ITI110 – DEEP LEARNING PROJECT

MILESTONE REPORT - Feb 2022

FACIAL RECOGNITION

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1. Introduction

This milestone report is an extension to the report proposal that we submitted in January 2022. In this report, we will focus on elaborating our progress in the next few sections.
Our approach is to do individual experiments on selected deep learning architectures and then carefully select our final model. We will then add the rest of the elements to complete this face recognition project.

2. Modeling Experimentations

Each of us selected a deep learning model architecture to experiment and will pick the best possible choice based on several factors to further fine-tune it as our final model. Below are our write-ups which dictate our effort, experiments, limitations and recommendations by us.

2.1. ResNet50 with Triplett Loss Architecture (Experiment done by Yap Jing Yang)

Yap Jing Yang had come up with a short 10-mins video(MileStone_Writeup_YapJingYang.mp4) to explain his portion of work. The video is submitted together with this report.

2.2. Siamese Network with Triplet Loss (Experiment done by Looi)

Algorithm for get triplet using “np.random.choice” for y val label and train label.
Negative image= random pick ‘n’ image.
Anchor,positive image= random pick ‘a’ not equal to ‘n’, followed by using ‘a’ to pick ‘p’ same person but different jpg file.
F1-score results (refer to Appendix 1):
i) 2 conv layer - 0.1
ii) Mobilenet (~0.6% of trainable conv layer set to true) - 0.24
iii) Resnet50 (only conv5 trainable set to true) - 0.27
GPU memory problem:
Run2 Resnet50, image size must reduce to 100x100.
Run3 Resnet50, image size reduce to 100x100 and batch size reduce to 32

2.3. EfficientFaceNet (Experiment done by Ng Wei Xiang)

The EfficientNet B0 was used as the backbone for the encoder model. Various methodologies are experimented and several features highlighted in the following sections.

2.3.1. Siamese Network

The first model is the standard siamese network with triplet loss that tries to pull embeddings of identical class together while pushing embeddings of different classes away. It comprises of the EfficientNet B0 backbone with its corresponding default input shape of 224 x 224, followed by a pooling layer, then a dense layer and lastly a L2 normalisation layer, which acts as the output embedding of the encoder. The normalisation layer provides an additional constraint that defines a relationship between the cosine similarity and euclidean distance metrics, and is especially useful if the latter is used as it would then be otherwise unbounded.

2.3.2. Semi-Freezing of Pretrained Backbone

While the model is initiated with the weights pretrained on ImageNet, our application is specifically on facial dataset and so the pretrained weights in the latter layers might not be as suitable. However, the first few layers would still be useful as they capture more basic structures such as edges. As such, several experimentations are done with different proportions of the backbone frozen midway.

2.3.3. Online Semihard Triplet Mining

As pointed out in the FaceNet paper, selecting the triplets at random often times leads to trivial triplets which are too easy. On the other hand, hard triplet mining is also an option and is in fact explored, it does not lead to model convergence. As such, semihard triplet mining is explored to ensure that the triplets are decently difficult so that the model could learn from them.

However, offline mining is extremely computationally expensive as it requires the model to process all valid triplet permutations of the entire dataset per epoch. Instead, online mining does it similarly but on the batch level, which is more efficient.

2.3.4. Global Depthwise Convolution

Inspired by the MobileFaceNets paper, instead of using the usual global average pooling to collapse the feature maps, a depthwise convolution layer with filter size equaling to the feature map size is used to act as the pooling functionality, but with the added relaxation that each pixel of each feature map can be treated with different importance.

2.3.5. Knowledge Distillation

Using FaceNet as the teacher, the encoder model is trained to produce embeddings as close as possible, based on cosine similarity or euclidean distance, to the target embedding produced by

FaceNet on the same input. While the FaceNet embedding might not be perfect, this allows our smaller encoder model to mimic FaceNet and accelerate its learning.

2.3.6. Encoder Model Evaluation

After training, the model will first be used to generate the embeddings for all the images in the testing dataset. Thereafter, for each class in the testing dataset, one of the embeddings will then be registered in the database. The unregistered images are then compared against all the registered embeddings and the class with the highest cosine similarity is chosen as the model prediction. Lastly, the classification report can be generated for comparison.

It should be noted that this performance would not be reflective of the actual performance on the ground as the concept of unidentified class is undefined. However, this evaluation methodology is sufficient at this point in time as we are only doing the evaluation for model comparison.

2.3.7. Encoder Model Comparison

The first is the model that is initialised with pretrained weights on ImageNet and trained with triplet loss. Unfortunately, the model only managed to achieve a testing accuracy score of about 0.46 and macro F1 of about 0.33. Although it is much higher than random guessing, which puts the accuracy score at about 0.0056, it is not close to ideal at all, considering that FaceNet managed to achieve an accuracy score of about 0.89 and macro F1 of about 0.76. This might be due to the limited dataset and capacity of the model.

The second model is trained using knowledge distillation with cosine similarity as the loss. This model managed to achieve a much better testing accuracy score of about 0.74 and macro F1 of about 0.62. While there is still a gap between the model and FaceNet, it seems to be pretty good considering that the model is more than five times smaller. The reason might be that the model finds it easier to learn from the teacher embeddings rather than through triplet loss, and it could leverage what the larger model has learned while keeping itself compact.

The third model is a combination of the other two models by initiating using the pretrained weights from distillation and trained with triplet loss. The idea is to hopefully finetune the distilled model to get a better performance. However, there is only a slight improvement in performance to a testing accuracy of about 0.76 and macro F1 of about 0.66. This is probably because the FaceNet embedding itself is not perfect and so this extra finetuning could help to push the embeddings slightly in the right direction.

2.3.8. Verification Models

After generating the embeddings, we explored using another shallow neural network that takes in two embeddings and outputs the probability of them being identical. Apart from trying with just

the standard shallow classifier, some transformations are also introduced in order to achieve certain desirable properties.

2.3.9. Embedding Transformations

In the usual shallow neural network, the two embeddings are passed into the network separately followed by concatenation. This network however does not possess the commutative property that a function should have when calculating similarity. In other words, the output probability would usually be different by swapping the two input embeddings, when in fact we expect the probability to remain unchanged. As such, transformations are made on the two embeddings such that it retains the original information up to commutativity in the newly mapped space.

Also, rather than taking any possible transformation, the transformation of element wise multiplication and squared difference are used since they incorporate meaningful distance metrics, corresponding to cosine similarity and squared euclidean distance respectively, that might facilitate learning. It can easily be shown that the original input can be deduced given the new transformation up to commutativity.

2.3.10. Verification Model Evaluation

The evaluation methodology is slightly adjusted to fit the verification context. The embeddings are still first generated for all images in the testing dataset. Then, for each embedding, it is compared against all other embeddings to determine whether each pair is identical or not based on a certain threshold, which is taken to be the threshold at which a maximum of 0.1% of False Acceptance Rate (FAR) is obtained.

2.3.11. Verification Model Comparison

The first is the model that based its prediction directly by computing cosine similarity between two embeddings. It managed to achieve an accuracy score of about 0.98 and macro F1 of about 0.83, which seems acceptable, noting FaceNet accuracy score of about 0.99 and macro F1 of about 0.92.

However, the second model where a shallow classifier is used unfortunately also achieved the same performance as the first. As such, it does not seem worthwhile to have an additional classifier model.

2.3.12. Summary

All in all, the third encoder model with no additional classifier managed to achieve a decent performance and is the best among all other experimentation runs.

2.4. MobileNet with Triplet Loss Architecture (Experiment done by George)

MobileNetV1 is a lightweight deep NN based on streamlined architecture and built by using separable convolution. The core layer made by MobileNetV1 is a deep separable filter, and a deep separable convolution is a form of deconvolution. It proposes a high-performance architecture with hyperparameters, which can make the model smaller and the calculation speed faster, and it is efficient for face recognition systems.

This particular architecture is an experiment using the Triplet Loss function to train the neural network, and the output is a 128-dimensional vector space. The selected Triplets contain two matching face thumbnails and a non-matching face thumbnail, and the Loss function targets distinguishing positive and negative classes by distance boundaries.

Before starting the training and calculating the Triplet Loss to make the distance between the same images, we must apply L2 feature normalization after MobileNet CNN and face embedding before the Triplet Loss function. Ideally, the positive image should be closer to the anchor, and the negative image should be away from the anchor image.

The initial hyperparameter setting on the model is set with 30 epochs, 64 batch sizes, the learning rate is 0.02. The f1-score accuracy is 0.42, the average precision score is 0.46, and the average recall score is 0.44. This is not the ideal model as the minimum threshold is at least a score of 0.5, and the best target threshold is at least a score of 0.8. Next, fine-tuning the hyperparameters by changing the batch size to 128 and the learning rate to 0.002. The f1-score accuracy is 0.45, the average precision score is 0.49, and the average recall score is 0.47. On the final run, fine turning on the hyperparameters by changing the batch size to 64 and the learning rate to 0.0002. The f1-score accuracy is 0.46, the average precision score is 0.5, and the average recall score is 0.48.

Although changing different hyperparameter settings, the accuracy score does not meet the minimum threshold score of 0.5. However, overall, the computation time is reasonable fast due to the model's architecture. Therefore, it is worth exploring further and improving the accuracy by changing the model to the MobileNet related model and fine-tuning the parameters, FaceNet or Fast FaceNet model, for example.

3. Conclusion

After weighing the pros and cons of the different models that we had experimented, we decided to use the model devised by Ng Wei Xiang. The main reason being his model is more complete as our models are lacklustre in several ways and his model has shown the potential to achieving higher heights with more training and fine-tuning.

4. Next Course of Action

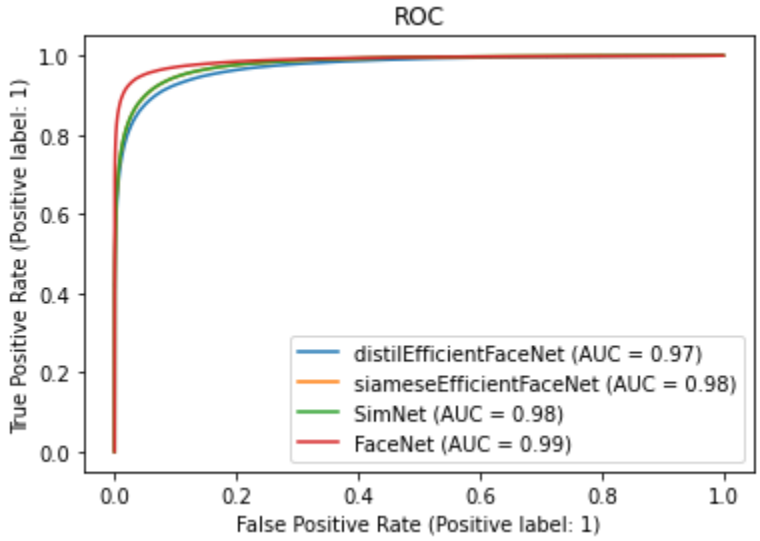
Now we have chosen our model, we will aim to add the following functions to complete the project:

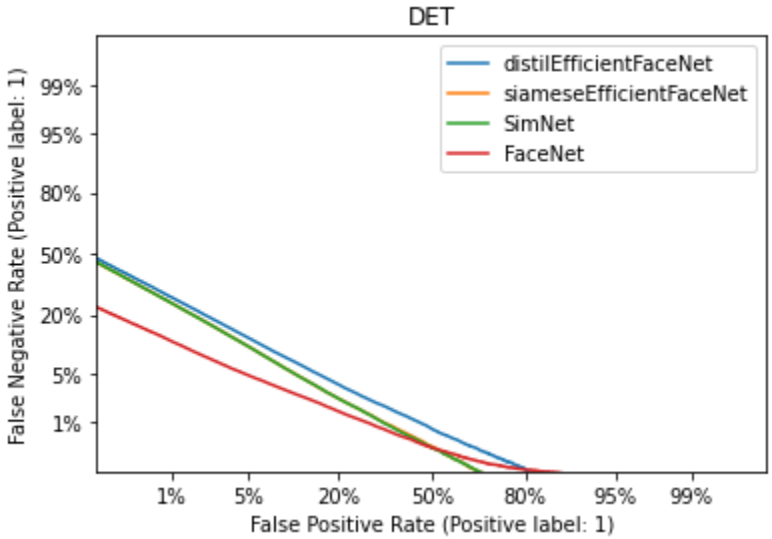
1) HTML function to use webcam to read in the name input and image.
2) MTCNN function to detect and crop face.
3) Verification function to verify identity.

Annex A. References

1) Pins Face Recognition Kaggle Dataset
   https://www.kaggle.com/hereisburak/pins-face-recognition
2) Labeled Faces in the Wild Dataset
   http://vis-www.cs.umass.edu/lfw/
3) FaceNet: A Unified Embedding for Face Recognition and Clustering
   https://arxiv.org/pdf/1503.03832.pdf
4) Tensorflow Documentation
   https://www.tensorflow.org/
5) Triplet Loss and Online Triplet Mining in TensorFlow
   https://omoindrot.github.io/triplet-loss
6) MobileFaceNets: Efficient CNNs for Accurate RealTime Face Verification on Mobile Devices
   https://arxiv.org/ftp/arxiv/papers/1804/1804.07573.pdf

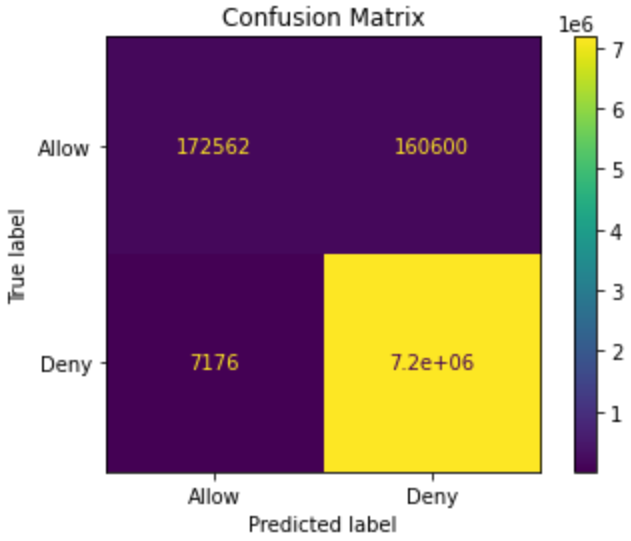
Annex B. EfficientFaceNet Performances





Threshold: 0.5443

	precision	recall	f1-score	support
Allow	0.9601	0.5180	0.6729	333162
Deny	0.9781	0.9990	0.9884	7182660
accuracy			0.9777	7515822
macro avg	0.9691	0.7585	0.8307	7515822
weighted avg	0.9773	0.9777	0.9745	7515822


Confusion Matrix
1e6
7
6
5
4
3
2
1
Allow
Deny
True label
172562
160600
7176
7.2e+06
Allow
Deny
Predicted label

Annex C. Looi's Model Performances

Base model: 2 conv layers

run	Batch size	Image size	model	Number of Epoch	F1-score for test dataset
1	128	160X160	Two conv layers	13	0.1

Base model: Mobilenet

run	Batch size	Image size	model	Number of Epoch	F1-score for test dataset
1	128	160X160	Set 54 onward trainable to true (~0.6% conv layers)	27	0.24

Base model: Resnet50

run	Batch size	Image size	model	Number of Epoch	F1-score for test dataset
1	128	160X160	Set Conv5, last layer trainable to true	22	0.27
2	128	100x100	Set Con4 layer onward trainable to true	26	0.27
3	38	100x100	Set Con3 layer onward trainable to true	55	0.18

Run 2 - f1 score

	precision	recall	f1-score	support
alycia_dabnem_carey	0.21	0.11	0.15	210
bobby_morley	0.61	0.12	0.21	136
gloria_macapagal_arroyo	0.20	0.37	0.26	43
henry_cavil	0.48	0.11	0.18	193
jimmy_fallon	0.19	0.30	0.23	112
katharine_mcphee	0.14	0.09	0.11	176
leonardo_dicaprio	0.27	0.30	0.28	243
lleyton_hewitt	0.39	0.45	0.42	40
morena_baccarin	0.34	0.48	0.40	174
scarlett_johansson	0.19	0.20	0.19	200
stephen_amell	0.53	0.29	0.38	158
tuppence_middleton	0.27	0.52	0.36	132
zendaya	0.24	0.48	0.32	136
accuracy			0.27	1953
macro avg	0.31	0.29	0.27	1953
weighted avg	0.31	0.27	0.25	1953