

# Enhancing Image Classification Performance: A Comparative Analysis of Optimization Algorithms

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**Abstract:** *In this paper, optimization algorithms are subjected to a comparative investigation. These include several optimization methods, including Adam, RMSprop, and SGDM, which might enhance the precision and discriminative ability of cutting-edge convolutional neural networks (CNNs). Adam excelled in performance in identifying different image classes with a 100% accuracy rate. In addition, Adam also achieved a mean ROC-AUC (Receiver Operating Characteristic - Area Under the Curve) score of 100%, highlighting their unmatched ability to discern between positive and negative cases. Moreover, the results of this work highlight Adam's potential as a strong tool for image classification jobs where high accuracy and reliable discrimination are essential. Adam's dominance over RMSprop and SGDM highlights its potential to improve face image classification tasks, pushing the limits of what is possible in the field of computer vision and deep learning.*

**Keywords:** Deep Learning, Image Classification., Optimization Algorithms, ResNet50

## I. INTRODUCTION

Image classification is a key task in the field of computer vision and machine learning with several applications, such as object detection and recognition [1]. The optimization strategies used during training have a substantial impact on how well image classification models function [2]. Adam, SGD with Momentum (SGDM), and RMSprop are a few examples of optimization algorithms that are crucial for adjusting model parameters and directing the convergence of deep neural networks [3] [4]. Recent years have seen a huge increase in interest in the topic of deep learning due to improvements in hardware capabilities, dataset accessibility, and algorithmic developments. Therefore, to increase the precision and speed of image classification models, researchers and practitioners are always working to enhance the efficiency and efficacy of optimization strategies [5].

Among the most popular optimization algorithms in deep learning are Adam, SGDM, and RMSprop. Each of these approaches demonstrates distinct traits, advantages, and disadvantages that may have a big effect on the training procedure and final classification results. By conducting a methodical and thorough comparative examination of these optimization techniques in the context of image classification, this research aims to fill the knowledge gap. Therefore, it is necessary to carry out a thorough comparison analysis of these optimization techniques to reveal their relative benefits and drawbacks in the context of image classification tasks.

On the other hand, Matlab is one of the powerful tools for implementing machine learning and deep learning. The libraries and modules are purposely designed to support the challenging process of obtaining a specific goal for vision based approach. This paper utilized ResNet50 CNN pre-trained architecture. Each optimization algorithm was applied and evaluated based on the performance on accuracy and roc-auc scores. The dataset used was from localized face images which were used during the training process.

To construct image classification models, this study aims to provide useful insights into the selection and application of optimization techniques. By systematically contrasting Adam, SGDM, and RMSprop, the researcher aimed to investigate the knowledge necessary to make decisions about optimization strategies, ultimately opening the door for improved image classification performance and the development of various computer vision applications.

**II. METHODOLOGY**

**2.1 Data**

The images used in this study were collected from 8 local sources. Presented in Fig. 1 are the sample of images used during the experiment. Each image was processed based on standard pre-processing techniques. Images were cropped, isolating the face image of a person, and were resized based on the requirement of ResNet50 architecture using Adobe Photoshop software. With the application of image augmentation, each class representation was increased to 150 images. Deep Learning needs a huge amount of data to come up with an outstanding performance and to prevent overfitting [6].

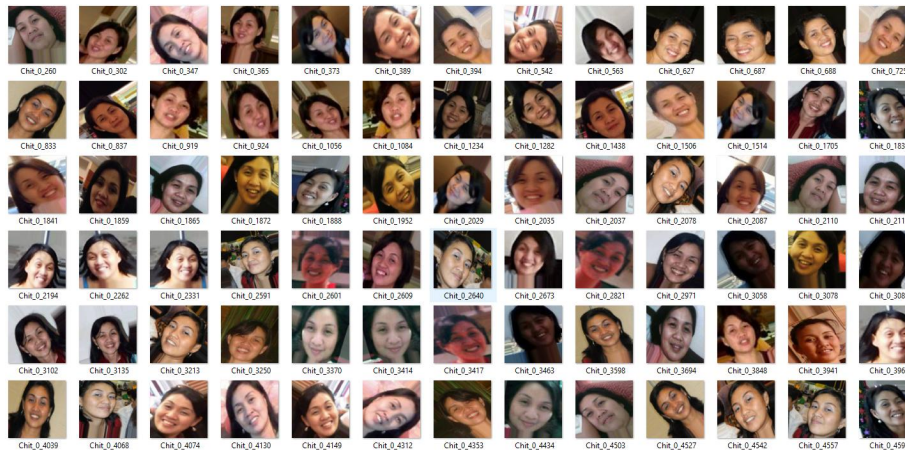


Fig. 1. Sample of images used as dataset.

**2.2 Hardware Specification**

TABLE I: Hardware requirements

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

**2.3 Software Specification**

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 |

**2.4 Hyperparameter Values**

ResNet50 was used to experiment with the performance of the 3 optimization algorithms namely: Adam, RMSProp, and SGDM. Applying this pre-trained architecture requires a Deep Learning Toolbox along with the different computer vision libraries and packages [7]. ResNet50 was used based on the smaller number of layers (50 layers). Each of these

algorithms used a batchsize of 8, a learning rate of .0001, and an epoch of 30. Observations were made as to the training and validation accuracy.

### 2.4 Performance Evaluation

The performance of each optimization algorithm was determined by the roc-auc and accuracy scores. Matlab was used to automatically generate the different ratings of the metrics. Accuracy was calculated using the formula [8]:

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

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.

The ROC-AUC (receiver operating characteristic) curve is an evaluation index for binary classification problems, and the area under the curve measures the classifier's ability to classify an object in an image. The higher the AUC, the better the model's performance in distinguishing between positive and negative classes.

## III. RESULTS AND DISCUSSION

### 3.1 Generated roc-auc curve

Presented in Fig. 2 – Fig. 4 were the individual curves or roc-auc. A higher AUC score indicates less overlap between the distributions and implicates a better model for the prediction of classes in image classification as to the True Positive Rate and False Positive Rate.

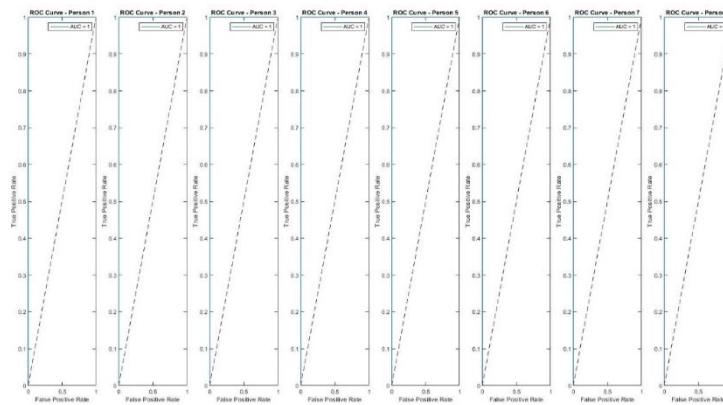


Fig. 2. Individual class ROC-AUC curves of ResNet50 with Adam

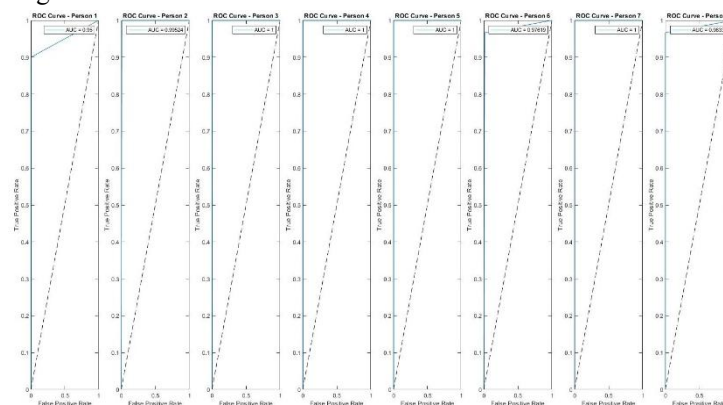


Fig. 3. Individual class ROC-AUC curves of ResNet50 with SGDM

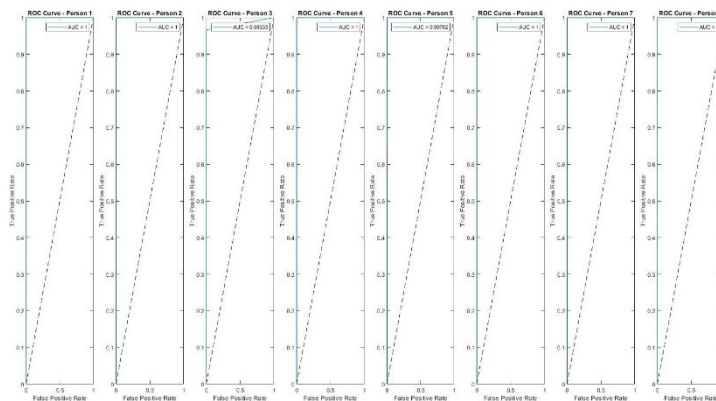


Fig. 4. Individual class ROC-AUC curves of ResNet50 with SGDM

### 3.2 Summary of Scores

The outcome of the experiments demonstrates Adam as a top-performing optimization algorithm among Rmsprop and SGDM (Stochastic Gradient Descent with Momentum) as shown in Table III for face image classification. The accomplishment of Adam was able to complete the image categorization tasks with 100 percent accuracy and roc-auc. This result indicates that the model used to train Adam has successfully discovered how to distinguish between the various classes in our datasets with the highest accuracy.

TABLE III: summary of accuracy and mean roc-auc scores

| Optimizers     | Accuracy      | roc-auc       |
|----------------|---------------|---------------|
| <b>Adam</b>    | <b>100%</b>   | <b>100%</b>   |
| <b>Rmsprop</b> | <b>99.58%</b> | <b>99.76%</b> |
| <b>SGDM</b>    | <b>97.92%</b> | <b>98.84%</b> |

## IV. CONCLUSION

The findings of this study emphasize Adam's remarkable performance, putting it as the best image classification optimization technique among SGDM and RMSprop with 100% accuracy and 100% ROC-AUC scores. Even though these results are promising, more study is required to confirm the algorithm's effectiveness across other datasets and classification issues, as well as to examine its generalizability and robustness to various hyperparameter settings.

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