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Spectrogram-driven Emotion Detection from Electroencephalogram

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Introduction

Emotions profoundly shape cognition, guiding decision-making, social interactions and motivation. They shape how individuals interpret, respond and interact with their surroundings [1].

Electroencephalography is the measure of brain's electrical activity that reflects neural oscillations, network dynamics and offers crucial insights into neurocognition [2].

Spectrogram visualizes the dynamic spectral composition of EEG signals, enabling emotion recognition more reliable, accurate and efficient.

The research paper presented here proposes spectrogram based deep learning classification to advance EEG-based emotion recognition system.

Problem Statement

01

Traditional EEG-based emotion recognition cannot completely capture the complex temporal and spectral characteristics of EEG signals.

02

Spectrogram based emotion detection from EEG is not available.

03

Classifiers fail to incorporate both spatial and temporal aspects of EEG data, limiting their effectiveness.

Research Objectives

01 To transform the processed EEG signals into spectrogram based representations for improved emotion recognition.

02 To benchmark the effectiveness of the proposed model against state-of-the-art deep learning architectures and prior studies in EEG-based emotion recognition.

Related Works

Table 1: Related Works

Work	Feature Extraction Method	Models Used	Accuracy	Limitations
Q. Zhao [3]	DE	DE-CNN-RNN	95%	1. Exploring only one feature. 2. Did not handle EEG Signals variablities across different individuals.
A. N. A. Gul [4]	DE, DCAU, RASM, DASM	SVM, DNN	SVM- 79.4% DNN - 79.8%	1. Study is conducted in a controlled environment and no analysis is done on how the model performs in real-world EEG noise and artifacts.
H. Shrara [5]	-	SVM, RF, LSTM	SVM - 90% RF - 93% LSTM - 97%	1. Small dataset (10 participants) limits generalizability. 2. Limited emotion categories; no mixed emotions considered
P. Kar [6]	WPD	SVM	64.06%	1. Discrepancies between established emotion labels and actual physiological responses suggest potential labeling inaccuracies 2.Limited classification accuracy

Methodology

Proposed Workflow

Phase 1

Data Collection

SJTU Emotion EEG dataset

No. of channel used 15

Sampling Frequency 200 Hz

Phase 2

EEG Processing

Extraction of 675 MATLAB files carrying signals

Phase 3

Feature Extraction

Short Time Fourier Transform

Spectrograms (Time and frequency representation)

Phase 4

Classification

Convolutional Neural Networks

Dataset

SJTU Emotion EEG Dataset (SEED) [7,8]

15 Volunteers

Chinese emotional movie clips

62 channels with 1000 Hz Sampling rate

Downsampled to 200 Hz

Methodology (Cont.)

Feature Extraction

Generated energy-time-frequency representations, visualized as spectrograms

Short Time Fourier Transform (STFT) provided spectrograms of selected channels

$$STFT\ \{x(t)\}(\tau, w) = \int x(t)\omega(t-\tau)e^{-i\omega t}\,dt$$

Fig. 1. Equation of STFT [9]

Table 2: Parameters used for STFT

Parameters	***Conditions***
Sampling Frequency	256 Hz
Length of each segment	256
No. of Points to overlap	128
No.of FFT Points	128

15 Channels Used

FP1,FP2,F3,F4,F8,F7,AF3,AF4,F2,P5,P3,PZ,C3,C4,CZ

Methodology (Cont.)

Spectrograms

Table 3: Parameters used in image processing

Parameters	*Conditions*
Batch Size	40
Brightness	0.8
Random Contrast	Lower = 0.32 Upper =1.1
Random Rotation	0.03
Random Zoom	0.4

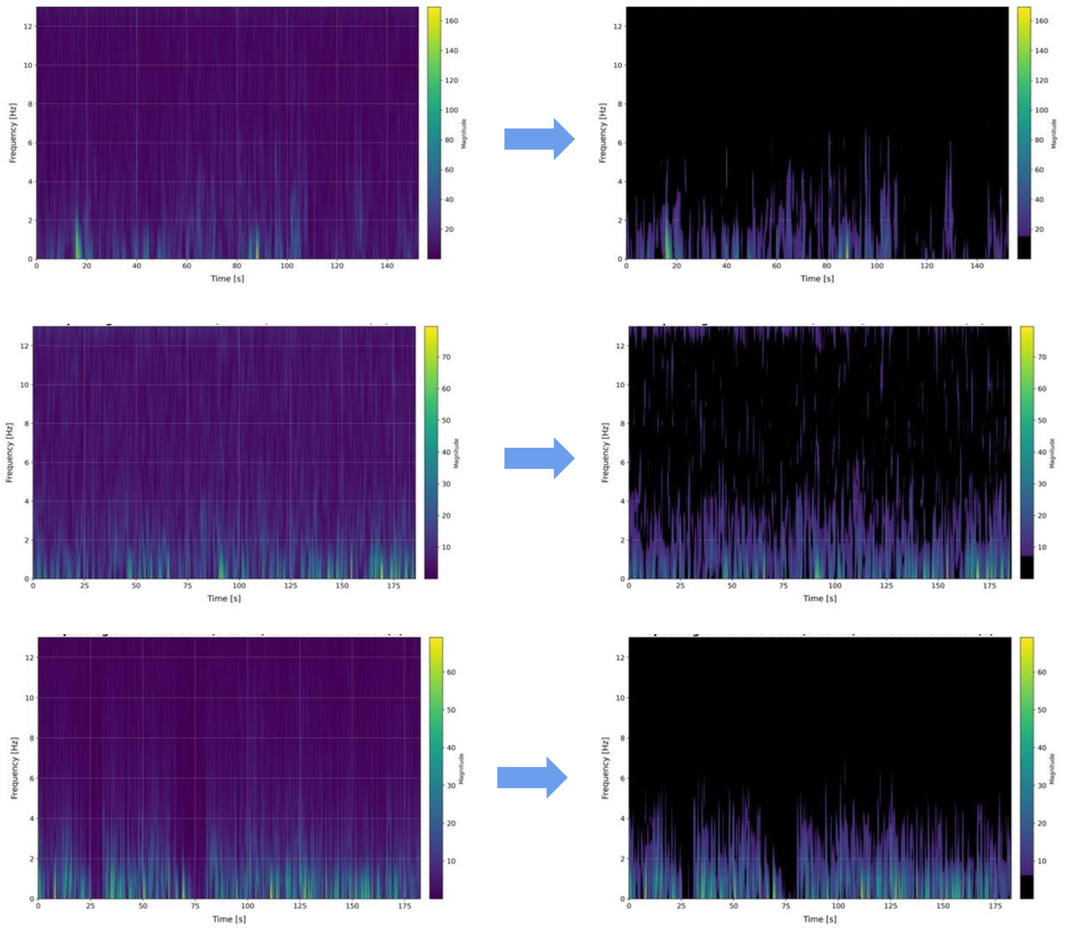

Fig. 1. Original Spectrograms derived from MATLAB (left) and processed Spectrograms (right)

Methodology (Cont.)

CNN Model Architecture

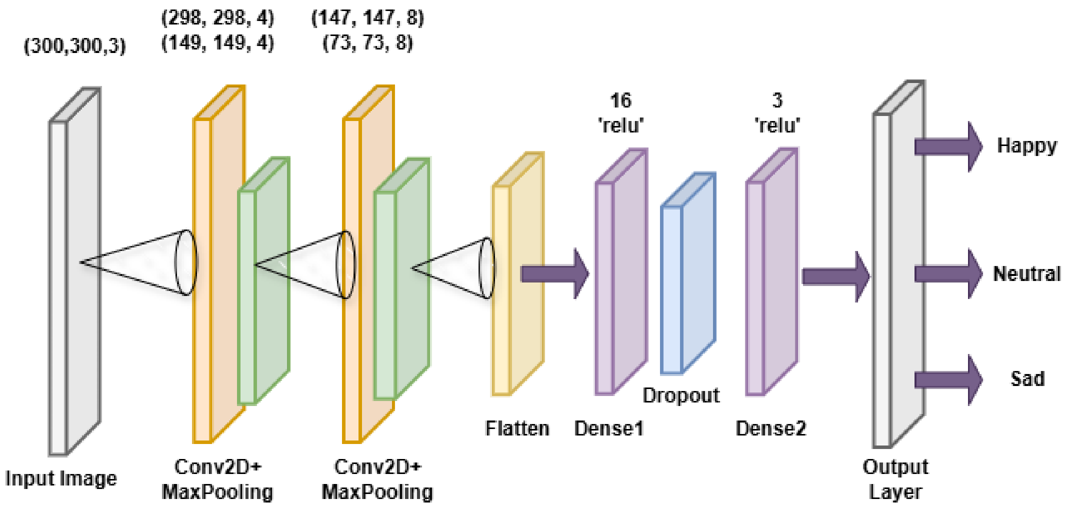

Fig. 2. The CNN Architecture

Table 4: Parameters used in CNN Model

Parameters	***Conditions***
Learning Rate	0.0001
Optimizer	'Adam'
Epochs	10
Activation Function	ReLU
Dropout	0.5

Results

Performance Evaluation

Performance metrics used

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

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

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

$$F1-Score = \frac{(2*recall*precision)}{recall+precision}$$

Table 5: Parameters used in image processing

Data Condition	No. of trained Images	Performance Metrices			
		Accuracy	Precision	Recall	F1-score
Processed Image	10125	0.9980	0.9900	0.9900	0.9900

Results (Cont.)

Performance Evaluation for Pre-trained Models

Table 6: Performance evaluation with pre-trained models

Models	Class Labels	Performance Metrics			Overall accuracy
		Precision	Recall	F1-score	
VGG16	1	1.00	1.00	1.00	0.99
	0	1.00	1.00	1.00	
	-1	1.00	1.00	1.00	
VGG19	1	1.00	1.00	1.00	0.98
	0	0.97	1.00	0.98	
	-1	1.00	0.97	0.90	
InceptionNet	1	1.00	0.81	0.90	0.94
	0	1.00	1.00	1.00	
	-1	0.85	1.00	0.92	

Comparison with Recent Studies

Table 7: Comparison with recent studies

Work	Feature Extraction Method	Models Used	Accuracy
Q. Zhao [3]	DE	DE-CNN-RNN	95%
A. N. A. Gul [4]	DE, DCAU, RASM, DASM	SVM, DNN	SVM- 79.4% DNN - 79.8%
H. Shrara [5]	-	SVM, RF, LSTM	SVM - 90% RF - 93% LSTM - 97%
P. Kar [6]	WPD	SVM	64.06%
Proposed Work	**STFT**	**CNN**	**99.80%**

Conclusion

- A comprehensive study on emotion recognition using EEG signals using an effective feature extraction method has been done.
- Proposed CNN model achieved a high accuracy of 99.80% leveraging the Spectrograms generated by Short Time Fourier Transfrom method.
- The findings underscore deep learning models in interpreting EEG signals for emotion detection & provides a foundation for working with time-frequency representations.

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THANK YOU

Q&A