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 1, June 2023

Optimization of Resnet50 using Random Search 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*: This study used the ResNet50 architecture and optimum configurations performed by Random Search to provide the values of an exhaustive investigation into the field of face recognition using Transfer Learning approach. The model's outstanding capability to succeed in an image classification task is demonstrated by its performance measures, which include precision (99.60%), recall (99.58%), and F1-score (99.59%).These findings highlight the importance of hyperparameter optimization as well as the capability of well-structured deep-learning models to produce astounding levels of accuracy and reliability.*

Keywords: Hyperparameter Optimization, Random Search, ResNet50, Transfer Learning

I. INTRODUCTION

Human identification and recognition challenges have been aided by the advancement of biometric approaches. Biometrics is a study of physical and behavioral characteristics which can be used for human identification [1]. These characteristics are used by software developers to create a strong foundation for a comprehensive framework for creating robust and secure identification and verification solutions. These applications are widely used in the daily activities and transactions of humans. The military used in surveillance and security, banks, and other online applications for authentication and verification purposes [2].

Face Recognition is one the promising biometric applications that combines the detection and recognition, results from captured human face images. According to [3] this technology is a method by which the identification of a human can be determined from one's various unique face image sets. The huge information generated from human face images can be processed to create a face recognition system [4]. The classical approaches of face recognition combine OpenCV libraries for detection and recognition respectively. These days, lots of achievements to increase the level of accuracy in facial recognition are evident with the integration of Artificial Intelligence. In addition, as cameras are getting more powerful and continue to upgrade to high-definition features, there is an increase in detection and recognition accuracy using deep learning models. The actual advantages of face-based identification over other biometrics are uniqueness and acceptance [3] since the face is the most exposed biometric feature and can be quickly obtained without physical contact [3].

One of the challenges of face recognition is the source of the dataset used for the training process. Images are presented with different lighting and quality. This study used facial photos obtained from photo album collections. These were processed according to image preprocessing techniques such as cropping, resizing, and image augmentation. The collected images were split into training and validation. With the use of Matlab, ResNet50 was experimented as the architecture for implementing Transfer Learning [5]. The hyperparameters were tuned using Random Search [6]. This optimization method has proven to provide an optimal value compared with a manual approach. It saves time and computational cost to obtain the result [7].

II. METHODOLOGY

2.1 Hardware

For training and data processing in deep learning, a computer has to have powerful hardware specifications. To conduct this study, a personal computer with 16 GB of RAM, an NVidia GTX-1660i GPU with 6 GB of RAM, and an Intel

Core i7-8700 CPU running at 3.20 GHz were used. Additionally, photographs from photo album collections of a person were collected and converted to digital format using a scanner.

2.2 Software

The computer system requires Microsoft Windows version 10 64-bit with an installed Anaconda Navigator 2.3.2. Jupyter Notebook and Spyder, which both employ Python scripts, werethe Integrated Development Environments used. Installed alongside the computer vision's library withTensorflow and OpenCV. Deep Learning Toolbox was also included, along with Matlab R2020a. Images of faces were resized and cropped using Adobe Photoshop as part of the preprocessing techniques. Moreover, Adobe Photoshop was used to convert pictures into JPEG files.

2.3 Face Image Collection

In this study, eight (8) selected/identified local sources were used as classes. Photos were collected from photo albums and Facebook and wereused as the dataset. These collected images were grouped according to class labels. A scanner was used to convert raw images to JPEG file format.

2.4 Image Preprocessing

The preprocessing method of images were performed using Adobe Photoshop and Python programming language. Since the collected images contain different dimensions, initially, all raw images were cropped to isolate the face images. Next wasto resize the images to the dimension required by Deep CNN pre-trained architectures. Not all images are of good quality, contrast needs to be improved. To achieve this, histogram equalization was used to redistribute the lightness values and enhance the definitions of the edges of each region. Image were also augmented to increase the sample size.

2.5 Data Splitting and Training

After the preparation of the images, they were fed to ResNet50 architectures. The images (dataset) were divided into training and validation data. 70% of the face images were allocated for training while the remaining 30% were used for testing and validation.

2.6 Optimization of Transfer Learning Using Random Search

The optimization of transfer learning with ResNet50 using Random Search across various hyperparameters represents a systematic approach to fine-tuning deep learning models. This study explores the impact of different batch sizes (8, 16, 32), learning rates (0.01, 0.001, 0.0001), and epochs (10, 20, 30) while employing the RMSprop optimizer. Random Search allows us to efficiently traverse this hyperparameter space, seeking optimal configurations for the classification task [7].

2.7 Performance Evaluation

This study used precision, recall, and F1-Score to evaluate the performance of the optimized architecture with the following details: [8]:

$$Precision = \frac{True\ Positive}{True\ Poositive + False\ Positive}$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$F1 - score = \ 2\frac{Precision - Recall}{Precision + Recall}$$

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 1, June 2023

III. RESULTS AND DISCUSSION

3.1 Learning and Loss Curve of the Optimized ResNet50

Fig. 1 presents the learning and loss curves of optimized ResNet50 after the training process. This curve can help determine if the model generated learning problems such as underfit or overfit. The process finishes at 2400 iterations in 21 minutes and 33 seconds after 20 epochs.

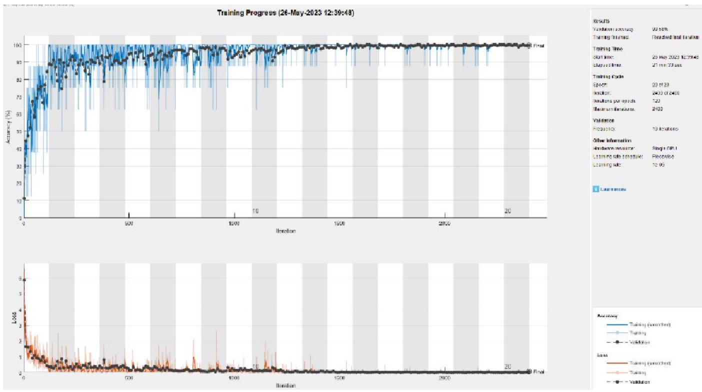

Fig. 1. The generated learning and loss curve of Optimized ResNet50

3.2 Confusion Matrix

Achieving an overall accuracy of 99.6% across 8 classes in a confusion matrix reflects exceptional performance in a multi-class classification task. This high accuracy indicates that the model is adept at correctly classifying instances from a diverse set of categories.

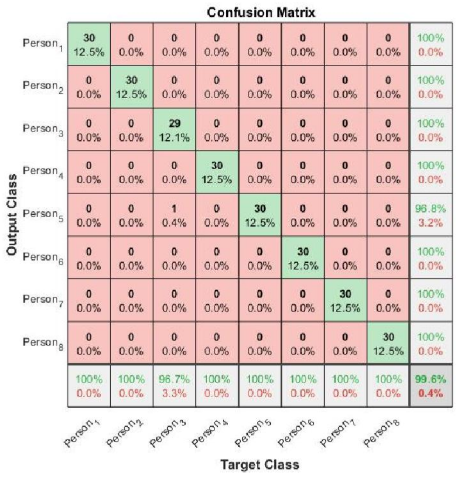

Fig. 2. Generated confusion matrix

3.3 Evaluation Result

After conducting transfer learning with ResNet50 using the optimized configuration determined through Random Search, the obtained results are highly promising presented in Table I. The precision of 99.60%, recall of 99.58%, and an F1-score of 99.59% indicate an exceptional level of performance. These metrics collectively reflect the model's ability to effectively discriminate between classes with an extraordinarily high degree of accuracy and reliability. Such results are indicative of a robust and well-tuned model, showcasing its potential for demanding applications where precision and recall are of utmost importance. This outcome underscores the significance of thoughtful hyperparameter optimization in achieving top-tier performance in deep learning tasks.

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 1, June 2023

TABLE I

INDIVIDUAL SCORES OF METRICS USING INCEPTIONV3

Metrics	Scores
Precision	99.60%
Recall	99.58%
F1-Score	99.59%

IV. CONCLUSION

The study's conclusion following the use of transfer learning with ResNet50, applying the optimal configuration through Random Search, have produced outstanding results of 99.60% for precision, 99.58% for recall, and 99.59% for f1-score. These ratings underline the critical importance of hyperparameter adjustment and optimization in getting exceptional performance in deep learning applications. The model's ability to continuously reach such high metrics puts it as a valuable tool for tasks where precision and recall are crucial, demonstrating the potential of well-structured and fine-tuned deep learning models in addressing difficult image classification issues.

REFERENCES

[1]. Dargan, S. & Kumar, M. (2020). A Comprehensive Survey on the Biometrics Recognition System Based on Physiological and Behavioral Modalities. Expert System with Applications. Volume 143.https://doi.org/10.1016/j.eswa.2019.113114

[2]. Q. Xiao and X. D. Yang, "A facial presence monitoring system for information security," 2009 IEEE Workshop on Computational Intelligence in Biometrics: Theory, Algorithms, and Applications, Nashville, TN, USA, 2009, pp. 69-76, doi: 10.1109/CIB.2009.4925689.

[3]. Adjabi, I.; Ouahabi, A.; Benzaoui, A.; Taleb-Ahmed, A. Past, Present, and Future of Face Recognition: A Review. Electronics 2020, 9, 1188.https://doi.org/10.3390/electronics9081188

[4]. SerignModou Bah, Fang Ming. An improved face recognition algorithm and its application in attendance management system. Array, 2020, vol. 5, https://doi.org/10.1016/j.array.2019.100014.

[5]. I. Z. Mukti and D. Biswas, "Transfer Learning Based Plant Diseases Detection Using ResNet50," 2019 4th International Conference on Electrical Information and Communication Technology (EICT), Khulna, Bangladesh, 2019, pp. 1-6, doi: 10.1109/EICT48899.2019.9068805.

[6]. F. F. Firdaus, H. A. Nugroho, and I. Soesanti, "Deep Neural Network with Hyperparameter Tuning for Detection of Heart Disease," 2021 IEEE Asia Pacific Conference on Wireless and Mobile (APWiMob), Bandung, Indonesia, 2021, pp. 59-65, doi: 10.1109/APWiMob51111.2021.9435250.

[7]. A. Nugroho and H. Suhartanto, "Hyper-Parameter Tuning based on Random Search for DenseNet Optimization," 2020 7th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE), Semarang, Indonesia, 2020, pp. 96-99, doi: 10.1109/ICITACEE50144.2020.9239164.

[8]. Ahmad, I., et al. Optimizing Pretrained Convolutional Neural Networks for Tomato Leaf Disease Detection. 2020, vol. 2020