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Peafowl- Optimized XGBoost Model for Intelligent Human Stress Detection

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ABSTRACT: Stress is a tremendous impact on human health, often leading to psychological and physiological diseases if not diagnosed or controlled. This work provides an intelligent human stress detection system based on a Peafowl-Optimized XGBoost classifier that achieves good accuracy and reliability in stress recognition. The system takes physiological signal data as input and applies Gaussian filtering and Z-score normalization during preprocessing to remove noise and normalize characteristics. Subsequently, entropy-based feature extraction is used to capture complicated signal fluctuations associated with stress levels. The collected features are then classified using an XGBoost model improved by the Peafowl algorithm, which improves the model's convergence speed and classification accuracy. Experimental results show that proposed model achieves 98% accuracy, precision, recall and F1 score with overall classification accuracy of 98.5% confirming its effectiveness for accurate stress level detection.

Keywords: stress detection, peafowl optimized XG-Boost, Gaussian filtering, Entropy based feature extraction, Machine learning.

1. Introduction

Stress is a natural component of everyday life, impacting people in a change of ways. While mild stress is manageable, prolonged or high levels of stress pose considerable risks to safety and well-being. In other words, chronic stress seriously disrupt daily living, damage performance in important situations, and impair managerial skills. Chronic stress has been linked to variety of health problems, including cardiac arrhythmias, depression, and a weakened immune system, which increase the risk of serious illnesses like cancer [1].It is a diverse disease that affects both adults and children equally. Because of strenuous physical and mental demands placed on employees, the workplace recently become a major source of stress. It could also be due to employees not having the resources they need to accomplish their work successfully, or employees' needs not being satisfied [2]. Stress is a manner of responding to overpowering demands or challenges from a scenario, manifesting as emotional, physical, or behavioural changes by human body [3].

This stage focuses on preparing raw physiological data for effective stress analysis.The median filter smoothes physiological signals by changing each value with median of its neighbors, eliminating impulsive noise while maintaining edges. Its limitations include poorer efficacy against high-frequency noise and possible distortion with large window widths, which impair stress detection accuracy [4]. Z-score normalization standardizes physiological signals by subtracting mean and dividing by standard deviation, resulting in a consistent scale across characteristics. This allows the classifier to analyse data more efficiently and increases model stability. However, it is potentially vulnerable to outliers, which might skew normalized values and reduce stress detection accuracy [5]. Mean normalization adjusts physiological signals by subtracting the mean and scaling by the range, centring the data on zero to ensure uniformity across characteristics. This enhances the classifier's performance and stability. However, it is susceptible to extreme results and not properly manage outliers, reducing stress detection accuracy [6]. The Gaussian filter smoothes physiological signals by minimizing noise while keeping key patterns, resulting in more accurate human stress detection. In essence, preprocessing guarantees that the incoming data is clean and uniform, allowing for reliable feature extraction.

This section focuses on statistical and signal-based techniques used to extract useful information from physiological data. In human stress detection, the mean and standard deviation are often employed to assess physiological signals such as heart rate, skin conductance, and EEG data. The mean is an average figure that indicates overall activity levels, but the standard deviation shows variability, which reflect stress responses. These processes aid in quantifying the consistency and variations in physiological rhythms. However, these constraints include their inability to capture complicated, nonlinear stress dynamics or environmental elements that influence emotional states [7]. The root mean square (RMS) is used to calculate amplitude of physiological signals such as heart rate variability, EMG, and EEG activity. It measures total strength or intensity of signal fluctuations, which aids in detecting increased physiological arousal associated with stress. RMS effectively summarizes signal strength and is less sensitive to minor fluctuations or noise. However, its disadvantage is that it does not capture temporal or nonlinear patterns in stress reactions, thus missing minor emotional shifts [8]. The variance measures the degree of fluctuation in physiological signs including heart rate, EEG, and skin conductance. It emphasizes how much the signals fluctuate over time, providing information on stress-related abnormalities or increased arousal. Variance aids in identifying periods of instability or odd responses in the data. However, its shortcoming is that it simply reflects overall dispersion and cannot account for temporal patterns or nonlinear dynamics associated with stress [9]. Entropy analysis in human stress detection quantifies the unpredictability and complexity of physiological signals, assisting in the assessment of stress levels by examining variability in heart rate, respiration, and other biomarkers. These extracted features form the foundation for effective classification of stress levels.

The classification phase includes machine learning models to assign discovered features to suitable stress categories. Logistic regression predicts stress levels by modelling the link between physiological or behavioural characteristics and stress states with a sigmoid function. It is simple, rapid, and easy to understand, but it has constraints when dealing with non-linear patterns, outliers, and complex feature relationships [4]. A Multilayer Perceptron (MLP) learns complex, non-linear correlations between input variables like heart rate, EEG signals, or facial data and associated stress levels using interconnected layers of neurons. It uses back propagation to change connection weights and reduce prediction error. MLPs effectively detect minor stress patterns that linear models miss. However, they demand huge datasets, are computationally intensive, and is susceptible to overfit if not adequately regularized [5]. Linear Discriminant Analysis (LDA) is used in stress detection to categorize stress levels based on characteristics such as heart rate. It seeks to optimize class separability but is constrained by assumptions of normalcy and equal covariance, which are not be valid in real-world data. LDA also struggles with high-dimensional data and overfitting when there are more features than samples. Despite this, it is still useful in controlled environments with obvious characteristics [6]. XGBoost is a powerful machine learning technique that utilizes gradient boosting to achieve excellent accuracy and efficiency in classification and regression problems. In conclusion, these classification algorithms improve prediction accuracy and model adaptability.

This section covers optimization strategies that fine-tune classifier parameters to increase model accuracy. Particle Swarm Optimization (PSO) is a population-based technique that is inspired by the social behavior of birds and fish. It is commonly used in human stress detection to maximize model parameters and classification accuracy. It works by launching a swarm of particles that traverse the search space, adjusting their positions depending on individual and collective best practices to attain the best results. PSO improves stress detection performance by fine-tuning factors like heart rate variability, EEG, and skin conductance parameters. However, PSO has shortcomings, such as sluggish convergence in high-dimensional data, susceptibility to local minima, and the necessity for precise parameter tweaking. Furthermore, huge datasets raise the processing cost, reducing the efficiency of real-time stress analysis [7]. The Genetic Algorithm (GA) is based on natural selection that is used in human stress detection to pick optimal characteristics and improve model accuracy. It uses mechanisms like selection, crossover, and mutation to generate a population of solutions that are the greatest fit for identifying stress levels from physiological signals like ECG, EEG, or GSR. GA rapidly searches complex search areas, which aids in the identification of important stress indicators. However, it has shortcomings such as poor convergence time, high computational cost, and sensitivity to parameter changes. Additionally, GA face premature convergence, resulting in inadequate feature selection or erroneous stress classification [8]. POA improves feature selection and classification accuracy in human stress detection by replicating peafowls' adaptive and selective behaviours. Overall, optimization ensures that model parameters converge efficiently, resulting in improved detection performance.

1.1 Related Works

Albaladejo *et al* (2023) [7] have developed Evaluating ML Models and Transfer Learning for Stress Detection using Heart Rate. It investigates at the various model configurations perform in recognizing stress patterns as well as knowledge from one dataset be transferred to another to improve accuracy and flexibility. However, the approach has disadvantages, such as differences in individual heart rate responses, a scarcity of various datasets, and the possibility of overfitting when applying models to different populations or sensor types.

Rizwan *et al* (2020) [8] have proposed ECG-Based Stress Detection using SVM for COVID-19 Pandemic Management. It extracts relevant features from ECG data, trains the SVM classifier, and determines whether a person is stressed or not. The system is capable of managing high-dimensional data and providing accurate stress detection when the features are suitably selected. However, obstacles include sensitivity to noisy or irregular ECG readings, the requirement for careful feature selection, and worse performance when applied to various populations without retraining. Furthermore, SVM struggle with huge datasets due to computational complexity.

Khan *et al* (2023) [9] have implemented Stress Classification from VR Simulations using Decision Trees. It works by identifying essential elements from data like heart rate, skin conductance, and EEG, and then using a decision tree model to classify stress responses. Decision trees are simple to use, straightforward to read, and tolerate numerical categorical data efficiently. However, complications include a tendency to overfit, sensitivity to noisy or imbalanced data, and poor generalization to new patients or situations without retraining. Complex physiological patterns are often oversimplified, compromising accuracy.

Chen *et al* (2024) [10] have proposed Student Mental Health Recognition Using K-Means Clustering. This approach employs K-means clustering to detect trends in students' mental health data, grouping individuals with similar behavioural or physiological characteristics. It works by preprocessing data, identifying important features, and grouping pupils into clusters that represent different levels or types of mental health disorders. The method is simple, unsupervised, and computationally efficient, making it ideal for huge datasets. However, it has constraints, including sensitivity to initial cluster center selection, difficulties handling non-spherical or overlapping clusters, and the necessity to predefine the number of clusters. Furthermore, the results is difficult to comprehend when applied to complicated or noisy mental health data.

Ensar Arif *et al* (2024) [11] have developed Voice-Based Stress Detection using SVM. The SVM-based stress detection system uses voice signals to classify stress levels by extracting variables including pitch, tone, and speech rate. It works by training an SVM classifier on labelled voice samples to discriminate stressed from unstressed states. SVM is effective at handling high-dimensional feature spaces and attains decent accuracy even with limited training data. However, its shortcomings include sensitivity to loud or low-quality audio, the necessity for careful feature selection, and lower performance when speech features vary greatly among persons. Furthermore, SVM necessitate tremendous computer resources for very large datasets.

1.2 Objectives

- To develop an intelligent human stress detection model based on physiological signal data.
- To reduce noise and normalize data, the input signals are pre-processed with Gaussian filtering and Z-score normalization.
- To accurately recognize stress patterns, significant characteristics should be extracted using entropy analysis.
- To improve accuracy and speed of convergence, use Peafowl optimization algorithm on the XGBoost classifier.
- To determine the proposed model's performance in identifying stress levels and compare it to existing methods.

2. Proposed System Description

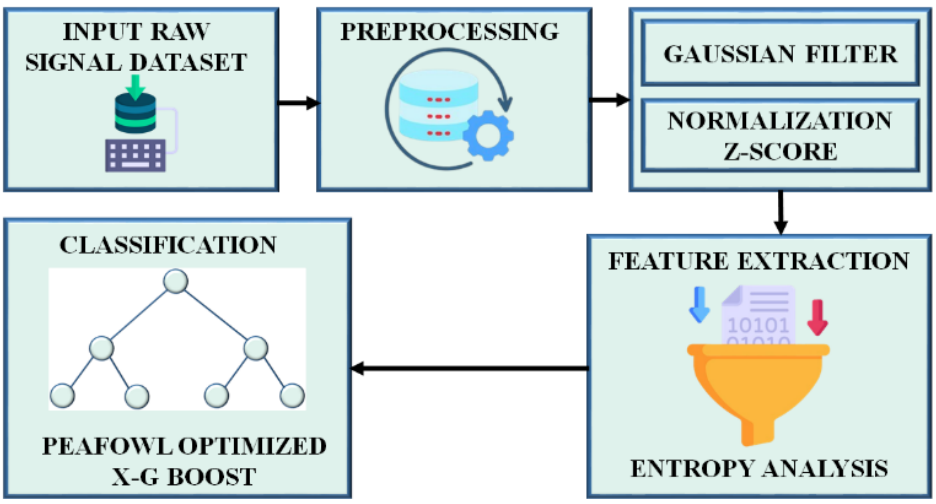

Figure 1: *Block diagram of proposed system*

The proposed model for intelligent human stress detection utilizes a Peafowl-optimized XGBoost algorithm to effectively process physiological inputs and properly classify stress levels. The method starts with the implementation of a signal dataset containing stress-related physiological indicators like heart rate and electro dermal activity. These signals frequently contain noise and inconsistencies; thus, a preprocessing stage employs a Gaussian filter to remove undesirable disturbances and a Z-score normalization algorithm to standardize the data, assuring consistency across all samples. Following preprocessing, the refined signals are subjected to feature extraction using entropy analysis, which captures the complexity and irregularity patterns found in physiological signals that indicate stress. The extracted features are then sent to the classification phase, where XGBoost model, which has been tuned using the Peafowl method, provides efficient learning and precise stress level categorization. The Peafowl optimization improves the performance of XGBoost by fine-tuning its settings, resulting in faster convergence and higher accuracy. Finally, the model produces an output demonstrating the predicted stress level, resulting in a dependable and intelligent system for early detection and monitoring of human stress.

3. Proposed System Modelling

3.1 Prreprocessing by Guassian Filter

In human stress detection, the filtering model calculates the present stress state x_t from a series of physiological signals $y_{1:t}$ such as heart rate, electrodermal activity, and breathing. The model starts with the prediction phase, written as:

$$p(x_t|y_{1:t-1}) = \int p(x_t|x_{t-1})\, p(x_{t-1}|y_{1:t-1})dx_{t-1} \quad (1)$$

Which predicts the current state based on previous stress levels and observed signals. This stage moves prior knowledge forward in time to estimate the likely stress condition before fresh data are collected. The update step is provided by

$$p(x_t|y_{1:t}) = \frac{p(y_t|x_t)p(x_t|y_{1:t-1})}{\int p(y_t|x_t)p(x_t|y_{1:t-1})dx_t} \quad (2)$$

It uses the most recent physiological measurements to fine-tune the projected stress level. Because physiological responses are nonlinear and non-Gaussian, these equations are approximated using Gaussian-based filters such as the Gaussian Filter (GF) or the Unscented Kalman Filter (UKF), which provide accurate real-time stress variation estimates.

To address nonlinearity, the GF approximates the belief $p(x_t|y_{1:t-1})$ as a Gaussian distribution.

$$p(x_t|y_{1:t-1}) \approx N(x_t|\mu_{xt}, \Sigma_{xtxt}) \quad (3)$$

The anticipated mean and covariance are represented by μ_{xt} and $\sum_{xtxt}$, which are determined via moment matching. This approximation incorporates the stress state's expected value as well as its uncertainty. Prior to estimate, physiological characteristics are standardized using Z-score normalisation.

$$Z = \frac{X-\mu}{\sigma} \quad (4)$$

To reduce inter-individual variability and ensure that all features contribute equally to the stress prediction model. This normalization increases numerical stability and uniformity between people and recording settings.

The anticipated state is updated with a combined Gaussian approximation of the latent state and the related physiological observations.

$$q(x_t, y_t) = N\left(\begin{bmatrix} x_t \\ y_t \end{bmatrix} \begin{bmatrix} \mu_{xt} \\ \mu_{yt} \end{bmatrix}, \begin{bmatrix} \Sigma_{xtxt} & \Sigma_{xtyt} \\ \Sigma_{ytxt} & \Sigma_{ytyt} \end{bmatrix}\right) \quad (5)$$

Which identifies the correlation between the underlying stress state and the observed aspects. The detected signals are then used to condition the posterior stress distribution.

$$q(x_t|y_t) = N\big(x_t|\mu_{xt} + \Sigma_{xtyt}\Sigma_{xtyt}^{-1}(y_t - \mu_{yt}), \Sigma_{xtxt} - \Sigma_{xtyt}\Sigma_{ytyt}^{-1}\Sigma_{xtyt}^{T}\big) \quad (6)$$

Allowing the model to update the projected stress level based on new normalized physiological inputs.

The computational difficulty of this procedure is primarily due to the covariance matrix operations, which require $O(N^3 + M^3)$ calculations, where $N$the stress is state dimension and M is the number of physiological characteristics. Despite this, Z-score normalization improves stability and accelerates convergence, making Gaussian-based filtering a dependable and effective method for detecting dynamic human stress from multimodal physiological data.

3.2 XGBoost Classifier

The XGBoost algorithm is a sophisticated tree-based machine learning technique that has demonstrated exceptional performance in data categorization tasks, particularly in detecting stress levels based on physiological signals. It is a scalable and efficient gradient boosting system that is capable of handling complicated and nonlinear data patterns, making it ideal for human stress detection applications.

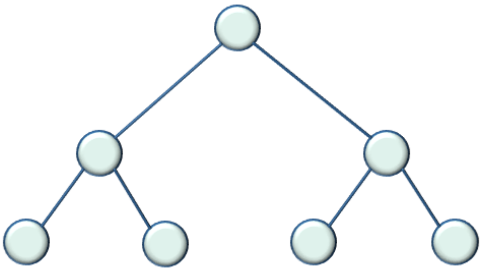

Figure 2: *XGBoost classifier*

In this study, the XGBoost classifier is used to identify stress levels by analysing physiological characteristics such as heart rate, electro dermal activity, and body temperature. The approach creates ensemble of several Classification and Regression Trees (CARTs), with each tree gradually improving the model's prediction accuracy. The projected stress class for an input sample $\hat{y}_i$ is derived by adding the contributions from all the trees, as shown in Eq. (8).

$$\hat{y}_i = \emptyset(x_i) \quad (7)$$

$$\hat{y}_i = \sum_{k=1}^{k} f_k(x_i), f_k \in F \quad (8)$$

Here, x_i symbolizes the input feature vector, and F represents the set of all tree functions. To improve generalization and reduce overfitting, a regularization term is added to the goal function, as stated in Eq. (9).

$$\mathcal{L}(\emptyset) = \sum l(\hat{y}_i, y_i) + \sum \Omega(f_k) \quad (9)$$

The first term, $l(\hat{y}_i, y_i)$, calculates the loss between projected and actual stress levels, while $\Omega(f_k)$ adds a penalty to control model complexity. The regularization function is stated in Eq. (10).

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \quad (10)$$

In this equation, γ and λ are tuning parameters that determine the strength of regularization, T is the number of leaves in each tree, and w_j is the leaf weight.

XGBoost's gradient boosting technique lowers the overall loss function by taking the first and second derivatives of the loss, which improves the optimization process. Each iteration t, the model changes leaf weights based on gradient data, allowing accurate modification of decision boundaries between stress and non-stress classes. Eq. (11) calculates the ideal weight for each leaf node.

$$\mathrm{w}_\mathrm{j}^* = \frac{\sum_{\mathrm{i} \in \mathrm{I_j}} \mathrm{g_j}}{\sum_{\mathrm{i} \in \mathrm{I_j}} \mathrm{h_i} + \lambda} \quad (11)$$

This enables the classifier to successfully distinguish between stress and non-stress conditions by altering the leaf weights in response to physiological signal fluctuations. The Peafowl Optimization approach is used to fine-tune XGBoost's hyperparameters, including tree depth, learning rate, and regularization coefficients. Inspired by peafowl mating and display behavior, this optimization strategy improves global search capability and convergence speed, resulting in better model performance.

The overall model is evaluated using a confusion matrix, which shows right and wrong classifications under calm and stressed settings.

The XGBoost classifier developed with Peafowl Optimization has good classification accuracy and robustness, making it dependable tool for detecting human stress levels.

3.3 Peafowl Optimization

The POA is a nature-inspired metaheuristic technique that optimizes parameters and feature selection process for detecting human stress. Each peafowl represents a potential solution corresponding to a certain combination of physiological traits or model parameters. Adult peafowls represent the most effective solutions, while juveniles learn from them via iterative revisions.

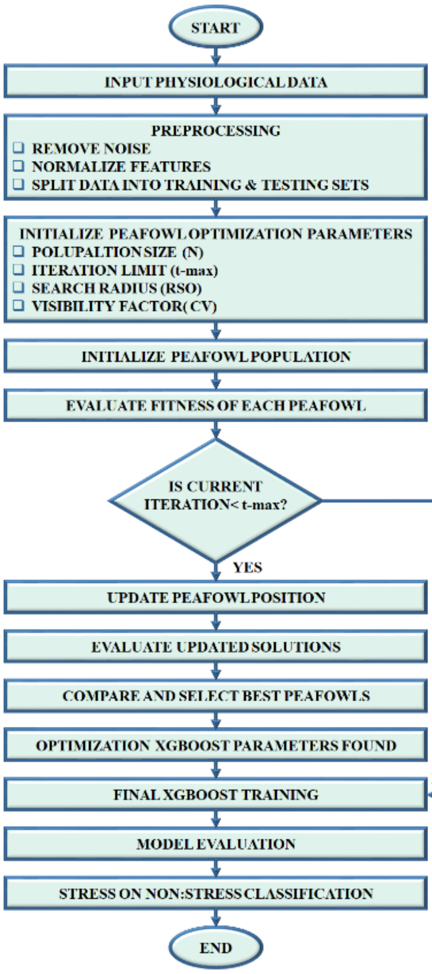

Figure 3: *Flowchart of peafowl optimization*

During optimization, each solution changes its location in the search space depending on its fitness value, which is determined by the XGBoost classifier's accuracy in detecting stress levels. High-fitness people direct others to more optimal places, boosting convergence and exploration balance.

The simplified position updating technique is described as follows:

$$xuci = xuci(t) + r_i \cdot R_s \cdot \frac{x\circ_i}{||x\circ_i||}, i = 1,2, ..5 \quad (12)$$

Where $xuci$ represents the position of the i^{th} solution, R_s signifies the search radius, xo_i is a random direction vector, and r_i is a random coefficient that controls the movement intensity.

$$x \circ = 2 \cdot rand(1, Dim) - 1 \quad (13)$$

$$R_s(t) = R_{s\circ}\left(1 - \frac{t}{t_{max}}\right)^{0.01} \quad (14)$$

The random direction vector and dynamic radius adjustment are defined as:

Where t and t_{max} are the current and maximum iteration counts, and Rso is the initial search radius defined as:

$$Rs_\circ = cv \cdot (XU - XL) \quad (15)$$

Here, XU and XL indicate the upper and lower search bounds, respectively, while CV (set to 0.2) is the visibility factor that determines the exploration scale.

The Peafowl Optimization Algorithm uses an adaptive mechanism to fine-tune XGBoost settings and choose the most significant stress-related features from physiological data, resulting in higher classification accuracy and faster convergence.

4. Result and Discussion

In this section of the study, the outcomes from the experiments to test proposed framework for detecting stress from sensor data. It use a variety of different statistical and visual techniques as well as a series of comparative studies to demonstrate the effectiveness of the methods used to preprocess, analyse features, and classify data.

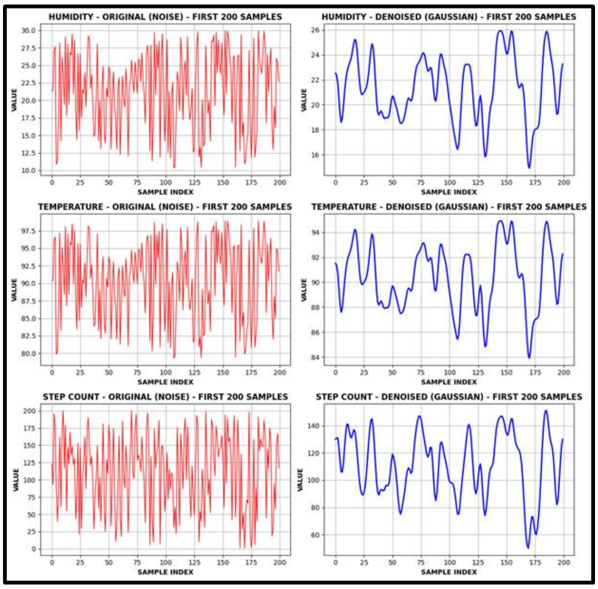

Figure 4: *Original vs Gaussian denoised sensor signals*

Figure 4 shows the first 200 samples of humidity, temperature, and step count data prior to and after Gaussian denoising and illustrates the reduction of noise and the clearer underlying trends in the data.

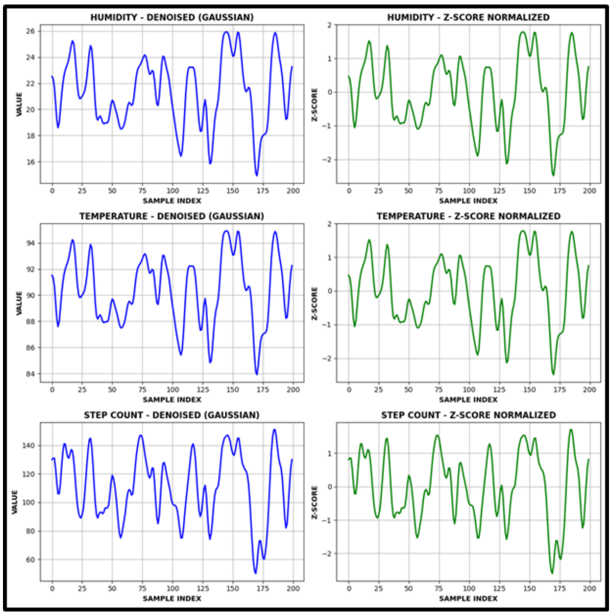

Figure 5: *Denoised sensor signals and corresponding Z-score normalized values*

Figure 5 displays the humidity, temperature, and step count signals after Gaussian denoising, as well as the Z-score normalized humidity, temperature, and step count signals, showing that the shape of the signal is preserved and the values have been rescaled to units of standard deviation

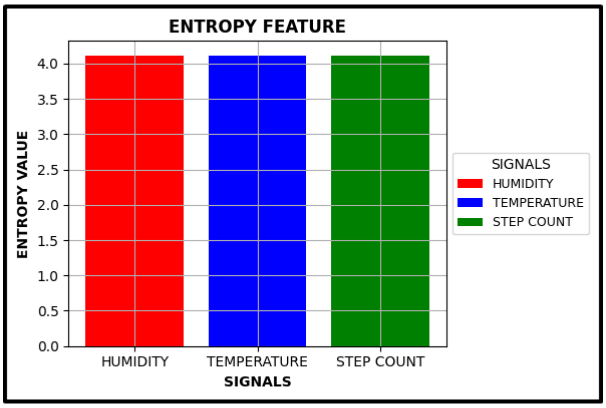

Figure 6: *Entropy values for humidity, temperature and setup count signals*

Figure 6 shows the entropy for all three signals is approximately 4.1, indicating that the complexity of each signal is similar to all three signals are similarly complex.

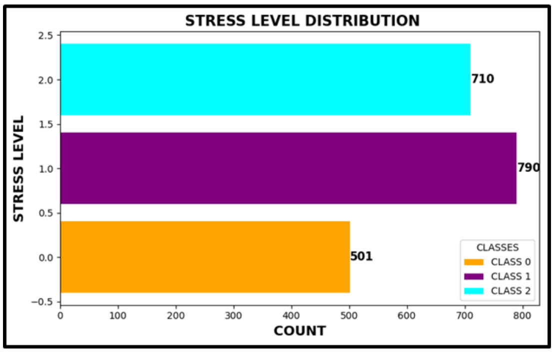

Figure 7: *Stress level distribution across different classes*

Figure 7 displays the distribution of stress levels across the three classes, showing that Class 0 has 501 counts, Class 1 has 790 counts, and Class 2 has 710 counts.

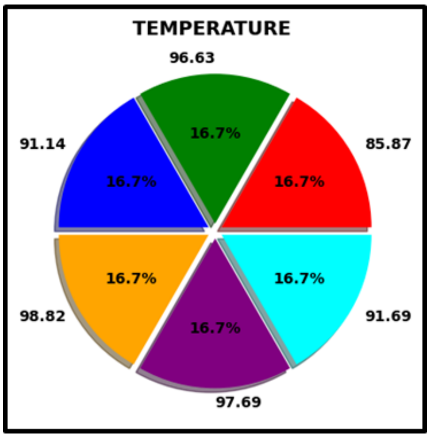

Figure 8: *Temperature distribution across different segments*

Figure 8 shows the temperature value distribution as a pie chart separated by six segments with the temperature values ranging from 85.87 to 98.82 as shown. Each segment represents 16.7% of the total value.

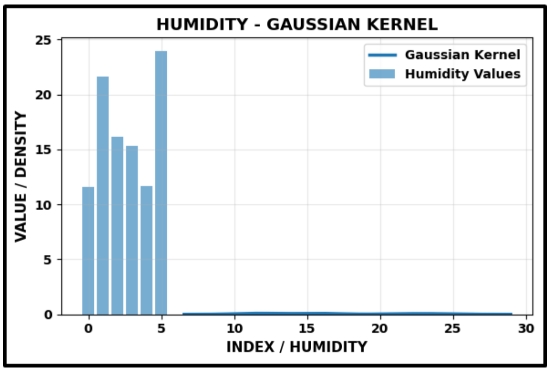

Figure 9: *Humidity distribution with Gaussian kernel*

Figure 9 shows the humidity value distribution as bars, with the humidity values ranging from approximately 11 to 24 plotted as bars, along with a Gaussian kernel curve spanning the 0–30 range of humidity.

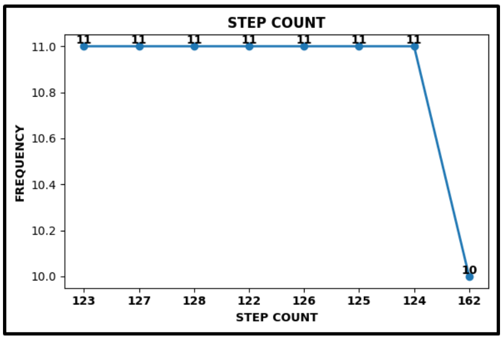

Figure 10: *Step count frequency distribution*

Figure 10 shows a bar chart of the frequency of different step counts. A frequency of 11 occurs for step counts from 123–128, with a sharp decrease to 10 at step count 162.

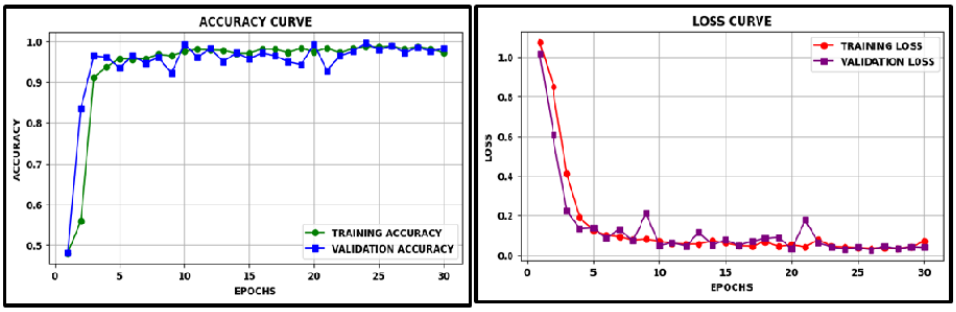

Figure 11. Training and validation accuracy and loss curve

Figure 11 indicates high accuracy (close to a value of 1.0), with a steep decline in training loss on the loss curve and a more erratic fluctuation in validation loss. After a few epochs, the validation loss curve stabilizes.

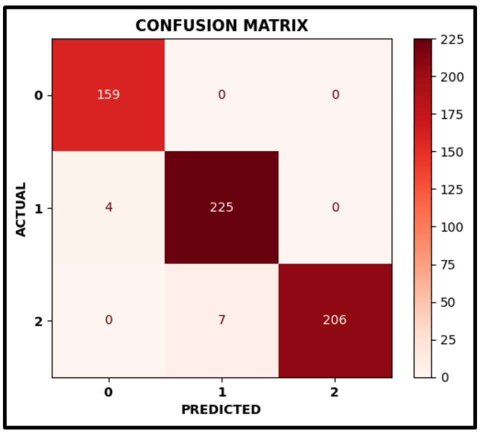

Figure 12: *Confusion matrix*

Figure 12.shows number of correct vs incorrect predictions for each class with correct predictions shown along the main diagonal of matrix. The number of correct predictions are as follows: 159 (class 0), 225 (class 1), 206 (class 2). Only 4 and 7 misclassifications occurred for classes 0 and 1, respectively.

Table 1: *Model performance metrics*

Performance Metrics	
Accuracy	0.98%
Precision	0.98%
Recall	0.98%
F1 score	0.98%

Table 1. displays performance metrics of proposed approach. Each performance metric obtained the same result, which was 0.98, in terms of accuracy, precision, recall and F1-score. This shows that the

proposed approach had both balanced and strong classification ability across all metrics.

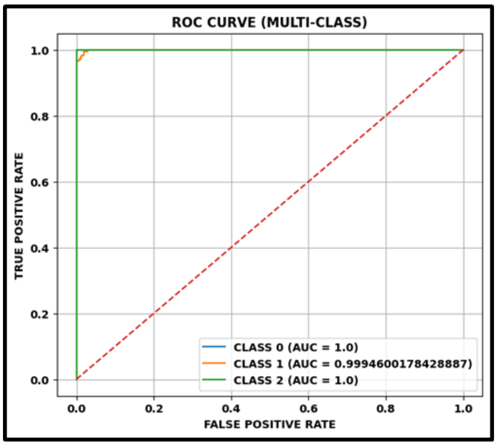

Figure 13: *ROC curve*

In Figure 13. The ROC curve shows a plot of true positive rates (TPR) and the false positive rates (FPR) for all classes, and the area under the ROC curves (AUCs) for the three classes is as follows: Class 0 (AUC = 1.0), Class 1 (AUC = 0.9995), Class 2 (AUC = 1.0).

Table 2: *Comparative accuracy of different methods*

Method	Accuracy
SWELL-KW[20]	92%
SVM[8]	97%
Proposed	985

Table 2. According to the comparison presented in the table, SWELL-KW (92%), SVM (97%) and the proposed method (98.5%) all provide similar results; however, the proposed method is clearly superior to the other two methods when looking at overall performance.

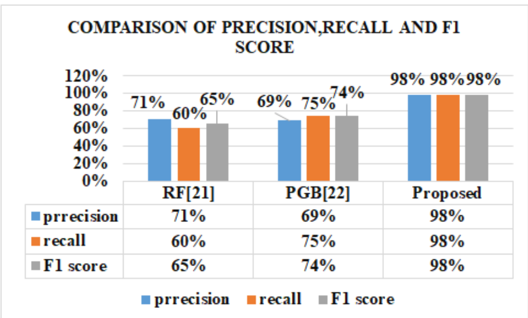

Figure 14: *Comparison of precision, recall and F1 score*

Figure14. depicts a comparison of precision, recall and F1 score between RF, PGB, and the proposed method wherein the proposed approach provided the highest level of performance at 98%.

5. Conclusion

The PO-XGBoost model for human stress detection using intelligent algorithms is shown to be effective. The addition of Gaussian denoising and Z-score normalization significantly increase the quality of the sensor signals without losing patterns in the humidity, temperature or step counts. Results from the entropy analysis support that the signals contain information that is equally complex and the features are valid. With an accuracy of 98% in each of precision, recall, and F1 score, and stable training and validation curves with a ROC area under the curve near one, it is clear that the PO-XGBoost model outperformed the comparable models of SWELL-KW, SVM, RF and PGB. The proposed approach is a durable, accurate and efficient framework for real-time human stress detection and intelligent health applications.

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