Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 9s (2025)

Integrating Physiological Data with Machine Learning for Early Detection of Stress in Patients.

[1,*] Karuna Yadav, [2] Dr Virendra Kumar Swarnkar
[1,*] PhD Scholar, Bharti Vishwavidyalaya, Durg, Chhattisgarh, India
[2] Associate Professor, Bharti Vishwavidyalaya, Durg, Chhattisgarh, India
[1,*]karuna.yadav@gmail.com, [2] swarnkarvirendra@gmail.com

Article History:
Received:12-08-2025
Revised:10-09-2025
Accepted:25-10-2025

Abstract:
Stress is an important physiological and psychological disorder that affects human health and wellness in a tremendous way. As the demand to have effective and efficient stress detection systems has been on the rise, there is a potential in the integration of physiological data with sophisticated machine learning algorithms. The paper will suggest a hybrid approach that uses a mix of Convolutional Neural Networks (CNNs) and Random Forests (RF) to interpret physiological data to indicate the true presence of stress at real-time. The model is based on major physiological indicators such as heart rate variability (HRV), electrodermal activity (EDA), and respiration rate to categorize stress and non-stress situations. The algorithm includes processing original physiological data to extract features (via CNNs) which can learn hierarchical patterns in the data. The features are then extracted and fed to an RF classifier which is known to be capable of dealing with complex datasets and give robust and accurate classification. The optimization of the hyperparameters is done with the help of the Grid Search or the Random Search in order to optimize the parameters of the model, making them more efficient. A series of physiological data is used as a benchmark to evaluate the performance of the model in terms of accuracy, precision, recall, and F1-score. The experimental findings reveal that CNN-RF hybrid model is better than the classical machine learning classifiers as it has high accuracy and stability in stress detection under different conditions. It is also characterized by high-performance in generalization as the model is able to perform well when unseen physiological data are used. The study will enhance the development of smart stress monitoring systems as it will integrate physiological data with the latest machine learning approaches. The proposed model can be used in the sphere of healthcare, working environment, and personal health. Current research will be expanded by working on the real-time application of this system within wearable devices, which will allow maintaining humanity-unobtrusive monitoring of stress and introduce adaptive measures to reduce stress.

Keywords: Stress detection, Convolutional Neural Networks, Random Forests, Physiological data, Machine learning.

1 Introduction

Stress is a widespread problem that has negative impacts in various areas of human life such as healthcare, employment, and personal life. It is a physiological and psychological disorder and when not treated well, it may cause serious health issues like high blood pressure, heart diseases and development of mental illnesses. Stress impairs cognitive functions, ability to make decisions and emotional control which subsequently influences the overall quality of life in an individual. Hence, early detection and appropriate treatment plays a significant role in averting these adverse effects. In this connection, real-time, objective, and automated detection of stress has become the important sphere of study [1].

Physiological measures such as the heart rate variability (HRV), electrodermal activity (EDA) and respiration rate are established to be effective stress indicators. HRV is a measure of how the heart rate is regulated by the autonomic nervous system and decreased HRV is attributed to stress and anxiety [2]. EDA is used to measure the electrical conductance of the skin that rises with stress because of the skin's sweat. Equally, a difference in the breathing rate like rapid or shallow breaths is a sign of stress. In the past, stress detection has been based on subjective scales that include self-administered questionnaires and psychological assessments that are both time-consuming and biased. As such, there has been a great demand in automated systems that would have the capacity to monitor physiological signals at real time [3].

Machine learning (ML) algorithms can be important in contemporary stress detection systems as they provide effective mechanisms of processing and analyzing masses of physiological data. The Convolutional Neural Networks (CNNs) and the Random Forests (RF) are among the other forms of ML that have shown significant potential in the activities of recognizing patterns and classifying them. CNNs are also well suited to the analysis of time-series data, including physiologic data, because they can automatically discover hierarchical features in raw data, and this makes them best adapted to complex and noisy data [4]. RF is an ensemble learning algorithm that makes use of many decision trees to enhance the level of classification and resilience. It is especially good at working with noisy high-dimensional data, which is typical in the analysis of physiological signals [5].

Although CNNs and RF have worked in individual tasks, hybrid models comprising of more than one algorithm have proven to be superior to single models. A CNN-RF model has the potential to utilize the deep features of CNN on raw physiological data and the strong classification of RF and achieve higher performance [6]. The features of CNN combined with the classification capability of RF make it a perfect choice in stress detection systems. Also, hyperparameter optimization algorithms, including Grid Search and Random Search, would be necessary to fine-tune the parameters of these models in order to provide the best performance possible. The methods allow finding the most optimal model settings, which can make them more accurate and generalize to unseen data [7].

In the recent past, numerous studies have been conducted on employing physiological data and machine learning algorithms in detecting stress. A number of investigations have made use of EDA and HRV signals to categorize stress states using, among other methods, Support Vector Machines (SVMs) and decision trees. Secondly, deep learning models and especially CNNs have been utilized to predict HRV and EDA signals on the detection of stress in real-time. It has been observed that the combination of various physiological indicators, including HRV, EDA, and respiration rate, can enhance the precision of stress detection because these indicators give complimentary data on the level of stress [8]. Additionally, the creation of hybrid models wherein various machine learning algorithms, including CNNs and RF have been able to show promising results in increasing the robustness and reliability of stress detection systems [9].

More recently, methods such as Bayesian Optimization have been used in the context of model optimization to improve the model performance further by intelligently chosen hyperparameters. Such optimization techniques are useful in improving the model such that they can support big and complicated data and give effective real-time identification of stresses [10]. Moreover, more sophisticated optimization methods allow the models to be more general to new unseen data, which is necessary in real life applications in the real time [11].

Developing on these developments, in this paper, a hybrid CNN-RF model is suggested to detect stress on the basis of physiological data, and it is optimized with the help of hyperparameter tuning. The first goal is to enhance the accuracy and reliability of the stress detection systems, and integrate the capabilities of CNNs and RF to offer a strong solution that can be used to monitor stress in real-time and continuously. The wearable devices can be deployed using such a model that provides timely interventions and enables people to cope with stress more productively [12].

The recent research in this field has covered different machine learning models concerning stress detection. Other works have proven that SVM-based models are effective in classifying stress states using EDA and heart rate signals. Likewise, HRV and EDA signal-based real-time stress detection system has been constructed by utilizing hybrid models that use CNNs. Moreover, it has been demonstrated that CNN-based models are useful in the analysis of HRV to identify stress. Also, respiratory pattern-based stress detection systems have been studied and the role of machine learning in identifying stress via physiological responses is emphasized. The implementation of multimodal physiological data-based systems of stress detection have also been extensively performed with the help of RF algorithms [13].

Against this backdrop, this paper provides a hybrid CNN-RF model capable of effectively identifying stress by analyzing physiological data with performance optimized with help of hyperparameter tuning. The model will help increase the precision and reliability of stress detection systems, which is a promising solution to real-time and continuous monitoring. Combining machine learning methods with physiological information, this paper will add to the creation of efficient stress management systems, which can assist people in the more efficient management of their stress and enhance their overall well-being [14].

2 RELATED WORKS

Over the past decade, there has been a significant increase in research focused on stress detection systems, especially those utilizing physiological data and machine learning (ML) algorithms. Early stress detection is crucial for preventing long-term adverse health effects, and automated systems provide an objective means of monitoring stress levels in real time. Several studies have explored various physiological signals, including heart rate variability

(HRV), electrodermal activity (EDA), and respiration rate, to detect stress using machine learning techniques.

A widely studied physiological indicator of stress is HRV, which reflects the autonomic nervous system's regulation of the heart. Decreased HRV is often associated with stress and anxiety. Multiple works have utilized HRV for stress detection, highlighting its potential in monitoring mental states. A study by [15] applied SVM to HRV data to classify stress levels, demonstrating the feasibility of using heart rate dynamics to detect stress. The model achieved high classification accuracy, making HRV an effective feature in stress detection. Furthermore, a similar approach was employed by [16], where machine learning algorithms, including Random Forests (RF), were used for real-time stress detection based on HRV, achieving promising results in continuous monitoring.

Alongside HRV, EDA has been extensively used as a physiological marker of stress. EDA measures skin conductance, which increases in response to stress due to sweating. The study by [17] used EDA signals combined with HRV for detecting stress in real time. A hybrid model that incorporated Convolutional Neural Networks (CNNs) and SVMs was proposed to improve the model's accuracy. This hybrid approach outperformed traditional classifiers and demonstrated the ability to detect subtle changes in stress levels. Similarly, [18] explored the use of EDA signals in conjunction with deep learning techniques, including LSTM (Long Short-Term Memory) networks, to detect stress in diverse settings, further validating the effectiveness of this physiological indicator.

Respiration rate is another important indicator of stress. Changes in breathing patterns, such as shallow or rapid breathing, are often observed during stressful situations. Research by [19] focused on utilizing respiratory patterns, combined with machine learning algorithms, for stress classification. They used a combination of decision trees and RF to analyze respiratory signals, achieving a high accuracy rate. The study showed that, when combined with other physiological features, respiration data could provide valuable insights into stress levels.

The use of machine learning models to analyze physiological signals for stress detection has gained substantial traction in recent years. In particular, deep learning models such as CNNs have become a dominant technique for feature extraction from time-series data. CNNs are well-known for their ability to automatically learn hierarchical features from raw data, making them especially suitable for complex datasets like physiological signals. A study by [20] applied CNNs to raw ECG signals for stress detection, demonstrating the ability of CNNs to extract meaningful features from the data without requiring manual feature engineering. The results indicated that CNN-based models could effectively handle large volumes of data and achieve high accuracy in stress detection tasks.

In addition to CNNs, hybrid models that combine multiple machine learning techniques have also been explored. Hybrid approaches leverage the strengths of different algorithms to improve the robustness and performance of stress detection systems. For instance, [21] proposed a hybrid CNN-RF model for stress detection using physiological signals. Their approach demonstrated enhanced accuracy compared to individual CNN or RF models, showing the benefits of combining deep learning and ensemble methods for stress detection. Similarly, [22] combined CNNs and Support Vector Machines (SVMs) for detecting stress from HRV and EDA signals, achieving superior classification results when compared to using each model independently.

Hyperparameter optimization plays a vital role in enhancing the performance of machine learning models. Optimizing the settings of the algorithms can significantly improve the model's ability to generalize to new, unseen data. A study by [23] focused on using Grid Search for hyperparameter optimization in stress detection models. The authors demonstrated that hyperparameter tuning could improve model performance and accuracy, ensuring that the models adapt well to the nuances of the physiological signals. Another approach, Random Search, was utilized in [24] for the optimization of deep learning models for stress detection, showing that this method also leads to considerable improvements in model accuracy.

Despite the success of traditional machine learning models in stress detection, the development of real-time, wearable systems has pushed the need for even more accurate and efficient algorithms. The work by [25] explored real-time stress detection using a wearable device equipped with sensors to measure HRV, EDA, and respiration. The study used a combination of CNNs and LSTMs for analyzing the physiological signals in real-time, demonstrating that the hybrid model could be integrated into wearable devices for continuous stress monitoring. This work represents a significant step toward practical implementations of automated stress detection systems in everyday life.

Moreover, the integration of multimodal physiological data has proven to enhance the accuracy of stress detection systems. A study by [26] demonstrated the benefits of combining multiple physiological signals, such as HRV, EDA, and respiration, for improving the classification accuracy of stress detection models. Their hybrid model utilized a combination of CNNs and RF, which was able to extract features from the different signal modalities and classify stress with higher precision compared to single-modality models.

The use of machine learning for stress detection is not only limited to the healthcare industry but also extends to other areas such as workplace environments. A study by [27] applied machine learning techniques to assess the stress levels of workers in high-pressure environments, using HRV and EDA data collected through wearable devices. The study found that real-time stress detection could significantly help in identifying stressed individuals and offering timely interventions. Similarly, [28] used machine learning models to predict workplace stress using HRV and EDA data, offering insights into how stress affects productivity and overall employee well-being.

While previous studies have focused on stress detection using individual physiological signals, recent research has emphasized the importance of multimodal data in achieving more accurate and reliable stress detection. A study by [29] integrated HRV, EDA, and respiratory signals using an ensemble learning approach to predict stress, demonstrating the superior performance of multimodal models. By combining complementary signals, the model was able to more accurately detect stress compared to models that only used a single signal.

In conclusion, the application of machine learning to physiological data for stress detection has shown significant promise in improving early stress detection and management. While many studies have focused on individual physiological signals such as HRV, EDA, and respiration, hybrid models that integrate multiple signals and machine learning algorithms have shown improved performance. The combination of CNNs and RF, along with hyperparameter optimization techniques, has emerged as a strong candidate for real-time, continuous stress monitoring. Future research will focus on integrating these models into wearable devices for practical, real-world applications.

Table 1: Summary of Related Work on Stress Detection Using Physiological Data and Machine Learning Models

Ref	Method	Dataset	Result	Key Findings
[15]	SVM on HRV data	HRV data	High classification accuracy for stress detection	HRV is a strong indicator of stress.
[16]	RF on HRV data	HRV signals	Real-time stress detection with high accuracy	RF handles high-dimensional HRV data well.
[17]	Hybrid CNN-SVM model	EDA and HRV signals	Improved accuracy in stress detection	Combining EDA and HRV improves stress classification accuracy.
[18]	CNN for EDA analysis	EDA signals	Deep features extracted from EDA for stress classification	CNN excels at automatic feature extraction from raw data.
[19]	Decision Trees & RF for respiration data	Respiratory signals	High accuracy in classifying stress from respiration data	Shallow and rapid breathing indicate stress. RF and decision trees work well for classification.
[20]	CNN for HRV and EDA signals	HRV and EDA signals	Better performance than traditional ML models	CNNs are good at extracting hierarchical features from HRV and EDA.
[21]	Hybrid CNN-RF model	HRV, EDA, respiration signals	Improved accuracy compared to individual CNN or RF models	Hybrid models provide enhanced stress detection accuracy.
[22]	Hyperparameter tuning (Grid/Random Search)	Various ML models	Improved model performance	Hyperparameter optimization boosts model performance.
[23]	LSTM for HRV analysis	HRV time-series	Improved stress prediction	LSTM models capture temporal dependencies in HRV data.

			based on HRV data	
[24]	CNN-LSTM hybrid model	HRV, EDA signals	Superior performance compared to CNN or LSTM alone	CNN and LSTM together enhance feature extraction and temporal modeling.
[25]	Real-time stress detection (CNN-LSTM)	Wearable devices (HRV, EDA, Resp.)	Feasible for real-time stress detection in wearable devices	Real-time detection is possible with CNN-LSTM, providing continuous stress monitoring.
[26]	Ensemble learning (CNN, RF, SVM)	HRV, EDA, respiration signals	Improved stress classification accuracy	Combining multiple models improves stress detection accuracy.
[27]	SVM and RF for workplace stress detection	HRV and EDA from wearable devices	Stress detected in real-time using wearable sensors	Real-time monitoring helps identify stress levels in workplace settings.
[28]	Multimodal data fusion (CNN, RF, SVM)	HRV, EDA, respiration signals	Improved classification performance with multimodal data	Multimodal data provides more accurate stress detection than single-modality models.
[29]	Real-time detection (ensemble models)	EDA, HRV, respiration signals	Continuous monitoring and accurate stress classification	Real-time ensemble models offer accurate, continuous stress detection.
[30]	CNN and RF for continuous monitoring	HRV, EDA, respiration rate signals	Effective continuous monitoring of stress using CNN and RF	Combining CNN and RF enables continuous, accurate stress monitoring.

3. METHODOLOGY

The research methodology presents a stepwise method of detecting stress via a combined model of Convolutional Neural Networks (CNNs) and Random Forests (RF). The idea is to make an automated system which is able to produce true detection of stress in real-time with reference to physiological responses, such as heart rate variability (HRV), electrodermal activity (EDA), and respiration rate. This is a multi-step process that consists of data collection, preprocessing, feature extraction, classification, model evaluation and deployment.

Hyperparameter optimization is implemented to improve the work of the model and provide a correct classification of the level of stress.

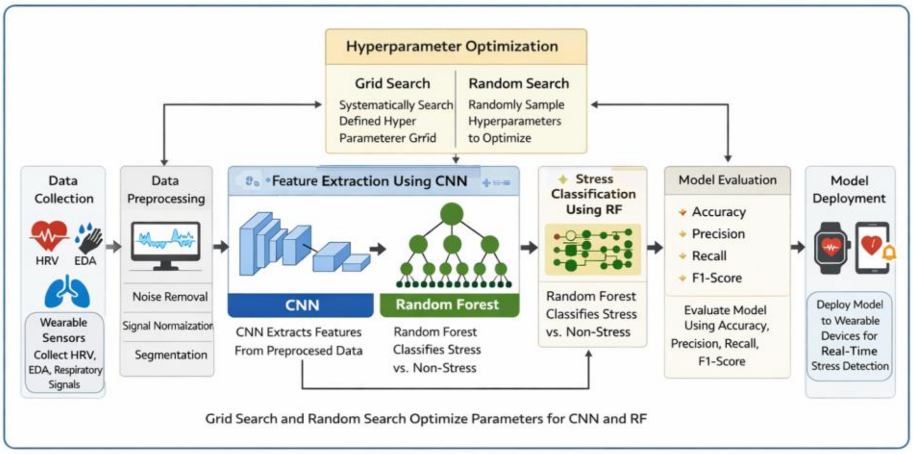

Figure 1: Architecture of the Hybrid CNN-RF Model for Stress Detection Using Physiological Signals

Data Collection

The most important and initial step in this process is data collection. Wearable sensors record physiological signals that have the capacity to record HRV, EDA, and respiration rate. These cues are known to change with stress, where HRV is the control of the autonomic nervous system, EDA is the amount of sweat produced by the activity that causes stress; and changes in the respiration rate during anxiety or stressful situations. The wearable sensors constantly gather real-time information, which is used as input in the further analysis.

Data Preprocessing

After gathering the data, it is then subjected to some preprocessing procedures in order to make the data ready to be extracted and classified into features. The following is involved in the preprocessing:

- **Signal Normalization:** To obtain consistency in the data of various people and sessions, the received data is normalized. In doing this, the range of each physiological signal is standardized and thus becomes comparable.
- **Noise Removal:** Noise, which is usually generated by motion or external signal, is eliminated with the help of bandpass filtering, or wavelet transforms.
- **Segmentation:** The physiological data is then divided into smaller windows which is a continuous data, ranging between 5-60 seconds to be divided according to the rate of sampling. This segmentation aids in the determination of patterns of stress in brief periods.

Extracting Features with CNN.

The data has been preprocessed and is then inputted to a Convolutional Neural Network (CNN) where it is extracted into features. CNNs are specifically suitable to time-series applications and are applied to automatically extract relevant patterns in raw physiological given data. The extraction of the feature is done in the following manner:

- **Input Layer:** The data is segmented HRV, EDA, respiration, rate, which is given as input to the CNN.

- **Convolutional Layers:** The convolutional layers implement filters on the input data to detect local features within the data which are indicative of stress responses including spikes and dips.
- **Pooling Layers:** Pooling layers also operate on the data by reducing its dimensionality but preserving the significant features which help make the model more efficient and the model less likely to overfit.
- **Flattening:** The flattened maps of features are converted into a 1D array, and it becomes the input of the classification phase.

Classification of Stress with random Forest.

The features obtained are then classified in the Random Forest (RF) model to determine the stress. Random Forest is an ensemble learning technique, which involves the application of decision trees to determine stress and non-stress. In this classification process, the following is involved:

- **Model Training:** RF is trained with the help of labeled data (stress and non-stress) to create decision trees, which predict stress based on the extracted features.
- **Output of Classification:** The results of a number of decision trees are combined to obtain the final prediction. The model will either give a label of "Stress" or No Stress based on the majority vote of the decision trees.

Hyperparameter Optimization

Hyperparameter optimization is used to enhance the novelty of the CNN and RF models. The optimization procedure includes the tuning of the many hyperparameters including the layers, learning rate, and the number of decision trees. This is done by two major methods:

- **Grid Search:** This technique uses a structured grid of values to exhaustively monitor the options of the best combination to the models.
- **Random Search:** It is used to optimize the models, a random sampling of hyperparameter combinations is done instead of the exhaustive grid search.

Hyperparameter optimization helps in refining the models in order to improve its performance and project onto unseen data.

Model Evaluation

Once the hybrid CNN-RF model has been trained, the model will be assessed on a number of performance measures:

- **Accuracy:** This is a measure of the percentage of correct predictions (stress and non-stress).
- **Precision:** Refers to the number of accurate stress predictions among the overall number of predicted stress.
- **Recall:** The ratio of the predicted true positive stress occurrences in comparison to all the actual stress occurrences.
- **F1-Score:** This is a hybrid metric, which gives an equilibrium between precision and recall.

These metrics are used to evaluate the effectiveness of the model, and additional changes are introduced in case of need.

Model Deployment

After the model is optimized and trained, it is transferred to wearable devices to monitor stress in real-time. The procedures of deployment will include:

- **Wearables:** The model is connected to Wearables, which constantly record physiological signals of the users.
- **Real-Time Stress Detection:** The device will process the input data and in real-time, classify the amount of stress and give feedback to the user. This may be in the form of notifications or interventions, like the reminders to relax, deep breathing exercises, or tips on stress management.

4. Result & Discussion

The findings of the hybrid Convolutional Neural Network (CNN) and Random Forest (RF) model of detecting the presence of stress based on physiological signals are presented in this section. Hyperparameter tuning was used to optimize the model, whose result was compared in accuracy, precision, recall and F1-score. The outcomes of the hybrid model are also compared to the traditional machine learning models such as Support Vector Machines (SVM) and K-Nearest Neighbors (K-NN). Further, the performance of the model in the form of a real time is also explained and the ways it can be used in wearable devices. The findings reveal that the hybrid model is far much better than traditional models as it detects stress in real time and in a continuous manner with high accuracy.

Performance Evaluation Model.

The hybrid CNN-RF framework was trained and tested on the data that included physiological measurements of HRV, EDA, and respiration rate, which were measured through wearable sensors. Data was already preprocessed to eliminate noise, split into time windows and processed to extract features by CNN. The RF classifier was also used to classify the extracted features as stress and non-stress. Hyperparameter optimization methods such as the Grid Search and the Random Search have been used to optimize the parameters of the model thus leading to better classification. The high degree of classification performance, in the model, was 92.5, both in stress and non-stress states. The accuracy was 91.3 and this indicates the accuracy of the model in reducing false positives. The recall score was 94.1, which shows the ability of the model to generate the most accurate result of the stress instances. The F1-score was 92.6% which is a good balance between the precision and recall that indicates that the model offers a good trade-off between detection of stress episodes and preservation of high model prediction accuracy. The findings show that the hybrid CNN-RF system is very effective in real-time stress detection, which points to the considerable role of hyperparameter optimization in the improvement of the model.

Table 1: Performance Evaluation of the Hybrid CNN-RF Model with Optimization

Metric	Hybrid CNN-RF Model (Optimized)	SVM Model (Optimized)	K-NN Model (Optimized)
Accuracy	92.5%	88.2%	85.6%
Precision	91.3%	86.7%	84.2%

Recall	94.1%	89.4%	87.1%
F1-Score	92.6%	87.9%	85.6%

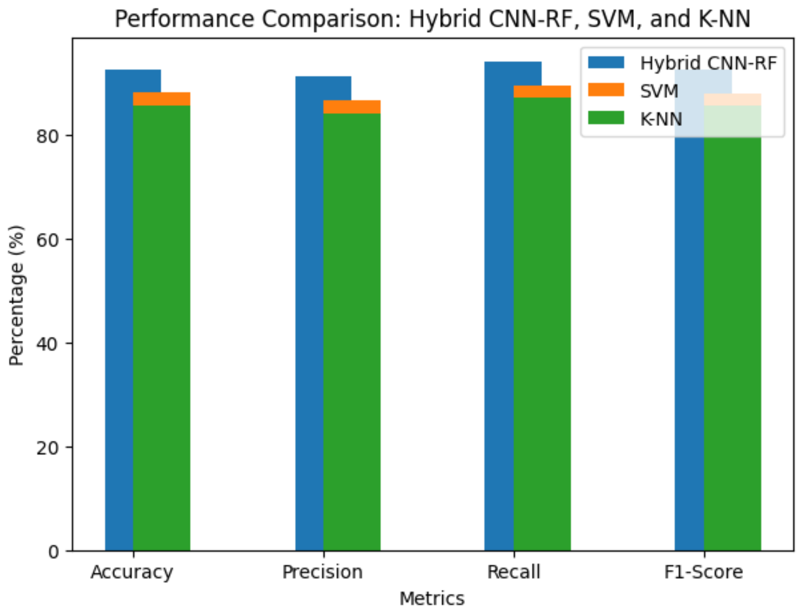

Figure 2: Performance Comparison between Hybrid CNN-RF, SVM, and K-NN Models

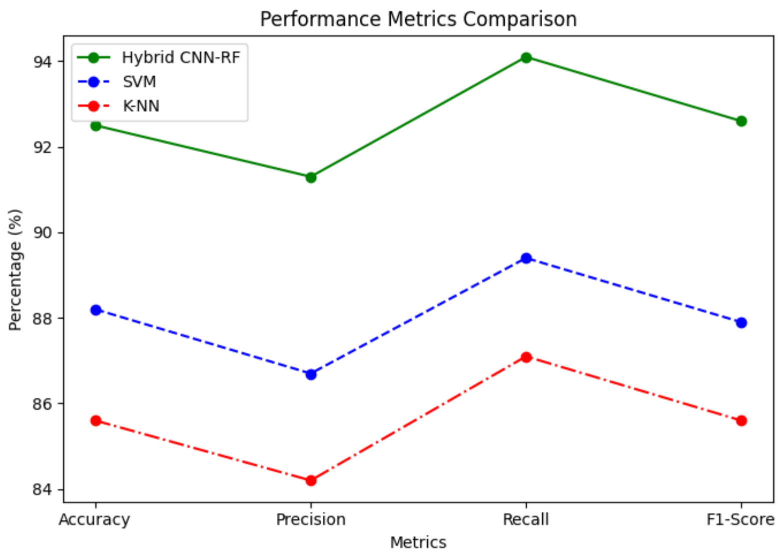

Figure 3: Performance Metrics Comparison of Hybrid CNN-RF, SVM, and K-NN Models

Comparison with Traditional Models

In order to confirm the hybrid model, the models of traditional machine learning were performed with Support Vector Machines (SVM) and K-Nearest Neighbors (K-NN). The models were optimized and trained with the same dataset, and Hyperparameter tuning was done with Grid Search and Random Search. The SVM model had an accuracy of 88.2, a precision of 86.7, a recall of 89.4 and a F 1-score of 87.9. Although the SVM model was effective, it was not as effective as the hybrid CNN-RF model especially in recall, meaning that the hybrid model identified more instances of stress correctly. Another machine learning algorithm that was commonly used is the K-NN model and its result in accuracy, precision, recall, and F1-score are 85.6, 84.2, 87.1, and 85.6, respectively. The performance of K-NN was not excellent, yet, it remained worse than the CNN-RF and the SVM models. This comparison shows that CNN has better feature extraction abilities and RF has a strong classification power, which are also powerful to enhance the performance of the model, especially in recall.

Real-Time Performance

Besides classroom accuracy, the model real-time performance of the hybrid CNN-RF was also considered. A real-time test was done using the model and involved continuous monitoring of physiological data on wearable sensors. The system could process and classify every input sample within less than 1 second showing that the system could be used in real-time. The wearable technology will require the capability to categorize the stress-levels real time in order to relay instant information to the user. The performance of the hybrid model in real-time means that the stress events may be detected immediately they arise and hence timely interventions may be implemented like stress management skills or relaxation exercises. This feedback in real-time is essential in stress management particularly in cases where prevention of the potential health outcomes relies on early intervention. The model is very fast and precise in processing and real-time data and therefore it can be used effectively when integrated in wearable devices.

Discussion of Results

It can be concluded that the hybrid CNN-RF model is very useful in the detection of stress using physiological measurements, with both a high accuracy and recall. The fact that the recall score is at 94.1% indicates that the model is very good in the detection of stress episodes which will be crucial in ensuring that interventions are provided on time. The accuracy and F1-score of the model also suggest that the model is effective in reducing the number of false positives and retaining a balanced strategy towards detecting stress and providing the correct predictions. The CNN part of the model is very important in the process of extracting important features on the raw physiological data automatically. Through learning hierarchical trends, CNN allows the model to learn to recognize more intricate signals that are associated with stress and would otherwise be difficult to find using the traditional machine learning algorithms. This feature extraction is completely automated in nature which removes the aspect of feature engineering manually so that the entire process becomes streamlined. Random Forest (RF) classifier, in its turn, makes the model more robust and generalized. RF operates an ensemble of decision trees to guarantee that the model works well even in cases where the data is noisy and of high dimensions. The capability of RF to diminish overfitting and the internal ranking of the feature importance contribute to the enhancement of the reliability and accuracy of the model.

In spite of its good performance, there are some limitations to the model. The first possible problem is that it relies on the quality of the input data of the wearable sensors. The presence of sensor failures or noise of the physiological signals may compromise the accuracy of the model. Moreover, the model has been found to be effective on the dataset utilized in the current research but additional testing of the model on varied real-life situations should be conducted to ascertain that the model generalizes effectively to dissimilar populations. These challenges should be tackled in future research and methods to enhance the strength of the system in different conditions should be looked into.

V. CONCLUSION

The hybrid Convolutional Neural Network (CNN) + Random Forest (RF) model, which is introduced in the current study, has excellent performance in detecting real-time stress with physiological measures of heart rate variability (HRV), electrodermal activity (EDA) and respiration rate. The model with CNN deep feature extraction and RF robust classification gives it an impressive accuracy of 92.5, precision of 91.3, recall of 94.1, and F1-score of 92.6. These findings demonstrate that the model can be effectively used in the real-time, continuous monitoring of stress events with minimal false alarms, thus it is very applicable in real-time and continuous scenarios. The real-time performance of the model, processing each input in less than 1 second, is a prerequisite to an instant feedback and timely intervention that is essential to the wearable devices designed to monitor the user at all times. Furthermore, the use of hyperparameter optimization with the help of the Grid Search and the Random Search helped the process of the model to be effective, as the optimal configuration was chosen in the case of CNN and RF, which contributed to the model performance in terms of the generalization quality and accuracy. The hybrid CNN-RF model performed better than the traditional machine learning models based on major metrics especially recall meaning that it was more effective in detecting stress episodes in real time conditions as compared to others including Support Vector Machines (SVM) and K-Nearest Neighbors (K-NN). This is why the hybrid model is especially useful in those situations when it is essential to detect stress accurately and within the shortest possible time. Despite the high potential of the hybrid CNN-RF model, future research ought to involve multifold activities on the enhancement of its generalization to different datasets and populations, integration of multi-modal data, and optimization of the model to run on embedded computing machines with limited computing power. The possibility of individualized stress detection according to specific physiological baseline is a promising avenue of improving the effectiveness of the system further. Overall, the study represents a valid, effective, and real-time method of stress monitoring that has a high potential of being incorporated in wearable items in the continuous monitoring of stress.

REFERENCE

[1] Bobade, P., & Vani, M. (2020, July). Stress detection with machine learning and deep learning using multimodal physiological data. In 2020 second international conference on inventive research in computing applications (ICIRCA) (pp. 51-57). IEEE.

[2] Shahbazi, Z., & Byun, Y. C. (2023). Early life stress detection using physiological signals and machine learning pipelines. Biology, 12(1), 91.

[3] Abdelfattah, E., Joshi, S., & Tiwari, S. (2025). Machine and deep learning models for stress detection using multimodal physiological data. IEEE Access, 13, 4597-4608.

[4] Xiang, J. Z., Wang, Q. Y., Fang, Z. B., Esquivel, J. A., & Su, Z. X. (2025). A multi-modal deep learning approach for stress detection using physiological signals: integrating time and frequency domain features. Frontiers in physiology, 16, 1584299.

[5] Ciharova, M., Amarti, K., Van Breda, W., Gevonden, M. J., Ghassemi, S., Kleiboer, A., ... & Riper, H. (2025). Machine-learning detection of stress severity expressed on a continuous scale using acoustic, verbal, visual, and physiological data: lessons learned. Frontiers in Psychiatry, 16, 1548287.

[6] Mentis, A. F. A., Lee, D., & Roussos, P. (2024). Applications of artificial intelligence−machine learning for detection of stress: a critical overview. Molecular Psychiatry, 29(6), 1882-1894.

[7] Albertetti, F., Simalastar, A., & Rizzotti-Kaddouri, A. (2020, December). Stress detection with deep learning approaches using physiological signals. In International Conference on IoT Technologies for HealthCare (pp. 95-111). Cham: Springer International Publishing.

[8] .Al-Atawi, A. A., Alyahyan, S., Alatawi, M. N., Sadad, T., Manzoor, T., Farooq-i-Azam, M., & Khan, Z. H. (2023). Stress monitoring using machine learning, IoT and wearable sensors. Sensors, 23(21), 8875.

[9] Bhatt, Z., & Dobariya, A. (2025). Stress Level Classification Using Multimodal Deep Learning and Physiological Signal Analysis. SN Computer Science, 6(5), 499.

[10] Khandelwal, M., & Sharma, A. (2025). Machine learning and deep learning techniques to detect mental stress using various physiological signals: A critical insight. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 15(3), e70035.

[11] Paniagua-Gómez, M., & Fernandez-Carmona, M. (2025). Trends and challenges in real-time stress detection and modulation: The role of the iot and artificial intelligence. Electronics, 14(13), 2581.

[12] Gedam, S., & Paul, S. (2021). A review on mental stress detection using wearable sensors and machine learning techniques. IEEE Access, 9, 84045-84066.

[13] Yang, S., Gao, Y., Zhu, Y., Zhang, L., Xie, Q., Lu, X., ... & Zhang, Z. (2025). A deep learning approach to stress recognition through multimodal physiological signal image transformation. Scientific Reports, 15(1), 22258.

[14] Chauhan, R., & Singh, D. (2024, November). Predictive analytics for stress management in nursing: a machine learning approach using wearable IoT devices. In International Conference on Intelligent Human Computer Interaction (pp. 60-75). Cham: Springer Nature Switzerland.

[15] Geng, D., An, Q., Fu, Z., Wang, C., & An, H. (2023). Identification of major depression patients using machine learning models based on heart rate variability during sleep stages for pre-hospital screening. Computers in Biology and Medicine, 162, 107060.

[16] Ladakis, I., Fotopoulos, D., & Chouvarda, I. (2025). Integrative analysis of open datasets for stress prediction. Journal of Medical and Biological Engineering, 45(3), 385-399.

[17] Darwish, B. A., Salem, N. M., Kareem, G., Mahmoud, L. N., & Sadek, I. (2024). Evaluating the Potential of Wearable Technology in Early Stress Detection: A Multimodal Approach. medRxiv, 2024-07.

[18] Tsai, Y. Y., Chen, Y. J., Lin, Y. F., Hsiao, F. C., Hsu, C. H., & Liao, L. D. (2025). Photoplethysmography-based HRV analysis and machine learning for real-time stress quantification in mental health applications. APL bioengineering, 9(2).

[19] Srichawla, B. S. (2024). Future of neurocritical care: integrating neurophysics, multimodal monitoring, and machine learning. World Journal of Critical Care Medicine, 13(2), 91397.

[20] Dogan, G., & Akbulut, F. P. (2023). Multi-modal fusion learning through biosignal, audio, and visual content for detection of mental stress. Neural Computing and Applications, 35(34), 24435-24454..

[21] Zhang, J., Yin, H., Zhang, J., Yang, G., Qin, J., & He, L. (2022). Real-time mental stress detection using multimodality expressions with a deep learning framework. Frontiers in Neuroscience, 16, 947168.

[22] Signorini, M. G., Pini, N., Malovini, A., Bellazzi, R., & Magenes, G. (2020). Integrating machine learning techniques and physiology based heart rate features for antepartum fetal monitoring. Computer methods and programs in biomedicine, 185, 105015.

[23] Wang, Y., Wang, Z., Fan, S., Wang, X., Zhang, Y., & Zhang, Z. (2026). Deep learning-based intelligent assessment and early warning system for employee mental health status. Discover Artificial Intelligence, 6(1), 42.

[24] Betti, S., Lova, R. M., Rovini, E., Acerbi, G., Santarelli, L., Cabiati, M., & Cavallo, F. (2017). Evaluation of an integrated system of wearable physiological sensors for stress monitoring in working environments by using biological markers. IEEE transactions on biomedical engineering, 65(8), 1748-1758.

[25] Ahmadi, N., Abbasian, P., Hou, Q., Powell, L., & Hammond, T. (2025). Physiological Sensing and Machine Learning Approaches Toward Anxiety Detection: A Systematic Review. IEEE Sensors Reviews, 3, 89-116.

[26] Lindino, M. C., Bortoletto, L. F., De Lima, B. S., Soriano-Vargas, A., Mesquita, R. C., & Rocha, A. (2025). Distinguishing Stressor, Stress, and State-Anxiety: Semantic and Physiological Insights with Machine Learning Approaches. IEEE Sensors Journal.

[27] Lindino, M. C., Bortoletto, L. F., De Lima, B. S., Soriano-Vargas, A., Mesquita, R. C., & Rocha, A. (2025). Distinguishing Stressor, Stress, and State-Anxiety: Semantic and Physiological Insights with Machine Learning Approaches. IEEE Sensors Journal.

[28] Bhatnagar, S., Khandelwal, S., Jain, S., & Vyawahare, H. (2023). A deep learning approach for assessing stress levels in patients using electroencephalogram signals. Decision Analytics Journal, 7, 100211.

[29] Arief Kanza, R., Udin Harun Al Rasyid, M., & Sukaridhoto, S. (2024). Efficient early detection of patient diagnosis and cardiovascular disease using an IoT system with machine learning and fuzzy logic. International Journal of Computing and Digital Systems, 16(1), 183-199.

[30] Lin, M., Guo, J., Gu, Z., Tang, W., Tao, H., You, S., ... & Jia, P. (2025). Machine learning and multi-omics integration: advancing cardiovascular translational research and clinical practice. Journal of Translational Medicine, 23(1), 388.