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Application of Domain Adaptive Deep Learning Model for Face Recognition with Grid Search Optimization

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Abstract: *This study examined the effectiveness of domain-adaptive deep learning models in the field of face recognition with ResNet50 pre-trained architecture. The model demonstrated excellent accuracy in the manual approach, achieving 93.57%, highlighting ResNet50's intrinsic skills in feature extraction and classification tasks. Furthermore, by using Grid Search Optimization, the accuracy increased to an astounding 100%, emphasizing the significant role of hyperparameter adjustment in optimizing the model's performance. These findings highlight the potential of domain adaptation methods to improve face recognition systems and highlight Grid Search Optimization as a key strategy for achieving the accuracy levels required for real-world implementations.*

Keywords: Domain Adaptive Deep Learning, Grid Search, ResNet50, Transfer Learning

I. INTRODUCTION

Biometric recognition of humans requires unique characteristics including fingerprint, retina, iris, and face [1]. Out of these characteristics, the face gives an advantage since it is the most exposed part of human biometric features [2]. It can be easily extracted with the use of image-capturing devices. Face recognition technology has emerged as a pivotal force in the realms of security, access control, and human-computer interaction [3]. The capability to accurately identify individuals from images or video frames has substantial implications for various applications [4].However, difficulties brought on by various lighting conditions, stance variations, and image quality disparities seen in real-world scenarios frequently hamper the effectiveness of face recognition systems [5]. This paperexplored the capability of face recognition technology by integrating three vital processes: Domain Adaptive Deep Learning Models (DADLMs), the powerful ResNet50 architecture, and Grid Search Optimization techniques.

The combination of machine vision and image processing is the most popular technique in developing face recognition systems [6]. The processes were reinforced by classification algorithms in Convolutional Neural Networks. With its ability to automatically extract important features from an image, this method can build a strong foundation for the automatic identification and authentication of individuals [6]. However, designing this technology needs further exploration which expresses interest for researchers, specifically in CNN methods applying transfer learning and optimization process.

This study demonstrates how DADL models can improve the performance of face recognition software. The strength of state-of-the-art deep learning architectures and techniques [7], combined with the power of grid search optimization to fine-tune model hyperparameters believed to create an outstanding model. ResNet50 was chosen as the pre-trained architecture to be used for training eight classes on the dataset. The class selection was coming from local personalities. Each class contained 30 images from photo album collections. These photos were preprocessed with methods like cropping, resizing, and augmentation. Experiments were done through a manual and optimized approach. Each output is evaluated by inspecting the learning and loss curves along with the generation of accuracy scores.

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 Dataset and Image Preprocessing

Images were collected from 8 local individuals to represent the classes. Each class consists of 30 face images. These images were coming from the photo albums of the individuals. Photos were scanned using a scanner to convert it to digital format. Preprocessing techniques were applied to the raw images. Cropping and resizing were done in Adobe Photoshop to isolate face photos. Image augmentation was also applied to increase theimage samples using Python programming language. Fig. 1 presents the image sample used in the study.

Fig. 1. Sample of the image used in the study

2.4 Transfer Learning using Manual and Optimize Configuration

There were two experiments conducted in this study. The first was using the manual approach of transfer learning using batchsize (5), learning rate (.0001), and epoch (30). Initial evaluation was made by generating the accuracy score. The second part was the execution of transfer learning with the application of grid search. The impact of batch sizes (8, 16, 32), (0.01, 0.001, 0.0001), and epochs (10, 20, 30) employing Adam optimizer. Both experiments used ResNet50 pre-trained architecture. The final evaluation was conducted by comparing the accuracy result from the manual approach to the optimized configuration.

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2.5 Performance Evaluation

This study used accuracy to evaluate the performance of the two methods used with the formula: [8]:

$$Accuracy = \frac{True\ Ppsotive + True\ Negative}{True\ Ppsotive + True\ Negative + False\ Positive + False\ Negative}$$

III. RESULTS AND DISCUSSION

3.1 Learning and Loss Curves

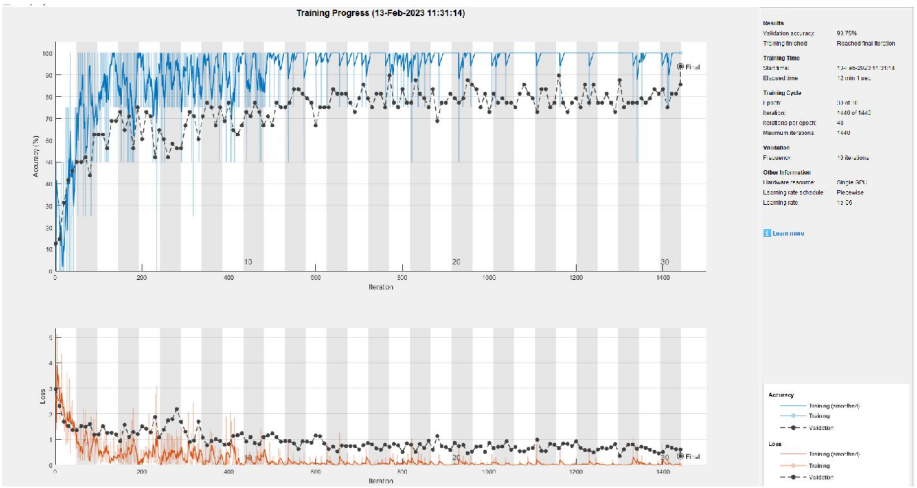

Fig. 2. Learning and loss curve of ResNet50 using the manual approach

Fig 2 presented the learning and loss curve after performing transfer learning with ResNet50 using a manual approach. Accuracy scored 93.57% after 1440 iterations in 30 epochs. Based on the observation of the curves it was seen that it generated an overfitting which is not good for model application.

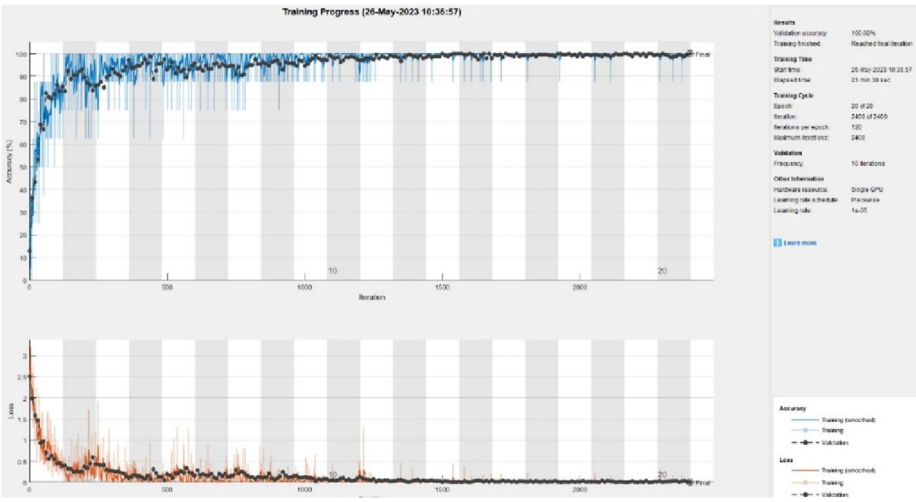

Fig. 3. Learning and loss curve of optimized ResNet50 using a grid search

With the application of the configuration generated by grid search of ResNet50 in transfer learning, visual observation indicated that the model showed a good fit. It also generated a 100% accuracy after 2400 iterations in 20 epochs as shown in Fig. 3.

3.2 Evaluation Result

The generated accuracy scores presented in Table III prove a significant advantage of Optimized ResNet50 having a 100% perfect rating. In contrast, manual configuration of finding an optimal performance of the architecture generated a 93.75%. This implies the consideration of using optimization algorithms like grid search to find the right combination of hyperparameters.

TABLE IIIII: Model comparison

Metrics	Accuracy
ResNet50 (Manual)	**93.75%**
ResNet50 (Optimized)	**100%**

IV. CONCLUSION

In this study, two approaches for face recognition were investigated in the transfer learning method utilizing the ResNet50 architecture. The manual method's excellent 93.57% accuracy demonstrates ResNet50's intrinsic strength in feature extraction and classification tasks. However, the use of Grid Search Optimization in the second technique resulted in an exceptional accuracy of 100%, highlighting the crucial significance of hyperparameter tuning in further improving the model's performance. These results highlight the potential of domain adaptive deep learning models for face recognition, with Grid Search Optimization emerging as a critical tool to push the boundaries of accuracy, making it a valuable technique for face recognition applications.

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