An Emotion-Based Movie Recommendation System Using Convolutional Neural Network

By

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I would like to express my sincere thanks and appreciation to my supervisor, Miss Tseu Kwan Lee who has given me this bright opportunity to engage in a deep learning project. It is my first step to establish a career in Artificial Intelligence (AI) field. A million thanks to you.

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ABSTRACT

With the growing number of movies released each year, movie recommender systems are becoming more and more important in providing recommendations to users efficiently. However, one of the challenges in developing the recommendation system is the system itself must be accurately enough to record the user's profile, in order to determine their movie preferences. Therefore, a web-based movie recommendation system with Convolutional Neural Network (CNN) model is proposed in this study, to recognize human emotion from facial images. The movie recommendation process will be carried out by capturing the user’s emotion in order to save their searching time rather than manually going through all of the movies to find and pick the most suited one.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
CBF	Content Based Filtering
CF	Collaborative Filtering
CNN	Convolutional Neural Network
ReLU	Rectified Linear Unit
SVM	Support Vector Machine

CHAPTER 1

INTRODUCTION

1.1 Problem Statement and Motivation

A common issue in movie recommendation system is the constant change of user preferences. For example, a person may have a particular interest in comedy movie today but may have a different intention tomorrow. This makes the recommendation of system much more difficult as the user preferences are random and unpredictable. In addition, the traditional methods of recommendation such as CBF and CF fail to understand and capture the user's constantly changing preferences as it does not consider the impact of user emotion [1].

Furthermore, there is a wide range of movies for a specific genre on the Internet such as action, horror, comedy, drama, science fiction, thriller movies and so on. When a person seeks to find out the best movie in a particular category, manually going through each of the single category is quite tedious and time consuming. As a result, manual searching is inefficient and can be further improved [2]. In this case, an emotion-based movie recommendation system is critical in recommending the finest movie in a short period.

The motivation of this project is to develop a movie recommendation system based on emotion that can keep up with the continuous changing of user preferences. This is due to the system's ability to recognize users' emotions in real time. Following that, the system will suggest a number of movies based on the user's current mood. As a result, the suggested system is capable of resolving the unpredictable and constantly changing user preferences that prior recommendation approaches have encountered.

Finally, the proposed system is able to recommend movies according to the user’s emotion in an efficient way. Instead of manually browsing through the thousands of movies available online, the proposed method utilizes the user's face expression to recommend movies efficiently. In this way, the method also saves time by avoiding the need to manually browse through all of the movies which is time consuming and sometime user might end up with not able to find the movies they wish to watch.

1.2 Project Scope

The end product of this project is a web application which will recommend movies based on user emotion. To begin with, a deep learning model will be trained using CNN to recognize user facial expression. Next, the model will be validated with performance metric such as k-fold cross validation to assess the performance of model. After integrating the model into the web application, the proposed system would be able to recommend movies to users based on the user's emotion in real time. In addition, the web application will include a login page to allows users to gain access to the system by entering their username and password. A database will be implemented to store user's data for authentication and user's recommended movies. The web application will have a user profile page that lists out all the recommended movies and his preferences on movie genre. In the end, the web application will be deployed and hosted in the cloud using cloud application platforms such as Heroku, PythonAnywhere or Digital Ocean to enable any user to access the web application through online.

1.3 Project Objectives

To gain an understand on this domain, existing methods used in movie recommendation system such as Content Based Filtering and Collaborative Filtering were studied. Upon understand the existing method, this project applies artificial intelligence techniques such as CNN to develop the emotion recognition model. The model will classify and predict human emotions after it has been trained. By integrating the model into the web application, the web application will predict the user's emotion and make movie recommendations based on it.

The sub-objectives of this project are as follow:

1. To study the existing methods and artificial intelligence techniques in building an emotion recognition model implemented into the web application.

2. To propose a movie recommendation system based on human emotion prediction.

3. To develop the proposed method in recommending relevant movies to user based on human emotion.

4. To evaluate the effectiveness of the proposed method in recommending relevant movies to user.

1.4 Innovation and Contribution

The innovation of this project is the implementation of deep learning in facial recognition. It can also be applied in many real-world applications such as security systems, identifying people on social media platforms and validating people's identities. In this project, facial recognition is applied to identify the human emotion to make movie recommendations. By applying deep learning techniques, the CNN model will learn to recognize human emotion from the training set that contains thousands of human faces. The CNN model learns by passing through a series of convolution layers with filter, pooling, and fully connected layers. After the training is completed, the model will be able to predict human emotion.

Aside from that, users can benefit from this application in a number of ways. To begin, users can learn about their emotions addition to receiving a selection of movies to view. Furthermore, they will not have to waste time manually searching for a desired movie as the system will capture their emotion through facial recognition and proposed the relevant videos to them. This is able to enhance the user's movie viewing experience.

Moreover, the contribution of this project is the system can be applied in the field of recommendation systems. This is because recommendation systems require a lot of data to make suggestions effectively. Thus, the collection of user's emotions can provide an additional information to help generate a better decision in recommending product.

1.5 Background Information

A movie recommendation system is a system which collects user data based on user's interaction activities with the system and recommends related movies to them. Traditional techniques used in movie recommendation system include Content Based Filtering (CBF) that recommends items based on similarities in the user's historical interests and Collaborative Filtering (CF) which employs user to user comparison to find likeminded users [1].

As technology advances, artificial intelligence (AI) techniques are emerging as an alternative to traditional methods. According to Schiavini, recommendation engines apply AI techniques to offer rapid and to-the-point recommendations that are tailored to each customer's needs and interests [3]. For example, machine learning is applied in analyzing emotion based on user reviews, Support Vector Machine (SVM) is used to classify human emotion and neural networks are utilized to extract features from facial images. Even though the research in the field of movie recommendation systems have been ongoing for decades, interest remains high due to the abundance of practical applications and the problem-rich subject. Some of the problems include the constant changing of user preferences and the inefficiency of searching movies manually.

Hence, this project focused on the movie recommendation system based on human emotions. The proposed system will apply Convolutional Neural Network (CNN) to develop a deep learning model that can recognize human emotion and recommend a set of movies in relation to the current emotion of users. Human emotion is an important aspect in recommending products as human beings experience a wide range of emotions as they go about their daily lives. Typically, emotion refers to a strong, subjective affective state that arises in response to anything we see or hear and are frequently assumed to be actively felt and deliberate [4].

CHAPTER 2

LITERATURE REVIEW

2.1 Previous Works

2.1.1 Machine Learning in Emotion Detection

Yu et al. developed a Support Vector Machine (SVM) model to classify all seven kinds of emotions including anger, dispute, bear, happiness, sadness, secure, and neutral. These emotions are separated into two subcategories which are the positive and negative emotions. The subcategories are continued to be divided until a distinct category is formed c. On the other hand, the technique used in movie recommendation is Content Based Filtering (CBF). CBF is used to offer products to customers based on the similarity of their previous choices. Furthermore, the Cosine Similarity algorithm is applied to access the quality of songs in relation to the users' present feelings.

Figure 2.1 shown the confusion matrix on FER2013 dataset [6] where the accuracy result of the model is approximately 62.10%. The probability of finding happy or surprise faces is the highest, at 83%. The model has the lowest recognition accuracy on fear, at only 23%. Meanwhile, the model correctly predicts anger 60% of the time, disgust 29% of the time, and sadness 53% of the time.

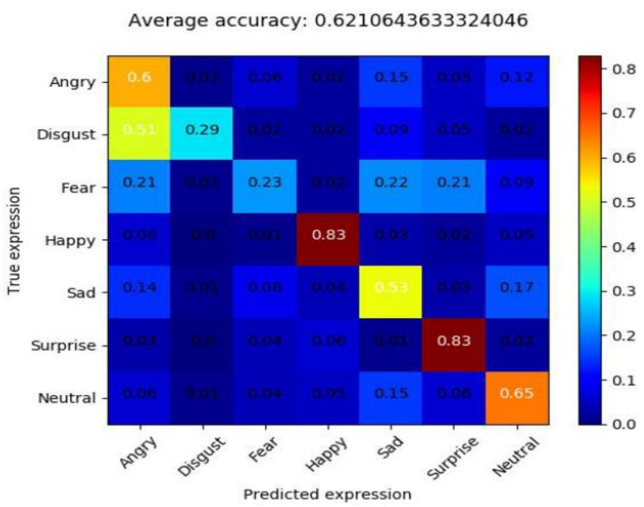


Figure 2.1 Confusion Matrix on FER2013 Dataset [5]

The benefit of using this technique is it can meet the users' listening needs by applying emotion recognition. However, the limitation is the risk of overfitting during training process will increase as the number of learning parameters increase.

Saraswat proposed another method for movie recommender system by analyzing emotion from user generated contents such as reviews and comments. They include emotion lexicons such as happiness, sadness and surprise which can be used in movie recommendations. The most important step in emotion analysis of reviews is the data preprocessing step. This step is critical for filtering out unnecessary content and extracting only the important information [7].

The reviews in the corpus are tokenized first, then changed to lowercase. Then, to remove the suffix from the term and reduce the tokens to their underlying word, stemming is done. For example, 'happier', 'happily', and 'happiness' are converted to their root word 'happy'. Followed with the process of emotion profiling of movies based on reviews is carried out. It is worth knowing that a given review may convey more than one emotion. In the beginning, the weights for all six emotions (joy, fear, sadness, anger, love, and surprise) are initialized to zero. Each word in the review serves as a token, and if the token matches one of the emotion lexicons, the value of the emotion's strength is increased by the token's weight. Upon reading all of the review tokens, the emotion strengths of each emotion will reflect the review's emotion profile.

The advantage of using emotion-based method is it provides more accurate recommendation compared to rating-based cosine item similarity. However, there exists a certain degree of blurriness and fuzziness between the lexicons of emotion features [7].

2.1.2 Deep Learning in Emotion Detection

Zhang devised a movie recommendation system using Deep Residual Network (ResNet-38) to detect the emotion of users. For the Kaggle-fer2013 dataset, the model achieves an accuracy of 64.02 percent. The Deep Residual Network is invented to solve the degradation problem in which the accuracy of model will become worse when the number of network layers increase [8].

To extract features from images, Input layer, Convolutional layer and Batch Normalization Layer as well as a rectified linear unit (ReLU) activation function are used. Besides that, there are four Residual Structures to prevent the data error from worsening as the model depth increases. The graphical representation of the Residual Structure is shown in Figure 2.2.

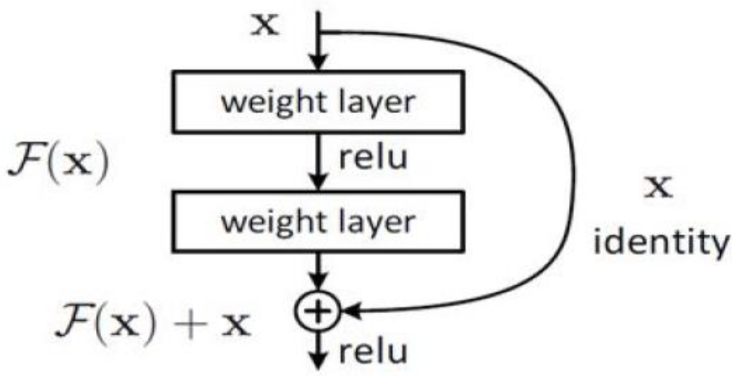


Figure 2.2 Structure of residual learning [8]

After ResNet-38 predicts the emotion of user, the system uses it to pair with the specific genre of movie. Then, the system uses web crawling to get a list of recommended movies from www.imdb.com [9] based on the movie genre.

The benefit of using residual learning is the model can be trained easier than learning directly from the original features. This is because it is harder to train deeper neural network. In addition, the users' privacies are not violated because there is no personal information collected from the movie recommendation system. However, the limitation of this model is the size of Kaggle-fer2013 dataset is limited. Therefore, researchers can apply Generative Adversarial Network to enlarge both training set and test set to further improve the accuracy of model.

Minaee et al. proposed a method for facial expression recognition using a deep learning approach based on an attentional convolutional network. This method achieves a high accuracy rate by focusing on feature-rich parts of the face such as the forehead, eyes, eyebrows and mouth, while other parts of the face like ears and hair play little role in determining the facial expression. Figure 2.3 shows the important regions when detecting facial expressions. It is worth noting that different emotions will have different prominent areas of face images. For example, the important region for detecting happiness and fear is around the mouth, while for anger the area around the eyes and eyebrows is more important than other regions [10].

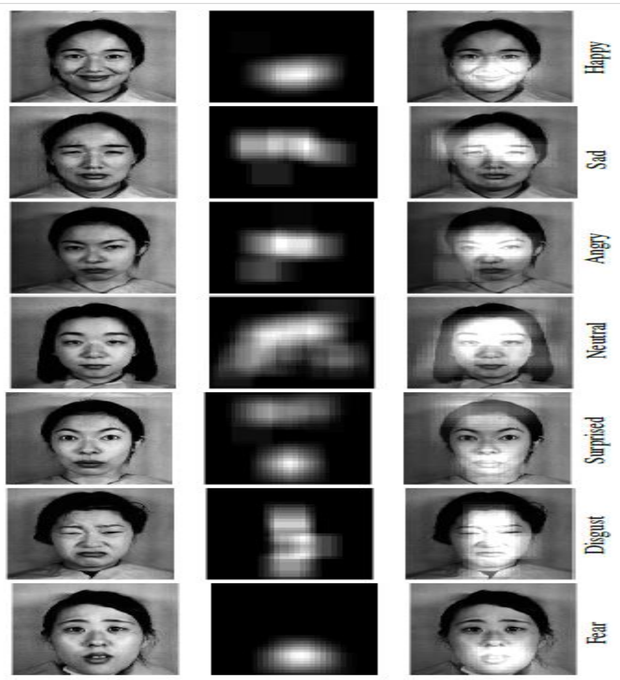


Figure 2.3 The important regions for detecting facial expressions [10]

Figure 2.4 illustrates the proposed model architecture. For feature extraction, the model has four convolutional layers with the two of them passed to max-pooling layer and ReLU activation function. Then, they are transmitted to a dropout layer and two fully connected layers. On the other hand, the spatial transformer (localization network) is made up of two convolutional layers, each followed by max-pooling and ReLU, as well as a fully connected layer. The spatial transformer module is in charge of concentrating on the regions of the face that have the most impact on the classifier's outcome. After that, Adam optimizer is used to train the model.

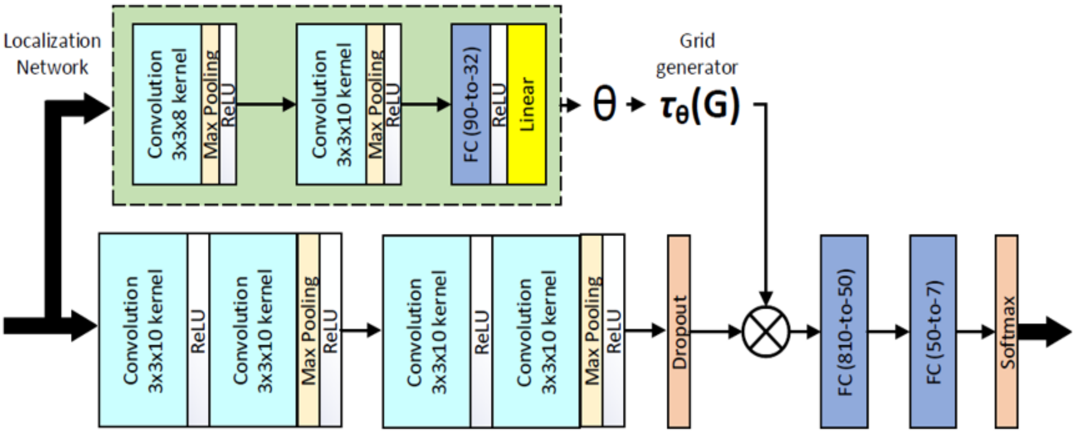


Figure 2.4 Architecture of attentional convolutional network [10]

The advantage of using an attentional convolutional network to highlight the crucial parts of the face is that it can achieve promising results with less than 10 layers of neural network. It can even compete with deeper networks for emotion recognition.

Based on Table 2.1, the proposed model can achieve an accuracy rate of around 70.0% on FER 2013 dataset. For FERG dataset, the accuracy rate of model is around 99.3%. Moreover, the accuracy rate on JAFFE is around 92.8%. The model reaches an accuracy rate of around 98.0% on CK+ dataset. However, the accuracy of the model could be doubted as the author does not test the trained model on test set, and overfitting could have happened as the accuracy rate is too well.

Table 2.1 Classification accuracy on four datasets

Dataset	Accuracy rate
FER 2013	70.0%
FERG	99.3%
JAFFE	92.8%
CK+	98.0%

2.2 Applications of Emotion Detection in Movie Recommendation System

In 1972, an emotional psychologist Paul Ekman suggested there are six basic emotions that could be deduced from facial expressions which are happiness, sadness, fear, anger, surprise, and disgust. Happiness is a sense of pleasure that can be associated with contentment, joy, delight, satisfaction, and well-being. On the contrary, sadness is a temporary emotional state marked by disappointment, grief, hopelessness, apathy, and a depressed mood. Furthermore, fear is expressed in a variety of facial expressions, including avoidant, self-protective, and vigilant when facing some sort of danger. Anger is a strong emotion that is marked by feelings of hatred, agitation, frustration, and antagonism toward others. Moreover, disgust is a sense of revulsion can be triggered by a variety of factors, including an unpleasant taste, sight, or smell. Lastly, surprise is characterized by a physiological startle response in reaction to something unexpected and is usually relatively brief [11].

With the growth of technology, artificial intelligence techniques are emerging as an alternative method to traditional movie recommendation system. Compared to the traditional approaches such as CBF and CF, artificial intelligence techniques are able to capture the human emotion and apply it in the recommendation field. Human emotion plays a significant role in this domain as it reflects the continuous changing of user preferences. Furthermore, emotion can be captured in real time to be used as recommendations based on user’s current mood. Other than that, mentioned that emotions can be recognized when a person watches a movie. For example, individuals show joy when viewing a comedy. A depressed person might watch a fast-paced action film since the unfolding of movie scenes can help them overcome their negative emotions. Hence, the collecting of human emotions can provide additional information that can help to generate better movie recommendations.

2.3 Comparison of Previous Studies

Table 2.2 shows the comparison between the techniques as discussed above.

Table 2.2 Comparison on the techniques used in movie recommendation system

Year	Paper title	Technique used	Advantage	Disadvantage
2015	Improving Web Movie Recommender System Based on Emotions	Hybrid combination of Content Based Filtering and Collaborative Filtering	This approach eliminates the Cold-start problem.	Machine learning is not implemented as the users' emotion is determined from choosing the colors.
2020	Movies and Pop Songs Recommendation System by Emotion Detection through Facial Recognition	Deep Residual Network (ResNet-38)	Training of model is easier than direct learning from the original features. Do not infringe users' privacies.	The size of Kaggle-fer2013 dataset is limited.
2020	Research on Automatic Music Recommendation Algorithm Based on Facial Micro-expression Recognition	Facial micro-expression recognition, SVM, Content Based Filtering, Cosine Similarity algorithm	The model can meet the users' listening needs by applying emotion recognition.	The risk of overfitting during training process will increase as the number of learning parameters increase.
2020	Analyzing emotion-based movie recommender system using fuzzy emotion features	Compiling emotion lexicon based on user reviews	The model provides more accurate recommendation compared to rating-based cosine item similarity.	There is a certain degree of blurriness and fuzziness between the lexicons of emotion features.
2021	Deep-Emotion: Facial Expression Recognition Using Attentional Convolutional Network	Attentional convolutional network	The model can extract features from the crucial parts of the face. The model has less than 10 network layers.	The accuracy of model is too well, model has likely overfit the data

2.4 Proposed Solution

This project aims to build a web application with a deep learning model that can recognize 7 kinds of human emotion including neutral, anger, happiness, sadness, disgust, fear, and surprise. The model will be developed by using Convolutional Neural Network (CNN). It is a type of Artificial Neural Network (ANN) that is specifically designed to extract complex features from images and convert them into lower dimension without losing any information. CNNs have been applied in many fields like image and video recognition, pattern recognition and artificial intelligence. CNN consists of mainly four layers which are the convolution, pooling, flatten and fully connected layers [12].

Figure 2.5 shows the architecture of CNN. A convolution layer contains a set of filters which is applied over the original image to extract different features. The output is passed through an activation function such as a rectified linear unit (ReLU) to change the negative values to zero while remain the positive values. Next, a pooling layer is usually placed between two successive convolutional layers. Pooling layers reduce the number of features and dimensionality of the network without losing any of its characteristic [13]. For example, max pooling is performed to obtain the maximum value in a specific filter region. After that, the flattening layer is used to convert the two-dimensional matrices into a single dimensional matrix before fed to the fully connected layers. Finally, the fully connected layers form the last layer in the network to classify the data into various group [14].

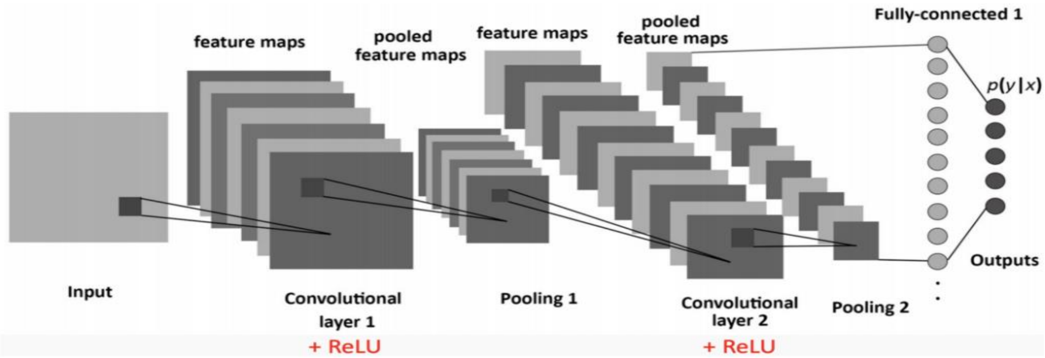


Figure 2.5 Architecture of CNN [14]

CHAPTER 3

SYSTEM METHODOLOGY

3.1 Design Specifications

3.1.1 Methodologies and General Work Procedures

The proposed web application was developed using Jupyter Notebook and Flask. Jupyter Notebook is a popular web-based interactive computational notebook among data scientists. Firstly, the deep learning model is trained in Jupyter Notebook until it obtains a high accuracy rate. The algorithm used to train the model was Convolutional Neural Network (CNN) because CNN is specifically designed to extract complex features from the images [15]. After that, the model was exported from the notebook and integrated into the web app using Flask. It is a framework that allows developers to build a web application using Python.

Figure 3.1 shows the overall system framework. To access the web application, user must first login into his/her account. The user can then press a button to activate his web cam, which the cam will record his/her facial expressions in real time. Then the information will be sent to CNN model, where the model analyses the data and predicts the emotion. A PostgreSQL database is used to store the predicted emotion data. Based on the user's emotion, the web application will provide a list of movies to the user. Finally, all of the recommended movies are stored in PostgreSQL.

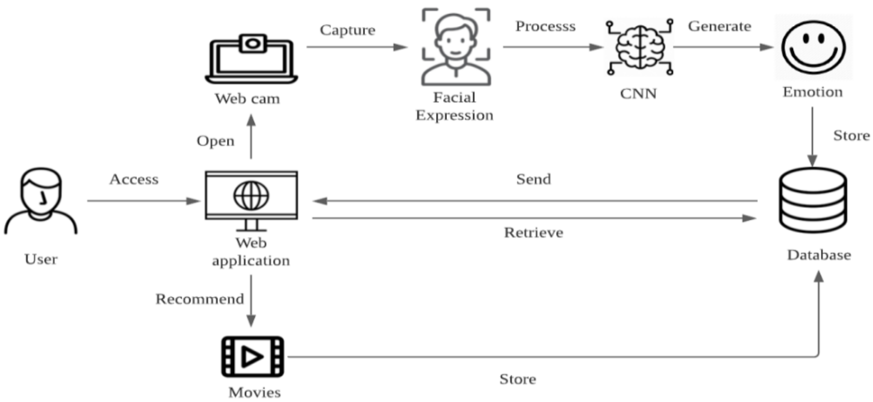


Figure 3.1 Overall system framework

3.1.2 Requirements

Functional Requirements

- The system shall allow new user to create/register a new account by filling up a sign-up form.
- The system shall allow current/existing user to login to an account by entering a username and password.
- The system shall authenticate the login of the user by verifying the correct user credentials.
- The system shall allow user to logout upon the end of session.
- The system shall let user to switch on and off the personal device (laptop) peripheral (camera) for allowing emotion detection.
- The system shall display the emotion tracking results including the facial expression and emotion.
- The system shall provide a list of recommended movies to user based on the emotion predicted.

Non-functional Requirements

Usability

- The system shall be able to provide ease for user to obtain movie recommendations.
- The system shall be simple to learn for both novices and experienced users by utilizing familiar icons and menu hierarchy.
- The system shall be able to display informative feedback by showing success and error messages.

Performance

- The system shall be able to capture the user emotion from facial expression in less than 10 seconds.
- The system shall be able to recommend movies in less than 10 seconds.

Accuracy

- The system shall be able to predict the user emotion precisely to get the relevant movie recommendations.

3.1.3 System Performance Definition

The targeted accuracy for the emotion recognition model is 80%. Furthermore, the model should be able to recognize all seven kinds of emotion. In addition, the web application should be able to provide movie recommendations to users based on their emotions.

3.1.4 Verification Plan

Table 3.1 Verification Plan

No	Test Case Description	Test Data	Expected Result	Actual Result	Pass/ Fail
1	Check if users can login with correct email and password.	Email: cks@gmail.com Password: 12345678	Login should be successful	Login was successful	Pass
2	Check if users can login without entering email and password.	Email: Password:	Login should fail	Login was failed and a message "Please fill out this field" was shown	Pass
3	Check if users can login with an incorrect email.	Email: ks@gmail.com Password: 12345678	Login should fail	Login was failed and a message "Email is incorrect!" was shown	Pass
4	Check if users can login with an incorrect password.	Email: cks@gmail.com Password: 1234	Login should fail	Login was failed and a message "Password is incorrect!" was shown	Pass
5	Check if users can register with the same email address	Name: chong Email: cks@gmail.com Password: 12345678	Register should fail	Register was failed and a message "Email has been registered!" was shown	Pass
6	Check if users can register with a password less than 8 characters	Name: chong Email: ckh@gmail.com Password: 1234	Register should fail	Register was failed and a message "Password must have 8 characters!" was shown	Pass
7	Check if users can get the recommended movies	User emotion	Users should get a list of recommended movies	Three recommended movies were displayed	Pass

3.2 System Design

3.2.1 Use Case Diagram

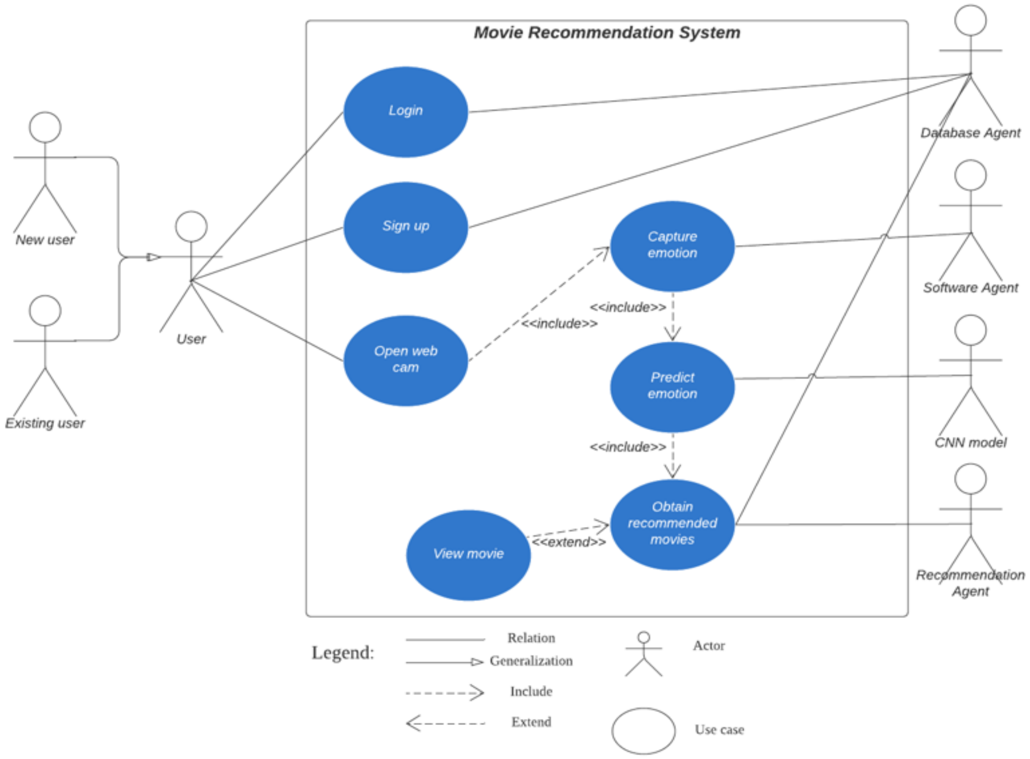


Figure 3.2 Use case diagram

Table 3.2 Use case description

Actors	Preconditions	Normal flow	Alternative flow
User	User’s emotion must be predicted to get movie recommendations.	1. User logins or registers an account. 2. User opens web cam. 3. User obtains movie recommendations.	At step 3, user can click on the link to view the movie.
Database agent	-	1. Database agent authenticates user during login and stores user credentials during sign up. 2. Database agent stores movie recommendations.	-
Software agent	User must open web cam to capture emotion	Software agent captures user’s emotion	-
CNN model	User’s emotion must be captured	CNN model predicts the user emotion	-
Recommendation agent	User’s emotion must be predicted to get movie recommendations.	Recommendation agent provides movie recommendations to user	-

3.2.2 Activity Diagram

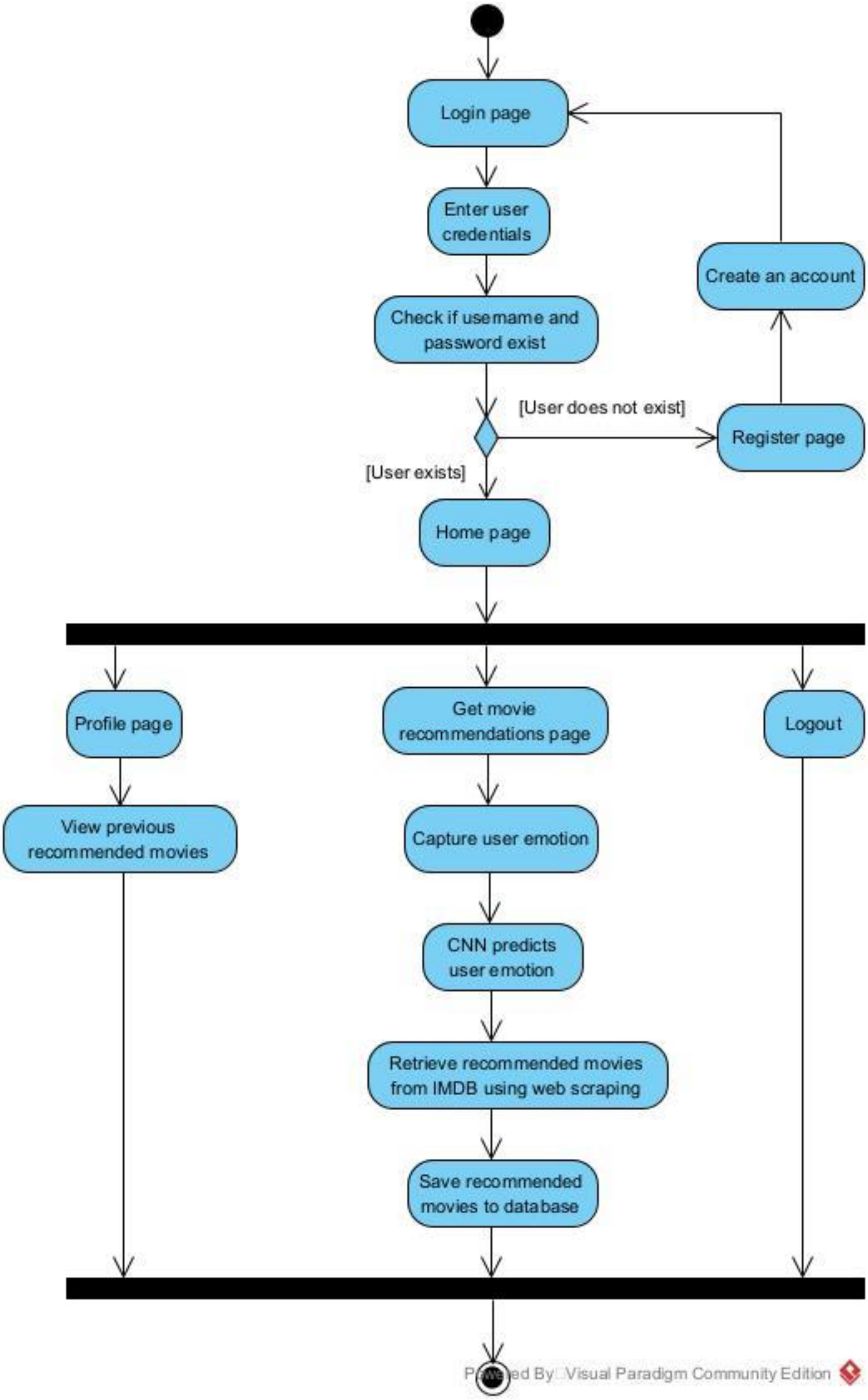


Figure 3.3 Activity diagram

According to Figure 3.3, this system will display the login page when the users access the web application. The system will redirect them to the home page if both of their username and password exist in the database. On the other hand, if the user does not exist, they have to register a new account. After logging in, users can access their prior movie recommendations by clicking on their profile. Moreover, when users click on get movie recommendations, the system captures the user's emotion and passes it to the CNN model for prediction. After that, the system will use the predicted emotion to retrieve recommended movies from IMDB using web scraping. The recommended movies will be saved in the database by the system. Finally, users can click on logout to exit the system.

3.2.3 CNN Architecture

The proposed emotion recognition model will consist of four convolutional layers with 32, 32, 64 and 64 filters respectively. Each layer consists of a conv2D, max-pooling, dropout, and batch-normalization layer. The conv2D is used to specify the 3x3 convolution kernel. Next, the max-pooling layer is applied to reduce the dimensionality of the network by obtaining the highest value in the 2x2 windows. Moreover, the dropout layer is included to avoid overfitting. To improve performance, batch-normalization is added at every layer. Finally, a fully connected layer of size 1024 and a SoftMax output layer are added to classify the data into seven classes of emotion. The overview of the proposed CNN architecture is shown in Figure 3.4.

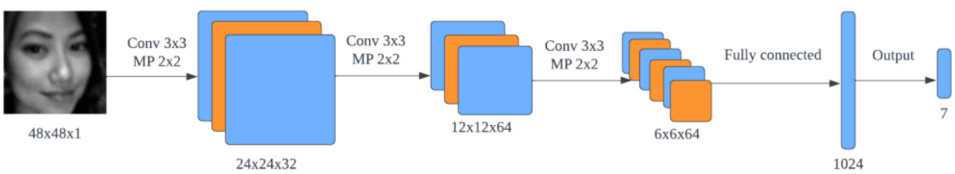


Figure 3.4 CNN architecture

3.2.4 Wireframe

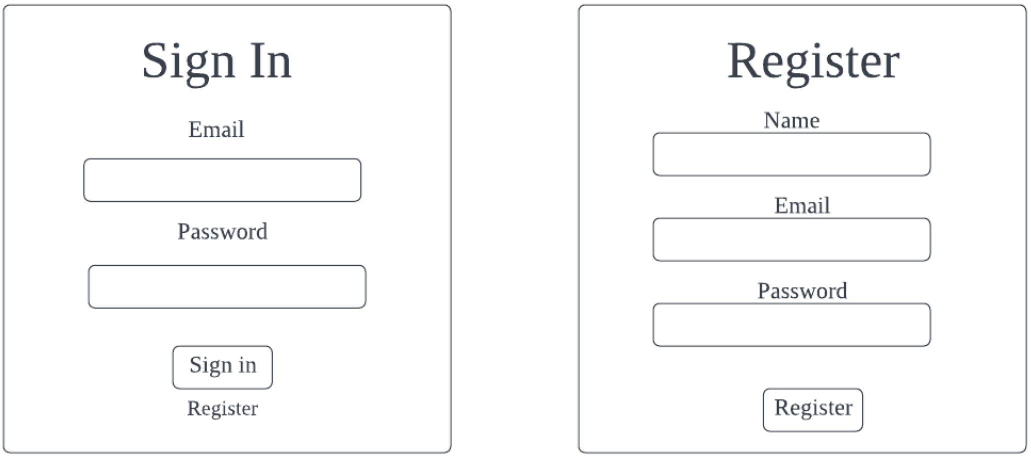


Figure 3.5 Sign in and register page

The sign in page has two inputs which are email and password while the register page has three inputs including name, email, and password.

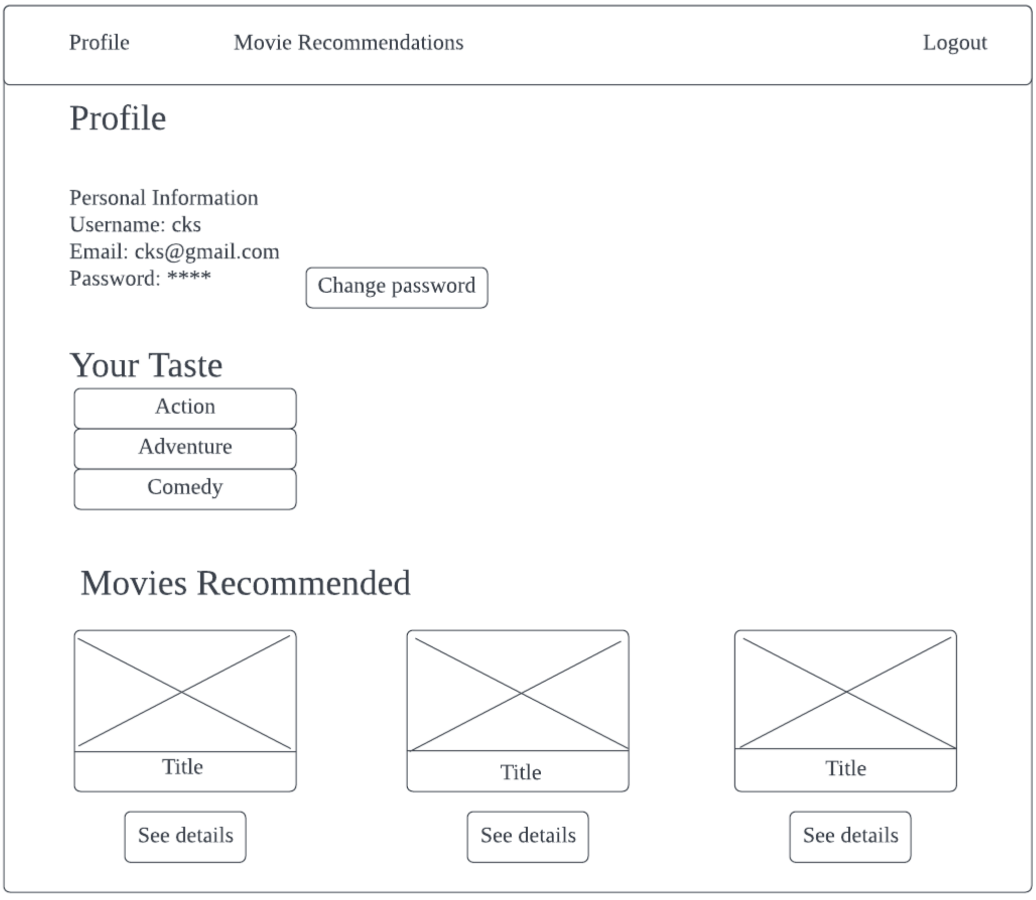


Figure 3.6 User profile page

The user profile page has three sections which are personal information, your taste and movies recommended. In personal information, the user credentials are displayed. Based on the most recent recommendations, your taste will reflect the movie genre that users are most likely to watch. Finally, movie recommended section shows the system's previous movie recommendations.

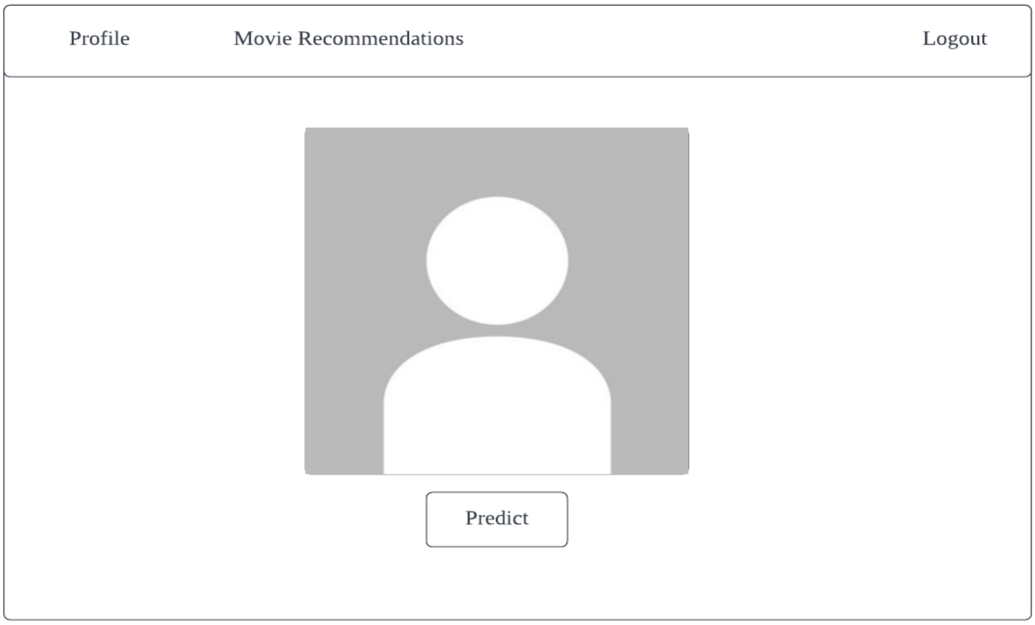


Figure 3.7 Predict emotion

During emotion prediction, users have to open their web cam to allow the web application to capture their facial emotion. Users can click on the predict button to get their movie recommendations.

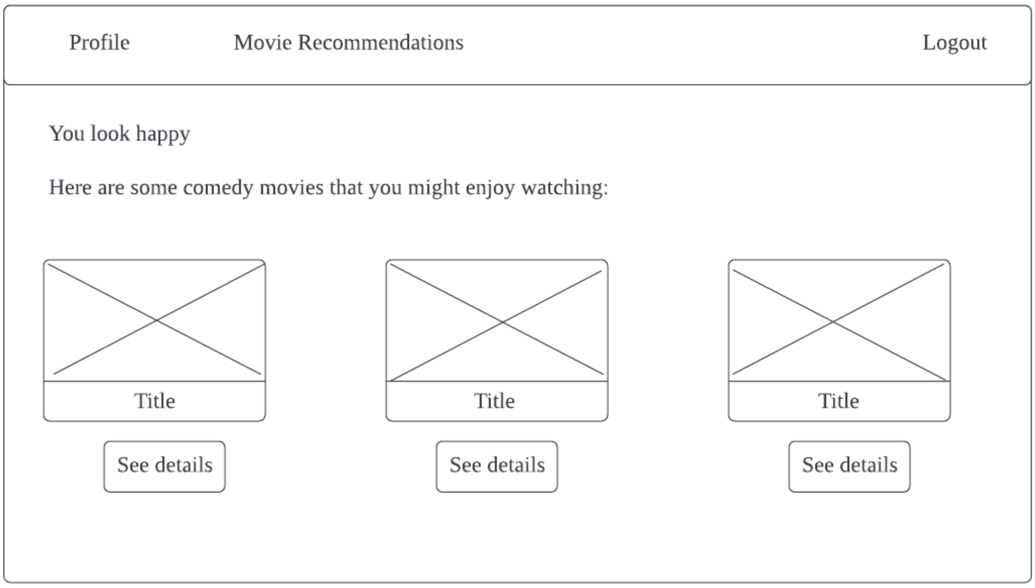


Figure 3.8 Movie recommendations

In the first line, the predicted user's emotion is displayed. Furthermore, the web application shows the movie genre that users are most likely to watch based on their emotions. Finally, three movie recommendations will be extracted from the IMDB website using web scraping and displayed on the screen where users can click on the see details button to learn more about the movies.

3.2.5 Data Dictionary

Users Entity

Table 3.3 Users Entity

Field Name	Data Type	Field Length	Constraint	Description
id	integer	10	Primary Key	User id, auto incremental
email	varchar	64	Unique, not null	User's email
username	varchar	64	Not null	User's name
password_hash	varchar	128	Not null	User's hashed password

Movies Entity

Table 3.4 Movies Entity

Field Name	Data Type	Field Length	Constraint	Description
id	integer	10	Primary Key	Movie id, auto incremental
movie_title	varchar	64	Not null	Movie's title
movie_url	varchar	200	Not null	Movie's URL
movie_description	varchar	1000	Not null	Movie's description
image_url	varchar	200	Not null	Movie's image URL
user_id	integer	10	Foreign Key	User id

3.3 Timeline

No	Task Name	Start Date	End Date	Duration (In Days)
1	**Chapter 4 System Implementation**	4/7/2022	24/7/2022	21
2	Split training set into validation set	4/7/2022	4/7/2022	1
3	Data augmentation	5/7/2022	7/7/2022	3
4	Add early stopping and checkpoint	8/7/2022	9/7/2022	2
5	Train model	10/7/2022	11/7/2022	2
6	Improve website user interface	12/7/2022	21/7/2022	10
7	Implement password change	22/7/2022	24/7/2022	3
8	**Chapter 5 System Evaluation and Dis**	25/7/2022	14/8/2022	21
9	Evaluate performance of model	25/7/2022	31/7/2022	7
10	Fine tune model	1/8/2022	7/8/2022	7
11	System testing	8/8/2022	14/8/2022	7
12	**Chapter 6 Conclusion**	15/8/2022	17/8/2022	3
13	Work done	15/8/2022	17/8/2022	2
14	Future work	18/8/2022	19/8/2022	1

Figure 3.9 Gantt Chart

CHAPTER 4

SYSTEM IMPLEMENTATION

4.1 Hardware Setup

A personal laptop will be used to develop the system. Table 4.1 illustrate the specification of the laptop:

Table 4.1 Specifications of laptop for development

Description	Specifications
Model	Aspire A514-52G
Processor	Intel Core i5-10210U
Operating System	Windows 10
Graphic	NVIDIA GeForce MX350
Storage	512 GB
RAM	8GB

4.2 Software Setup

Among the software used in this project development are

- Python
- Jupyter Notebook
- OpenCV
- Visual Studio Code
- Flask
- PostgreSQL
- Werkzeug
- Beautiful Soup

Python

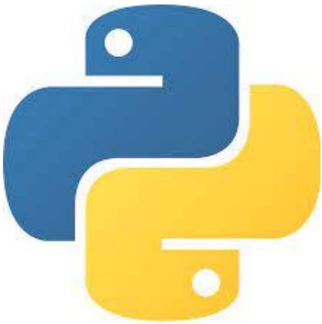


Figure 4.1 Python

Python [16] is a high-level interpreted programming language. It is used to develop the emotion recognition model due to its simplicity and access to many great libraries such as TensorFlow and Keras.

Jupyter Notebook

Figure 4.2 Jupyter Notebook

Jupyter Notebook [17] is an open-source, web-based computational notebook that is popular among data scientists because it is interactive and easy to use. It serves as an IDE to code and run the emotion recognition model.

OpenCV

Figure 4.3 OpenCV

OpenCV [18] is a library for computer vision and image processing. In this project, it is used to perform face recognition by extracting the human face from an image.

Visual Studio Code

Figure 4.4 Visual Studio Code

Visual Studio Code [19] is a code editor that is compatible with the majority of the operating systems including Windows, macOS and Linux. It offers debugging assistance, code completion, and incorporated Git version management.

Flask

Figure 4.5 Flask

Flask [20] is a back-end framework for building web applications with Python. In this project, it is used to implement the user authentication and routing, connect the database as well as integrate the emotion recognition model to the web app.

PostgreSQL

Figure 4.6 PostgreSQL

PostgreSQL [21] is a relational database that store and manage data. In this project, recommended movies are stored in PostgreSQL so that users can access them anytime.

Werkzeug

Werkzeug [22] is a library used to hash the user's password before storing it in database to enhance security.

Beautiful Soup

Beautiful Soup [23] is a Python web scarping library for pulling data out of HTML and XML files. In this project, it is used to extract the movies data from IMBD website.

Table 4.2 Summary of software used in this project

Software	Version	Description
Python	3.10	Python is used to develop the model due to its simplicity and access to many great libraries such as Scikit-learn and TensorFlow.
Jupyter Notebook	3.4.6	Jupyter Notebook is a web-based computational notebook that is popular among data scientists because it is interactive and easy to use.
OpenCV	4.5.5.62	OpenCV is a library for computer vision and image processing such as face recognition.
Visual Studio Code	1.69.1	Visual Studio Code is a code editor that is compatible with Windows, macOS, and Linux.
Flask	1.1.2	Flask is used to build a web application and integrate the model into the web app.
PostgreSQL	14	PostgreSQL is a relational database that stores and manages data. In this project, recommended movies are stored in PostgreSQL so that users can access the list of movies.
Werkzeug	2.0.2	Werkzeug is a library used to hash the user's password for security purposes.
Beautiful Soup	4.10.0	Beautiful Soup is a Python web scraping library for pulling data out of HTML and XML files.

4.3 Emotion Recognition Model

Part 1 – Data Preprocessing on FER2013 Dataset

Based on Figures 4.7 and 4.8, the FER2013 dataset contains seven emotion classes which are angry, disgusted, fearful, happy, neutral, sad, and surprised. The total number of images in the training set is 28709 and the test set has a total of 7178 images.

Furthermore, there is an imbalanced distribution of images among the emotions. For example, Figure 4.7 and Figure 4.8 show the lack of disgusted images in both the training set (436 images) and the test set (111 images).

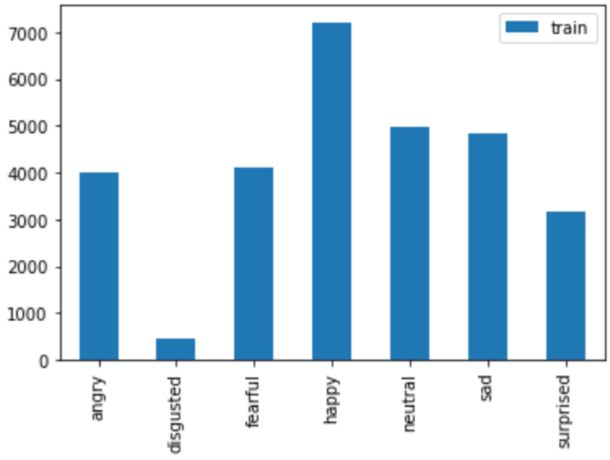


Figure 4.7 Number of images in training set

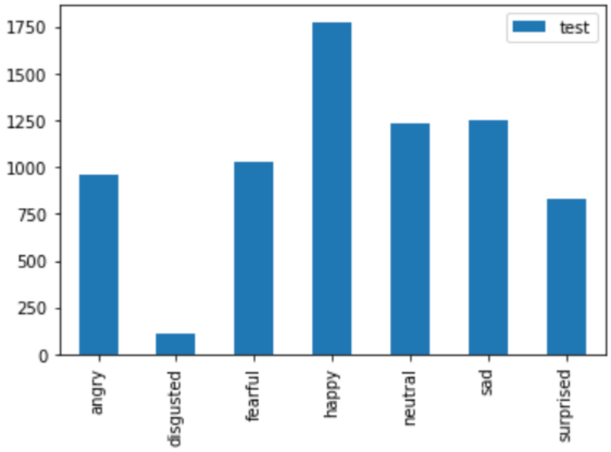


Figure 4.8 Number of images in test set

After that, 20% of images are separated from the training set to form the validation set. The validation set is used to evaluate the model performance during training. In addition, data augmentation is used to generate new images from the existing images by flipping and shifting the images horizontally and vertically. This is done because there is fewer number of images in the disgusted emotion. Moreover, the target size is set to (48, 48) as the images of the dataset are in the size of 48x48 pixels. The color mode is set to grayscale as the images are black and white. Below shows the code for data augmentation.

```
generator = ImageDataGenerator(width_shift_range = 0.1,
                               height_shift_range = 0.1,
                               horizontal_flip = True,
                               validation_split=0.2)

training_set = generator.flow_from_directory('dataset/train',
                                        target_size = (48, 48),
                                        color_mode = 'grayscale',
                                        batch_size = 128,
                                        class_mode = 'categorical',
                                        shuffle = True,
                                        subset = 'training')

validation_set = generator.flow_from_directory('dataset/train',
                                        target_size = (48, 48),
                                        color_mode = 'grayscale',
                                        batch_size = 128,
                                        class_mode = 'categorical',
                                        shuffle = False,
                                        subset = 'validation')

test_datagen = ImageDataGenerator()


test_set = test_datagen.flow_from_directory('dataset/test',
                                        target_size = (48, 48),
                                        color_mode = 'grayscale',
                                        batch_size = 128,
                                        class_mode = 'categorical',
                                        shuffle = False)
```

Part 2 – Building the CNN

The CNN model was developed based on the architecture of system design covered in Chapter 3. In the Conv2D layer, the activation function used is a rectified linear unit (ReLU) to change the negative values to zero while remaining the positive values. Moreover, batch-normalization is added to improve the model performance. Next, the pool size in the MaxPooling2D is set to (2, 2) to identify the largest value in the 2x2 windows, reducing the resolution of image by 2. Finally, the dropout layer is included to avoid overfitting. Below shows the code to build the CNN.

```
# Initialising the CNN
cnn = Sequential()

# Adding the 1st CNN Layer
cnn.add(Conv2D(filters = 32, kernel_size = (3, 3), activation = 'relu',
padding = 'same', input_shape = (48, 48, 1)))
cnn.add(BatchNormalization())
cnn.add(MaxPooling2D(pool_size = (2, 2)))
cnn.add(Dropout(0.2))

# Adding the 2nd CNN Layer
cnn.add(Conv2D(filters = 32, kernel_size = (3, 3), activation = 'relu',
padding = 'same'))
cnn.add(BatchNormalization())
cnn.add(MaxPooling2D(pool_size = (2, 2)))
cnn.add(Dropout(0.2))

# Adding the 3rd CNN Layer
cnn.add(Conv2D(filters = 64, kernel_size = (3, 3), activation = 'relu',
padding = 'same'))
cnn.add(BatchNormalization())
cnn.add(MaxPooling2D(pool_size = (2, 2)))
cnn.add(Dropout(0.2))

# Adding the 4th CNN Layer
cnn.add(Conv2D(filters = 64, kernel_size = (3, 3), activation = 'relu',
padding = 'same'))
cnn.add(BatchNormalization())
cnn.add(MaxPooling2D(pool_size = (2, 2)))
cnn.add(Dropout(0.2))

# Flatten
cnn.add(Flatten())

# Fully connected layer
cnn.add(Dense(units = 1024, activation = 'relu'))
cnn.add(BatchNormalization())
cnn.add(Dropout(0.2))

# Output layer
cnn.add(Dense(units = 7, activation = 'softmax'))
```

Part 3 – Training the CNN

Adam optimizer is used to update the neural network weights and learning rate. Furthermore, the categorical cross-entropy is used as the loss function in the output layer. An early stopping is added to stop the training when the validation accuracy does not improve further. Then, the model is trained on the training set and evaluated on the validation set for 100 epochs using an initial learning rate of 0.001. Below shows the code to compile and train the CNN.

```
opt = Adam(learning_rate = 0.001)
cnn.compile(optimizer = opt, loss = 'categorical_crossentropy',
metrics = ['accuracy'])

es = EarlyStopping(monitor='val_accuracy', mode ='max', verbose=1,
patience = 10)
checkpoint=ModelCheckpoint('best_model2.h5', monitor='val_accuracy',
mode = 'max', verbose = 1)


callbacks_list = [es, checkpoint]

cnn.fit(x=training_set, validation_data=validation_set, epochs=100, batch
_size=128, callbacks=callbacks_list)
```

In each epoch, the CNN will update the weights of the neurons in order to minimize the loss function which is the difference between the neural network output and the actual output. After training the model for 39 epochs, the model achieved an accuracy of 74.98% which is an improvement from FYP 1 as the model only needs to go through 39 epochs to reach around 70%. This has gradually decreased the time taken for training the model.

```
Epoch 37/100
180/180 [==============================] - ETA: 0s - loss: 0.6981 - accuracy: 0.7390
Epoch 37: saving model to best_model2.h5
180/180 [==============================] - 89s 493ms/step - loss: 0.6981 - accuracy: 0.7390 - val_loss: 1.3976 - val_accurac
y: 0.5795
Epoch 38/100
180/180 [==============================] - ETA: 0s - loss: 0.6795 - accuracy: 0.7481
Epoch 38: saving model to best_model2.h5
180/180 [==============================] - 77s 430ms/step - loss: 0.6795 - accuracy: 0.7481 - val_loss: 2.7526 - val_accurac
y: 0.5172
Epoch 39/100
180/180 [==============================] - ETA: 0s - loss: 0.6693 - accuracy: 0.7498
Epoch 39: saving model to best_model2.h5
180/180 [==============================] - 92s 509ms/step - loss: 0.6693 - accuracy: 0.7498 - val_loss: 1.2933 - val_accurac
y: 0.5774
Epoch 39: early stopping
```

Figure 4.9 Accuracy of model

Part 4 – Fine Tuning Model

The hyperparameters that were chosen for fine tuning include the learning rate, optimizer, and batch size. Then, the model is trained using different combinations of the hyperparameters including learning rate of 0.01 and 0.001, Adam and SGD optimizers as well as 64 and 128 batch sizes. After that, the model is evaluated on the validation set to determine the optimal hyperparameters which result in the most accurate predictions. Below shows the code snippet for fine tuning.

```
def evaluate_model(training_set, validation_set, learning_rate,     optim
izer, batch_size):


    optimizerD= {'Adam': Adam(learning_rate=learning_rate),
            'SGD': SGD(learning_rate=learning_rate)}
    optimizerL = optimizerD[optimizer]

    # Train model
    cnn = create_model()
    cnn.compile(optimizer = optimizerL, loss = 'categorical_crossentropy'
, metrics = ['accuracy'])
    cnn.fit(x = training_set, validation_data = validation_set,     batch
_size = batch_size, epochs = 50)

    # Evaluate model
    _, acc = cnn.evaluate(validation_set)

    return acc


parameters = {'learning_rate': [0.001, 0.01],
              'optimizer': ['Adam', 'SGD'],
              'batch_size':[64, 128],
}


cv_results_df = pd.DataFrame(columns=['batch_size', 'learning_rate', 'opt
imizer', 'score'])

for i in list(ParameterGrid(parameters)):
    batch_size = i.get('batch_size')
    learning_rate = i.get('learning_rate')
    optimizer = i.get('optimizer')
    score = evaluate_model(training_set, validation_set,
                      learning_rate, optimizer, batch_size)

    series_values = pd.Series({'batch_size': batch_size,
                          'learning_rate': learning_rate,
                     'optimizer': optimizer,
                'score': score})
    cv_results_df = cv_results_df.append(series_values,
                                ignore_index=True)
```

4.4 Web Development

The front-end of the website which is the graphical user interface (GUI) is developed using HTML and CSS. Bootstrap is used to create most of the components, such as the sign-in and register form, card, as well as the button. On the other hand, the back end of the website which is the server-side of the website is constructed using the Flask framework.

Route design

Flask handles the app routing by mapping a specific URL to a particular page to perform some tasks. For example, the URL('/login') binds to the login page. Below shows the code snippet for route design.

```
@app.route("/")
def entry():
    return redirect("/login")

@app.route("/login", methods=["GET", "POST"])
def login():
    form = LoginForm()
    if form.validate_on_submit():
        user = User.query.filter_by(email=form.email.data).first()
        try:
            if user.check_password(form.password.data) and user is not None:
                login_user(user)
                flash("Logged in successfully!", "info")
                next = request.args.get("next")
                if next == None or not next[0] == "/":
                    next = url_for("profile")
                return redirect(next)
            else:
                flash("Password is incorrect!", "danger")
        except:
            flash("Email is incorrect!", "danger")
    return render_template("login.html", form=form)

@app.route("/register", methods=["GET", "POST"])
def register():
    form = RegistrationForm()
    if form.validate_on_submit():
        user = User(email=form.email.data, username=form.username.data,
            password=form.password.data)
        db.session.add(user)
        db.session.commit()
        return redirect(url_for("login"))
    return render_template("register.html", form=form)
```

Setting up database connection

Based on the source code below, the web application was connected to the PostgreSQL database by configuring the database URI and disabling tracking. A database object called "db" was created using the SQLAlchemy library to interact with the database.

```
import os
from flask import Flask
from flask_sqlalchemy import SQLAlchemy
from flask_migrate import Migrate
from flask_login import LoginManager

login_manager = LoginManager()

app = Flask(__name__)

app.config["SECRET_KEY"] = "mysecretkey"

app.config[
    "SQLALCHEMY_DATABASE_URI"
] = "postgresql://postgres:postgresql@localhost:5432/test2"

app.config["SQLALCHEMY_TRACK_MODIFICATIONS"] = False

db = SQLAlchemy(app)
Migrate(app, db)

login_manager.init_app(app)
login_manager.login_view = "login"
```

Create database tables

With the database connection established, the database object generated earlier was used to create two database tables which are user table and movie table. The user table stores the user credentials such as email and password for login authentication. The user's password is saved in hash form instead of plain text to increase the security of the web application. In addition, the movie table stores data about movies such as the movie's title, description, image, and link. The user_id is a foreign key that links the movie and user tables as shown in the code snippet below.

```
from myproject import db, login_manager
from werkzeug.security import generate_password_hash,
check_password_hash
from flask_login import UserMixin
```

```
@login_manager.user_loader
def load_user(user_id):
    return User.query.get(user_id)
class User(db.Model, UserMixin):
    __tablename__ = "users"
    id = db.Column(db.Integer, primary_key=True)
    email = db.Column(db.String(64), unique=True, index=True)
    username = db.Column(db.String(64))
    password_hash = db.Column(db.String(128))

    post = db.relationship("Movie", backref="viewer", lazy=True)

    def __init__(self, email, username, password):
        self.email = email
        self.username = username
        self.password_hash = generate_password_hash(password)

    def check_password(self, password):
        return check_password_hash(self.password_hash, password)

class Movie(db.Model):
    __tablename__ = "movies"
    users = db.relationship(User)

    id = db.Column(db.Integer, primary_key=True)
    user_id = db.Column(db.Integer, db.ForeignKey("users.id"),
nullable=False)
    movie_title = db.Column(db.String(64))
    movie_url = db.Column(db.String(200))
    image_url = db.Column(db.String(200))
    movie_desc = db.Column(db.String(1000))

    def __init__(self, user_id, movie_title, movie_url, image_url,
movie_desc):
        self.user_id = user_id
        self.movie_title = movie_title
        self.movie_url = movie_url
        self.image_url = image_url
        self.movie_desc = movie_desc
```

Below shows some of the screenshots of the website.

Login page

Users have to enter their email and password to login into the web application.

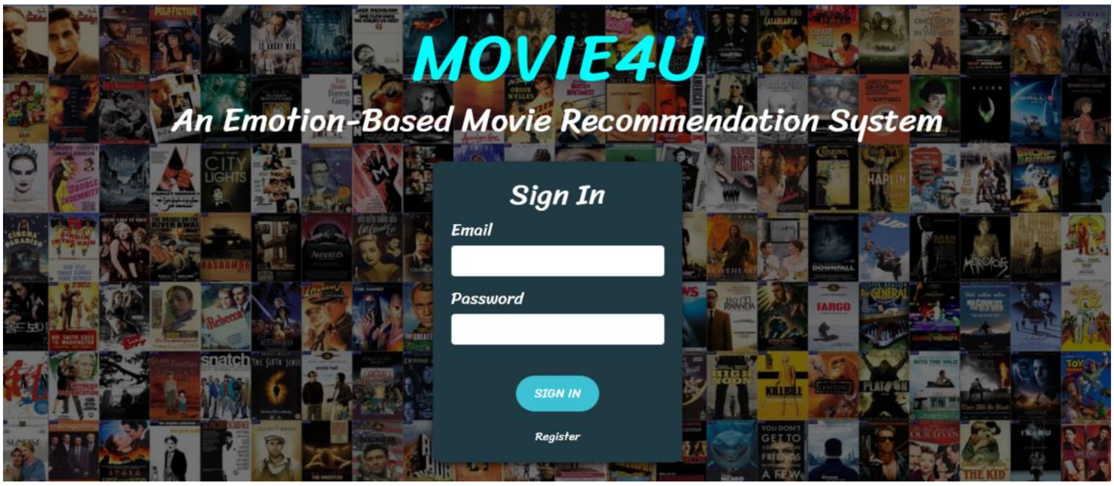


Figure 4.10 Login page

Register page

Users can register a new account by entering a username, email, and password. The email must be unique, and the password must have at least eight characters.

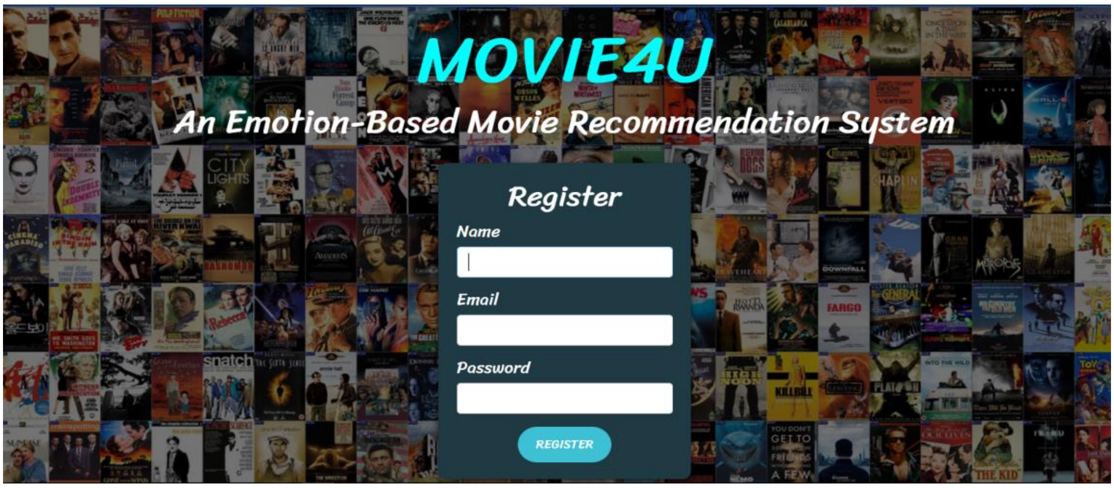


Figure 4.11 Register page

Profile page

Users could view their personal information such as username and email on the profile page. In addition, they can change their password.

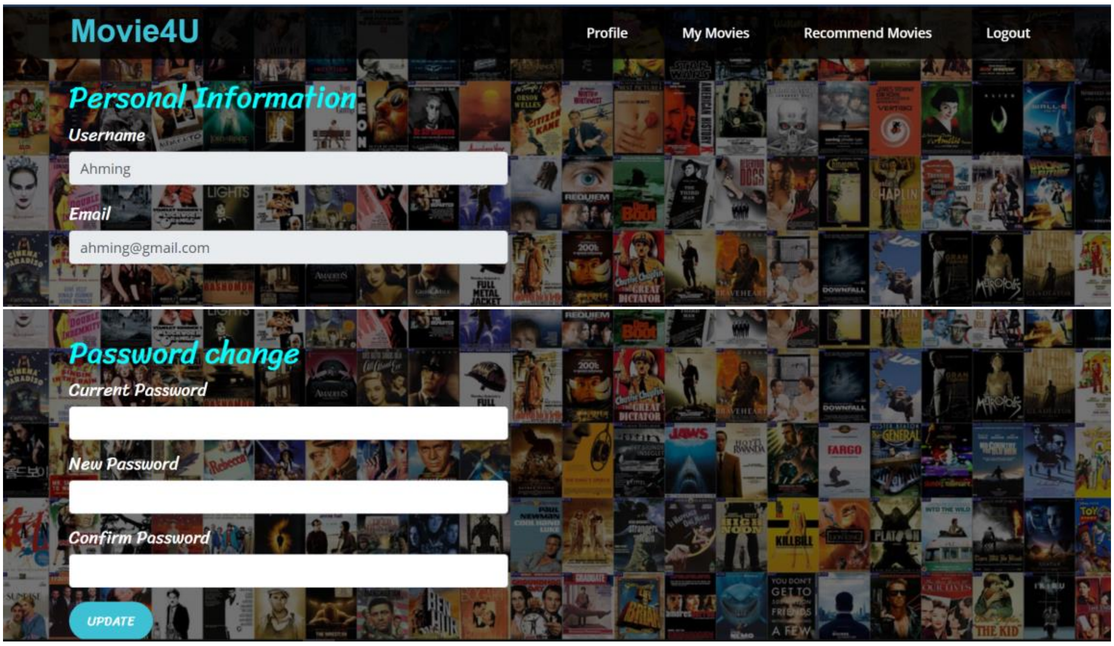


Figure 4.12 Profile page

My movies page

On my movies page, all of the previous movies recommended to the user are shown. The movies are arranged from most recent to oldest.

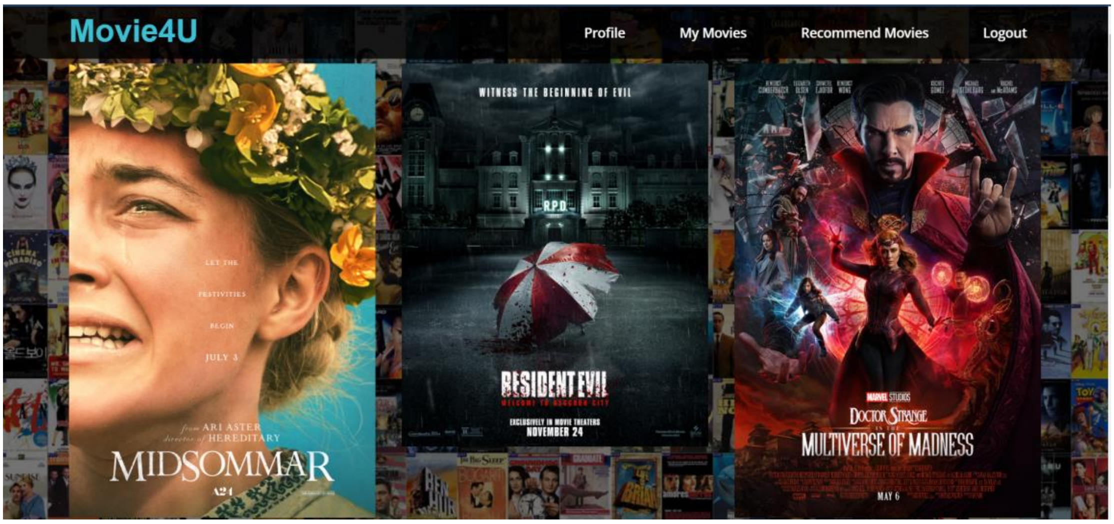


Figure 4.13 My movies page

When a card is hovered, the movies' title, synopsis, and a link to the IMDB website are presented as shown in Figure 4.14.

Figure 4.14 Movie's title, description, and link

Emotion prediction page

Based on Figure 4.15, users must open their webcam to allow the web application to capture their emotions for movie recommendations.

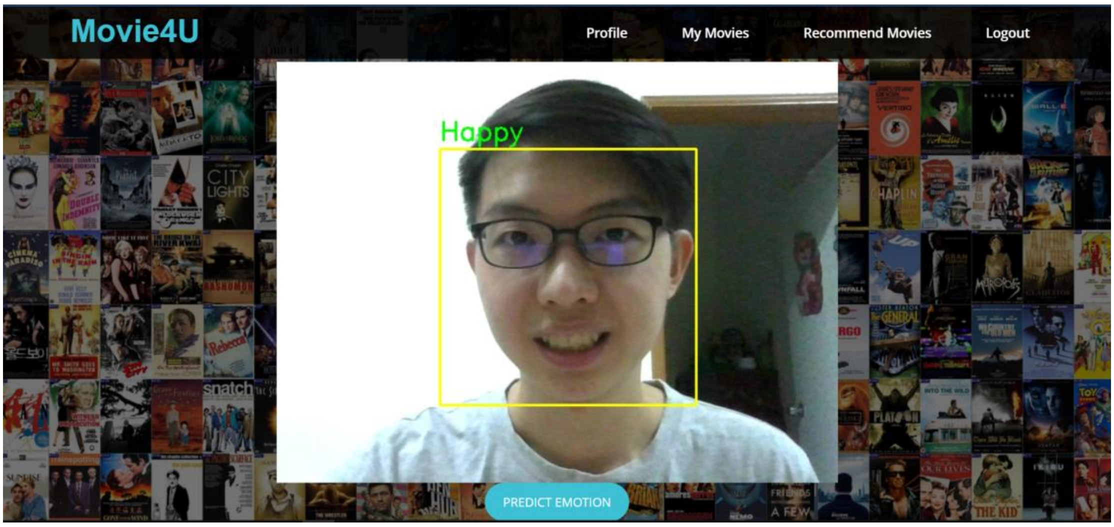


Figure 4.15 Emotion prediction page

Movie recommendation page

After the users click on the predict button, the web application will recommend three movies from the genre that they might like. The movies come from the top 50 movies on the IMDB website.

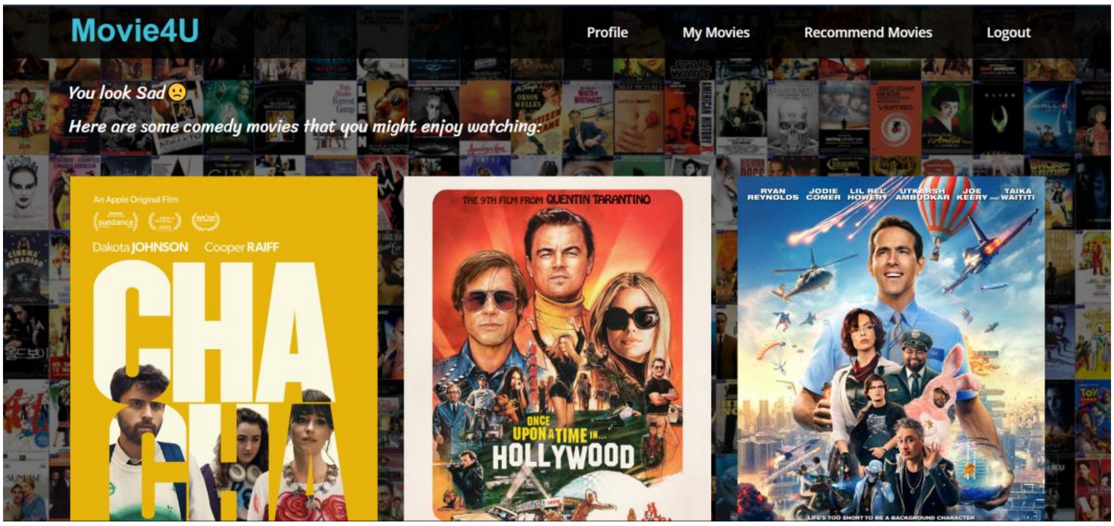


Figure 4.16 Movie recommendations based on emotion

CHAPTER 5

SYSTEM EVALUATION AND DISCUSSION

5.1 Evaluating Model Performance

Based on Figure 5.1.1, the trained model has a low precision of 0.42 in distinguishing the fearful images and a precision of 0.45 in sad images. This is most likely because these two facial expressions are quite similar to each other. In addition, the model has a low recall of 0.49 for angry emotion. This means that the model has trouble identifying the angry images out of all the images labeled as angry.

	precision	recall	f1-score
angry	0.51	0.49	0.50
disgusted	0.58	0.62	0.60
fearful	0.42	0.46	0.44
happy	0.83	0.77	0.80
neutral	0.53	0.54	0.53
sad	0.45	0.47	0.46
surprised	0.73	0.73	0.73

Figure 5.1.1 Precision, recall and f1-score

Based on Figure 5.1.2, the confusion matrix shows that angry emotion has a high misclassification. For example, the model has wrongly predicted 133 surprised images as angry. This is probably because of the similarity between angry and surprise emotions as both facial expressions have raised eyebrows. Moreover, the model also misidentified 134 angry images as fear, 115 angry images as sad, and 154 angry images as surprise, resulting in a low recall.

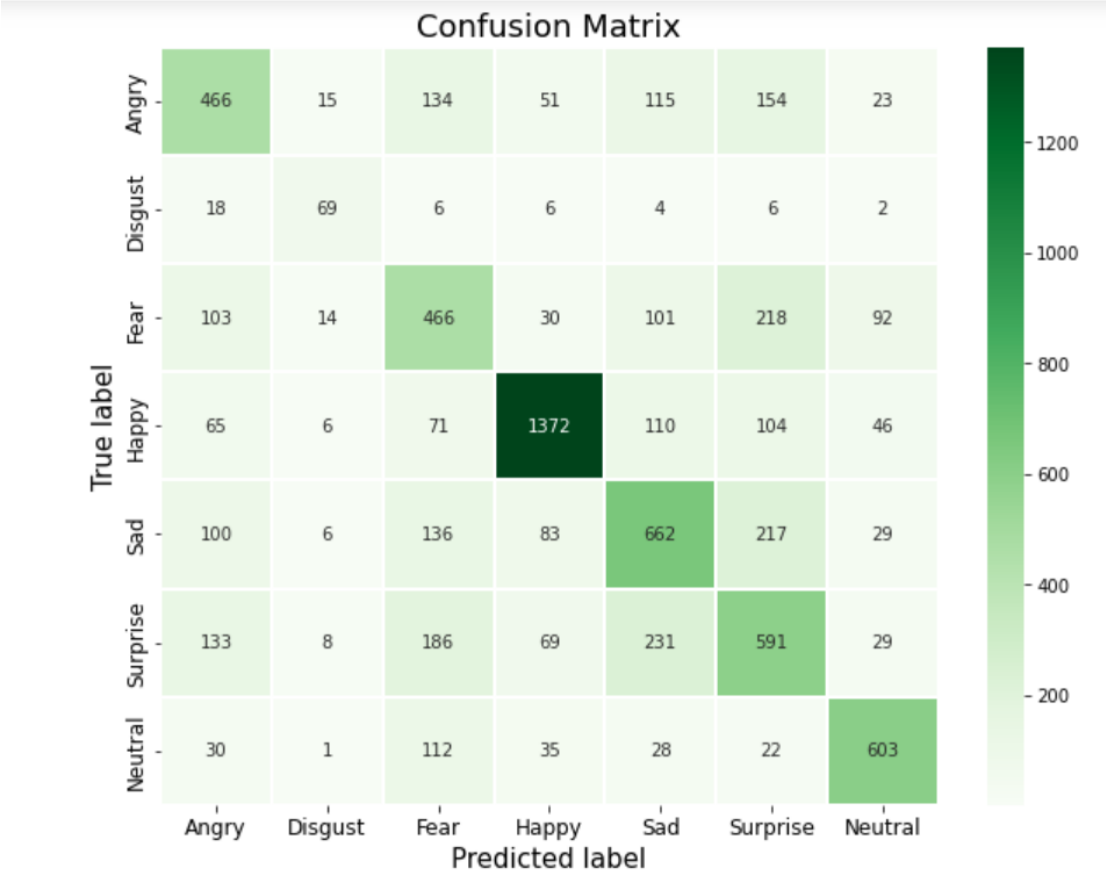


Figure 5.1.2 Confusion matrix

5.2 Result of Fine Tuning

Figure 5.2.1 shows the result of fine tuning. It is found that the combination of 128 batch size, 0.001 learning rate and Adam optimizer obtains the highest score of 0.60 when the model was evaluated on the validation set. After that, the model was retrained using the above hyperparameters to achieve a better accuracy.

	batch_size	learning_rate	optimizer	score
0	64	0.001	Adam	0.599199
1	64	0.001	SGD	0.429716
2	64	0.010	Adam	0.577600
3	64	0.010	SGD	0.570632
4	128	0.001	Adam	0.602682
5	128	0.001	SGD	0.453405
6	128	0.010	Adam	0.588922
7	128	0.010	SGD	0.569587

Figure 5.2.1 Result of fine tuning

5.3 System Testing

The web application's features that were tested in this project include

- Login
- Register
- Password Change
- Emotion Recognition

5.3.1 Login

Table 5.1 Login decision table

Condition			
C1: Enter the wrong email	T	-	-
C2: Enter the wrong password	-	T	-
C3: Enter the correct email and password	-	-	T
Action			
A1: Display the error message	T	T	F
A2: Redirect user to profile	F	F	T

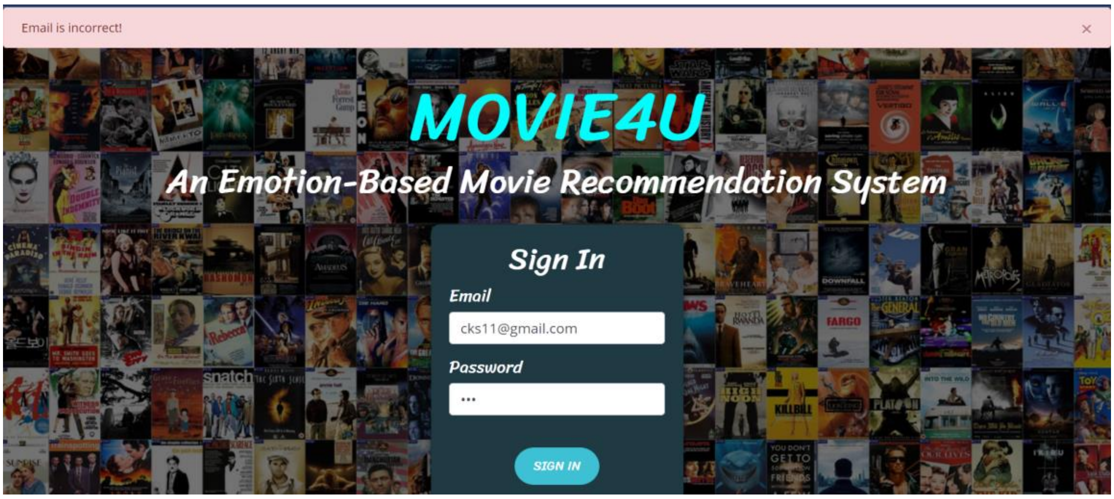


Figure 5.3.1 Enter the wrong email

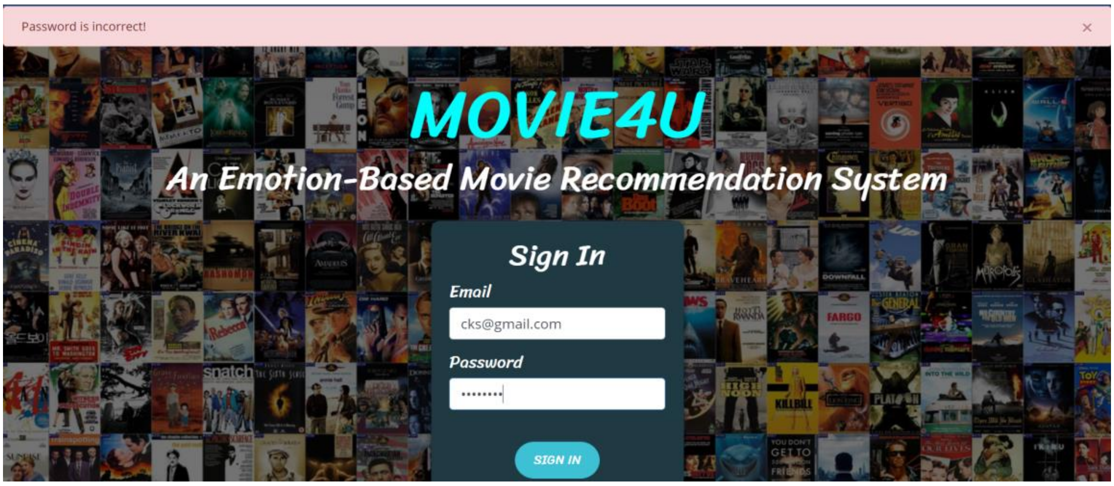


Figure 5.3.2 Enter the wrong password

5.3.2 Register

Table 5.2 Register decision table

Condition			
C1: Enter an existing email	T	-	-
C2: Enter a password with less than eight characters	-	T	-
C3: Enter the correct email and password	-	-	T
Action			
A1: Display the error message	T	T	F
A2: Redirect user to login	F	F	T

Figure 5.3.3 Enter an existing email

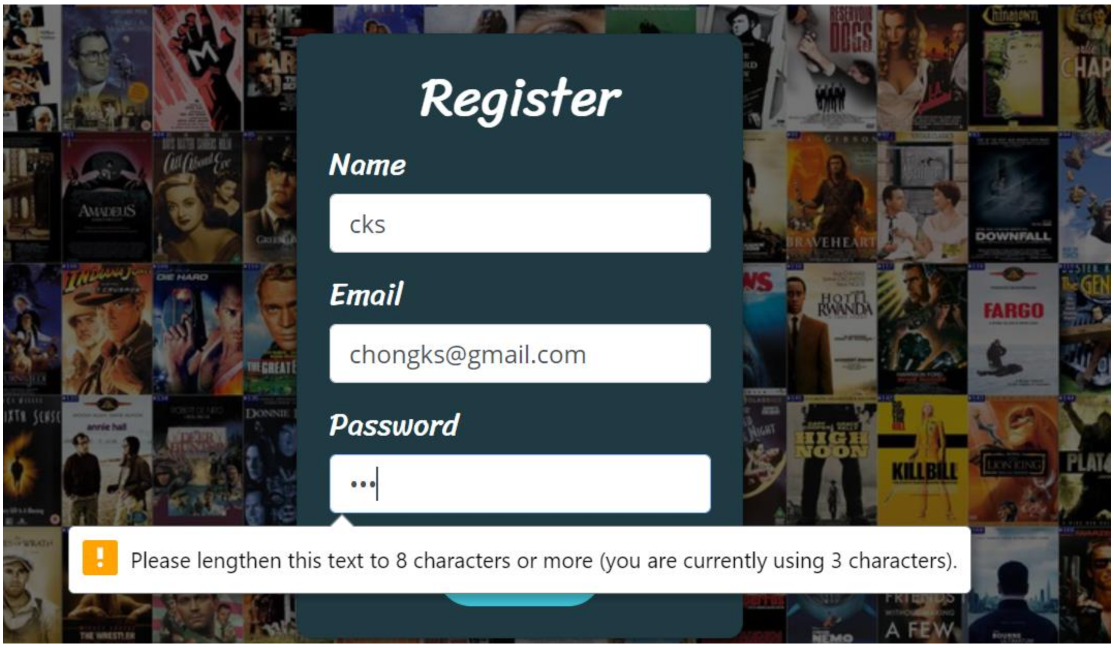


Figure 5.3.4 Enter a password with less than eight characters

5.3.3 Password Change

Table 5.3 Password change decision table

Condition				
C1: Enter the wrong old password	T	-	-	-
C2: Enter a new password with less than eight characters	-	T	-	-
C3: Enter a different new password and confirm the password	-	-	T	-
C4: Enter all correct passwords	-	-	-	T
Action				
A1: Display the error message	T	T	T	F
A2: Update password	F	F	F	T

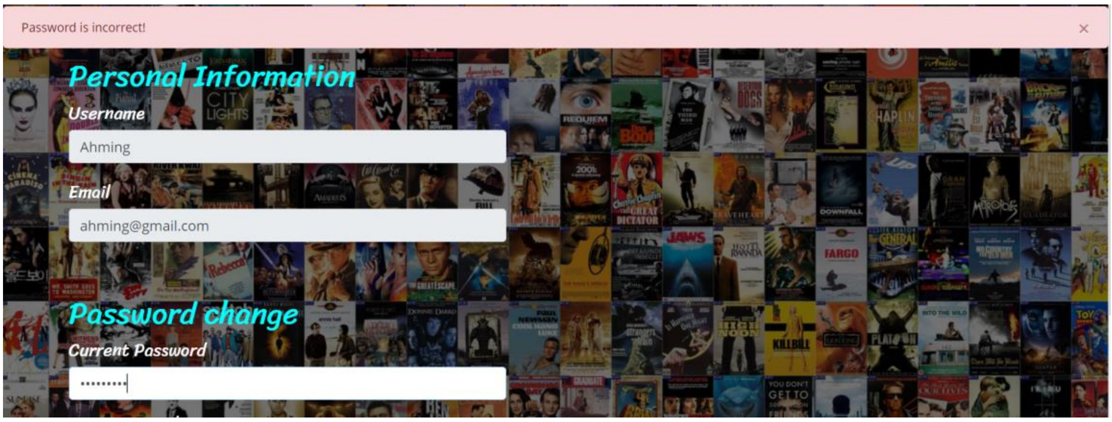


Figure 5.3.5 Enter the wrong password

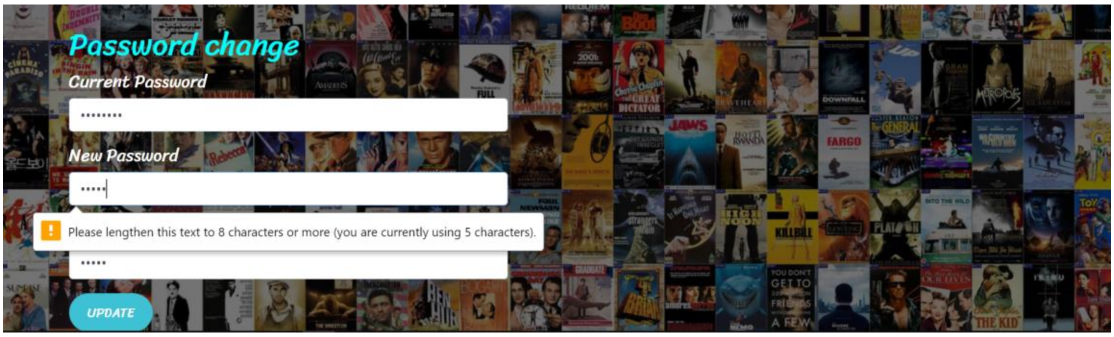


Figure 5.3.6 Enter a new password with less than eight characters

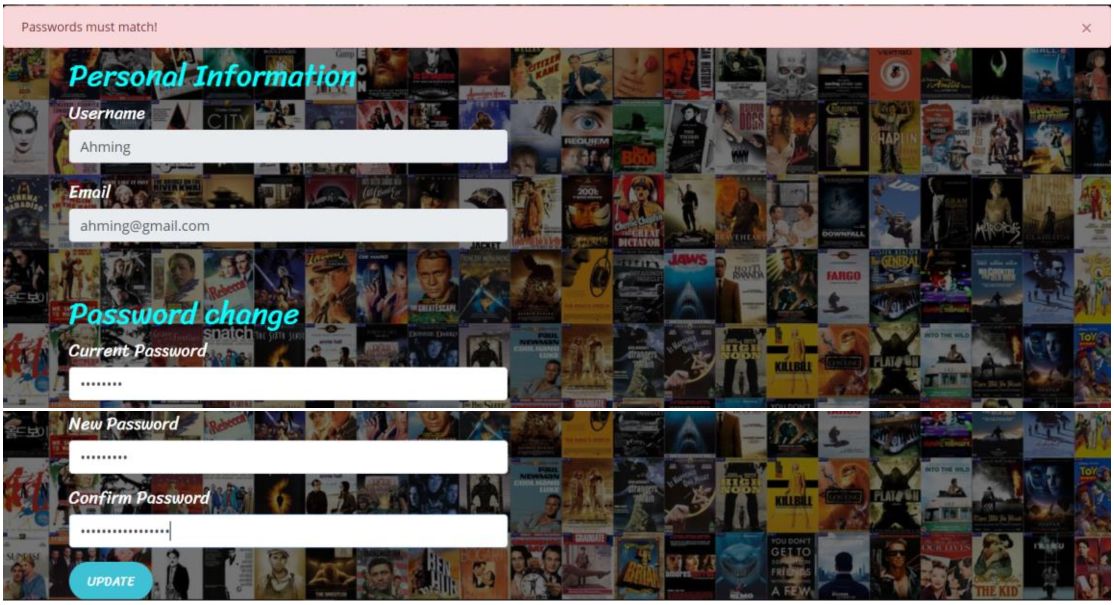


Figure 5.3.7 Enter a different new password and confirm the password

5.3.4 Emotion Recognition

The model was tested on myself as the subject in order to make sure that it can identify all different kinds of human emotions including neutral, happy, surprise, sad, angry, disgust, and fear.

Figure 5.3.8 Neutral face

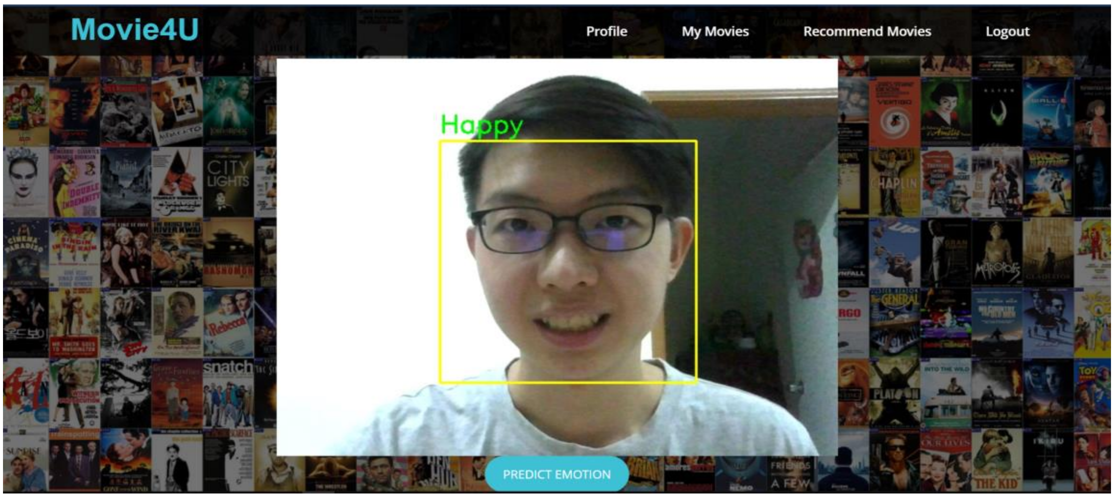


Figure 5.3.9 Happy face

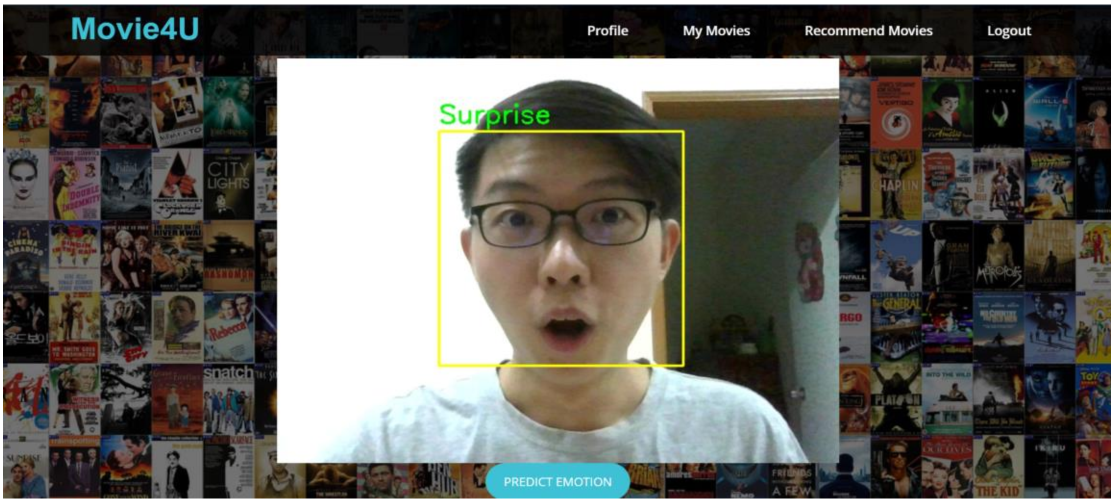


Figure 5.3.10 Surprised face

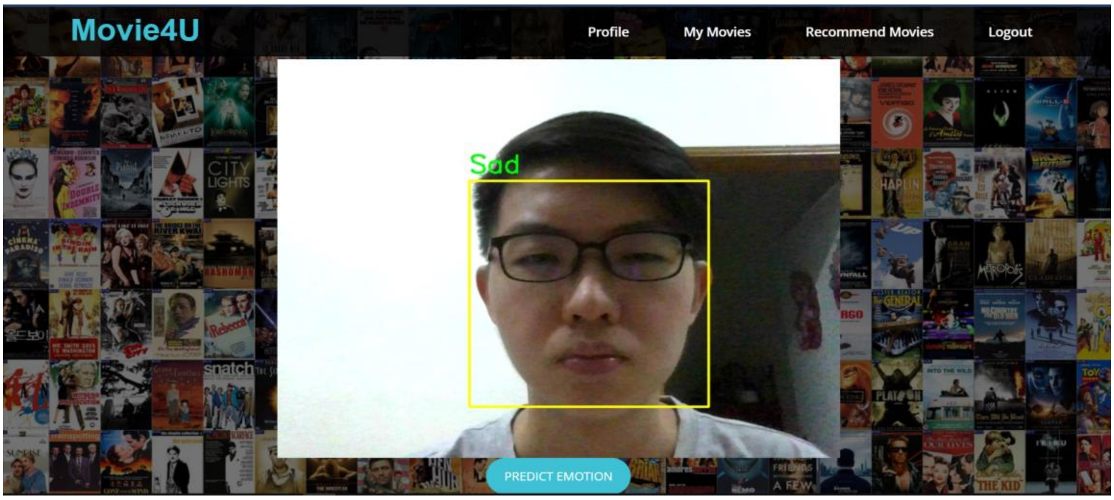


Figure 5.3.11 Sad face

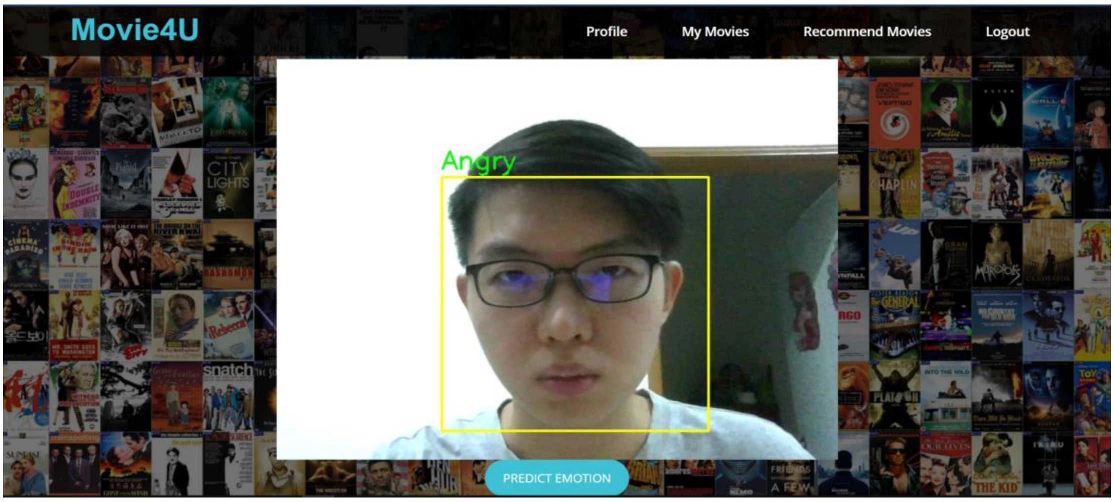


Figure 5.3.12 Angry face

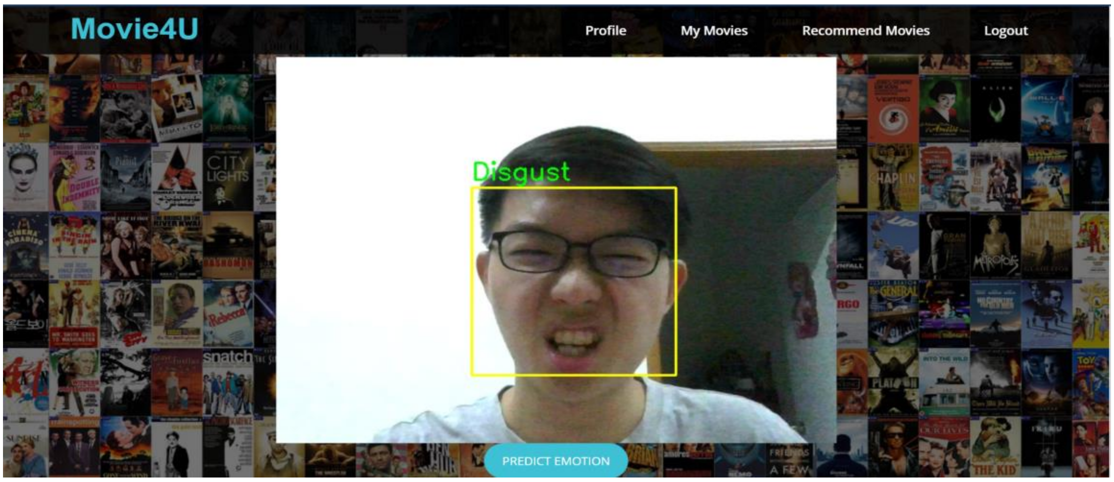


Figure 5.3.13 Disgusted face

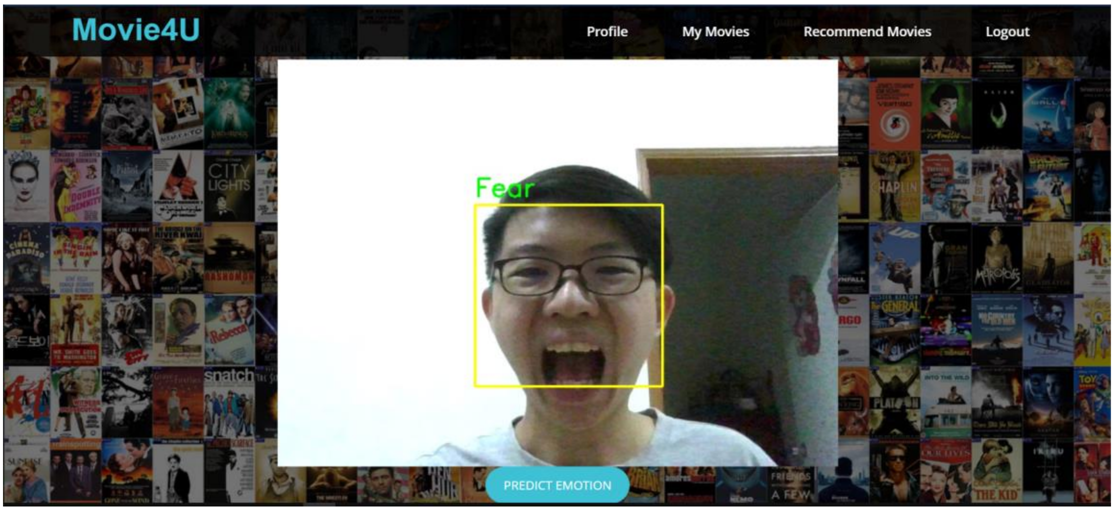


Figure 5.3.14 Fearful face

Besides testing the model on myself, the model was also evaluated on other users. Table 5.4 shows the result of emotion detection on four users. Based on Table 5.4, the effectiveness of emotion recognition can be calculated using the formula below.

$$Effectiveness = \frac{Number\ of\ tasks\ completed\ successfully}{Total\ number\ of\ tasks\ undertaken}\ X\ 100\%$$

$$= \frac{18}{28}\ X\ 100$$

$$= 64.29\%$$

The overall result is quite good as the emotion recognition model can identify most of the six emotions except disgust. This is probably because disgust is a difficult and rarely used expression in our daily life.

Table 5.4 Result of emotion detection

No	Neutral	Happy	Sad	Surprise	Angry	Disgust	Fear
User 1	/	/	x	/	x	x	/
User 2	/	/	/	x	/	x	/
User 3	/	/	/	x	/	x	/
User 4	/	/	x	x	/	x	/

5.4 Analysis

The following analysis is based on the findings of a survey consists of 12 questions which was conducted through Google form. There are a total of 30 users participated in this survey. The full survey questions can be referred in the Appendix.

4. In the past week, how often do you spend time in watching movie?

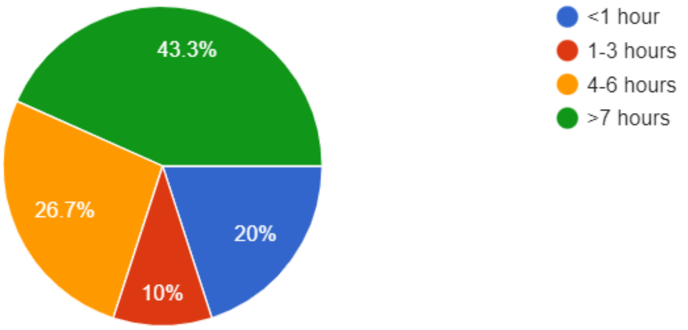


Figure 5.4.1 Weekly amount of time spent watching movies

Figures 5.4.1 shows that 43.3% of the respondents watch movies for more than seven hours a week while 10% of them spend only one to three hours watching movie.

5. Which platform do you normally used to watch movie?

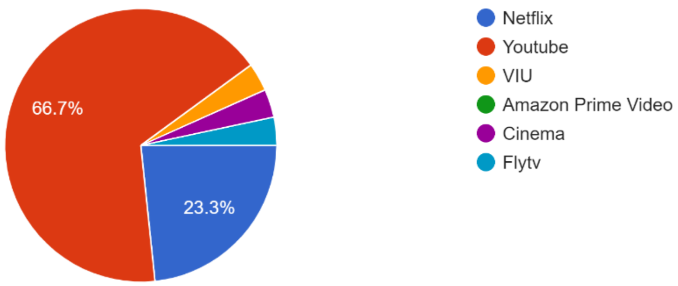


Figure 5.4.2 Platform used to watch movie

Figure 5.4.2 shows that the majority of the respondents which is 66.7% opt to use YouTube to watch movies. This is probably because YouTube offers a lot of contents and is free of charge.

6. When you are HAPPY, what kind of movies do you want to watch?

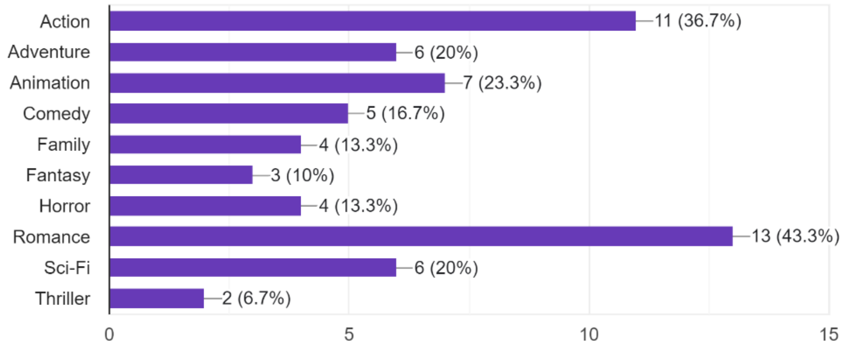


Figure 5.4.3 Movies to watch when feeling happy

Based on Figure 5.4.3, 43.3% of respondents said that they like to watch romantic movies when feeling joyful.

7. When you are SAD, what kind of movies do you want to watch?

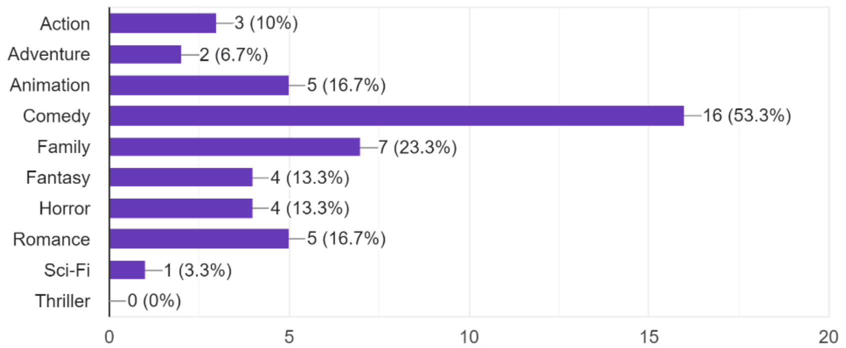


Figure 5.4.4 Movies to watch when feeling sad

53.3% of the respondents think that watching comedy movies can help to make them feel happier as shown in Figure 5.4.4.

8. When you are NEUTRAL, what kind of movies do you want to watch?

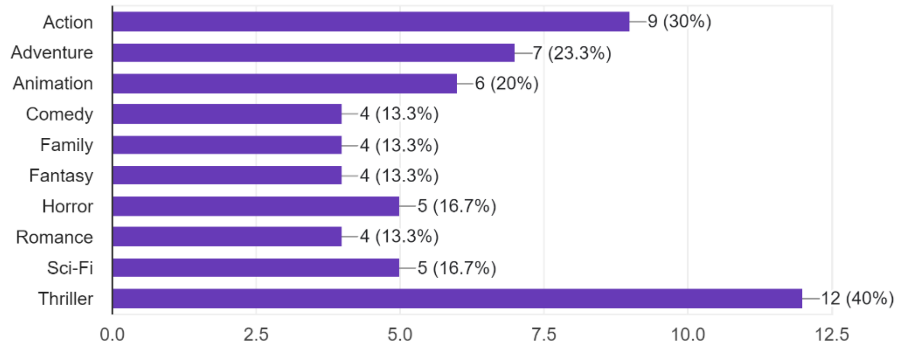


Figure 5.4.5 Movies to watch when feeling neutral

Figure 5.4.5 shows that 40% of the respondents prefer to watch thriller movies when they are neutral. This is most likely because thriller movies are exciting and engage viewers throughout the film.

9. When you are SCARED, what kind of movies do you want to watch?

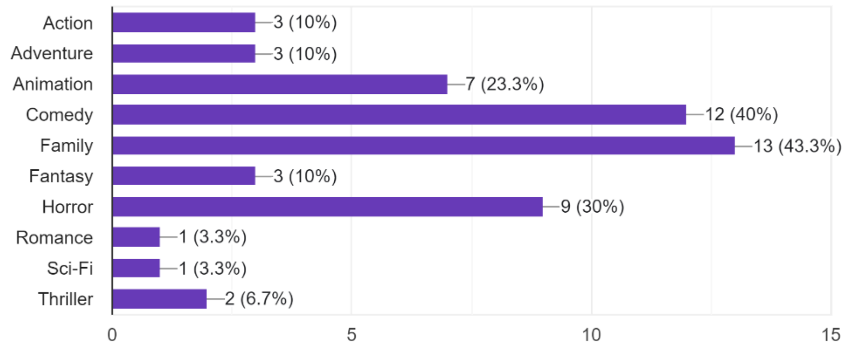


Figure 5.4.6 Movies to watch when feeling scared

43.3% of the respondents choose to watch family movies as it can help to comfort their moods as seen in Figure 5.4.6.

10. When you are SURPRISED, what kind of movies do you want to watch?

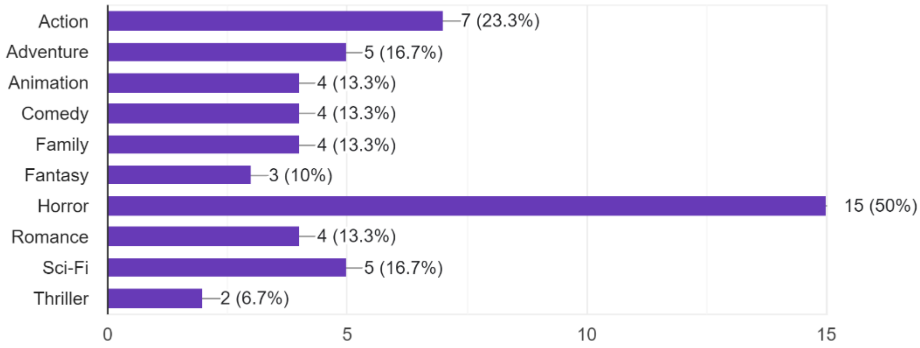


Figure 5.4.7 Movies to watch when feeling surprised

Based on Figure 5.4.7, half of the respondents like to watch horror films to experience surprise.

11. When you are ANGRY, what kind of movies do you want to watch?

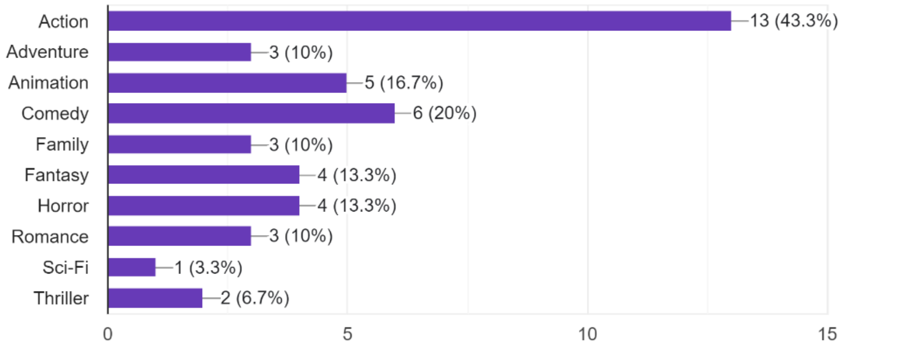


Figure 5.4.8 Movies to watch when feeling angry

From Figure 5.4.8, it is found that when feeling angry, 43.3% of the respondents choose to watch action movies because the fast-paced scene can help them to reduce stress.

12. When you are DISGUSTED, what kind of movies do you want to watch?

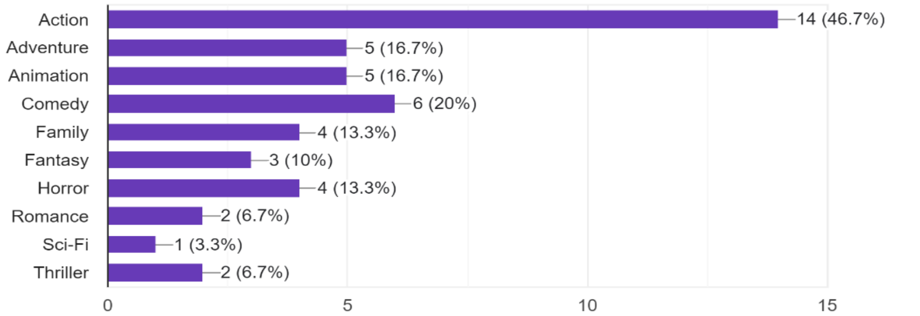


Figure 5.4.9 Movies to watch when feeling disgusted

Figure 5.4.9 shows that 46.7% of the respondents prefer to watch action movies when feeling disgusted.

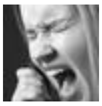
5.5 Project Challenges

One of the challenges faced during the implementation of the CNN model is that the number of images in the FER2013 dataset is not evenly distributed. For example, there are very few images of disgusted faces in the training set and test set. As a result, the emotion recognition model was unable to identify the disgusted emotion. This issue can be solved by applying data augmentation to generate more disgusted images by padding, cropping, and flipping the images.

Furthermore, human emotions are highly subjective as they can have multiple interpretations in some cases. For example, Figure 5.5.1 shows some of the images in the FER2013 dataset that contains two possible labels that are both acceptable. Therefore, it may be challenging for the model to tell apart two emotions that are quite similar to each other.

Surprise/Happy

Sad/Fear



Fear/Angry

Figure 5.5.1 FER2013 images with two possible labels

Other than that, another difficulty faced during web development is the large number of movies with a total of 3500 movies, 50 movies for each of the seven emotions that have to be inserted manually into the database. This issue has been solved by using web scraping to extract the movies from IMDB website, instead of retrieving them from a database. Furthermore, this ensures that the recommended movies are always up to date as they were extracted from the top 50 movies on IMDB website.

The last challenge is the deployment of the web application to Heroku. The OpenCV library was unable to access the user's camera directly as the web application was hosted on the Heroku server. However, other features such as login, register and password change are still functioning. The Heroku app can be accessed at http://cks-fyp.herokuapp.com/.

5.6 Objectives Evaluation

After two semesters, this project has achieved the following objectives:

1. To study the existing methods and artificial intelligence techniques in building an emotion recognition model implemented into the web application.

In order to construct an emotion recognition model, this project have investigated on the artificial intelligence approaches including machine learning and deep learning. The literature review discussed about an example of machine learning techniques which is SVM that can classify emotions into negative and positive emotions. In addition, there are also deep learning methods that make use of a neural network such as deep residual network and attentional convolutional network.

2. To propose a movie recommendation system based on human emotion prediction.

An emotion-based movie recommendation system was proposed. It uses the emotion recognition model to provide real-time movie recommendations to users according to their emotions.

3. To develop the proposed method in recommending relevant movies to user based on human emotion.

The model was developed using CNN which has convolutional layers, pooling layers, flatten layers and fully connected layers. The model was able to recognise and predict human emotions from an image. Based on the outcome, the movie genres that the users might like were determined.

4. To evaluate the effectiveness of the proposed method in recommending relevant movies to the user.

Along with myself, the model was tested on four other people to determine the performance of the model in the real world. Furthermore, the effectiveness of the model was calculated based on the result of emotion recognition.

CHAPTER 6

CONCLUSION

An emotion-based movie recommendation system is needed because the current movie recommendation system is incapable of capturing users' ever-changing movie preferences. In addition, manually selecting one movie to watch is inefficient and could be improved. Therefore, this project was developed to recognize user emotions in real-time and provide users with personalized movie recommendations based on their current mood.

CNN was chosen to train the emotion recognition model because it can extract complex features from images. The architecture of the CNN used in this project consists of four convolutional layers in which each convolutional layer has the conv2D, max-pooling, dropout, and batch-normalization layers. Following that, a fully connected layer and an output layer are added to classify the images into seven classes of emotion. After training the model, it has achieved 74.98% accuracy. Then, the model was hosted on the web application. The Flask framework was used to implement the back end of the web application which includes the user authentication, routing, and connecting the web application to the PostgreSQL database to store the user credentials and their movie recommendations.

For future development, the accuracy of the model can be further improved by expanding the dataset by applying different data augmentations techniques. This is because there are very few disgusted images in the training set and test set. Moreover, the current model uses multi-class classification which generates only one predicted emotion with the highest probability. Therefore, multi-label classification can also be explored to allow for multiple outputs of emotion. This can help to handle images that have multiple possible labels of emotion. Besides that, the user profile page may have a feature which shows the users' preferences in movie genre. This data can help to provide a more accurate movie suggestions based on their latest taste. Finally, the web application will be deployed to a cloud platform such as Heroku, allowing any user to access it via the internet.

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APPENDIX

FINAL YEAR PROJECT WEEKLY REPORT

(Project II)

Trimester, Year: June, 2022	**Study week no.: 4**
Student Name & ID: Chong Kok Sian, 19ACB00256	
Supervisor: Tseu Kwan Lee	
Project Title: An Emotion-Based Movie Recommendation System Using Convolutional Neural Network	

1. WORK DONE
[Please write the details of the work done in the last fortnight.]

- Split 20% of the training set into validation set
- Added data augmentation

2. WORK TO BE DONE

- Train the model using validation set

3. PROBLEMS ENCOUNTERED

- -

4. SELF EVALUATION OF THE PROGRESS

- So far so good

Supervisor's signature

Student's signature

FINAL YEAR PROJECT WEEKLY REPORT

(Project I)

Trimester, Year: June, 2022	**Study week no.: 6**
Student Name & ID: Chong Kok Sian, 19ACB00256	
Supervisor: Tseu Kwan Lee	
Project Title: An Emotion-Based Movie Recommendation System Using Convolutional Neural Network	

1. WORK DONE [Please write the details of the work done in the last fortnight.] • Added early stopping and checkpoint • Trained the model using validation set • Evaluated the model performance
2. WORK TO BE DONE • Improve on the website user interface design
3. PROBLEMS ENCOUNTERED • -
4. SELF EVALUATION OF THE PROGRESS • So far so good

Supervisor's signature

Student's signature

FINAL YEAR PROJECT WEEKLY REPORT

(Project I)

Trimester, Year: June, 2022	**Study week no.: 8**
Student Name & ID: Chong Kok Sian, 19ACB00256	
Supervisor: Tseu Kwan Lee	
Project Title: An Emotion-Based Movie Recommendation System Using Convolutional Neural Network	

1. WORK DONE

[Please write the details of the work done in the last fortnight.]

- Improved the website user interface design
- Implemented the password change feature

2. WORK TO BE DONE

- Test the website for any error
- Deploy the website to Heroku

3. PROBLEMS ENCOUNTERED

- -

4. SELF EVALUATION OF THE PROGRESS

- So far so good

Supervisor's signature

Student's signature

FINAL YEAR PROJECT WEEKLY REPORT

(Project I)

Trimester, Year: June, 2022	**Study week no.: 10**
Student Name & ID: Chong Kok Sian, 19ACB00256	
Supervisor: Tseu Kwan Lee	
Project Title: An Emotion-Based Movie Recommendation System Using Convolutional Neural Network	

1. WORK DONE
[Please write the details of the work done in the last fortnight.]

- Finished writing the report

2. WORK TO BE DONE

- Finalize and check the report
- Submit the report to Turnitin
- Deploy the website to Heroku

3. PROBLEMS ENCOUNTERED

- -

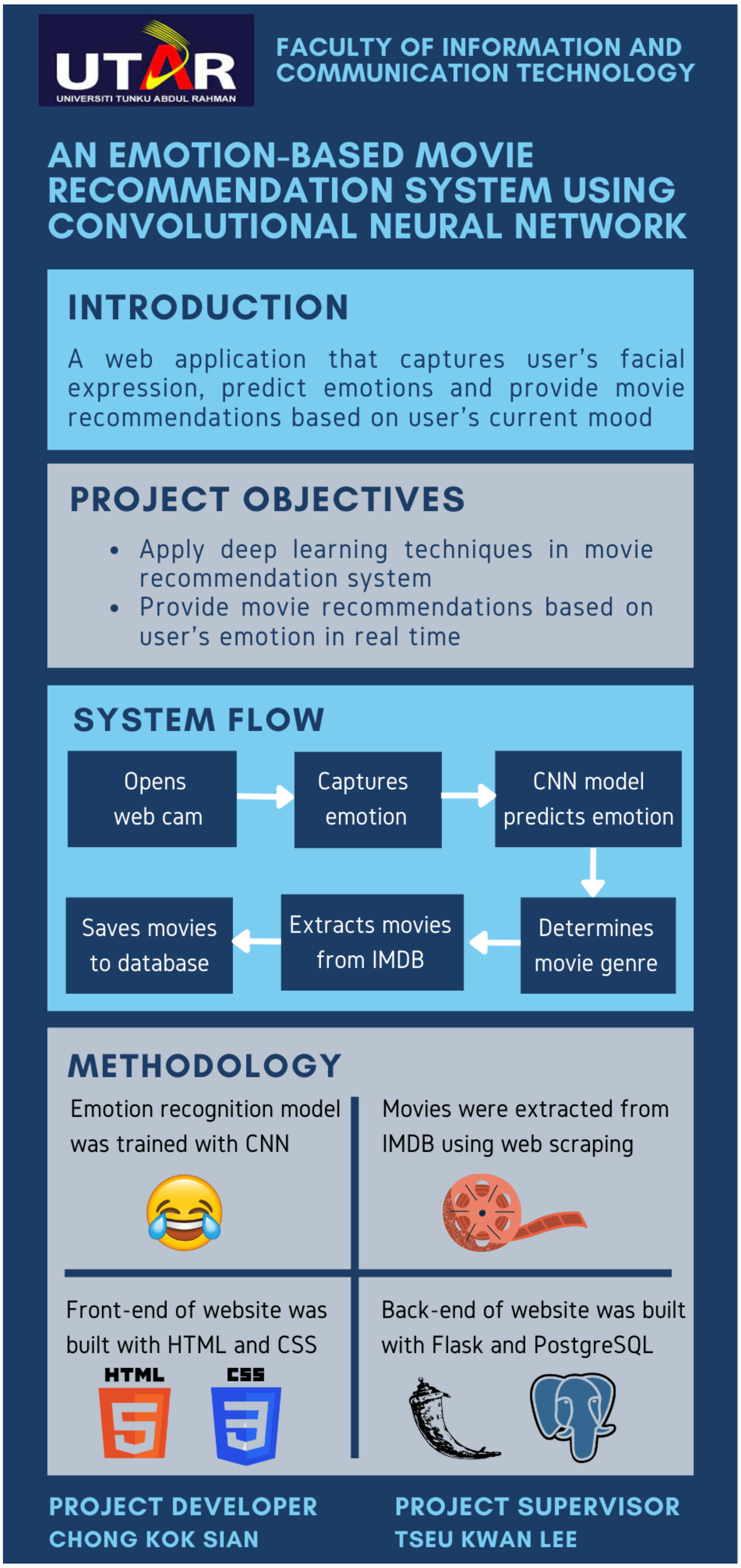
4. SELF EVALUATION OF THE PROGRESS

- So far so good

Supervisor's signature

Student's signature

POSTER


UTAR
UNIVERSITI TUNKU ABDUL RAHMAN
FACULTY OF INFORMATION AND COMMUNICATION TECHNOLOGY
AN EMOTION-BASED MOVIE RECOMMENDATION SYSTEM USING CONVOLUTIONAL NEURAL NETWORK
INTRODUCTION
A web application that captures user's facial expression, predict emotions and provide movie recommendations based on user's current mood
PROJECT OBJECTIVES
• Apply deep learning techniques in movie recommendation system
• Provide movie recommendations based on user's emotion in real time
SYSTEM FLOW
Opens web cam
Captures emotion
CNN model predicts emotion
Determines movie genre
Extracts movies from IMDB
Saves movies to database
METHODOLOGY
Emotion recognition model was trained with CNN
Movies were extracted from IMDB using web scraping
Front-end of website was built with HTML and CSS
HTML
CSS
Back-end of website was built with Flask and PostgreSQL
PROJECT DEVELOPER
CHONG KOK SIAN
PROJECT SUPERVISOR
TSEU KWAN LEE

GOOGLE FORM QUESTIONS

1. Gender *

- ○ Male
- ○ Female

2. Age *

- ○ 1-17
- ○ 18-25
- ○ 26-35
- ○ 36-45
- ○ Above 45

3. Race *

- ○ Malay
- ○ Chinese
- ○ Indian
- ○ Bumiputera
- ○ Other: ____

4. In the past week, how often do you spend time in watching movie? *

- ◯ <1 hour
- ◯ 1-3 hours
- ◯ 4-6 hours
- ◯ >7 hours

5. Which platform do you normally used to watch movie? *

- ◯ Netflix
- ◯ Youtube
- ◯ VIU
- ◯ Amazon Prime Video
- ◯ Other: ____________

6. When you're HAPPY, what kind of movies do you want to watch? *

- ☐ Action
- ☐ Adventure
- ☐ Animation
- ☐ Comedy
- ☐ Family
- ☐ Fantasy
- ☐ Horror
- ☐ Romance
- ☐ Sci-Fi
- ☐ Thriller

7. When you're SAD, what kind of movies do you want to watch? *

- [ ] Action
- [ ] Adventure
- [ ] Animation
- [ ] Comedy
- [ ] Family
- [ ] Fantasy
- [ ] Horror
- [ ] Romance
- [ ] Sci-Fi
- [ ] Thriller

8. When you're NEUTRAL, what kind of movies do you want to watch? *

- [ ] Action
- [ ] Adventure
- [ ] Animation
- [ ] Comedy
- [ ] Family
- [ ] Fantasy
- [ ] Horror
- [ ] Romance
- [ ] Sci-Fi
- [ ] Thriller

9. When you're SCARED, what kind of movies do you want to watch? *

- [ ] Action
- [ ] Adventure
- [ ] Animation
- [ ] Comedy
- [ ] Family
- [ ] Fantasy
- [ ] Horror
- [ ] Romance
- [ ] Sci-Fi
- [ ] Thriller

10. When you're SURPRISED, what kind of movies do you want to watch? *

- [ ] Action
- [ ] Adventure
- [ ] Animation
- [ ] Comedy
- [ ] Family
- [ ] Fantasy
- [ ] Horror
- [ ] Romance
- [ ] Sci-Fi
- [ ] Thriller

11. When you're ANGRY, what kind of movies do you want to watch? *

- [ ] Action
- [ ] Adventure
- [ ] Animation
- [ ] Comedy
- [ ] Family
- [ ] Fantasy
- [ ] Horror
- [ ] Romance
- [ ] Sci-Fi
- [ ] Thriller

12. When you're DISGUSTED, what kind of movies do you want to watch? *

- [ ] Action
- [ ] Adventure
- [ ] Animation
- [ ] Comedy
- [ ] Family
- [ ] Fantasy
- [ ] Horror
- [ ] Romance
- [ ] Sci-Fi
- [ ] Thriller

PLAGIARISM CHECK RESULT

An Emotion-Based Movie Recommendation System Using Convolutional Neural Network

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