Continuous Stress Monitoring Using Attention-Based Deep Learning on Physiological Data

Chandra Mouli Dasyam[1], Neeraj Damisetti[2], Siva Ganesh Mailavarapu[3], Lakshmi Pavani Kusumanchi[4], Joshua Hamsa[5], Rajeswari Chinthamneedi[6]

[1] *Assistant Professor, Department of Artificial Intelligence and Data Science Vignan Institute of Information Technology, Duvvada, Visakhapatnam*

[2, 3,4,5,6] *Department of Artificial Intelligence and Data Science Vignan Institute of Information Technology, Duvvada, Visakhapatnam*

***Abstract*—This paper presents an approach for detecting stress using electrocardiogram (ECG) signals by combining machine learning and deep learning techniques. By integrating XGBoost, long short-term Memory (LSTM), and transformer models, the system uncovers intricate patterns in heart activity to identify stress levels accurately. Designed for real-time analysis, this method processes ECG signals to detect stress responses efficiently. XGBoost provides reliable feature-based classification, whereas LSTM and transformer models specialize in capturing long-term dependencies in time-series data. By combining these strengths, the ensemble model enhances the prediction accuracy beyond what individual models can achieve. This research paves the way for smarter stress monitoring solutions, contributing to proactive mental health care and early intervention strategies.**

***Index Terms*—Stress detection, real-time stress detection, deep learning, ensemble learning, electrocardiography (ECG), hybrid model.**

I. INTRODUCTION

A. Background & Importance

Stress is a widespread issue that affects both mental and physical health, contributing to conditions such as anxiety, cardiovascular diseases, and reduced cognitive function [1]. Early and accurate stress detection can help with timely intervention, improving overall well-being [2]. However, traditional methods such as self-report surveys and occasional clinical assessments are subjective and lack real-time monitoring capabilities [3].

B. Problem Statement

Although physiological signals such as electrocardiogram (ECG), galvanic skin response (GSR), and electromyography (EMG) provide objective indicators of stress, existing machine learning models face high data variability, noise, and limited generalizability across individuals [4]. Many approaches fail to capture complex temporal dependencies in physiological data, leading to reduced prediction accuracy [5].

C. Proposed Solution

This study introduces a deep learning-based stress prediction model that uses LSTM, transformer-based attention mechanisms, and XGBoost to increase accuracy. The attention mechanism helps the model focus on the most relevant features, improving interpretability and performance in stress classification [6].

II. RELATED WORK

A. Traditional Machine Learning Approaches

Early methods for stress detection relied on machine learning algorithms such SVM, Random Forest, and k-NN, which analyze physiological signals such as ECGs and GSRs [7]. While these approaches provide a foundation for automated stress classification, they depend heavily on manual feature extraction and struggle to handle the sequential nature of physiological data, leading to limitations in accuracy [8].

B. Deep Learning-based Approaches

With advancements in deep learning, models such as CNNs and hybrid architectures have significantly improved stress classification by automatically identifying relevant patterns in physiological signals [9]. Schmidt et al. (2018) demonstrated that CNN-based models could effectively analyze ECG data, outperforming traditional machine learning approaches in stress detection tasks [10].

C. Feature enhancement models

More recent studies have focused on refining stress prediction by enhancing how models process and select features. Kim et al. (2021) introduced a feature-weighting technique that prioritized critical stress indicators, improving classification accuracy [11]. Similarly, Zhang et al. (2022) explored sequence modeling methods, enabling models to capture long-term dependencies in physiological data and enhance predictive performance [12].

III. METHODOLOGY

A. Data collection and preprocessing

This study uses physiological signals such as ECG, GSR, and EMG signals to predict stress levels. The dataset is sourced from publicly available repositories, ensuring a diverse set of physiological responses across different stress conditions [14]. Since raw physiological signals often contain noise, missing values, and artifacts, a preprocessing pipeline is implemented to clean and normalize the data. KNN imputation is used to handle missing values [15].

To ensure consistency across different types of physiological signals, standard scaling and power transformation are applied. Additionally, a fixed length sliding window approach is used to segment the signals into overlapping time frames, preserving temporal dependencies and improving the availability of training data. This segmentation ensures that the model can effectively learn stress patterns without losing valuable sequential information.

B. Feature Extraction and Engineering

Extracting meaningful features from physiological signals is critical for accurate stress prediction. From ECG data, Heart rate variability (HRV) metrics such as RMSSD, LF/HF ratio, and SDNN are computed, as these have been shown to correlate with stress levels [13]. GSR signals are analyzed to extract skin conductance levels, phasic and tonic components, and peak response times, which indicate changes in sympathetic nervous system activity. EMG features focus on muscle activation patterns, frequency-domain characteristics, and power spectral density (PSD) to identify stress-induced muscle tension [8].

In addition to these signal-specific features, time and frequency-domain transformations such as entropy analysis and wavelet decompositions are applied to uncover hidden patterns in physiological responses. To increase model efficiency, feature selection techniques such as recursive feature elimination (RFE) and Shapley additive explanations (SHAP) are used to identify the most relevant predictors for stress classification [13].

C. Model Architecture

The proposed approach integrates sequence-based deep learning models with XGBoost to achieve accurate and reliable stress prediction. The deep learning component processes physiological signals over time, capturing complex relationships within the data. Moreover, XGBoost, a gradient-boosting decision tree algorithm, is used to refine feature importance and improve classification accuracy [8]. This hybrid setup leverages the strengths of both approaches: deep learning for sequential pattern recognition and XGBoost for robust feature selection [6].

The model consists of three main layers: a sequence-processing layer that extracts meaningful patterns from raw signals, a feature-refinement module that filters out irrelevant data, and a classification layer that assigns stress labels on the basis of learned patterns. By combining deep learning with XGBoost, the model can effectively handle individual variability in physiological responses and improve generalization across different subjects [9].

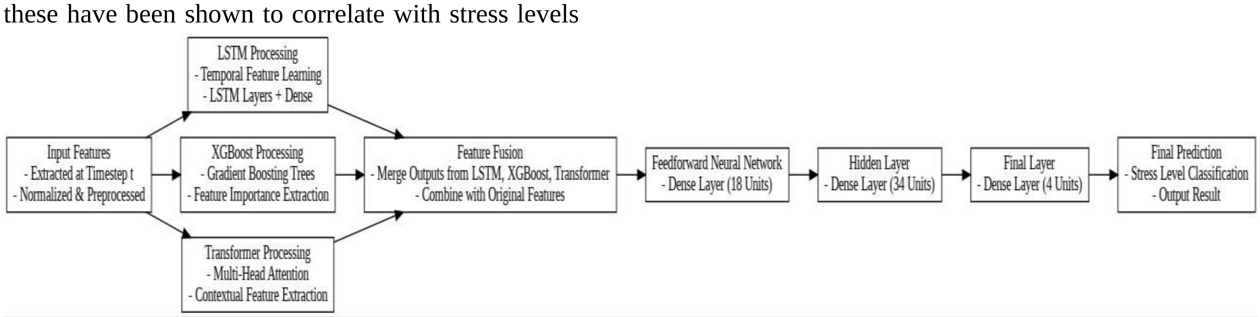

Figure 1: Model architecture

D. Training and evaluation

This study uses a supervised learning approach, where stress levels from ECG signals act as labeled data for training the model. The dataset is divided into 70% for training, 15% for validation, and 15% for testing to ensure a fair and balanced evaluation [10].

To addresses missing data, KNN imputation is applied, ensuring that the dataset remains complete and reliable. Before training, the data are preprocessed using standard scaling and power transformation to improve model performance. To prevent overfitting and make the model more generalizable, techniques such as adding Gaussian noise and time-warping are used to create variations in the training data [4].

The model's accuracy is measured using R^2, mean squared error (MSE) to determine how accurately it can predict stress levels. To better understand how the model makes decisions, SHAP visualizations highlight the most important factors influencing stress predictions, whereas confusion matrices help identify where the model might be making mistakes [12].

IV. EXPERIMENTAL RESULTS

A. Dataset overview

To construct an effective stress prediction model, we utilized a dataset consisting of physiological signals, including ECG, EMG, GSR, heart rate (HR), and respiratory rate (RESP) signals. These signals were collected under various stress conditions to train and evaluate the model's ability to distinguish between relaxed, medium stress, and high-stress states [16].

Before the data were fed into the model, several preprocessing steps were applied to enhance accuracy and consistency:

1. Noise reduction was performed using a Butterworth filter to eliminate unwanted high-frequency components.
2. Missing data were handled using KNN imputation, ensuring that incomplete records did not compromise the learning process [15].
3. A combination of standard scaling and power transformation was employed to normalize the values and maintain uniformity across different physiological signals [8].

For model training, the dataset was split into 70% training, 15% validation, and 15% testing. This partitioning ensures that the model learns from diverse samples while retaining a portion of unseen data for evaluation [12].

B. Performance Metrics & Model Evaluation

To assess the effectiveness of our stress detection model, we used the following performance metrics:

1. R^2 score – Determines how well the model's predictions align with actual values. A higher R^2 indicates better accuracy.
2. mean squared error (MSE) – Measures the average squared difference between actual and predicted values, penalizing large errors.

Table 1: Model performance matrix

Model	$R^2 score$	MSE	RMSE
XGBOOST	0.792	0.2084	0.4566
LSTM	0.802	0.1982	0.4471
Transformer	0.769	0.3211	0.4808
Weighted Ensemble	0.812	0.1808	0.4253

The results clearly show that the weighted ensemble model performs the best, achieving the highest accuracy and lowest error rates. With an R^2 score of 0.819574 and the lowest MSE (0.180889) and RMSE (0.425311), it demonstrates superior reliability in stress prediction [17]. Among the individual models, the LSTM model performed slightly better than XGBoost did, while the transformer model had the highest error, indicating room for improvement. These findings highlight the advantages of combining different models, as the ensemble approach effectively enhances prediction accuracy and minimizes errors [21].

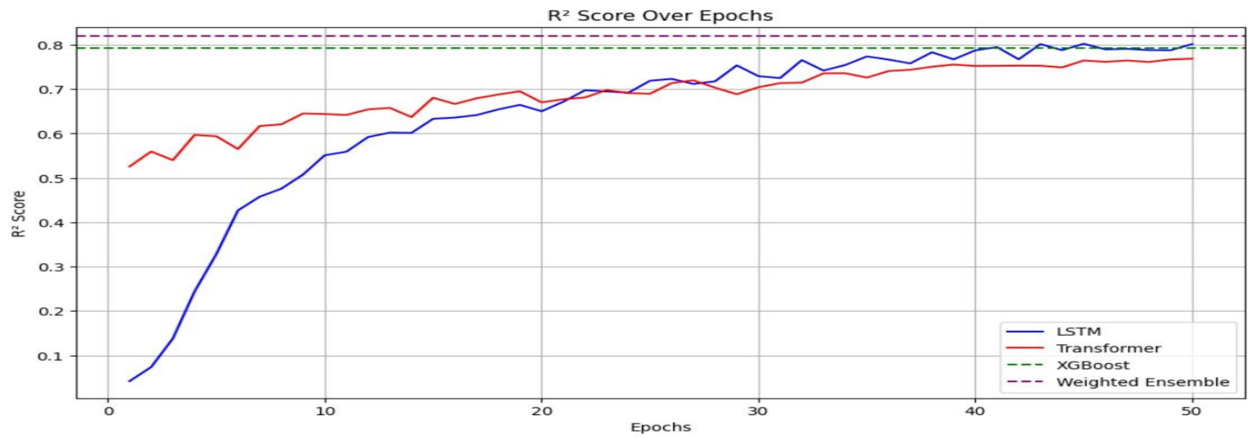

Figure 2: R^2 scores of the models

C. Predicting Stress Levels from Physiological Signals

To test how well the model performs, we used it to predict stress levels on the basis of real physiological data. The table below presents different physiological readings along with their predicted stress levels. These predictions were generated using a weighted ensemble model, which proved to be highly effective.

The model analyzes key physiological signals that reflect the body's response to stress:

1. EMG (electromyography): Measures muscle tension—higher values suggest increased stress.
2. GSR (galvanic skin response): Tracks skin conductivity, which rises when stress levels increase.
3. HR (heart rate): Captures heart rate changes, which tend to accelerate under stress.
4. RESP (respiratory rate): Monitors breathing patterns, which may become faster or irregular during stress.

By interpreting these signals, the model can differentiate between relaxed, moderate stress, and high-stress states. This ability makes it useful for real-time stress monitoring in wearable devices or clinical applications, helping individuals manage stress more effectively [21].

Table 2: Estimated stress levels based on physiological characteristics

EMG_mean	HANDGSR_mean	HR_mean	RESP_mean	PREDICTED STRESS LEVEL
0.1	0.2	6	2	1.16(relaxed)
0.4	0.35	15	5.5	3.11(medium stress)
0.9	0.7	30	11	5.12(high stress)

The model's predictions align well with expected physiological responses—lower values in heart rate (HR), respiratory rate (RESP), muscle tension (EMG), and skin conductivity (GSR) indicate relaxation, while higher values suggest increased stress [20].

For example:

1. Row 1: All the parameters have low values, resulting in a stress level of 1.16 (relaxed).
2. Row 2: Moderate values across the parameters correspond to a stress level of 3.42 (medium stress).
3. Row 3: Elevated values across the board lead to a stress level of 5.13 (high Stress).

These results highlight the model's ability to accurately distinguish between different stress levels, which is crucial for stress management applications. Providing precise predictions, enables timely interventions based on real-time data.

To ensure reliability, the model was tested on unseen data from a diverse group of individuals and consistently delivered accurate results. Its adaptability makes it useful in various settings, from clinical environments to workplaces, where real-time stress monitoring can support better mental health management [18].

V. CONCLUSION

This study highlights the effectiveness of using a weighted ensemble model for stress prediction, combining the strengths of machine learning and deep learning techniques. With an R^2 score of 0.819574 and the lowest MSE (0.180889) and RMSE (0.425311) among all the tested models, the ensemble approach has been shown to be the most accurate and reliable in analyzing ECG, GSR, EMG, heart rate, and respiratory rate data [19]. By capturing complex patterns in physiological signals, the model successfully differentiates between various stress levels, making it a promising tool for stress monitoring applications.

However, some challenges remain. The dataset, while effective, is limited in diversity, and the model currently functions in batch-processing mode, making real-time stress prediction a challenge. Additionally, while the ensemble model enhances accuracy, further work is needed to optimize computational efficiency and improve inference speed for real-time applications [17].

Moving forward, future improvements will focus on expanding the dataset for better generalization, refining transformer-based models for higher efficiency, and integrating real-time stress prediction capabilities. With these advancements, this model could be applied in mental health monitoring, workplace wellness programs, and real-time stress management tools, offering valuable insights for individuals and organizations looking to monitor and manage stress effectively [25].

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