IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 19 September 2023, accepted 28 September 2023, date of publication 5 October 2023, date of current version 11 October 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3322294

RESEARCH ARTICLE

Cross-Subject Channel Selection Using Modified Relief and Simplified CNN-Based Deep Learning for EEG-Based Emotion Recognition

LIA FAROKHAH[1,2], RIYANARTO SARNO[1], (Senior Member, IEEE), AND CHASTINE FATICHAH[1], (Member, IEEE)

[1]Department of Informatics, Faculty of Intelligent Electrical and Informatics Technology, Institut Teknologi Sepuluh Nopember (ITS), Surabaya 60111, Indonesia
[2]Department of Informatics, Faculty of Technology and Design, Institut Teknologi dan Bisnis ASIA Malang, Malang 65142, Indonesia

Corresponding author: Riyanarto Sarno (riyanarto@if.its.ac.id)

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by Rina Dewi Indahsari of Institut Teknologi dan Bisnis ASIA Malang Under Application No. 5, and performed in line with Emotion Analysis Data.

ABSTRACT Emotion recognition based on EEG has been implemented in numerous studies. In most of them, there are two observations made: first, extensive implementation is negatively associated with the performed validation. Cross-subject validation is more difficult than subject-dependent validation due to the high variability between EEG recordings caused by domain shifts. Second, a large number of channels requires extensive computation. Efforts to reduce channels are impeded by decreased performance as the number of channels is decreased; therefore, an effective approach for reducing channels is required to maintain performance. In this paper, we propose collaboration on 2D EEG input in the form of scalograms, CNN, and channel selection based on power spectral density ratios coupled with the relief method. The power ratio is derived from the power band's power spectral density. Based on the trial selection with various conditions, the collaboration of the proposed scalogram and PR-Relief (power ratio-Relief) produced a stable classification rate. For analysis, the Database for Emotion Analysis of Physiological Signals (DEAP) has been employed. Experimental results indicate that the proposed method increases the accuracy of cross-subject emotion recognition using 10 channels by 2.71% for valence and 1.96% for arousal, respectively. Using 10 channels for subject-dependent validation, the efficacy of the valence and arousal classes increased by 2.41% and 1.2%, respectively. Consequently, by pursuing collaboration between input interpretation and stable channel selection methods, the proposed collaborative method achieves a better result.

INDEX TERMS Channel selection, emotion recognition, validation, cross-subject, scalogram.

I. INTRODUCTION

Emotion recognition is an affective computing research that is actively researched. Several studies have employed facial expressions [1], [2], voices [3], [4], body gestures [1], and brain signals [5] to identify emotions. EEG is an instrument for measuring the activity of brain signals [6], [7]. EEG emotion recognition is a valid psychological signal for emotion recognition [8], [9]. EEG has been utilized in numerous disciplines, including medicine, psychology, education, marketing, law, and transportation, among others [10], [11], [12], [13], [14], [15], [16], [17]. Extensive EEG usage is negatively associated with anticipated validation. EEG signal validation is predominantly intra-subject or dependent subjects. Inter-subject or cross-subject validation is one of the most difficult aspects of emotion recognition [18], [19], [20]. This type of emotion recognition is extremely unpredictable due to domain shifts between EEG recordings [21], [22], [23], [24], [25]. In addition to variability, there is a propensity to utilize EEG channels that are sufficiently large to maintain the same

The associate editor coordinating the review of this manuscript and approving it for publication was Deepak Mishra.

level of performance regardless of the cost of computation [26], [27], [28], [29], [30], [31], [32]. Methods for channel selection or reduction are required to achieve competitive performance with less computation.

Several ways have been proposed and intensively researched for EEG classification. First, transforming 1D EEG into 2D or 3D form to strengthen the use of deep learning. The use of 2D or 3D forms of EEG facilitates the interpretation of signal analysis and the use of deep learning methods [33]. Several previous studies obtained the best cross-subject validation results using 2D EEG interpretation [26], [27], [29]. Second, the channel selection method is used to find significant information and reduce computation [26], [30]. Cross-subject channel selection methods are more limited as compared to independent subjects [26]. Third, the use of deep learning to strengthen classification validation [34], [35], [36].

In most of the existing research, several common problems have been observed which are critical to be addressed to advance the emotion recognition field. Firstly, in cross-subject classification, limitations arise from the variability in channel selection across different subjects [22], [37], [38]. In dependent subject scenarios, the optimal EEG channels for emotion analysis can differ significantly from one individual to another, making it challenging to establish a universal channel selection strategy that applies consistently across multiple subjects [39]. As a result, studies including cross-subject validation using channel reduction are rare [26]. Secondly, existing channel selection approaches often rely on heuristic methods or feature ranking techniques, which may not fully capture the intricate relationships between EEG channels and emotional states. These methods may also overlook non-linear dependencies and inter-channel interactions that could be vital for accurate classification [40]. Thirdly, Convert 1D EEG signals to 2D or 3D EEG. Several investigations, such as transforming 1D EEG data to Pearson's Correlation Coefficient images of channel correlation of EEG sub-bands, have been conducted [41], transform 1D EEG to gray image with six level [42], scalogram images [28], spectrogram images [26], [27], [43], Transformation of 1D EEG to spectrogram images offers the greatest performance, especially for cross-subject validation [26], [27]. Conventional deep learning techniques applied to Short-Time Fourier Transform (STFT)-based 2D representations of EEG data may not exploit the full potential of the data and can reside on very large computational resources [26], [27]. In addition, the wavelet-transform, which produces 2D image scalograms, has been studied, but its performance is unsatisfactory [28].

In the domain of emotion recognition using EEG data, a critical challenge lies in optimizing classification accuracy while mitigating computational complexity. Currently, the reliance on transfer learning with pre-trained models, such as DenseNets or ResNets or CNN with deep layer, applied to all EEG channels necessitates substantial computational resources. Such approaches have been successful in attaining a higher classification rate of over 99 percent in dependent subject cases [44], [45], while other accuracies remain limited to 78 – 92 percent in the case of cross-subject [26], [27], [29] while exploring the DEAP dataset. Despite attaining satisfactory outcomes, these approaches overlook the inherent variability in optimal channel selection across different individuals in cross-subject classification scenarios. Within subjects, EEG channels that are most relevant for emotion analysis can significantly differ, rendering a universal channel selection strategy impractical. To address these issues, there is a compelling need to explore simplified CNN architectures tailored to EEG data. These architectures should be complemented by novel channel selection approaches capable of enhancing cross-subject classification accuracy, thereby reducing computational demands and improving the efficiency of emotion recognition systems. These limitations have helped develop the motivation for this work which is centering around the following:

i. A need to explore further deep learning architectures under various 2D image generation techniques still exists apart from using transfer learning STFT images, and scalogram with low performance.
ii. The channel selection method for classifying cross-subject emotions is still limited in comparison to dependent subject emotion classification.
iii. There is a need to combine cross-subject channel selection methods with simplified deep learning architecture and image generation methods to reduce the computational load and enhance performance.

Considering the gaps identified above and the listed motivational factors, this study aims to contribute to the knowledge base as follows:

The research aims to overcome the highlighted challenges and limitations by contributing as follows:

A. IMPROVED CROSS-SUBJECT CHANNEL SELECTION

The research introduces an advanced channel selection approach for cross-subject emotion classification, leveraging power bands and ratios to enhance the Relief method. By selecting the most relevant EEG channels that capture emotional patterns consistently across different individuals, we address the challenge of variability in channel selection, improving the generalizability and efficiency of emotion recognition models.

B. EXPLORATION OF MORLET TRANSFORM IMAGES

The study explores an innovative approach to generating 2D images from EEG data using the Morlet Transform (scalogram). In contrast to conventional Short-Time Fourier Transform (STFT) methods, Morlet Transform images offer a new perspective on feature extraction, potentially revealing intricate temporal and spectral information crucial for accurate emotion classification. This exploration expands the repertoire of image-based EEG analysis techniques. In addition, the wavelet family has been exploited for improved performance to existing research.

C. SIMPLIFIED DEEP LEARNING MODEL

To reduce computational cost while maintaining classification accuracy, this research introduces a simplified deep learning architecture tailored to EEG emotion recognition tasks. The architecture had been added in our recent publication also [26] yet tailored for spectrogram images. Instead of relying on resource-intensive transfer learning models, our approach optimizes model efficiency, making it more computationally friendly or resource-constrained applications. This contribution aims to streamline the implementation of emotion recognition systems without compromising performance.

The proposed research is based on a simplified deep learning architecture and channel selection approach that leads towards closer and resource-constrained real-time implementation. In addition, research for cross-subject validation is more likely to be implemented widely than dependent subject validation. Cross-subject validation has a better generalization model than dependent-subject validation. This makes this research applicable across a wide range of industries where emotion recognition enables the development of interactive applications such as content delivery, personalized experiences, and enhanced security. In healthcare, for example, determining a patient's emotional state using wearable devices in real-time can help in the early diagnosis of various problems related to stress and mental health. Likewise, in the automotive sector, human-machine interaction can be improved, resulting in a safer driving environment, by recognizing the driver's emotional state.

The paper is organized in the following manner: Section I provides an overview of the relevant background of the situation at hand. The subsequent part provides an overview of previous research conducted on the topic of emotion recognition in cross-subject 2D environments. However, we will supplement our knowledge with some non-2D research. Section III describes the dataset, methodology proposed, and evaluation. In Section IV, the results of experimental research on cross-subject validation with selected channels are compared to previous studies. Section V serves as the conclusion segment.

II. RELATED WORK

In the domain of EEG-based emotion classification problems, the DEAP dataset is the most studied public dataset [5], [46]. The comprehensive literature review presented herein encapsulates a multifaceted exploration of research pertaining to EEG-based emotion recognition. This review encompasses two distinct categories of articles, each contributing unique insights to the field. First, this study into studies focused on channel selection methods within EEG signals using the DEAP dataset, encompassing a diverse array of techniques aimed at isolating the most informative channels for emotion analysis. Second, this study explores articles that make use of all 32 EEG channels (DEAP dataset) or a subset while integrating various deep learning models, while keeping a focus on model performance associated with this approach.

In the context of channel selection, several prior studies are described, that may or may not employ 2D image generation and use of deep learning. This is done to enhance the comparability of performance outcomes. Kouka et al. [30] conducted channel selection experiments. In the valence class, using the Binary Many-Objective Particle Swarm Optimization with Cooperative Agents (BMaOPSO-CA) method with 8 channels on valence and 16 channels on arousal have an accuracy between 69.56% and 83.50%, respectively [30]. The NMI selection approach with input PSD and SVM classifiers yielded 74.41% valence (8 channels) and arousal (10 channels) accuracy of 73.64% [47]. Goshvarpour and Goshvarpour employing the sLORETA selection method and input lagged Poincare indicator and SVM classifier deliver valence (5 channels) and arousal (5 channels) performance of 74.41% and 74.71%, respectively [48]. Topic et al. used ReliefF and NCA approach for selection channels with accuracy on valence and arousal around 80% [49]. Javidan et al. validate cross-subject performance in the valence class (2 channels) utilizing the RReliefF selection strategy with input MSCE and SVR classifiers, yielding an accuracy of 67.45% [50]. Msonda et al. [51] reconstruct features (using 2, 3, 4, 5, 6, 7, and 8 channels) and search for the minimal errors using Adaboost, LR, Linear SVC, Polynomial SVC, and RF, with average performance results between 50 and 60%. Using locally robust feature selection (LRFS), Yin et al. execute channel selection for cross-subject classification with an estimated accuracy of 60% for valence and arousal classes [52]. Arjun et al. [24] employed the attention channel when combined with the LSTM and autoencoder for cross-subject classification and obtained rate of accuracy for 65.9% and 69.0%, respectively, for valence and arousal classes. Yang et al. used ReliefF and random forest to choose the top 10 and 11 channels for dependent subject and cross-subject classification, respectively, with cross-subject outcomes of 81.27% and 82.37% for valence and arousal classifications [53]. Pandey and Seeja used frontal lobe channel to channel selection with accuracy on valence and arousal around 50% until 60% [28]. Reference [26] used best single collaboration with confusion matrix as an indicator for channel selection with accuracy on valence and arousal around 92%. The application of reduction channels for cross-subject classification has not been thoroughly investigated. Additionally, the result can be enhanced. A summary of the existing articles on channel selection has been presented in Table 1.

Some cross-subject studies are based on 2D or 3D forms with 32 channels. Yin et al. [55] presented a 3D cube ECLGCNN that was based on graphs and had 84% accuracy in the valence class and 85% accuracy in the arousal class. Pandey and Seeja conducted research using CNN architecture, achieving 59% and 59% accuracy for valence and arousal, respectively [28]. Using Inception Resnet-V2, Cimtay and Ekmekcioglu achieved a valence of 72.81% [29]. Using 2D frame sequences and BiDCNN, Huang et al. achieved 68% valence accuracy and 63% arousal accuracy [56]. Another study used a matrix sequence-based

TABLE 1. Summary of the channel selection approaches.

Article	Channel Selection Approach	No. of Channels	Cross-Subject	Accuracy
[30]	BMaOPSO-CA, PSD	Valence: 8, Arousal: 16	Yes	Valence: 69.56%, Arousal: 83.50%
[47]	NMI, PSD, SVM	Valence: 8, Arousal: 10	No	Valence: 74.41%, Arousal: 73.64%
[48]	sLORETA, lagged Poincare, SVM	Valence: 5, Arousal: 5	No	Valence: 74.41%, Arousal: 74.71%
[49]	R-HOLO-FM	Valence: 10 Arousal: 10	No	Valence: 83.26%, Arousal: 83.85%
[49]	N-HOLO-FM	Valence: 10 Arousal: 10	No	Valence: 81.88%, Arousal: 82.45%
[50]	ReliefF, MSCE, SVR	Valence: 2	Yes	Valence: 67.45%
[28]	Frontal lobe	Valence: 10 Arousal: 10	Yes	Valence: 61%, Arousal: 58% (10)
[51]	Feature Reconstruction, Various Classifiers	2-8 Channels	Yes	Avg. 50% - 60%
[24]	Attention Channel, LSTM, Autoencoder		Yes	Valence: 65.9%, Arousal: 69.0%
[53]	ReliefF, Random Forest	Valence: 10, Arousal: 11	Yes	Valence: 81.27%, Arousal: 82.37%
[54]	NCA	Valence: 10 Arousal: 10	Yes	Valence: 83.9%, Arousal: 84.3%
[26]	Best single collaboration with confusion matrix	Valence: 10 Arousal: 10	Yes	Valence: 92.1%, Arousal: 92.2%
Proposed Approach	Relief-based channel selection using Power Bands and Ratios	Valence: 10 Arousal: 10	Yes	Discussed in the Results Section

meta-learner with a class performance of 69.92% for valence and 68.89% for arousal [57]. Pusarla et al. conducted three experiments simultaneously on cross-subject validation [27]. First, using a spectrogram in conjunction with the DenseNet-121 architecture yields performance in the 85.57% valence class. In a second experiment, they collaborated on DCERNET architectures and Softmax to achieve a valence class performance of 88.57 percent. Thirdly, they combined DCERNET and SVM to achieve 88.10% valence class performance. Farokhah et al. [26] integrated the development of a simplified CNN architecture, the best single collaboration for channel selection, and a spectrogram with the greatest accuracy in the valence and arousal classes, achieving 98.3% and 96.7% accuracy with 32 channels, respectively. Tang et al. [32] used the spatial-temporal information learning network (STILN) technique, achieving valence and arousal accuracy rates of 67.52 and 68.31 percent, respectively. The presentation of the entire study utilizes 32 channels. Using 10 front channels and CNN architecture, Pandey and Seeja [28] achieved valence and arousal accuracy of 61% and 58%, respectively. In [58], the authors propose an EEG-based emotion recognition model (AP-CapsNet) with subject-dependent and cross-subject experiments, achieving high accuracies of 62.7% and 63.51% in valence and arousal class. In [59], MTLFuseNet combines VAE and GCN/GRU for EEG-based emotion recognition, outperforming state-of-the-art methods with accuracies of 71.33% to 73.28%. Reference [31] introduces a subject-independent or cross-subject approach with Inception-V3 CNN achieving accuracies of average 90.7%. Reference [60] presents BiSMSM for EEG-based emotion recognition, achieving 63.10% to 61.89% accuracy. In [61], an ensemble method outperforms existing approaches with 64.22% to 84.44% accuracy. Reference [62] presents a transfer learning framework achieving accuracy of 65.7% to 64.22% accuracy. Reference [54] introduces an automated cross-subject framework with impressive accuracies of 83.9% to 84.3%. Our recent paper Farokhah et al. [26] proposed a simplified CNN and spectrogram with 32 channels that achieve 98.3% and 96.7% valence and arousal class accuracy, respectively. These papers collectively contribute diverse approaches to EEG-based emotion recognition, each demonstrating promising results in addressing various challenges. A summary of the articles making use of deep learning methods on all 32 channels has been presented in Table 2.

III. MATERIALS AND METHOD

The methodology adopted in this study comprises a multi-step approach, starting with a meticulous channel selection technique. Through the extraction of features such as band power and their ratios and subsequent application of the ReliefF method, we discern the most informative EEG channels. These selected channels are then subjected to the Morlet transform, transforming the data into 2D images that effectively encapsulate intricate temporal and spectral information. Subsequently, employing a simplified deep learning architecture, we conduct a precise classification task, categorizing emotional states into valence and arousal groups. For dependent subject and cross-subject performance analysis, the model employs two additional validation techniques, namely random split, and leave-one-out subject. The architecture proposed in this research was validated using the publicly available DEAP dataset. The dependent subject and cross-subject validation portions of the emotional validation

TABLE 2. Recent articles on deep learning for EEG classification.

Article	Deep Learning Method	Cross-Subject	Accuracy	No. of Channels
[55]	3D cube ECLGCNN	Yes	Valence: 84%, Arousal: 85%	32
[28]	CNN architecture	Yes	Valence: 59%, Arousal: 58%	32
[29]	Inception Resnet-V2	Yes	Valence: 72.81%	32
[56]	BiDCNN	Yes	Valence: 68%, Arousal: 63%	32
[57]	Meta-learner, matrix sequence	Yes	Valence: 69.92%, Arousal: 68.89%	32
[27]	DenseNet-121, DCERNET, SVM	Yes	Valence: 85.57%, Valence: 88.57%, Valence: 88.10%	32
[32]	STILN	Yes	Valence: 67.52%, Arousal: 68.31%	32
[58]	AP-CapsNet	Yes	Valence: 62.7%, Arousal: 63.51%	32
[59]	MTLFuseNet	Yes	Valence: 71.33%, Arousal: 73.28%	32
[31]	Inception-V3 CNN	Yes	Average of accuracy 90.7%	32
[60]	BiSMSM	Yes	Valence: 63.10%, Arousal: 61.89%	32
[61]	Ensemble Method	Yes	Valence: 65.7%, Arousal: 64.22%	32
[62]	Transfer Learning	Yes	Average of accuracy 64.40%	32
[52]	LRFS	Yes	Valence & Arousal: Approx. 60%	32
[26]	Simplified CNN with spectrogram	Yes	Valence: 98.3%, Arousal: 96.7%	32
Proposed Approach	Simplified CNN with Morlet Images	Yes	Discussed in the Results Section	10

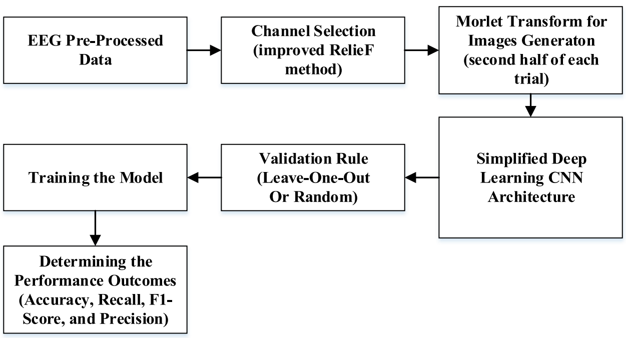


FIGURE 1. Proposed research framework.

experiment using EEG are separated into two segments. The general proposed research framework order is depicted in Fig. 1.

A. DEAP DATASET

DEAP is an open-source database that is known to offer EEG, physiological, and audiovisual signals that can be widely used in the domain of computing and emotion recognition. Numerous subjects are involved in the experimentation which can aid in gathering a diverse set of information under the controlled environment as they experience a variety of emotional stimuli. Primarily, DEAP offers access to numerous kinds of physiological signals including EEG, ECG, GSR, and others, yet in this study, EEG data available for 32 subjects has been employed. Each of the subjects has been exposed to numerous types of 40 video clips (1 minute each) associated with content related to different emotional states. The associated EEG responses are recorded at a high sampling rate utilizing BioSemi ActiveTwo EEG instruments with 32 principal channels. The data is later passed on through pre-processing stages that involve data downsampling to 128 Hz, removal

TABLE 3. DEAP dataset attributes.

Attributes	Description
Subject	32 (16 men dan 16 women)
Stimuli	40 videos; One-minute clips
Number of Trials	40 trials per subject
Channels	32 channels
Rating Scale	*Arousal*, *Valence*
EEG Data	*Array shape* 40x32x8064 *(Trials, Channel, data)*
Labels	*Array Shape* 40x4 (trial's label)
Ground Truth	Participant SAM Questionnaire

of the EOG artifacts, and application of a bandpass filter from 4 to 45 Hz. The reference label information is also available in the form of self-reported valence and arousal ratings against each of the video clips. A summary of the EEG dataset employed has been presented in Table 3.

The dataset is significantly associated with the type of experimentation carried out in this study. Initially the Morlet transformation services as an effective tool to analyze these very large signals under the time and frequency domains. This can help determine the contained patterns and features in the EEG signals that can be correlated with the emotional states. This approach helps in capturing the oscillatory patterns and the spectral components in the EEG data while linking them to the emotional states. This can further help in capturing the subtle patterns of changes in brain activities that are largely present in high-sampled DEAP EEG data under dynamic conditions.

Thus the expected outcomes from the dataset entail the successful extraction of the features related to the unique patterns of emotional responses using the Morlet transform. These features are then subject to deep learning Convolutional Neural Networks to analyze the classification accuracy. Thus in summary the DEAP dataset acts as an effective data

TABLE 4. Parameter of scalogram.

Parameters	Value
Sampling Frequency (fs)	128 Hz
Width Parameter (w)	5
Time Vector (t)	Ranging from 0 to 1 with 4032-time points
Time Step (dt)	Calculated based on the time vector
Frequency Vector (freq)	Ranging from 1 Hz to half of the sampling frequency (fs/2) with 100 frequency points
Widths Parameter (scale/frequency resolution)	Calculated based on the width parameter (w), sampling frequency (fs), and frequency vector (freq)
Morlet Type	Morlet2

resource in the given experimentation design to analyze the performance of each of the proposed stages of work.

B. SCALOGRAM GENERATION

The Scalogram used for image generation is the Morlet Transform (also known as the Gabor-Morlet transform). It is a widely used mechanism for the generation of time-frequency analysis by combining Fourier Transform and Gabor Transform. The EEG signals (primarily non-stationary signals), exhibit time-frequency dependencies over time that are being captured using the Morlet transform. The method is based on the convolution of complex sinusoidal waves, by using a complex sinusoidal Gaussian windowing approach characterized by central frequency and bandwidth.

For a given channel c and participant p, X_{cp} represents the preprocessed version of the selected data, at time t. The Gabor-Morlet wavelet $\varphi(t)$ can be defined as:

$$\varphi(t) = A.e^{\frac{-(t-t_0)^2}{2\sigma^2}} e^{-j2\pi f_0(t-t_0)} \tag{1}$$

here A is the normalization constant, t_0 is the wavelet center,σ is the width of the wavelet, and f_0 is the central frequency of the wavelet.

Here t represents the time, σ is the standard deviation of the Gaussian window, f_0 is the central frequency of the wavelet. The potential benefit of using the Morlet transform is that it offers a good compromise between the localization of time and frequency. The Gaussian window keeps the wavelet concentrated across time and frequency domains, thus enabling it to capture temporal and spectral information simultaneously. The complex value representation of the signal through the Morlet transform is provided in the time-frequency domain (unlike frequency domain representation in the case of the Fourier transform). The results generated using the Morlet transform are the representation of EEG signals as 2D color images representing time and frequency axis. Some of the parameters used for making the transform are described in Table 4.

The RGB images are generated by scaling the scalogram to size of 224 × 224×3. The dimensions of the input size for transfer learning models utilized in this work have been selected based on acknowledged standards. Additionally, these dimensions are further normalized to ensure optimal training operations. In order to ensure correct inference of hidden trends, it is beneficial to normalize pixel values within the range of 0 to 1. The transformation of all channels into pictures is followed by the application of channel selection and classification modes. Morlet images were generated for channel number 3 of a specific recording, representing both high and low for valence and arousal classes. The architectural framework suggested in this study was assessed for its efficacy by employing the publicly accessible DEAP dataset. The emotional validation experiment utilizing EEG is divided into two distinct segments: the dependent subject validation and the cross-subject validation. Four sample images are depicted in Fig. 2.

C. PROPOSED CHANNEL SELECTION

The EEG pre-processing involves the application of band-pass filters for the removal of noise and other artifacts contained within the signal. The Morlet Transform applied as part of this study infers the time-frequency dependency of the data contained as a 1D stream. The selection of the channels employed in this study makes use of an improved Relief model, that analyses the significance of the data contained in each channel to the classification outcomes. We call it Power ratio-relief (PR-Relief). Unlike the traditional Relief methods adopted which use raw data to choose the best channel, this study makes use of PSD band powers with ratio across the four channels alpha (α), beta (β), gamma (γ), and theta (θ), along with their ratios. This band power serves as a feature of the Relief method, which then determines the scores of the individual channels under the high and low valence classesN_c. Ratios are utilized to characterize significant connections between power band characteristics. Ratios can assist in identifying patterns or tendencies that may not be apparent when examining individual features. Some previous studies have employed features extraction approaches applied to relief and reliefF methods [49], [63], [64], [65], [66], [67], however, they differ from the suggested PSD and ratios approach made part of this study.

The PSD across individual bands has been computed using the Welch method, whose mathematical representation is given in Eq. 2. Given the frequency range f_{min} to f_{max}:

$$PSD_{band,c,p}(f) = \frac{1}{N}\left|\sum_{k} X_{c,p}(f_k)\right|^2 \tag{2}$$

where N represents the total number of samples, while the summation is performance over the frequency bins f_k ranging between f_{min}, f_{max} depending upon the specific band under consideration.

Algorithm 1 presents the approach adopted for the channel selection through the Relief method as part of this study:

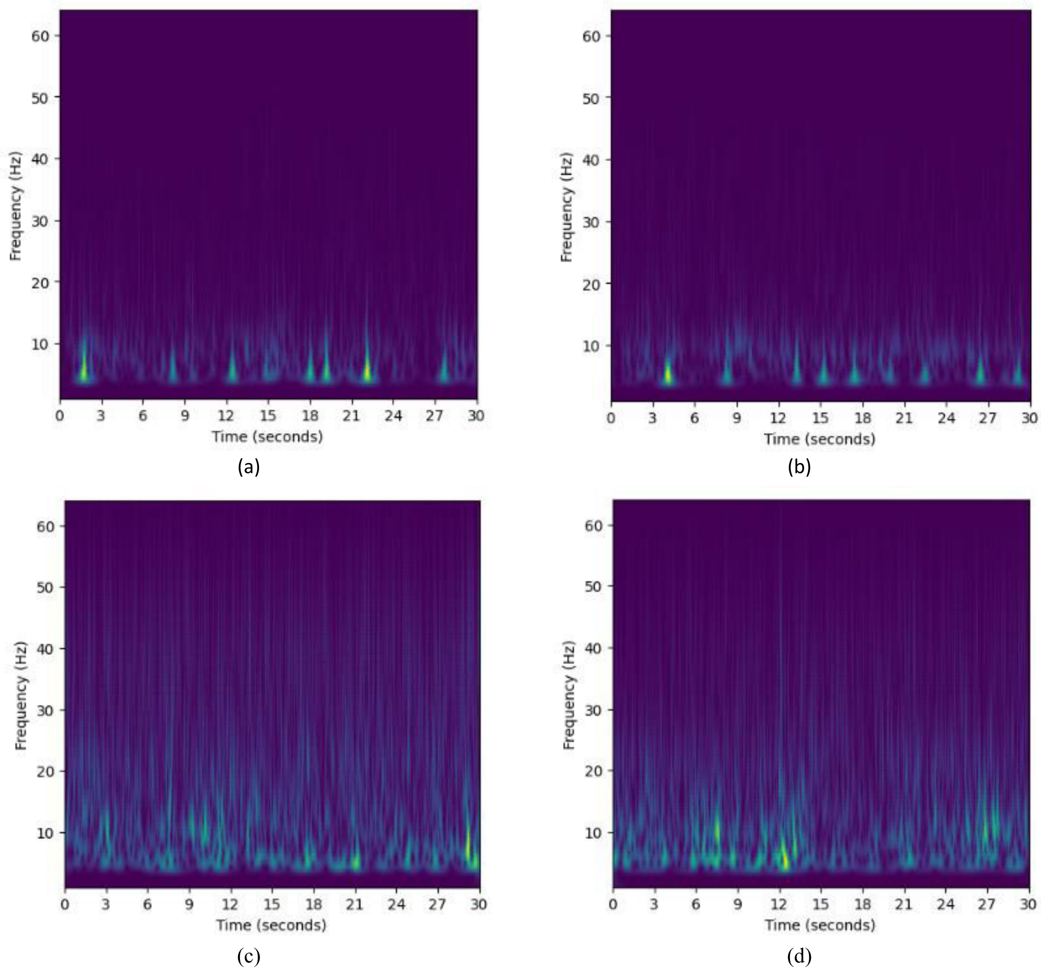


FIGURE 2. Scalograms for individual recording at subject 1 on channel 3. a. High valence (Trial 11), b. Low valence (Trial 24), c. High arousal (Trial 1), d. Low arousal (Trial 13).

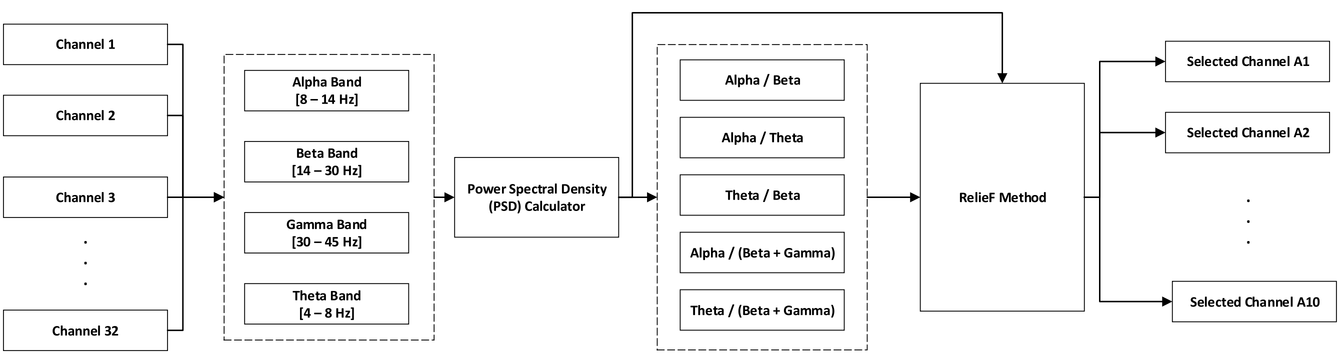


FIGURE 3. Proposed method of channel selection.

The present study involves the process of channel selection through the examination of individual channels, followed by the identification and selection of the top 10 channels based on the power ratio derived from the power band's Power Spectral Density. The weight of the ten greatest channels capable of correctly classifying the valence class. This study employs a classification indicator for dependent subjects based on valence class (low-high) for the channel selection process. The selected classification class is valence class. The results of channel selection are then applied to the advanced classification of valence and arousal classes. Fig. 3 depicts the sequence of the proposed channel selection method. The selection of the validation rule involves the use of a random split in the ratios 70:10:20 for training, validation, and testing.

Algorithm 1 Power Ratio Relief Method for the Channel Selection

Input: EEG Data X, Trials T, Bands α, β, γ, θ

Output: Selected Channels S

Process Starts:

1. $D \leftarrow X\{T\}$
2. $D_B \leftarrow$ Bandpower $D(\theta), D(\alpha), D(\beta), D(\gamma), D(\alpha/\beta), D(\alpha/\gamma), D(\gamma/\beta), D(\alpha/\beta/\gamma), D(\theta/\beta/\gamma)$
3. $N_c \leftarrow$ high valence, low valence
4. $R \leftarrow$ ReliefF Scores (D_B, N_c, kwargs $= 10$)
5. **for** i in range (10) **do**
6. $S(i) \leftarrow$ max_index(R)
7. discard(max_index(R))
8. **End**

D. ARCHITECTURE FOR CLASSIFICATION

After the 1D to 2D EEG transformation generates a 2D EEG scalogram, the scalogram will be used as input for classification using deep learning. This study applies streamlined architecture. This architecture has been established in previous studies [26]. The architecture for classification is shown in Fig. 4.

The is designed to effectively process 2D Morlet Images derived from EEG channel data for emotion classification. This architecture consists of several essential layers, each contributing to the model's ability to extract meaningful features and make accurate predictions. The Input Layer serves as the initial entry point for the 2D Morlet Images, providing the raw image data to the neural network. The first Convolutional Layer, with 32 filters and Rectified Linear Unit (ReLU) activation, performs feature extraction. It identifies low-level patterns in the Morlet Images, such as edges and basic shapes. The second Convolutional Layer, with 64 filters and ReLU activation, further refines feature extraction, capturing more complex and higher-level patterns. The MaxPooling layer reduces spatial dimensions, helping the network focus on the most relevant features while reducing computational complexity. Two additional Convolutional Layers with 64 filters and ReLU activation allow for deeper feature extraction, potentially identifying intricate patterns related to emotion. Dropout layers prevent overfitting by randomly deactivating neurons during training, encouraging robust feature learning. The first Dense (fully connected) layer with 256 neurons and ReLU activation further consolidates the learned features, enabling complex relationships between extracted features to be captured. A dropout layer with a rate of 0.7 further regularizes the network, promoting generalization. The second Dense layer with 128 neurons and ReLU activation continues to capture higher-level abstractions in the data. Another dropout layer with a rate of 0.5 aids in preventing overfitting, ensuring the model's generalizability. The final Dense layer, employing the softmax activation function, produces probability distributions over the different emotional classes, enabling the network to make emotion predictions.

TABLE 5. Hyperparameter of deep learning.

Parameter	Value
Batch size	32 (dependent-subject) and 16 (cross-subject)
Epoch	300
Optimizer	Adam
Learning rate	lr = 1e-4
Decay	decay = 1e-7
Data Split	70:20:10 (training, testing, validation)
Activation function	Softmax
Loss	MSE

The outcomes are rendered as high-valence, low-valence, or high-arousal, low-arousal.

The following simulation parameters have been adopted for carrying out the training and evaluation of the model as presented in Table 5.

E. EVALUATION

This publication provides more depth about cross-subject validation. Dependent subject validation was used as supplementary knowledge with 70:20:10 random split as training: validation: testing. Concerning cross-subject validity, the leave-one-out takes into account the training of the model based on N-1 individuals while using the left-one individual as the validation data. Finally, the model has been trained and tested under numerous performance metrics. The matrices are determined based on the True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). These include accuracy, recall, precision, and F1-Score, the mathematical models for each of these performance metrics have been provided below.

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$F1Score = \frac{2(Precision)(Recall)}{Precision + Recall} \tag{6}$$

F. PLATFORM AND MODEL COMPLEXITY

The experimentation and implementation performed in this study make use high-performance computing platform accessed through the Google Colab version equipped with state-of-the-art GPUs. Access to GPUs including NVIDIA V100 and NVIDIA T4 was granted along with RAM access of up to 54 GBs. This enabled an efficient execution of the complex experimentations enabling rapid model training and evaluation. Additionally, the use of standard libraries like TensorFlow for the development of deep learning models helps further optimize the underlying computations on

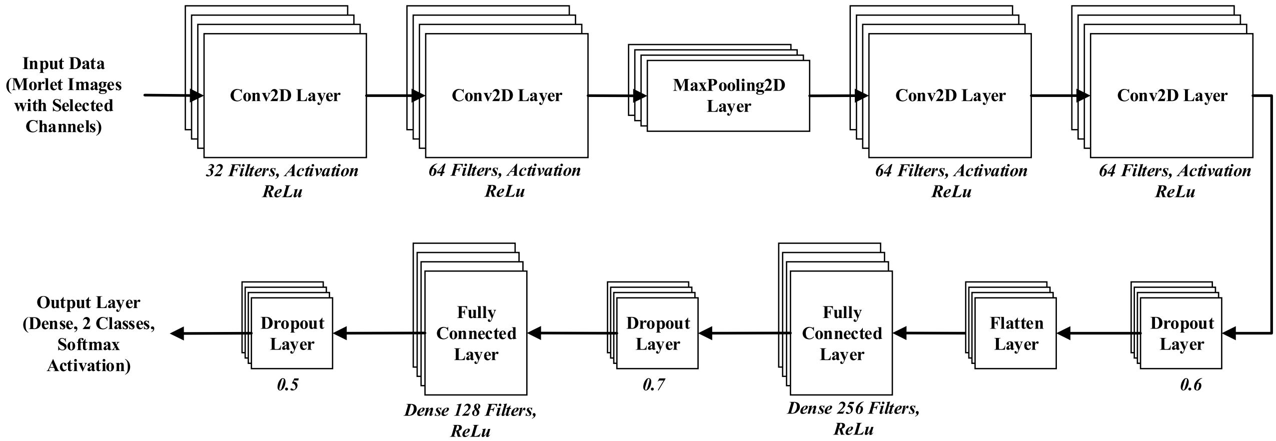


FIGURE 4. Simplified CNN architecture.

TABLE 6. Models' complexity comparison.

Model	Trainable Parameters	Number of Layers
ResNet50	25.5 M	50
DenseNet121	7.98 M	121
AlexNet	60 M	
CNN		
InceptionResnetV2	55.9 M	572
DCERNET	51,7 M	50
Simplified CNN Architectures	46,1 M	13

the GPU environment. Since the study claims an adoption of simplified CNN architecture, therefore, it is imperative to analyze the complexity of the model compared to some standard architectures and developed architecture in existing research especially cross-subject validation in Table 6. This is due to the fact that a number of previous studies ignored specific computational details. The architecture has been compared with some of the most commonly used transfer learning architectures for 2D image classification including ResNet50, DenseNet121, and InceptionResNetV2. Additionally, DCERNET architecture was incorporated. This architecture was created for cross-subject emotion validation. This study involved conducting experiments utilizing a standard architectural framework. One issue that arises when employing a standard architecture with deep layers is the significant consumption of Random Access Memory (RAM), especially when handling 32 channels with 32 participants utilizing the DEAP dataset. The Google Colab system is going to trigger a runtime restart in order to prevent the execution of the subsequent process. This is not happening when employing a developed architecture (Simplified CNN) [26]. The comparison has been made in terms of trainable parameters and the number of layers that comprise convolutional layers, dropout, and pooling layers. A summary has been presented in Table 6.

TABLE 7. Comparison of cross-subject performance results with different trials.

No	Method of Trials	Performance	
		Valence	Arousal
1	Random Trials (18 trials)	94.63%	94.27%
2	Collaboration with LastFM Ground Truth (18 trials)	95.01%	94.1%
3	All Trials	94.01%	93.08%

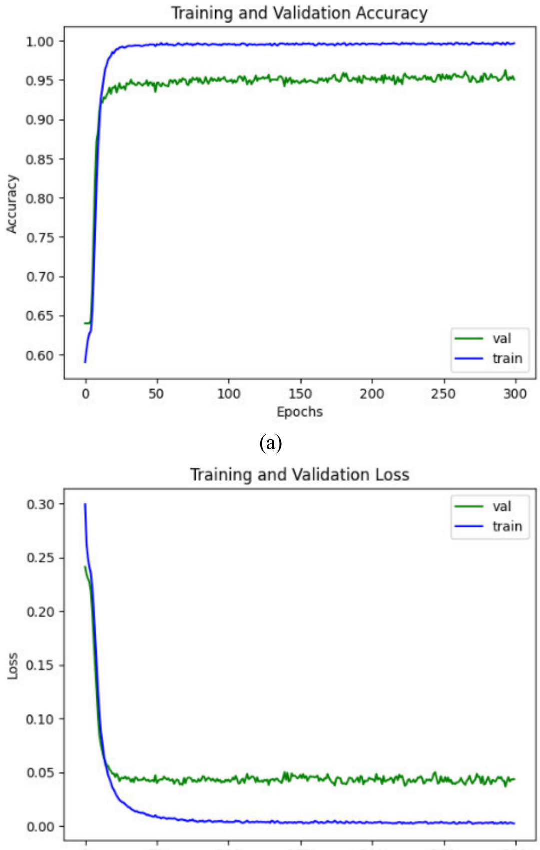
TABLE 8. Performance of dependent subject with 10 channels.

Performance	Valence	Arousal
Accuracy of training	99.70%	99.66%
Loss of training	0.0024	0.0024
Accuracy of validation	95.05%	94.10%
Loss of validation	0.0436	0.0561
Performance Metrics (Testing)		
Precision	94.8%	98.3%
Recall	88.8%	86.5%
Accuracy	94.4%	94.6%
F1 Score	91.7%	92%

IV. RESULT AND DISCUSSION

A. PROPOSED SELECTED CHANNELS WITH VARIOUS TRIALS TREATMENT

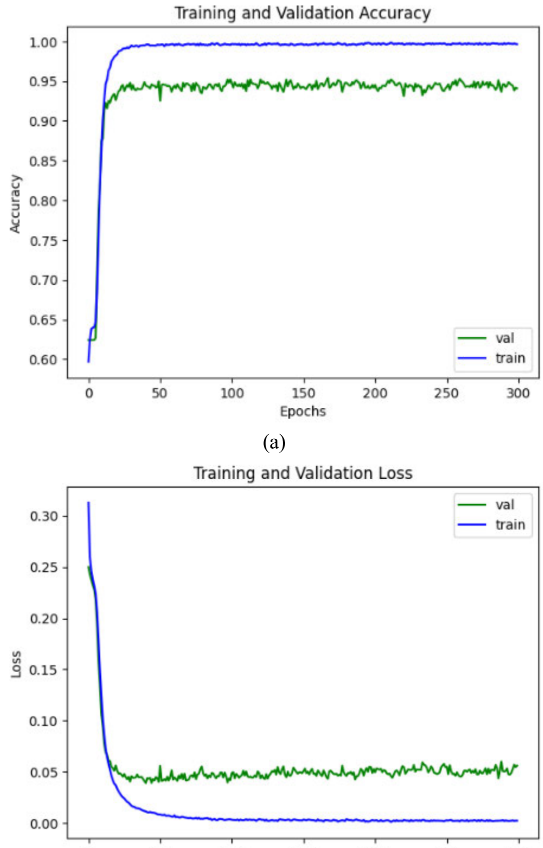
In the process of channel selection, we proposed the power ratio of the Relief (PR-Relief) method. PR relief is a method for channel selection based on relief weighting that employs the ratio feature between power bands. This is illustrated in Figure 3. In the procedure for channel selection, we tested the channels resulting from different selection methods of trials using three distinct methods, along with the results of



(a)

(b)

FIGURE 5. Training curves for Valence. a. training and validation accuracy. b. training and validation loss.



(a)

(b)

FIGURE 6. Training curves for arousal a. training and validation accuracy. b. training and validation loss.

inter-subject classification performance. Initially, the use of 18 randomized clinical trials. Second, select 18 trials from the DEAP dataset based on the LastFm Website supplementary ground truth (online assessment). Third, use all trials (40 trials). Only one or two channels are distinguishable among the obtained channel results. The top ten channels determined by random sampling are 5, 6, 7, 8, 9, 10, 11, 15, 19, and 27 (FC5, FC1, C3, T7, CP5, CP1, P3, Oz, Fz, CP6). Using the trial with additional ground truth from LastFm as a guide, ten channels are obtained: 5, 6, 7, 8, 9, 10, 15, 19, 22, and 27 (FC5, FC1, C3, T7, CP5, CP1, Oz, Fz, CP6). Using all trials, ten channels with the numbers 5, 6, 7, 8, 9, 10, 11, 15, 26, and 27 (FC5, FC1, C3, T7, CP5, CP1, P3, Oz, T8, CP6) were obtained. Then, we conducted a cross-subject validation test with 32 participants by calculating the average of 20 participants. Table 7 summarizes the result.

The DEAP dataset includes the TagFM of ground truth as one of its features. TagFM is a website that validates the emotions that the average person experiences when watching a stimulant video. According to the TagFM survey (Which is provided by the DEAP dataset), only 18 trials are provided with ground truth in the DEAP dataset. This is added to the analysis of the trials chosen for use because they have publicly available ground-truth references. The proposed selected channel utilizing PR-Relief (power ratio-relief) has the advantage of not requiring the use of all trials, thereby reducing computation. In addition, the efficacy of channel selection in the classification of emotions produces nearly identical results. This shows the consistency of the channel selection results under varied conditions of trials.

TABLE 9. Cross-subject performance outcomes with varying input treatment or channel selection method.

Input	Selection Channel Method	Performance
Spectrogram[26]	Our proposed RP-Relief	Arousal class: 92.26%
Proposed scalogram	Our proposed RP-Relief	Arousal class: 94.1%
Spectrogram[26]	Single channel collaboration [26]	Valence class: 92.3%
Proposed scalogram	Single channel collaboration [26]	Valence class: 93. 75%

TABLE 10. Result of cross-subject performance for valence class.

Subject (Leave one out)	Precision	Recall	Accuracy	F1 score
s01	96	93.1	96.2	94.6
s02	95.4	88.8	94.3	92
s03	96.3	88.8	94.6	92.4
s04	95.8	89.8	94.9	92.7
s05	96.8	89.8	95.2	93.2
s06	95.2	89.9	94.5	92.5
s07	97	87.1	94.2	91.8
s08	93.7	90.6	94.3	92.1
s09	96.8	90.5	95.4	93.5
s10	95.4	89.1	94.4	92.1
s11	94.9	91.6	95.1	93.2
s12	95.6	92.5	95.8	94
s13	96.6	91.9	95.9	94.2
s14	94.2	92.6	95.3	93.4
s15	96.4	90.9	95.5	93.6
s16	95.7	90.4	95.1	92.9
s17	94.9	90.8	94.9	92.8
s18	96.5	90.1	95.1	93.2
s19	96.3	88	94.4	92
s20	95.2	91.3	95.1	93.2
s21	95.4	88.6	94.2	91.9
s22	94.7	89.9	94.5	92.3
s23	93.3	91.1	94.2	92.2
s24	95.9	88.2	94.4	92.7
s25	94.2	91.8	94.9	93
s26	96.7	89.5	95	93
s27	96.5	88.6	94.5	92.4
s28	96.9	91.4	95.7	94.1
s29	96	87.2	94	91.4
s30	95.2	89.1	94.3	92
s31	95.5	87.6	93.8	91.4
s32	95.7	88.4	94.3	91.9

TABLE 11. Result of cross-subject performance for arousal class.

Subject (Leave one out)	Precision	Recall	Accuracy	F1 score
s01	95.6	90	95	92.7
s02	93.5	89	93.8	91.2
s03	94.4	80.1	94.8	92.2
s04	94.2	89	94.3	91.6
s05	93.6	86	93.1	89.7
s06	94.3	87.1	93.8	90.6
s07	92.5	90.8	94.3	91.6
s08	94.8	89.5	94.5	92.1
s09	94.6	86.3	93.5	90.3
s10	94	90	94.6	92
s11	92.5	90.6	94.2	91.6
s12	93	90.3	94.1	91.6
s13	94.4	88.8	94.1	91.5
s14	93.2	89.9	94.2	91.5
s15	95.2	90.2	95	92.6
s16	95.3	86.6	93.8	90.7
s17	93.9	90.6	94.6	92.2
s18	92.5	85.8	92.4	90
s19	92.7	91	94.3	91.9
s20	96	85.8	93.6	90.6
s21	93.7	90.9	94.6	92.3
s22	95.7	87.6	94.2	91.5
s23	94.4	91	95	92.7
s24	95.1	85.5	93.2	90.1
s25	95	89.6	94.6	92.2
s26	93.1	87.9	93.5	90.4
s27	94.4	91.2	95	92.8
s28	96.9	88.4	95	92.4
s29	93.5	88.8	93.9	91.1
s30	96.2	87.1	94.3	91.4
s31	93.9	90.3	94.6	92.1
s32	94.9	86.1	93.4	90.3

B. VALIDATION OF EMOTION RECOGNITION

1) EXPERIMENT OF DEPENDENT SUBJECT

Validating the dependent subject or intra-subject emotion classification using 10 channels. These ten channels were generated from the previous channel selection process using the proposed PR-Relief Method. We use a 10% random split of the data for testing. The performance results for the testing accuracy of the emotion classification in the valence and arousal classes were 94.4% and 94.6%, respectively. This result is up compared to all previous studies [26]. The dependent subject's performance results have improved, according to a comparison of current research to previous research on the topic [26]. Fig. 5 depicts the training and validation accuracy for the valence class then training and validation loss. Fig. 6 depicts training and validation for the arousal class then training and validation loss. Details of the experiment are shown in Table 8.

2) EXPERIMENT OF CROSS-SUBJECT

a: CROSS-SUBJECT WITH VARIOUS INPUTS AND SELECTED CHANNEL

In this investigation, we attempted to compare it to our previous research [26], which utilized the input spectrogram and

TABLE 12. Cross-subject performance comparison with previous studies.

Model	Article	Channels used	Accuracy	
			Valence	Arousal
3D Cube - ECLGCN N	[55]	32 channels	84%	85%
CNN	[28]	32 channels	59%	58%
Inception Resnet-V2	[29]	32 channels	72,81 %	-
2D BiDCNN	[56]	32 channels	68%	63%
Raw EEG + CNN (Meta-learner)	[57]	32 channels	69.92 %	68.89 %
DenseNet 121	[27]	32 channels	85.5%	-
DCERNet +softmax	[27]	32 channels	88.57 %	-
DCERNet +SVM	[27]	32 channels	88.1%	-
STILN	[32]	32 channels	67.52 %	68.31 %
CNN	[28]	10 frontal channels:	61%	58%
Simplified CNN+ Spectrogram +Best single collaboration	[26]	10 Channels	92.1%	92.2%
Simplified CNN+ Scalogram + Ratio power-Relief	Proposed Method	10 Channels	94.81 %	94.16 %

single-best collaboration to select channels. We attempted to conduct experiments with input modifications using spectrogram versus scalogram, using either the new channel selection method (PR-Relief) or the old channel selection method (single best collaboration) [26]. We only test specific groups to compare changes (for example, just valence or just arousal classes for testing time efficiency). Table 9 shows the experiment's particulars. Table 9 displays the results of cross-subject classification using 32 subjects, with one out-subject average remaining until the twentieth subject.

According to Table 9, the combination of the proposed input and proposed channel selection yields the highest performance.

b: CROSS-SUBJECT WITH PROPOSED INPUT AND PROPOSED SELECTED CHANNEL

For both dependent subjects and cross-subjects using 10 selected channels, we use the previously developed architecture [26]. This architecture has a smaller number of parameters than the architectures used in other cross-subject classifications [26]. For validation, this study uses a leave-one-out subject and then takes an average of 32 subjects. Leave one out of the subject is a validation standard for cross-subject classification that strictly separates the subject in the training and validation processes [26], [27], [56]. The results of cross-subject classification for the valence class are shown in Table 10 and Table 11 for the arousal class.

As shown in Tables 9 and 10, the cross-subject classification validation using our proposed scalogram and proposed PR-Relief (10 channels of channel selection) yielded an average accuracy of 94.81% for the valence class and 94.16% for the arousal class. The accuracy performance is used as a performance indicator to compare with previous studies.

C. COMPARISON WITH PREVIOUS RESEARCH ON CROSS-SUBJECT EMOTION RECOGNITION

To show the contribution to performance enhancement and the proposed method, this study presents the results of previous research with various channel numbers. In addition, it is explained in Subchapter II Related Work for previous research in other domains. Table 12 is a comparison of performance outcomes.

The collaboration of the proposed method in input interpretation using a scalogram and the channel selection method using PR-Relief (Power ratio -Relief) resulted in an increase in accuracy performance of around 2% from the previous highest research in inter-subject or cross-subject validation. In the 2D EEG and 3D EEG domains in Table 12 as well as other domains in Sub-Chapter II Related Work. The accuracy performance produced in this study resulted in the highest performance.

V. CONCLUSION

In this paper, we were able to improve the accuracy of emotion recognition for cross-subject validation by keeping computations lighter through channel selection or reduction. The processing of data for emotion recognition using EEG with a large number of channels needs significant resources. A pair of tasks have been completed. First, propose and determine the best interpretation of the input that will be used for the classification of emotions using a scalogram. Second, propose a channel selection method based on the preponderance of the power band ratio via the relief method. Third, collaboration of scalogram, PR-Relief for channel selection, and simplified CNN for classification have proposed. In the proposed channel selection, the number of experiments on trials led to stable performance in terms of classification accuracy. The proposed collaboration process between the input and the channel selection method generates important information, namely that the interpretation of the input and the channel selection method influences the classification results of emotions. Compared to previous studies, collaborative EEG representation, simplified CNN, and channel selection methods produced the highest performance. Validation of cross-subject emotion classification that collaborates with channel selection in the image domain is still limited. As additional information to demonstrate a genuine contribution, this study includes additional domain research in subchapter II Related work. Our research keeps going showing the highest accuracy performance compared to previous 2D or other research domains. In future research, the incorporation of reinforcement learning techniques holds promise for dynamic and run-time channel selection personalized to each subject. By formulating the channel selection task as a Markov decision process, reinforcement learning algorithms can adaptively identify the most informative EEG channels during real-time emotion recognition tasks. This approach will allow the system to continuously refine channel selection strategies based on the subject's specific emotional responses, effectively mitigating the cross-subject variability challenge. The development of reinforcement learning-based agents that optimize channel selection in an online and subject-specific manner represents a compelling direction to enhance the adaptability and accuracy of EEG-based emotion recognition system.

REFERENCES

[1] S. C. Leong, Y. M. Tang, C. H. Lai, and C. K. M. Lee, "Facial expression and body gesture emotion recognition: A systematic review on the use of visual data in affective computing," *Comput. Sci. Rev.*, vol. 48, May 2023, Art. no. 100545, doi: 10.1016/j.cosrev.2023.100545.

[2] I. Lasri, A. Riadsolh, and M. Elbelkacemi, "Facial emotion recognition of deaf and hard-of-hearing students for engagement detection using deep learning," *Educ. Inf. Technol.*, vol. 28, no. 4, pp. 4069–4092, Apr. 2023, doi: 10.1007/s10639-022-11370-4.

[3] Y. B. Singh and S. Goel, "A systematic literature review of speech emotion recognition approaches," *Neurocomputing*, vol. 492, pp. 245–263, Jul. 2022, doi: 10.1016/j.neucom.2022.04.028.

[4] S. Chamishka, I. Madhavi, R. Nawaratne, D. Alahakoon, D. De Silva, N. Chilamkurti, and V. Nanayakkara, "A voice-based real-time emotion detection technique using recurrent neural network empowered feature modelling," *Multimedia Tools Appl.*, vol. 81, no. 24, pp. 35173–35194, Oct. 2022, doi: 10.1007/s11042-022-13363-4.

[5] D. W. Prabowo, H. A. Nugroho, N. A. Setiawan, and J. Debayle, "A systematic literature review of emotion recognition using EEG signals," *Cognit. Syst. Res.*, vol. 82, Dec. 2023, Art. no. 101152, doi: 10.1016/j.cogsys.2023.101152.

[6] R. Agarwal, M. Andujar, and S. Canavan, "Classification of emotions using EEG activity associated with different areas of the brain," *Pattern Recognit. Lett.*, vol. 162, pp. 71–80, Oct. 2022, doi: 10.1016/j.patrec.2022.08.018.

[7] A. J. Bidgoly, H. J. Bidgoly, and Z. Arezoumand, "A survey on methods and challenges in EEG based authentication," *Comput. Secur.*, vol. 93, Jun. 2020, Art. no. 101788, doi: 10.1016/j.cose.2020.101788.

[8] M. N. Munawar, R. Sarno, D. A. Asfani, T. Igasaki, and B. T. Nugraha, "Significant preprocessing method in EEG-based emotions classification," *J. Theor. Appl. Inf. Technol.*, vol. 87, no. 2, pp. 176–190, 2016.

[9] Y. Wu, M. Xia, L. Nie, Y. Zhang, and A. Fan, "Simultaneously exploring multi-scale and asymmetric EEG features for emotion recognition," *Comput. Biol. Med.*, vol. 149, Oct. 2022, Art. no. 106002, doi: 10.1016/j.compbiomed.2022.106002.

[10] E. P. Torres, E. A. Torres, M. Hernández-Álvarez, and S. G. Yoo, "EEG-based BCI emotion recognition: A survey," *Sensors*, vol. 20, no. 18, pp. 1–36, 2020, doi: 10.3390/s20185083.

[11] D. Sunaryono, R. Sarno, and J. Siswantoro, "Gradient boosting machines fusion for automatic epilepsy detection from EEG signals based on wavelet features," *J. King Saud Univ. Comput. Inf. Sci.*, vol. 34, no. 10, pp. 9591–9607, 2021, doi: https://doi.org/10.1016/j.jksuci.2021.11.015.

[12] S. Vidhusha, B. Divya, A. Kavitha, R. V. Narayanan, and D. Yaamini, "Cognitive attention in autism using virtual reality learning tool," in *Proc. IEEE 18th Int. Conf. Cognit. Informat. Cognit. Comput. (ICCICC)*, Jul. 2019, pp. 159–165, doi: 10.1109/ICCICC46617.2019.9146086.

[13] J. Korpysa, "Neuroentrepreneurship a new paradigm in the management science," *Proc. Comput. Sci.*, vol. 176, pp. 2605–2614, 2020, doi: 10.1016/j.procs.2020.09.309.

[14] K. Gainsford, B. Fitzgibbon, P. B. Fitzgerald, and K. E. Hoy, "Transforming treatments for schizophrenia: Virtual reality, brain stimulation and social cognition," *Psychiatry Res.*, vol. 288, Jun. 2020, Art. no. 112974, doi: 10.1016/j.psychres.2020.112974.

[15] T. Xu, Y. Zhou, Z. Wang, and Y. Peng, "Learning emotions EEG-based recognition and brain activity: A survey study on BCI for intelligent tutoring system," *Proc. Comput. Sci.*, vol. 130, pp. 376–382, Jan. 2018, doi: 10.1016/j.procs.2018.04.056.

[16] F. Focquaert, "Neurobiology and crime: A neuro-ethical perspective," *J. Criminal Justice*, vol. 65, Nov. 2019, Art. no. 101533, doi: 10.1016/j.jcrimjus.2018.01.001.

[17] B. T. Nugraha, R. Sarno, D. A. Asfani, T. Igasaki, and M. N. Munawar, "Classification of driver fatigue state based on EEG using emotiv EPOC+," *J. Theor. Appl. Inf. Technol.*, vol. 86, no. 3, pp. 347–359, 2016.

[18] F. Lotte, L. Bougrain, A. Cichocki, M. Clerc, M. Congedo, A. Rakotomamonjy, and F. Yger, "A review of classification algorithms for EEG-based brain–computer interfaces: A 10 year update," *J. Neural Eng.*, vol. 15, no. 3, Jun. 2018, Art. no. 031005, doi: 10.1088/1741-2552/aab2f2.

[19] E. Lashgari, D. Liang, and U. Maoz, "Data augmentation for deep-learning-based electroencephalography," *J. Neurosci. Methods*, vol. 346, Dec. 2020, Art. no. 108885, doi: 10.1016/j.jneumeth.2020.108885.

[20] O. Özdenizci, Y. Wang, T. Koike-Akino, and D. Erdogmus, "Learning invariant representations from EEG via adversarial inference," *IEEE Access*, vol. 8, pp. 27074–27085, 2020, doi: 10.1109/ACCESS.2020.2971600.

[21] T. Krumpe, K. Baumgärtner, W. Rosenstiel, and M. Spüler, "Non-stationarity and inter-subject variability of EEG characteristics in the context of Bci development," in *Proc. 7th Graz Brain-Comput. Interface Conf.*, Sep. 2017, pp. 260–265, doi: 10.3217/978-3-85125-533-1-48.

[22] E. Jeon, W. Ko, J. S. Yoon, and H.-I. Suk, "Mutual information-driven subject-invariant and class-relevant deep representation learning in BCI," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 2, pp. 739–749, Feb. 2023, doi: 10.1109/TNNLS.2021.3100583.

[23] J. Liu, X. Shen, S. Song, and D. Zhang, "Domain adaptation for cross-subject emotion recognition by subject clustering," in *Proc. Int. IEEE/EMBS Conf. Neural Eng. (NER)*, May 2021, pp. 904–908, doi: 10.1109/NER49283.2021.9441368.

[24] Arjun, A. S. Rajpoot, and M. R. Panicker, "Subject independent emotion recognition using EEG signals employing attention driven neural networks," *Biomed. Signal Process. Control*, vol. 75, May 2022, Art. no. 103547, doi: 10.1016/j.bspc.2022.103547.

[25] K. Sharma, A. Dash, and D. Kumar, "Investigating the effect of EEG channel selection on inter-subject emotion classification," in *Proc. 13th Int. Conf. Cloud Comput., Data Sci. Eng., Confluence*, 2023, pp. 312–316, doi: 10.1109/Confluence56041.2023.10048851.

[26] L. Farokhah, R. Sarno, and C. Fatichah, "Simplified 2D CNN architecture with channel selection for emotion recognition using EEG spectrogram," *IEEE Access*, vol. 11, pp. 46330–46343, 2023, doi: 10.1109/ACCESS.2023.3275565.

[27] N. Pusarla, A. Singh, and S. Tripathi, "Learning DenseNet features from EEG based spectrograms for subject independent emotion recognition," *Biomed. Signal Process. Control*, vol. 74, Apr. 2022, Art. no. 103485, doi: 10.1016/j.bspc.2022.103485.

[28] P. Pandey and K. R. Seeja, "Subject independent emotion recognition system for people with facial deformity: An EEG based approach," *J. Ambient Intell. Humanized Comput.*, vol. 12, no. 2, pp. 2311–2320, Feb. 2021, doi: 10.1007/s12652-020-02338-8.

[29] Y. Cimtay and E. Ekmekcioglu, "Investigating the use of pretrained convolutional neural network on cross-subject and cross-dataset EEG emotion recognition," *Sensors*, vol. 20, no. 7, pp. 1–20, 2020, doi: 10.3390/s20072034.

[30] N. Kouka, R. Fourati, R. Fdhila, P. Siarry, and A. M. Alimi, "EEG channel selection-based binary particle swarm optimization with recurrent convolutional autoencoder for emotion recognition," *Biomed. Signal Process. Control*, vol. 84, Jul. 2023, Art. no. 104783, doi: 10.1016/j.bspc.2023.104783.

[31] B. Zali-Vargahan, A. Charmin, H. Kalbkhani, and S. Barghandan, "Deep time-frequency features and semi-supervised dimension reduction for subject-independent emotion recognition from multi-channel EEG signals," *Biomed. Signal Process. Control*, vol. 85, Aug. 2023, Art. no. 104806, doi: 10.1016/j.bspc.2023.104806.

[32] Y. Tang, Y. Wang, X. Zhang, and Z. Wang, "STILN: A novel spatial–temporal information learning network for EEG-based emotion recognition," *Biomed. Signal Process. Control*, vol. 85, Aug. 2023, Art. no. 104999, doi: 10.1016/j.bspc.2023.104999.

[33] D. Shah, G. Gopan, and N. Sinha, "An investigation of the multi-dimensional (1D vs. 2D vs. 3D) analyses of EEG signals using traditional methods and deep learning-based methods," *Frontiers Signal Process.*, vol. 2, pp. 1–15, Jul. 2022, doi: 10.3389/frsip.2022.936790.

[34] S. Gong, K. Xing, A. Cichocki, and J. Li, "Deep learning in EEG: Advance of the last ten-year critical period," *IEEE Trans. Cognit. Develop. Syst.*, vol. 14, no. 2, pp. 348–365, Jun. 2022, doi: 10.1109/TCDS.2021.3079712.

[35] R. Bajpai, R. Yuvaraj, and A. A. Prince, "Automated EEG pathology detection based on different convolutional neural network models: Deep learning approach," *Comput. Biol. Med.*, vol. 133, Jun. 2021, Art. no. 104434, doi: 10.1016/j.compbiomed.2021.104434.

[36] Y. Roy, H. Banville, I. Albuquerque, A. Gramfort, T. H. Falk, and J. Faubert, "Deep learning-based electroencephalography analysis: A systematic review," *J. Neural Eng.*, vol. 16, no. 5, Oct. 2019, Art. no. 051001, doi: 10.1088/1741-2552/ab260c.

[37] C. Ieracitano, N. Mammone, A. Hussain, and F. C. Morabito, "A novel explainable machine learning approach for EEG-based brain–computer interface systems," *Neural Comput. Appl.*, vol. 34, no. 14, pp. 11347–11360, Jul. 2022, doi: 10.1007/s00521-020-05624-w.

[38] Y. Luo and B.-L. Lu, "EEG data augmentation for emotion recognition using a conditional Wasserstein GAN," in *Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2018, pp. 2535–2538, doi: 10.1109/EMBC.2018.8512865.

[39] J. Li, S. Qiu, Y.-Y. Shen, C.-L. Liu, and H. He, "Multisource transfer learning for cross-subject EEG emotion recognition," *IEEE Trans. Cybern.*, vol. 50, no. 7, pp. 3281–3293, Jul. 2020.

[40] A. Khosla, P. Khandnor, and T. Chand, "A comparative analysis of signal processing and classification methods for different applications based on EEG signals," *Biocybernetics Biomed. Eng.*, vol. 40, no. 2, pp. 649–690, Apr. 2020, doi: 10.1016/j.bbe.2020.02.002.

[41] M. R. Islam, M. M. Islam, M. M. Rahman, C. Mondal, S. K. Singha, M. Ahmad, A. Awal, M. S. Islam, and M. A. Moni, "EEG channel correlation based model for emotion recognition," *Comput. Biol. Med.*, vol. 136, Sep. 2021, Art. no. 104757, doi: 10.1016/j.compbiomed.2021.104757.

[42] W. Lin, C. Li, and S. Sun, "Deep convolutional neural network for emotion recognition using EEG and peripheral physiological signal," in *Proc. Int. Conf. Image Graph*, 2017, pp. 385–394, doi: 10.1007/978-3-319-71589-6_33.

[43] Y.-H. Kwon, S.-B. Shin, and S.-D. Kim, "Electroencephalography based fusion two-dimensional (2D)-convolution neural networks (CNN) model for emotion recognition system," *Sensors*, vol. 18, no. 5, p. 1383, Apr. 2018, doi: 10.3390/s18051383.

[44] Y. Wang, L. Zhang, P. Xia, P. Wang, X. Chen, L. Du, Z. Fang, and M. Du, "EEG-based emotion recognition using a 2D CNN with different kernels," *Bioengineering*, vol. 9, no. 6, p. 231, May 2022, doi: 10.3390/bioengineering9060231.

[45] J. Cho and H. Hwang, "Spatio-temporal representation of an electoencephalogram for emotion recognition using a three-dimensional convolutional neural network," *Sensors*, vol. 20, no. 12, p. 3491, Jun. 2020, doi: 10.3390/s20123491.

[46] H. Donmez and N. Ozkurt, "Classification of emotional states from multi-channel EEG signals by convolutional neural networks," in *Proc. Innov. Intell. Syst. Appl. Conf. (ASYU)*, 2022, pp. 1–6, doi: 10.1109/ASYU56188.2022.9925308.

[47] Z.-M. Wang, S.-Y. Hu, and H. Song, "Channel selection method for EEG emotion recognition using normalized mutual information," *IEEE Access*, vol. 7, pp. 143303–143311, 2019, doi: 10.1109/ACCESS.2019.2944273.

[48] A. Goshvarpour and A. Goshvarpour, "A novel approach for EEG electrode selection in automated emotion recognition based on lagged poincare's indices and sLORETA," *Cognit. Comput.*, vol. 12, no. 3, pp. 602–618, May 2020, doi: 10.1007/s12559-019-09699-z.

[49] A. Topic, M. Russo, M. Stella, and M. Saric, "Emotion recognition using a reduced set of EEG channels based on holographic feature maps," *Sensors*, vol. 22, no. 9, p. 3248, Apr. 2022, doi: 10.3390/s22093248.

[50] M. Javidan, M. Yazdchi, Z. Baharlouei, and A. Mahnam, "Feature and channel selection for designing a regression-based continuous-variable emotion recognition system with two EEG channels," *Biomed. Signal Process. Control*, vol. 70, Sep. 2021, Art. no. 102979, doi: 10.1016/j.bspc.2021.102979.

[51] J. R. Msonda, Z. He, and C. Lu, "Feature reconstruction based channel selection for emotion recognition using EEG," in *Proc. IEEE Signal Process. Med. Biol. Symp. (SPMB)*, Dec. 2021, pp. 1–7, doi: 10.1109/SPMB52430.2021.9672258.

[52] Z. Yin, L. Liu, J. Chen, B. Zhao, and Y. Wang, "Locally robust EEG feature selection for individual-independent emotion recognition," *Exp. Syst. Appl.*, vol. 162, Dec. 2020, Art. no. 113768, doi: 10.1016/j.eswa.2020.113768.

[53] L. Yang, S. Chao, Q. Zhang, P. Ni, and D. Liu, "A grouped dynamic EEG channel selection method for emotion recognition," in *Proc. IEEE Int. Conf. Bioinf. Biomed. (BIBM)*, Dec. 2021, pp. 3689–3696, doi: 10.1109/BIBM52615.2021.9669889.

[54] A. Anuragi, D. S. Sisodia, and R. B. Pachori, "EEG-based cross-subject emotion recognition using Fourier-bessel series expansion based empirical wavelet transform and NCA feature selection method," *Inf. Sci.*, vol. 610, pp. 508–524, Sep. 2022, doi: 10.1016/j.ins.2022.07.121.

[55] Y. Yin, X. Zheng, B. Hu, Y. Zhang, and X. Cui, "EEG emotion recognition using fusion model of graph convolutional neural networks and LSTM," *Appl. Soft Comput.*, vol. 100, Mar. 2021, Art. no. 106954, doi: 10.1016/j.asoc.2020.106954.

[56] D. Huang, S. Chen, C. Liu, L. Zheng, Z. Tian, and D. Jiang, "Differences first in asymmetric brain: A bi-hemisphere discrepancy convolutional neural network for EEG emotion recognition," *Neurocomputing*, vol. 448, pp. 140–151, Aug. 2021, doi: 10.1016/j.neucom.2021.03.105.

[57] S. Bhosale, R. Chakraborty, and S. K. Kopparapu, "Calibration free meta learning based approach for subject independent EEG emotion recognition," *Biomed. Signal Process. Control*, vol. 72, Feb. 2022, Art. no. 103289, doi: 10.1016/j.bspc.2021.103289.

[58] S. Liu, Z. Wang, Y. An, J. Zhao, Y. Zhao, and Y.-D. Zhang, "EEG emotion recognition based on the attention mechanism and pre-trained convolution capsule network," *Knowl.-Based Syst.*, vol. 265, Apr. 2023, Art. no. 110372, doi: 10.1016/j.knosys.2023.110372.

[59] R. Li, C. Ren, Y. Ge, Q. Zhao, Y. Yang, Y. Shi, X. Zhang, and B. Hu, "MTL-FuseNet: A novel emotion recognition model based on deep latent feature fusion of EEG signals and multi-task learning," *Knowl.-Based Syst.*, vol. 276, Sep. 2023, Art. no. 110756, doi: 10.1016/j.knosys.2023.110756.

[60] W. Li, Y. Tian, B. Hou, J. Dong, S. Shao, and A. Song, "A bi-stream hybrid model with MLPBlocks and self-attention mechanism for EEG-based emotion recognition," *Biomed. Signal Process. Control*, vol. 86, Sep. 2023, Art. no. 105223, doi: 10.1016/j.bspc.2023.105223.

[61] R. Li, C. Ren, X. Zhang, and B. Hu, "A novel ensemble learning method using multiple objective particle swarm optimization for subject-independent EEG-based emotion recognition," *Comput. Biol. Med.*, vol. 140, Jan. 2022, Art. no. 105080, doi: 10.1016/j.compbiomed.2021.105080.

[62] Q. She, X. Shi, F. Fang, Y. Ma, and Y. Zhang, "Cross-subject EEG emotion recognition using multi-source domain manifold feature selection," *Comput. Biol. Med.*, vol. 159, Jun. 2023, Art. no. 106860, doi: 10.1016/j.compbiomed.2023.106860.

[63] R. J. Urbanowicz, M. Meeker, W. La Cava, R. S. Olson, and J. H. Moore, "Relief-based feature selection: Introduction and review," *J. Biomed. Informat.*, vol. 85, pp. 189–203, Sep. 2018, doi: 10.1016/j.jbi.2018.07.014.

[64] J. Zhang, M. Chen, S. Zhao, S. Hu, Z. Shi, and Y. Cao, "ReliefF-based EEG sensor selection methods for emotion recognition," *Sensors (Switzerland)*, vol. 16, no. 10, pp. 1–15, 2016, doi: 10.3390/s16101558.

[65] A. Goshvarpour and A. Goshvarpour, "Matching pursuit-based analysis of fNIRS in combination with cascade PCA and reliefF for mental task recognition," *Exp. Syst. Appl.*, vol. 213, Mar. 2023, Art. no. 119283, doi: 10.1016/j.eswa.2022.119283.

[66] L. Tong, J. Zhao, and W. Fu, "Emotion recognition and channel selection based on EEG signal," in *Proc. 11th Int. Conf. Intell. Comput. Technol. Automat. (ICICTA)*. Piscataway, NJ, USA: Institute of Electrical and Electronics Engineers, Oct. 2018, pp. 101–105, doi: 10.1109/ICICTA.2018.00031.

[67] Y. Liu and G. Fu, "Emotion recognition by deeply learned multi-channel textual and EEG features," *Future Gener. Comput. Syst.*, vol. 119, pp. 1–6, Jun. 2021, doi: 10.1016/j.future.2021.01.010.

LIA FAROKHAH was born in Jombang, in August 1990. She is currently pursuing the Ph.D. degree in computer science with Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia. She is a Lecturer and a Researcher with the Department of Computer Science, Institut Teknologi dan Bisnis ASIA Malang.

RIYANARTO SARNO (Senior Member, IEEE) received the Ph.D. degree, in 1992. He is currently a Professor with the Department of Informatics, Institut Teknologi Sepuluh Nopember (ITS). He is the author of more than five books and more than 300 scientific articles, led him incorporated in the top 2% world ranking scientist by Standford University, in 2020. He is interested in research projects about machine learning, the Internet of Things, and knowledge engineering. His research interests include electronic nose, image processing, and signal processing.

CHASTINE FATICHAH (Member, IEEE) was born in Pasuruan, in December 1975. She received the bachelor's degree in informatics, the master's degree in computer science, and the Ph.D. degree in computational intelligence, in 2000, 2008, and 2012, respectively. She is currently a Professor of intelligent computation and vision with the Department of Informatics, Faculty of Intelligent Electrical and Informatics Technology, Institut Teknologi Sepuluh Nopember (ITS). She received the Young Researcher Award from *Journal of Advanced Computational Intelligence and Intelligent Informatics* (JACIII) (Fuji Press), Tokyo, Japan, in 2014.