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Experimental Comparison of the Effect of Image Augmentation Technique to Raw Data for Image Classification

Shem L. Gonzales

Faculty, College of Engineering and Information Technology

Surigao del Norte State University-Del Carmen Campus, Philippines

rclegaspi@ssct.edu.ph

Abstract*: Deep Learning models advance the methodology of image classification. But, the performance of the model depends on the diversity of the image used for training. This study examines the effect of image augmentation on the performance of ResNet50 as a baseline model with an SVM classifier for feature extraction. Two parallel experiments were conducted based on 30 raw images and with image augmentation from 8 class representations. The evaluation metrics showcase a remarkable increase of 31% in f1-score and 7.6% in ROC-AUC. The findings enhancement in F1-score ad ROC-AUC underscores the role of image augmentation as a powerful tool to reinforce the model's performance for image classification*

Keywords: Computer Vision, Deep Learning, Image Augmentation

I. INTRODUCTION

Deep learning model development has made tremendous progress in image classification problems in recent years [1]. Different applications in identification and recognition tasks mark the capability of the model's architectures to perform well with its architectural design. However, a huge amount of photos is the primary concern during the training process. The amount and quality of the available training data have a significant impact on how well these models work. The ability of deep learning models to generalize is improved by the use of image augmentation techniques, which have become indispensable tools for increasing the amount and diversity of training datasets [2][3]. These techniques involve applying a variety of transformations to the original images, resulting in augmented versions that are often more robust and representative of real-world scenarios [3].

This paper aims to conduct a comprehensive experimental comparison between the performance of deep learning models trained on raw, unaltered image data and those trained on augmented images using various augmentation techniques. By methodically examining the effects of image augmentation on image classification, we want to clarify the advantages and difficulties of using augmentation techniques to improve the accuracy and robustness of image classification models. The method took the ways of image rotation, flip, and zoom to increase the sample size used for dataset representation.

Two experiments were conducted during the study. First was to use 30 images, second was the augmented images. Throughout the experiment, raw data were tested based on Deep CNN's ResNet50 architecture. Support Vector Machine (SVM) was utilized to extract important features in an image.By quantitatively evaluating the models' performance on a standardized evaluation metric such as F1-score and ROC-AUC, this work intended to uncover the impact of each augmentation technique on enhancing model generalization and robustness.Additionally, by acquiring knowledge of the advantages and disadvantages of augmentation methods, this paper helped practitioners consider image augmentation techniques to successfully enhance the performance of their image classification models.

II. METHODOLOGY

2.1 Hardware and Software

Hardware and software is an important factor in deep learning processing. Hardware provided the computational tasks needed for intricate training processes for model creation. This study used an Intel I7 processor with 36GB RAM, 6 GB

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GPU, and 1TB storage device. The software framework and tools used were Matlab R2020 with deep learning models and Python programming language with installed computer vision libraries such as OpenCV and TensorFlow.

2.2 Data

Images were collected from eight individuals. Initially, raw images were composed of 30 images per class. After the generation of the evaluation metrics, the second experiment used the augmented image with 120 images per class. The application of flipping, zooming, and rotating of all images from raw photos were applied to increase the number of image samples.

Fig. 1. Sample of raw images.

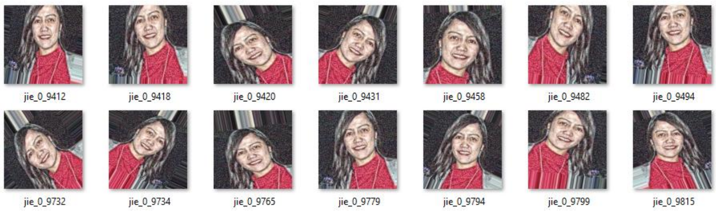

Fig. 2. Sample of augmented images.

TABLE I: Classes and number of images per class

Classes	Raw Image	Augmented Image
Person 1	30	**120**
Person 2	30	**120**
Person 3	30	**120**
Person 4	30	**120**
Person 5	30	**120**
Person 6	30	**120**
Person 7	30	**120**
Person 8	**30**	**120**

2.3 Process

Image augmentation is used in computer vision tasks to expand the dataset by generating additional images from original images. The objective is to improve the performance of the Deep Learning model for image classification problems. The use of ResNet50 architecture was experimented with SVM for feature extraction. In this study, raw images were trained in ResNet50 which served as the baseline model. This was done to have a reference for comparison to evaluate the impact of image augmentation. Another experiment was conducted with the use of augmented images. The number of additional images was presented in Table 1. The same architecture and hyperparameters with values were used for the two experiments to ensure a fair comparison. The evaluation metrics were f1-score and ROC-AUC ratings[5].

III. RESULTS AND DISCUSSION

3.1 ROC-AUC Curves

Presented in Fig. I and Fig. II were the individual curves of ROC-AUC using ResNet50 with SVM classifier from raw and augmented images respectively. These curves are visualized between the plot of sensitivity and specificity. The use of these metrics is very important relating to the accuracy of the model [6].

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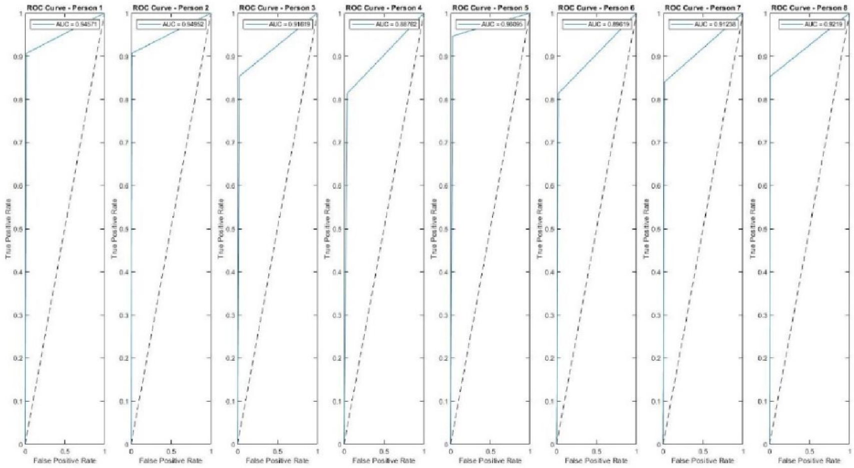

Fig. 3. Individual class ROC-AUC curves of ResNet50 with SVM from raw images.

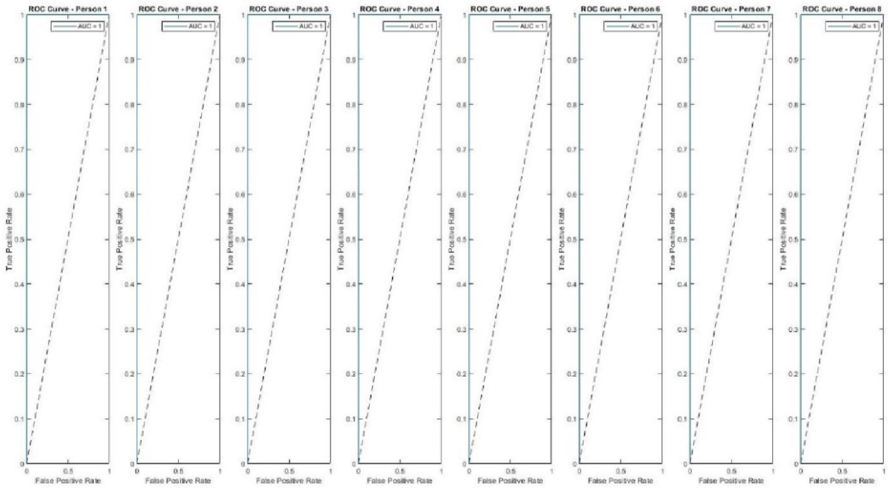

Fig. 4. Individual class ROC-AUC curves of ResNet50 with SVM from augmented images.

3.2 ROC-AUC Scores of Raw Image and Augmented Images

The values in Table II summarized the score generated from Fig. 1 and Fig. II. Although the performance of the used baseline model (ResNet50) performed well in raw images, evidently it was increased with the application of augmented images.

TABLE III: Individual class scores of ROC-AUC from raw and augmented images

Classes	ROC-AUC Score	
	Raw Images	Augmented Images
Person 1	94.57%	100%
Person 2	94.95%	100%
Person 3	91.61%	100%
Person 4	88.76%	100%
Person 5	96.09%	100%
Person 6	89.61%	100%
Person 7	91.23%	100%
Person 8	92.16%	100%

3.3 Evaluation Metrics Generated

Summarizing the generated average ratings of F1-Scores and ROC-AUC scores was presented in Table III. Quantitatively, image augmented maximize the model in all used evaluation metrics.

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TABLE IIIII: Summary of performance evaluation metrics

Metrics	Scores	
	Raw Images	**Augmented Images**
Mean F1-Score	76.26%	100%
ROC-AUC	92.37%	100%

IV. CONCLUSION

With the findings of this study, the image augmentation method proved a significant method to increase the performance of ResNet50 with SVM showcasing improvements in both F1-score and ROC-AUC metrics. This work highlights the accuracy of image augmentation in improving the performance of image classification models with an outstanding 31% rise in the F1-score and a remarkable 7.6% improvement in ROC-AUC.These results imply that image augmentation improves the robustness and generalization of the model by adding diverse variations to the training data, making the model more capable of handling and detecting subtle patterns that might have been missed with raw data alone.

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