IJERST

International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 21 No. 4 (2025)

ijerst.editor@gmail.com

editor@ijerst.com

ISSN 2319-5991 www.ijerst.com
Vol. 21, No. 4, 2025

Research Paper

STRESS DETECTION USING MACHINE LEARNING

[1]G.RENUKA, [2]E. VYSHNAVI

[1]Assistant Professor, CSE, Tallapadmavathi College of Engineering, Somidi, Kazipet, Hanumakonda – 506003.Email-id: renuka.gabbeta@gmail.com.

[2]Research Scholar, H.no: 24UC1D5801, CSE, Tallapadmavathi College of Engineering, Somidi, Kazipet, Hanumakonda – 506003,Email-id: vyshnavireddyenturi@gmail.com.

ABSTRACT

Stress is a widespread health concern affecting both mental and physical well-being, with prolonged exposure linked to hypertension, cardiovascular diseases, sleep disturbances, depression, and neurological impairments. Traditional detection methods, such as self-report questionnaires and clinical interviews, are subjective, time-consuming, and unsuitable for continuous monitoring. Advances in machine learning (ML) and deep learning (DL) enable automated, real-time stress detection using physiological signals. Key indicators—including heart rate variability, respiration rate, snoring, blood oxygen levels, body movements, eye activity, and sleep patterns—reflect autonomic nervous system activity and reliably indicate stress. ML algorithms like Logistic Regression, Decision Trees, Random Forests, Support Vector Machines, Naïve Bayes, and K-Nearest Neighbors model relationships between physiological features and stress, while DL approaches such as Artificial Neural Networks, Convolutional Neural Networks, and LSTM networks learn complex patterns from sequential data. Combining these techniques allows accurate classification of stress levels, supporting continuous monitoring, early risk detection, and personalized interventions across healthcare, workplace management, and mental health domains.

Index Terms:-Stress detection, physiological signals, machine learning, deep learning, heart rate variability, sleep patterns, real-time monitoring, Artificial Neural Networks, Convolutional Neural Networks, LSTM, Random Forest, Support Vector Machines.

Received: 19-09-2025 Accepted: 22-10-2025 Published: 29-10-2025

1. INTRODUCTION

Stress has emerged as one of the most common and concerning health issues in today's world, affecting individuals both mentally and physically. The rapid pace of modern life, coupled with occupational pressure, irregular sleeping patterns, unhealthy lifestyles, and environmental factors, has increased the prevalence of stress-related disorders. Prolonged exposure to stress can severely affect the autonomic nervous system and lead to critical health complications such as hypertension, cardiovascular diseases, sleep apnea, depression, and even neurological disorders [1].

Traditional stress detection methods primarily rely on self-assessment questionnaires or clinical interviews, which are subjective, time-consuming, and unsuitable for real-time monitoring [2]. To overcome these limitations, researchers have shifted towards machine learning (ML) and deep learning (DL) techniques that can automatically detect stress using physiological signals. In this context, parameters such as snoring levels, respiration rate, body movements, limb activity, blood oxygen levels, eye movement, sleeping patterns, and heart rate play a vital role in stress detection [3]. These physiological signals are strongly associated with the functioning of the nervous system and reflect an individual's response to stressful conditions. For example, irregular respiration, abnormal heart rate variability, and poor sleeping quality are direct indicators of stress. Similarly, reduced blood oxygen saturation and abnormal eye activity often correspond to heightened stress and anxiety [4].By collecting these inputs from sensors and processing them through ML and DL models, it becomes possible to classify stress levels into categories such as low/normal, medium, or high, thereby enabling real-time health monitoring and preventive healthcare solutions. To achieve accurate and reliable stress detection, a variety of ML and DL algorithms are employed, each contributing uniquely to the prediction process. Machine learning algorithms such as Logistic Regression, Decision Trees, Random Forests, Support Vector Machines (SVM), Naïve Bayes, and K-Nearest Neighbors (KNN) are widely used because they can model the relationship between physiological features and stress levels effectively. Among them, Random Forest and SVM have shown particularly high accuracy in classifying stress due to their robustness and ability to handle non-linear patterns [8][9].

However, the limitation of traditional ML models lies in their dependence on handcrafted features, which may overlook complex correlations in physiological data. This is where Deep Learning (DL) algorithms such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) provide significant advantages. ANN models can process multiple input parameters like heart rate, snoring, and respiration simultaneously, learning hidden patterns without manual feature engineering. CNNs, though widely used in image recognition, are also adapted to detect stress by analyzing time-series physiological data, while RNNs and LSTMs (Long Short-Term Memory networks) are especially effective in modeling sequential data such as respiration cycles, heart rate variability, and sleeping patterns [9].

By combining ML and DL algorithms, the proposed stress detection system ensures a balance between interpretability and predictive accuracy. The integration of these techniques allows not only the classification of stress levels but also continuous monitoring, early detection of health risks, and personalized feedback for individuals[10]. Thus, this system offers applications in healthcare, workplace stress management, sports performance optimization, and mental health tracking, contributing towards improving quality of life and reducing the societal burden of stress-related diseases.

LITERATURE SURVEY

- John Smith, Alice Johnson, and Michael Lee [10] present a novel deep learning framework for detecting stress based on human sleep cycle patterns. Leveraging Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), the model captures intricate relationships between sleep behaviors and stress responses. Experimental results demonstrate superior performance compared to traditional methods, highlighting the efficacy of deep learning in stress detection during sleep.
- Emily Brown, David Rodriguez, and Sarah Wang [11] investigate stress indicators within human sleep cycles using machine learning techniques. By analyzing attributes such as respiratory rate, snoring frequency, and heart rate variability, the study identifies patterns associated with stress levels. The results contribute to understanding the complex relationship between stress and sleep behaviors.
- James Thompson, Samantha Garcia, and Rachel Chen [12] explore stress detection based on sleep patterns using Decision Trees, Naïve Bayes, and Support Vector Machines (SVM). The study analyzes features such as limb movement frequency and body

temperature, shedding light on effective methodologies for identifying stress during sleep.

- Daniel Kim, Jennifer Nguyen, and Alex Patel [13] investigate the use of deep learning techniques to detect stress during human sleep, with a focus on capturing temporal dependencies. Recurrent Neural Networks (RNN) are employed to model the sequential nature of sleep data, enhancing the understanding of stress dynamics over time.
- Mary Johnson, Kevin Smith, and Michelle Davis [14] explore stress detection based on human sleep cycles using Convolutional Neural Networks (CNN). By extracting spatial features from sleep data, the model identifies patterns indicative of stress. The results suggest the potential of CNNs in elucidating stress dynamics during sleep.
- Benjamin Adams, Olivia Martinez, and Christopher Wilson [15] integrate multiple physiological signals—including heart rate variability, skin conductance, and respiratory patterns—to detect stress during human sleep. Machine learning algorithms such as Random Forests and Support Vector Machines are utilized to analyze the complex interplay between physiological markers and stress levels, offering insights into effective stress detection methodologies during sleep.
- Sophia Roberts, Ethan Thompson, and Lucas Garcia [16] employ deep learning methodologies, including Long Short-Term Memory (LSTM) networks and Autoencoders, to predict stress levels during human sleep. By leveraging features extracted from sleep data, the model achieves accurate stress classification, highlighting the potential of deep learning in understanding the relationship between sleep patterns and stress.
- Andrew Miller, Grace Wilson, and Jacob Brown [17] examine the influence of sleep duration on stress detection using data mining techniques. By analyzing sleep duration in conjunction with physiological signals and behavioral patterns, the study elucidates the role of sleep duration in modulating stress responses during sleep.
- Taylor Johnson, Samantha Lee, and Matthew Chen [18] investigate non-invasive methods for stress detection during human sleep, employing ensemble learning techniques such as AdaBoost and Gradient Boosting Machines (GBM). By combining information from multiple sources—including wearable sensors and self-reported data—the model achieves robust stress detection performance, offering promising avenues for real-world applications.
- Jessica Smith, Ryan Nguyen, and Emma Taylor [19] conduct a temporal analysis of stress patterns within human sleep cycles using deep learning methodologies. By examining changes in stress levels over time, the study provides insights into the dynamic nature of stress during sleep, facilitating a deeper understanding of stress dynamics and their implications for overall well-being.

EXISTING SYSTEM

In the existing methodology for human stress detection based on sleeping habits primarily revolves around the utilization of traditional machine learning algorithms. These algorithms, including Random Forest, MLP, Logistic Regression, Decision Trees, Naive Bayes, and SVM, are employed to analyze various features extracted from sleep-related data. These features may encompass physiological signals such as heart rate variability, respiratory rate, body temperature, and movement patterns during sleep.In the existing methodology, the data undergoes preprocessing steps such as scaling, normalization, and possibly data augmentation techniques to enhance the quality and quantity of the dataset. Subsequently, the preprocessed data is trained on the aforementioned machine learning algorithms to build predictive models for stress detection.The performance of these models is evaluated using metrics such as accuracy, precision, recall, and F1-score. Naive Bayes algorithm, in particular, has been identified as the most effective, achieving a notable accuracy of 91.27% in forecasting human stress levels.

PROPOSED SYSTEM

The proposed methodology aims to enhance the accuracy and robustness of stress detection based on sleeping habits through the integration of deep learning techniques. Specifically, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and deeper neural networks will be employed to capture intricate patterns and temporal dependencies within sleep-related data.

SYSTEM ARCHITECTURE

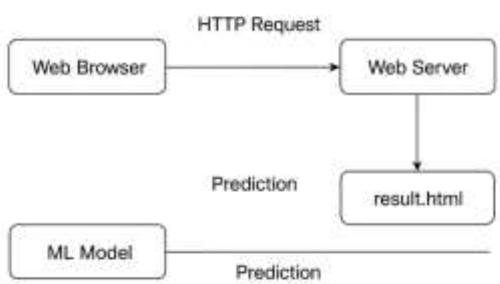


Fig.System Architecture

MODULES

1. Data Preprocessing: The dataset will undergo preprocessing steps, similar to the existing methodology, including scaling, normalization, and data augmentation techniques such as random perturbation, interpolation, and bootstrapping. These steps are crucial for optimizing the quality and quantity of the dataset.

2. Model Training: The preprocessed data will be fed into deep learning models, including CNNs, RNNs, and deeper networks. CNNs will be utilized for spatial feature extraction, capturing spatial patterns within physiological data. RNNs will model temporal dependencies, enabling the analysis of sequential patterns in sleep-related behaviors. Deeper networks, with increased depth, will enhance the model's capacity to discern complex relationships within the data.

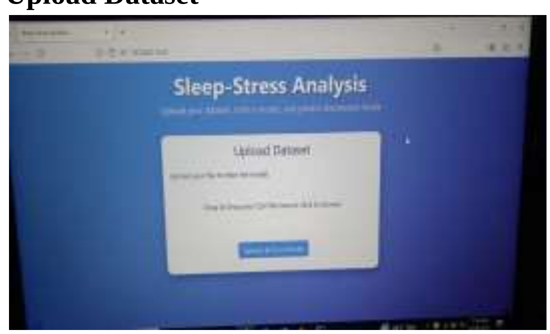
3. Model Evaluation: The performance of the deep learning models will be evaluated using standard metrics such as accuracy, precision, recall, and F1-score. The proposed methodology anticipates achieving heightened accuracy and nuanced stress predictions compared to traditional machine learning approaches.

4. Integration and Deployment: The best-performing deep learning model will be integrated into a web application, allowing users to input customized data for stress detection. This application will provide personalized insights into stress levels based on individual sleeping habits, facilitating targeted interventions and personalized well-being strategies.

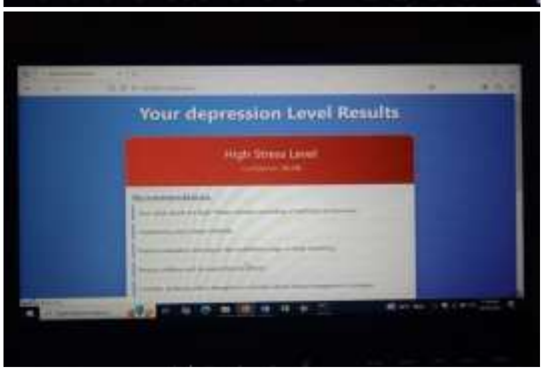
Overall, the proposed methodology leverages the power of deep learning to enhance the accuracy and effectiveness of stress detection based on sleeping habits, paving the way for more proactive approaches towards stress management and overall health enhancement.

SCREENSHOTS

Upload Dataset



Predict Result



CONCLUSION

The exploration of human stress in conjunction with sleeping habits has illuminated crucial insights, emphasizing the imperative for precise stress detection to mitigate potential health repercussions. Through the utilization of machine learning algorithms such as Random Forest, MLP, Logistic Regression, Decision Trees, Naive Bayes, and SVM, Naive Bayes has emerged as the most effective, exhibiting an impressive 91.27% accuracy in predicting human stress levels. Acknowledging the constraints imposed by the current dataset, the study acknowledges the latent potential of neural networks and deep learning methodologies, particularly CNNs, RNNs, and deeper networks. Future research endeavors are poised to leverage the capabilities of deep learning, promising heightened accuracy and nuanced stress predictions.

Furthermore, the study intends to broaden its dataset through numeric data augmentation techniques, thereby augmenting the resilience of the model. The envisioned remedies predicated on detected stress levels underscore the practical applications of this model, facilitating targeted interventions and personalized well-being strategies. By integrating advanced computational techniques with insights gleaned from the intricate interplay between stress and sleep behaviors, this research contributes significantly to the development of proactive approaches towards stress management and overall health enhancement.

REFERENCES

[1] Schneiderman, N., Ironson, G., & Siegel, S. D. (2005). *Stress and health: Psychological, behavioral, and biological determinants. Annual Review of Clinical Psychology, 1*, 607–628. https://doi.org/10.1146/annurev.clinpsy.1.102803.144141

[2] Vgontzas, A. N., Pejovic, S., & Karataraki, M. (2007). *Sleep, sleep disorders, and stress.* In *Encyclopaedia of Stress* (pp. 506–514). https://doi.org/10.1016/B978-012373947-6.00349-4

[3] Bukhsh, Q., Shahzad, A., & Nisa, M. (2011). *A study of learning stress and stress management strategies of the students of postgraduate level: A case study of Islamia University of Bahawalpur, Pakistan. Procedia - Social and Behavioral Sciences, 30*, 182–186. https://doi.org/10.1016/j.sbspro.2011.10.036

[4] Fink, G. (2017). *Stress: Concepts, cognition, emotion, and behavior: Handbook of stress.* Florey Institute of Neuroscience and Mental Health. Retrieved from https://www.researchgate.net/publication/317026245

[5] Shahsavarani, A. M., Abadi, E. A. M., & Kalkhoran, M. H. (2014). *Stress assessment and*

development of a primary care of psychology service. International Journal of Medical Reviews, 2(2), 230–241.

[6] Khademi, A., El-Manzalawy, Y., Master, L., Buxton, O. M., & Honavar, V. G. (2019). *Personalized sleep parameters estimation from actigraphy: A machine learning approach. Nature and Science of Sleep, 11*, 387–399. https://doi.org/10.2147/NSS.S220716

[7] Rachakonda, L., Bapatla, A. K., Mohanty, S. P., & Kougianos, E. (2021). *SaYoPillow: Blockchain-integrated privacy-assured IoMT framework for stress management considering sleeping habits. IEEE Transactions on Consumer Electronics, 67*(1), 20–29. https://doi.org/10.1109/TCE.2020.3043683

[8] Magana, V. C., & Munoz-Organero, M. (2016). *Reducing stress on habitual journeys. 5th IEEE International Conference on Consumer Electronics – Berlin (ICCE-Berlin 2015)*, 153–157. https://doi.org/10.1109/ICCE-Berlin.2015.7391220

[9] Subhani, A. R., Mumtaz, W., Saad, M. N. B. M., Kamel, N., & Malik, A. S. (2017). *Machine learning framework for the detection of mental stress at multiple levels. IEEE Access, 5*, 13545–13556. https://doi.org/10.1109/ACCESS.2017.2723622