

PERFORMANCE EVALUATION OF CONVOLUTIONAL  
NEURAL NETWORK (CNN) FOR EEG EMOTION  
CLASSIFICATION

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UNIVERSITI TEKNIKAL MALAYSIA MELAKA

**PERFORMANCE EVALUATION OF CONVOLUTIONAL  
NEURAL NETWORK (CNN) FOR EEG EMOTION  
CLASSIFICATION**

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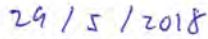
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## **DEDICATION**

Dedicated to my beloved family and friends

## ABSTRACT

Emotion classification through facial expression or speech intonation is not reliable as human can hide their emotion when expressing their feelings. Therefore, a deep learning technique, Convolutional Neural Network (CNN) is implemented and optimized in this project to analyze human emotion in a more reliable manner. Experimental paradigm is designed by using audio-visual stimuli selected from IAPS and IADS-2 database to acquire EEG data with different emotions. The proposed CNN algorithm is trained on the collected EEG data and then validated by using an open source dataset (SEED). The proposed CNN algorithm achieves the best accuracy of 65% (2 classes of emotion) and 82% (3 classes of emotion) from EEG data collected in the lab and SEED dataset, respectively.

## ABSTRAK

Klasifikasi emosi melalui ungkapan wajah atau ucapan intonasi tidak boleh dipercayai kerana manusia boleh menyembunyikan emosi mereka ketika menyatakan perasaan mereka. Oleh itu, satu teknik “deep learning”, iaitu Convolutional Neural Network (CNN) telah diguna dan diubahsuai dalam projek ini untuk menganalisis emosi manusia dengan cara yang lebih boleh dipercayai. Eksperimen dirancang dengan menggunakan rangsangan “audio-visual” yang dipilih dari pangkalan data IAPS dan IADS-2 untuk memperolehi isyarat EEG dengan emosi yang berbeza. Algoritma CNN yang dicadangkan telah dilatih dengan data EEG yang dikumpul dalam makmal dan kemudian disahkan dengan menggunakan dataset sumber terbuka (SEED). Algoritma CNN yang dicadangkan mencapai ketepatan terbaik dengan 65% (2 kelas emosi) dan 82% (3 kelas emosi) daripada data EEG yang dikumpulkan dalam makmal dan SEED.



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## TABLE OF CONTENTS

<b>Declaration</b>	
<b>Approval</b>	
<b>Dedication</b>	
<b>Abstract</b>	<b>i</b>
<b>Abstrak</b>	<b>ii</b>
<b>Acknowledgements</b>	<b>iii</b>
<b>Table of Contents</b>	<b>iv</b>
<b>List of Figures</b>	<b>viii</b>
<b>List of Tables</b>	<b>xii</b>
<b>List of Abbreviations</b>	<b>xiii</b>
<b>CHAPTER 1 INTRODUCTION</b>	<b>1</b>
1.1 Project Overview	1
1.2 Objectives	4
1.3 Problem Statement	4
1.4 Scope of Work	5
1.5 Thesis Outline	6

<b>CHAPTER 2 BACKGROUND STUDY</b>	<b>7</b>
2.1 Definition of Emotion	7
2.1.1 Emotion Models	9
2.2 Electroencephalogram (EEG)	11
2.2.1 History of Electroencephalogram (EEG)	12
2.2.2 International 10/20 System	13
2.2.3 Event Related Potentials (ERP)	14
2.3 Neural Network	17
2.4 Convolutional Neural Network (CNN)	18
2.4.1 Convolution	19
2.4.2 Non-Linearity	19
2.4.3 Pooling / Subsampling	20
2.4.4 Dropout	21
2.4.5 Classification	22
2.5 Comparison between Neural Network and CNN	22
2.6 Related Works	23
<b>CHAPTER 3 METHODOLOGY</b>	<b>28</b>
3.1 Research Methodology	28
3.2 Experimental Design	30
3.2.1 Material Selection for Experimental Design	30

3.2.1.1	International Affective Picture System (IAPS)	30
3.2.1.2	International Affective Digitalized Sounds (2nd Edition (IADS-2)	31
3.2.2	Stimuli Design	31
3.2.3	Experimental Paradigm	32
3.2.4	Participants	33
3.2.5	Experimental Context	34
3.2.6	EEG Data Acquisition	37
3.2.7	Preprocessing of Raw EEG Signal	37
3.2.8	Segmentation and Labelling	38
3.3	STJU Emotion EEG Dataset (SEED)	39
3.3.1	Data Arrangement and Labelling for SEED Dataset	40
3.4	Proposed CNN Algorithm	42
<b>CHAPTER 4 RESULTS AND DISCUSSION</b>		<b>45</b>
4.1	Dataset Used in the Project	45
4.2	Proposed CNN with EEG Data Collected in The Lab (2 emotion classes)	46
4.2.1	Comparison between the Performance with Different Parameter Setting	50
4.2.2	Comparison between Confusion Matrix	51
4.2.3	Significant Test for Different Parameter Setting	53
4.3	Proposed CNN with Open Source EEG Dataset (SEED, 3 emotion classes)	53

4.3.1 Comparison between the Performance of Different Parameter Setting	57
4.3.2 Comparison between Confusion Matrix (SEED)	58
4.3.3 Significant test for different parameter setting	61
<b>CHAPTER 5 CONCLUSION AND FUTURE WORKS</b>	<b>62</b>
5.1 Conclusion	62
5.2 Future Work	64
<b>REFERENCES</b>	<b>65</b>
<b>APPENDIX A</b>	<b>70</b>
<b>APPENDIX B</b>	<b>71</b>
<b>APPENDIX C</b>	<b>72</b>
<b>APPENDIX D</b>	<b>73</b>
<b>APPENDIX E</b>	<b>74</b>
<b>APPENDIX F</b>	<b>77</b>
<b>APPENDIX G</b>	<b>80</b>
<b>APPENDIX H</b>	<b>83</b>
<b>APPENDIX I</b>	<b>88</b>
<b>APPENDIX J</b>	<b>100</b>

## LIST OF FIGURES

Figure 1.1: The model of Sophia [2]	2
Figure 1.2: Emotion detection through external clues [4]	3
Figure 1.3: Emotion detection through EEG signal	3
Figure 2.1: Schachter-Singer Theory [7]	8
Figure 2.2: Lazarus Theory [7]	8
Figure 2.3: Discrete emotions claimed by Paul Ekman [10]	10
Figure 2.4: Bi-dimensional model of emotion [13]	10
Figure 2.5: Early recordings of human EEG from Berger's notebook [16]	13
Figure 2.6: The International 10/20 system electrode position [18]	14
Figure 2.7: The components of an ERP waveform [20]	15
Figure 2.8: The basic structure of a neural network [25]	18
Figure 2.9: Example of a CNN architecture [27]	18
Figure 2.10: Illustration of convolution [28]	19
Figure 2.11: Commonly used activation functions [30]	20
Figure 2.12: Maximum pooling (a) and average pooling (b) [31]	21
Figure 2.13: Illustration of dropout [32]	22
Figure 3.1: Flowchart for research methodology	29

Figure 3.2: Selected pictures from IAPS database	32
Figure 3.3: Selected audio clips from IADS database	32
Figure 3.4: Experimental paradigm	33
Figure 3.5: Electrodes position for the experiment	35
Figure 3.6: Instrumental set-up for the experiment	36
Figure 3.7: Visualization of generated TTL pulse in PC1	36
Figure 3.8: Illustration of EEG signal acquisition	37
Figure 3.9: Segmentation and labelling for EEG data collected in the lab	39
Figure 3.10: Experimental paradigm for SEED dataset [38]	40
Figure 3.11: Segmentation and labeling for SEED dataset	41
Figure 3.12: Selected channels in SEED dataset	42
Figure 3.13: Proposed CNN architecture	43
Figure 4.1: Accuracy curve for subject 8 with parameter setting 1	48
Figure 4.2: Accuracy curve for subject 8 with parameter setting 2	49
Figure 4.3: Accuracy curve for subject 8 with parameter setting 3	49
Figure 4.4: comparison between the performance of the CNN with different parameters setting (EEG data collected in the lab)	51
Figure 4.5: Confusion matrix for 8 subjects	52
Figure 4.6: Combined confusion matrix for 8 subjects	52
Figure 4.7: Accuracy curve for subject 11 with parameter setting 1	56
Figure 4.8: Accuracy curve for subject 11 with parameter setting 2	56
Figure 4.9: Accuracy curve for subject 11 with parameter setting 3	57
Figure 4.10: Comparison between the performance of the CNN with different parameters setting (SEED dataset)	58

Figure 4.11: Confusion matrix for 15 subjects (SEED)	60
Figure 4.12: Combined confusion matrix for 15 subjects	60
Figure I.1: Accuracy curves for subject 1 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c)	89
Figure I.2: Accuracy curves for subject 2 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c)	91
Figure I.3: Accuracy curves for subject 3 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c)	92
Figure I.4: Accuracy curves for subject 4 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c)	94
Figure I.5: Accuracy curves for subject 5 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c)	95
Figure I.6: Accuracy curves for subject 6 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c)	97
Figure I.7: Accuracy curves for subject 7 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c)	98
Figure I.8: Accuracy curves for subject 8 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c)	100
Figure J.1: Accuracy curves for subject 1 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c)	102
Figure J.2: Accuracy curves for subject 2 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c)	104
Figure J.3: Accuracy curves for subject 3 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c)	105
Figure J.4: Accuracy curves for subject 4 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c)	107
Figure J.5: Accuracy curves for subject 5 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c)	109
Figure J.6: Accuracy curves for subject 6 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c)	110



Figure J.7: Accuracy curves for subject 7 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c) 112

Figure J.8: Accuracy curves for subject 8 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c) 113

Figure J.9: Accuracy curves for subject 9 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c) 115

Figure J.10: Accuracy curves for subject 10 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c) 116

Figure J.11: Accuracy curves for subject 11 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c) 118

Figure J.12: Accuracy curves for subject 12 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c) 119

Figure J.13: Accuracy curves for subject 13 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c) 121

Figure J.14: Accuracy curves for subject 14 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c) 122

Figure J.15: Accuracy curves for subject 15 with different parameter setting: setting 1 (a), setting 2 (b) and setting 3 (c) 124

## LIST OF TABLES

Table 1.1: Properties of EEG data in study [5]	4
Table 1.2: The properties of dataset used in the project	5
Table 2.1: Comparison between discrete model and dimensional model	11
Table 2.2: The characteristics of brain wave frequencies [15]	12
Table 2.3: Label of different letters based on International 10/20 system [18]	14
Table 2.4: Properties of ERP components	16
Table 2.5: Related works for EEG emotion classification through conventional approach	25
Table 2.6: Related works for EEG emotion classification using deep learning network	27
Table 3.1: Properties of the experiment	35
Table 3.2: Label for EEG signal collected in the lab	39
Table 3.3: Label for SEED dataset	42
Table 4.1: Properties of datasets used in the project	46
Table 4.2: Comparison of the results with different setting of parameters	48
Table 4.3: Confirmation of parameter setting with significant test (EEG data collected in the lab)	53
Table 4.4: Comparison of the results with different setting of parameters for SEED dataset	55
Table 4.5: Confirmation of parameter setting with significant test (SEED dataset)	61

## LIST OF ABBREVIATIONS

BCI	:	Brain Computer Interface
CNN	:	Convolutional Neural Network
DBN	:	Deep Belief Network
EEG	:	Electroencephalograms
ERP	:	Event Related Potential
IADS-2	:	International Affective Digitalized Sounds
IAPS	:	International Affective Picture System
ISI	:	Inter-Stimulus Interval
KNN	:	K-Nearest Neighbors
LDA	:	Linear Discriminant Analysis
LR	:	Logistic Regression
NB	:	Naive Bayes
PNN	:	Probabilistic Neural Networks
SEED	:	SJTU Emotion EEG Dataset
SVM	:	Support Vector Machine
TMSi	:	Twente Medical Systems International Porti System
TTL	:	Transistor-transistor logic pulse
UTeM	:	Universiti Teknikal Malaysia Melaka

# CHAPTER 1

## INTRODUCTION

This chapter consists of five sections. The overview of the project is firstly presented in this chapter. The objectives of this study are stated in section 1.2. Section 1.3 is the problem statement regarding to the study. Section 1.4 discusses the scope of work. The thesis outline is presented in the final section of this chapter.

### 1.1 Project Overview

Emotions can be defined as sensory projection to stimuli which involves thoughts, physiological changes and expression of feelings [1]. In recent years, emotion recognition system playing an increasingly important role in enhancing the experience of human-machine interaction. For instance, the importance of emotion recognition in human-machine interaction has clearly shown by a human-like robot named Sophia. Sophia is a social robot created by Hanson Robotics which is able to recognize and

process emotional data during conversation with human [2]. The model of Sophia is shown in Figure 1.1.

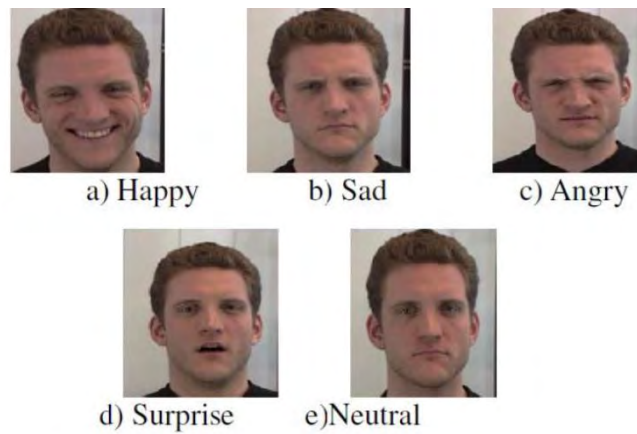


**Figure 1.1: The model of Sophia [2]**

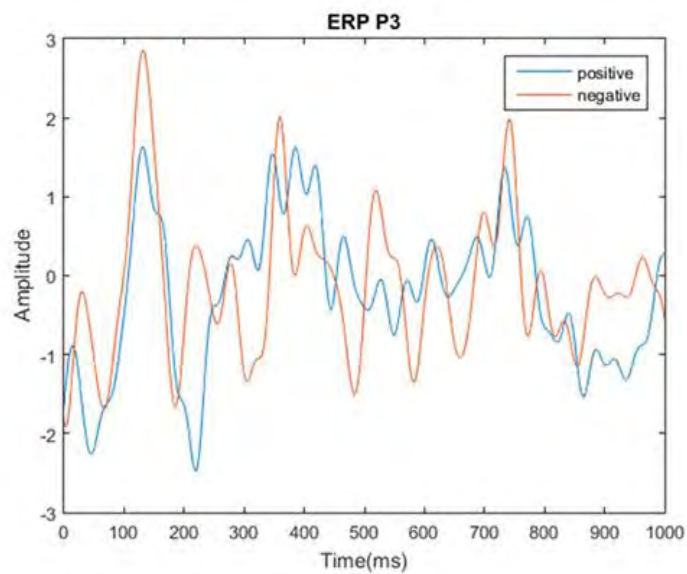
Various research has been carried out to study human emotions. Generally, human emotion can be classified through the external appearance clues and the “inner” emotion reflected by brain activities. Emotion detection through external clues such as text, speech intonation and facial expression are commonly used to classify emotion as it is a direct reflection of emotion which is able to be easily detected. On the other hand, emotion classification through the “inner” emotion reflected in electroencephalograms (EEG) signal with the aid of deep learning technique becoming popular in recent years as EEG decoding plays an important role in most brain computer interface (BCI) for clinical applications. The researches revealed that the characteristic of EEG signals with high temporal resolution allow it to react to emotional stimuli in millisecond. This indicate that emotion classification using EEG signal is a more reliable approach as compared to the external appearance clues that can be hidden and faked in expression [3].

In light of this, a deep learning technique, convolutional neural network (CNN) algorithm is implemented in this project to decode EEG signals with different

emotional states. This project begins with experimental design for EEG signal acquisition. The raw EEG signals will be preprocessed and rearranged before fed into the proposed CNN architecture to be classified into different emotional states.



**Figure 1.2: Emotion detection through external clues [4]**



**Figure 1.3: Emotion detection through EEG signal**

## 1.2 Objectives

There are three objectives in this project which listed as below:

- i. To design and develop an experiment to acquire EEG signal with different emotions.
- ii. To analyze and optimize the parameters of CNN architecture for EEG emotion classification.
- iii. To validate the CNN architecture for EEG emotion classification in terms of classification accuracy.

## 1.3 Problem Statement

Emotions detection through text, speech tone and facial expression are not reliable enough as human can fake their expression of feelings. To cope with this situation, an EEG-based emotion classification system has been designed to classify human emotion by using EEG signal. Nevertheless, the EEG-based emotion classification system in study [5] only yield about 59% accuracy with the EEG data collected in the lab. Therefore, this project is aims to develop and optimize the parameters of the CNN model in order to improve the performance for EEG emotion classification. Different modality of stimuli will be designed to induce emotion for EEG data acquisition.

**Table 1.1: Properties of EEG data in study [5]**

<b>Stimuli</b>	Picture (IAPS)
<b>No. emotional category</b>	2
<b>Classification accuracy</b>	59%

#### 1.4 Scope of Work

This project is intended to implement a CNN algorithm that able to classify different emotions by using EEG signal as input. Experimental paradigm is designed to induce two classes of emotion (positive and negative) for EEG signal acquisition purpose. MATLAB script is written for preprocessing of the acquired raw EEG signal. The implementation of CNN algorithm is done in python (v2.7.12) with TensorFlow (V1.0.0) as framework.

The CNN algorithm is trained with both EEG data collected in the lab as well as an open source dataset (SEED). The categorization of emotion for both EEG data collected in the lab and SEED are based on dimensional model of emotion. There are two classes of emotion included in the EEG data collected in the lab, which is positive and negative emotions. On the other hand, a total of three classes of emotions, which is positive, neutral, and negative emotions are included in SEED dataset. The properties of datasets used in the project are summarized in Table 1.2.

**Table 1.2: The properties of dataset used in the project**

<b>Dataset properties</b>	<b>EEG data collected in the lab</b>	<b>Open source dataset (SEED)</b>
<b>Emotion model</b>	Dimensional model	Dimensional model
<b>Stimuli</b>	Picture (IAPS) and audio clips (IADS-2)	Movie clip
<b>Category of emotion</b>	Two emotions (positive and negative)	Three emotions (positive, neutral and negative)