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EEG-Based Emotion Recognition Using CWT Scalograms and MobileNetV2 Transfer Learning

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ABSTRACT

EEG-based emotion recognition is an important task in affective computing; however, conventional machine learning methods are limited in reliably extracting emotional features because brain signals are highly non-stationary and noisy. To overcome the limitation, we present a deep learning framework that integrates CWT-based RGB scalogram generation and transfer learning with MobileNetV2 for reliable emotion classification using EEG. In this way, the raw EEG data is first standardized and transformed into time–frequency scalograms using the Morlet wavelet with different scales, which are then resized and duplicated into three channels as RGB inputs to MobileNetV2. The pretrained MobileNetV2 feature extractor is finetuned on three emotions: Negative, Neutral, and Positive. Experimental results on the EEG Brainwave Emotions dataset show well-converged learning and good generalization, with an overall accuracy of 84.78%, and per-class accuracies of 96.5% (Neutral), 90.8% (Negative), and 66.9% (Positive). The proposed method effectively addresses the limited feature separability in raw EEG vectors by leveraging time–frequency representations and deep CNN feature extraction. Our results verify that the EEG-to-scalogram conversion, in conjunction with LDTL, is a promising, efficient solution for real-time generalized emotion recognition and affective computing.

Keywords: EEG emotion recognition; RGB scalogram; Continuous Wavelet Transform (CWT); MobileNetV2;

I.INTRODUCTION

Electroencephalography (EEG)-based emotion recognition has become an important research area in affective computing, healthcare, and brain–computer interface (BCI) applications because EEG signals provide direct information about human brain activity. Compared with facial expressions and speech, EEG signals are less affected by external environmental conditions and offer more reliable emotional information. However, EEG signals are highly nonlinear, non-stationary, and noisy, making accurate emotion classification a challenging task [1].

Recent advances in deep learning have significantly improved EEG emotion recognition by automatically extracting informative features from complex brain signals. Continuous Wavelet Transform (CWT) has been widely adopted to convert one-dimensional EEG signals into two-dimensional time–frequency representations that preserve both temporal and spectral characteristics, thereby enhancing feature learning [1], [8]. Furthermore, convolutional neural networks

(CNNs) have demonstrated excellent capability in learning discriminative representations from EEG scalograms [6], [9].

Transfer learning has further improved EEG-based emotion recognition by utilizing pretrained deep neural networks that reduce training time while improving classification performance. Lightweight architectures such as MobileNetV2 provide efficient feature extraction with lower computational complexity, making them suitable for real-time applications [2], [5]. Recent survey papers have also highlighted the growing importance of transfer learning, multimodal learning, and explainable deep learning for next-generation EEG emotion recognition systems [3]–[5], [11]–[13].

Motivated by these developments, this work proposes a Continuous Wavelet Transform (CWT)-based MobileNetV2 transfer learning framework for EEG emotion recognition. The proposed system transforms EEG signals into RGB scalogram images and employs a pretrained MobileNetV2 model for efficient feature extraction and classification of Negative, Neutral, and Positive emotional states. Experimental results demonstrate that the proposed framework provides reliable emotion recognition while maintaining low computational complexity.

II.RELATED WORK

Almanza-Conejo *et al.* [1] proposed an EEG emotion recognition framework using Continuous Wavelet Transform (CWT) and convolutional neural networks, demonstrating that time–frequency scalograms significantly improve emotional feature extraction compared with raw EEG signals.

Dwivedi *et al.* [2] presented an optimized deep learning model for EEG emotion recognition and reported superior classification performance over conventional machine learning methods. Pillalamarri and Shanmugam [3] reviewed multimodal EEG-based emotion recognition techniques and emphasized the importance of deep learning for improving recognition accuracy. Similarly, Sreehari *et al.* [4] provided a comprehensive survey of deep learning models, datasets, and preprocessing methods used in EEG emotion recognition.

Ma *et al.* [5] analyzed recent deep learning techniques for EEG-based emotion recognition and identified feature extraction and model generalization as major research challenges. Aslan and Akin [6] demonstrated the effectiveness of CNNs trained on EEG scalogram images for biomedical signal classification, while Altameem *et al.* [7] compared several machine learning algorithms for EEG signal classification and showed the superiority of deep learning approaches.

Elrefaiy *et al.* [8] introduced an EEG emotion recognition framework based on invariant wavelet scattering convolution networks, achieving robust classification through wavelet-based feature extraction. Aslan [9] proposed an efficient CNN model for emotion recognition with improved computational efficiency. Rahul *et al.* [10] reviewed automated EEG signal classification methods and highlighted the effectiveness of deep learning in biomedical applications.

Recent review studies by Huy-Tung *et al.* [11], Golafrouz *et al.* [12], and Mohammed *et al.* [13] emphasized the increasing adoption of transfer learning, multimodal learning, explainable artificial intelligence, and lightweight neural networks for EEG emotion recognition. Amer and Belhaouari [14] discussed modern EEG signal processing techniques for healthcare applications, while Wei [15] demonstrated the effectiveness of optimized deep learning models across engineering domains. Roy *et al.* [16] proposed a hybrid deep learning framework for EEG-based stress detection, and Sharma *et al.* [17] showed that wavelet-based deep learning methods significantly improve physiological signal classification.

Although existing studies have achieved promising results, challenges such as inter-subject variability, limited labeled EEG datasets, and computational complexity continue to affect recognition performance. To address these limitations, the proposed work integrates Continuous Wavelet Transform (CWT) with MobileNetV2 transfer learning, providing an efficient and accurate framework for recognizing Negative, Neutral, and Positive emotional states from EEG signals.

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III. METHODOLOGY

Overview

As shown in the fig 1 presents the overall architecture of the proposed EEG-based emotion recognition system. The process begins by collecting EEG signals from the Feeling EEG Brainwave Dataset. The acquired signals are then pre-processed through label encoding and feature normalization to improve data quality and consistency. Next, the Continuous Wavelet Transform (CWT) with the Morlet wavelet converts the one-dimensional EEG signals into two-dimensional time–frequency scalograms, capturing both temporal and frequency information. These scalogram images are used as input to the pretrained MobileNetV2 model for deep feature extraction using transfer learning. Finally, the extracted features are classified into three emotional states—Positive, Neutral, and Negative—and the model performance is evaluated using standard metrics such as accuracy, precision, recall, and F1-score.

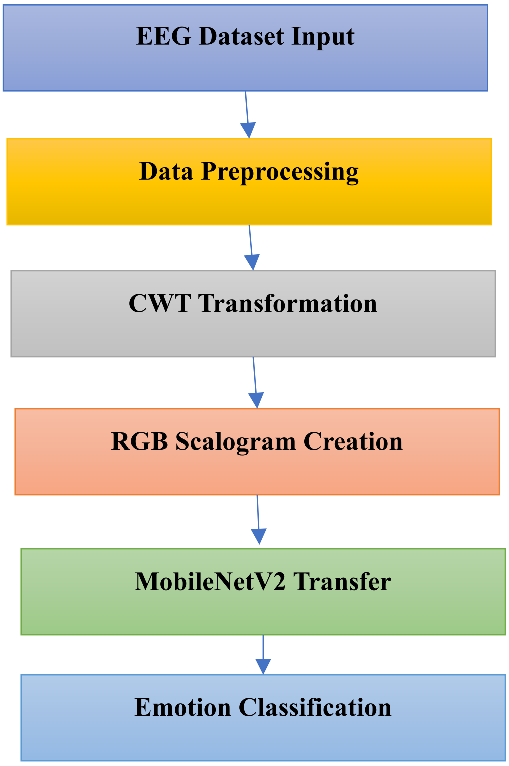

Fig 1: Proposed System Architecture

A.EEG Data Acquisition and Preprocessing

The EEG data were collected from the Feeling EEG Brainwave Dataset, which contains 2,548 features representing brain activity for three emotion classes: Negative, Neutral, and Positive. The emotion labels were converted into numerical values using Label Encoding, and the EEG features were normalized using StandardScaler to improve data consistency. The dataset was then divided into 80% training and 20% testing using stratified sampling to maintain class balance.

B.CWT-Based Time–Frequency Transformation

The preprocessed EEG signals were transformed into time–frequency scalograms using the Continuous Wavelet Transform (CWT) with the Morlet wavelet. This transformation captures both temporal and frequency information, improving emotion-related feature representation. The generated scalograms were normalized, resized to 224 × 224 pixels, and converted into RGB images for compatibility with the deep learning model.

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C.MobileNetV2 Transfer Learning

The RGB scalogram images were provided as input to a pretrained MobileNetV2 model. The convolutional layers were frozen to preserve pretrained features, while the original classifier was replaced with a new fully connected layer for three-class emotion classification. Only the classification layers were trained, reducing computational cost while improving learning efficiency.

D. Model Training

The proposed model was trained using the Adam optimizer with the categorical cross-entropy loss function. Training was performed for 10 epochs, allowing the network to learn meaningful emotion-related features from the EEG scalogram images and accurately classify the three emotional states.

E. Performance Evaluation

The trained model was evaluated on the test dataset using accuracy, precision, recall, F1-score, confusion matrix, and classification report. The experimental results demonstrate that the combination of CWT-based scalograms and MobileNetV2 transfer learning provides effective and reliable recognition of Negative, Neutral, and Positive emotional states.

IV RESULTS AND ANALYSIS

A. Experimental Setup

The proposed EEG-based emotion recognition system was evaluated using the test dataset to assess its classification performance and generalization capability. The MobileNetV2 transfer learning model exhibited stable convergence during training, with the training loss decreasing consistently over 10 epochs, indicating effective learning without significant overfitting. The Continuous Wavelet Transform (CWT)-based scalograms successfully captured discriminative time–frequency characteristics of EEG signals, enabling the model to learn meaningful emotional features.

Experimental results demonstrate that the proposed framework achieved an overall classification accuracy of 84.78%. The confusion matrix revealed that the majority of EEG samples were correctly classified, with the Neutral emotion achieving the highest recognition performance and minimal class confusion. Although a small number of misclassifications occurred between the Positive and Negative emotion classes due to similarities in EEG patterns, the strong diagonal distribution confirms the robustness of the proposed model.

Furthermore, class-wise evaluation showed recognition accuracies of 96.5% for Neutral, 90.8% for Negative, and 66.9% for Positive emotions. The relatively lower accuracy for Positive emotion indicates greater inter-subject variability in EEG responses. Overall, the results demonstrate that integrating CWT-based time–frequency representations with MobileNetV2 transfer learning provides an effective and computationally efficient framework for automatic EEG emotion recognition, achieving reliable performance across multiple emotional categories.

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B. Visualization

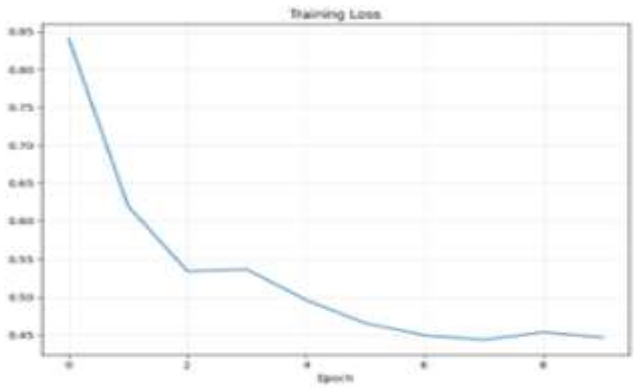

Fig 2: Training Loss Curve

The fig 2 illustrate the training loss of the proposed MobileNetV2-based EEG emotion recognition model over 10 epochs. The loss decreases from approximately 0.84 to 0.45, indicating that the model effectively learns meaningful features from the EEG scalogram images. The gradual reduction and stable convergence in the final epochs demonstrate successful optimization with minimal overfitting. These results confirm the effectiveness of the proposed framework in achieving reliable emotion recognition with an overall accuracy of 84.78%.

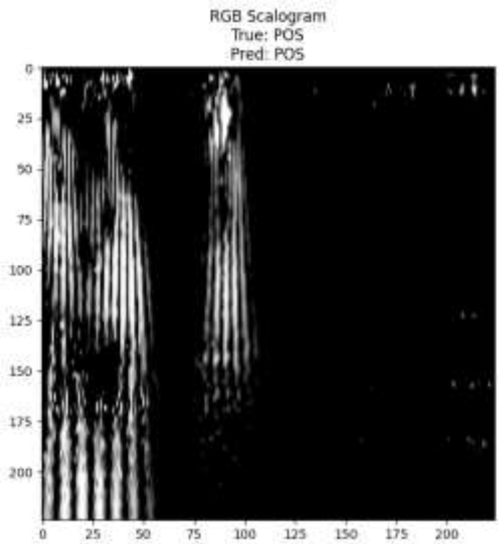

Fig 3: RGB Scalogram with True and Predicted Emotion

The fig 3 illustrates a representative RGB scalogram generated from an EEG signal using the Continuous Wavelet Transform (CWT). The scalogram captures the time–frequency characteristics of the EEG signal, providing rich features for emotion recognition. In this example, the true label and the predicted label are both Positive (POS), indicating that the proposed MobileNetV2 transfer learning model accurately recognized the emotional state. This result demonstrates the effectiveness of the CWT-based feature representation and the robustness of the proposed emotion recognition framework.

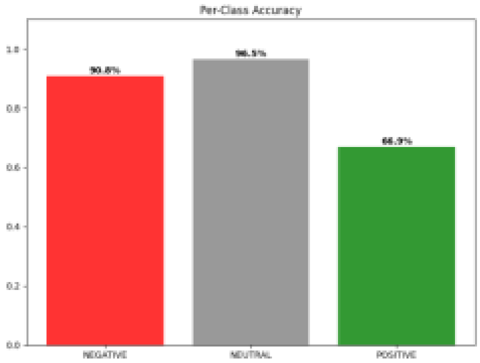

Fig 4: Per-**Class Accuracy**

The fig 4 illustrates the per-class accuracy of the proposed MobileNetV2-based EEG emotion recognition model. The Neutral class achieved the highest accuracy of 96.5%, followed by the Negative class with 90.8%, indicating strong recognition performance. The Positive class obtained an accuracy of 66.9%, reflecting the greater variability and overlap of positive EEG patterns with other emotions. Overall, the results demonstrate that the proposed framework effectively recognizes different emotional states while maintaining robust overall classification performance.

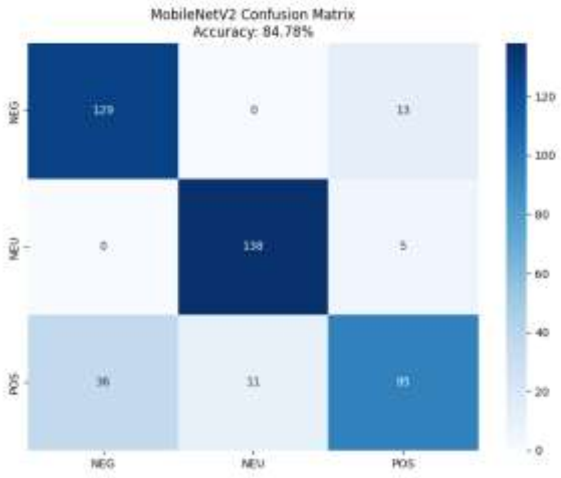

Fig 5: Confusion Matrix of MobileNetV2 Predictions

The fig 5 illustrates the confusion matrix of the proposed MobileNetV2-based EEG emotion recognition model. The model achieved an overall classification accuracy of 84.78%. Most Negative (129) and Neutral (138) samples were correctly classified, demonstrating strong recognition performance for these classes. The Positive class recorded 95 correct predictions, with some misclassifications due to overlapping EEG patterns among emotional states. Overall, the strong diagonal values indicate that the proposed CWT-based MobileNetV2 framework effectively learns discriminative features for accurate EEG emotion classification.

V.CONCLUSION

In this research, a successful emotion recognition system based on EEG and gray-scale emotional time-frequency features, combined with transfer learning from MobileNetV2, is proposed. The presented method converts raw EEG signals into time–frequency images, thereby effectively addressing the challenge of extracting non-stationary emotional features from non-stationary brain signals. Quantitative results showed strong performance , with an overall accuracy of 84.78% and high recognition rates for Neutral and Negative emotions. These results demonstrate the effectiveness of EEG scalogram representations and lightweight deep learning for emotion recognition applications, ensuring practicality in terms of computation and well-adapted for real-time affective computing and brain–computer interfacing.

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