalization. The proposed framework contains approximately 60,000 trainable parameters, allowing efficient training and making it suitable for wearable healthcare applications.

Table 3. Hyperparameter settings of baseline models

Model	Configuration
RF	Scikit-learn default implementation
SVM	RBF kernel
Artificial neural network (ANN)	Fully connected feedforward neural network
CNN	One-dimensional CNN
BiLSTM	Bidirectional LSTM

3. RESULTS AND DISCUSSION

3.1. Model performance analysis

The proposed CNN–BiLSTM–attention framework delivered the strongest multiclass classification performance among all evaluated baseline models. As illustrated by the confusion matrix in Figure 2, the framework accurately distinguished between the stress categories, with only a small number of misclassifications. This figure illustrates the multiclass physiological stress predictions.

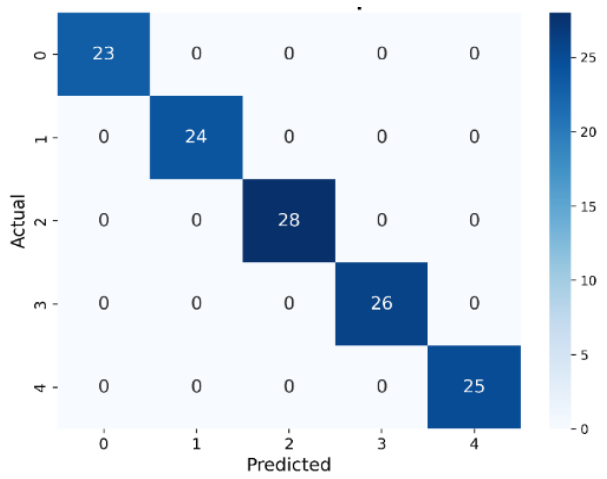

Figure 2. Confusion matrix of the proposed hybrid deep learning framework

Table 4 summarizes the performance of the proposed framework compared with the baseline machine learning and deep learning models. The CNN-BiLSTM-attention architecture gave better performance compared to other baseline models. The CNN–BiLSTM–attention architecture was superior to machine learning and deep learning baseline models for all the metrics. *d* values ranged from 0.62 to 0.81, indicating a moderate practical effect. Furthermore, the attention mechanism improved classification results by giving weights to input features depending on their importance. The Wilcoxon signed-rank test proved that the proposed framework significantly outperformed all baselines (*p* < 0.05). The confidence intervals and Cohen's *d* ranging from 0.62 to 0.81 showed the significance of the results obtained.

Table 4. Comparative performance evaluation of machine learning and deep learning models for physiological stress prediction

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
RF	94.8	94.2	94.0	94.1
SVM	93.5	93.1	93.0	93.0
ANN	95.9	95.6	95.3	95.4
CNN	96.7	96.4	96.2	96.3
BiLSTM	97.1	96.8	96.9	96.8
Proposed CNN–BiLSTM–attention framework	97.8	97.5	97.4	97.4

3.2. Learning behavior and convergence analysis

The curves for training and validation accuracy and loss demonstrate smooth convergence and closeness, which indicates minimal risk of overfitting. Also, similar loss values are an additional confirmation of consistent learning and good generalization of the model under the investigated dataset conditions. The training and validation loss curves shown in Figure 3 illustrate the model's convergence behavior during training.

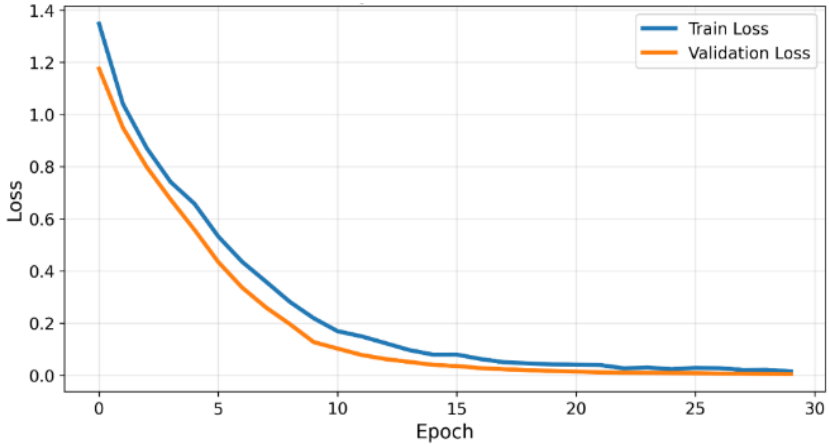

Figure 3. Training and validation loss curves illustrating the optimization process of the proposed framework

3.3. Receiver operating characteristic and classification separability analysis

The receiver operating characteristic (ROC) curves and area under the curve (AUC) values are presented in Figure 4. They demonstrate the proposed model's ability to distinguish between the five stress categories. The high AUC values indicate good class separability and support the classification performance reported in Table 4.

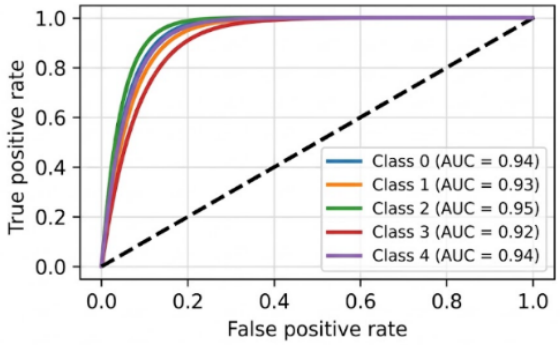

Figure 4. ROC curves and AUC analysis of the proposed physiological stress prediction framework

3.4. Feature importance and explainability analysis

The SHAP-based feature importance analysis presented in Figure 5 provides insights into contribution of individual physiological variables to the predictions generated by the proposed framework [19], [21], [22]. The results indicate that limb movement, respiration rate, blood oxygen level, body temperature, and snoring-related features contribute to the classification of physiological stress, with variations in their relative importance. These findings suggest that stress prediction is influenced by multiple physiological indicators rather than a single measurement. The identification of these influential features improves the interpretability of the proposed deep learning model and provides a better understanding of the physiological parameters associated with different stress levels. However, the SHAP

results represent model-specific feature contributions and should not be interpreted as evidence of causal relationships.

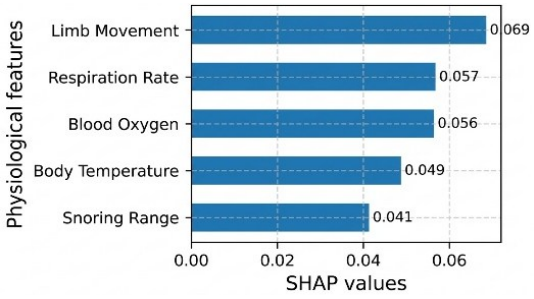

Figure 5. SHAP-based feature importance analysis showing how physiological signals contribute to multiclass stress prediction

3.5. Robustness evaluation

Noise was added to the network to imitate noise present in the signal generated by wearable sensors. Figure 6 shows that the proposed framework maintains consistent performance despite the presence of moderate levels of noise hence, the framework shows robustness. However, more tests need to be done on real-world disturbances.

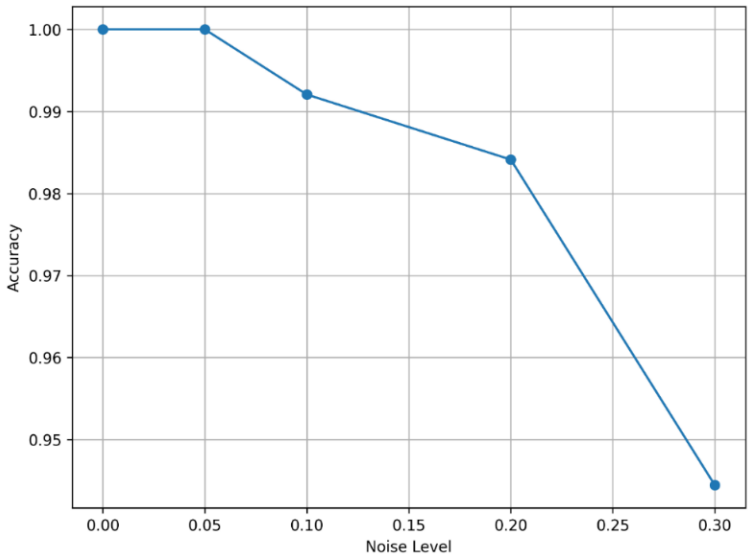

Figure 6. Robustness evaluation of the proposed framework under Gaussian noise injection

3.6. Ablation study

The ablation results in Table 5 show that combining CNN, BiLSTM, and attention improves classification performance. CNN achieved 94.2% accuracy, which increased to 95.9% with BiLSTM and 95.4% with attention. The complete CNN–BiLSTM–attention model achieved the highest accuracy of 97.8%, demonstrating the benefits of combining all three components.

Table 5. Ablation study of proposed CNN–BiLSTM–attention framework

Model	Accuracy (%)
CNN	94.2
CNN + BiLSTM	95.9
CNN + attention	95.4
CNN + BiLSTM + attention	97.8

3.7. Discussion

The results obtained from the suggested CNN–BiLSTM–attention framework were quite encouraging in terms of classifying multiclass stress. The confusion matrix and ROC analysis showed perfect classification and discrimination between classes of stress. Moreover, SHAP analysis revealed heart rate, respiration rate, body temperature, and sleep-related factors as the most important physiological features. These findings are consistent with established physiological stress responses, where elevated heart rate and respiration together with disturbed sleep are commonly associated with increased stress. The proposed framework maintained stable predictive performance under moderate Gaussian noise and outperformed conventional machine learning models by effectively learning nonlinear physiological relationships through adaptive attention. Although the computational complexity supports future wearable healthcare applications, additional validation using larger subject-independent datasets is required before practical deployment.

3.8. Limitations of the study

Despite the successful robustness of the model with respect to the introduction of additional Gaussian noise, other potential problems that could appear in the context of wearables health care devices include the problem of motion artifacts, loss of sensor data, signal drifting, and different variations in the sensor calibration. None of the mentioned items was studied in the current research. Moreover, subject-independent validation cannot be done due to the fact that no subjects' identification numbers are provided within the dataset from SaYoPillow. Thus, similar patterns from a physiological point of view could have occurred in both training and test sets, affecting predictive performance. Although the dataset size is relatively small for deep learning applications, dropout regularization, reduced model complexity, early stopping, and stratified cross-validation were employed to mitigate overfitting. Future research should evaluate the proposed framework on larger, more diverse, and subject-independent wearable datasets to strengthen its generalizability and support its practical application.

4. CONCLUSION

This study proposed an explainable CNN–BiLSTM–attention framework for multiclass physiological stress prediction using wearable healthcare data. The proposed framework achieved promising classification performance by learning informative physiological feature representations and improving multiclass stress prediction. SHAP analysis identified heart rate, respiration rate, body temperature, and sleep-related variables as the most influential physiological indicators, improving the interpretability of the proposed framework. The proposed framework also demonstrated stable predictive performance under moderate Gaussian noise, indicating its potential for wearable healthcare applications.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Kashif I. K. Sherwani				✓	✓	✓			✓	✓	✓		✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

The data supporting the findings of this study are publicly available through the SaYoPillow dataset repository, as described in reference [35]. The dataset contains physiological measurements and corresponding stress labels used in the present study. No new data were generated during this research.

REFERENCES

[1] R. M. Montgomery and M. A. V. M. Gouvea, "Impact of chronic stress on physical and mental health: a detailed analysis," *Journal of Genetic Engineering and Biotechnology Research*, vol. 6, no. 2, pp. 1–7, 2024, doi: 10.33140/JGEBR.

[2] G. Gupta, M. Khan, K. I. Sherwani, and Manaullah, "Overview of the effect of physiological stress on different biological signals," in *2023 International Conference on Recent Advances in Electrical, Electronics & Digital Healthcare Technologies (REEDCON)*, May 2023, pp. 251–255, doi: 10.1109/REEDCON57544.2023.10150828.

[3] A. O. Pataca *et al.*, "Use of machine learning for predicting stress episodes based on wearable sensor data: a systematic review," *Computers in Biology and Medicine*, vol. 198, Nov. 2025, doi: 10.1016/j.compbiomed.2025.111166.

[4] G. Taskasaplidis, D. A. Fotiadis, and P. D. Bamidis, "Review of stress detection methods using wearable sensors," *IEEE Access*, vol. 12, pp. 38219–38246, 2024, doi: 10.1109/ACCESS.2024.3373010.

[5] E. Lazarou and T. P. Exarchos, "Predicting stress levels using physiological data: real-time stress prediction models utilizing wearable devices," *AIMS Neuroscience*, vol. 11, no. 2, pp. 76–102, 2024, doi: 10.3934/Neuroscience.2024006.

[6] S. Gedam and S. Paul, "A review on mental stress detection using wearable sensors and machine learning techniques," *IEEE Access*, vol. 9, pp. 84045–84066, 2021, doi: 10.1109/ACCESS.2021.3085502.

[7] M. P. -Gómez and M. F. -Carmona, "Trends and challenges in real-time stress detection and modulation: the role of the IoT and artificial intelligence," *Electronics*, vol. 14, no. 13, Jun. 2025, doi: 10.3390/electronics14132581.

[8] K. Kakhi, S. K. Jagatheesaperumal, A. Khosravi, R. Alizadehsani, and U. R. Acharya, "Fatigue monitoring using wearables and AI: trends, challenges, and future opportunities," *Computers in Biology and Medicine*, vol. 195, Sep. 2025, doi: 10.1016/j.compbiomed.2025.110461.

[9] C. Ding, Y. Zhang, and T. Ding, "A systematic hybrid machine learning approach for stress prediction," *PeerJ Computer Science*, vol. 9, Feb. 2023, doi: 10.7717/peerj-cs.1154.

[10] P. Bobade and M. Vani, "Stress detection with machine learning and deep learning using multimodal physiological data," in *2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA)*, Jul. 2020, pp. 51–57, doi: 10.1109/ICIRCA48905.2020.9183244.

[11] M. N. Rastgoo, B. Nakisa, F. Maire, A. Rakotonirainy, and V. Chandran, "Automatic driver stress level classification using multimodal deep learning," *Expert Systems with Applications*, vol. 138, Dec. 2019, doi: 10.1016/j.eswa.2019.07.010.

[12] E. Vavrinsky, V. Stopjakova, M. Kopani, and H. Kosnacova, "The concept of advanced multi-sensor monitoring of human stress," *Sensors*, vol. 21, no. 10, May 2021, doi: 10.3390/s21103499.

[13] G. Vos, K. Trinh, Z. Sarnyai, and M. R. Azghadi, "Generalizable machine learning for stress monitoring from wearable devices: a systematic literature review," *International Journal of Medical Informatics*, vol. 173, May 2023, doi: 10.1016/j.ijmedinf.2023.105026.

[14] F. M. Talaat and R. M. El-Balka, "Stress monitoring using wearable sensors: IoT techniques in medical field," *Neural Computing and Applications*, vol. 35, no. 25, pp. 18571–18584, Sep. 2023, doi: 10.1007/s00521-023-08681-z.

[15] T. Iqbal *et al.*, "Stress monitoring using wearable sensors: a pilot study and stress-predict dataset," *Sensors*, vol. 22, no. 21, Oct. 2022, doi: 10.3390/s22218135.

[16] P. Schmidt, A. Reiss, R. Duerichen, C. Marberger, and K. V. Laerhoven, "Introducing WESAD, a multimodal dataset for wearable stress and affect detection," in *20th ACM International Conference on Multimodal Interaction*, Oct. 2018, pp. 400–408, doi: 10.1145/3242969.3242985.

[17] Y. S. Can, N. Chalabianloo, D. Ekiz, and C. Ersoy, "Continuous stress detection using wearable sensors in real life: algorithmic programming contest case study," *Sensors*, vol. 19, no. 8, Apr. 2019, doi: 10.3390/s19081849.

[18] M. Kyrou, I. Kompatsiaris, and P. C. Petrantonakis, "Deep learning approaches for stress detection: a survey," *IEEE Transactions on Affective Computing*, vol. 16, no. 2, pp. 499–517, Apr. 2025, doi: 10.1109/TAFFC.2024.3455371.

[19] I.-O. Wiratsin and C. Ragkhitwetsagul, "Effectiveness of explainable artificial intelligence (XAI) techniques for improving human trust in machine learning models: a systematic literature review," *IEEE Access*, vol. 13, pp. 121326–121350, 2025, doi: 10.1109/ACCESS.2025.3575022.

[20] S. N. Saw, Y. Y. Yan, and K. H. Ng, "Current status and future directions of explainable artificial intelligence in medical imaging," *European Journal of Radiology*, vol. 183, Feb. 2025, doi: 10.1016/j.ejrad.2024.111884.

[21] N. M. Imam, A. Ibrahim, and M. Tiwari, "Explainable artificial intelligence (XAI) techniques to enhance transparency in deep learning models," *IOSR Journal of Computer Engineering*, vol. 26, no. 6, pp. 29–36, Dec. 2024, doi: 10.9790/0661-2606012936.

[22] Z. Sadeghi *et al.*, "A review of explainable artificial intelligence in healthcare," *Computers and Electrical Engineering*, vol. 118, Aug. 2024, doi: 10.1016/j.compeleceng.2024.109370.

[23] B. H. M. V. D. Velden, H. J. Kuijf, K. G. A. Gilhuijs, and M. A. Viergever, "Explainable artificial intelligence (XAI) in deep learning-based medical image analysis," *Medical Image Analysis*, vol. 79, Jul. 2022, doi: 10.1016/j.media.2022.102470.

[24] M. Gjoreski, M. Luštrek, M. Gams, and H. Gjoreski, "Monitoring stress with a wrist device using context," *Journal of Biomedical Informatics*, vol. 73, pp. 159–170, Sep. 2017, doi: 10.1016/j.jbi.2017.08.006.

[25] A. Mohamed, K. Abdelqader, and K. Shaalan, "Explainable artificial intelligence: a systematic review of progress and challenges," *Intelligent Systems with Applications*, vol. 28, Dec. 2025, doi: 10.1016/j.iswa.2025.200595.

[26] P. Sharma *et al.*, "Perform a comparative study based on conventional machine learning approaches for human stress level detection," in *Design and Forecasting Models for Disease Management*, Hoboken, New Jersey: Wiley, 2025, pp. 237–251, doi: 10.1002/9781394234073.ch10.

[27] S. Shikha, D. Sethia, and S. Indu, "KRAFS-ANet: a novel framework for EEG-based stress classification using channel selection and optimized ensemble stacking," *International Journal of Machine Learning and Cybernetics*, vol. 16, no. 5–6, pp. 3359–3380, Jun. 2025, doi: 10.1007/s13042-024-02455-2.

[28] J. Chen, M. Abbod, and J.-S. Shieh, "Pain and stress detection using wearable sensors and devices—a review," *Sensors*, vol. 21, no. 4, Feb. 2021, doi: 10.3390/s21041030.

[29] M. S. Ali, M. A. Motin, and S. Kabir, "ReTeNet: a residual encoder and transformer encoders network for stress monitoring from wearable device," *IEEE Signal Processing Letters*, vol. 32, pp. 3635–3639, 2025, doi: 10.1109/LSP.2025.3607767.
[30] S. Yang *et al.*, "A deep learning approach to stress recognition through multimodal physiological signal image transformation," *Scientific Reports*, vol. 15, no. 1, Jul. 2025, doi: 10.1038/s41598-025-01228-3.
[31] B. Behinaein, A. Bhatti, D. Rodenburg, P. Hungler, and A. Etemad, "A transformer architecture for stress detection from ECG," in *2021 International Symposium on Wearable Computers*, Sep. 2021, pp. 132–134, doi: 10.1145/3460421.3480427.
[32] S. Nerella *et al.*, "Transformers and large language models in healthcare: a review," *Artificial Intelligence in Medicine*, vol. 154, Aug. 2024, doi: 10.1016/j.artmed.2024.102900.
[33] A. Anwar, Y. Khalifa, J. L. Coyle, and E. Sejdic, "Transformers in biosignal analysis: a review," *Information Fusion*, vol. 114, Feb. 2025, doi: 10.1016/j.inffus.2024.102697.
[34] A. M. Alqudah and Z. Moussavi, "A review of deep learning for biomedical signals: current applications, advancements, future prospects, interpretation, and challenges," *Computers, Materials & Continua*, vol. 83, no. 3, pp. 3753–3841, 2025, doi: 10.32604/cmc.2025.063643.
[35] L. Rachakonda, A. K. Bapatla, S. P. Mohanty, and E. Kougianos, "SaYoPillow: a blockchain-enabled, privacy-assured framework for stress detection, prediction, and control considering sleeping habits in the IoMT," 2020, *arXiv:2007.07377*.

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