Tiny-VRN: A Lightweight Variational Residual Network for EEG-Based Emotion Recognition

Sivaraj Nimishan*, Selvarajah Thuseethan†, Shanmuganathan Vasanthapriyan‡ and Roshan G. Ragel*
* University of Peradeniya, Sri Lanka
E-mail: nimishan@eng.pdn.ac.lk
† Charles Darwin University, Australia
E-mail: thuseethan.selvarajah@cdu.edu.au
‡ Sabaragamuwa University of Sri Lanka, Sri Lanka
E-mail: priyan@foc.sab.ac.lk
* University of Peradeniya, Sri Lanka
E-mail: roshanr@eng.pdn.ac.lk

***Abstract*—Emotion recognition from EEG signals is essential for advancing human-computer interaction, mental health monitoring, and adaptive systems. While deep learning has shown promise in decoding complex EEG patterns, existing models introduce significant computational overhead, limiting their suitability for real-time and resource-constrained applications. This paper addresses the research gap in developing lightweight yet accurate models for direct EEG signal processing by proposing Tiny-VRN, a compact neural architecture tailored for EEG-based emotion recognition. The objective is to design an efficient model that maintains high classification performance while significantly reducing complexity. Tiny-VRN integrates residual learning with a variational bottleneck in a fully connected framework, using stacked dense residual blocks to capture temporal dependencies. Compared to a strong baseline, ResNet1D, Tiny-VRN reduces parameter count by over 75% (473,865 vs. 107,543 parameters) and cuts training time by more than half across both the GAMEEMO and LUMED datasets. Despite its compact design, Tiny-VRN achieves superior accuracy: 93.65% on GAMEEMO and 94.42% on LUMED, outperforming ResNet1D on all metrics. These findings underscore Tiny-VRN's effectiveness in balancing accuracy and efficiency, offering a practical solution for deploying EEG-based emotion recognition systems in real-time and edge-computing environments. The proposed model sets a new benchmark for compact EEG classifiers, with implications for scalable and responsive affective computing applications.**

I. Introduction

Emotion recognition plays a crucial role in enhancing human-computer interaction by enabling systems to understand and respond to users' emotional states. Electroencephalography (EEG) stands out among physiological signals for its capacity to directly reflect brain activity and provide detailed emotional insights, offering objective data that cannot be easily manipulated or faked by the subject [1]. EEG's non-invasive nature and high temporal resolution make it a valuable tool for applications in mental health monitoring, adaptive human-computer interaction, and personalized user experiences [2], [3]. EEG-based emotion recognition has therefore emerged as a promising yet challenging research area, particularly due to the complexity and variability of neural signals. To effectively interpret these signals, deep learning methods have become increasingly important [4].

In addition to direct signal processing, several studies have applied transfer learning approaches by converting raw EEG signals into spectrograms or other image-like representations. These transformations enable the use of pre-trained image-based models, such as Residual Networks (ResNet), for improved classification performance [5]. ResNet architectures are widely adopted due to their use of skip connections, which facilitate effective training of deep networks by mitigating the vanishing gradient problem [6]. However, the process of converting EEG signals into image-based formats introduces additional computational and storage overhead, making such methods less suitable for real-time or resource-constrained environments.

Motivated by the need for efficient and direct EEG processing, One-dimensional (1D) ResNet architectures operating directly on raw EEG signals have demonstrated strong performance in physiological signal tasks such as epileptic seizure detection [7] and user identification using electromyography [8]. Recent enhancements, incorporating residual learning techniques, such as shortcut connections and identity mappings, along with batch normalization layers, have further improved the stability and generalization of these models [9].

Despite these advancements, many deep learning models remain over-parameterized and are not ideal for low-power devices or real-time inference. This creates a need for architectures that are both compact and capable of modeling the temporal and spatial dynamics of EEG data effectively. To address these challenges, this study introduces a novel lightweight architecture—Tiny Variational Residual Network (Tiny-VRN). The proposed model integrates residual learning with a variational bottleneck to reduce parameter count while maintaining high classification performance. Tiny-VRN is designed specifically for efficient EEG-based emotion recognition, aiming to establish a new benchmark on modern datasets with improved accuracy and computational efficiency. The overall workflow diagram of the proposed approach is presented in Fig. 1, depicting preprocessing steps, emotion

979-8-3315-7206-8/25/$31.00

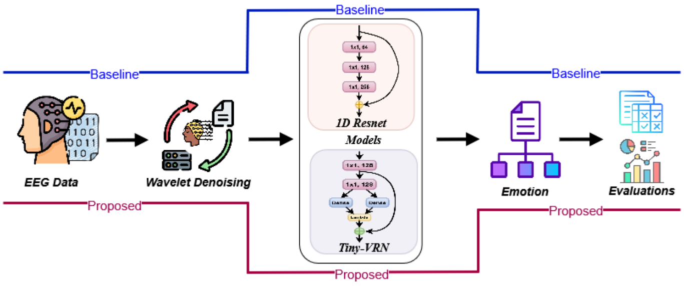

Fig. 1. The overall workflow of the 1D ResNet baseline and the proposed Tiny-VRN approach

classification models, and evaluations.

II. Related Work

In the field of EEG-based emotion recognition, numerous advanced models have been proposed, aiming to surpass the performance of conventional baseline neural networks. Researchers have explored a range of deep learning architectures, including CNNs [10], and hybrid models [11], to better capture the temporal and spatial features of EEG signals. A few researchers have explored the application of 1D-Neural architectures for EEG signal analysis in emotion recognition, leveraging their ability to capture repetitive and distinct patterns from one-dimensional EEG channel data. Song et al. [12] proposed a 1D CNN model for emotion recognition based on physiological signals. The architecture comprises two convolutional layers, each followed by a max-pooling layer, and a flatten layer to prepare the features for classification. The model achieved classification accuracies of 61.34% for arousal and 59.88% for valence on MAHNOB-HCI dataset. Aldawsari et al. [13] proposed a 1D-CNN-based framework for emotion recognition, which was evaluated on widely used EEG datasets including DEAP, MAHNOB-HCI, and SEED. Their approach demonstrated competitive accuracy compared to conventional deep learning models, highlighting the effectiveness of 1D-CNN architectures in capturing emotional patterns from EEG signals.

While these models have significantly improved classification accuracy, many are computationally intensive and require substantial hardware resources, limiting their applicability in resource-constrained environments [14]. To address these challenges, recent studies have focused on developing lightweight and efficient models tailored for resource-constrained settings, such as wearable devices or edge computing platforms. Techniques for designing compact neural architectures have been employed to reduce model complexity without significantly compromising performance.

Li and Gao [15] proposed a lightweight sequence-to-sequence model, 1D-ResNet-SE-LSTM, for classifying sleep stages into five classes using single-channel raw EEG signals. The model combines a 1D residual CNN with a squeeze-and-excitation module for feature extraction and an LSTM network to capture stage transitions of sleep EEG signals. Fan et al. [16] introduced LResCapsule, a network that integrates a lightweight ResNet to extract multi-level emotional features directly from raw EEG signals, combined with a capsule-based classifier designed to capture the spatial relationships between global and local feature representations. The authors in [17] employed an end-to-end approach to classify emotions using a pretrained state-of-the-art CNN model, InceptionResNetV2. They enhanced the model by adding additional layers to increase its depth and improve its classification performance. Their study utilized three datasets: DEAP, LUMED, and SEED. The model achieved accuracies of 86.56% on the SEED dataset, 72.81% on the DEAP dataset, and 81.8% on the LUMED dataset.

While deep learning models have achieved high accuracy in EEG-based emotion recognition, they often rely on a large number of parameters or require converting signals into images, which adds computational and storage overhead. This work addresses the need for a more efficient solution by introducing a lightweight neural network that operates directly on raw EEG data, enabling practical deployment in real-time or resource-constrained settings.

III. Methods

A. Datasets

To the best of our knowledge, publicly available affective databases that utilize physiological signals for emotion recognition remain limited. Among these, the DEAP and SEED datasets are most widely used [18]. Another notable resource is the MAHNOB-HCI dataset, a comprehensive multimodal database for emotion recognition and implicit tagging research [19]. However, these datasets were introduced over a decade ago and may not fully reflect recent advancements in recording technologies and experimental methodologies. More recent contributions to the field include the GAMEEMO and LUMED datasets, which offer updated experimental protocols and more contemporary data. In this study, we focus on the GAMEEMO and LUMED datasets due to their recent availability and relevance to current research challenges.

1) GAMEEMO: The GAMEEMO dataset contains EEG signals collected from 28 participants using the portable and wearable 14-channel EEG device, EMOTIV EPOC+. Instead of traditional stimuli, participants played four emotion-specific games (boring, calm, horror, funny), each lasting 5 minutes, totaling 20 minutes of data per participant. After each game, arousal and valence were rated using the SAM scale. Recordings are labeled G1–G4 and organized into 28 subject folders (S01–S28) [20].

2) LUMED: The LUMED (Loughborough University Multimodal Emotion Dataset) provides electroencephalography (EEG) recordings from 11 participants (4 females and 7 males) in response to emotionally evocative audio-visual stimuli. EEG signals were collected using an 8-channel ENOBIO system at 500 Hz. Participants watched 16 minutes of videos, each lasting 1–2.5 minutes, with 20-second gray screens between clips to reset emotions. Valence labels (positive, neutral, negative) were self-reported after each session. Each participant has 11

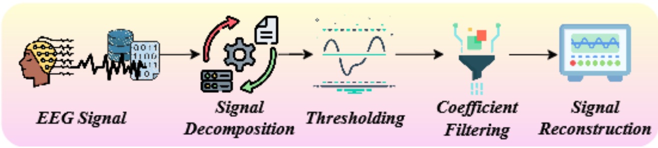

Fig. 2. Visualization of the wavelet denoising approach applied for EEG artifact removal

EEG recordings, organized in a single folder for ease of use in affective computing research [17].

B. Data Preprocessing

Wavelet de-noising using the Daubechies (db4) wavelet was applied to remove artifacts and enhance EEG signal quality (Fig. 2). This method is widely regarded as the most effective EEG preprocessing technique [21]. The denoising process was implemented as follows:

- **Decomposition:** EEG signals were decomposed into wavelet coefficients using a 4-level Discrete Wavelet Transform (DWT) to balance detail and efficiency.
- **Thresholding:** A universal threshold was computed using:
$$\text{Threshold} = \sqrt{2 \cdot \log(N)} \cdot \frac{1}{\sqrt{2}} \tag{1}$$
where N is the signal length and the dot operator $(\cdot)$ represents scalar multiplication.
- **Coefficient Filtering:** Soft thresholding was applied to suppress noise while preserving key features.
- **Reconstruction:** The denoised signal was reconstructed using the inverse wavelet transform with the filtered coefficients.

C. Proposed Approach

This study introduces a novel lightweight architecture, the **Tiny-VRN**, tailored for efficient EEG-based emotion recognition. The model leverages the strengths of residual learning and variational inference to handle high-dimensional and noisy EEG features in a compact form.

The Tiny-VRN model accepts one-dimensional EEG feature vectors as input. The architecture comprises three key modules: a dense projection layer, stacked residual blocks, and a variational bottleneck, followed by a classification layer. The overall architecture is illustrated in Fig. 3.

A Tiny Residual Block is introduced to efficiently learn non-linear feature transformations while maintaining gradient flow, we employ a lightweight residual block. Each block applies two dense layers interleaved with batch normalization, followed by an additive skip connection and ReLU activation. The block output is:

$$\mathbf{y} = \text{ReLU}\left(\text{BN}(\mathbf{W}_2 \cdot \text{BN}(\mathbf{W}_1 \cdot \mathbf{x})) + \text{Proj}(\mathbf{x})\right), \tag{2}$$

where $\mathbf{W}_1$, $\mathbf{W}_2$ are dense layer weights, and $\text{Proj}(\mathbf{x})$ applies a linear layer only if needed.

$$\text{Proj}(\mathbf{x}) = \begin{cases} \text{Dense}(\mathbf{x}), & \text{if } \dim(\mathbf{x}) \neq \text{filters} \\ \mathbf{x}, & \text{otherwise} \end{cases} \tag{3}$$

We then introduced a Variational Bottleneck Layer to encourage robust and compressed feature representations. The output of the residual stack is passed through a variational bottleneck inspired by the Variational Autoencoder (VAE) framework. The latent distribution is parameterized as a Gaussian with a learned mean $\boldsymbol{\mu}$ and log-variance $\log \boldsymbol{\sigma}^2$, computed as:

$$\boldsymbol{\mu} = \mathbf{W}_\mu \cdot \mathbf{z} + \mathbf{b}_\mu, \tag{4}$$
$$\log \boldsymbol{\sigma}^2 = \mathbf{W}_{\log \sigma^2} \cdot \mathbf{z} + \mathbf{b}_{\log \sigma^2}, \tag{5}$$

where $\mathbf{z}$ is the feature vector from the last residual block and b is bais . A latent vector $\mathbf{z}_{\text{latent}}$ is sampled using the reparameterization trick:

$$\mathbf{z}_{\text{latent}} = \boldsymbol{\mu} + \boldsymbol{\sigma} \odot \boldsymbol{\epsilon}, \quad \boldsymbol{\epsilon} \sim \mathcal{N}(0, \mathbf{I}). \tag{6}$$

here and $\odot$ denotes element-wise multiplication. Finally, the sampled latent representation is passed to a dense layer with a softmax activation for multi-class emotion classification:

$$\hat{\mathbf{y}} = \text{softmax}(\mathbf{W}_c \cdot \mathbf{z}_{\text{latent}} + \mathbf{b}_c), \tag{7}$$

where $\hat{\mathbf{y}}$ is the predicted probability distribution over emotion classes.

D. Experimental Setup

The model is trained using the Adam optimizer with sparse categorical cross-entropy as the loss function. The initial learning rate is set to 0.001, and training is conducted with a batch size of 32 for up to 100 epochs. Early stopping is employed with a patience of 10 epochs, monitoring the validation loss to prevent overfitting. A 5-fold cross-validation scheme is employed to assess generalizability. Each fold uses an 80-20 split of training and validation data. The final model is evaluated on the test set, with accuracy and F1-score as primary performance metrics. No explicit dropout layers are used; however, batch normalization is included after every dense or convolutional layer to promote stability and regularization. Residual connections further enhance gradient flow and feature reuse. To benchmark performance, a baseline **ResNet1D** model is used as a strong feature extractor for EEG-based emotion classification. This serves as a point of comparison to evaluate the effectiveness of the proposed architecture.

The ResNet1D architecture employs a series of stacked 1D convolutional layers integrated with residual connections, enabling efficient feature extraction from temporal EEG data. It features multiple convolutional blocks with increasing filter depths (64, 128, 256), each followed by batch normalization, ReLU activation, and shortcut connections that facilitate gradient flow during training. Pooling layers are used to reduce the temporal dimension, and the extracted features are passed through fully connected layers for final emotion classification. This model contains approximately 473,865 trainable parameters and is optimized for learning spatiotemporal EEG patterns.

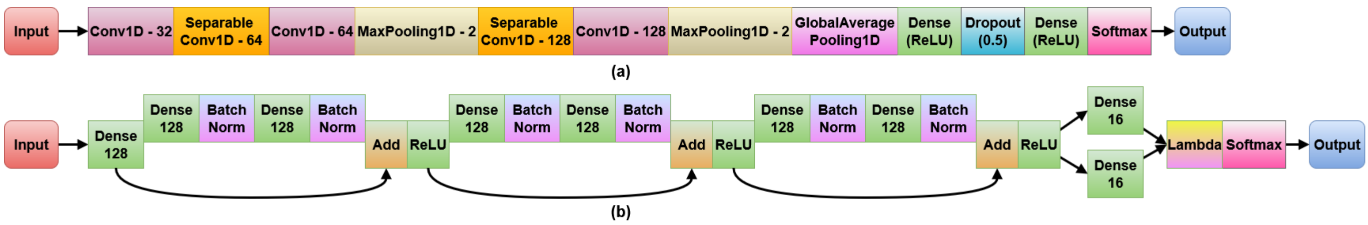

Fig. 3. Overview of the (a) Baseline 1D ResNet Architecture and (b) Proposed Tiny-VRN Architecture

In contrast, the Tiny-VRN model is a compact residual network composed entirely of dense layers. It begins with an input layer followed by a sequence of dense layers of uniform width (128 units), interleaved with batch normalization and non-linear ReLU activations. Residual (skip) connections are employed to stabilize training and encourage feature reuse. A variational bottleneck is introduced with a latent dimension of 16, acting as a regularized compression layer. The final layers project the learned representations through narrower dense layers, followed by a custom feature fusion implemented via a lambda layer and an output layer for classification. Despite its simplicity, Tiny-VRN effectively captures expressive patterns due to its residual structure and deep stacking of non-linear transformations, totaling approximately 107,543 parameters, over four times smaller than ResNet1D. Both models are evaluated to compare their efficiency and accuracy in EEG-based emotion recognition, with particular attention to their depth, parameter efficiency, and generalization capability.

The use of skip connections allows dense transformations to preserve and combine both shallow and deep feature representations, compensating for the absence of explicit local temporal filters.

The proposed architecture is implemented using the TensorFlow open-source machine learning framework and the Python programming language. The experiments are accelerated with the use of an *Nvidia Tesla K40c GPU server*.

IV. Results and Discussion

A. Performance

This study highlights that the proposed Tiny-VRN architecture is more efficient than the baseline ResNet1D in terms of both parameter count and training time. Tiny-VRN integrates densely connected layers in a compact design, enabling it to learn complex temporal patterns in EEG signals with significantly fewer parameters. Specifically, the Tiny-VRN model contains 107,543 trainable parameters, whereas the baseline ResNet1D model includes 473,865 parameters, indicating a reduction of more than 75% in model complexity.

For the GAMEEMO dataset, ResNet1D required 2.25 hours, whereas Tiny-VRN completed training in just 0.89 hours. Similarly, on the LUMED dataset, the baseline ResNet1D required approximately 1.47 hours to train, while Tiny-VRN reduced the training time to 0.71 hours. These results clearly indicate that Tiny-VRN is more computationally efficient and better suited for emotion recognition tasks on EEG data, especially in scenarios where training time and resource constraints are critical considerations.

TABLE I
Comparison of Studies on Datasets and Accuracy (%)

Dataset	Study	Method	Accuracy
GAMEEMO	Ari et al., 2022 [10]	CNN	77.66
	Alakus et al., 2020 [22]	biLSTM	76.91
	Abdulrahman et al., 2022 [23]	biLSTM	70.89
	Nimishan et al., 2025 [24]	KAN	80.79
	Proposed Approach	**Tiny-VRN**	**93.65**
LUMED	Cimtay et al. 2020 [17]	CNN	81.80
	Dickinson et al., 2022 [25]	SVM	63.50
	Nimishan et al., 2025 [24]	KAN	90.95
	Proposed Approach	**Tiny-VRN**	**94.42**

Bi-directional Long Short Term Memory (biLSTM), Convolutional Neural Network (CNN), Kolomogorov-Arnold Network (KAN)

B. Evaluations

The classification accuracies of recent studies on EEG-based emotion recognition for the GAMEEMO and LUMED datasets are summarized in Table I. These prior results establish a benchmark for evaluating the effectiveness of the proposed architecture. Accuracy measures the proportion of correct predictions across all classes, while the F1 score balances precision and recall, offering insights into the model's effectiveness in handling imbalanced data. These are computed using standard formulas: Accuracy = $(tp + tn)/(tp + tn + fp + fn)$ and F1 score = $tp/(tp + 1/2(fp + fn))$, where tp, fp, tn, and fn denote true positives, false positives, true negatives, and false negatives, respectively.

TABLE II
Comparison of Tiny-VRNs' performance on different datasets against baseline ResNet1D

Dataset	Resnet1D		Tiny-VRN	
	Accuracy	**F1 Score**	**Accuracy**	**F1 Score**
GAMEEMO	90.41	90.32	$93.65_{+3.24}$	$93.37_{+3.05}$
LUMED	92.19	91.54	$94.42_{+2.23}$	$94.33_{+2.79}$

Table II presents a side-by-side comparison between the baseline ResNet1D and the proposed Tiny-VRN model using accuracy and F1 score as the primary evaluation metrics. Improvements achieved by Tiny-VRN over the baseline are indicated as subscript values. Tiny-VRN model outperforms the baseline ResNet1D on both datasets. To evaluate the consistency and reliability of the models, we report the standard deviation (SD) of accuracy across 5-fold cross-validation. SD provides a measure of performance stability and helps determine whether observed improvements are consistent across folds. On the GAMEEMO dataset, Tiny-VRN achieved an accuracy of 93.65% ± 0.66, while ResNet1D reached 91.54% ± 0.68. For the LUMED dataset, Tiny-VRN obtained 94.42% ± 1.48, compared to 92.19% ± 1.47 for ResNet1D. These improvements are also reflected in the F1 scores, which indicate better balanced class-wise performance and consistent classification across different cross-validation folds.

TABLE III
COMPARISON OF TINY-VRNS' INFERENCE AGAINST BASELINE RESNET1D

Model	Inference Time (s)	MFLOPS	Model Size (MB)
Resnet1D	0.12 ± 0.03	3.9	5.58
Tiny-VRN	0.04 ± 0.01	0.21	1.38

Inference benchmarking was conducted in a CPU-only environment using TensorFlow Lite with the XNNPACK delegate. Details of inference time, MFLOPS, and model size are shown in Table III. Experiments were run on an Intel(R) Xeon(R) CPU @ 2.60GHz with 32 GB RAM, but memory was capped at 3 GB to simulate an edge device. Each model predicted 1000 EEG samples per dataset, and the mean inference time with standard deviation (in seconds) was recorded.

The Fig. 4 shows the confusion matrices for the continuous emotion dimensions of Valence and Arousal on the GAMEEMO dataset. Accuracy rates for these continuous emotions are provided in subfigures (a) and (b) for the Valence and Arousal emotions of the 1D ResNet model, and in subfigures (c) and (d) for the Valence and Arousal of the Tiny-VRN model, respectively. Fig. 5 presents the confusion matrices for emotion ratings on the LUMED dataset. Subfigures (a) and (b) illustrate the emotion ratings for each level using the baseline 1D ResNet model and the proposed Tiny-VRN model, respectively. The confusion matrices reveal that the Tiny-VRN model outperformed the 1D ResNet model in accurately predicting valence emotions. In contrast, the 1D ResNet model predominantly misclassified emotion ratings as neutral.

The results indicate that the Tiny-VRN model consistently delivered strong performance across most emotion levels. However, the primary misclassifications occurred within adjacent emotion levels. Overall, the results confirm that Tiny-VRN not only offers a more compact and efficient solution but also delivers superior emotion recognition performance across diverse EEG datasets.

V. CONCLUSIONS

This study presents Tiny-VRN, a novel lightweight architecture for EEG-based emotion recognition that combines residual learning and variational inference in a densely connected, fully connected framework. By replacing convolutional layers with stacked dense layers and incorporating efficient residual blocks, Tiny-VRN significantly reduces model complexity—achieving over 75% fewer parameters than the baseline ResNet1D—while maintaining strong representational power. Experimental evaluations across two benchmark EEG datasets, GAMEEMO and LUMED, demonstrate that Tiny-VRN not only accelerates training time but also consistently surpasses ResNet1D in classification accuracy and F1 score. These findings validate Tiny-VRN as a computationally efficient and high-performing alternative for emotion recognition tasks, making it particularly suitable for real-world applications with limited computational resources.

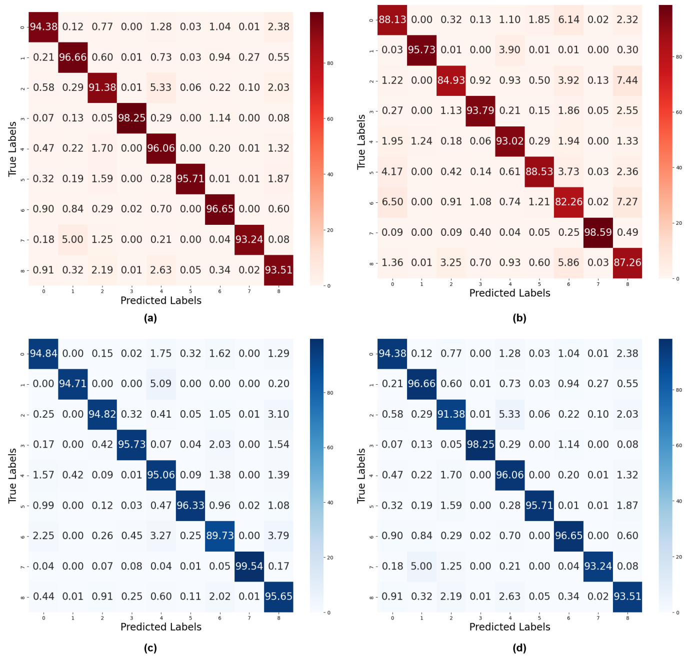

Fig. 4. Confusion matrices showing emotion ratings on the GAMEEMO dataset: (a) and (b) for Valence and Arousal using the 1D Resnet model, and (c) and (d) for Valence and Arousal using the Proposed Tiny VRN model

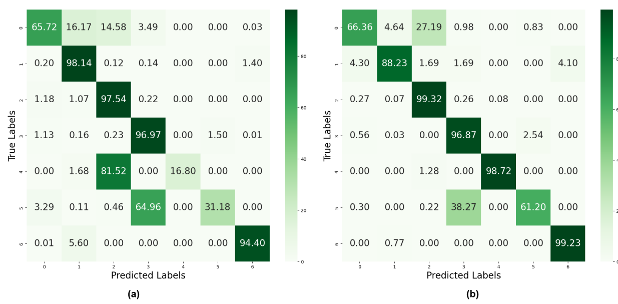

Fig. 5. Confusion matrices showing emotion ratings on the LUMED dataset: (a) Baseline 1D ResNet, (b) Proposed Tiny VRN

ACKNOWLEDGMENT

The authors acknowledge the support received from the LK Domain Registry in publishing this paper. The authors

also recognize the importance of publicly available datasets in advancing EEG-based Emotion Recognition.

References

[1] M. K. Ahirwal and M. R. Kose, "Emotion recognition system based on eeg signal: A comparative study of different features and classifiers," in *2018 second international conference on computing methodologies and communication (iccmc)*, IEEE, 2018, pp. 472–476.

[2] T. Beyrouthy, N. Mostafa, A. Roshdy, A. S. Karar, and S. Alkork, "Review of eeg-based biometrics in 5g-iot: Current trends and future prospects," *Applied sciences*, vol. 14, no. 2, p. 534, 2024.

[3] L. Balcombe and D. De Leo, "Human-computer interaction in digital mental health," in *Informatics*, MDPI, vol. 9, 2022, p. 14.

[4] M. Jafari, A. Shoeibi, M. Khodatars, *et al.*, "Emotion recognition in eeg signals using deep learning methods: A review," *Computers in Biology and Medicine*, vol. 165, p. 107 450, 2023.

[5] K. C. Vidyasagar, K. R. Kumar, G. A. Sai, M. Ruchita, and M. J. Saikia, "Signal to image conversion and convolutional neural networks for physiological signal processing: A review," *IEEE Access*, 2024.

[6] J. Chen, C. Min, C. Wang, Z. Tang, Y. Liu, and X. Hu, "Electroencephalograph-based emotion recognition using brain connectivity feature and domain adaptive residual convolution model," *Frontiers in Neuroscience*, vol. 16, p. 878 146, 2022.

[7] H. Alshaya and M. Hussain, "Eeg-based classification of epileptic seizure types using deep network model," *Mathematics*, vol. 11, no. 10, p. 2286, 2023.

[8] R. Ganiga, M. SN, W. Choi, and S. Pan, "Resnet1d-based personal identification with multi-session surface electromyography for electronic health record integration," *Sensors*, vol. 24, no. 10, p. 3140, 2024.

[9] W. Wang and B. Li, "A novel model based on a 1d-rescnn and transfer learning for processing eeg attenuation," *Computer Methods in Biomechanics and Biomedical Engineering*, vol. 26, no. 16, pp. 1980–1993, 2023.

[10] B. Ari, K. Siddique, Ö. F. Alçin, M. Aslan, A. Şengür, and R. M. Mehmood, "Wavelet elm-ae based data augmentation and deep learning for efficient emotion recognition using eeg recordings," *IEEE Access*, vol. 10, pp. 72 171–72 181, 2022.

[11] S. Bagherzadeh, K. Maghooli, A. Shalbaf, and A. Maghsoudi, "A hybrid eeg-based emotion recognition approach using wavelet convolutional neural networks and support vector machine," *Basic and Clinical Neuroscience*, vol. 14, no. 1, p. 87, 2023.

[12] T. Song, G. Lu, and J. Yan, "Emotion recognition based on physiological signals using convolution neural networks," in *Proceedings of the 2020 12th international conference on machine learning and computing*, 2020, pp. 161–165.

[13] H. Aldawsari, S. Al-Ahmadi, and F. Muhammad, "Optimizing 1d-cnn-based emotion recognition process through channel and feature selection from eeg signals," *Diagnostics*, vol. 13, no. 16, p. 2624, 2023.

[14] F. Wu, J. Liu, J. Yang, L. Zhang, Y. He, and Z. Lin, "Learning multiband-temporal-spatial eeg representations of emotions using lightweight temporal convolution and 3d convolutional neural network," *IEEE Access*, 2024.

[15] W. Li and J. Gao, "Automatic sleep staging by a hybrid model based on deep 1d-resnet-se and lstm with single-channel raw eeg signals," *PeerJ Computer Science*, vol. 9, e1561, 2023.

[16] C. Fan, J. Wang, W. Huang, *et al.*, "Light-weight residual convolution-based capsule network for eeg emotion recognition," *Advanced Engineering Informatics*, vol. 61, p. 102 522, 2024.

[17] 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, p. 2034, 2020.

[18] H. Liu, Y. Zhang, Y. Li, and X. Kong, "Review on emotion recognition based on electroencephalography," *Frontiers in Computational Neuroscience*, vol. 15, p. 758 212, 2021.

[19] H. A. Hamzah and K. K. Abdalla, "Eeg-based emotion recognition datasets for virtual environments: A survey," *Applied Computational Intelligence and Soft Computing*, vol. 2024, no. 1, p. 6 091 523, 2024.

[20] T. B. Alakus, M. Gonen, and I. Turkoglu, "Database for an emotion recognition system based on eeg signals and various computer games–gameemo," *Biomedical Signal Processing and Control*, vol. 60, p. 101 951, 2020.

[21] M. Grobbelaar, S. Phadikar, E. Ghaderpour, *et al.*, "A survey on denoising techniques of electroencephalogram signals using wavelet transform," *Signals*, vol. 3, no. 3, pp. 577–586, 2022.

[22] T. Alakus and I. Turkoglu, "Emotion recognition with deep learning using gameemo data set," *Electronics Letters*, vol. 56, no. 25, pp. 1364–1367, 2020.

[23] A. Abdulrahman, M. Baykara, and T. B. Alakus, "A novel approach for emotion recognition based on eeg signal using deep learning," *Applied Sciences*, vol. 12, no. 19, p. 10 028, 2022.

[24] S. Nimishan, S. Thuseethan, R. G. Ragel, and S. Vasanthapriyan, "Boosting eeg-based emotion recognition with kolmogorov-arnold networks," in *5th International Conference on Advanced Research in Computing (ICARC)*, IEEE, 2025, pp. 1–6.

[25] R. Dickinson, N. Semertzidis, and F. F. Mueller, "Machine in the middle: Exploring dark patterns of emotional human-computer integration through media art," in *CHI Conference on Human Factors in Computing Systems Extended Abstracts*, 2022, pp. 1–7.