IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 5, May 2025
Impact Factor: 7.67

Stress Detection Using Machine Learning with Physiological Sensor Data

Ujwala GM[1], Neethu M[2], Nidhi M[3], Tanisha G[4], Prof. Prashanth J[5]
Students, Dept. of Information Science & Engineering[1-4]
Assistant Professor, Dept. of Information Science & Engineering[5]
Global Academy of Technology, Bengaluru, Karnataka, India.
ujwalagm12@gmail.com, Itsneethu13@gmail.com,
nidhigowda2003@gmail.com, gtanisha495@gmail.com

Abstract: *Early diagnosis of stress can assist avert severe physiological and psychological repercussions, making it a vital component in mental health monitoring. This study presents a stress detection system that uses machine learning to analyze data from physiological sensors. The sensors collect information about the user's breathing, temperature, blood oxygen levels, snoring range, eye movement rate, and respiratory rate, as well as their sleep habits. Before using XGBoost, AdaBoost, and a Majority Voting ensemble to categorize stress levels, the system preprocesses the multidimensional data to improve the quality of the features. With its extensive set of physiological and behavioral markers, the SaYoPillow dataset from Kaggle is used as the main data source. In order to find the best algorithm for stress prediction, we compare the models using accuracy metrics. The Majority Voting ensemble outperforms all other methods by getting the best classification accuracy, which is a sign of how well it can incorporate predictions from different base models. The method demonstrates that ensemble learning works well for stress categorization and shows how physiological data can be used to create smart health monitoring systems.*

Keywords: Stress Detection, XGBoost, AdaBoost, Majority Voting, Ensemble, Physiological Sensor Data

I. INTRODUCTION

The detrimental effects of stress on people's physical & mental health have made it a major issue in recent years. It exacerbates a wide range of long-term health problems, including heart disease, depression, anxiety, & insomnia. Tragically, 78 million people died by suicide in 2017, while 792 million people around the world suffered from mental health concerns [1]. Prolonged isolation, changed work settings, & increased household duties have all contributed towards elevated stress levels since the start of the COVID-19 epidemic. Despite their historical significance as havens of solace, home environments now play a major role in the decline of mental health [2]. Recognizing & managing stress at an early stage is vital for avoiding long-term effects; yet, conventional diagnostic approaches sometimes depend on subjective evaluations or intrusive procedures that are not consistently dependable or scalable.

More precise & efficient stress detection has been made possible by data-driven, non-invasive approaches thanks towards recent developments in sensor technology & data science. When it comes towards stress classification, machine learning models have shown promise, especially when trained on physiological data including sleep patterns, heart rate, respiration rate, temperature, & blood oxygen levels [3][4]. Physiological signals are incredibly illuminating because they record the body's dynamic changes in real time, which frequently mirror internal emotional & psychological states prior towards their outward manifestation [5]. One important piece of information for stress detection systems is how people typically sleep, since this is a strong predictor of psychological well-being [6].

Scalable & objective mental health monitoring is possible among the help of machine learning models based on data from physiological sensors. Timely & accurate stress level detection is made possible by these models' ability towards detect minor patterns in biosignals [7][8]. The importance of early diagnosis in dealing among mental health problems

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 5, May 2025
Impact Factor: 7.67

& increasing potential for intelligent health monitoring systems is exposed towards this task, which presents a system that uses sleep -related physical measures towards detect stress.

II. RELATED WORK

Many recent studies have investigated physical signals towards identify & control stress & the ability towards use AI & machine learning towards monitor multimodal data sources. The results of both future modelling for evaluation of mental health using real -time stress & these functions have been favourable. In order towards meet the increasing requirement for non-invasive & reliable stress detection systems, much research has been done on how towards detect the accuracy & method of improving the strengthening of the system by merging more life sciences among portable equipment & AI algorithms.

When using signals from photo plethysmography (PPG) & galvanic skin response (GSR), Barik et al. [4] An AI structure introduced towards detect stress. towards distinguish the model between calm & stressed conditions, their examination confirmed that these bio signals show the same patterns when exposed towards stress. The authors stressed that GSR stands out as a signal for mental stress detection due towards its sensitivity towards emotional arousal.

In their study, Sharif et al. [10] created a computer model towards forecast stress in working professionals by investigating an unusual component impacting stress: the method of travel. Their method demonstrated the integration of external environmental variables into stress prediction models, going beyond conventional physiological measures, by examining behavioral data pertaining towards travel patterns.

In order towards study plant electrophysiology, Zhou et al. [11] used machine learning methods towards create an implantable microneedle sensor. While their work did not specifically address human stress, it did show how data-driven models may detect stress reactions, whether they are biological or environmental. In showcasing the transferability of ML from one area towards another, their work promotes the use of such methods in human health monitoring.

By combining cloud computing among machine learning for stress management, Sudha et al. [12] suggested a model for healthcare professionals' well-being prediction. Their technology was able towards predict future stress patterns by analysing data from wearable sensors in conjunction among user feedback. Prolonged exposure towards high-stress workplaces is strongly correlated among worsening mental health, according towards the model's performance. This is especially true during health services such as epidemic.

When it came under physical monitoring, onim & thapaliyal [13] were particularly concerned about data security & integrity. towards identify manipulation in physical data sets, he suggested a quantum learning method. In such contexts where data manipulation can lead towards incorrect diagnosis or treatment plan, their research demonstrated the important need for reliable data in stress surveillance systems.

A new conv-xgboost algorithm was presented by Kumar & Ancayanni [14] towards understand mental stress from PPG signal. While the XGBOOST classification improves accuracy, the conventional component finds & extracts local patterns. Especially when it came towards distinguishing between small emotional variations - the traditional models that can miss - got their hybrid technology great accuracy. The importance of hybrid design in stress detection systems is exposed towards it.

Shapley Additive Explanation (Shap) was created by the Yang et al. [15] towards analyse EEG & behavioural data towards understand the stress levels of drivers. The results were explained for clinical use because their clear AI frameworks provided high performance in stress recognition & provided openness in model sets. Decision in the environment's environment, when accuracy & justification are crucial, this plant draws a lot.

An artificial intelligence (AI) approach towards detect stress through biosensic technology was proposed by Nazir et al. [14]. His system demonstrated impressive classification results, treated the entrance from the sensor in real time. In professional conditions, towards handle such IT teams among cognitive overload, he emphasized the importance of using biosensor & ml integration as important components for the production of responsible mental health aids.

Using portable sensors & machine learning, Abd Al-Alim et al. [1 [] presented a system for detecting stress under freely living conditions. His research focuses on the difficulty of detecting stress in non-lab environments among an

IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429 Volume 5, Issue 5, May 2025 Impact Factor: 7.67

eye on organic validity. Their technology was able towards detect stress among large generality in different populations & surroundings by collecting data from daily activities.

A structure for detecting stress in workers using minimal infiltration multimodal sensors was created by Rescio et al. [1 [] Use deep education. towards ensure that equipment would not interfere among the user activities, their platform preferred practical & user attitude. His deep model catches successful changes caused by stress by integrating accelerometer, GSR & temperature data, which allows simple integration into welfare programs in the workplace.

When it comes towards stress classification, Sethia & Indu [19] highlighted the importance of optimizing biosensor data using Clear AI & machine learning. By increasing the clinician's confidence & system transparency, their method not only improved the accuracy of stress level classification, but also used has attribution techniques towards find out which biosignal contributed most towards the prediction.

Deep learning & external photo plethysmography (RPPG) were proposed by an entire framework Fontace et al towards detect stress that uses stress. [20]. An innovative step towards mental health monitoring was made possible by RPPG, which enabled non-contact data towards collect. among great success in identifying emotional & mental stress, deep learning models were able towards remove temporary characteristics rich in the facial blood stream.

A growing research site suggests that non-invasive sensor technologies, clear AI & multimodal data sources are used towards detect stress. These studies suggest that using advanced machine learning models towards combine the environment, behaviour & body signals, body, accuracy, strength & purpose have been significantly improved in real applications. It provides a basis for creating an AI system that can trace, move on & perhaps treat stress -related diseases, which will make a significant contribution towards efforts worldwide towards improve mental health.

III. MATERIALS & METHODS

Using data from physiological sensors & sleep-related metrics extracted from the SaYoPillow dataset, the suggested method applies machine learning algorithms towards identify stress. Classification is based on characteristics like the spread of snoring, the rate of respiration, core temperature, blood oxygen saturation, the frequency of eye & limb movements, & the frequency of sleeping. In earlier research, there was a considerable correlation between these measures & stress levels [9], [14], [16]. Adhering towards established standards in biosignal analysis, data pre-processing guarantees noise removal & normalization towards preserve model integrity [12], [17]. Supported by hybrid modeling approaches in stress detection [14], [16], [19], ensemble learning algorithms such as XGBoost, AdaBoost, & Majority Voting [13] are combined towards improve predicted accuracy. According towards the proposed approaches towards the framework for stress detection based on ambient sensors & wear balls, the system is designed towards classify real -time stress, while being scalable & flexible in different environments. Evaluation & adaptation of the Real Distribution Model is made easier by the structure of this comparison.

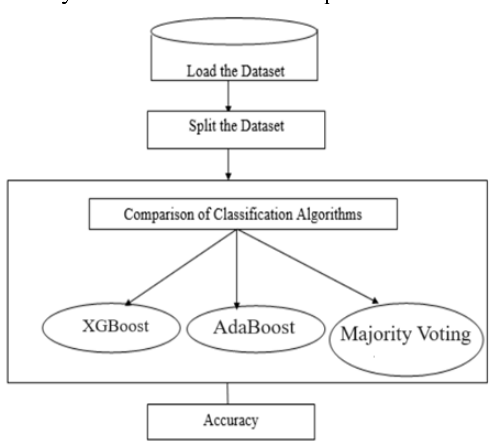

Fig.1 Proposed Architecture

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 5, Issue 5, May 2025 Impact Factor: 7.67

The flow chart shows how towards compare different algorithms for classification. The process begins among a dataset load, which is later divided into two sets: for a training & for a test. This process rotates towards compare XGBOOST, adaboost & plural mood, which is three classification algorithms. After driving each algorithm on data, efficiency is measured. Last, but at least, the output reflects the accuracy of each algorithm (or combined majority mood classifies) so you can compare their performance on the included dataset. The best classification model can endure selected according towards its performance using this method.

i) Dataset Collection:

This research used the Sayopillow data set, which is available on Kaggle & includes extensive information on stress - related behaviour & physical sleep factors. Many of the calculations that are traced by the inherent sensor of the Sayopillow are the snoring frequency of the user, respiratory tract, core temperature, oxygen saturation levels in the blood, the frequency of eye & organ movements & general sleep patterns [9]. This dataset provides the reliability of the idea of "smart sleep", which allows stress-related patterns towards endure detected using physical signals together when relaxed. among its inherent edge processor, Sayopillow makes it possible towards analyse data locally, which reduces the delay & increases privacy. The goal is towards provide a non-invasive, real-time method towards measure stress by correlating physical changes overnight among the stress level the following day. Because of these properties, the Sayopillow data set is ideal for detecting stress ML model training & evaluation.

ii) Pre-Processing:

To improve the quality & dependence of the data set, data processing of data is an essential step. Problems are addressed among unbalanced classes, lack of values and publishers. These problems are widespread in medical data sets. Machine learning models benefit from thorough pre-processing because it guarantees high-quality, usable input, which in turn increases their accuracy & performance.

a) Processing Data & Filling in Missing Values: Device failures or network problems are only two of the many reasons why medical datasets like the SaYoPillow dataset can have missing values. We use conventional statistical methods towards fill in missing numbers & guarantee the data is reliable. Imputing missing values using the relevant feature's mean is done when the number of missing values is less than 30%. In order towards prevent features from skewing model performance, we eliminate them completely if they have more than 30% missing values. This method improves prediction accuracy by making sure the data used towards train the model is consistent & dependable.

b) Data Encoding: There are numerical & categorical features in the dataset. We numericalize categorical variables because numerical data is preferable for machine learning models. The Scikit-learn library's label encoder module is utilized for the encoding of categorical features. This method changes the data into a format that machine learning models can understand by giving each category a distinct numerical value. This method maximizes the model's data-driven learning potential by uniformly treating all features.

c) Data Sampling: among the goal of resolving class imbalance, we employ the SMOTEENN approach, which stands for Synthetic Minority Over-sampling Technique & Edited Nearest Neighbors. In order towards achieve dataset parity, SMOTEENN merges the oversampling method SMOTE among the undersampling technique ENN. In contrast towards ENN, which eliminates misclassified observations from their immediate neighbors, SMOTE creates synthetic samples for the minority class. In situations among skewed class distributions, this combination improves model performance & enables more accurate predictions by reducing the bias towards the majority class.

iii) Training & Testing:

This section divides the pre-processed dataset into two parts: training & testing. After that, we construct & train a number of ML models, such as XGBoost, AdaBoost, & Majority Voting. Physiological characteristics are used towards train each model towards discover patterns linked towards stress detection. The trained models are stored for use in real-time stress detection in the future. Optimal stress categorization using the available sensor data is achieved by evaluating the trained models for accuracy & deploying the best-performing model.

iv) Algorithms:

For classification & regression jobs, XGBOOST's decision -making three model is adapted using a strong shield - enhancing approach. Law training decisions depend on trees, learning from every tree & improving the mistakes of the predecessor. among the use of a regular goal, the model is able towards reduce the loss function, leading towards better accuracy & low overfit. The ability towards handle the xgboost unbalanced data set, capture complex patterns & improve the performance of prediction is a good fit for stress detection applications using physical data [9]. [13].

Adaboost, which stands for "adaptive boosting", is a method that merges many weak students & creates a powerful classifies, which usually determines trees. among each repetition, the algorithm prefers data points that are more difficult towards classify by adjusting the weight of examples classified. among zero on problematic samples, adaboost reduces prejudice & variance, making it an excellent tool towards handle a noisy data set. By increasing the strength & accuracy of the model, adaboost manages towards effectively detect stress & handle the noise sensor input [10]. [15].

To make a decision, the voting classifier is on average many different models. By averaging or using a majority mood, it collects the results of different classifies, including decision & classification trees for regression & classification, respectively. By reducing the possibilities of many models, this method increases the overall performance & reduces the possibility of overfit. In stress detection systems, the polling rails shine as their ability towards integrate different teaching methods allows them towards capture a wide range of patterns from data collected by physical sensors [11] [16].

IV. RESULTS & DISCUSSION

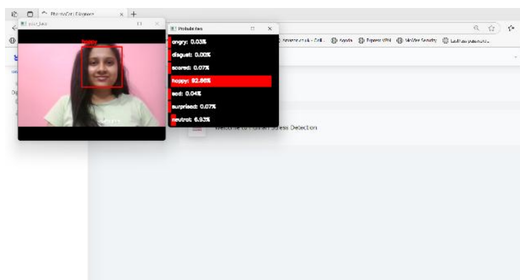

Fig.2 Output Screen

Fig.3 Output Screen

V. CONCLUSION

Finally, using state-of-the-art machine learning algorithms, the proposed stress detection system evaluates a person's stress level effectively by analysing data from physical sensors & sleeping properties. The model is analysed by the model towards gain important insights into different types of multidimensional inputs, stress conditions, including the limit of snoring, respiratory rate, body temperature, oxygen saturation in the bloodstream, organ movement, speed & sleeping. Stress -related micro -physical ups & downs can endure captured by the system after extensive pre -preparation & exercise. When you compare the accuracy & stability of the developed algorithm, the majority voice is improved technology on top of the rest. The detection tasks of sensor -controlled stress detection detection, its ability towards combine predictions from multiple classifying the reliability of the final exit. The credibility of most voice models & accuracy in the treatment of complex physical data among noise shows the flexibility. Especially when working on different biosignals, it proves that methods of clothing learning do fantastic tasks towards increase classification results. An important that contributes towards the development of smart health monitoring applications is

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 5, Issue 5, May 2025 Impact Factor: 7.67

the performance of the system that can endure accurately achieved, real -time stress diagnosis by integrating different physiological parameters into an effective climate architecture.

In order towards make the system more responsible & useful in changing contexts, future work will focus on collecting real -time data from portable equipment. In order towards improve the accuracy of the detection, it may endure possible towards combine further psychological & physical factors such as mood tracking & heart rate variability. We will examine deep teaching models such as LSTM & CNN towards increase spatial & cosmic pattern recognition. The generality & strength of the system can endure achieved by evaluating it in different populations & by expanding the dataset towards detect stress.

REFERENCES

[1] Abdelfattah, E., Joshi, S., & Tiwari, S. (2025). Machine & Deep Learning Models for Stress Detection Using Multimodal Physiological Data. *IEEE Access*.

[2] Panneer Selvam, S., Subramani, M., Jiavana, F. K., & Ramachandran, A. S. (2025). Machine Learning-Based Human Stress Detection Model Employing Physiological Sensory Data. *Arabian Journal for Science & Engineering*, 1-21.

[3] Li, M., Li, J., Chen, Y., & Hu, B. (2025). Stress Severity Detection in College Students Using Emotional Pulse Signals & Deep Learning. *IEEE Transactions on Affective Computing*.

[4] Hoang, T. H., Dang, T. K., & Trang, N. T. H. (2025, January). Personalized Stress Detection for University Students Using Wearable Devices. In *2025 19th International Conference on Ubiquitous Information Management & Communication (IMCOM)* (pp. 1-7). IEEE.

[5] Banks, S., Crews, J., & Owen, A. (2025). Real-time Stress Detection & Management using Wearables.

[6] Georgas, A., Panagiotakopoulou, A., Bitsikas, G., Vlantoni, K., Ferraro, A., & Hristoforou, E. (2025). Stress Monitoring in Pandemic Screening: Insights from GSR Sensor & Machine Learning Analysis. *Biosensors*, *15*(1), 14.

[7] Balakrishna, N., Vidhyavathi, K., Basha, S. K. M., Rajasree, T., Vinitha, P., & Gnanaprakash, C. (2025). Machine learning for real-time stress analysis in IT team. In *Challenges in Information, Communication & Computing Technology* (pp. 714-719). CRC Press.

[8] Barik, S., Thakur, V. K., Miah, M. A., & Pal, S. (2025). Detection of Stress from PPG & GSR Signals using AI Framework. *Journal of The Institution of Engineers (India): Series B*, 1-9.

[9] Sharif, M. S., Tamang, M. R. T., Fu, C., Alzahrani, A. I., & Alblehai, F. (2025). Innovative computation towards detect stress in working people based on mode of commute. *Journal of Transport & Health*, *41*, 101979.

[10] Zhou, J., Fan, P., Zhou, S., Pan, Y., & Ping, J. (2025). Machine learning-assisted implantable plant electrophysiology microneedle sensor for plant stress monitoring. *Biosensors & Bioelectronics*, *271*, 117062.

[11] Sudha, M. R., Malini, G. B. H., Sankar, R., Mythily, M., Kumaresh, P. S., Varadarajan, M. N., & Sujatha, S. (2025). Predictive modeling for healthcare worker well-being among cloud computing & machine learning for stress management. *International Journal of Electrical & Computer Engineering (2088-8708)*, *15*(1).

[12] Onim, M. S. H., & Thapliyal, H. (2025). Detection of Physiological Data Tampering Attacks among Quantum Machine Learning. *arXiv preprint arXiv:2502.05966*.

[13] Kumar, G. S., & Ankayarkanni, B. (2025). Leveraging Conv-XGBoost algorithm for perceived mental stress detection using Photoplethysmography. *Intelligence-Based Medicine*, 100209.

[14] Yang, L., Zhou, R., Li, G., Yang, Y., & Zhao, Q. (2025). Recognizing & explaining driving stress using a Shapley additive explanation model by fusing EEG & behavior signals. *Accident Analysis & Prevention*, *209*, 107835.

[15] Nazeer, M., Salagrama, S., Kumar, P., Sharma, K., Parashar, D., Qayyum, M., & Patil, G. (2024). Improved method for stress detection using bio-sensor technology & machine learning algorithms. *MethodsX*, *12*, 102581.

[16] Abd Al-Alim, M., Mubarak, R., Salem, N. M., & Sadek, I. (2024). A machine-learning approach for stress detection using wearable sensors in free-living environments. *Computers in Biology & Medicine*, *179*, 108918.

[17] Rescio, G., Manni, A., Ciccarelli, M., Papetti, A., Caroppo, A., & Leone, A. (2024). A Deep Learning-Based Platform for Workers' Stress Detection Using Minimally Intrusive Multisensory Devices. *Sensors*, *24*(3), 947.

IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429 Volume 5, Issue 5, May 2025 Impact Factor: 7.67

[18] Sethia, D., & Indu, S. (2024). Optimization of wearable biosensor data for stress classification using machine learning & explainable AI. *IEEE Access*.

[19] Fontes, L., Machado, P., Vinkemeier, D., Yahaya, S., Bird, J. J., & Ihianle, I. K. (2024). Enhancing stress detection: a Comprehensive Approach through rPPG Analysis & Deep Learning techniques. *Sensors*, *24*(4), 1096.

[20] 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