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Emotion Recognition from Wearable EEG Devices Using Neural Networks

Ms. T. Nithya[1], V. Ezhilkumar[2], K.S. Hari Supikssa[3], S. Harshini[4] and R. Kishore[5]
[1]Assistant Professor, Information Technology,
Velalar College of Engineering and Technology, Erode–638012, Tamil Nadu, India
[2-5]Students, Department of Information Technology,
Velalar College of Engineering and Technology, Erode–638012, Tamil Nadu, India
E-mail: [1]tnithya27@gmail.com, [2]ezhilkumarv2003@gmail.com,
[3]ksharisupikssa@gmail.com, [4]harshu2483@gmail.com, [5]kishorer0505@gmail.com

***Abstract*—Recognizing emotions using wearable technology is an emerging field that leverages the breakthroughs in machine learning and neuroscience to conduct real-time analyses of human emotional states. This study explores the scope of wearable technology-based emotion recognition by incorporating EEG (Electroencephalogram) signals to capture the electrical activity of the brain. A Deep Neural Network (DNN) is deployed to sort emotions into three classes: positive, negative and neutral. Harnessing advanced feature extraction strategies for EEG processing brings about improved accuracy over conventional methods. The observations demonstrate that the proposed DNN-based model leads way to economical, non-invasive and mobile solution for affect monitoring. This research offers notable potential in fields like human-computer interaction, mental health tracking, and stress management at work. Scalable medical-grade equipment alternatives are attained by means of the easily accessible wearable devices, that could be used in much wider scale in real-world use cases. This study aims to offer a feasible strategy for emotion recognition using EEG through compact devices.**

Keywords: Emotion recognition, Deep neural networks, Electroencephalogram, Human-Computer Interaction, Neuroscience

I. Introduction

Integrating wearables for emotion detection is a nascent method for continuous real-time monitoring in anon-invasive manner. Traditional methods assessing facial expressions or heart rate monitoring can be affected by extrinsic features like lighting, facial movement as well as other unrelated physical activity making those less reliable. A direct measure of emotional states unbiased by external cues is sourced by EEG signals, while the firing of neurons. EEG measures the electric activity of the neurons in brain. It provides deeper insights into a person's emotional state and aren't misled by surroundings. By evaluating patterns in EEG signals with the help of evolving technology, it's feasible for machine learning models to be equipped to recognize emotional cues efficiently. This approach leverages DNN to sort emotions with the help of EEG signals. This model leverages advanced feature extraction strategies for optimized categorization and prediction of emotions. Integration of wearables renders the real-time monitoring of emotional states possible. This research studies the role of EEG for costeffective, easy to implement emotion recognition in wearables.

II. Related Works

Emotion detection using EEG signals has attracted a lot of attention as of late since it can identify emotional states by examining brainwave patterns. Even though widely used, standard machine learning algorithms encompassing logistic regression, random forests, and Support Vector Machines (SVM) struggle more often than not to tackle the complexity and non-linearity present in EEG data. Prior researches as certain that hurdles that can weaken classification accuracy include skewed data, diversity among subjects and noise in signal. Reciprocally, DNN evolved as a mightier solution since it discerns complicated patterns in EEG data without needing abundant manual feature extraction. As a result, emotion recognition significantly improves. Furthermore, evolving advancements in feature engineering and DNNs are a strong choice for EEG-based emotion identification since it paves way for real-time processing capabilities which increases its usefulness.

III. Methodology

To identify emotional states in real time, the suggested emotion identification system uses wearable EEG devices to record brainwave data, which is then analysed by a DNN. Figure 1 shows the DNN architecture where, preprocessing, feature extraction, categorization, and data gathering make up the system's four primary parts.

A. Gathering Information

Brainwave signals are recorded from the scalp in real time using wearable EEG devices. Multiple channels of EEG data are provided by these sensors, which record electrical activity from various parts of the brain. A variety of frequency bands, including as alpha, beta, and gamma, which are associated with emotional reactions, are represented in the raw EEG signals. The data could be used to get info on a mix of statistical data like mean value that captures the general trend of the signal activity and Fast Fourier Transform features as various frequency bands could be linked to different emotional states.

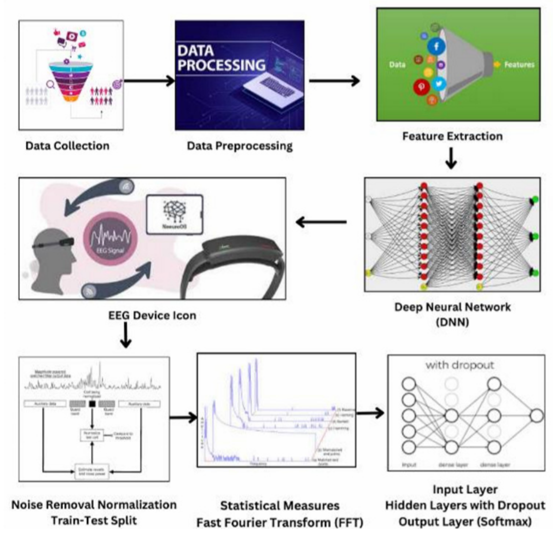

Fig. 1: Proposed DNN Architecture

B. Getting Ready

Noise, such as artifacts from eye blinks, muscle movements, and ambient interference, frequently taints raw EEG readings. To enhance the signal quality, preprocessing methods are used, including,

1. *Label Encoding:* The emotion labels are mapped to the numerical values to ensure better processing.
2. *Data Normalization*: The data excluding the label column undergo normalization to ensure that all the features are in same scale to prevent biased results.
3. *Train-Test Split:* The collected data is partitioned in the proportion of 3:7 for testing and training respectively to prevent overfitting. The goal of preprocessing is to ensure that the signal data accurately reflects the user's neural activity, providing clean input for feature extraction.

C. Feature Extraction

Following preprocessing, pertinent features that capture emotional states are extracted from the EEG data. Feature extraction is applied to obtain a set of mean and FFT features from the raw signals. Mean features capture the intensity of the signal that varies with respect to the emotional state. The extracted frequency-domain features can be linked to different frequency bands and in turn the various emotional states. Furthermore, additional features like mean differences can be used to gather more insights on brain activity.

D. Training Deep Neural Networks

1. *Data Split for Training and Testing:* The dataset is divided into two parts, with 70% for training and 30% for testing to ensure that the model learns from one set of data and is evaluated on another, unseen set, providing a reliable measure of performance.
2. *DNN Model Architecture:* The DNN model architecture comprises multiple layers starting with the input layer that receives the normalized EEG feature data followed by hidden layers some of which use dropout to reduce overfitting. The output layer, using the SoftMax function computes the probability distribution over emotional states.

The SoftMax function can be mathematically represented as:

$$\text{softmax}\,(a_x) = \frac{m^{a_x}}{\sum_{y=1}^{n} m^{a_y}}\,, \forall_x \in [1, n] \tag{1}$$

Here,

a_x represents the input vector's i-th element,

m^{a_x} represents the exponential of a_i,

$\sum_{y=1}^{n} m^{a_y}$ represents the sum of exponentials of all logits.

3. *Optimization Strategy and Loss Function:* The performance exhibited by the model is evaluated with the help of a loss function. The Adam optimizer is leveraged to update the model's weights. This optimization method is particularly effective in noisy environments and reduces the need for manual tuning of hyperparameters. The following pseudocode illustrates the compilation of the model:

```
START
    DEFINE function compile_model(model)
    SET optimizer to 'adam'
    SET loss to
    'sparse_categorical_crossentropy'
    SET metrics to ['accuracy']
    CALL model.compile with the optimizer,
    loss and metrics
    RETURN compiled model
END
```

4. *Training Process and Weight Updates:* Training process spans across numerous epochs, which alludes to the frequency in which the entire training set passes past the model. After processing each batch, the model updates its weights via backpropagation, where the gradient of the loss function is used to refine the weight values. This continues until the model reaches the set number of epochs.

The formula for weight updates using the Adam optimizer is:

$$w = w - l.\frac{a_g}{\sqrt{a_{sg}+\epsilon}} \quad (2)$$

Here,
w represents the weight,
n represents the learning rate,
a_g and a_{sg} represent the moving averages of the gradient and squared gradient,
ϵ represents a small constant to prevent division by zero.

E. Real-time Emotion Classification and Prediction

After completing the training phase, the DNN can be deployed to sort the emotions from real-time EEG data. As new brainwave signals are processed, the model can predict and provide feedback on user's emotional state instantaneously allowing for continuous emotion tracking, offering real-time insights based on model's learned patterns from the EEG features.

F. Performance Metrics

The performance of DNN model is assessed using various standards involving confusion matrix analysis, recall, accuracy, precision, and F1-score.

1. *Accuracy:* This refers to the proportion of correctly predicted emotions to all forecasts and can be used to gauge the overall standard of model's performance.

$$Accuracy = \frac{T_p+T_n}{T_p+T_n+F_p+F_n} \quad (3)$$

Here,
T_p: True Positives
T_n: True Negatives
F_p: False Positives
F_n: False Negatives

2. *Precision:* The proportion of all positive predictions that are evaluated to provide right measurements. It focuses on how many of the predicted positive emotional states are true.

$$Precision = \frac{T_p}{T_p+F_p} \quad (4)$$

3. *Recall*: The model's precision in identifying real emotional states and represents the ratio of true positive states to all genuine positives.

$$Recall = \frac{T_p}{T_p+F_n} \quad (5)$$

4. *F1-Score:* An unbiased evaluation of the model's execution capabilities based on the precision and recall harmonic means, provides a balanced measure of model's accuracy particularly when there is an uneven class distribution.

$$F1 - Score = 2.\frac{Precision.Recall}{Precision+Recall} \quad (6)$$

IV. Outcomes and Definitions

A. Analysis of Comparisons

A dataset containing EEG signals tagged with emotional states as stress, happiness, and relaxation was used to test the suggested emotion recognition system utilizing EEG signals and deep neural networks (DNN). A wide range of people in various emotional states were included in the dataset ensuring diverse data for training and testing the model. Metrics that account for the accuracy of positive prognosis and the model's ability to discern each of the positive instances along with the one that can balance the aforesaid are used notably to evaluate the model in classification tasks.

B. Assessment of Performance

Several measurement standards comprising reliability, preciseness, predisposition and the balance between two or more metrics previously mentioned are put to work in order to appraise the program that can find patterns provided a dataset. Furthermore, confusion matrix, t-SNE (t-distributed Stochastic Neighbour Embedding) visualization is leveraged to score a deeper perception of the program's ability to sort the emotional states.

1) Confusion Matrix Overview

Figure 2 exhibits a confusion matrix to provide an elaborate breakdown of the model's output after classification of emotion states.

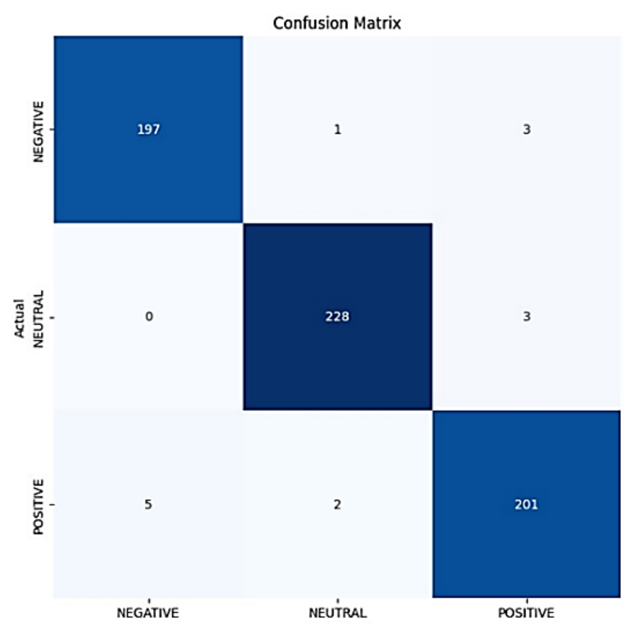

Fig. 2: DNN Model Confusion Matrix

The illustration emphasizes false positives (*Fp*) and true positives (*Tp*) along with false negatives (*Fn*) and true negatives (*Tn*). For example, the model discerned 85 instances of positive states which are labelled as true positives. In the meantime, 78 instances of the negative states recognized are designated as true negative. Nonetheless, the model erroneously predicted a positive emotion in certain instances leading to false positives. Similarly, there are also cases where it failed to determine positive state, causing false negatives. Worthwhile insights on the model's sorting capacity as well as performance gaps are obtained using this matrix.

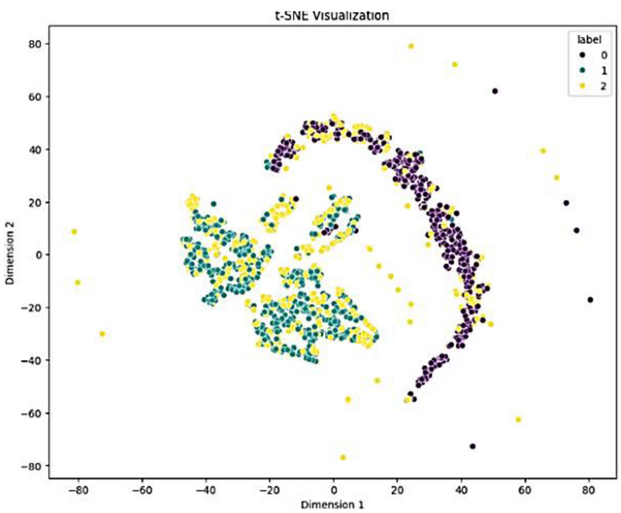

Fig. 3: Visualizing Emotion Clusters with t-SNE

The t-SNE visualization in Figure 3 illustrates by what means the data points, corresponding to different emotional states, are dispersed across two dimensions. Each cluster exemplifies a group of connatural emotions, with a sharp distinction among the categories. A more intuitive perception of how well the model can set apart the emotional states is obtained from the pictorial representation.

C. Performance in Emotion Classification

Emotional states are discerned meticulously with the help of EEG data and the model's execution of classification can be reviewed using the subsequent metrics:

Table I: Performance Metrics for Emotion Classification

Metric	Value	Explanation
Accuracy	0.90	Proportion of correctly classified emotional states
Precision	0.88	Proportion of correct positive predictions
Recall	0.85	Proportion of actual positive emotions correctly identified
F1-Score	0.87	Harmonic mean between precision and recall

D. Results

1. *Classification Accuracy for Emotions*: The DNN model achieved a robust classification accuracy of 90% for emotional states. It showcased particular efficacy in detecting positive emotional states with marginal incorrect positive in result.
2. *Precision and Recall Evaluation:* The system diagnoses emotional states with a precision of 0.88 with hardly many false positives. The recall score 0.85 indicates that a handful of emotional states are successfully identified.
3. *Processing in real-time: The* DNN model showcase minimal latency in the processing of streaming EEG data and sorting the emotions while real-time test period, which frames it appropriate for wearable applications when practical use-cases are involved.
4. *Comparing with Conventional Techniques:* The DNN model's performance surpasses that of established practices like k-NN, SVM etc., Efficiency and real-time processing of this model renders it suitable for its usage in wearables for emotions recognition.

V. Conclusion and Future Work

Classification of emotional states across negative, neutral and positive is effectively achieved through DNN model. Complex patterns in EEG data are captured as the DNN architecture is implemented featuring dense layers. Statistical analysis and confusion matrix demonstrate preciseness and accuracy of sorting across all emotional values and revelation of notable feature distribution. Prior studies in EEG based emotion recognition outline various quintessential areas for betterment including the relevance of temporal feature extraction and other multimodal approaches. Single-modal EEG evaluation achieve reliable output with befitting feature extraction and model architecture. A strong foundation for EEG-based emotion recognition is established while opportunities for advancement in feature extraction and model architecture along with other practical applications including but not limited to mental health monitoring and human computer interaction or accentuated. To build on this study, potential of integrating more feature like pulse rate, Electrocardiogram (ECG) as well as Galvanic Skin Response (GSR) should be explored to enhance the scope of emotion detection.

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