IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.301

Volume 3, Issue 2, July 2023

Performance Evaluation of Face Recognition Model in Deep Learning using Old Facial Photos: A Mathematical Modelling Using SVM Supervised Learning

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Abstract: *Deep Learning has been a remarkable state-of-the-art method in any classification challenge, particularly in face recognition applications. In this paper, Feature Extraction in face recognition using Deep CNNs handpicked pre-trained CNN architectures such as InceptionV3, MobileNetV2, ResNet50, and VGG19 were experimentally explored. Initially, these architectures extracted important features from eight (8) classes of face photos with large age differences of ten (10) years from the present age of an individual. The features were processed with the application of a Support Vector Machine (SVM) classifier to enhance its performance. The evaluation of each model was based on average scores ofaccuracy, precision, recall, and f1-score. The results concluded an accuracy of 84.60%, a weighted precision of 85%, a weighted recall of 84.60%, and a weighted f1-score of 84.60% obtained by ResNet50.Further, ResNet50 has the highest obtained 98% generated ROC-AUC score. With the results presented, ResNet50 isrecommended for application development related to face recognition with the consideration of large age gaps of 10 years.*

Keywords: Deep Learning, Face Recognition, Feature Extraction, Image Augmentation, SVM Classifier

I. INTRODUCTION

Face recognition technology has been observed in many applications. It is one of the biometric applications that can be used for the identification and recognition of an individual based on physical and behavioral characteristics (Dargan& Kuman, 2019). Surveillance and security software are now used by the military for tracking high-value individuals for recognition and verification. In work areas, this technology has been the new way of attendance monitoring for employee authentication. With the integration of Deep Learning techniques, face recognition's capability has almost surpassed human-level accuracy in solving identification and recognition problems.

Deep learning employs multiple processing layers to learn data representations with varying degrees of feature extraction. This emerging technology has reshaped the face recognition (FR) research landscape (Hangaragi, S, Singh, T., & Neelima, N., 2023; Wang & Den, 2021). In particular, deep convolutional neural networks have recently gained popularity in face recognition, and several deep learning methods have been proposed (Guo & Zhang, 2019). In practice, however, many factors influence face recognition. Inunconstrained face recognition, the face images may have many variations, such as low resolution, pose variation, complex illumination, and motion blur, resulting in low recognition accuracies (Guo & Zhang, 2019; Kumar, et al., 2020). Several studies have looked into how deep CNN architectures and SVM classifiers can be used for face recognition tasks (Basly, et al., 2020e; Keerthana, et al, 2023). With the combination of CNNs feature extraction output and SVM Classification, the greater performance of the classificationmodel created was recorded (Tripathi, 2021; Tao & Wei, 2022).

Despite the success achieved by Deep Learning techniques in face recognition tasks, developing a model that can accurately recognize faces in old facial photos remains a challenge. Old facial photos may be low resolution, have variations in lighting and pose, and have undergone aging and changes in appearance, all of which can have a

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significant impact on the model's performance. This study seeks to address the challenges in recognizing faces in old facial photos with ten (10) years of age difference from the query image.

Thus, this study aimed to develop and evaluate a face recognition model utilizing pre-trained neural network architectures such as InceptionV3, ResNet50, MobileNetV2, and VGG19. By combining the methods of feature extraction plus SVM classification, the models were evaluated according to accuracy, precision, recall, f1-score as well as the ROC-AUC plots and scores using the One-versus-Rest approach.

II. METHODS

2.1 Materials

The materials used in this study were a combination of computer hardware and software. The software was developed using a Python programming language with the integration of Keras, TensorFlow, OpenCV, and other necessary libraries to support image processing. Handpicked pre-trained convolutional neural network (CNN) architectures such as MobileNetV2, ResNet50, InceptionV3, and VGG19 were installed for performance comparison in face recognition with large age gaps.

Deep learning requires higher computer hardware specifications. Table 1 presents the hardware used in this study:

Hardware Components	Specification
CPU	Intel® Core™ i7-8700 @ 3.20Ghz 3.18Ghz
Memory	16GB RAM
Storage	1TB HDD
GPU	6GB NVDIA GTX1660
Scanner	L3210

Table 1. Computer hardware specification

2.2 Face Dataset Collection

The images used in this study were from old photos with an age difference of 10 years as presented in Fig. 1. Eight (8) individuals participated in this study. Each individual who served as a class was composed of 30 images per class. These images went to pre-processing techniques. Raw images from photo albums were scanned and cropped using a scanner and photo editor. The images were also resized according to the neural network architecture requirement. Contrast Limited Adaptive Histogram Equalization was also applied to the images to minimize noise amplification.

Fig. 1. Sample of face images

2.3 Image Augmentation

The experimental performance of any classification depends on the number of images that were used in performing classification problems. In this paper, a limited number of images per class has been observed due to the lack of raw images that were collected. The Image Augmentation method was used to populate the different images in the class (Xu. etal., 2023; Ammar, et al., 2022). Each image in the class was processed to obtain four (4) images per image. The process contributed 150 images per class for a total of 1200 images of the entire dataset.

2.4 Feature Extraction with SVM Classifier in Deep Pre-trained CNN

Feature extraction in face recognition using Deep CNN involves using a pre-trained CNN to extract high-level features from the input face image (Jogin, et al., 2018). The experiment of this study conducted feature extraction from pre-trained CNN such as InceptionV3, MobileNetV2, ResNet50, and VGG19. The last layer of the networks was removed and used the output of the second last layer as the feature representation (Jiang, et al., 2021). The output was represented by high-dimensional features which are described as an input image. The output was trained using an SVM

DOI: 10.48175/IJARSCT-12321

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classifier on a labeled dataset wherein each image in the dataset is associated with a label that indicates the class to which the image belongs.

2.5 Performance Evaluation

The performance of every pre-trained CNN architecture that was used in this experiment was based on accuracy, precision, recall, and f1-score as tailored in the study of Ahmad, et al (2020). The formula are shown below. Also, ROC-AUC was determined as additional metrics for evaluation (Coulibaly, et al., 2022).

$$Accuracy = \frac{TP + TN}{2!\,TP + TN + FP + FN}$$

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

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

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

where:

TP = True Positive
TN = True Negative
FP = False Positive
FN = False Negative

III. RESULTS

Individual Scores of VGG19, InceptionV3, MobileNetV2, and ResNet50 Architectures

The individual performance of the Pre-trained CNN used in this study as to Precision, Recall and F1-Score are presented in Tables 2, 3, 4, and 5. The highest scores were obtained by ResNet50.

Table 2. Scores of VGG19 architecture

Class	Precision	Recall	F1-Score
Person_1	.67	.67	.67
Person_2	.89	.71	.79
Person_3	.76	.69	.72
Person_4	.58	.79	.67
Person_5	.87	.84	.85
Person_6	.73	.83	.77
Person_7	.78	.74	.76
Person_8	.79	.79	.79

Table 3. Scores of InceptionV3 architecture

Class	Precision	Recall	F1-Score
Person_1	.38	.37	.38
Person_2	.67	.63	.65
Person_3	.61	.61	.61
Person_4	.37	.54	.44
Person_5	.58	.61	.59
Person_6	.50	.48	.49
Person_7	.48	.41	.44
Person_8	.60	.50	.55

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Table 4. Scores of MobileNetV2 architecture

Class	Precision	Recall	F1-Score
Person_1	.56	.52	.54
Person_2	.79	.89	.84
Person_3	.82	.64	.72
Person_4	.53	.67	.59
Person_5	.73	.77	.75
Person_6	.80	.83	.81
Person_7	.88	.82	.85
Person_8	.65	.62	.64

Table 5. Scores of ResNet50 architecture

Class	Precision	Recall	F1-Score
Person_1	.77	.85	.81
Person_2	.86	.89	.87
Person_3	.93	.75	.83
Person_4	.72	.75	.73
Person_5	.94	.97	.95
Person_6	.87	.90	.88
Person_7	.85	.82	.84
Person_8	.80	.83	.82

Performance Comparative Summary

Table 6. CNN Scores as to Accuracy, Weighted Precision, Weighted Recall, and Weighted F1-Score

CNN	Accuracy	Precision	Recall	F1-Score
ResNet50	84.60%	85%	84.60%	84.60%
VGG19	75.40%	76.60%	75.40%	75.60%
MobileNetV2	72.90%	73.50%	72.90%	72.90$
InceptionV3	52.50%	53.20%	52.50%	52.60%

Tbl. 6 shows the accuracy and the weighted precision, recall, and f1-score of four Deep CNN architectures used namely VGG19, InceptionV3, MobileNetV2, and ResNet50. The highest performance based on the score was generated coming from ResNet50 architecture.

ROC-AUC Plots and Scores

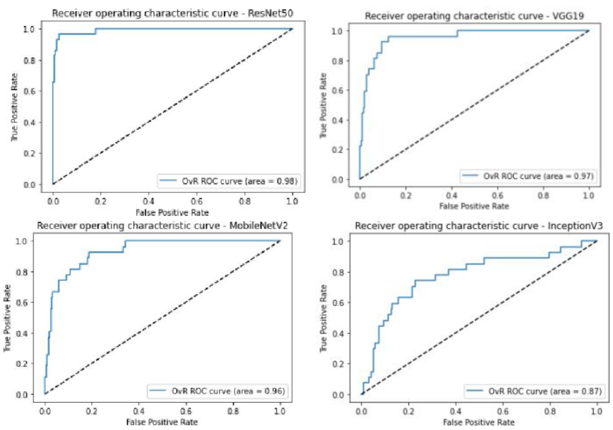

Fig. 2. ROC-AUC plots with scores of the used CNN architectures

Fig. 2. presented the plots of True Positive and False Positive Rates of each CNN architecture used in this study. ResNet50 ranked the highest ROC-AUC scores with 98%. This was followed by VGG19 with 97%, 96%, and 87% for MobileNetV2 and InceptionV3 respectively. This implies that ResNet50 can highly obtain more positive examples than negative examples from a prediction of face photos with 10 years of age gaps than VGG19, MobileNetV2, and InceptionV3.

IV. CONCLUSION AND FUTURE WORKS

The findings of this study were based on the results generated after the experiment. The process involved the use of Deep Convolutional Neural Network architectures namely ResNet50, VGG19, MobileNetV2, and InceptionV3 for feature extraction. The generated features were processed into an SVM classifier for maximizing the performance based on the metrics stated. This concluded that ResNet50 outperformed VGG19, MobileNetV2, and InceptionV3 based on accuracy, precision, recall, f1-score, and ROC-AUC scores.

Although ResNet50 showed superior outcomes with a 10-year age gap, it is advised to expand the study to include age gaps of 20 and 30 years.

V. ETHICAL CONSIDERATIONS

This study used different face photos collected from local individuals. The real names were replaced with an array of variables to conceal their identities.

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