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Feature Extraction Face-Off: A Comparative Analysis of InceptionV3 and VGG19 for Face Recognition

Shem L. Gonzales

Faculty, College of Engineering and Information Technology,
Surigao del Norte State University-Del Carmen Campus, Philippines
slgonzales@ssct.edu.ph

Abstract*: Face Recognition is one of the popular interest of researchers due to its demand in security and authentication. Although traditional approaches such as LBPH and Eigenfaceshave still proven their performance, newly state-of-the-art algorithms are available for application. This study compared the performance of two CNN pre-trained architectures namely: InceptionV3 and VGG19 with an SVM classifier. Besides VGG19's respectable results, it lags behind InceptionV3 by 3.86% in precision, 3.23% in recall, 3.54% in f1-score, and 1.85% in roc-auc score.*

Keywords: Deep Learning, InceptionV3, VGG19

I. INTRODUCTION

In a rapid computer vision and deep learning application, face recognition is one of the pivotal tasks nowadays. Convolutional Neural Network is a state-of-the-art method for developing face recognition software. With the application of pre-trained architecture, this approach minimizes the costly consideration of hardware requirements during the training process. Also, the choice of feature extraction method plays an important role in a comprehensive analysis of the performance of the target deep learning architectures. Various pre-trained architectures are available that can be investigated depending on the classification task. This study experimentedwith the performance of two powerful CNN architectures namely: InceptionV3 and VGG19 in localized datasets for face recognition to weigh their performances.

Several face recognition systems were developed using different algorithms. LBPH (Local Binary Pattern Histogram) has been seen in different applications along with Haar Cascade [1] as a package in computer vision libraries. LBPH operates as an effective texture operator by thresholding the nearest pixel and reflecting the result as a binary number [2]. Eigenfaces was also used most widely in face recognition by representing faces in a grayscale forming a flattened image matrix. The matrix is converted by using PCA to apply the concept of dimensionality reduction to minimize a large dataset and transform it into a smaller dataset but still represents the same information as to original dataset [3] [4]. The Euclidean distance is also applied to calculate the distance between the eigenvector and eigenfaces [5].However, these methods are traditional ways of creating a face recognition model. New algorithms have been designed to fill the limitations of the traditional approaches.

This study used Deep Learning's pre-trained architecture such as InceptionV3 and VGG19. Since these CNNs use a deeper layer for feature extraction, they can generate important hidden values that can be used for an accurate face recognition model. Also, the capability of SVM (Support Vector Machine) reinforces a stronger classification approach that increases the performance of the pre-trained architecture shedding light on their effectiveness in extracting informative facial features and enhancing their performance. The evaluation metrics are precision, recall, f1-score and roc-auc rating.

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II. METHODOLOGY

2.1 Hardware

TABLE I: Hardware requirements

Hardware Components	Specification
CPU	Intel® Core™ i7-8700 CPU @ 3.20Ghz 3.18Ghz
Memory	16 GB RAM
Storage	1 TB HDD
GPU	6GB NVIDIA GTX-1660
Scanner	Epson L3210

2.2 Software

TABLE III: List of software

Name	License
64-bit Windows 10	Proprietary
Anaconda Navigator 2.3.2	Open-Source
Spyder 5.3.3	Open-Source
Python 3.9.15	Open-Source
OpenCV 4.6.0	Open-Source
Tensorflow 2.10.0	Open-Source
Matlab R2020a	Open-Source
Matlab R2020a Deep Learning Toolbox	Open-Source
Adobe Photoshop	Proprietary

2.3 Implementation Flow

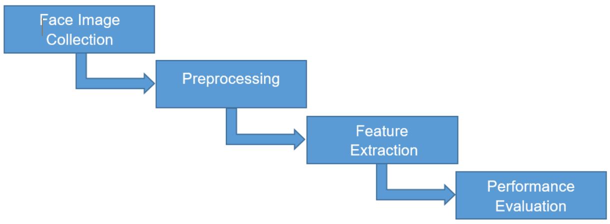

Fig. 1. The general approach of this study

2.4 Image Collection

Eight local personalities were identified for the study. 30 images of the personalities were collected from their photo album collections and stored in a folder. The collected raw images differed in dimension and quality as shown in Fig. 2.

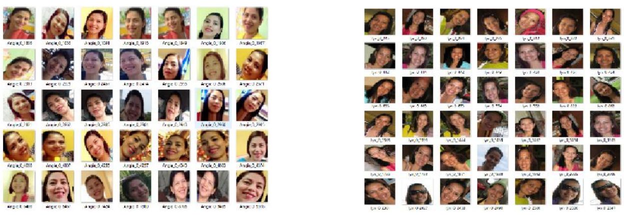

Fig. 2. Sample of raw images.

2.5 Feature Extraction

Pixels are represented in a computer by a matrix of numbers that indicate the brightness and intensity of the image. The process of feature extraction converts the raw data into workable numerical values while maintaining the accuracy of the information in the original data set. In this study, InceptionV3 and VGG19 were explored with the application of SVM (Support Vector Machine) Classifier. In CNN, deeper layers contain higher-level features, constructed using the lower-level features of earlier layers. At the end of each network, global pooling layers or dropout layers were

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employed to obtain the feature representation of the training and test images.The features extracted were used as predictor variables and fit a multiclass using a Support Vector Machine (SVM). Table III shows the layers and name of each CNN where feature extraction happens.

TABLE IIIII: location of CNN layer feature extraction

Architecture	Layer	Name	Type
InceptionV3	312	avg_pool	**Global Average Pooling**
VGG19	**44**	**Drop7**	**Dropout**

2.6 Performance Evaluation

This study used Precision, Recall,F1-Score, and ROC-AUC scoresto evaluate the performance of the model using feature extraction. The following formulas were used [6]:

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = 2\frac{P - R}{P + R}$$

where:

True Positive (TP) is an outcome where the model correctly predicts the positive class.

True Negative (TN) is an outcome where the model correctly predicts the negative class.

False Positive (FP) is where a negative result is treated as positive.

False Negative (FN) is when an outcome was incorrectly predicted as negative.

III. RESULTS AND DISCUSSION

3.1 Individual Scores using InceptionV3 and VGG19

The summary of individual Precision, Recall, and F1-scores is shown in Tables IV to V for the two CNN architectures used in this study. The results indicated the potential advantage of InceptionV2 compared to VGG19.

TABLE IVV: individual scores of metrics using inceptionv3

Classes	Precision	Recall	F1-score	ROC-AUC
Person 1	60.42%	64.44%	62.37%	**79.20%**
Person 2	94.12%	71.11%	81.01%	**85.23%**
Person 3	76.09%	77.78%	76.92%	**87.14%**
Person 4	75.56%	75.56%	75.56%	**86.03%**
Person 5	85.37%	77.78%	81.40%	**87.96%**
Person 6	78.26%	80.00%	79.12%	**88.41%**
Person 7	80.43%	82.22%	81.32%	**89.68%**
Person 8	**79.63%**	**95.56%**	**86.87%**	**96.03%**

TABLE V: individual scores of metrics using vgg19

Classes	Precision	Recall	F1-score	ROC-AUC
Person 1	58.67%	58.67%	58.67%	**76.38%**
Person 2	74.07%	80.00%	76.92%	**88%**
Person 3	77.33%	77.33%	77.33%	**87.04%**
Person 4	74.29%	69.33%	71.72%	**82.95%**
Person 5	78.95%	80.00%	79.47%	**88.47%**
Person 6	77.03%	76.00%	76.51%	**86.38%**
Person 7	76.92%	80.00%	78.43%	**88.28%**
Person 8	**81.69%**	**77.33%**	**79.45%**	**87.42%**

3.2 Summary of Weighted Scores

Table VI summarizes the result of weighted Precision, Recall, F1-score, and ROC-AUC from InceptionV3 and VGG19. The rating indicated the dominance of InceptionV3 based on the metrics used.

TABLE VI: weighted scores of metrics

Architecture	Precision	Recall	F1-score	ROC-AUC
InceptionV3	78.73%	78.06%	78.39%	**87.46%**
VGG19	**74.87%**	**74.83%**	**74.85%**	**85.61%**

IV. CONCLUSION

The comparative analysis of InceptionV3 and VGG19 has yielded valuable insights into their respective capabilities with the SVM classifier. InceptionV3 emerged as the top performer compared with VGG19 in multiple dimensions of evaluation from precision, recall, f1-score, and ROC-AUC ratings.This architecture demonstrates a superior ability to balance precision and recall, resulting in a higher F1score. Moreover, its ROC-AUC score signifies excellent discriminative power in distinguishing between positive and negative instances. On the other hand, VGG19, while still achieving respectable results, lags slightly behind InceptionV3. This study of using InceptionV3 and VGG19 for face recognition has provided valuable guidance for practitioners and researchers for future works.

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