Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 44 No. 7
July 2023

Mental Stress Detection Using Ensemble Machine Learning Method

*1 **Vanisha P. Vaidya**
vanisha.vaidya@gmail.com
Department of Computer Science and Engineering
Dr. A. P. J. Abdul Kalam University, Indore ,India

*2 **Dr Suresh S. Asole**
suresh_asole@yahoo.com
Department of Computer Science and Engineering
Babasaheb Naik College of Engineering,Pusad ,India

Abstract: These days, it's common for people to feel mild to severe psychological strain in an array of circumstances. A person can benefit from a reasonable amount of stress, but excessive stress has a detrimental influence on mental health and raises the risk of thoughts of suicide if left unchecked for an extended period of time.Long-term stress has been shown to be related to physical health issues. It is essential to be able to identify stress at a young age and assist individuals in realising and resolving it before significant harm is done since a growing number of people are experiencing stress. Machine learning approaches have become quite prominent in research in the area of stress detection. In this study, we focused on identifying stress management using machine learning techniques on the mental stress dataset, which was acquired from a 2014 survey that evaluates views on mental stress and the frequency of mental stress sickness in the IT sector.We observed that ADA-Boost had the highest accuracy rate of all the machine learning models (81.75%, AUC of 0.8185), using the provided dataset to train and test them.

Keywords*:* Mental Stress Detection, Machine Learning, ADA-Boost

1. Introduction:

Today, managing stress has become essential for people of all generations, and this issue requires extensive global attention since, according to the survey, 86% of people worldwide experience stress, compared to 89% of people in India. Approximately 75% of the local community lacks the confidence to discuss their pressures with a care provider and the expense of bringing up the issue as one of the challenges. Thus, the study of stress and its management is currently the most popular topic among scholars (Source: 2018 Cigna 360° Well-Being Survey – Future Assured).

Stress is the body's physical, behavioural, and expressive response to external as well as internal factors (such as the occurrence of illnesses and infectivity, lack of sleep, feeling exhausted, emotions, and expectations), including workplace tension, interpersonal disputes, contamination, chemical & physical climate, poor job health, and illness.One of the causes of stress is when a person encounters an unusual scenario and struggles to cope with the worry and anxiety that comes with it. A person often experiences stress when their mental and physical resources or instruments readily available to them don't meet their demands at that particular time[1].

Other physiological indicators include an elevated pulse (Heart Rate Variability), a particular respiration rate, galvanic skin, the length of the apprenticeship, strain in the muscles, etc.The autonomic nervous system's (ANS) first functions should be according to the body's physiological reaction to stress. [2]. Chronic stress would upset the balance between the sympathetic and parasympathetic ANS, which are the two divisions of ANS. While enhancing the sympathetic branch, the parasympathetic branch may be reduced. The heart function should then be informed of this change in information, which is often calculated using electrocardiogram (ECG) signals in medical equipment. As a result, the ECG data signal is widely accepted around the world as a legitimate and trustworthy input signal for the evaluation of human stress.

The variation of heart rate (HRV) is one of several variables[3], The most crucial signal variance detection for analysing ECG data is thought to be the difference between two subsequent ECG signal pulses' time intervals. Since only R peaks are necessary for measurement and R levels have the highest ECG intensity, HRV is unaffected by interference and disruption.[3]. As a result, HRV is a widely utilised stress management technique.Upon identification of any of the R spikes, HRV characteristics for stress detection can be obtained[3]. Typically, a certain duration is chosen, and the functions inside the frame are measured.

Several ways can be found to estimate a person's degree of stress utilising machine learning and deep learning techniques.The individual's daily activities, stress from job or other commitments, and workplace are all included in various datasets. Electrocardiogram (ECG) signals, Electroencephalogram (EEG), Electromyogram (EMG), and Heart Rate Variability (HRV) datasets that are available from many research groups can be utilised to train machine learning algorithms to detect human stress at an early stage.

In this study effort, we are primarily focused on psychological wellbeing prediction. analysing data from a 2014 survey that looked at perceptions of mental health and the incidence of mental health concerns in the IT sector using machine learning.

Using a stress management dataset, we developed an ensemble technique in this article to identify the mental stress of several machine learning classification models and compare the performance. The dataset was trained and evaluated using machine learning techniques, and the results showed that ADA-Boost obtained 81.75% accuracy with an AUC of 0.8185..Using analysis of data and visualisation, we were also able to glean some conclusions from the information.

2. Literature Review:

In diverse locations and climates, Monika Chauhan et al. suggested employing a variety of pre-planning tactics to detect stress using electrocardiographs and physiological data.[4]. The framework uses Support Vector Machines (SVM) to classify a person's typical mood and tension[5], Linear discriminant analysis (LDA) and decision trees [6]. They discovered that their model had an accuracy of about 90%.

A. Alberdi et al.'s most accurate stress detection systems showed that using signals from the body is much more precise than using the other modalities[7]. The research shows that behavioural & contextual information may be utilised to properly detect stress, so this is not to argue that they cannot be employed. There is more work to be done in this field, though. Additionally, the outcomes showed that ECG and EDA are the most precise physiological markers for stress detection when HRV properties are taken into account. In order to create a considerably less intrusive and all-encompassing monitoring system that is much more workable in real life, the same level of precision, if not more, would be required when using data collected in different modalities, such as behavioural reactions.

The rate of variation between each beat in time is known as HRV. The Autonomic Nervous System (ANS), which regulates the body's automatic functions like heartbeat, respiration, digestion, blood pressure, urine production, and pupil dilation and constriction, is the subject of this study.In this work, S. Ishaque et al. use signal processing and machine learning to synthesise and assess studies on HRV pertaining to morbidity, pain, tiredness, stress, and exercise. The significance of HRV research and the constraints on approaches that may be addressed to improve study quality have been carefully considered. 25 papers that only considered the ECG, EDA, PPG, and RESP analyses of physiological signals examined the reasons for increased/decreased HRV. Lower HRV was associated with increased stress and morbidity.High HRV was typically associated with great health, although it might occasionally indicate clinical conditions like tiredness[8].

Luz Santamria-Granados et.al [9]used the Deep Convolutional Neural Network for Emotion recognition on a Physiological Signals Dataset (AMIGOS) to research the recognition of mental stress.It is possible to detect an individual's effective state by comparing these behavioural signals with the intensity and valence data of this dataset. Additionally, it is urged to provide data for emotion analysis based on conventional machine learning techniques in order to ascertain the characteristics of physiological signals in the domains of time, frequency, and non-linearity.In this programme, fully connected network layers (FCN) are utilised to forecast emotions and CNN is used to autonomously gather physiological signalling functions.The experimental results on the AMIGOS dataset show that the approach used in this research provides a greater level of accuracy in the categorization of emotional states as compared to the results previously obtained by the dataset's developers.

Wanqing Wu et.al [10]The authors of the study, "Quantitative Assessment for Self-tracking of Acute Stress Based on the Triangulation Principle in Wearable Sensor Systems," suggest a model based on logistic regression that integrates data from the psychological (Stress Response Inventory, SRI), biochemical (salivary cortisol), and physiological (HRV measures) domains via a principle of triangulation in order to achieve high reliability and consistency during stress assessment.The proposed model, which focused on the link between salivary cortisol levels and time-/frequency-domain HRV properties, resulted in the creation of a mental stress index (MSI).

MinijaMi, et.al. [11]offered a method for real-time stress recognition using peripheral physiological indicators in an effort to reduce human error and improve the effectiveness of regressive stress recognition.The proposed paradigm was presented as a transductive model that focused on transductive learning and saw local learning as a benefit of the neighborhood's knowledge of excellent instruction.

Assessing the acute stress response using physiological signs:In contrast to a quantitative evaluation of stress analysis research by Adriana Arza and colleagues, a multivariable approach is presented to comprehensively quantify the physiological stress reaction using stress biomarkers obtained from skin temperature, heart rate, and pulse wave signals.Additionally, following the suggested method, five statistically distinct stress thresholds brought on by the tasks completed were also determined[12].

In this study, Mahesh Bhargavi et al. outline the specifications that an authoritative dataset for multimodal human stress detection should meet. Reviews of scientific and medical research isolate the standards that are centred on current practises and objective facts. None of these data sets was found to fully satisfy the requirements to be registered as a dataset for comparison. Future attempts may potentially focus on developing such a comparison dataset while addressing the existing standards[13].

Each of the developed systems first built classification models using machine learning methods after gathering attributes using a different method. Support vector machine, random forest, and K-Nearest Neighbours are three of the best classification algorithms, however heart rate, heart rate variability, and skin conductance traits are superior at predicting a person's stress level.This shows how sensors on clothing and machine learning algorithms may be used to use physiological data to accurately and reasonably determine stress in an individual[14].

In the most recent research on virtual reality (VR) stress evaluation presented by Z. Ahmad et al., three levels of stress were identified[15]. While riding a simulated roller coaster, nine people had their ECGs taken.The VR experience was then manually divided into three levels of stress in 10-second intervals by three evaluators.Then we offer a unique multimodal deep fusing model that can predict stress from a single 1-second frame utilising spectroscopy and 1D ECG data.Trials show that the suggested approach works better than baseline deep learning methods (2.5% increase in accuracy) and conventional HRV-based machine learning models (9% increase in accuracy).In order to demonstrate the model's superiority, we also offer findings using the reference WESAD dataset.

The method for identifying human stress in this work by P. Karthikeyan et al. involves analysing short-term (less than 5 min) ECG and HRV data[16]. It is more reliable and increases the rate of stress detection when many pieces of data from the same sensor are used. This study employed a stress-inducing technique, data collection, pre-processing, feature extraction, and classification to identify stress. A stress-inducing activity using Stroop colour words was delivered to each individual, and an ECG signal was captured simultaneously. High-frequency, baseline wandering was removed using a technique for wavelet de-noising. A discrete wavelet transform (DWT) was used to extract the HRV signal from the pre-processed ECG data. The noise peaks in the HRV data were eliminated using the ectopic beat reduction technique. Due of uneven HRV signal sampling (LSP), the Lomb-Scargleperiodogram has been successfully utilised to identify stress. Uneven sampling and power spectrum information concerns have been handled by the use of LSP in short-term HRV signals (32 s), and theory and experiment have demonstrated the short-term HRV signal's dependability. According to theoretical study, at least 25 seconds worth of online or offline ECG data are needed to analyse ANS activity associated to stress. The HRV signal (FFT) has been replaced with an ECG-based stress assessment. Using PNN and kNN classifiers with different smoothing factors and k values, different ECG and HRV characteristics were divided into normal and stress categories. The total average classification accuracy for short-term ECG and HRV signals was 94.66 percent in the subject-dependent mode and 91.66 percent in the subject-independent mode.

Based on the hypothesis that anomalous heart rate periods are frequently brought on by a stressor or uplifting events, Z.Feng et al. proposed a method for merging heartbeat rates and language postings on microblogs for stress diagnosis.[17]. The author had begun by identifying an individual's aberrant heart rate intervals and then linking them with a temporally synchronised and highly matched abnormal posting (stressful/exciting) period discovered from microblogs. The four-month user study with ten willing college students showed that matching post-based detection outcomes to ECG-based identification results can achieve over 84% accuracy for detecting exciting or stressful periods and about 70% accuracy for detecting stressful or uplifting events.The outcomes also showed that SDNN is the most reliable ECG signal indication for identifying daily excessive heart rate and stress.

3. Materials And Methods:

1. **Dataset:**As noted earlier, we investigated stress detection using machine learning utilising the dataset obtained from a 2014 survey that evaluates views on mental stress and the frequency of mental stress diseases in the IT sector. The dataset's (1259*27) representation.
2. **Pre-processing and Encoding Data:**Missing values make up the dataset utilised for this investigation. To address various columns' missing values, we worked with the Pandas missing value handling technique[18]. We removed the accessible columns comments, work_interface, state, and self_employed since they had missing data so that the remaining columns could be processed.Following data cleaning, we used sklearn's Label Encoder methods to encrypt any string-valued data that was present in the dataset[19].
3. **Covariance Matrix& Feature Selection:**We used the covariance matrix and the pandas corr() function to analyse the relationship between the features[20]. The covariance matrix is seen in picture 1 below.We used the feature selection approach to identify the top 10 characteristics that had the greatest influence on the target variable since the dataset we evaluated for this study included a high number of features (26) and we wanted to be able to detect mental stress early. The top 10 characteristics are displayed together with their covariance values in figure 2 below.

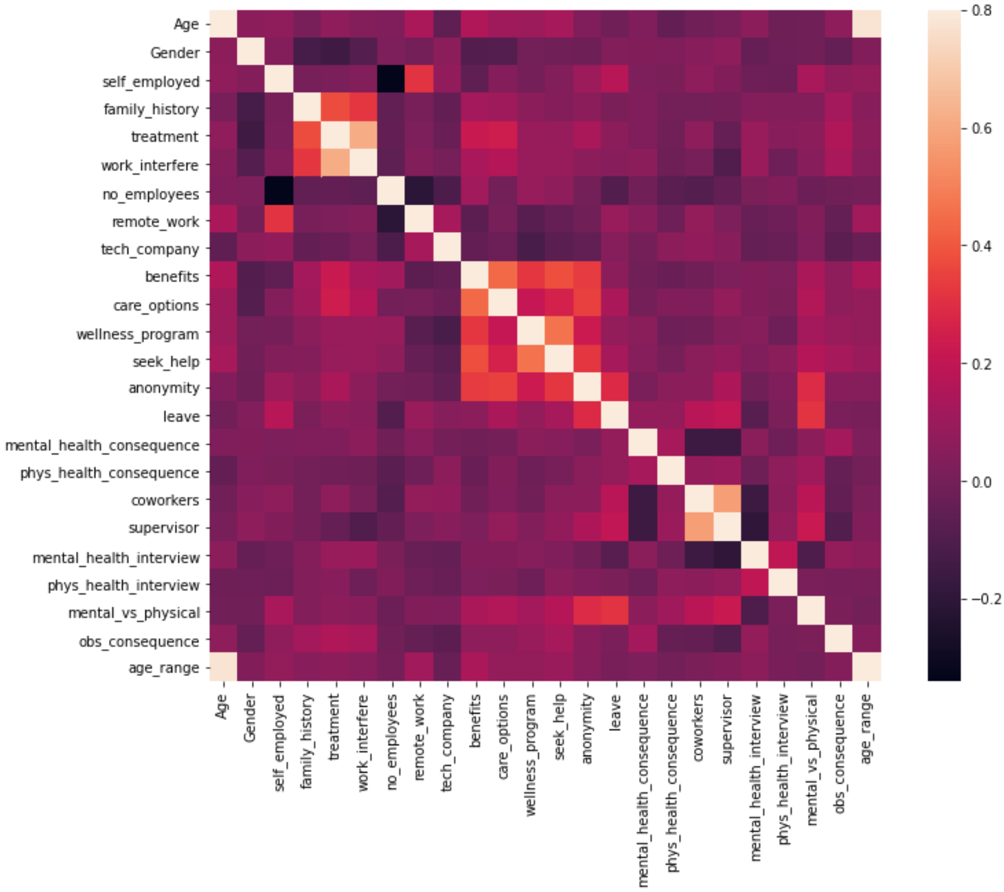

Figure 1: Covariance Matrix

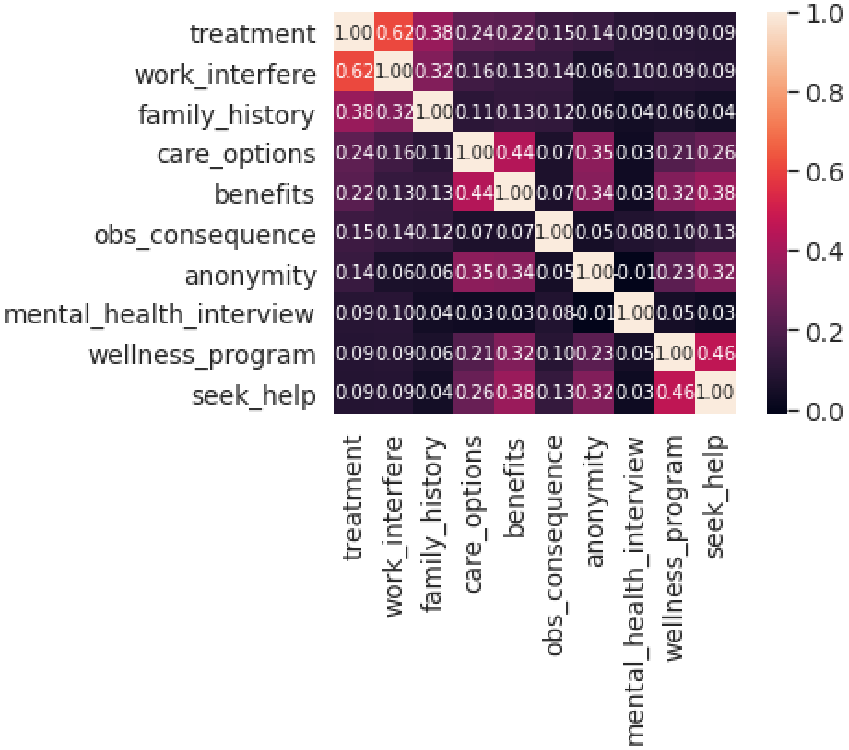

Figure 2: Top 10 Feature Co-Variance Matrix

4. Figure 2 shows that work_interface and the goal variable have the largest correlation, 0.62,

followed by wellness_program and benefits, 0.46 and 0.44 respectively.

5. **Data Exploratory Analysis**:We performed a lot of Data Exploratory Analysis (DEA) to understand the data from a close perspective after cleaning the data and prior applying machine learning to the dataset. This will help us use the appropriate machine learning model on the supplied dataset. We conducted analysis by creating an age column for the density histogram, the overall gender distribution of psychological stress identification and its treatment, the likelihood of mental stress conditions, the likelihood of mental health conditions specific to different age groups, etc. Considering the constraint of paper length, we are putting only the following graph for the probability of age group-wise mental health conditionsas shown in Figure 3.

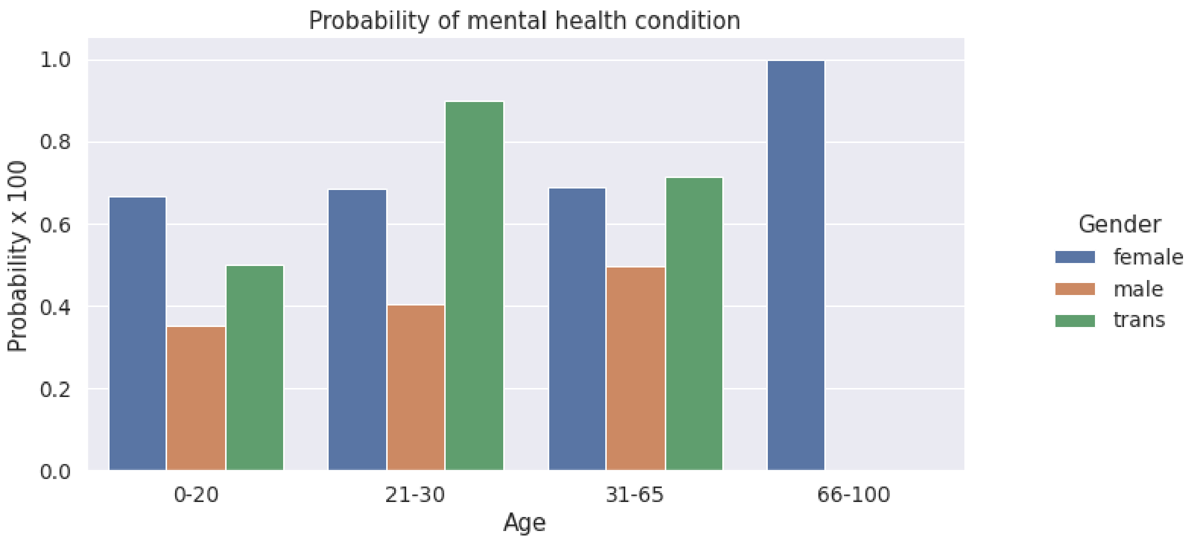

Figure 2: Probability of Mental Health Condition Age Group Wise

The barplot in Figure 3 shows the psychological health of men, women, and transgender persons by age range. We may conclude that, when compared to other genders, ladies have much better mental health in the age range of 66 to 100.And from age 21 to 64, transgender people have far better mental health than men do.

6. **Scaling and Fitting:**We also used a min-max scaler[21]Use the provided dataset to improve the model's performance.The top attributes shown in Figure 4 below were chosen for our machine learning model's final evaluation.

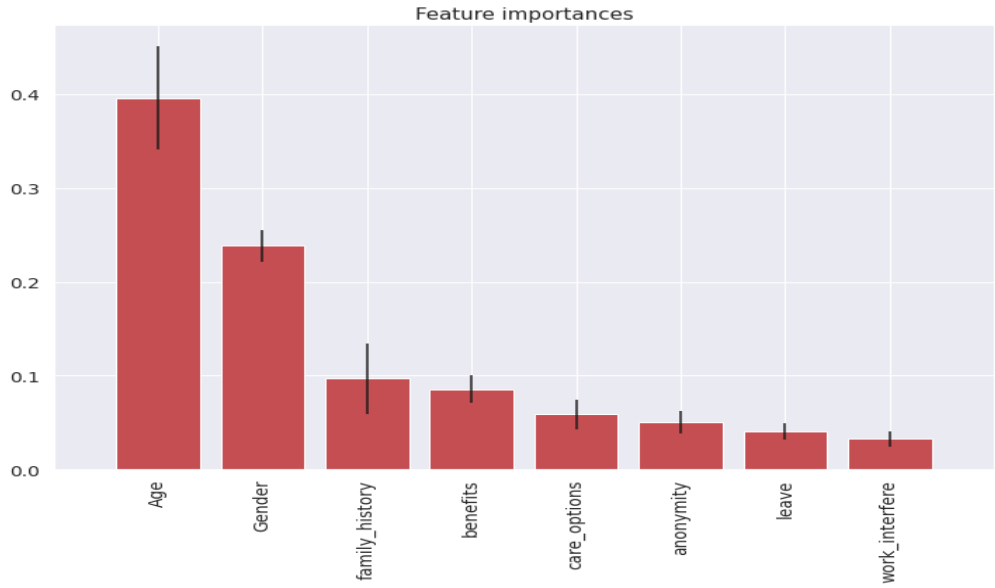

Figure 3: Feature Importance Matrix

7. **Model Evaluation:**Following DEA and feature extraction, we used a variety of classification models based on machine learning to analyse the dataset and predict mental stress. For this, the data was divided using random state 1 and a train-test split ratio of 70:30. We used cross-validation with 10 folds to obtain an objective machine learning model, using GridSearchCV for parameter tweaking[22]Added to RandomizedSearchedCV with 10 fold cross-validation, 5 random states, and 10 repetitions.The categorization error rate, the false-positive rate, accuracy, area under the curve (AUC) score, and cross-validated AUC score were the metrics used to evaluate the model. Confusion matrix was developed. Additionally, the ROC curve for several classifier models is shown.

4. Results And Discussion:

Using the confusion matrix, ROC curve, and precision-recall (PR) curve, we evaluated the suggested ensemble Ada-Boost model's performance in classifying stress signals. [23]. One can evaluate how well the predicted value corresponds to the actual seen value using a matrix termed the confusion matrix.

Table 1 presents the results of the formulae used to evaluate the performance of the classification model, including accuracy, specificity, sensitivity, precision, and negative predictive values. (1)– (5). Formula (1) Accuracy is defined as the likelihood of correctly categorising all low-stress and non-stress circumstances.The letters TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) are used in the formula to signify true positive, true negative, false positive, and false negative, respectively.

$$Accurcay = \frac{(TP+TN)}{TP+TN+FP+FN} \quad (1)$$

Sensitivity is the percentage of data that are accurately identified as being free of stress compared to all free of stress data (actual observed data).

$$Sensitivity = \frac{TP}{FN+TP} \quad (2)$$

The percentage of data that are accurately identified as under stress amongst all under-stress data (actual observed data) is known as specificity.

$$Specificity = \frac{TN}{TN+FP} \quad (3)$$

Precision is the proportion of data properly identified as being free of stress by the stress algorithm for classification to the total amount of data correctly identified as being free of stress.

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

The ratio of the real worth without the stress data to the data that was properly diagnosed as being under stress is the negative predictive value.

$$Negative\ Predicted\ Value = \frac{TN}{TN+FN} \quad (5)$$

Table 1: Classification performance assessment of stress prediction

Model	Accuracy	Classification Errors	False Positive Rate	Precision	AUC Score	Cross Validated AUC
Logistic Regression	0.79	0.2037	0.2565	0.7644	0.7968	0.8753
KNN	0.8042	0.1957	0.2931	0.7511	0.8052	0.8782
Decision Tree	0.8068	0.1931	0.3193	0.7415	0.8082	0.8818
Random Forest	0.8121	0.1878	0.3036	0.75	0.8134	0.8934
Ada Boost	0.8174	0.1825	0.2827	0.7610	0.8185	0.8746

We can create different machine-learning models utilising all of these dataset items.The model that performed the best overall was ADA-Boost, which had an AUC of 87.46% and an accuracy rate of 81.74%.

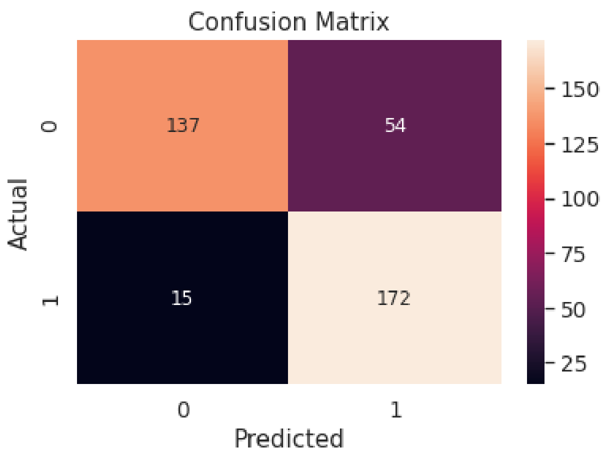

Figure 5 (a): Confusion Matrix Adaboost Classifier

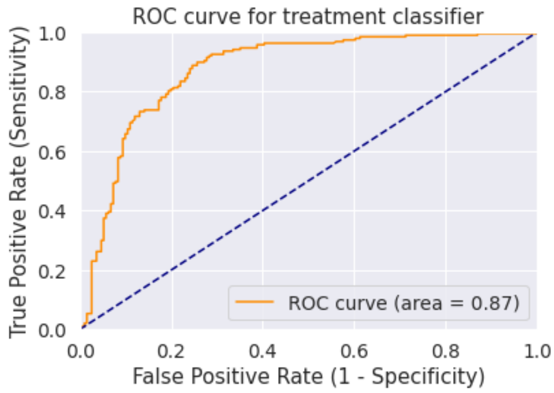

Figure 4(b): ROC Curve Ada-Boost Classifier

Discussion: To improve the classification of mental stress and prevent overfitting, an optimal combination of models was created in this study using a min-max scalar to scale the data. Additionally, just the top 10 characteristics were picked for artificial intelligence model training and testing in order to forecast in less time.An evaluation of the classifier's performance was done using a confusion matrix, ROC, and other metrics. Classification by KNN [24]earned a cross-validation Area Under Curve (AUC) score of 87.82%, a Precision of 75.11%, and an overall accuracy score of 80.42%. The decision tree classifier[25] achieved an 80.68% accuracy score, and 74.15% precision and the cross-validated AUC score was 88.18%. The Random Forest [26]performedwith an 81.21 % accuracy score, 76.10% precision, and 89.34% cross-validated AUC Score. The Adaboost, on the other hand, had the best performance, scoring 81.74% accuracy, 76.10% precision, and 87.46% cross-validated AUC.By using just the top 10 characteristics from the dataset that had the greatest influence on mental stress, we employed the conventional scaling strategy, which helped us increase the model's performance in comparison to prior work.

5. Conclusion:

In this paper, we suggested a more precise ensemble model based on the Adaboost Classifier to distinguish between different types of mental stress. The top 10 characteristics were chosen, and conventional scaling was applied to the dataset, to prevent algorithm overfitting and increase classifier accuracy. The suggested ensemble model has an 87.46% cross-validated AUC score, an accuracy of 81.74% for stress classification, and a precision of 76.10%. By using neural networks on the given dataset, we hope to significantly increase accuracy in the future.Given that it can rapidly and reliably categorise the stress that contemporary individuals experience, the stress classifier that we have presented is anticipated to be useful in the management of mental stress.Through routine stress management, it is also anticipated to help in the prevention of several ailments including diabetes, high blood pressure, and depression.

References:

[1] A. Sharma and R. Jain, "A STUDY ON STRESS AND ITS EFFECTS AT WORKPLACE: A LITERATURE REVIEW," vol. 5, 2018, Accessed: Sep. 22, 2021. [Online]. Available: www.jetir.org.

[2] R. Sharma, D. Goel, M. Srivastava, and R. Dhasmana, "Differences in Heart Rate and Galvanic Skin Response among Nurses Working in Critical and Non-critical Care Units," *J. Clin. Diagnostic Res.*, vol. 12, pp. 9–12, Nov. 2018, doi: 10.7860/JCDR/2018/35602.12244.

[3] R. Castaldo, P. Melillo, U. Bracale, M. Caserta, M. Triassi, and L. Pecchia, "Acute mental stress assessment via short term HRV analysis in healthy adults: A systematic review with meta-analysis," *Biomed. Signal Process. Control*, vol. 18, pp. 370–377, 2015, doi: 10.1016/j.bspc.2015.02.012.

[4] M. Chauhan, S. V. Vora, and D. Dabhi, "Effective stress detection using physiological parameters," *Proc. 2017 Int. Conf. Innov. Information, Embed. Commun. Syst. ICIIECS 2017*, vol. 2018-Janua, pp. 1–6, 2017, doi: 10.1109/ICIIECS.2017.8275853.

[5] R. Ribeiro and J. P. Cunha, "A regression approach based on separability maximization for modeling a continuous-valued stress index from electrocardiogram data," *Biomed. Signal Process. Control*, vol. 46, pp. 33–45, Sep. 2018, doi: 10.1016/j.bspc.2018.06.006.

[6] P. M. Mohan, V. Nagarajan, and S. R. Das, "Stress measurement from wearable photoplethysmographic sensor using heart rate variability data," *2016 International Conference on Communication and Signal Processing (ICCSP)*. IEEE, 2016, doi: 10.1109/iccsp.2016.7754331.

[7] A. Alberdi, A. Aztiria, and A. Basarab, "Towards an automatic early stress recognition system for office environments based on multimodal measurements: A review," *J. Biomed. Inform.*, vol. 59, pp. 49–75, 2016, doi: https://doi.org/10.1016/j.jbi.2015.11.007.

[8] S. Ishaque, N. Khan, and S. Krishnan, "Trends in Heart-Rate Variability Signal Analysis," *Front. Digit. Heal.*, vol. 3, p. 13, 2021, doi: 10.3389/fdgth.2021.639444.

[9] L. Santamaria-Granados, M. Munoz-Organero, G. Ramirez-Gonzalez, E. Abdulhay, and N. Arunkumar, "Using Deep Convolutional Neural Network for Emotion Detection on a Physiological Signals Dataset (AMIGOS)," *IEEE Access*, vol. 7, no. c, pp. 57–67, 2019, doi: 10.1109/ACCESS.2018.2883213.

[10] W. Wu, S. Pirbhulal, H. Zhang, and S. C. Mukhopadhyay, "Quantitative Assessment for Self-Tracking of Acute Stress Based on Triangulation Principle in a Wearable Sensor System," *IEEE J. Biomed. Heal. Informatics*, vol. 23, no. 2, pp. 703–713, 2019, doi: 10.1109/JBHI.2018.2832069.

[11] M. Li, L. Xie, and Z. Wang, "A transductive model-based stress recognition method using peripheral physiological signals," *Sensors (Switzerland)*, vol. 19, no. 2, 2019, doi: 10.3390/s19020429.

[12] A. Arza *et al.*, "Measuring acute stress response through physiological signals: towards a quantitative assessment of stress," *Med. Biol. Eng. Comput.*, vol. 57, no. 1, pp. 271–287, 2019, doi: 10.1007/s11517-018-1879-z.

[13] B. Mahesh, E. Prassler, T. Hassan, and J. U. Garbas, "Requirements for a Reference Dataset for Multimodal Human Stress Detection," *2019 IEEE Int. Conf. Pervasive Comput. Commun. Work. PerCom Work. 2019*, pp. 492–498, 2019, doi: 10.1109/PERCOMW.2019.8730884.

[14] B. Ramani, "An Energy-Efficient Stress Monitoring System Using Physiological Data," vol. 9, no. 8, pp. 132–137, 2021.

[15] Z. Ahmad, S. Rabbani, M. R. Zafar, S. Ishaque, S. Krishnan, and N. Khan, "Multi-level Stress Assessment from ECG in a Virtual Reality Environment using Multimodal Fusion," Jul. 2021,

Accessed: Sep. 22, 2021. [Online]. Available: https://arxiv.org/abs/2107.04566v1.

[16] P. Karthikeyan, M. Murugappan, and S. Yaacob, "Detection of human stress using short-term ECG and HRV signals," *J. Mech. Med. Biol.*, vol. 13, no. 2, pp. 1381–1384, 2013, doi: 10.1142/S0219519413500383.

[17] Z. Feng, N. Li, L. Feng, D. Chen, and C. Zhu, "Leveraging ECG signals and social media for stress detection," *Behav. Inf. Technol.*, vol. 40, no. 2, pp. 116–133, Jan. 2021, doi: 10.1080/0144929X.2019.1673820.

[18] "pandas - Python Data Analysis Library." https://pandas.pydata.org/ (accessed May 08, 2023).

[19] "sklearn.preprocessing.OneHotEncoder — scikit-learn 0.24.0 documentation." https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.OneHotEncoder.html (accessed Jan. 02, 2021).

[20] M. C. Sarathjith, B. S. Das, S. P. Wani, and K. L. Sahrawat, "Variable indicators for optimum wavelength selection in diffuse reflectance spectroscopy of soils," *Geoderma*, vol. 267, pp. 1–9, Apr. 2016, doi: 10.1016/j.geoderma.2015.12.031.

[21] Y. xue Su, H. Xu, and L. jiao Yan, "Support vector machine-based open crop model (SBOCM): Case of rice production in China," *Saudi J. Biol. Sci.*, vol. 24, no. 3, pp. 537–547, Mar. 2017, doi: 10.1016/j.sjbs.2017.01.024.

[22] F. Faisal, M. M. Nishat, M. A. Mahbub, M. M. I. Shawon, and M. M. U. H. Alvi, "Covid-19 and its impact on school closures: A predictive analysis using machine learning algorithms," *2021 Int. Conf. Sci. Contemp. Technol. ICSCT 2021*, 2021, doi: 10.1109/ICSCT53883.2021.9642617.

[23] L. Breiman, "Random Forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001, doi: 10.1023/A:1010933404324.

[24] L. N. Sharma, R. K. Tripathy, and S. Dandapat, "Multiscale Energy and Eigenspace Approach to Detection and Localization of Myocardial Infarction," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 7, pp. 1827–1837, Jul. 2015, doi: 10.1109/TBME.2015.2405134.

[25] A. Priya, S. Garg, and N. P. Tigga, "Predicting Anxiety, Depression and Stress in Modern Life using Machine Learning Algorithms," *Procedia Comput. Sci.*, vol. 167, pp. 1258–1267, 2020, doi: https://doi.org/10.1016/j.procs.2020.03.442.

[26] D. Steyrl, G. Krausz, and K. Koschutnig, "Early Stress Detection and Analysis using EEG signals in Machine Learning Framework," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 1116, no. 1, p. 012134, Apr. 2021, doi: 10.1088/1757-899X/1116/1/012134.