

# Enhancing EEG-Based Stress Detection Using ICA, Relative Difference, and Convolutional Neural Networks

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**Abstract:** EEG-based stress detection is crucial for early mental health monitoring, but signal quality is often degraded by artifacts and baseline variability. This study proposes an optimized preprocessing method combining Independent Component Analysis (ICA) for artifact removal and Relative Difference for baseline reduction. Using the SAM-40 EEG dataset, features were extracted with Differential Entropy and structured into a 3D EEG cube to preserve spatial-frequency information. A Convolutional Neural Network (CNN) classified stress levels into low and high categories. The proposed approach achieved 94.44% accuracy, with 100% precision for the high stress class and 81.82% recall. These results highlight the effectiveness of combining ICA and baseline reduction to enhance deep learning-based EEG signal processing for stress detection.

**Keywords:** SAM-40 dataset, Stress Detection, ICA, Relative Difference, CNN

## INTRODUCTION

Workplace stress is a significant issue that negatively impacts workers' mental health, productivity, and overall well-being (ILO, 2020), (Executive, 2020). Conventional stress detection methods, such as self-report questionnaires like the Perceived Stress Scale (PSS) (Kogar & Koğar, 2023), are limited by subjectivity and cannot capture real-time fluctuations in stress levels (Fontes, et al., 2024). In response, physiological signal-based approaches, particularly electroencephalogram (EEG) signals, have emerged as objective alternatives for stress detection (Al-Shargie, et al., 2018). EEG records brain activity and has been proven effective in identifying brainwave pattern changes associated with stress, particularly in the theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz) bands (Gaikwad & Paithane, 2017). However, EEG analysis faces major challenges due to artifacts originating from eye movements (EOG), muscle contractions (EMG), and external noise (Urigüen & Garcia-Zapirain, 2015), (Islam, et al., 2021), which can significantly degrade the accuracy of stress classification systems.

Various techniques have been proposed for artifact removal in EEG signals. Independent Component Analysis (ICA) has been widely used to separate artifact sources based on statistical independence (Jung, et al., 2000). Comparisons between ICA, Principal Component Analysis (PCA), and Singular Spectrum Analysis (SSA) show that ICA is more effective in isolating ocular and muscular artifacts (Mohammadi, et al., 2016), (Wirawan, et al., 2021). However, ICA alone struggles with nonlinear artifacts and physiological variability among individuals (Li, et al., 2019). Other studies have proposed baseline correction methods such as Difference, Fractional Difference, and Relative Difference (Yang, et al., 2018), with the Relative Difference method shown to be the most effective for reducing inter-individual variability while preserving relevant EEG structures (Yang, et al., 2018).

Furthermore, research by (Islam, et al., 2021) demonstrated that muscle artifacts could reduce stress classification accuracy from 85% to 62%, and (Tamburro, et al., 2018) showed that artifact contamination can increase the false-positive rate by up to 28% in stress detection. These findings underline the importance of robust preprocessing before EEG classification.

To address these challenges, this study proposes a combined signal preprocessing approach by integrating ICA for artifact removal and baseline reduction using the Relative Difference method. ICA is employed to separate and eliminate primary artifacts such as eye movements and muscle contractions, while Relative Difference normalization minimizes baseline variations among subjects, enhancing signal consistency (Wirawan, et al., 2021). Features are extracted using Differential Entropy (DE) and structured into a three-dimensional EEG cube for deep learning-based classification using Convolutional Neural Networks (CNNs) (Wirawan, et al., 2022) (Zhao, et al.,

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2020). CNNs are selected for their ability to recognize spatial and temporal patterns from EEG feature maps, offering improved classification performance.

While previous studies have separately employed ICA for artifact removal (Jung, et al., 2000) and Relative Difference for baseline normalization (Yang, et al., 2018), the integration of both methods into a unified preprocessing pipeline for EEG-based stress detection has rarely been explored. Most existing approaches either focused solely on artifact removal or baseline correction, neglecting the synergistic effect of combining both (Islam, et al., 2021).

The novelty of this research lies in the integration of ICA and Relative Difference to simultaneously enhance artifact removal and reduce inter-subject variability, leading to a more stable and accurate EEG-based stress detection system. Moreover, the system is designed to operate using real-world EEG data (SAM-40 dataset) (Ghosh, et al., 2022), supporting applications in workplace mental health monitoring and real-time stress management interventions.

## METHOD

This research employs several methods and techniques to process EEG data for optimizing stress detection accuracy through artifact removal using Independent Component Analysis (ICA) and baseline reduction using the Relative Difference method. As shown in Figure 1 illustrates the stages of the proposed methodology.

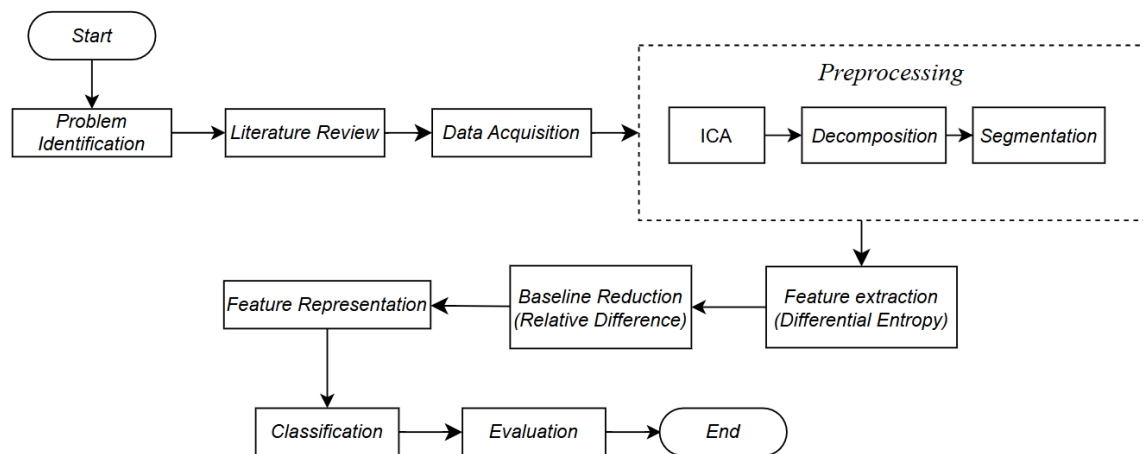


Figure 1. Research Flow Stages

### Data Description

This research utilizes the publicly available SAM-40 dataset (Ghosh, et al., 2022), which contains EEG recordings from 40 participants performing three types of cognitive stress-inducing tasks: the Stroop Color-Word Test, arithmetic operations, and mirror image recognition. Each EEG recording is labeled based on a self-reported stress level ranging from 1 to 10. In this research, stress scores are categorized into two classes: Low Stress (scores 1–5) and High Stress (scores 6–10) (Zhao, et al., 2020).

The EEG signals were recorded using 32 electrodes positioned, sampled at 128 Hz. Each trial lasted for 60 seconds, including both baseline (relaxation) and task conditions.

### Preprocessing

The raw EEG data underwent pre-processing using methods:

#### A. Independent Component Analysis (ICA)

Independent Component Analysis (ICA) is a statistical technique used to separate multichannel observed signals into underlying source signals based on the assumption of mutual statistical independence (Jung, et al., 2000). In the context of EEG analysis, ICA is particularly effective for isolating neural activity from non-neuronal artifacts, such as eye movements (EOG), muscle contractions (EMG), and external interferences (Urigüen & Garcia-Zapirain, 2015), and in this study, ICA was implemented using the MNE-Python library. Independent Component Analysis (ICA) can be described by the following simple equation (1):

$$X = AS \quad (1)$$

Where  $S$  represents a set of  $m$  source signals,  $A$  represents the mixing matrix that combines these source signals, and  $X$  represents the resulting mixed signals.

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A simple example of the above equation can be found in the cocktail party problem, where two people are speaking in different languages. Two microphones record the voices of both individuals, resulting in mixed sounds. Therefore, there are two mixed signals from both individuals.

The main idea of ICA is to identify the sources  $S$  under the assumption that these sources are statistically independent of each other. This means that the joint probability density function (pdf) of the components is the product of the density functions of all the original signals equation (2):

$$P(s) = \prod p(s_i) \tag{2}$$

Where  $p(s_i)$  is the pdf of the original signal  $s_i$ , and  $P(s)$  is the joint density function. Using a vector  $V$ , the goal of ICA is to find a matrix  $U$  such that equation (3):

$$V = UXV = UXV = UX \tag{3}$$

Where  $V$  is an estimation of the source signal  $S$ . From the equations above, it is clear that the matrix  $U$  is an estimation of the inverse of the mixing matrix  $A$ .

**B. Decomposition**

Decomposition in EEG signal processing refers to the process of separating the signal into more specific frequency components, commonly known as frequency bands. EEG signals are composed of multiple frequency ranges, namely delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (>30 Hz). Each frequency band is associated with different cognitive states. For instance, delta and theta waves are often linked to sleep and relaxation, while beta and gamma waves are related to high mental activity and stress conditions (Teplan, 2022).

In order to extract relevant information from each frequency band, signal processing techniques such as the Fast Fourier Transform (FFT) and Wavelet Transform are commonly used. The FFT provides a global spectral analysis of the EEG signals, whereas the Wavelet Transform allows a time-frequency analysis, enabling the detection of dynamic changes in brain activity during cognitive tasks (Adeli, et al., 2023). Through decomposition based on frequency, the underlying information embedded in EEG signals becomes more accessible and can be analyzed more effectively for stress detection.

**C. Segmentation**

Segmentation is the process of dividing continuous EEG recordings into smaller time epochs to facilitate further analysis. By segmenting EEG signals into shorter time windows, it becomes possible to detect local temporal variations in brain activity that may be associated with stress responses (Zhao, et al., 2020).

As shown in Figure 2, segmentation in this study was performed by dividing the EEG signals into non-overlapping epochs of 1-second duration, with each epoch encompassing all recorded frequencies, channels, experimental conditions, and participants (Wirawan, et al., 2021).

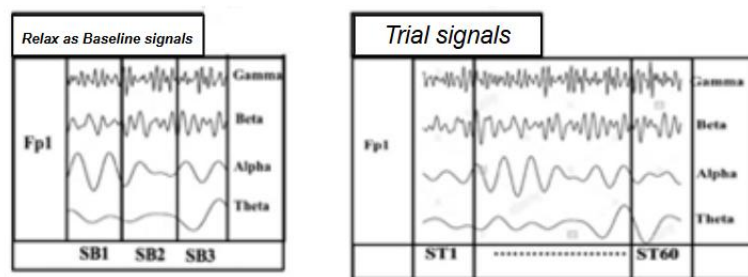


Figure 2. Segmentation Process

**Feature Extraction**

Feature extraction is a crucial step in EEG-based stress detection, aiming to capture relevant characteristics that represent cognitive and emotional states. In this research, Differential Entropy (DE) is used as the main feature extraction technique.

DE measures the complexity of a continuous random variable and is particularly suitable for EEG signals due to their continuous and non-stationary nature. It is also closely related to the concept of Minimum Description Length, which describes the amount of information contained in a signal (Wirawan, et al., 2021). The general formula for DE of a continuous random variable  $X$  with a probability density function  $f(x)$  equation (4):

$$h(X) = \int_x f(x) \log(f(x)) dx \tag{4}$$

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In the context of EEG analysis, it is often assumed that EEG signals within short time windows follow a Gaussian distribution. Under this assumption, the DE can be simplified and calculated based on the variance  $\sigma^2$  of the signal as follows equation (5):

$$h(X) = \frac{1}{2} \log(2\pi e \sigma^2) \tag{5}$$

where  $\sigma^2$  denotes the variance of the EEG signal within a specific frequency band,  $\pi$  is the mathematical constant pi, and  $e$  is Euler's number.

In this study, after the segmentation process, DE features are extracted across five frequency bands (Delta, Theta, Alpha, Beta, and Gamma) for each EEG channel, both in baseline and task conditions. These features are further utilized for feature normalization using the baseline reduction technique with the Relative Difference method, and later organized as input for classification using Convolutional Neural Networks (CNN).

**Baseline reduction**

Baseline reduction is a critical stage to minimize inter-subject physiological variability in EEG signals and to emphasize neural responses specific to cognitive stress. This study implements the Relative Difference (RD) method, which normalizes the Differential Entropy (DE) features extracted from task-related EEG epochs with respect to each subject’s baseline activity. The RD method consists of two primary computational steps. First, the DE value obtained from each task segment is represented equation (6):

$$Exper\_v_j^i = DE_{i,j} \tag{6}$$

where  $DE_{i,j}$  denotes the DE feature for the  $i$ -th frequency band in the  $j$ -th 1-second segment during the stress-inducing task. Second, the baseline mean for each frequency band is calculated by averaging all DE values from the baseline phase equation (7):

$$BaseMean_{v,i} = \frac{\sum_{k=1}^N Base\_v_k^i}{N} \{Base\_v_k^i\} \in R^c \tag{7}$$

where  $Base\_v_k^i$  refers to the DE feature in the  $i$ -th frequency band at the  $k$ -th baseline segment, and  $N$  is the total number of baseline segments. Finally, the normalized DE feature is computed equation (8):

$$Final\_v_j^i = \frac{Exper\_v_j^i}{BaseMean_{v,i}} \tag{8}$$

As shown in Figure 3, this approach allows each feature from the task phase to be scaled relative to its corresponding baseline average, highlighting stress-induced variations in brain activity while suppressing individual physiological biases. The Relative Difference method is effective in producing robust, discriminative features for subsequent classification (Wirawan, et al., 2021).

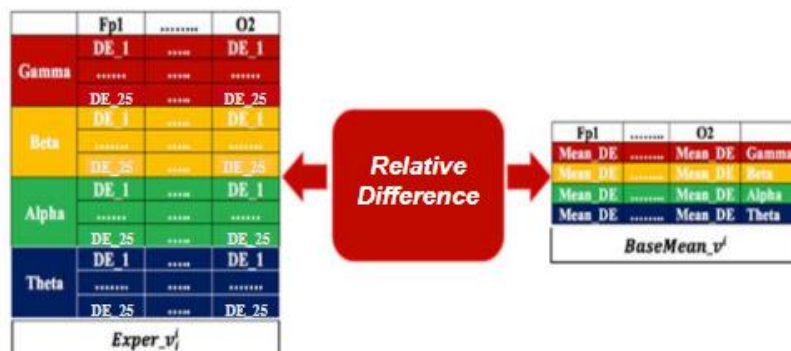


Figure 3. Baseline Reduction Using Relative Difference.

**Fitur Representation**

The process of EEG-based stress detection requires a well-structured feature representation to retain the spatial, spectral, and temporal characteristics of neural signals. Following the baseline reduction phase, Differential Entropy (DE) features are organized into a three-dimensional (3D) feature cube that integrates electrode spatial positioning, frequency-band specificity, and temporal segmentation.

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The spatial dimension corresponds to the distribution of EEG channels across the scalp, the spectral dimension reflects the activity within standard frequency bands, and the temporal dimension represents fixed-length time windows. This multi-dimensional representation enables Convolutional Neural Networks (CNNs) to learn intricate spatial-spectral relationships, thereby improving the model's ability to accurately detect stress-related EEG patterns (Wirawan, et al., 2021), as shown in Figure 4.

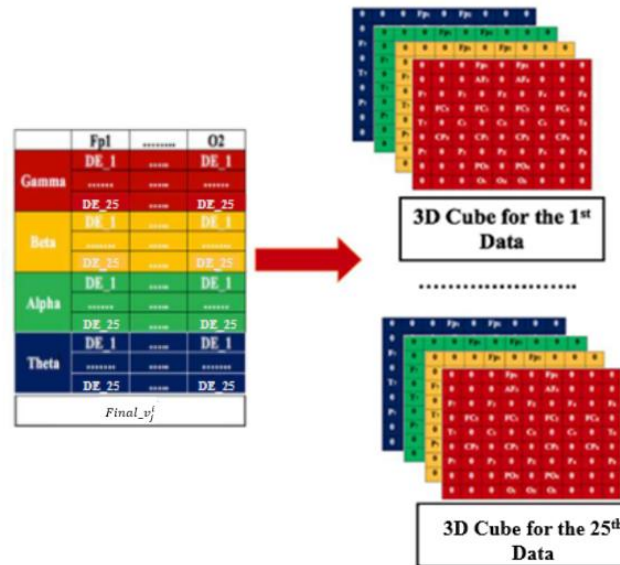


Figure 4. 3D Feature Representation for a Single Participant.

### Data Analysis

Convolutional Neural Network (CNN) was utilized as the primary classification model to analyze EEG features and detect stress levels, and in this study, the CNN was implemented using the *Keras* library. CNN has shown strong capabilities in extracting hierarchical patterns from structured data, particularly in domains involving spatial and temporal dimensions such as EEG signal analysis (Wirawan, et al., 2021), as shown in Figure 5.

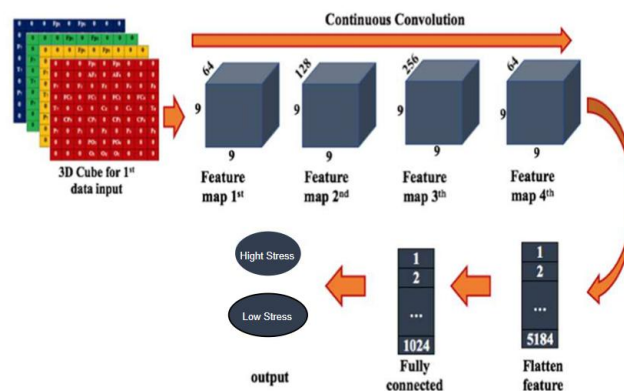


Figure 5. CNN Architecture

In this study, the input to the CNN was a three-dimensional feature cube consisting of Differential Entropy (DE) values that were normalized using the Relative Difference method. The model architecture was adapted from prior work on EEG-based emotion recognition (Wirawan, et al., 2021) and consisted of the following four main stages:

1. Convolutional Layers: The convolution operation was performed in four successive stages. The first three layers used a 4×4 filter with ReLU activation, SAME padding, and standard stride. The fourth convolution layer employed a 1×1 filter with identical activation and padding settings. These layers extracted multi-scale spatial and spectral patterns from the input features.
2. Flattening Layer: The output of the final convolutional layer was reshaped into a one-dimensional feature vector of 5184 neurons, preparing the data for dense layer processing.

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3. Fully Connected Layer: The flattened vector was passed to a fully connected layer with 1024 neurons, activated using the softmax function and regularized by a dropout rate of 0.5 to reduce overfitting.
4. Output Layer: The final layer consisted of two neurons representing binary stress levels (Low and High Stress), corresponding to the classification targets.

The model training employed cross-entropy loss and the Adam optimizer. Key training parameters included a learning rate of  $1 \times 10^4$ , a batch size of 128, and 50 training epochs which were adopted directly from the architecture developed by (Wirawan, et al., 2021) to maintain methodological consistency. Therefore, this study did not conduct separate hyperparameter tuning but retained the proven configurations to ensure comparability and reliability within EEG-based stress detection research.

### Model Evaluation

The performance of the proposed classification model was evaluated using standard metrics commonly applied in supervised learning tasks. These include accuracy, precision, recall, and F1-score, which were computed based on the confusion matrix.

Accuracy reflects the proportion of correctly classified EEG segments out of the total number of predictions. Precision measures the ability of the model to correctly identify positive instances among those predicted as positive, while recall indicates the proportion of actual positive instances that were correctly classified. The F1-score, defined as the harmonic mean of precision and recall, provides a balanced measure of the model's effectiveness, especially under class imbalance conditions.

In this study, the confusion matrix was constructed by comparing the predicted class labels with the true labels from the SAM-40 dataset. These labels were derived from experimental protocols that assigned stress levels based on task conditions. Evaluation was conducted for each of the four experimental scenarios: (1) without ICA and Baseline Reduction, (2) using Independent Component Analysis (ICA), (3) using Relative Difference (RD), and (4) using a combination of ICA and RD. The evaluation results provided insights into the contribution of each preprocessing method to overall classification performance.

### Experimental Setup

This study utilized the SAM-40 dataset, which contains EEG recordings from 40 participants performing cognitive stress tasks. EEG signals were recorded using 32 channels at a sampling rate of 128 Hz and segmented into 1-second epochs. Feature extraction was conducted using Differential Entropy (DE) across five frequency bands, followed by baseline normalization using the Relative Difference method and artifact removal with ICA.

The resulting features were structured into a 3D cube and served as input to a Convolutional Neural Network (CNN). The model was trained and evaluated across four scenarios: (1) without ICA and Baseline Reduction, (2) ICA only, (3) Relative Difference only, and (4) ICA combined with Relative Difference.

## RESULT

### Data

The dataset used in the experiment was SAM-40, a publicly available collection of EEG recordings from 40 subjects who completed three types of cognitive stress-inducing tasks: Stroop Color-Word Test, arithmetic problem solving (Maths), and mirror image recognition (Mirror), along with a relaxation phase. EEG signals were recorded using 32-channel electrode placement at a sampling rate of 128 Hz.

Stress level assessment was based on subjective ratings provided by each participant following the completion of every cognitive task. Participants rated their perceived stress using a numerical scale from 1 (minimal stress) to 10 (maximum stress). For the purpose of binary classification in this study, ratings were divided into two categories: Low Stress (ratings  $\leq 5$ ) and High Stress (ratings  $> 5$ ). This approach allowed for a clear distinction between low and high stress conditions based on participants' self-perception.

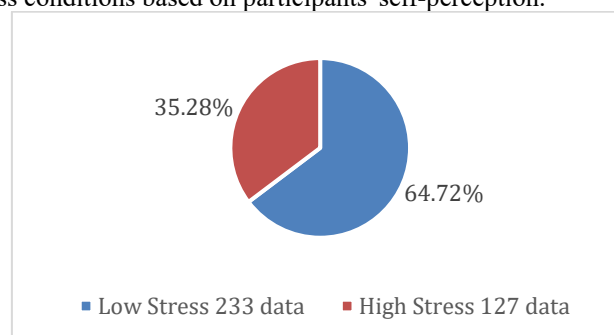


Figure 6. Distribution of The Labeled Data

As shown in Figure 6, the distribution of the labeled data includes 233 instances (64.72%) of Low Stress and 127 instances (35.28%) of High Stress. This class distribution illustrates a moderate imbalance between the two categories, which was considered during the evaluation and interpretation of classification results.

**Evaluation of Combined Application of ICA and Baseline Reduction Using Relative Difference Method**

The EEG data in this study was classified using a Convolutional Neural Network (CNN) trained on Differential Entropy (DE) feature cubes from the preprocessed EEG signals. The CNN architecture and settings followed (Wirawan, et al., 2021), ensuring consistency and comparability with validated EEG-based classification approaches.

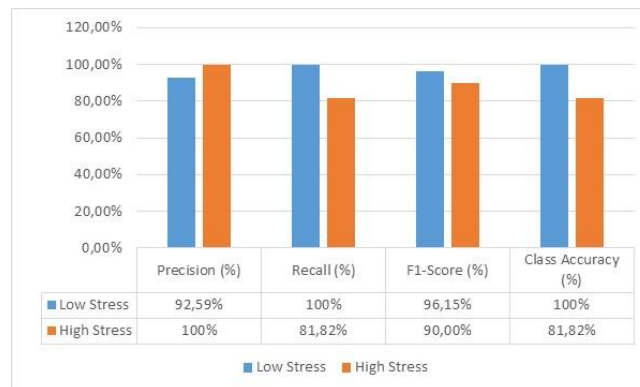


Figure 7. Performance with ICA and Relative Difference

Figure 7 Classification performance achieved when applying both Independent Component Analysis (ICA) and baseline reduction using the Relative Difference method. This configuration yielded the highest overall results, with: Accuracy: 94.44%; Precision (High Stress): 100.00%; Recall (High Stress): 81.82%; F1-Score (High Stress): 90.00% These results indicate that the combination of artifact removal and baseline normalization significantly improves feature quality. ICA enhances signal clarity by removing physiological noise, while Relative Difference reduces inter-subject variability. Together, they enable the CNN to effectively detect stress-related brain activity with both high sensitivity and specificity.

**Evaluation of ICA Application Without Baseline Reduction**

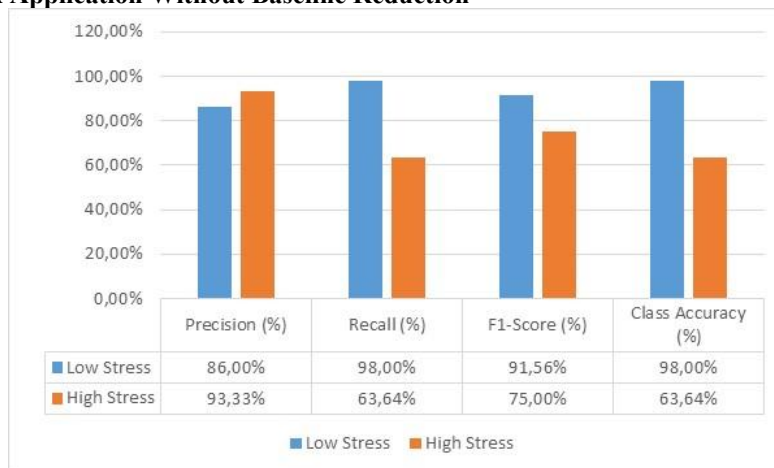


Figure 8. Performance with ICA Only

In this scenario (Figure 8), only ICA was applied during preprocessing. The CNN model achieved: Accuracy: 87.50%; F1-Score (High Stress): 75.00% Although artifact removal improves classification by reducing noise, the absence of baseline correction limits the model's ability to generalize across subjects. This highlights that ICA alone is insufficient to address inter-individual variability present in EEG signals.

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**Evaluation of Baseline Reduction Only Using Relative Difference Method**

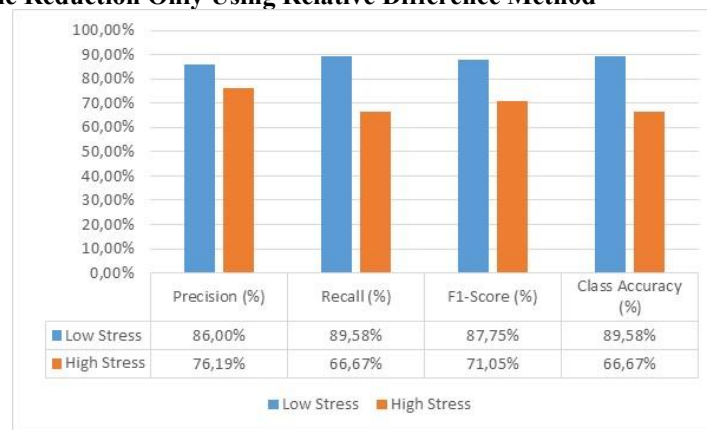


Figure 8. Performance with Relative Difference Method

Figure 8 shows the result of applying Relative Difference without ICA. The classification performance reached: Accuracy: 81.94% F1-Score (High Stress): 71.05% This scenario demonstrates that baseline normalization helps align individual signal baselines, improving the model’s discriminative capability. However, the remaining artifacts still degrade signal quality, thereby reducing classification precision.

**Evaluation Without ICA and Baseline Reduction**

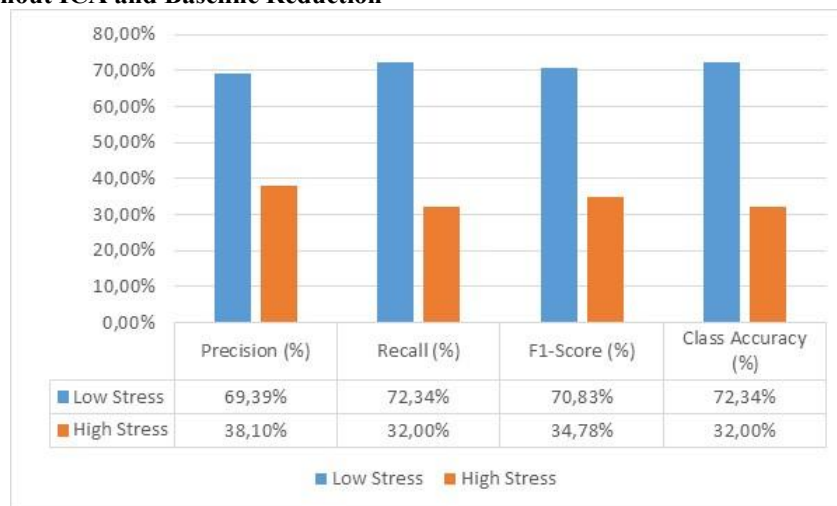


Figure 9. Performance Without ICA and Relative Difference Method

In the absence of any preprocessing (Figure 9), the CNN was trained on raw EEG signals. The model achieved the lowest performance: Accuracy: 58.33%; F1-Score (High Stress): 34.78% This confirms that EEG signals are highly susceptible to noise and individual differences, which significantly impair classification performance when unprocessed.

**Summary of All Evaluation Scenarios**

Table 1 Performance Metrics

Skenario Evaluasi	Accuracy (%)	Precision (Low Stress) (%)	Recall (Low Stress) (%)	F1-Score (Low Stress) (%)	Precision (High Stress) (%)	Recall (High Stress) (%)	F1-Score (High Stress) (%)
Without ICA & Baseline	58,33%	69,39%	72,34%	70,83%	38,10%	32,00%	34,78%
ICA Only	87,50%	86,00%	98,00%	91,56%	93,33%	63,64%	75,00%
Baseline Reduction Only	81,94%	86,00%	89,58%	87,75%	76,19%	66,67%	71,05%
ICA + Baseline	94,44%	92,59%	100,00%	96,15%	100,00%	81,82%	90,00%

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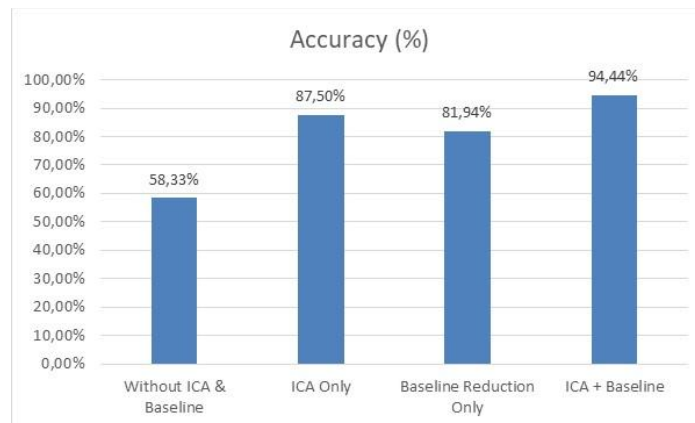


Figure 10. Comparison of Classification Accuracy Across Scenarios.

Figure 10 and Table 1 summarize the performance across all experimental configurations. The highest classification metrics were achieved in the combined preprocessing scenario, confirming the complementary roles of ICA and baseline normalization in enhancing model performance.

It is also important to note the impact of data distribution on classification outcomes. The dataset exhibited a class imbalance, with 64.72% labeled as Low Stress and only 35.28% as High Stress. This imbalance affected the model's ability to recognize High Stress instances, as reflected in the consistently lower recall for that class across all scenarios.

Per-class analysis showed that Low Stress conditions were easier to detect, likely due to more stable and homogeneous EEG signals during relaxation, leading to a recall of 100% in the combined scenario. In contrast, High Stress detection was more challenging, with the best recall reaching only 81.82%, indicating the influence of signal variability and limited sample size in that class.

Overall, ICA contributed effectively to removing external noise, while the Relative Difference method stabilized signal baselines across participants. The combination of these techniques produced cleaner and more consistent DE features, resulting in significantly improved classification performance.

## DISCUSSIONS

The findings of this study demonstrate that applying Independent Component Analysis (ICA) during preprocessing and implementing baseline reduction through the Relative Difference (RD) method after feature extraction substantially enhances the performance of the developed EEG-based stress classification model. Among all experimental configurations, the model trained using both ICA and Relative Difference achieved the highest performance, with an accuracy of 94.44% and an F1-score of 90.00% for the high-stress class. These results affirm that combining effective noise removal and feature normalization strategies is crucial for improving the reliability and generalizability of EEG classification models.

The inclusion of ICA in the preprocessing stage contributed to improved classification accuracy (87.50%) by effectively suppressing physiological artifacts such as ocular and muscular interference. In contrast, when only Relative Difference was applied after feature extraction using Differential Entropy (DE) the model reached an accuracy of 81.94%. This suggests that although ICA enhances signal clarity at the source level, Relative Difference plays a key role in adjusting for individual baseline variations, which improves feature discriminability.

Importantly, previous studies comparing CNN with traditional classifiers in EEG-based stress detection have shown that CNN consistently outperforms SVM and Random Forest in terms of classification accuracy and robustness. For example, Pratama et al. (2020) demonstrated that CNN achieved higher accuracy compared to SVM when classifying mental stress using EEG signals, highlighting the capability of CNN in capturing spatial and spectral patterns effectively. Similarly, Al-Shargie et al. (2018) confirmed that CNN provided superior performance in stress classification tasks compared to SVM, particularly when using artifact-free EEG data. These findings align with the results of this study, emphasizing the effectiveness of CNN combined with ICA and Relative Difference in enhancing EEG-based stress detection systems.

From a neurophysiological perspective, the superiority of ICA+RD in recognizing high stress is attributed to its ability to isolate relevant neural oscillations (theta, alpha, beta bands) associated with stress responses while minimizing noise and inter-individual variability. ICA effectively separates neural signals from artifacts, while RD normalizes the neural activity patterns across individuals by referencing each participant's baseline, allowing stress-induced cortical activation patterns to be detected more distinctly (Al-Shargie, et al., 2018; Wirawan, et al., 2021).

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The poorest performance (accuracy: 58.33%) occurred when the model was trained on raw EEG features without any form of preprocessing or normalization. This underscores the critical importance of addressing both artifact contamination and physiological variability to avoid distorted learning signals and biased classification outcomes.

From a class-specific perspective, the model consistently achieved higher recall for the Low Stress class compared to the High Stress class in all scenarios. This is likely influenced by the greater consistency and stability of EEG signals during relaxed conditions. The lower recall in the High Stress class may be attributed to greater signal variability, exacerbated by the class imbalance within the dataset (only 35.28% labeled as High Stress). This limitation highlights the potential need for future work to incorporate techniques such as class reweighting, oversampling, or adaptive loss functions.

In summary, the combined application of ICA and post-extraction baseline normalization using the Relative Difference method significantly improves classification accuracy and interpretability. This integrated approach contributes to the development of a more discriminative and participant-independent EEG-based stress detection model, with strong potential for further exploration in cognitive monitoring and mental health assessment.

### CONCLUSION

This study successfully developed a stress level classification system based on EEG signals using a Convolutional Neural Network (CNN). The implementation of a combined preprocessing approach artifact removal via Independent Component Analysis (ICA) and baseline normalization using the Relative Difference method proved to be the most effective configuration.

Experimental results showed that this combined approach achieved the highest classification performance, with an accuracy of 94.44%, 100% precision for the High Stress class, recall of 81.82% for High Stress, and 100% recall for Low Stress. In contrast, the absence of preprocessing led to a significant performance drop, with accuracy falling to 58.33% and recall for High Stress declining to 32.00%.

These findings highlight the critical role of artifact removal and baseline stabilization in enhancing the quality of extracted EEG features. Together, they contribute substantially to improving the robustness and accuracy of EEG-based stress classification systems using deep learning.

### ACKNOWLEDGMENT

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