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Emotion recognition and classification using Inception EfficientNet based on electroencephalography signals

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ABSTRACT

Emotions are intricate psychological phenomena arising from the interaction of internal cognitive states and external environmental inputs. The manual extraction of electroencephalography (EEG) signals results in less optimal performance of learning models. To overcome this, a novel EEG-based emotion recognition and classification (EEG-EMRE) model has been proposed for the detection and classification of emotions. Initially, the input EEG-Signals are pre-processed using quantum signal processing (QSP) to enhance the quality by removing the noise from the signal. The enhanced signals are fed into an improved Inception EfficientNet for extracting the relevant features. The Penta types of emotions, such as happy, sad, anger, scared, and anxiety, are classified using a bidirectional-k nearest neighbors (KNN) classification network. The performance of the proposed EEG-EMRE approach is evaluated using the F1-Score, recall, specificity, accuracy, and precision. The proposed Inception EfficientNet for feature extraction network improves the overall accuracy by 0.41%, 1.52%, 0.63%, 1.55% better than ResNet, AlexNet, GoogleNet, and DenseNet. The proposed EEG-EMRE method achieves an overall accuracy by 0.68%, 1.77%, and 0.52% better than the linear formulation of differential entropy (LF-DfE), extreme learning machine wavelet auto encoder (ELM-W-AE), and attention-based convolutional transformer neural network (ACTNN), respectively.

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1. INTRODUCTION

Emotions play a critical role in human decision-making, interaction, and thought processes. Automatic emotion recognition systems are becoming more and more feasible as technology and our knowledge of emotions progress [1]. Numerous studies use the discrete emotion model, this includes joy, sorrow, surprise, rage, fear, and disgust [2]. The dynamic process of emotion recognition focuses on an individual's emotional state, therefore the feelings that correspond to their behaviors vary from person to person [3]. Humans generally use a variety of methods to express their emotions. It is important to interpret emotions accurately in order to ensure meaningful communication [4]. It is important to recognize emotions in our everyday lives because they influence social contact and human decision-making. People communicate their emotions in a variety of ways, such as through body language, facial expressions, and expressive speech [5]. The emotional state of a subject can also be predicted by using signals from multiple modalities [6]. It is impossible to determine someone's emotional state based only on what is in front of our eyes. This is among the arguments in favor of treating emotional recognition as a multimodal issue. [7].

Electroencephalography (EEG)-based emotional analysis has proven effective in human-computer interface, security, and medical science. EEG is a suitable technique for capturing human emotion because it has been applied in a number of studies to understand human emotion [8]. The identification of emotional changes from EEG signals has recently attracted the attention of researchers in the field of brain computer interfaces (BCI). Direct attachment of EEG signals to the scalp allows for the reading of changes in brain activity at the commencement of emotional state changes, providing more accurate information [9], [10]. EEG data emotion assessment relies on a variety of factors, including frequency bands, number of channels, statistical feature extraction methods, and characteristics [11], [12]. However, the existing EEG-based emotion recognition has achieved good accuracy, they still suffer from noise sensitivity, limited feature diversity, and poor generalization across subjects. Most conventional pre-processing techniques fail to effectively denoise complex EEG signals. Additionally, deep models often require high computational cost and lack adaptability to real-time emotion variations. To overcome these challenges, a novel EEG-EMRE has been proposed for detecting and classification emotions based on EEG signals. The main contributions of the proposed work are summarized as: i) the quantum signal processing (QSP) technique is used to pre-process EEG signals for enabling quantum-inspired enhancement and effective removal of external noise, ii) a hybrid architecture integrates the ability to capture more scales concurrently of Inception modules and compound scaling efficiency of EfficientNet resulting in the relevant and more compact EEG feature representations, iii) bidirectional- k-nearest neighbors (KNN) classifier involves a forward and backward processing of features dependencies to enhance recognition and identification of complex emotions, and iv) this combination of these three-distinct components in a single deep framework that reduce the manual feature engineering and assure uniform learning across the stages.

Additionally, the scientific question that will guide this study is how EEG-based emotion recognition can be improved using advanced signal processing and hybrid deep learning architectures. In particular, it explores three important aspects: i) How can QSP enhance EEG signal quality for accurate emotion detection? ii) Can a hybrid Inception–EfficientNet architecture effectively extract multi-scale EEG features for emotion classification? iii) Does the bidirectional-KNN classifier improve recognition performance compared to conventional EEG-based emotion recognition models?

Many studies have been conducted in recent years to apply machine learning (ML) and deep learning (DL) approaches for classifying different emotional types in EEG data. These approaches focus on automatically learning discriminative temporal and spatial patterns from EEG signals to improve recognition performance. This comprehensive overview of several recent investigations highlights the evolution of ML and DL models for EEG-based emotion classification. Yin *et al.* [13] suggested a cutting-edge DL model (ERDL) as a revolutionary technique for detecting emotions in EEG data. The fusion model extracts graph domain information using multiple GCNNs, while temporal aspects are extracted using LSTM cells that monitor changes in the interaction between two channels over time. Joshi and Ghongade [14] proposed linear formulation of differential entropy (LF-DfE) feature extractor in conjunction with the bidirectional long short-term memory (BiLSTM) network classifier to identify emotions in EEG recordings. Experimental findings from the proposed feature extractor LF-DfE employing the BiLSTM network were superior to those from previous techniques. Ari *et al.* [15] proposed an extreme learning machine wavelet auto encoder (ELM-W-AE) for Efficient Emotion Recognition Using EEG Recordings. The GGW activation function received the highest assessment scores when the ELM-W-AE structure's accomplishments of the different activation functions were investigated. Bagherzadeh *et al.* [16] suggested a new emotion recognition system using multichannel EEG signals and fine-tuned CNNs based on effective connection. The ResNet-50 works best when used on dDTF images in the alpha band experiments in order to categorize the five emotional states.

Siam *et al.* [17] suggested a real-time technique to implement emotion identification in robotic vision applications. The results of the simulation demonstrate that they outperform previous attempts in this field, with a 97% accuracy rate in identifying human emotions. Zhou *et al.* [18] developed a novel transfer learning paradigm for EEG signal-based emotion identification. Pairwise learning using an adaptive pseudo labeling technique is based on the aligned feature representations, which reduce the impact of label noise on modelling by encoding the proximity connections between samples. Gong *et al.* [19] proposed a novel EEG-based attention-based convolutional transformer neural network (ACTNN) for emotion recognition. The attention weight distribution suggests that the gamma band of EEG signals and the brain's prefrontal and lateral temporal lobes may be more strongly linked to human emotion. Yan *et al.* [20] presented the X-GWO-SVM technique, that improves the possibility for research and exploitation of emotion recognition based on a single channel. The iRealcare and WESAD datasets have mean accuracy of 93.37% and 95.93%, from this leave-single-subject-out cross-validation. Several deep learning techniques were employed in the literature review for the prediction and classification of emotions. The high sensitivity of EEG-based emotion recognition to physiological abnormalities and ambient noise affects the data quality. To address this a novel EEG-EMRE has been proposed for the detection and classification of emotions.

The structure of this document is as follows. The proposed EEG-EMRE for emotion categorization is explained in section 2, and section 3 presents the findings of the proposed model. The conclusion and proposals for additional research are included in section 4.

2. PROPOSED METHOD

In this research a novel EEG-EMRE has been proposed for the detection and classification of emotions. Initially the gathered EEG signals data are pre-processed using QSP to remove the noise and enhance the quality of the signal. Then the Inception EfficientNet is used to extract the relevant features from noise free enhanced signals. The Penta types of emotions such as happy, sad, anger, scared and anxiety are classified using bidirectional-KNN classifier. Figure 1 illustrates the proposed EEG-EMRE method.

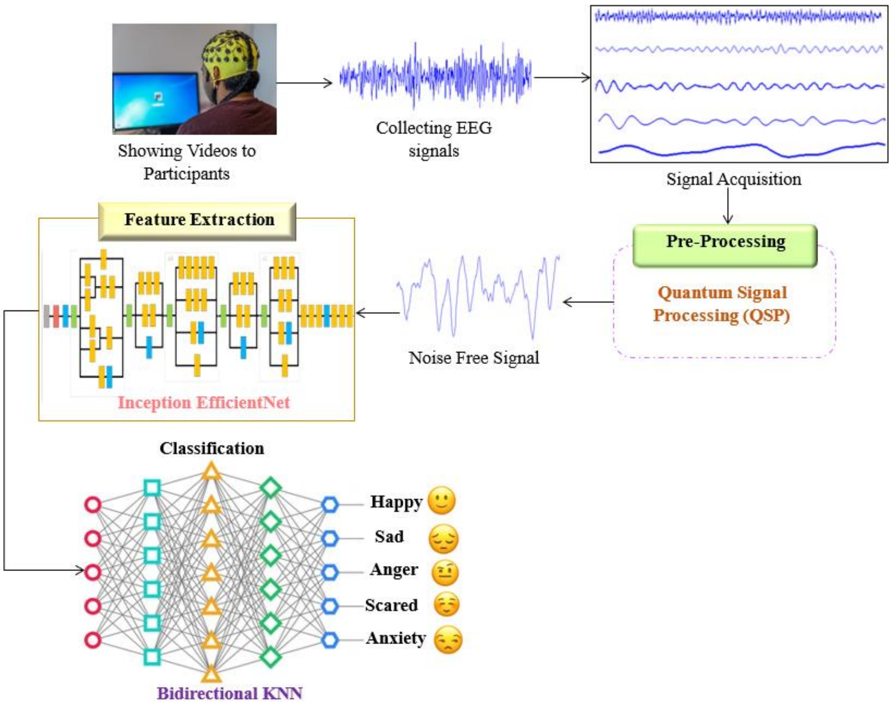

Figure 1. Proposed EEG-EMRE method

2.1. Quantum signal processing

The QSP toolbox can be used to design quantum algorithms with asymptotically optimal costs. The formulation of quantum signal processing is often done according to two conventions. The first one involves the expression of the signal operator in the ρ_a basis and the signal processing in the ρ_b basis. The second one involves the expression of the signal operator in the ρ_b basis and the signal processing in the ρ_a basis. The signal operator in the ρ_b basis is defined as:

$$D_{\rho_b} = \begin{bmatrix} c^{jS} & 0 \\ 0 & c^{-jS} \end{bmatrix} \tag{1}$$

A Hadamard gate applied to both sides of the Ancilla Qubit allows the expression of the signal operator on the basis.

$$D_{\rho_a} = \begin{bmatrix} \cos(S) & j\sin(S) \\ j\sin(S) & \cos(S) \end{bmatrix} \tag{2}$$

It demonstrates that both of these formalisms are nearly the same at a high level, even though the shapes of the polynomials that can be constructed in both bases differ. In the D_{ρ_a} formalism, the QSP findings are frequently expressed as (3).

$$\begin{bmatrix} R(cos(S)) & -G(cos(S))\sin(S) \\ G(cos(S))\sin(S) & R(\cos(S)) \end{bmatrix} = \left(\prod_{i=1}^{f} P_b\,(\varphi_i)D_{\rho_a}\right)P_b(\varphi_0) \tag{3}$$

Implementing Hadamard to Ancilla prior to and following the QSP sequence can get around this restriction and basically turn it into the D_{ρ_b} formalism. This illustrates that any real polynomial with parity d mod2 can be implemented in such a way that deg $(R) \leq f$ and (4).

$$\begin{matrix} R(c^{jS)} & -G(c^{jS})^{\dagger} \\ G(c^{jS}) & R(c^{jS})^{\dagger} \end{matrix} = \left(\prod_{i=1}^{f} P_a(\varphi_i)S_{\rho_b}\right)P_a(\varphi_0) \tag{4}$$

The number of the constraints mentioned above are lessened by the formalism mentioned above. But because the polynomial R must be real and have definite parity, four distinct instances to produce an arbitrary complex polynomial with definite parity, the linear combination of unitaries (LCU) of QSP must be applied.

2.2. Inception EfficientNet

In this section the Inception EfficientNet is processed to extract the features from the noise free enhanced signals. The Inception module is crucial for the proposed sign recognition model, designed to capture input frame characteristics across different scales and resolutions. It utilizes convolutional layers to extract features with varying filter sizes. MBConv employs direct connections among bottlenecks that involves fewer channels due to a compression layer following the channel extension. This architecture's deep separable convolutions significantly reduce calculations by a factor of k² compared to standard layers, where k represents the kernel size of the 2D convolution window. Architecture of Inception EfficientNet is described in Figure 2.

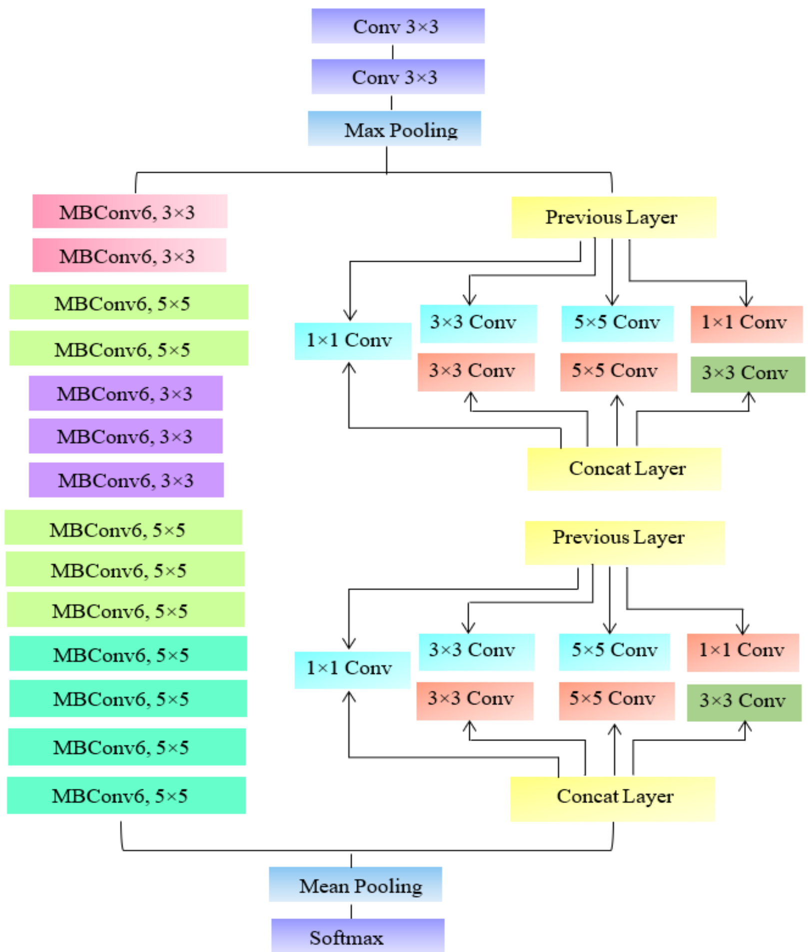

Figure 2. Architecture of Inception EfficientNet

In compound scaling, depth, breadth, and resolution are all scaled equally using the compound coefficient φ and the guidelines provided.

$$depth: d = \alpha^{\phi} \tag{5}$$

$$width: w = \beta^{\phi} \tag{6}$$

$$resolution: r = \gamma^{\phi} \tag{7}$$

$$\alpha \geq 1, \beta \geq 1, \gamma \geq 1 \tag{8}$$

where the constants can be found through grid search α, β *and* γ. The number of resources available is managed by the user-defined coefficient for model scaling ϕ, and the distribution of these extra resources over the network's resolution, depth, and width is determined by α, β *and* γ respectively. The floating-point operations (FLOPs) in a typical convolution operation are proportional to d, w^2, r^2.

Partial channels are not altered by InceptionNet are identified as a branch of identity mapping. For the processing channels, InceptionNet uses $3 \times 3,\ 1 \times f_u, and\ f_t \times 1$ kernels as branches to decompose the depthwise operations in the Inception style. In particular, they divided input X into four groups based on the channel dimension,

$$Y_{tu}, Y_u, Y_t, Y_{id} = Split(Y) \tag{9}$$

where g is the convolution branches' channel numbers. To find the branch channel numbers using $d = r_d S$ set ratio r_d. The necessary features are extracted when the splitting inputs are given into several parallel branches.

2.3. Bidirectional-KNN for classification

The KNN supplemented the benefits of these techniques are combined with BiLSTM to create an efficient cybersecurity resource for attack graph construction. Assume for the moment that the attack training set $\varphi = \{(x_m, y_m)\}_{m=1}^{\xi}$ is provided, with $x_m \epsilon \mathbb{R}^{\varsigma}$ being the m—th input vector while serving as the output variable's label vector. Through the use of graph $f_m = \forall(x_m: \varphi)$, where ∀ is the transformation function, each input vector is rebuilt using this manner. The two hyperparameters that need to be ascertained the A and ℵ the learning procedure do not explicitly make use of the distance function or the nearest neighbor numbers; rather, they are just used to run the KNN search's transformation function ∀ from φ. Every KNN occurrence is looked for from $\varphi \setminus \{(x_m, y_m)\}$ entrenched on the distance function ℵ, as shown by (10).

$$\wp(x_m) = \left\{\left(x_m^{(j)}, y_m^{(j)}\right)\right\}_{j=1}^{d} \tag{10}$$

The BiLSTM is constructed to conduct graph representation $\mathcal{G} = \forall(x: \varphi)$ for input vector and offer the training φ to identify the equivalent label vector y as $\mathbb{Y} = \ell(\mathcal{G}) = \ell(\forall(x; \varphi)$ in order to discover the KNN regulation from the attack training set. When ν^j was first embedded into a ς dimensional starting node, a vector using the embedded function $\mathfrak{B}$ as $\mathcal{N}^{(0),j} = \mathfrak{B}(\mathfrak{v}^j), j = 0, \ldots.. d$ was indicated. The update and message functions ρ and τ are the two primary functions that are used to perform a message passing procedure to graph constructs. Vectors $\mathcal{N}^{(w),j}$ have their node representation changed as (11) and (12).

$$\vartheta^{(w),j} = \sum_{i|\mathfrak{v}^j \epsilon \lambda / \mathfrak{v}^i} \tau(e^{j,i}) \mathcal{N}^{(w-1),j}, \mathcal{A}j \tag{11}$$

$$\mathcal{N}^{(w),j} = \rho\left(\mathcal{N}^{(w-1),j}, \vartheta^{(w),j}\right), \mathcal{A}j \tag{12}$$

Furthermore, the method identifies a specified task KNN rule under the attack training data$\varphi = \{(x_m, x_m)\}_{m=1}^{\xi}$. The forward hidden states (H) and the backward hidden states are calculated by using the (13) to (15).

$$\vec{h}_t = \sigma\left(\mathcal{V}_{x\vec{h}} x_t + \mathcal{W}_{\vec{h}\vec{h}} \vec{h}_{t-1} + d_{\vec{h}}\right) \tag{13}$$

$$\overleftarrow{h}_t = \sigma(\mathcal{V}_{x\overleftarrow{h}\, x_t} + \mathcal{W}_{\overleftarrow{h}\overleftarrow{h}} \overleftarrow{h}_{t-1} + d_{\overleftarrow{h}}) \tag{14}$$

$$\mathcal{H}_t = \mathcal{V}_{x\vec{h}} + \mathcal{V}_{\overleftarrow{h}z} \vec{h} + d_z \tag{15}$$

The Bi-LSTM processes integrated attack stages $\overleftarrow{h}_t$ during training and testing. Moreover, the developed attack graph was installed in the line of ledgers, enhancing network security by making hackers unable to access or edit information.

3. RESULTS AND DISCUSION

The performance of the proposed EEG-EMRE approach is assessed in this section using a variety of evaluation criteria. A Windows computer with an Intel Core i7 CPU and 16GB of RAM is used to build and test the proposed framework using the Python programming language and its libraries. The proposed EEG-EMRE framework was implemented and evaluated on the SJTU emotion EEG dataset (SEED) and its performance was validated using standard statistical metrics such as accuracy, precision, recall, specificity, and F1-score. Comparative results against existing models demonstrate the superior accuracy and robustness of the proposed method, providing quantitative evidence for its effectiveness.

3.1. Dataset description

The SEED Dataset was gathered by Shanghai Jiao Tong University's Brain and Cognition Laboratory for the purpose of classifying emotions using EEG signals. It includes 15 subjects' EEG data after they viewed 15 carefully chosen movie segments meant to evoke three different emotional states: positive, neutral, and negative. A 62-channel EEG device was used to record data, which was then down sampled to 200 Hz from the initial 1000 Hz sampling rate. The dataset consists of preprocessed EEG signals with differential entropy (DE) characteristics that are frequently employed in tasks involving the classification of emotions. SEED has been widely used for affective computing and deep learning-based emotion recognition.

3.2. Performance analysis

The effectiveness of the classification technique is evaluated using statistical metrics: F1 score, accuracy, precision, recall, and specificity.

$$Accuracy = \frac{True^{+} + True^{-}}{True^{+}+True^{-}+False^{+}+False^{-}} \tag{16}$$

$$Precision = \frac{True^{+}}{True^{+}+False^{+}} \tag{17}$$

$$Recall = \frac{True^{+}}{True^{+}+True^{-}} \tag{18}$$

$$Specifivity = \frac{True^{-}}{True^{-}+False^{+}} \tag{19}$$

$$F1 - Score = 2\frac{(Precision*Recall)}{(Precision+Recall)} \tag{20}$$

where true-positive, false-positive, true-negative, and true-positive are all represented by the symbols $True^{+}$, $True^{-}$, $False^{+}$, and $False^{-}$, according to their sequence. The effectiveness of the proposed method for emotion classifying such as happy, sad, anger, scared and anxiety are demonstrated in Table 1. Overall accuracy, precision, recall, specificity, and F1-Score values are attained by the suggested approach of 99.36%, 97.16%, 97.28%, 90.68% and 90.73%, respectively.

Table 1. Performance analysis of proposed method

Classes	Accuracy	Precision	Recall	Specificity	F1-Score
Happy	98.65%	97.41%	97.45%	90.28%	92.85%
Sad	98.92%	95.72%	95.82%	89.71%	88.69%
Anger	99.78%	96.64%	96.73%	92.65%	90.87%
Scared	99.63%	97.52%	97.68%	88.92%	87.53%
Anxiety	99.81%	98.52%	98.72%	91.85%	93.69%

Based on 100 epochs and a predefined accuracy range, the accuracy curve was shown in Figure 3. More epochs in the image increase the accuracy of the proposed method for categorizing human emotions. Figure 4 demonstrates the decrease in loss as the proposed model runs through additional epochs. It displays the epochs together with the corresponding loss range. Different types of face emotions are classified using the proposed method. Following 100 training epochs, 99.47% detection accuracy and a minimal error rate are demonstrated by the proposed model.

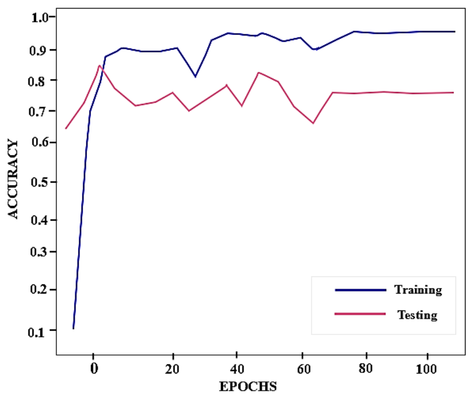

Figure 3. Accuracy graph of the proposed EEG-EMRE method

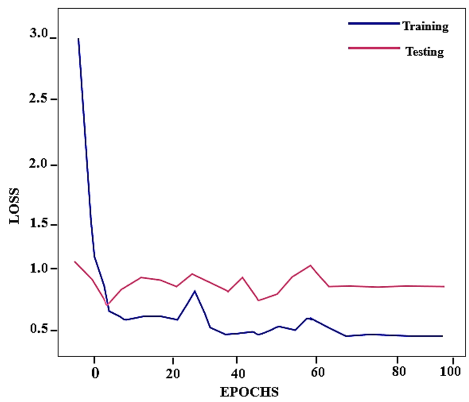

Figure 4. Loss graph of the proposed EEG-EMRE method

3.3. Comparative analysis

Based on several feature extraction networks the proposed method has been compared with other traditional network. The outcome of a comparison of feature extraction methods is displayed in Table 2. The table compares the proposed Inception EfficientNet to other traditional deep neural networks. The proposed Inception EfficientNet is more effective than a high accuracy rate compared to another feature extraction network. The proposed model increases the overall accuracy by 0.41%, 1.52%, 0.63%, 1.55% and 2.56% better than ResNet, AlexNet, GoogleNet, DenseNet and MobileNet, respectively. According to Table 3 the proposed improves the overall accuracy by 0.68%, 1.77% and 0.52% better than LF-DfE, ELM-W-AE, and ACTNN, respectively. The accuracy of this model is 99.36%, that is better than other models in producing accurate results.

Table 2. Comparison with another neural network

Method	Accuracy	Precision	Recall
ResNet [21]	98.95%	95.85%	94.85%
AlexNet [22]	97.84%	96.51%	89.83%
GoogleNet [23]	98.73%	90.83%	95.73%
DenseNet [24]	97.81%	95.79%	96.26%
MobileNet [25]	88.11%	84.25%	84.05%
Inception EfficientNet (proposed)	99.36%	97.16%	97.28%

Table 3. Accuracy comparison of existing techniques and proposed techniques

Author	Technique	Accuracy
Joshi and Ghongade [14]	LF-DfE	98.68%
Ari *et al.* [15]	ELM-W-AE	97.59%
Gong *et al.* [19]	ACTNN	98.84%
Proposed method	EEG-EMRE	99.36%

3.4. Discussion

The proposed EEG-EMRE framework demonstrated a significant improvement in EEG-based emotion recognition performance through the integration of QSP, Inception–EfficientNet, and bidirectional-KNN components. The reliability of feature extraction was improved by the QSP module by reducing the noise and preserving key brain features, which improved signal quality. The bidirectional–KNN classifier improved the identification of intricate emotional transitions, while the hybrid Inception–EfficientNet model effectively extracted multi-scale temporal–spatial information from EEG signals. The resulting accuracy of 99.36% on the SEED dataset confirms the superior performance of the proposed model compared with conventional models. Moreover, the proposed model improves the overall accuracy by 0.68%, 1.77% and 0.52% better than LF-DfE, ELM-W-AE, and ACTNN, respectively.

The proposed approach provides a more cohesive and comprehensible pipeline for emotion classification in contrast to previous studies. In contrast to conventional models that rely mostly on manual feature engineering or single-level deep learning frameworks, EEG-EMRE improves efficiency and resilience by combining compound-scaled feature extraction with quantum-inspired pre-processing techniques. The proposed work is significant because it has the potential to combine deep learning and quantum signal processing for emotion-aware robotics. The findings enhance the precision of emotion recognition and system flexibility, which advances the domains of affective computing and human–robot interaction. Furthermore, these results can help with the creation of emotion-responsive automation systems, intelligent assistive robots, and personalized healthcare monitoring.

Despite its promising results, the proposed EEG-EMRE framework has limited generalizability across different settings due to its solely evaluation on the SEED dataset. The efficacy of the proposed model may be impacted by differences in electrode locations, EEG acquisition methods, and personal emotions in practical applications. Future research will focus on validating the model using multiple publicly available and real-time EEG datasets to enhance cross-subject robustness. Additionally, the QSP module increases computational requirements that will be reduced by optimizing it for lightweight processing. Furthermore, real-time implementation on wearable or robotic platforms will be explored to evaluate its adaptability for emotion-aware automation and human–robot interaction environments.

4. CONCLUSION

In this paper a novel EEG-EMRE has been proposed for the detection and classification of emotions. The EEG signals are pre-processed using QSP to remove the noise from the signal. The proposed EEG-EMRE method uses an improved Inception EfficientNet for extracting the features from noise free enhanced signals. The Bidirectional-KNN classification network is used to classify the Penta types of emotions such as happy, sad, anger, scared and anxiety. The proposed EEG-EMRE method's performance is assessed using F1-Score, accuracy, precision, recall, and specificity. The proposed Inception EfficientNet for feature extraction network improves the overall accuracy by 0.41%, 1.52%, 0.63%, 1.55%, and 2.56% better than the ResNet, AlexNet, GoogleNet, DenseNet, and MobileNet. The proposed EEG-EMRE method achieves overall accuracy by 0.68%, 1.77%, and 0.52% better than LF-DfE, ELM-W-AE, and ACTNN. Future research could concentrate on improving classification accuracy through the use of cutting-edge deep learning models and quantum signal processing optimization for emotion recognition based on real-time EEG data. Additionally, the proposed framework can be used in robotic and emotion-aware automation systems, where real-time emotion detection is essential for enhancing human-machine cooperation. The automated or robotic systems that use sthe proposed EEG-EMRE system can have emotion-based control systems that allow them to modify their behavior based on the emotional state of the individual. This increases the applicability of the proposed framework beyond emotion classification to practical automation and intelligent robotics contexts.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

INFORMED CONSENT

I certify that I have explained the nature and purpose of this study to the above-named individual, and I have discussed the potential benefits of this study participation. The questions the individual had about this study have been answered, and we will always be available to address future questions.

ETHICAL APPROVAL

My research guide reviewed and ethically approved this manuscript for publishing in this journal.

DATA AVAILABILITY

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

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