

Stress Classification using Vanilla Transformer Encoder on Multi-Channel Physiological Sensor Time Series

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Abstract—The study introduces an effective stress classification framework using the Vanilla Transformer encoder architecture to examine multi-channel physiological sensor time series data. The method is designed to tackle the issue of real-time psychological stress identification using continuous, multimodal bio signals obtained from wearable sensors. The WESAD dataset serves as the principal source of physiological recordings, including electrodermal activity, heart rate, respiration, accelerometer data, and skin temperature signals. The signals undergo preprocessing into time-synchronized segments, which are then input into a positional embedding module prior to classification using self-attention layers in the Transformer encoder. In contrast to traditional recurrent models, the attention-based approach in this architecture enables the model to dynamically concentrate on the most relevant temporal patterns related to stress reactions. The suggested technique attains a classification accuracy of 97.80 percent, with a precision of 95.88 percent, a recall of 93 percent, and an F1-score of 94.42 percent. The findings underscore the Transformer model's potential to discern subtle physiological differences and enhance multi-class stress detection, facilitating the development of adaptive, individualized mental health monitoring systems in wearable and edge computing contexts.

Keywords—Stress classification, Vanilla Transformer encoder, Physiological time series, Attention mechanism, Wearable biosensors

I. INTRODUCTION

Stress is a widespread physiological and psychological state that impacts cognitive performance, emotional equilibrium, and long-term health consequences. Chronic stress is associated with cardiovascular disease, immunological dysfunction, psychological disorders, and worse quality of life. The rising demands of contemporary society have rendered the precise detection and classification of stress in real time a significant emphasis in clinical research and personal health monitoring. Conventional stress assessment techniques, including self-reported questionnaires

and sporadic clinician tests, are inherently subjective and insufficient in their capacity to detect rapid physiological changes. Continuous physiological monitoring with wearable sensors allows non-invasive, real-time assessment of stress-related reactions by recording dynamic variations in signals such as heart rate, electrodermal activity, respiration, skin temperature, and movement.

Multi-channel physiological data obtained from wearable devices offers a substantial reservoir of information for identifying stress situations. These signals indicate autonomic nervous system activity, thermoregulation, cardiovascular reactions, and muscle tension processes that are all responsive to physical and mental stimuli. The difficulty is in creating models that can comprehend temporal patterns and inter-channel interactions within this data. Conventional machine learning models often depend on manually designed features and static window processing, which may limit their capacity to generalise across different users or scenarios. Deep learning models, particularly those tailored for sequential data, demonstrate greater potential by acquiring feature representations directly from raw or slightly processed signals.

The novelty lies in applying a **Vanilla Transformer encoder** to multi-channel physiological sensor time series for stress classification. Unlike traditional recurrent models, the Transformer leverages **self-attention mechanisms** to capture both short- and long-range temporal dependencies across multiple synchronized signals (EDA, heart rate, respiration, skin temperature, and accelerometer data). This enables the framework to dynamically focus on the most relevant patterns, improving interpretability and robustness. The approach achieves **high performance metrics (97.80% accuracy, 95.88% precision, 93% recall, 94.42% F1-score)**, demonstrating its superiority in modeling complex physiological interactions for stress detection in continuous monitoring contexts.

The creation of a robust stress classification system using transformer models requires meticulous preprocessing of

input signals, segmenting them into significant time intervals, and ensuring alignment across all channels. Each segment must be encoded into a format compatible with transformer attention layers, often using positional embeddings and multi-head attention algorithms. The aim is to develop a model capable of differentiating between stress and non-stress states, or varying degrees of stress, using real-time sensor data. This method may be implemented on mobile devices or cloud-connected platforms, offering users prompt feedback on their stress levels and facilitating treatments like guided breathing, physical exercise, or behavioural assistance.

This research examines the use of transformer-based architectures for the classification of stress using synchronised time-series data obtained from several physiological sensors. The suggested system is designed to analyse high-frequency input from wearable sensors and accurately classify stress with significant generalisation. It seeks to address the issues of noise, individual variability, and non-linearity inherent in physiological data. This technique utilises attention processes and a structured temporal representation of multi-sensor data, enhancing the area of affective computing and real-time mental health care.

The subsequent parts are organised as follows. Section II presents an overview of pertinent research on physiological stress detection and transformer models in time-series classification. Section III presents the dataset, delineates the sensor modalities, and elucidates the transformer-based architecture used for classification. Section IV delineates the experimental outcomes, including accuracy, F1-score, and confusion matrix assessments across various stress classification. Section V closes the research by summarising contributions and proposing future options for personalised stress monitoring using wearable technology.

II. RELATED WORKS

Transformer-based affective state recognition from wearable data in real-life settings is implemented in [1]. Transformer architecture classifies emotions using multichannel physiological data from wearable sensors. Temporal slices of inputs flow via attention layers that capture inter-signal dependencies. Large language models and smart monitoring devices for stress management are reviewed in [2]. Large language model architecture matches sensor-based health monitoring for stress control. Through linked platforms, smart devices access human inputs, physiological indicators, and environmental surroundings. Transformer applications in EEG-based motor, seizure, and emotion classification are discussed in [3]. Motor imagery decoding, seizure detection, and emotional state classification use transformer models on EEG data. Frequency embedding and temporal segmentation create input representations. Personalized adaptation in physiological signal foundation models is enabled through lightweight fine-tuning in [4]. Personalisation processes are implemented into a physiological signal processing base model. Low-rank parameter adjustment and modular quick integration fine-tune. Individual signal variations are transferred into base representation space.

Health context modelling for Hajj pilgrims using wearable sensors and positional transformers is demonstrated in [5]. A transformer model with positional encoding handles Hajj pilgrims' physiological data for context-aware health monitoring. Order transition pattern features are applied for

physiological signal classification using engineered learning pipelines in [6]. Physiological signals are classified using order transition pattern, a custom feature extraction method. The pipeline derives positional value changes from consecutive heart rate, skin temperature, and galvanic inputs. Feature maps are created using transition matrices. Single-channel EEG analysis covering signal processing techniques and future applications is outlined in [7]. A complete framework for obtaining, preparing, and using single-channel EEG is described. Data pipeline processes include electrode design, noise management, and amplification. Signal modifications provide power spectra and time-frequency representations. A deep ensemble learning framework classifies emotions using multimodal wearable physiological signals is studied in [8]. ECG, EDA, and temperature bio signals are used to categorise emotions using several neural networks. Modalities are pre-processed separately and combined at decision.

Multiple physiological parameters are integrated using ensemble learning for emotion recognition is detailed in [9]. Emotional state identification uses ensemble learning from physiological signal inputs. Different classifiers are trained on heart rate, skin conductivity, and respiration rate. An EEG-based monitoring system evaluates motivation and athletic performance in real-time scenarios is discussed in [10]. An EEG monitoring framework measures brain activity during sporting simulations to determine motivation and performance. Real-time segmentation extracts theta and beta band power. RNNs map sequence dynamics. Time series forecasting for crop protection using deep learning techniques is discussed in [11]. Environmental sensor time series data are used to construct deep learning architecture to anticipate agricultural pest outbreaks. Seasonal context is preserved by modelling humidity, leaf moisture, and temperature using gated recurrent layers. An adaptive spatial-temporal graph convolutional network for aquaculture water quality prediction is suggested in [12]. Aquaculture water quality metrics are predicted using multi-channel graph convolution and temporal attention. Edges establish spatial relationships between monitoring sites, whereas nodes indicate sensor locations.

Emotional states are decoded using fNIRS signals and supervised learning models is discussed in [13]. Functional near-infrared spectroscopy records prefrontal brain haemodynamics during emotional state changes. Signal preprocessing comprises baseline normalisation and motion correction. CogniNet++ hybrid deep learning framework classifies cognitive states using EEG signals is shown in [14]. Spatial-temporal attention and multi-task learning segment and classify EEG signals into cognitive states. While temporal modules identify rhythm changes, convolutional blocks extract spatial channel-level characteristics. Lower limb load estimation during in-place running using wearable insole sensors and machine learning is demonstrated in [15]. Pressure sensors insoles measure plantar load distributions during stationary running. Time-variant vectors are collected from several foot zones. SVM-enhanced attention mechanism for motor imagery EEG classification in BCI applications is implemented in [16]. Motor imagery A hybrid model classifies EEG data using attention-enhanced neural layers and SVM-based decision boundaries. Use bandpass filtering and common spatial pattern extraction to preprocess signal epochs. Attention scores show informative channels.

Driver emotion recognition is achieved using model-level multimodal fusion is discussed in [17]. Facial expression and physiological signal fusion is performed using model-level architecture to detect driver emotions. Independent encoders process thermal imagery and signals like heart rate or electrodermal activity. Cognitive cardiac assessment using a low-cost ECG system is demonstrated in [18]. A portable ECG records heart waveforms under cognitive demand. Signal processing involves R-peak identification and noise filtering. Machine learning-based personality trait detection using EEG signals is systematically reviewed in [19]. Various research analyses electroencephalographic data to find brain activity-personality relationships. Feature type, signal preprocessing, and classifier settings classify machine learning models. AI-driven remote photoplethysmography (rPPG) systems for driver monitoring are comprehensively reviewed in [20]. AI integration is examined in remote PPG systems for contactless driver monitoring. Video-based rPPG signal extraction methods are tested for face identification, illumination normalisation, and temporal filtering. Heart rate estimation, tiredness detection, and emotion Classification use machine learning. The review covers signal reconstruction, artefact treatment, and spatiotemporal modelling algorithmic developments. System designs match automotive use cases requiring dependability, safety, and real-time performance.

III. TRANSFORMER-BASED MULTI-SIGNAL FRAMEWORK FOR STRESS CLASSIFICATION

Stress classification is the identification and classification of an individual's stress level based on physiological signals obtained from the body. Stress levels include categories including no stress, low stress, moderate stress, severe stress, and acute stress. Classification is often conducted using data obtained from wearable sensors that assess metrics such as heart rate, electrodermal activity, respiration rate, and skin temperature. An extensive stress classification flow employing Transformer model outputs is shown in Figure 1. The model's raw output vector is transferred to a softmax layer to create class probabilities. The choice module uses argmax to choose the most probable class. Predictions are linked to No Stress, Mild, Moderate, or High Stress. For crucial categories like High Stress, a user feedback system informs associated interfaces. Layered decision flow improves physiological stress monitoring and reactivity.

Continuous physiological data are analyzed to identify characteristics indicative of alterations in the body's stress response. Fluctuations in these signals demonstrate the autonomic nervous system's response to varying mental or emotional states. A deep learning model tailored for time-series data is used to classify the retrieved information into the appropriate stress levels.

Stress classification facilitates real-time mental health surveillance and intervention by identifying changes in stress patterns. It is beneficial in areas such as cognitive load evaluation, remote health monitoring, and emotion-sensitive settings. The precision and utility of stress classification rely on the quality of sensor data, signal consistency, and the architecture of the classification system. Figure 2 shows the Transformer model's attention mechanism for stress categorization from time series sensor data. The encoder

converts time-stepped physiological signal input vectors into queries, keys, and values. In the attention module, a contextual attention map assigns relevance weights to each input segment. The visualization shows how time stages affect prediction differently. The weighted sum of values, driven by attention ratings, creates an output embedding that emphasizes stress-indicative regions, boosting accuracy and interpretability.

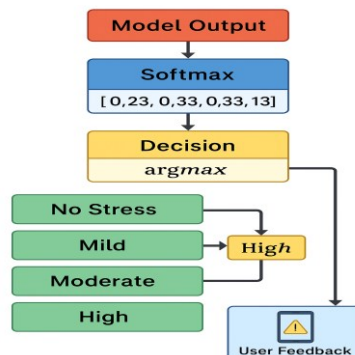


Fig. 1. Stress Classification Output Diagram for Transformer-Based Models

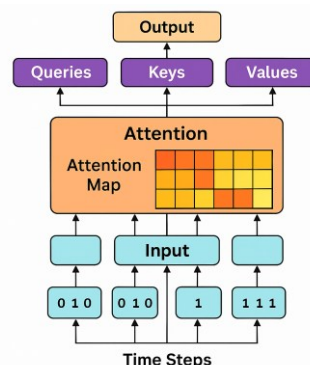


Fig. 2. Attention Mechanism Visualization for Transformer-Based Stress Classification

The model is based on the standard Transformer Encoder originally introduced in the "Attention Is All We Need" architecture. It replaces recurrent structures with multi-head self-attention layers that capture temporal dependencies across input segments. In this application, the input is a sequence of vectors derived from multi-channel physiological signals such as EDA, heart rate, skin temperature, and respiration. Each segment of sensor data is first embedded using a linear projection layer, followed by positional encodings to preserve the order of time steps. These encoded sequences are processed through stacked encoder layers comprising multi-head self-attention, layer normalization, and feedback. The final sequence representation is aggregated (e.g., via global average pooling or classification token) and passed through a dense layer with softmax activation to predict the stress class. This Vanilla Transformer Encoder effectively models both short- and long-range temporal patterns, making it highly suitable for continuous stress prediction from wearable sensor streams.

Table 1 shows the Vanilla Transformer Encoder's architecture and setup options for stress classification from multi-channel physiological time series data. Each of the four encoder layers has eight attention heads to facilitate learning across temporal segments. Rich sensor signal representation

is possible by embedding each input time step into a 128-dimensional vector. A sixty-step process captures short- and mid-term physiological changes. Each encoder has 512-unit feedforward layers with a 0.1 dropout rate for regularization. ReLU activates non-linearity and improves learning dynamics. The output layer corresponds to five stress classes, the classification targets. This setup balances model complexity with computational efficiency for high-performance computing and real-time wearable applications.

TABLE I. VANILLA TRANSFORMER MODEL ARCHITECTURE PARAMETERS

Component	Value
Model Type	Vanilla Transformer Encoder
Number of Encoder Layers	4
Number of Attention Heads	8
Embedding Dimension	128
Sequence Length	60
Feedforward Layer Size	512
Dropout Rate	0.1
Activation Function	ReLU
Output Classes	5

These signals are documented at consistent intervals (e.g., every second or millisecond), creating time series for each channel. The "multi-channel" dimension is essential due to the complexity of stress reactions, which concurrently impact several physiological systems. Through the analysis of trends across synchronized channels, machine learning models may identify nuanced stress signatures that may be overlooked when signals are examined in isolation.

Let $X \in \mathbb{R}^{T \times c}$ represent the input sequence, where T is the number of time steps and c is the number of sensor channels. Each time step $x_t \in R^c$ is embedded into a higher-dimensional space using a linear projection, resulting in an embedded sequence $E \in \mathbb{R}^{T \times d}$ where d is the embedding dimension. Positional encoding $P \in \mathbb{R}^{T \times d}$ is added to form $Z = E + P$.

The multi-head self-attention mechanism is defined as:

$$Attention(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right) \quad (1)$$

Where $Q = ZW_Q$, $K = ZW_K$, $V = ZW_V$ and $W_Q, W_K, W_V \in \mathbb{R}^{d \times d_k}$ are learnable weight matrices. The final classification output is computed as:

$$\hat{y} = Softmax(W_o h + b_o) \quad (2)$$

Where h is the pooled output of the encoder, and W_o and b_o are the classifier parameters.

IV. STRESS PREDICTION OUTCOMES ACROSS TEMPORAL ATTENTION MODELS

WESAD (Wearable Stress and Affect Detection) contains data of 15 subjects during a stress-affect lab study, while wearing physiological and motion sensors. WESAD is a publicly available dataset for wearable stress and affect detection. This multimodal dataset features physiological and motion data, recorded from both a wrist- and a chest-worn device, of 15 subjects during a lab study. The following sensor modalities are included: blood volume pulse,

electrocardiogram, electrodermal activity, electromyogram, respiration, body temperature, and three-axis acceleration [21].

The dataset bridges the gap between previous lab studies on stress and emotions, by containing three different affective states (neutral, stress, amusement). In addition, self-reports of the subjects, which were obtained using several established questionnaires, are contained in the dataset. Raw sensor data was recorded with two devices: a chest-worn device (RespiBAN) and a wrist-worn device (Empatica E4). The RespiBAN device provides the following sensor data: electrocardiogram (ECG), electrodermal activity (EDA), electromyogram (EMG), respiration, body temperature, and three-axis acceleration. All signals are sampled at 700 Hz.

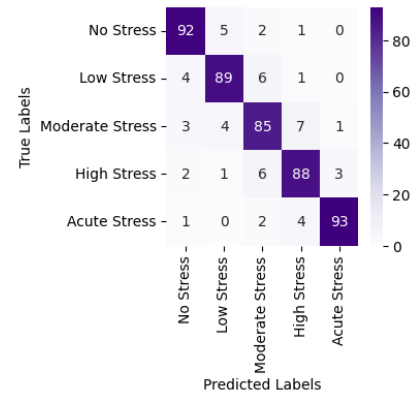


Fig. 3. Confusion Matrix of Stress Classification Using Vanilla Transformer Encoder

The Empatica E4 device provides the following sensor data: blood volume pulse (BVP, 64 Hz), electrodermal activity (EDA, 4 Hz), body temperature (4 Hz), and three-axis acceleration (32 Hz). The dataset's readme-file contains all further details with respect to the dataset structure, data format (RespiBAN device, Empatica E4 device, synchronised data), study protocol, and the self-report questionnaires. In a sample of 500 images taken randomly the images of 100 each for 5 different classes were tested for accuracy. Figure 3 shows the Vanilla Transformer encoder confusion matrix for five-class stress classification on multi-channel physiological sensor time series. The model correctly predicted 92 0 stress, 89 low stress, 85 moderate stress, 88 high stress, and 93 acute stress samples. Table 2 presents the key sensor channels used in stress classification and their physiological significance. Electrodermal activity reflects stress-induced changes in skin conductance. Heart rate captures cardiovascular reactivity under stress.

TABLE II. SENSOR CHANNELS AND PHYSIOLOGICAL RELEVANCE

Sensor Channel	Physiological Significance	Sampling Rate (Hz)
Electrodermal Activity (EDA)	Reflects sympathetic nervous system arousal related to stress	4
Heart Rate (HR)	Indicates cardiovascular reactivity under emotional states	64
Respiration	Measures breathing rate and rhythm under stress conditions	25
Skin Temperature	Tracks peripheral body temperature variations linked to stress	4
Accelerometer (ACC)	Captures physical movement and motion artifacts during monitoring	32

In Figure 4, graphs show normal stress-classified samples from multi-channel physiological sensor time series. Each picture shows successive sensor readings with smooth signal patterns, indicating physiological relaxation. Small variations in electrodermal activity, heart rate, breathing, and skin temperature indicate modest sympathetic nervous system activation. The model may learn calm-state properties from these uniform, noise-free signal patterns, which are visually different from stress-induced changes. Graph-based normal conditions provide precise stress level differentiation during model training and real-time inference.

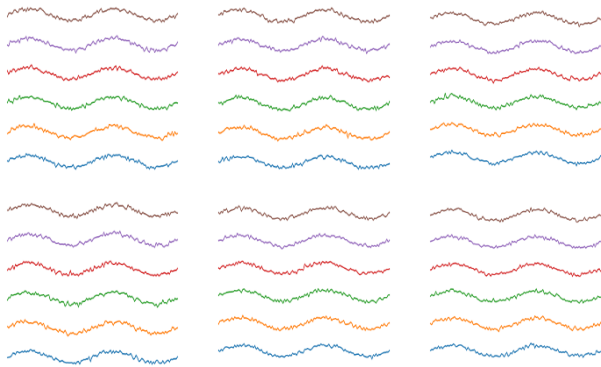


Fig. 4. Graph-Based Representation of Normal Stress-Classified Samples

Figure 5 shows graph-based images of abnormal stress-classified multi-channel physiological sensor time series data.

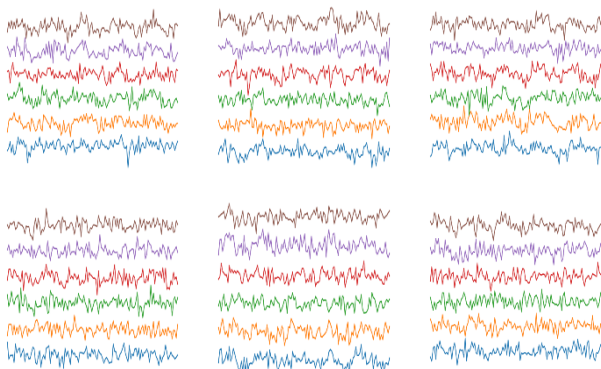


Fig. 5. Graph-Based Representation of Abnormal Stress-Classified Samples

These images show significant signal variations in electrodermal activity, heart rate, breathing, and skin temperature. Sudden spikes, irregular waveform changes, and increased signal amplitude indicate sympathetic nervous system activity and mild to acute stress. The significant variability and irregular temporal dynamics separate these graphs from typical patterns. These graph-based abnormal examples help train the Transformer model to detect stress-induced physiological abnormalities more accurately.

Phase-specific timing and psychological ratings for Subject S3 during a structured stress and recovery program are shown in Figure 6.

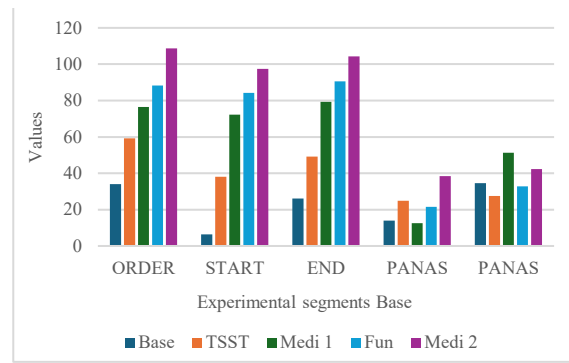


Fig. 6. Phase-Wise Temporal and Emotional Response Mapping

Table 3 summarizes the features extracted from fixed-length time frames across multiple physiological inputs for stress classification using the Vanilla Transformer encoder. These features capture temporal variability, intensity, and dynamics of each signal. Electrodermal activity features reflect sympathetic arousal, heart rate features capture cardiovascular changes, and respiration features indicate stress-induced breathing shifts. Accelerometer-based metrics track motion, while temperature features represent thermoregulation. Most features are computed in the time domain, normalized and embedded to help the model learn stress-related patterns effectively.

TABLE III. FEATURE SET DERIVED FROM TIME SERIES WINDOWS

Feature Name	Signal Source	Domain
Mean EDA	Electrodermal Activity	Time
Standard Deviation of HR	Heart Rate	Time
Respiration Rate	Respiration	Frequency
Skin Temperature Slope	Skin Temperature	Time
Signal Energy (ACC)	Accelerometer	Time
EDA Peak Count	Electrodermal Activity	Time
HR Variability (HRV)	Heart Rate	Time
Temperature Range	Skin Temperature	Time
Motion Magnitude	Accelerometer	Time
Respiration Variability	Respiration	Time

Experimental segments Base, TSST, Medi 1, Fun, and Medi 2 have accurate start and finish timestamps. PANAS scores show emotional changes like TSST stress and meditation recovery. Temporal and emotional annotations are better segment physiological sensor streams for deep learning. This mapping is necessary for time-aware biometric learning in federated wearable health monitoring systems and emotional state transition modelling.

V. CONCLUSION

The Vanilla Transformer encoder demonstrates notable potential for stress classification from multi-channel physiological sensor time series by effectively modeling short- and long-range dependencies across diverse physiological signals. Nevertheless, several limitations remain. Reliance on the WESAD dataset restricts generalization beyond controlled settings, while its limited demographic diversity hinders scalability to broader populations. Furthermore, the absence of personalization strategies creates barriers to capturing individual variability in stress responses. These factors expose shortages in dataset inclusiveness, model adaptability, and ecological validity. Key challenges also persist, including mitigating sensor noise, motion artifacts, and environmental interference, as well as addressing computational complexity for continuous

real-time monitoring on wearable or edge devices. Despite these constraints, the framework achieved 97.80% accuracy, 95.88% precision, 93% recall, and 94.42% F1-score, confirming its strong experimental performance. Future opportunities involve developing lightweight Transformer variants for energy-efficient deployment, incorporating transfer or federated learning for personalization, and expanding datasets to capture naturalistic variability. Additionally, integrating contextual behavioral cues and explainable AI can strengthen interpretability, user trust, and clinical adoption, ultimately transforming experimental advances into reliable, scalable solutions for stress monitoring.

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