

REAL-TIME FACIAL EXPRESSION RECOGNITION (FER) SYSTEM
FOR VIRTUAL MEETINGS USING JOINT LEARNING METHOD

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A project report submitted in fulfilment of the
requirements for the award of the degree of
Master of Engineering (Computer & Microelectronic Systems)”

School of Electrical Engineering
Faculty of Engineering
Universiti Teknologi Malaysia

JULY 2022

ACKNOWLEDGEMENT

In preparing project report, I was in contact with many people, researchers, academicians, and practitioners. They have contributed towards my understanding and thoughts. In particular, I wish to express my sincere appreciation to my main thesis supervisor, Dr. Mohd Azhar Bin Abdul Razak, for encouragement, guidance, critics and friendship. I am also very thankful to examiners Prof. Madya Ir. Ts. Dr. Nasrul Humaimi Mahmood, Prof. Madya Ts. Dr. Eileen Su Lee Ming Dr. Mohd Afzan Othman and Ts. Dr. Zaid Omar for their advices and opinions. Without their continued support and interest, this thesis would not have been the same as presented here.

I am also indebted to Universiti Teknologi Malaysia (UTM) for providing me a platform to conduct my study. The access granted for online publications material has enabled me to conduct my research with ease.

My fellow postgraduate student should also be recognised for their support. Their views and tips are useful indeed. Unfortunately, it is not possible to list all of them in this limited space. I am grateful to all my family member.

ABSTRACT

Ever since the whole world was being hit by the global pandemic, the lifestyle of the people has been drastically impacted. Virtual meetings, seminars and online lessons have started to become the new norm since due to the social distancing measures being implemented as well as the convenience it brings. The pandemic has made people realized that having virtual meetings not only reduces the risk of being exposed to an airborne disease, it also saves cost and time. However, the down side to virtual meetings is that speakers and audience tends to have lesser dynamics and speakers often felt difficult to get a grip of what their audiences' reaction are, even having all their faces displayed on the screen. This is where facial expression recognition would come in place. Facial Expression Recognition (or known as FER) is a field where algorithms would help automatically recognizes the expression/emotions of people based on their facial features. FER using computer vision in particular is not a new topic as there has been plenty of studies being conducted throughout recent years. However, many has figured that exist challenges such as for a computer to accurately recognize a person's expression through its facial features as every person express their emotions on their face differently due to their unique biometric features. Therefore, this project introduces a real-time facial expression recognition system where it would be able to accurately classify them into the 7 basic expressions which includes neutral, happy sad, angry, fear, disgust and surprise. It will be done by using the concatenation of facial identity and expression recognition pre-trained model. This project was able to improve the overall classification accuracy of the automatic recognition of facial expression, using facial identity parameters as an additional feature whereby a 7-class classification accuracy of 97.10% is being achieved on CK+ dataset while 76.72% is obtained on the FER2013. A real-time application of the system is also being demonstrated.

ABSTRAK

Sejak seluruh dunia dilanda pandemik global, gaya hidup rakyat telah terjejas secara drastik. Pertemuan maya, seminar dan pelajaran dalam talian mula menjadi norma baharu berikutan langkah penjarakan sosial yang dilaksanakan. Pandemik telah menyedarkan orang ramai bahawa mengadakan pertemuan maya bukan sahaja mengurangkan risiko terdedah kepada penyakit bawaan udara, ia juga menjimatkan kos dan masa. Walau bagaimanapun, kelemahan kepada mesyuarat maya ialah penutur dan penonton cenderung mempunyai dinamik yang lebih rendah dan penutur sering berasa sukar untuk memahami reaksi penonton mereka, walaupun semua wajah mereka dipaparkan pada skrin. Di sinilah pengecaman ekspresi muka akan dilaksanakan. Pengecaman Ekspresi Muka (atau dikenali sebagai FER) ialah medan di mana algoritma akan membantu mengecam secara automatik ekspresi/emosi orang berdasarkan ciri muka mereka. FER menggunakan penglihatan komputer khususnya bukanlah topik baru kerana terdapat banyak kajian yang dijalankan sepanjang tahun kebelakangan ini. Walau bagaimanapun, ramai yang menyedari bahawa wujud cabaran seperti penggunaan komputer untuk mengenali ekspresi seseorang dengan tepat melalui ciri-ciri wajahnya kerana setiap orang meluahkan emosi mereka pada wajah mereka secara berbeza disebabkan ciri biometrik mereka yang unik. Oleh itu, projek ini memperkenalkan sistem pengecaman ekspresi muka masa nyata di mana ia akan dapat mengklasifikasikannya dengan tepat ke dalam 7 ekspresi asas yang merangkumi neutral, gembira sedih, marah, takut, jijik dan terkejut. Ia akan dilakukan dengan menggunakan penggabungan identiti muka dan model pra-latihan pengecaman ekspresi. Projek ini dapat meningkatkan ketepatan pengelasan keseluruhan bagi pengecaman automatik ekspresi muka, menggunakan parameter identiti muka sebagai ciri tambahan di mana ketepatan klasifikasi 7 kelas sebanyak 97.10% dicapai pada dataset CK+ manakala 76.72% diperolehi pada FER2013 . Aplikasi masa nyata sistem juga telah ditunjukkan.

TABLE OF CONTENTS

	TITLE	PAGE
	DECLARATION	i
	ACKNOWLEDGEMENT	ii
	ABSTRACT	iii
	ABSTRAK	iv
	TABLE OF CONTENTS	v
	LIST OF TABLES	viii
	LIST OF FIGURES	ix
	LIST OF ABBREVIATIONS	xi
	LIST OF SYMBOLS	xii
	LIST OF APPENDICES	xiii
CHAPTER 1	INTRODUCTION	1
	1.1 Problem Background	1
	1.2 Problem Statement	3
	1.3 Hypothesis	4
	1.4 Research Goal	5
	1.4.1 Research Objectives	5
	1.5 Scope	5
	1.6 Proposal Outline	5
CHAPTER 2	LITERATURE REVIEW	7
	2.1 Introduction	7
	2.2 Related works	7
	2.2.1 Review on the popular database	23
	2.3 Critical Review	25
	2.4 Research Gap	28
	2.5 Chapter Summary	29

CHAPTER 3	RESEARCH METHODOLOGY	30
3.1	Introduction	30
	3.1.1 Project Overview	30
3.2	Platform Used	31
	3.2.1 Software Platform	31
	3.2.2 Hardware Platform	32
3.3	Network Architecture	32
3.4	Dataset Preparation	35
3.5	Model Training and Testing	37
3.6	Real-time Deployment	39
3.7	Project Milestones and Gantt Chart	40
3.8	Chapter Summary	42
CHAPTER 4	RESULT AND DISCUSSION	43
4.1	Introduction	43
4.2	Dataset Augmentation	43
4.3	ROI cropping	44
4.4	Pre-processing	48
4.5	Baseline Model	49
	4.5.1 Hyperparameter tuning	51
	4.5.2 Baseline Model Training Analysis	54
	4.5.3 Baseline Model Testing	56
4.6	CNN model with identity features concatenated	57
	4.6.1 Final model training Analysis	59
	4.6.2 Final Model Testing	60
4.7	Real-time performance testing	62
	4.7.1 Runtime performance	65
4.8	Proposed functionality on an actual video call system	66
4.9	Comparison With State-of-the-art Models	69
4.10	Chapter Summary	70
CHAPTER 5	CONCLUSION AND FUTURE WORK	71
5.1	Conclusion	71

5.2	Recommendation for future work	72
	REFERENCES	73
	Appendices A - D	82 - 93

LIST OF TABLES

TABLE NO.	TITLE	PAGE
Table 2.1	Table of Summary on Paper Review	15
Table 3.1	Distribution of Dataset	36
Table 3.2	Project Milestone	40
Table 3.3	Gantt Chart	41
Table 4.1	Result of performing digital image augmentation on CK+ dataset	44
Table 4.2	ROI cropping using Haar Cascade vs HOG on the CK+ dataset	44
Table 4.3	Difference between the cropped region of using Haar Cascade and HOG	45
Table 4.4	Misprediction of the HOG in low contrast region	47
Table 4.5	False positive of Haar Cascade	47
Table 4.6	Result of using different optimizers on the CK+ dataset	52
Table 4.7	Result of using different optimizers on the FER2013 dataset	52
Table 4.8	Batch size tuning for baseline model on CK+	53
Table 4.9	Batch size tuning for baseline model on FER2013	53
Table 4.10	Hyperparameter summary	54
Table 4.11	Baseline model classification Accuracy on CK+ dataset	56
Table 4.12	Baseline model classification Accuracy on FER2013 dataset	56
Table 4.13	Final model classification accuracy on CK+ dataset	60
Table 4.14	Final model classification accuracy on FER2013 dataset	61
Table 4.15	Associated color representation to each expression	65
Table 4.16	State-of-the-art models on CK+ dataset	69
Table 4.17	State-of-the-art models on FER2013 dataset	69

LIST OF FIGURES

FIGURE NO.	TITLE	PAGE
Figure 2.1	Dataset usage trend in recent years	23
Figure 2.2	Example images of FER2013 dataset	23
Figure 2.3	Example images of CK+ dataset	24
Figure 2.4	Example images of JAFFE dataset	24
Figure 2.5	Example images of SFEW dataset	25
Figure 3.1	Project Overview	30
Figure 3.2	Building block of a typical ResNet	33
Figure 3.3	Network Architecture of ResNet	34
Figure 3.4	Network Architecture of DeepID2	34
Figure 3.5	Proposed CNN architecture	35
Figure 3.6	Flow of the model training and testing	37
Figure 3.7	Flow of the Real-time Deployment	39
Figure 4.1	Haar Cascade on an uncontrolled video call environment	46
Figure 4.2	HOG on an uncontrolled video call environment	46
Figure 4.3	Image resizing for ResNet input requirement	48
Figure 4.4	Effect of Histogram Equalization	48
Figure 4.5	Effect of CLAHE	49
Figure 4.6	ResNet model loaded from Keras	50
Figure 4.7	Modified ResNet model for FER task	50
Figure 4.8	Best model are being saved after every epoch	51
Figure 4.9	Baseline model training accuracy on CK+	54
Figure 4.10	Baseline model training loss on CK+	55
Figure 4.11	Baseline model training accuracy on FER2013	55
Figure 4.12	Baseline model training loss on FER2013	55
Figure 4.13	Confusion Matrix of the baseline model on CK+ test set	56

Figure 4.14	Confusion Matrix of the baseline model on FER2013 test set	56
Figure 4.15	DeepID2 input structure	58
Figure 4.16	Snippet of the concatenated model structure	58
Figure 4.17	Final model training accuracy on CK+	59
Figure 4.18	Final model training loss on CK+	59
Figure 4.19	Final model training accuracy on FER2013	59
Figure 4.20	Final model training loss on FER2013	60
Figure 4.21	Confusion Matrix of the final model on CK+ test set	60
Figure 4.22	Confusion Matrix of the final model on FER2013 test set	61
Figure 4.23	Detecting happy expression from video sequence	62
Figure 4.24	Detecting different expressions from video sequence	62
Figure 4.25	Prediction on occluded face	63
Figure 4.26	False detection on face region	63
Figure 4.27	Real-time performance on capturing neutral (left) and happy (right) expressions	64
Figure 4.28	Real-time performance on capturing surprise (left) and sad (right) expressions	64
Figure 4.29	Real-time prediction time	65
Figure 4.30	Demonstration of integrating the model in a video call system	66
Figure 4.31	Demonstration of the view when overall expression is Happy	67
Figure 4.32	False positive on detecting face from conference call	67
Figure 4.33	Wrong prediction on conference call	67
Figure 4.34	Predicted expression from live video with faces being blocked out	68
Figure 4.35	Proposed implementation in a large group of video call	69

LIST OF ABBREVIATIONS

<i>AI</i>	-	Artificial Intelligence
<i>ANN</i>	-	Artificial Neural Network
<i>CK+</i>	-	Extended Cohn-Kanade
<i>CLAHE</i>	-	Contrast Limited Adaptive Histogram Equalization
<i>CNN</i>	-	Convolutional Neural Network
<i>CoV-2</i>	-	Severe Acute Respiratory Syndrome Corona Virus 2
<i>FER</i>	-	Facial Expression Recognition
<i>FIR</i>	-	Facial Identity Recognition
<i>GA</i>	-	Genetic Algorithm
<i>GB</i>	-	Gradient Boosting
<i>GCNN</i>	-	Graph Convolutional Neural Network
<i>GF</i>	-	Geometric Feature
<i>HCI</i>	-	Human Behaviour Interpretation
<i>HOG</i>	-	Histogram of Oriented Gradients
<i>JAFEE</i>	-	Japanese Female Facial Expression
<i>KDL</i>	-	Kernalized Dense Layer
<i>KNN</i>	-	K-Nearest Neighbour
<i>PSO</i>	-	Particle Swarm Optimization
<i>PLBP</i>	-	Pyramid Local Binary Pattern
<i>PLPQ</i>	-	Pyramid Local Phase Quantization
<i>ROI</i>	-	Region of Interest
<i>SFEW</i>	-	Static Facial Expressions in the Wild
<i>SVM</i>	-	Support Vector Machine
<i>UTM</i>	-	Universiti Teknologi Malaysia

LIST OF SYMBOLS

<i>fps</i>	-	Frame rate
$^{\circ}$	-	Degree symbol
%	-	Percentage
<i>e</i>	-	Error rate

LIST OF APPENDICES

APPENDIX	TITLE	PAGE
Appendix A	Project Codes	83
Appendix B	Project Demo Video Link	92
Appendix C	Plagiarism Check	93
Appendix D	CK+ Database Usage Agreement	94

CHAPTER 1

INTRODUCTION

1.1 Problem Background

The recent outbreak of the Coronavirus (or also known as COVID-19) has caused everyone in the world to be in a devastating state, affecting both the daily life and the health of every single person. Covid-19 which comes from the term Severe Acute Respiratory Syndrome Corona Virus 2 (SARS-CoV-2) is a type of pneumonia disease which is highly contagious and is transmitted through close contact between individuals, and because of that, physical classes and meetings have since been discouraged as it poses high infection risks to the attendees. Instead, virtual meetings, seminars and online lessons are starting to become the new norms as not only does it reduce the risk of people getting exposed to air-borne diseases, it also saves cost, as it eliminates the need of having a physical venue. On top of that, it also reduces the time wasted due to travelling as virtual meetings are as convenient as a click away. People have taken a liking towards this new norm of virtual meetings due to the countless benefits it brings. In fact, according to a survey conducted by McKinsey [1], 90% of the organizations are going to adopt some sort of hybrid work model where employees would have a combination of remote and on-site work in the post-pandemic situation. This indicates that even when the pandemic is over, this new norm of virtual meetings would still be relevant moving forward. However, as wonderful as it may sound, virtual meetings do have several drawbacks as well despite how much of a hassle it would save. Aside from the technical limitations, the most prominent disadvantage of virtual meetings is the loss of interpersonal interactions between the speakers and the audience [2]. There are actually many different forms of communication happening when people meet physically with each other and it is not limited to voice. Body language, specifically facial expressions, plays such a vital role in conveying a message, as it holds a good amount of information, which is often lost when meeting virtually. In fact, according to researches, two third of information are

transmitted through non-verbal signals when interacting with someone with 55% of the information communicated through facial expression [3] [4]. This nonverbal signal when in sync with the words that you're trying to say, would increase clarity and rapport towards the listeners [5]. This is something that is very difficult to be captured through online meetings especially when there is more than one person in the room. Even with everyone's video camera turned on, it is still very strenuous for both the speaker and the audience to get a grip of how well everyone is taking in the information which often leads to a lost in communication. This is where automatic Facial Expression Recognition would come in place.

Facial Expression Recognition (or most commonly known as FER) is a field where algorithms would help automatically recognizes the expression or emotions of people, based on their facial features. A Facial Expression Recognition task includes classifying a human face that are captured digitally in the form of video or image into discrete categories such as happiness, sadness, fear, surprise, disgust and anger, which are the 6 basic human emotions that are experienced by all races and cultures universally, as identified by psychologist Paul Eckman [6]. Not limited to online meetings, FER has actually been seen to have the potential to be applied in a wide variety of field. This includes Human-Computer Interaction especially with the recent spike in the robotics and AI industry, Human Behaviour Interpretation (HCI) such as criminal interrogation, and Virtual Reality (VR). FER is definitely not a new field that has just recently emerged. In fact, the US transportation Security Administration (TSA) has started tests on facial expression screening on surveillance through computers since 2003 where the program was supervised by Paul Ekman, renowned psychologist who was one of the pioneers in facial expression recognition [7]. Not until recently, this has become a hot topic once again with the advancement in Artificial Intelligence together with the current pandemic situation that we're in, which leads to a high demand in the industry.

Artificial Intelligence, specifically machine learnings has gained its popularity in recent years especially in the field of computer vision as it has the capability of modelling the human learning process where it takes in data, identify the common traits of the data from the same category and eventually it would be able to classify new data into the groups that it associates with [8]. The automatic identification of the important features without human intervention is what makes these algorithms special

and makes it suitable to be applied in computer vision tasks where it leads to a wide variety of application, such as plant disease identification [9][10][11] or the detection of coronavirus based on X-ray images [12][13][14].

Plenty of progress has been made on FER through adopting CNN in recent years and it had shown promising results. However, there are still multiple issues that are commonly faced across researches due to the complexity and the variations of expressions possessed by people. Some of the most common challenges is the way the input data is captured. For instance, variation in lighting intensity could affect the classification accuracy of the neural network, as with a poor quality of lighting, the captured data could contain insufficient information for the computer to process it [3] which leads to the need of pre-processing the captured data before feeding the it to the neural network. Furthermore, many has figured that it is rather difficult to distinguish between certain expression with each other due to their subtle differences, such as fear and disgust. Moreover, for a computer to recognize a person's expression through its facial features remain a challenging task as every person express their emotions on their face differently due to their unique biometric features.

Therefore, this project introduces a real-time facial expression recognition system where it would be able to accurately classify them into the 7 basic expressions, using the concatenation of Facial Identity Recognition (FIR) and Facial Expression Recognition (FER) pre-trained model. This would improve the overall classification accuracy of the automatic recognition of facial expression, using facial identity parameters as an additional feature so that the unique facial biometrics would be incorporated.

1.2 Problem Statement

With the pandemic situation that world is currently in, virtual meetings and conferences have since became the new norm and people have become fond of this new norm due to the convenience it brings. However, meeting virtually do not transmit the intended information well, compared to meeting physically as according to researches, most of the communication happens through nonverbal signals, which means that the facial expression plays an important aspect to fully understands what the presenter is trying to say and how well the audience is taking in the information

[5]. This is something that is very difficult to be captured through virtual calls as there are usually a lot of people in the room showing different camera views which sometimes could be very distracting especially in a large group. On top of that, many tends to be reluctant to turn on their camera due to privacy reasons. Therefore, it leads to a demand in having an algorithm to capture the audience's reaction and display how the audience is feeling instead of their actual faces, which would be so much convenient.

Over the years, there had been plenty of studies carried out on FER and there are several issues that are commonly seen which one of them is insufficient and unbalanced training dataset available. Some expressions such as happy are so much easier to obtain from the internet as people tends to upload more happy pictures on their social media, but expressions like disgust or sad are rare. Moreover, certain expressions are having quite closely related and have subtle differences which makes it difficult to distinguish. Another issue is that every person expresses their emotions differently due to their different biometric facial features which makes the algorithm difficult to generalize the features of a particular expression [15]. All of these contributes to the low accuracy obtained for multiclass classifications of facial emotions.

1.3 Hypothesis

Using a Facial Expression Recognition system that can accurately identify and classify people's emotions based on their facial characteristics can help establish a better communication in virtual calls. Transfer learning approach is a feasible option when there are limited and unbalanced dataset issue as it can utilize pre-trained weights to repurpose an existing CNN model on a new set of training data. Moreover, by using a joint learning method of Facial Identity Recognition and Facial Expression Recognition models would help in increasing the overall classification accuracy of facial emotions.

1.4 Research Goal

This leads us to the objective of this project, which is to develop a real-time Facial Emotion Recognition system for virtual meetings using CNN which would help to establish a better communication between the presenters and the audience.

1.4.1 Research Objectives

1. To evaluate the performance of the model of having identity features concatenated with expression features for classifying facial expressions on 2 types of datasets that are vastly different.
2. To deploy the model for real-time application that would assist in virtual meetings

1.5 Scope

This project covers the implementation of a real-time facial emotion recognition system by adopting transfer learning method of 2 different CNN models (FER and FIR), concatenate the features extracted from both models, and retrain them on a facial expression dataset. This project covers identifying the macro-expression of a human and does not include the detection of micro-expression where it detects the hidden change of human expression that occurs less than half of a second [16]. Moreover, unsupervised learning will not be part of the scope, the study mainly focuses on supervised learning algorithms, more specifically, convolutional neural networks. This work also does not include spatial-temporal learning or training using video sequence, but instead, the proposed project is to be trained with static images and implement in on a real-time webcam where it would analyse the expressions by frame.

1.6 Proposal Outline

The structure of this proposal is organized as follows: Chapter 1 will cover the introduction to the problem, a brief background on the main motivation of tackling this topic, the problem that has been captured, the hypothesis that has been concluded and what's planned to be achieved in this study. Continuing in Chapter 2, will be discussing

some of the emerging trends pertaining to the Facial Expression Recognition using deep learning models, followed by a comprehensive critical review on the popular techniques. Following Chapter 3, will be incorporating the detailed methodology for this work. Chapter 4 will be covering on the final results that has been obtained throughout this project. Eventually, Chapter 5 provides the concluding remarks of the whole report along with some recommendations for future work.

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