CO3519 Assignment 2 – Facial Emotion Recognition using Advanced AI

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## ***Introduction***

Facial Emotion Recognition (FER) encompasses computer vision tasks which are aimed at identifying various human emotions depicted via a face and then categorizing them into various emotional categories. The process of detecting emotions normally revolves around analysing facial landmark positions such as nose, eyebrows and mouth. Changes to these positions can be analysed and then categorised into emotions.

FER is deemed to be an important and advantageous application of Artificial Intelligence technologies, since much communication is non-verbal. The exact amount is contested, however some studies suggest up to 60-80% of communication is non-verbal, providing a significant area for potential use and deployment. FER also has numerous applications across various sectors from education, to autopilot systems, to neuroscience.

The previous paper on this topic discussed the implementation of an FER algorithm using Machine Learning via Histogram of Oriented Gradients feature extraction and Random Forest Emotion Classification. This was somewhat powerful; however, it also had some limitations.

* Performance was mixed across various emotions. Whereas the algorithm performed well on some emotions such as happiness and surprise, the algorithm struggled with classifying anger and sadness.
* Due to the simplicity of the model. underfitting was a problem. This meant that certain patterns in the data couldn’t be captured, and performance on the testing data for some emotions was comparatively poor.
* While some of the observed discrepancies could’ve potentially been due to biases in the training datasets, there was nonetheless deemed to be areas for improvement which could be built on by using a more complex algorithm.

To try and improve the performance of FER, this paper will discuss the implementation of an Advanced AI algorithm based on Convolutional Neural Networks (CNNs). These networks are specialized deep learning algorithms designed for tasks that involve object recognition. CNNs contain several key components…

* **Convolutional Layers** apply a sliding window function to the matrix of pixels. The sliding function is called a filter, and several filters can be applied.
* **Rectified Linear Unit Activation Functions** are applied after each convolution operation, aiding the network to learn non-linear relationships between image features. This makes the network stronger at identifying different patterns.
* **Pooling layers** pull the most significant features from a convoluted matrix by applying aggregation operations which reduce the dimension of the matrix. This in turn reduces the amount of memory when training the network
* **Fully connected layers** are the last layer of the CNN and their inputs correspond to the flattened one dimensional matrix generated by the last pooling layer.

An example architecture of a CNN can be found below…

A diagram of a diagram of a block diagram

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The potential CNN architectures that will be discussed include VGG and ResNet.

## ***Literature Review***

Visual Geometry Group (VGG) is a standard deep CNN. VGG-16 is an example of such network and consists of 16 layers. This model has been found to achieve a test data accuracy of 92.77% with the ImageNet dataset. Images of size 224x224x3 are passed through various layers. The convolution layer has a 3x3 filter size while the max pooling layer has a filter size of 2x2. VGG-19 consists of three more convolutional layers than VGG-16 which should allow it to capture more complex image features.

ResNet50 is another CNN consisting of 50 convolution layers, making it a deeper network than VGG-16 and VGG-19. There are four main sections, the convolutional layers which extract features from the input image, an identity block and convolutional block which process and transform the features extracted, and then the fully connected layers which are used to make the final classification. In addition, unlike VGG, ResNet-50 uses residual blocks which allows the network the skip certain connections which enables better performance.

Mascarenhas and Agarwal (2021) carried out feature extraction on a dataset of 6000 images which could be classified into 5 different categories; shoes, beauty, jewellery, watches and bags. Once the features were extracted, they were fed into the various models to classify the images. All of the images needed to be compressed since they were of too great a size to be inputted into the convolutional layers. Classification was tested using each algorithm with different numbers of epochs. The study found that ResNet50 exhibited the highest accuracy followed by VGG-19 and VGG-16. They also found that epoch values above 20 induced overfitting and values below 15 induced underfitting, indicating that an optimal range of epoch values is between 15 and 20. This gives some indication about the benefits, however a potential limitation of this study was that it was specifically covering the classification of images of objects into certain categories, not facial recognition. Therefore, further research was required to understand whether this was a consensus or an outlier.

The conclusion that ResNet50 produces higher accuracy than VGG appears to be a consensus across the literature. Truong Van Nguyen and Tuan Duc Chu (2023) also compared VGG and ResNet50 however this was specifically for facial recognition. The two algorithms were implemented to measure the accuracy of each one and compare them. The learning rate was set to the same value of 0.0001 for both algorithms and the models were trained for 80 epochs on 2900 face picture from 52 people. This makes this paper more relevant to this use case than Their study also found that the accuracy of ResNet-50 was higher than VGG-16, with values of 95.6% for ResNet and 94% for VGG-16. Both algorithms were more accurate than SVN at 88% highlighting the benefit of deep learning. However, while this study does cover the application of the algorithms for facial recognition, it only covers targeting a face in an image rather than classifying emotions.

Dhankhar (2019) on the other hand compares the algorithms for specifically classifying emotions. This study involved developing CNN models to classify emotions using VGG and ResNet 50, leveraging the Kaggle Facial Expression Recognition Challenge and Karolinska Directed Emotional Faces (KDEF) datasets. The images from the two datasets were classified into six separate emotions – anger, disgust, fear, happiness, sadness, surprise and neutral. The study once again backed up the consensus that ResNet is advantageous compared to VGG, since on both the KDEF dataset, and the KDEF dataset with transfer learning from the Kaggle models, ResNet-50 produced a higher accuracy score, but also a higher precision and recall score. This made the consensus that ResNet-50 would be advantageous over VGG even more clear, since it covered the specific use case which the model to be developed will be deployed for.

In conclusion, this literature review has indicated that ResNet-50 will be the appropriate CNN to use for this task. The literature has widely indicated that ResNet-50 produces higher levels of accuracy compared to more traditional CNNs such as VGG, both for general classification but also for facial recognition and facial emotion classification. Therefore, this will inform the development of a CNN model using ResNet-50.

## ***Datasets***

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The JAFFE dataset is a set of 213 images from 10 Japanese female subjects with various facial expressions. This dataset was created for non-commercial scientific research. Each of the ten subjects did seven facial expressions to correspond to the following emotions…

* Happiness
* Sadness
* Surprise
* Anger
* Disgust
* Fear
* Neutral

A sample of these images can be found in Appendix A.

The images are already in grayscale format and clearly show a face. Converting images to grayscale is important for this study since some detection algorithms like HOG are defined based on grayscale values, and generally using grayscale also reduces complexity which in turn reduces the demands on memory and processing power. There is also no evidence of significant background noise in the sample images that would need to be filtered out. A link to the dataset can be found here <https://paperswithcode.com/dataset/jaffe>. Before being inputted into the model, the various images were organised into their respective emotions and grouped together into folders.

The Cohn-Kanade Dataset (CK+) is a dataset that was created in 2000 for the purpose of promoting research into automatically detecting facial expressions. There are 593 video sequences from 123 different subjects ranging from 18 to 50 years old with various genders and heritage. This is advantageous compared to the JAFFE dataset since it only focuses on Japanese female subjects, meaning the model can be trained on a more diverse range of subjects. Once again, there is no evidence of significant background noise in the sample images that would need to be filtered out. A link to the dataset can be found here <https://www.kaggle.com/datasets/shuvoalok/ck-dataset?resource=download>.

Preprocessing of the images was required…

* **Image resizing :**  The images needed to be resized to 224x224 pixels. This is because ResNet expects input images to be of that size, so not resizing the images could’ve caused errors.
* **Tensor Conversion** : This was required to convert the images to PyTorch tensors. This is done to enable the images to be used more efficiently in a deep learning pipeline.
* **Normalization** : The images were normalized using the mean and standard deviation of the ImageNet dataset. This ensured that the input data was aligned with the expectations of the model, making the process of training the model more efficient.

## ***Model Development***

The model was developed using the

## ***Model Evaluation***

## ***Conclusion***

## ***Appendix***

Appendix A:

Appendix B : Diagram of implementation



A screenshot of a computer

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A graph of a line and a line

AI-generated content may be incorrect.

## ***References***

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