



Multi-Band EEG Spectrogram Decomposition with Residual Attention Network for Enhanced Stress Classification

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Abstract

Stress can affect both physical and mental health, and it is important to support faster intervention. EEG can record brain activity directly, but EEG signals are complex, noisy, and difficult to handle. This study explores how EEG spectrogram decomposition can improve stress classification accuracy using deep learning models. Decomposition was accomplished by splitting a single EEG spectrogram into five distinct segments based on frequency range. Deep neural networks resembling ResNet are well-suited for spectrogram data, as the iterative feature extraction across layers facilitates the identification of hidden patterns. Incorporating an attention module before the classification layer further strengthens the model's capabilities by highlighting the most pertinent features during the training process. The baseline architecture employed in this study was ResNet-152. By incorporating a Multi-Head Attention mechanism prior to the Fully Connected layer, the modified network is denoted as RAN-152. The combination of spectrogram decomposition, ResNet, and attention has been proven to improve classification accuracy in complex EEG data. Without these three together, the accuracy obtained was only 0.5479, while the combination of the three achieved the highest accuracy of 0.9026. Evaluation of other metrics such as precision, recall, and F1-score also confirms that the attention module is good enough to highlight important features while reducing noise, thereby making classification more balanced across classes. These findings show that the combination of EEG decomposition and attention can be a promising approach for stress detection.

Keywords: attention; decomposition; EEG; RAN; ResNet; spectrogram; stress

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1. Introduction

Stress is a global mental health issue that affects hundreds of millions of people and has a profound impact on productivity and well-being [1]. Psychologically, stress is defined as subjective experiences such as anxiety and emotional pressure, while physiologically, stress is characterized by changes in bodily responses such as heart rate and cortisol levels [2]. High levels and intensity of stress exposure can cause several health problems such as cognitive dysfunction, depression, and cardiovascular disease, as well as social problems such as decreased performance at work, or even financial loss [3]. Stress can also trigger dangerous impulsive actions such as suicide [4]. These stress risk factors make stress detection become crucial, thus requiring an effective method in the detection process [5]. Stress can be identified through three approaches, by analyzing

psychological, physiological, and behavioral data [6]. A psychological approach can be found when filling out questionnaires, but this approach is often subjective because it is based on personal perceptions and biases [7]. Unlike the psychological approach, the behavioral approach analyzes stress based on an individual's daily habits, such as through smartphone usage [8]. The physiological approach offers greater objectivity, as responses cannot be consciously altered to mask true feelings [9]. Data analyzed through physiological approach cannot be manipulated by the body, such as data generated while sleeping [10], data generated from the Electrodermal Activity sensor (EDA) [2], Electrocardiogram (ECG) [11], even Electroencephalogram (EEG) [7], [10], [12] - [16].

Among various physiological signals, EEG has its own advantages because it can directly record brain activity, thereby being more sensitive in capturing responses to

cognitive and emotional stress compared to peripheral markers such as heart rate on ECG or skin conductance on EDA [17]. EEG is also a valuable tool due to its ability to capture detailed temporal dynamics closely related to cognitive stress responses [18]. Signals are inherently difficult to interpret due to their complex structure, high temporal resolution, and susceptibility to noise. Consequently, processes such as noise reduction, pattern recognition, feature extraction, and activity-based classification present significant challenges in accurately detecting stress levels from EEG data [19]. A part of feature extraction in EEG is transformation into spectrograms that emphasize time-frequency features in brain waves [20].

EEG is high-modality data as it can be extracted in various forms, including spectrogram. The spectrogram has been proven effective in detecting several health conditions in previous studies. EEG signal successfully implemented to identify Major Depressive Disorder (MDD) in 19 EEG channels by dividing data into windows of a certain size, then a Fourier transform with Short-Time Fourier Transform (STFT) was performed on each window to produce a spectrogram. With the Inception Time architecture, the resulting accuracy reached 0.9167 [13]. Another study using spectrograms successfully detected driver fatigue with an accuracy of 0.97 using Encoder-Decoder CNN mechanism with the addition of Multihead Attention in several layers to provide more calculations on features deemed important during the extraction process [12]. Similar research to detect driver fatigue, also using spectrogram data input, achieved an accuracy of 0.8839 on LogMel-CRNN classification model, which is a combination of a 6-layer CNN and a Bi-directional RNN [14]. Further research also using EEG spectrograms aims to detect brain balance conditions, visualized based on the frequency band in the brain by generating five different spectrograms: delta spectrogram, theta spectrogram, alpha spectrogram, beta spectrogram, and gamma spectrogram. The accuracy produced is 0.84 [16].

The complexity of EEG data requires appropriate architecture. As a result, the information can be interpreted more effectively. Too shallow architecture causes the information obtained during the feature extraction process to be less efficient, but a very deep network architecture can increase overfitting of the information being studied [21]. In addressing this issue, a skip connection mechanism can be implemented to prevent vanishing gradients, especially in complex data such as EEG [15]. In line with the skip connection mechanism, the attention mechanism also plays a significant role in capturing features in EEG spectrograms. The Attention Layer enables the model to select the most relevant input segments rather than storing all information in a single fixed vector. The Attention mechanism addresses the limitations of CNN architecture in capturing long-term relationships in sequential data. When these two techniques are combined, skip connections ensure that information from previous layers remains available to deeper layers,

while attention helps the model filter the information that contributes most to the final decision. This is aligned with previous study that suggest using skip connections and attention mechanisms together yields better accuracy than using skip connections alone [22].

Beyond architectural influences, previous study underscores that the use of EEG-based spectrograms for stress detection presents unique challenges. The leveraging of deep learning models on EEG data converted into spectrograms has proven effective in revealing brain wave patterns across various health domains such as microsleep [12], depression [13], or fatigue [14]. Unfortunately, several previous studies have indicated the existence of gaps that require further exploration that spectrograms implementation specifically for stress detection has not been widely explored. Stress levels are influenced by signals across multiple frequency bands, and the detection requires interpreting contributions from all major bands. Such conditions render spectrogram-based analysis particularly demanding, as spectrograms storing the intensity of several frequencies often exhibit high variability caused by individual differences in brain responses [7]. Spectrograms that can represent the relative dominance of a frequency band provide advantages to tackle overlap information issue (hereinafter referred to as decomposition). Decomposition enables spectrograms to represent the relative dominance of each frequency band more clearly, isolates key signal components, and establishes sharper boundaries between frequencies. This study aims to recognize stress patterns in humans at three levels based on EEG decompose spectrograms. A signal decomposition process is proposed to understand the relative spectral patterns of each frequency band in the human brain. These spectrograms are used as input to a CNN model with a skip connection mechanism in ResNet and the addition of an Attention Layer.

2. Research Methods

This study consists of several stages. The process undertaken includes data collection, spectrogram transformation, analysis, and classification. The stages of the process are visualized in detail in Figure 1.

2.1 Experiment

This study used a primary dataset. Data collection was performed using Muse2 with a sampling rate of 256 Hz on four electrodes: AF7, AF8, TP9, and TP10. The visualization of the amplitude of the collected EEG is shown in Figure 2. All respondents were asked to move as little as possible to prevent interference and signal invalidity during the recording process [23]. Stress can be identified through changes in biological signals that arise when the body is under pressure. In inducing stress, the Trier Social Stress Test (TSST) was chosen because it consistently triggers an acute stress response that can be observed and measured directly through the biological signals produced by the body [2]. Data was collected in five sessions, as shown in Figure 3.

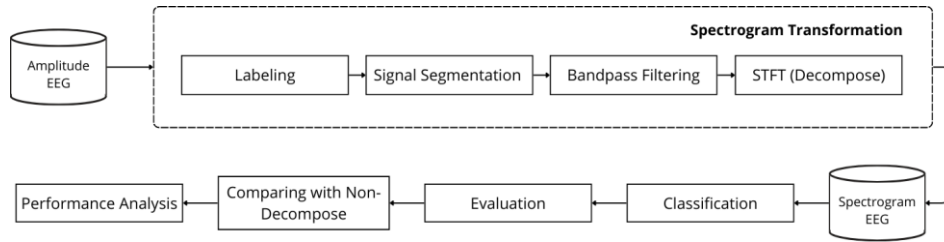


Figure 1. Experimental Method

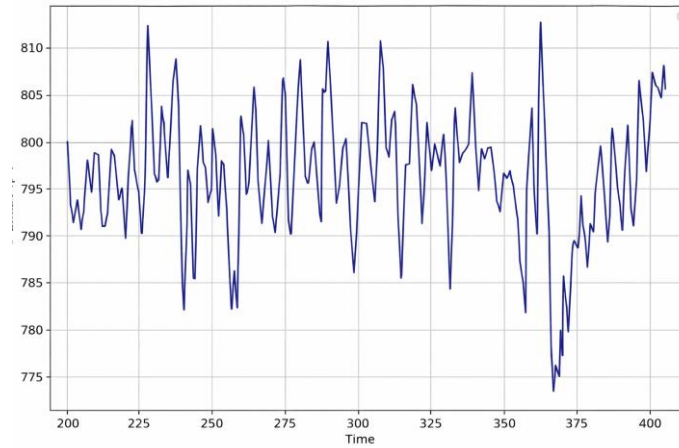


Figure 2. EEG Amplitude Data Sample

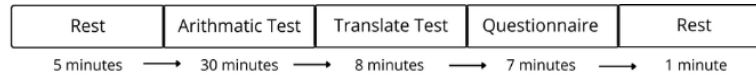


Figure 3. Data Collection Mechanism

2.2 Spectrogram Transformation

On the spectrogram, the x -axis represents time, the y -axis represents frequency, and the colors represent signal intensity: the highest intensity is represented by red, while the lowest intensity is represented by blue. Spectrogram transformation consists of several stages: labeling, signal segmentation, bandpass filtering, and Short-Time Fourier Transform (STFT). Stress labels are assigned based on signal fluctuations, with data with the greatest fluctuations labeled “High Stress,” the smallest fluctuations labeled “Mild Stress,” and fluctuations between the two values labeled “Moderate Stress” [7]. In each class, signals are segmented to enrich features [24]. Long segments provide better temporal representation but are less sensitive to frequency details, while short segments can improve frequency resolution but with limitations in temporal accuracy. Based on these considerations, 60 seconds was chosen as the length of each data segment. Next, Bandpass Filtering was implemented to isolate signals at frequencies of 1 Hz – 40 Hz which represent delta, theta, alpha, beta, and gamma signals [7]. STFT is conducted on the data by breaking it into segments with a window size of 128 samples and applying FFT to each segment. STFT is formulated in Equation 1, t represent the time index of the signal input, x_t is an input signal at a certain time, τ is the center of the window function that shifts over time, f shows the frequency with which the analysis is performed, $\omega(t - \tau)$ is a window function that selects a signal segment around a time τ , and N

states the total number of samples from the input signal. Without decomposition, the EEG signal is filtered using a 1–40 Hz bandpass filter and directly processed using STFT to generate a single spectrogram representing the overall frequency content. With decomposition, the EEG signal is first separated into delta, theta, alpha, beta, and gamma bands using bandpass filters. At the decomposition stage, STFT is superimposed on each bandpass result, yielding five spectrograms representing each frequency band.

$$S(f, \tau) = \sum_{t=0}^{N-1} x_t \omega(t - \tau) e^{-j2\pi f t} \quad (1)$$

2.3 Residual Attention Network (RAN)

The classification model is designed based on the problems analyzed in the datasets. Deep network architectures such as ResNet are ideal for spectrogram data because repeated feature extraction helps to find hidden patterns in the data as the number of layers increases. The skip connections in ResNet facilitate effective feature propagation across layers, making the architecture highly suitable for spectrogram-based classification. This mechanism supports deeper hierarchical feature extraction, thereby improving generalization and enhancing classification accuracy, particularly when dealing with complex medical data [15]. The pretrained ResNet model was chosen because of its ability to accelerate the training process by only adjusting the model without having to train from scratch. A total of 152 layers of Pretrained ResNet were used. Attention layers were added to highlight features

that contributed significantly during training with Multihead Self-Attention. Attention is calculated based on Equation 2. Each head performs the Self-Attention operation independently on its respective feature subset, which is formulated in Equation 3 to capture feature pattern correlations from different perspectives. The results of all head operations are then combined and projected back into a new feature vector, as shown in Equation 4.

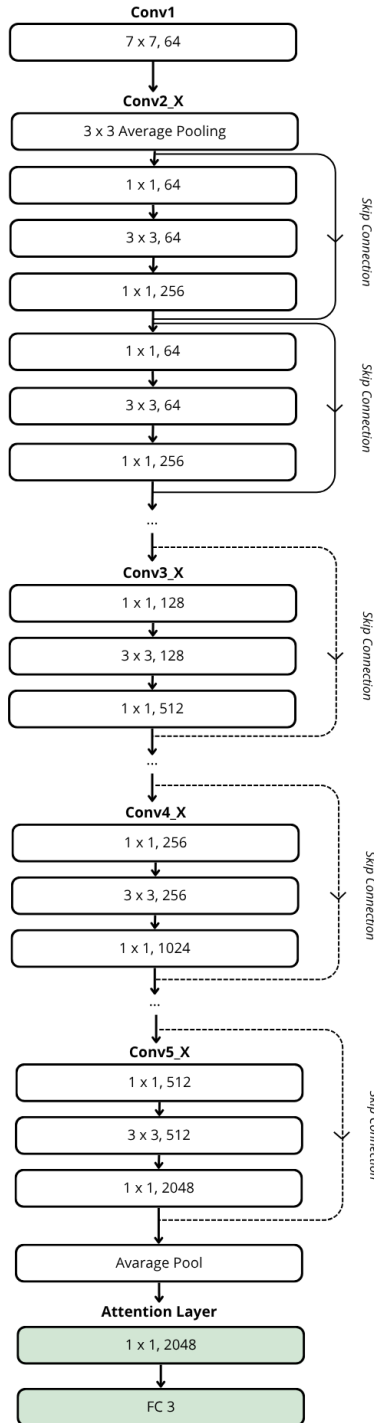


Figure 4. RAN -152 Architecture

This architecture is called the Residual Attention Network (RAN) and is illustrated in Figure 4. The hyperparameters utilized by RAN are shown in Table 1

[7]. In examining the effectiveness of the Attention added to ResNet-152, testing was conducted by comparing the performance of the ResNet-152 and RAN-152 models.

$$Attention(Q, K, V) = softmax\left(\frac{QK^t}{\sqrt{d_k}}\right) \times V \quad (2)$$

$$head_i = Attention(QW_i^Q, KW_i^K, VW_i^V) \quad (3)$$

$$Multihead(Q, K, V) = Concat(head_1, \dots, head_k)W^O \quad (4)$$

Table 1. Hyperparameter Setting of RAN-152

Hyperparameter	Value
Optimizer	Stochastic Gradient Descent
Learning Rate	0.001
Batch Size	32
Attention Head	8
Epoch	200
Early Stopping	Patience = 40

2.4 Evaluation Metrics

Model performance was evaluated using a confusion matrix that can assess the extent to which the model can classify data correctly based on its original label [25]. The performance of the developed classification model was evaluated using four metrics: accuracy, precision, recall, and F1-score. These metrics are defined as True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). The TP value is the number of correct predictions of the predicted class, while the TN value is the number of correct predictions of the class that was not predicted as that class. The FP and FN values are the number of incorrect predictions during the classification process. FP is the number of predictions from other classes that were predicted as the correct class, while FN is the number of predictions from classes that should have been correct but were predicted as other classes. Accuracy measures how well a model classifies data correctly, calculated by comparing the number of correct predictions in positive and negative classes to the total data tested, as shown in Equation 5. Precision measures how accurately a model classifies a particular class compared to the total number of predictions made for that class, as shown in Equation 6. Recall measures how well the model recognizes all instances that truly belong to a particular class, as shown in Equation 7. F1-Score is an evaluation metric that combines precision and recall into a single value using harmonic mean, as shown in Equation 8 [26].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

$$Precision = \frac{TP}{TP+FP} \quad (6)$$

$$Recall = \frac{TP}{TP+FN} \quad (7)$$

3. Results and Discussions

Brain waves are classified into five signals based on their frequency: delta, theta, alpha, beta, and gamma.

Generally, spectrograms display the intensity of each signal in a single image, as shown in Figure 5. Based on their frequency, each spectrogram image can provide information on five different signals, ranging from delta to gamma. Over time, the intensity of each signal also changes, as does the dominance of each signal. In the same time, each individual's signal response when performing certain activities is certainly different from one another. Figure 6 shows sample spectrogram data for activities in the same time segment. The delta signal appears to be the most dominant in respondent 1 in Figure 6 (a), but the dominant signals in respondent 2 in Figure 6 (b) are the delta and alpha signals, while all signals are dominant in respondent 3 in Figure 6 (c). Common spectrogram is inefficient in stress classification due to high data variability. Each spectrogram must store the frequency, intensity, and even the dominance of each signal, which can increase the potential for overlapping information.

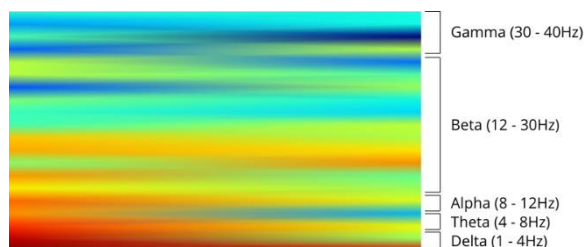


Figure 5. Spectrogram of EEG signals showing the distribution of brainwave frequency bands: Delta, Theta, Alpha, Beta, and Gamma

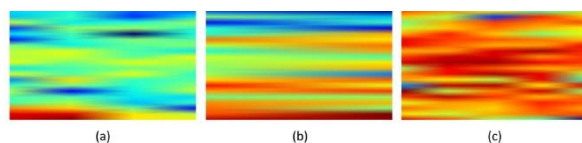


Figure 6. EEG Variability Response on Respondent (a), (b), and (c)

Data variability is tackled by decomposing the signal based on the delta, theta, alpha, beta, and gamma signal frequencies in the data transformation into a spectrogram. The spectrogram generated is separate for each frequency band [16] as shown in Figure 7. This signal decomposition aims to capture signals of each frequency band when given a stimulus that triggers stress, so that any changes that occur can be analyzed separately in each band. The decomposition separates one spectrogram into five distinct spectrograms. The main difference between spectrograms generated without and through the decomposition process is the signal pattern that is formed. Spectrograms without decomposition provide information on all frequency components that overlap each other. In Figure 5, the delta signal is the most dominant among the others, so the energy in the delta frequency range is extremely high and represents as red. However, after decomposition, the energy distribution is visualized separately. Decomposition works by separating the energy contribution of each frequency band. The red color in each spectrogram after decomposition reflects the relative energy in that frequency band. In the delta spectrogram in Figure 7 (a), the dominant energy in the

delta range remains red because the delta signal is indeed dominant. But in the alpha spectrogram in Figure 7 (b), even though the delta signal initially dominated overall, the alpha range remains red because the decomposition method in Bandpass Filtering isolates the energy in the alpha band only. In this process, the energy originating from the alpha band in the original signal is extracted and becomes the main focus of the alpha spectrogram, so that the color red appears in the alpha frequency range. The same applies to the beta, theta, and gamma spectrograms in Figures 7 (b), 7 (c), and 7 (e).

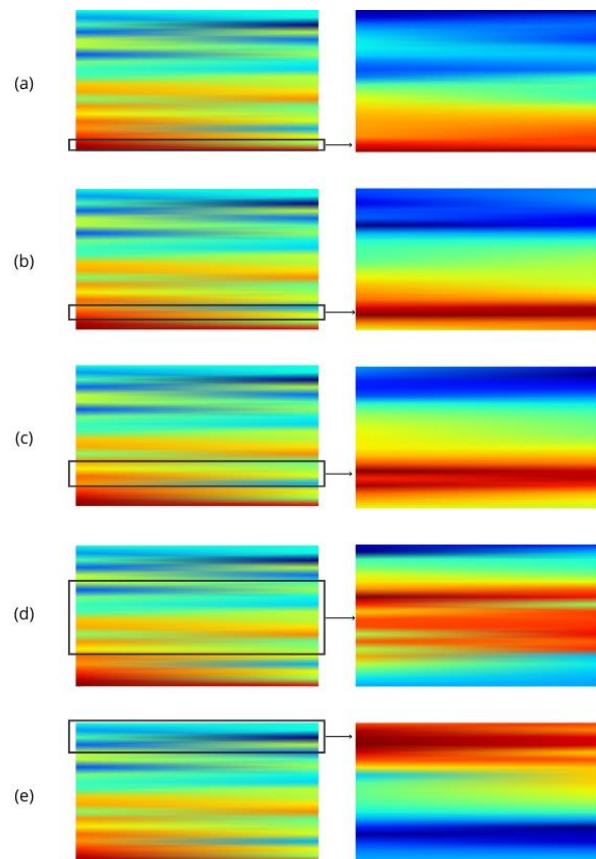


Figure 7. Decomposition Result of (a) Spectrogram Delta, (b) Spectrogram Theta, (c) Spectrogram Alpha, (d) Spectrogram Beta, (e) Spectrogram Gamma

The decomposition technique on spectrograms has several advantages. Decomposed spectrograms provide clearer information about the relative intensity of signals at specific frequency components. Before decomposition, some signals with high intensity appear dominant in red, while other signals appear less prominent and are marked in blue. The intensity of the dominant signals can mask signals with lower intensity. As a result, information about frequency components that may be relevant but have low intensity becomes less visible or even overlooked. Through decomposition, signal intensities that initially appear low can be visualized more clearly if the signal does indeed have relative dominance at the frequency being analyzed. The spectrogram produced through this decomposition can provide another perspective that is

more focused on the energy distribution at each frequency without being obscured by signals with very high intensity. By separating the signal into five spectrograms based on their relative frequency components, the amount of data increase and advantageous for deep learning models that rely on larger and more diverse training sets.

With regard to the non-decomposed results of previous studies [7], a comparison of the accuracy of the ResNet and RAN models on data with and without decomposition is shown in Table 2.

Table 2. Accuracy on Non-Decompose and Decompose Data

Model	Non-Decompose	Decompose
ResNet-152	0.5479	0.5287
RAN-152	0.5421	0.9026

This study reveals the important role of both the decomposition process and the addition of the attention mechanism in improving classification performance [27]. Architectural depth depends heavily on the complexity and clarity of the data. In ResNet-152, the accuracy on non-decomposed data was 0.5479, which decreased slightly to 0.5287 when applied to decomposed data. Despite its considerable depth, ResNet-152 was unable to optimally extract additional information from the decomposed representation. Models on non-decomposed data struggle to generalize and experiencing overfitting due to the high complexity and overlapping information present in the raw signals. In contrast, RAN-152 showed a performance improvement on stress detection. Accuracy increased from 0.5421 on non-decomposed data to 0.9026 on decomposed data. This confirms that the attention mechanism is able to focus learning on the most relevant features from the decomposition results. Alternatively, attention can act as an adaptive filter that amplifies important information while suppressing noise, thereby improving the feature representation that goes into the FCN for final classification. The classification report for the ResNet-152 model on the decompose data is shown in Table 3. The results show relatively low precision, recall, and F1-score values for classes 0 and 1, while class 2 performs better. ResNet-152 tends to be more effective in recognizing patterns associated with class 2 but has difficulty distinguishing between classes 0 and 1. ResNet tends to focus on global hierarchical representations where detailed decomposition information cannot be utilized effectively, even causing redundancy or noise.

Table 3. Evaluation Metrics ResNet-152 on Decompose Data

Class	Precision	Recall	F1-Score
0	0.4780	0.4222	0.4484
1	0.4663	0.5030	0.4840
2	0.6703	0.7006	0.6851

Overall, this model is not yet able to classify data consistently and accurately across all classes. As the consequence, the accuracy remains stagnant even when using decomposition representations. Accuracy trend on RAN-152 using decomposed data achieves high

performance is depicted in Figure 8. Training accuracy increased consistently from around 0.5 in the early epochs to exceed 0.9 in the 200th epoch, while testing accuracy showed a similar trend with values that were relatively higher than training accuracy in most epochs and remained stable at around 0.9 in the final stage. These findings strongly imply that RAN-152 is not only capable of learning data representations well, but also demonstrates strong generalization capabilities. In line with these results, the classification report of the RAN-152 model is presented in Table 4 and demonstrates more stable performance.

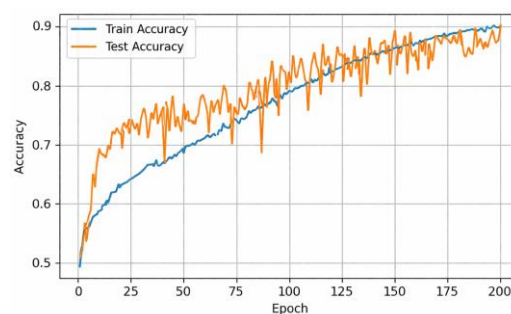


Figure 8. Accuracy Tren on RAN-152 Using Decomposed Data

Table 4. Evaluation Metrics RAN-152 on Decompose Data

Class	Precision	Recall	F1-Score
0	0.9023	0.8263	0.8626
1	0.9015	0.9395	0.9201
2	0.9040	0.9421	0.9227

All classes achieved consistently high precision, recall, and F1-score values. This improvement confirms that the attention mechanism is able to direct the model's focus on important features of the decomposition results, thereby improving the balance between precision and recall. With consistent performance across all classes, RAN-152 proves to be more adaptive and effective than ResNet-152.

4. Conclusions

This study successfully proved that signal decomposition in EEG spectrograms can improve stress classification performance. The decomposition process breaks down a single spectrogram, which originally represented the overall signal intensity, into five separate spectrograms, each focusing on a specific frequency range. The information in the spectrogram becomes more structured and the boundaries between frequency components become clearer. In addition, this study also highlights the important role of the attention module in improving classification results. In data without decomposition, attention does not contribute significantly because the information is still raw and disorganized, preventing optimal feature selection. However, when applied to decomposed data, attention is able to emphasize more relevant features, thus improving accuracy. These findings confirm that the combination of spectrogram decomposition and attention is a more effective approach for analyzing complex EEG signals. The best result achieved was an

accuracy of 0.9026. Despite this improvement, this study was limited to exploring the ResNet architecture with a depth of 152 layers and the application of the Multihead Attention module, so the best configuration between ResNet, attention, and decomposition may be found in other combinations that have not been tested. Further exploration can be conducted on ResNet and RAN with five different depths: 18, 34, 50, 101, and 152.

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