Wearable EEG-Based Stress Recognition Using Deep Learning Models

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***Abstract*—Frequent stress significantly impacts human's cognitive function and quality of life, creating a demand for objective, real-time monitoring solutions. Although electroencephalography (EEG) provides a direct window into brain activity related to stress, most research is based on high-density lab equipment. This study investigates the possibility of using low-channel wearable EEG devices for practical stress recognition. We evaluated three deep learning models: CNN, LSTM, and the TSCeption architecture on the public PASS dataset, which includes EEG recorded during cognitive and physical tasks. The models address stress quantification as regression, 3-class, and 21-class classification problems. The results show that the TSCeption model achieves the highest accuracy and robustly generalizes to unseen subjects in a leave-one-subject-out validation. This work demonstrates the potential of compact wearable EEG systems as a foundation for deployable continuous stress monitoring applications.**

I. Introduction

Stress recognition is an important focus in current psychophysiology, neuroscience, and health research [1]. Both long-term and acute stress significantly affect cognitive performance, decision-making, emotional well-being, and overall quality of life. Therefore, the fast pace and high demands of modern life create a clear need for objective and practical methods to monitor stress in everyday settings.

Traditional methods for monitoring stress usually involve subjective questionnaires or the measurement of physiological signals such as heart rate, galvanic skin response, and movement patterns [2]. While commonly used, these approaches have limitations, including delays between measurements, inconvenience for regular use, and possible misinterpretation of data. Electroencephalography (EEG) offers a valuable alternative by recording brain activity in near real-time, providing a direct and objective measure related to stress levels.

EEG captures neural activity linked to mental effort, emotional changes, and automatic responses—all key elements of stress [3]. Unlike other physiological signals, EEG records the brain's direct response to stressors in the environment. This makes it a highly useful tool for building automated stress detection and personal monitoring systems.

Advances in EEG technology and data analysis have made it possible to use these devices in daily life. Modern wearable EEG devices are designed to be used outside of laboratory settings. However, this also introduces challenges, as wearable devices typically have fewer electrodes, lower spatial resolution, and are more vulnerable to noise and artifacts. Therefore, balancing ease of use with data quality remains a key goal in creating effective, real-world stress monitoring systems.

This study builds on our earlier work that uses four-channel EEG data to monitor a person's psychophysiological state. We propose an approach for the automatic recognition of stress using signals from a wearable, low-channel EEG device. In this work, stress is conceptualized as a functional brain state marked by changes in neural activity due to changed cognitive and emotional load. The main aim is to identify stable patterns in EEG signals that can distinguish stressed states from neutral ones, even with a limited number of channels.

To classify stress, we use a machine learning model capable of extracting relevant spatio-temporal features from EEG data. Special attention is given to the model's robustness to differences between individuals and to artifacts that are common in real-world recordings. By applying deep learning, the model can automatically learn complex patterns in the data, which helps improve accuracy even with limited input from few EEG channels.

Using low-channel EEG for stress recognition opens the door to affordable and scalable monitoring systems. These could be applied in healthcare, workplace settings, and personal wellness, for purposes such as early stress detection, evaluating the effectiveness of interventions, and developing adaptive technologies that respond to a user's state. Despite challenges like noise and individual variability, our results support the practical potential of wearable, low-channel EEG devices for stress recognition.

The rest of the paper is organized as follows: Section II reviews existing approaches to stress recognition based on EEG and related physiological signals. Section III describes the dataset, data preprocessing, model architectures, training procedures, and evaluation metrics. Section IV presents the discussion of key findings and limitations. Section V concludes with future research directions.

II. Related Work

Research in the field of automatic recognition of stress states traditionally relies on the analysis of peripheral physiological signals, such as electrocardiogram (ECG), heart rate variability (HRV), electrodermal activity (EDA), as well as on subjective self-reports and the results of psychometric questionnaires [4]. Models based on ECG and derived HRV indicators demonstrate high performance in stress classification using both classical machine learning methods and deep neural networks. In particular, Kang et al. proposed a modified CNN–LSTM architecture for mental stress classification from ECG, using FFT and spectrogram-based preprocessing, and reported an accuracy of 98.3%, noting a 14.7% improvement compared to previous results [5]. Despite the strong performance, ECG-based pipelines may remain sensitive to preprocessing choices and recording conditions, motivating complementary modalities and robust evaluation in realistic settings.

In contrast to peripheral signals that primarily reflect autonomic activity, electroencephalography is considered a promising tool for stress recognition due to its ability to capture cortical dynamics with high temporal resolution [6]. EEG-based stress studies commonly analyze changes in theta, alpha, and beta rhythm bands and leverage spectral features such as power spectral density (PSD) derived from short windows of brain activity. A representative example of low-complexity feature engineering is the use of ratio-based markers: Wen et al. extracted PSD via a modified Welch FFT procedure and used the Theta/Beta power ratio with k-means clustering followed by an SVM classifier to distinguish three stress levels (low, moderate, high), reporting an overall accuracy of 90% [7]. Building on related clustering-assisted labeling ideas but using different features and a different protocol, Wen and Mohd Aris recorded prefrontal EEG from two channels (Fp1, Fp2) in 50 participants under stress-inducing VR stimuli and an IQ test, and reported 98% accuracy for three-level stress classification using k-means pre-labeling and SVM based on beta-band absolute power at the right prefrontal site (Fp2) [8]. These results support the relevance of beta-related spectral markers and illustrate how labeling strategies and feature choice can affect performance.

Recent work increasingly focuses on automated extraction of stress-related EEG structure using hybrid pipelines that combine artifact purification and multi-domain representations with learned feature extractors. Dong et al. applied ICA for EEG purification, represented signals in time, frequency, and time–frequency domains via fractional Fourier transform, and employed a two-layer 2D-PCANet with SVM classification, achieving an average accuracy above 92% on a self-collected dataset with 15 participants and two stress-inducing tasks [9]. Transfer-learning-style feature extraction has also been explored on high-density EEG and multitask paradigms: Afify et al. proposed a short-term stress detection approach on the SAM 40 dataset (32 channels, 40 patients) spanning four tasks (Stroop, arithmetic, mirror-identical image search, and relaxation), where each 25 s task segment was repeated three times, yielding 480 EEG signals across 120 trials per task. Using VGGish as a feature extractor and a CNN classifier in a spectrogram-based pipeline, they reported 99.25% accuracy with k-fold validation [10]. More generally, fusion-oriented deep architectures integrating time–frequency feature extraction with sequence models and attention-like mechanisms (e.g., BiLSTM layers coupled with Transformer components) are being investigated to capture temporal patterns and global context in EEG during stress-related activity [11]. System-level trends and methodological gaps in EEG-based stress quantification, including reproducibility and standardization issues, are comprehensively discussed in a systematic review covering 275 studies published from 2003 to January 2025 [6].

Alongside classification, quantitative stress estimation via regression has also been investigated. Perez-Valero et al. proposed a framework for predicting self-perceived stress level (SPSL) from EEG spectral features during a stress–relax session (MIST stressor followed by a 360-degree VR relaxation experience) in 23 participants, reporting MSPE = 10.62 $\pm$ 2.12 and R^2 = 0.92 $\pm$ 0.02 for individual regression models [12]. Comparative studies further indicate that strong performance can be achieved using relatively simple statistical descriptors over multi-channel EEG. Fernandez et al. evaluated multiple models for students' stress detection and showed that the mean and standard deviation computed over 19 EEG channels consistently outperformed alternative feature sets, with LightGBM demonstrating superior performance compared to CNN, kNN, and SVM across evaluated scenarios [13]. In VR-based stress elicitation with a larger cohort, Marcolin et al. reported that classical ML models can reach very high accuracy when EEG-derived stress indicators are labeled via post-experimental self-assessment: kNN achieved around 70% accuracy, while eXtreme Gradient Boosting and Random Forest exceeded 98% accuracy on data from 87 participants [14].

In parallel, multi-modal stress recognition systems that combine brain and peripheral physiology are progressing, motivated by the complementary nature of cortical and autonomic responses. Hemakom et al. studied ECG- and EEG-based stress detection and multilevel classification while accounting for gender differences. For low/high stress detection, they reported best average accuracy of 79.81% (females, RBF-SVM) and 73.77% (males, kNN) using unimodal models, while combining ECG and EEG increased the average accuracy to at least 87.58% (males, high stress) and up to 92.70% (females, high stress). For multilevel stress classification using ECG and EEG, the reported accuracy was 62.60% for females and 71.57% for males [15]. These findings support the value of multimodal fusion, while also highlighting that inter-individual factors can materially affect model performance and should be considered in evaluation protocols [6].

A key trend in recent years has been the transition from laboratory-only experiments to continuous stress monitoring in real-world conditions using wearable sensors. Can et al. developed a continuous stress detection system with modality-specific artifact removal and feature extraction tailored for real-life settings, and evaluated it during a nine-day algorithmic programming contest involving 21 participants. Using heart activity, skin conductance, and accelerometer signals, their system discriminated contest stress, higher cognitive load during lectures, and relaxed activities, demonstrating feasibility of unobtrusive long-term monitoring outside the laboratory [16]. A broad perspective on wearable stress detection - including stress physiology at the ANS and HPA levels, sensing modalities, and analysis technologies - is provided by Taskasaplidis et al. in a comprehensive review of stress detection methods using wearable sensors [4]. Within wearable EEG specifically, Affanni et al. designed and characterized a six-channel EEG headband for stress-related brain activity measurement during driving, reporting a measurement error of 6 μV, a bandwidth of 0.8–44 Hz, a resolution of 50 nV (via oversampling), and approximately 10 h of continuous WiFi transmission. In a driving-simulator study with ten volunteers, they observed higher estimated beta-wave power (stress-related) in manual driving compared to autonomous driving scenarios [17]. At the same time, moving toward wearable deployment increases sensitivity to motion and real-life artifacts and amplifies the importance of robust preprocessing and model generalization across days and individuals, which remains an active challenge for practical stress monitoring systems [6], [16].

In this context, the task of stress recognition based on data from wearable EEG (including low-channel configurations) using deep learning methods, with a specific focus on robustness to artifacts and individual differences, remains relevant and practically significant [4], [6].

III. An Approach

This section describes the dataset used, the preprocessing steps for EEG signals, the formalization of stress recognition tasks, the architectures of the models used, the training procedures, and the quality assessment methods. Additionally, a leave-one-subject-out scheme is presented to evaluate the inter-individual generalizability in the 21-class classification setting.

A. General Description

This study aims to automatically recognize stress levels based on EEG signals obtained from a low-channel wearable device. The target variable is subjective stress ratings, which are assigned on a 21-point scale and represented as integers ranging from 1 to 21.

Three task settings are considered for the same initial labeling. In the first setting, a regression task is solved, where the model predicts a numerical value for the stress level. In the second setting, a three-class classification is performed, where the range of 1-21 is divided into three equal intervals: 1-7, 8-14, and 15-21. In the third setting, a 21-class classification is performed, where each class corresponds to a specific stress level value.

Three models were trained and compared for all three settings: a convolutional neural network, a recurrent LSTM network, and the TSCeption model [18]. The overall pipeline includes signal preprocessing, fixed-length window segmentation, sample formation for the chosen task setting, model training, and quality assessment on held-out data. Visual representation of described approach is shown on Figure 1.

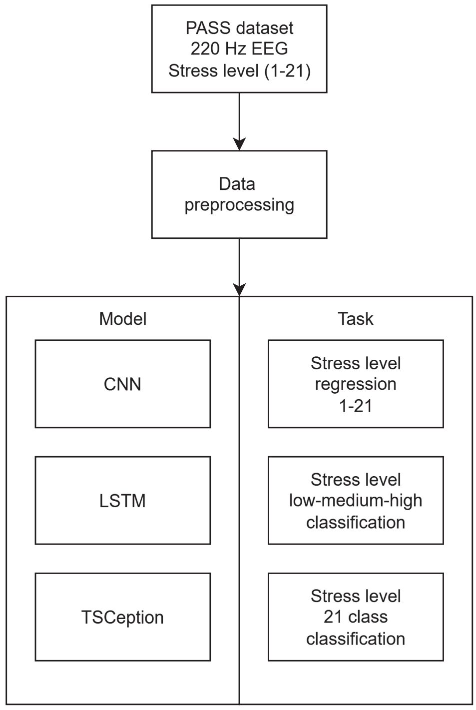

Fig. 1. General description of the approach

B. Public Dataset

The study utilizes the public PASS dataset [19], which was created to investigate stress responses during simultaneous cognitive load and physical activity. The experimental paradigm revolves around playing a computer game while performing controlled cycling on a stationary bike, allowing for the consideration of the impact of physical activity on the quality of physiological signals and the stability of the models.

The dataset includes recordings from 48 subjects. However, in this study only Parts 2 and 3 of the PASS dataset were used, comprising data from 35 participants, since Part 1 was not available to the authors. Two game scenarios were used to manipulate stress, corresponding to two levels of stress exposure. The less stressful condition involved playing the game TIMEframe, while the stressful condition was set by playing the game Outlast. The intensity of physical activity varied at three levels, set by the target pedaling speed of 0, 18, and 24 km/h. Each subject completed all six combinations of stress level and physical activity level in a balanced and pseudo-random order. Each condition lasted for 10 minutes. Before each condition, a baseline period of approximately 2 minutes was performed at the same pedaling intensity, but without any game activity, followed by the condition and a short break. The EEG was recorded using the Muse wearable system with four electrodes (TP9, AF7, AF8, and TP10) and a reference point (Fpz). The EEG was sampled at a rate of 220 Hz. The data streams were transmitted to a computer via Bluetooth, and the boundaries of the conditions were marked using start and end triggers, which were then manually verified for accuracy. In addition to the EEG, PASS also includes peripheral modalities, but this study focuses solely on the EEG and subjective assessments. The target labels were derived from the NASA-TLX questionnaire, which was completed after each condition and involved answering questions on a 21-point scale. The experimental version of the NASA-TLX

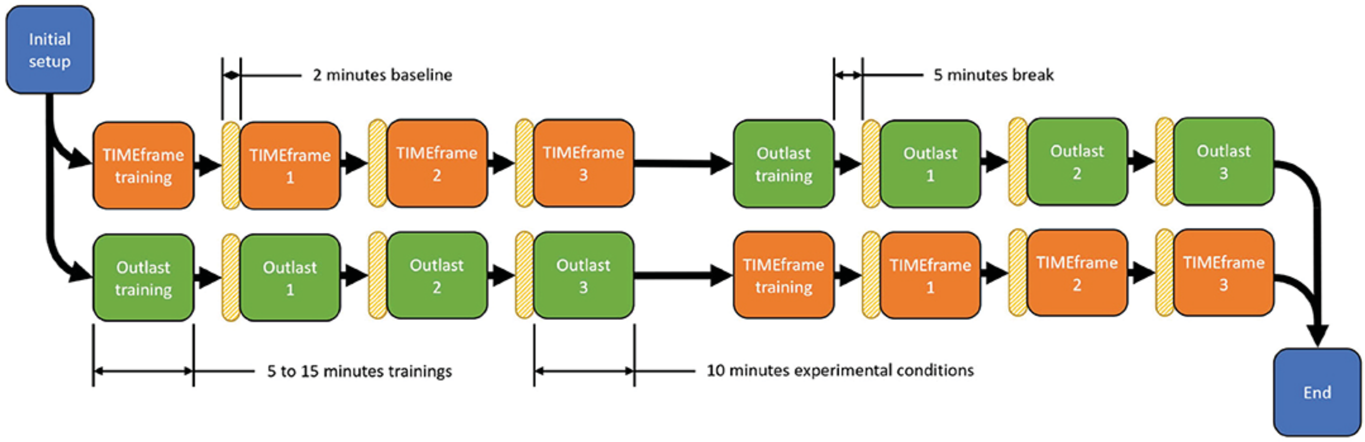

Fig. 2. PASS dataset record overview [19]

included additional questions related to stress. In this study, the target variable was a quantitative assessment of stress on a 1-to-21 scale, which was then interpreted in three different problem formulations: regression, three-class classification, and 21-class classification.

The regression task is formulated as predicting the numerical value of the stress level on a 1-21 scale from an EEG segment.

In the three-class classification task, the label is constructed as belonging to one of three equal intervals: low level corresponds to values 1-7, medium level corresponds to 8-14, and high level corresponds to 15-21.

In the 21-class classification task, the target variable is categorical, where each class corresponds to one integer stress level on a 1-21 scale.

C. Data Preprocessing

Raw EEG signals from the PASS dataset were preprocessed to enhance signal quality and remove noise typical for wearable recordings. A bandpass filter was applied with a frequency range of 1-40 Hz to retain relevant neural oscillations (delta through low-gamma bands) while attenuating slow drifts, power-line interference, high-frequency muscle artifacts, and low-frequency ocular artifacts such as eye blinks and saccades.

Signal was then normalized by subtracting the mean and dividing by the standard deviation, computed across all time points, to ensure zero mean and unit variance. This step facilitates stable training across different signal amplitudes and subjects.

Finally, the continuous signals were segmented into non-overlapping windows of 1 second (220 samples at 220 Hz sampling rate), preserving temporal structure while creating fixed-length inputs suitable for the deep learning models.

D. Model Architectures and Training

Three neural network architectures were implemented and evaluated for EEG-based stress detection.

A Convolutional Neural Network (CNN) was used to extract local temporal patterns and inter-channel regularities from EEG segments. The architecture was built around a sequence of three one-dimensional convolutional layers with batch normalization and non-linear activations, designed to hierarchically extract features across different temporal scales. To capture long-range dependencies within the feature maps, a multi-head attention mechanism was incorporated. The resulting features were then aggregated via global average pooling and passed through a series of fully connected layers to produce the final classification output.

An LSTM model was used to account for the temporal dynamics and sequential dependencies of the EEG signal. The architecture employed a bidirectional LSTM with two layers to process the input sequence in both forward and reverse directions, capturing comprehensive contextual information. An attention mechanism was applied to the sequence of LSTM hidden states to weight the importance of different time steps. The final aggregated representation was then projected through multiple fully connected layers to generate the classification logits.

The TSCeption model was used as a specialized architecture for analyzing EEG time series, combining multi-scale temporal convolutions and spatial convolutions across channels [18]. In all three task formulations, this model demonstrated the best final performance in terms of the main quality metrics compared to the standard CNN and LSTM, so it was selected for additional evaluation using the leave-one-subject-out scheme in the 21-class classification task formulation.

All models were trained using the Adam optimizer. For the regression formulation, a mean squared error loss function was used, while for the classification formulations, categorical cross-entropy was used. Regularization techniques, including dropout, and early stopping based on validation metrics were employed to mitigate overfitting. To address class imbalance in the classification tasks, strategies such as applying class weights or weighted sampling during batch formation were utilized. Models underwent systematic hyperparameter tuning specific to their architectures, using grid search over learning rate (1e-4 to 1e-2), batch size (32-128), dropout (0.2-0.5).

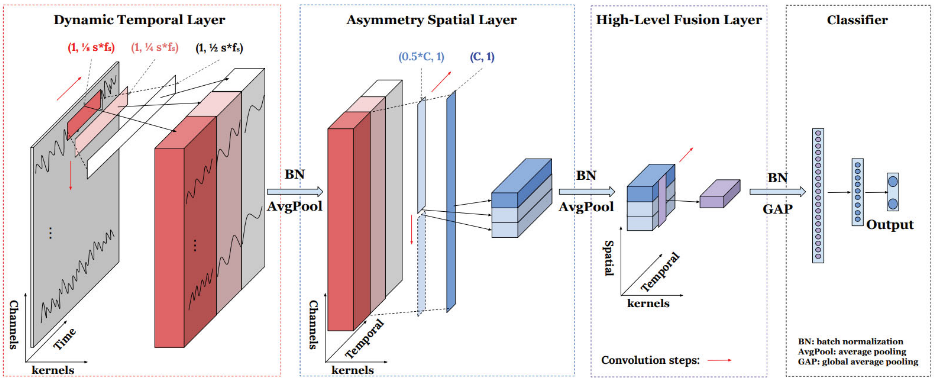

Fig. 3. TSCeption model architecture [18]

Five-fold cross-validation on training data ensured robust selection prior to hold-out evaluation.

E. Evaluation Metrics

Model performance was assessed using standard metrics: MAE and RMSE for regression; Accuracy and Macro F1-score for classification tasks. Results are shown at Tables I-III. We used a hold-out scheme with train/validation/test splits for primary evaluation and leave-one-subject-out cross-validation (LOSO-CV) for inter-subject generalization assessment. Note that hold-out refers to a single random split of data into training and held-out test sets, while LOSO-CV excludes all data from one subject per fold.

TABLE I. REGRESSION RESULTS

Model	MAE	RMSE
CNN	0.956	0.975
LSTM	0.998	1.094
TSCeption	0.820	0.898

TABLE II. THREE-CLASS STRESS CLASSIFICATION RESULTS

Model	Accuracy	Macro F1-score
CNN	0.764	0.740
LSTM	0.669	0.647
TSCeption	0.809	0.808

TABLE III. 21-CLASS STRESS CLASSIFICATION RESULTS

Model	Accuracy	Macro F1-score
CNN	0.645	0.512
LSTM	0.630	0.458
TSCeption	0.709	0.652

F. Leave-One-Subject-Out Evaluation

For the 21-class classification, a leave-one-subject-out cross-validation was performed for the TSCeption model. At each step, the data of one subject was completely excluded from the training and used only for testing, while the training was performed on the combined data of the remaining subjects. The procedure was repeated for all subjects, and the final metrics were averaged.

This protocol allows us to evaluate the model's ability to generalize to new users that are not present in the training set. The final averaged LOSO metrics are presented in Table IV, while the accuracy/F1-score distribution for each participant is shown in Figure 4.

TABLE IV. LOSO-CV RESULTS FOR 21-CLASS CLASSIFICATION USING TSCEPTION

Metric	Mean
Accuracy	0.564
Macro F1-score	0.433

Table V compares EEG performance, where PASS baseline denotes binary stress classification (stress - no stress) using hand-crafted features [19], while our TSCeption uses raw EEG for 21-class stress levels.

TABLE V. EEG PERFORMANCE COMPARISON WITH PASS BASELINE

Method	Scheme	Amount of classes	Accuracy
PASS baseline	k-fold CV	2	0.74
PASS baseline	LOSO-CV	2	$\sim$0.50
Our TSCeption	Hold-out	21	0.709
Our TSCeption	LOSO-CV	21	0.564

To enhance interpretability, Figure 5 visualizes mean signal importance from the TSCeption model, overlaid on a 1 second EEG sample.

IV. DISCUSSION

Stress ratings in the PASS dataset come from NASA-TLX questionnaires, which are inherently subjective. Each participant experiences and reports cognitive load and emotional strain differently, even under the same game-bike conditions. This label noise makes it challenging for deep learning models to learn consistent patterns, particularly in the demanding 21-class setup, where the model must distinguish stress levels

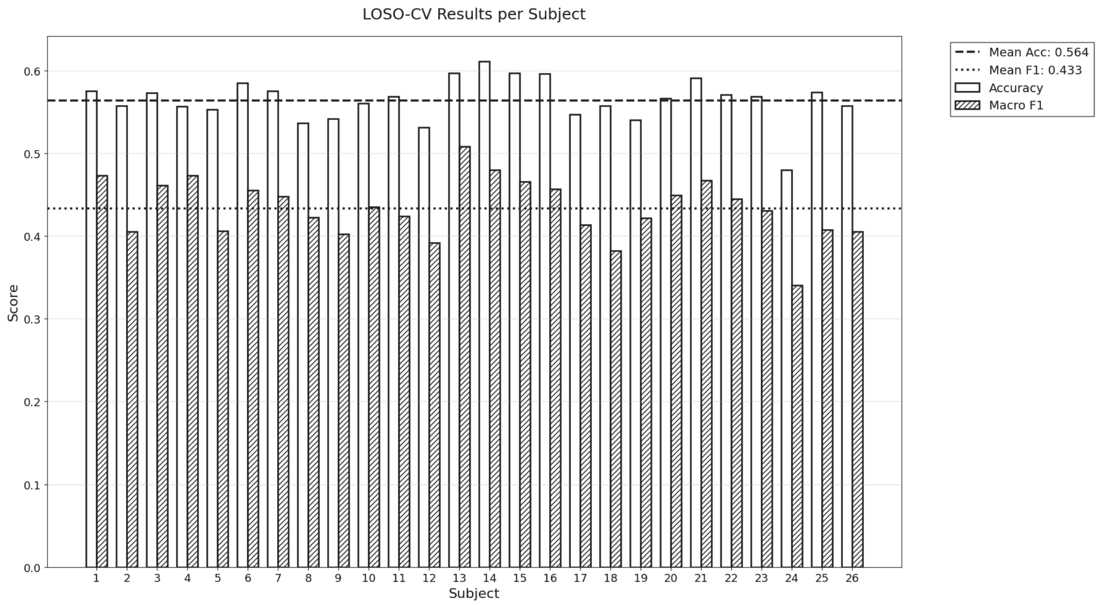

Fig. 4. LOSO Evaluation Results for Each Participant

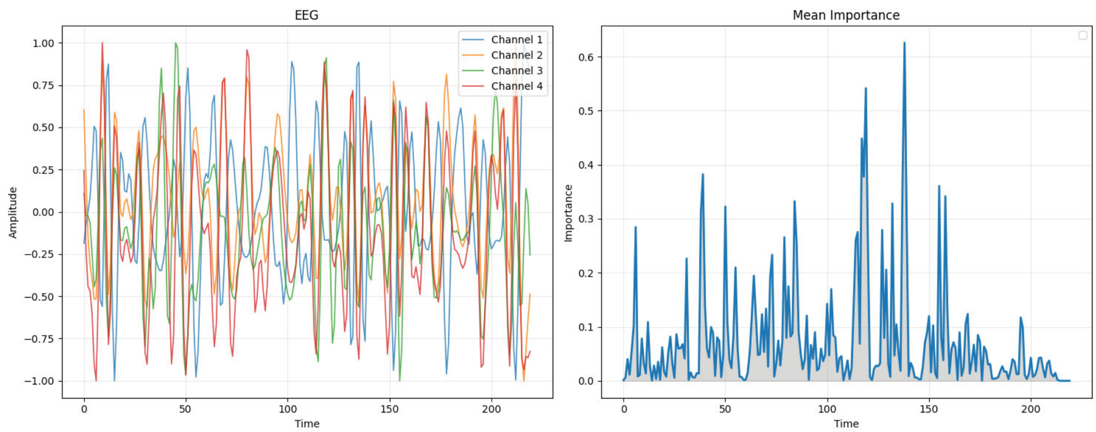

Fig. 5. Mean signal importance on 1 second EEG sample

on the 1-21 scale. To address this, we also tested a 3-class grouping (low: 1-7, medium: 8-14, high: 15-21), which provides a broader decision range less sensitive to individual rating biases. In this setup, TSCeption achieved high held-out accuracy of 0.809, demonstrating effectiveness when granularity is reduced.

The performance drop in leave-one-subject-out validation reflects real-world inter-subject variability, including differences in physiology, electrode contact, and individual stress baselines. Despite this, TSCeption achieves solid results without any information about physical activity levels (0, 18, or 24 km/h pedalling speeds). The model successfully extracts stress-related EEG signatures even with motion artifacts and sympathetic nervous system activation from exercise, demonstrating robustness that bodes well for wearable deployment.

One-second non-overlapping windows were selected for model training based on established findings that short windows optimally balance emotional variability capture with classification stability [20]. Their results showed that relatively short windows are sufficient for reliable emotion classification and that excessively long windows do not necessarily improve performance. In fact, shorter windows allow models to adapt more effectively to the dynamic character of affective processes while preserving computational efficiency.

V. Conclusion

This work demonstrates the applicability of low-channel wearable EEG for automatic stress level recognition in various task settings. Based on PASS data containing subjective stress ratings on a 1-21 scale, three approaches to formalizing the target variable were considered: numerical stress level regression, three-class classification based on equal ranges, and 21-class classification. The comparison of CNN, LSTM, and TSCeption models demonstrated that neural network approaches are capable of extracting informative patterns from a limited number of EEG channels and providing stable results when processing data collected under conditions of simultaneous cognitive load and physical activity. The TSCeption model showed the best performance and was further evaluated using the leave-one-subject-out scheme, confirming its ability to generalize to new subjects without including their data in the training process.

Despite the achieved results, the task of stress recognition using low-channel EEG remains sensitive to artifacts, inter-individual variability, and the influence of motor activity present in the data collection protocol. Further work will focus on improving the models' resilience to these factors through advanced augmentation and domain adaptation techniques, as well as by considering contextual conditions more thoroughly, including the level of physical activity. Integrating additional physiological modalities available in PASS is a promising direction, which can enhance the reliability of stress estimation and reduce the ambiguity of EEG interpretation in real-world settings. Finally, additional research is needed on more diverse samples and in ambulatory scenarios to evaluate the transferability of the models and their suitability for continuous stress monitoring in practical applications.

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