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Reducing Training Time in Skin Cancer Classification Using Convolutional Neural Network with Mixed Precision Implementation

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Abstract

In the field of skin cancer classification, machine learning and deep learning have been extensively utilized, particularly with convolutional neural network (CNN) architectures. However, there remains room for exploration to achieve optimal performance. This study investigates the use of the MobileNetV3Large architecture for transfer learning, chosen for its efficiency in low-power and memory-constrained applications. To further enhance performance, black-hat morphological transformation and oversampling techniques were applied to the ISIC 2020 dataset. Additionally, mixed precision training was implemented to reduce training time. The research aimed to compare the accuracy, precision, recall, F1-score, and training time of models trained with and without mixed precision. The findings revealed that while the model without mixed precision achieved superior performance with accuracy, precision, recall, and F1-score metrics reaching 98%, both models yielded an AUC-ROC of 1. Notably, mixed precision training significantly reduced training time by 1,646 seconds (27 minutes and 26 seconds), representing an 8.39% speed increase. These results suggest that mixed precision can meaningfully accelerate model training while maintaining competitive performance. The practical implications of this research include its potential to improve the efficiency of skin cancer classification models, making them more suitable for real-time clinical applications, particularly in resource-constrained environments.

Keywords: *Skin Cancer, MobileNetV3Large, Transfer Learning, Mixed Precision, Metric Evaluation.*

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1. Introduction

Skin cancer is one of the most common types of cancer with an increasing incidence rate, placing a heavy burden on the healthcare system [1]. This is supported by statistical data released by GLOBOCAN in 2018, compiled by the International Agency for Research on Cancer (IARC), showing that melanoma and non-melanoma skin cancers rank 19th and 5th respectively as the most common cancers [2]. In the same year, the World Health Organization (WHO) recorded 14 million new patients and 9.6 million deaths caused by cancer, with skin cancer being the most significant type of cancer contributing to increased mortality rates [3].

In Indonesia, skin cancer ranks third after cervical cancer and breast cancer. The incidence of skin cancer is found in 5.9 - 7.8% of all types of cancer per year. The most common skin cancer in Indonesia is basal cell carcinoma (65.5%), followed by squamous cell carcinoma (23%), malignant melanoma (7.9%), and other skin cancers [4]. The International Agency for Research on Cancer (IARC) concluded in 2009 that ultraviolet (UV) radiation is a cause of skin cancer in humans. UV radiation helps the development of melanoma and non-melanoma cancers (basal cell carcinoma and squamous cell carcinoma), which are more common in individuals with skin sensitive to sunlight and those living closer to the equator [5].

To determine the type of skin cancer, a direct diagnosis by a doctor using biopsy and microscopic procedures is required. A biopsy is performed by taking a small piece of the cancerous cell to be checked and examined in detail by a doctor or dermatologist. This testing technique requires a considerable amount of time for a dermatologist and carries the risk of accidents during the biopsy process [6]. With the advancement of technology, there is an alternative way to classify skin

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cancer: the application of machine learning and deep learning, which is believed to assist the public in the classification of skin cancer.

In general, machine learning and deep learning can perform self-training without repetitive coding by humans. Deep Learning is an advanced level of machine learning that requires an initial set of data called a dataset to predict outcomes. Deep Learning will generate output based on training and test data. After evaluation, deep learning can make predictions on data [7]. One of the most commonly used deep learning algorithms is the convolutional neural network [7] [8]. Convolutional Neural Network has been utilized to solve high-level computation tasks related to difficult visual tasks and usually deals with image classification, segmentation, object detection, video processing, natural language processing, and speech recognition [7].

Convolutional Neural Network itself has a set of architectural layers such as convolutional layers, pooling layers, and fully connected layers, commonly referred to as the convolutional neural network model. Several pre-trained convolutional neural network models include AlexNet, ResNet50, GoogleNet, VGG16, ResNet101, VGG19, InceptionV3, InceptionResNetV2, DenseNet, CGG19, and MobileNet [8]. One technique commonly used in developing a convolutional neural network model is transfer learning. According to Sulistya et al. [8], transfer learning is a process of using pre-trained models on other problems to solve new problems. Transfer learning can greatly assist in developing a model because there is no need to build a model from scratch. Therefore, convolutional neural network algorithms and transfer learning techniques can be utilized to create a model for classifying skin cancer.

Several previous studies have developed models to classification skin cancer using SVM and KNN, achieving an evaluation metric accuracy of 70.61% with KNN [9]. Another study using VGG16 with 6594 training samples from the Kaggle dataset titled "Skin Cancer: Malignant vs Benign" achieved an evaluation metric accuracy of 93.18% [10]. A study using a convolutional neural network architecture achieved an accuracy of 96% with a dataset of 2000 images [11].

Further research using the ResNet152 architecture with the ISIC 2017 dataset containing a total of 2742 images achieved evaluation metrics of 90.4% accuracy, 82% sensitivity, 92.5% specificity, and 87.2% balanced accuracy [12]. Another study using the AlexNet architecture to classify benign and malignant cases, using the ISIC 2019 dataset with a total of 25,331 images, achieved an evaluation metric of 81.26% accuracy, 84.66% precision, 86.71% recall, and 82.14% f1-score [13].

A study by Poornima et al. [14] using the ISIC dataset with the VGG16 architecture achieved 97% accuracy. Another study to classify skin cancer using the ISIC 2020 dataset with a total of 33,126 images achieved an evaluation metric accuracy of 98.39% by combining three pre-trained models: ResNet, VGGNet, and MobileNet [15]. Lastly, a study by Rashid et al. [16] using the MobileNetV2 architecture with the ISIC 2020 dataset achieved an average accuracy of 98.20%, utilizing evaluation metrics accuracy, precision, recall, f1-score, and AUC-ROC.

For this study, the dataset to be used is the ISIC 2020 dataset. This dataset includes ten types of skin diseases: unknown, nevus, melanoma, seborrheic keratosis, lentigo NOS, lichenoid keratosis, solar lentigo, cafe-au-lait macule, and atypical melanocytic proliferation. These ten types of diseases are further divided into two classes: benign and malignant, with the aim of this dataset being to classify between the two. This dataset is the latest release by the International Skin Imaging Collaboration (ISIC), providing the largest collection of digital images needed by researchers for diagnosing skin diseases using artificial intelligence techniques, and it is open source [17]. The ISIC 2020 dataset is sourced from various sources such as Hospital Clinic de Barcelona, Medical University of Vienna, Memorial Sloan Kettering Cancer Center, Melanoma Institute Australia, University of Queensland, and University of Athens Medical School. This dataset is more varied than the previously released ISIC datasets, with a total of 33,126 images. The training images are divided into two categories: 32,542 benign images and 584 malignant images. Additionally, several relevant datasets on the Kaggle website are sourced from the ISIC dataset.

Considering the data imbalance between benign and malignant classes in the ISIC 2020 dataset, a further analysis is needed to choose a model with a pre-trained convolutional neural network architecture and the evaluation metrics to be used. According to previous studies, the MobileNet architecture has better performance compared to other architectures. This is also supported by research conducted by Duman and Tolan [17] which found that although MobileNet has a smaller size, it can have better performance compared to other architectures such as ResNet and NasNet. Based on this explanation, the architecture to be used in this study is MobileNet, specifically the MobileNetV3Large variation which can perform more complex training. The evaluation metrics to be used in this study are accuracy, precision, recall, f1-score, and AUC-ROC.

To assist in model training, several additional methods will be employed such as morphological transformations, techniques to address data imbalance, optimization selection, and the implementation of mixed precision. Morphological transformation using black-hat operation is conducted to detect and remove hair or noise obstructing the images to help the model recognize diseases. This approach is based on the study conducted by Khan et al. [11], which compared models trained on datasets with and without black-hat

application, finding that the model trained on the dataset with black-hat application performed better.

To address the data imbalance between benign and malignant classes, this study will use the oversampling technique. Oversampling is a method to balance data by adding samples to the minority class. The reason for using this technique is based on research conducted by Werner et al. [18] which compared preprocessing techniques and found that oversampling is the most commonly used technique and effective in maintaining data integrity. The optimization technique to be used is the Adam optimizer, which is based on the study by Valova et al. [19] that sought the best optimization method for image classification on imbalanced datasets, finding that Adam optimizer provided good performance in training. The importance of skin cancer classification in medical diagnosis has led to extensive research utilizing deep learning techniques, particularly convolutional neural networks (CNNs). However, many existing methods struggle with long training times and computational inefficiencies. One approach that seeks to address these challenges is mixed precision implementation, which involves the combination of float32 and float16 data types. Float16 is leveraged to enhance performance and speed up training, while float32 is employed to store variables and ensure numerical stability [20]. Despite the success of CNNs in skin cancer classification, there remains room for improvement in terms of training efficiency and model scalability.

This study, titled "Skin Cancer Classification Using Convolutional Neural Network With Mixed Precision Implementation," is motivated by the need to overcome the limitations of conventional methods in skin cancer detection, such as high computational costs and prolonged training times. Mixed precision offers a potential solution by balancing speed and accuracy, making it suitable for medical applications where quick and reliable diagnoses are critical. In addition to exploring the benefits of mixed precision, this research also builds on previous literature that has successfully applied deep learning and CNNs to skin cancer classification, offering a comparative analysis of performance metrics such as accuracy, precision, and recall with and without mixed precision.

2. Research Methods

The collection of the dataset that will be used for model training. Then, preprocessing the dataset using black-hat morphology and oversampling from the existing classes. At this stage, the class data will also be split into training and validation sets. Next is training the model using transfer learning with the MobileNetV3Large architecture. MobileNetV3Large is the latest version of the MobileNet architecture, and the reason for choosing MobileNet is that research conducted by Singha and Roy [15] and Rashid et al. [16] showed that MobileNet achieved the best accuracy when compared to other models. Finally, evaluating the model's performance using metrics such as accuracy, precision, recall, F1-score, AUC-ROC, and training time. Figure 1, displaying the workflow of developing a skin cancer classification model:

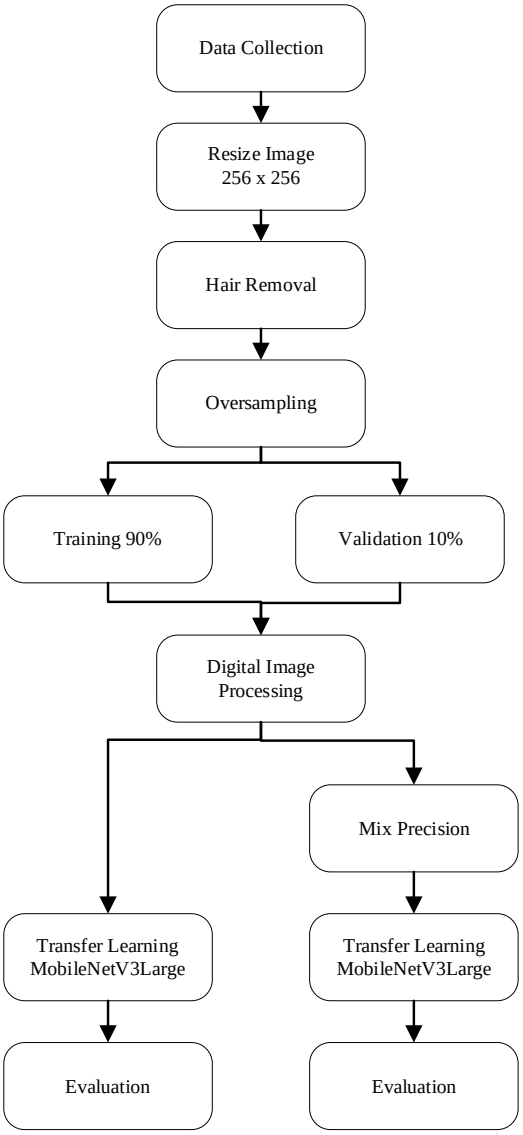

Figure 1. Flow Research

The model development will be conducted twice. The first development will not use mixed precision, while the second development will use mixed precision in the training. The model with mixed precision and the model without mixed precision will be compared with the hypothesis that the model applying mixed precision will have better performance and shorter training time.

In the preprocessing stage, several actions will be taken. First, the dataset will be resized to a uniform size of 256 x 256, as the dataset contains images of varying sizes. Then, each image in each class will undergo black-hat morphology to remove obstructing objects from the images. Next, the malignant class will be augmented to reach 32,542 images by applying augmentation techniques as conducted by Rashid et al. [16] achieved an accuracy of 98%. These techniques include a rotation

range of 40° to flip the images, a width shift range of 0.2 to shift the images horizontally, a shear range of 0.2 to stretch the images, a horizontal flip to create mirror versions of the images, and a brightness range from 0.5 to 1.5 to adjust the image brightness. Once the number of images in the malignant class matches that of the benign class, the next step is to split the dataset into 90% training data and 10% validation data. Table 1 shows the dataset distribution used for model training with a ratio of 90% for training and 10% for validation:

Table 1. Ratio Split Data

Class	Training	Validation
Benign	29.288	3.254
Malignant	29.288	3.254
Total	58.576	6.508

After splitting the data into training and validation sets, the next step is to perform image augmentation on the training data using the same transformations and settings as in the study conducted by Rashid et al. [16]. The training augmentations include a rotation range of 25°, width shift range and height shift range of 0.1 each to shift the image width and height, a shear range of 0.2, a zoom range of 0.2, and a brightness range to adjust image brightness from 0.5 to 1.5. Additionally, a channel shift range of 0.05 will be applied to shift the color pixels in the image, and the nearest fill mode will be used to fill in new pixels after augmentation.

Next, two models will be created using different approaches. The first model will be trained with transfer learning using the MobileNetV3Large architecture without using mixed precision. The second model will be trained with transfer learning using the MobileNetV3Large architecture and applying mixed precision. The parameters used in training will include the Adam optimizer with a learning rate of 0.001, and training will run for 20 epochs, as referenced in the study by Poornima et al. [14], which compared the training of various models with different epoch counts. Training will be conducted on Google Colab using a T4 GPU.

Research instruments are the measurement tools used in the research activities. In this study, the research instruments for model development are accuracy, precision, recall, F1-score, and AUC-ROC. Additionally, to help evaluate the model's performance, a confusion matrix (CM) and the training time for each model will be used. These evaluation metrics can be measured using the Sklearn library.

3. Results and Discussions

The ISIC 2020 dataset contains various types of diseases, including atypical melanocytic proliferation, cafe-au-lait macule, lentigo NOS, lichenoid keratosis, melanoma, seborrheic keratosis, solar lentigo, and unknown.

Each of these diseases is further divided into two classes: benign and malignant. The aim of this dataset is to classify between the two. Table 2 displays the distribution of disease types based on their classes:

Table 2. Distribution of Disease

Benign	Malignant
atypical melanocytic proliferation, cafe-au-lait macule, lentigo NOS, lichenoid keratosis, seborrheic keratosis, solar lentigo, and *unknown*.	Melanoma

In prior research on skin cancer classification, the primary focus has been on improving model performance metrics such as accuracy, precision, and recall, with less emphasis on training efficiency or computational cost. For instance, various studies achieved impressive accuracy rates using deep learning architectures VGG16 reached 93.18%, while a CNN architecture scored 96% accuracy with smaller datasets. However, these studies provided limited insights into the models' training durations or resource requirements.

Among the studies, Rashid et al.'s work stands out as particularly successful, achieving a high accuracy of 98.2% using MobileNetV2 on the ISIC 2020 dataset. Their study not only achieved superior performance metrics but also balanced accuracy, precision, recall, f1-score, and AUC-ROC, which together represent a comprehensive evaluation of model efficacy. Comparing Rashid et al.'s results to those from models using architectures like ResNet152 or AlexNet, which achieved slightly lower accuracies, highlights Rashid et al.'s model as a top performer, particularly for balancing high classification accuracy with generalizability across evaluation metrics.

Our study builds on these performance achievements by incorporating mixed precision to improve training efficiency without a substantial loss in accuracy. Additionally, we applied black-hat morphology as a preprocessing step to reduce noise and remove hair artifacts from the images, following the methodology described in Khan et al.'s study. Black-hat morphology is particularly effective for enhancing the visibility of skin lesion boundaries by suppressing darker regions in the image, which often include hair or shadows. By using this technique, we could enhance image clarity and ensure that noise did not interfere with the model's ability to identify critical features of benign and malignant lesions.

By analyzing both model accuracy and training time, we provide a more holistic perspective that can guide future research in optimizing not only the accuracy of skin cancer classification models but also their computational efficiency. This approach allows us to maintain high performance in image classification while also addressing practical concerns in model training, such as resource usage and processing time, which are crucial for large datasets like ISIC 2020.

The convolutional neural network model used for transfer learning is the latest variation of the MobileNet

architecture, namely MobileNetV3Large. The TensorFlow library is used to import MobileNetV3Large, and after importing it, parameters such as input_shape set to (224, 224, 3) will be added according to the recommended size for MobileNetV3Large.

Next, include_top will be set to false as the default dense layers are not needed. Additional layers are also added, including GlobalAveragePooling2D to transform 3D metrics into a 1D vector, Dense layers to learn data representations, and a Dropout layer to reduce overfitting. Finally, another Dense layer is added to produce interpretable outputs from the model. Figure 2 shows the summary of the first model that has been created:

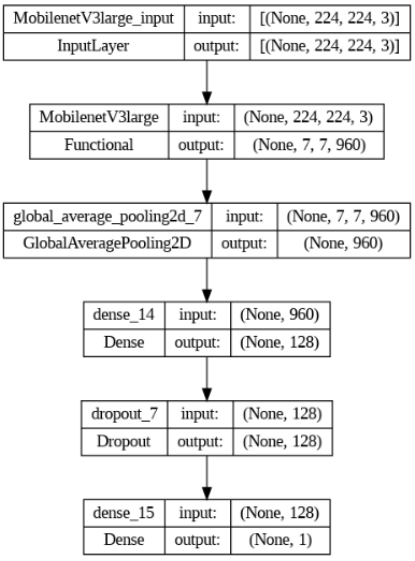

Figure 2. Model summary

3.1 Preprocessing Result

After resizing the images to 256 x 256 pixels, the next step is to apply transformations to reduce noise in the images. One way to reduce noise is by applying black-hat morphology. Figure 3 shows the result of applying black-hat morphology to an image. Then, oversampling will be applied to the malignant class to balance the number of samples between the benign and malignant classes. Table 3 shows the results of applying the oversampling technique:

Table 3. Comparison of The Number of Images

Stages	Benign	Malignant
Original	32.542	584
Oversampling	32.542	32.542

Oversampling applies augmentation to duplicate images by creating new variations through several techniques: a rotation range of 40° to flip the images, a width shift range of 0.2 to shift the images horizontally, a shear range of 0.2 to stretch the images, horizontal flip to create mirror versions of the images, and a brightness range from 0.5 to 1.5 to adjust the image brightness.

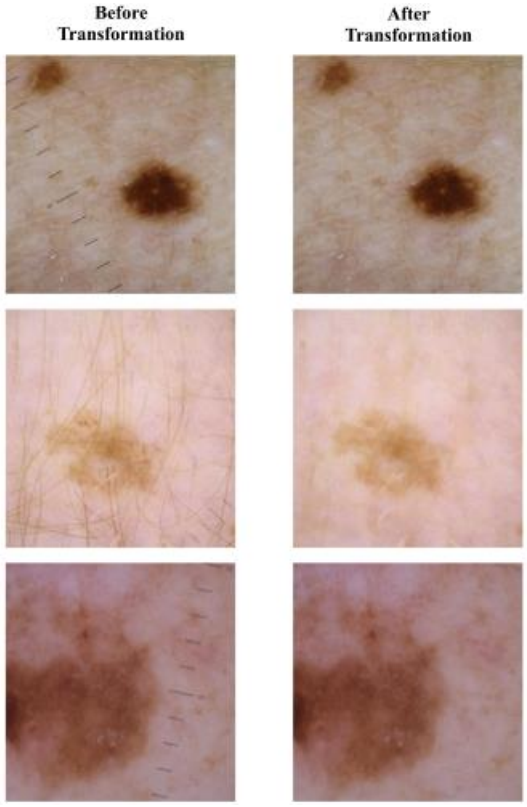

Figure 3. Transformation result

3.2 Training Result

The first convolutional neural network model to be evaluated is the one that does not use mixed precision and only applies transfer learning with the MobileNetV3Large architecture. This model achieved a significant validation loss of approximately 6.6% and attained an accuracy of 98%.

The next convolutional neural network model for skin cancer classification to be evaluated is the one that uses mixed precision during training. This model achieved a validation loss of 8.9% and a validation accuracy of 97%. Figure 4 will show the visual comparison of the two models:

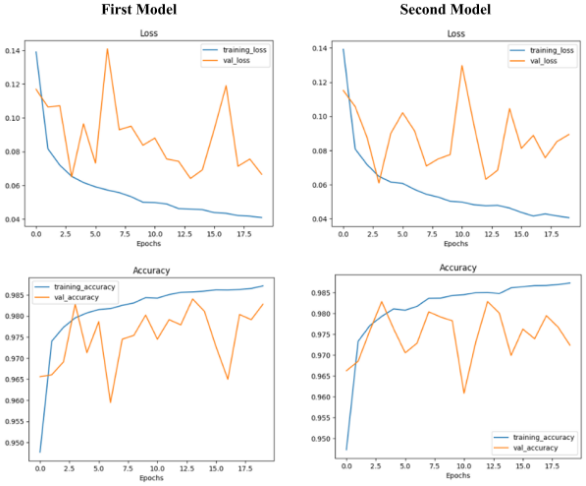

Figure 4. Performance Visualization of Both Models

The evaluation metric AUC-ROC for both models shows a value of 1.0 on the ROC curve, indicating excellent and reliable performance in differentiating between positive and negative classes. This can be seen in Figure 5.

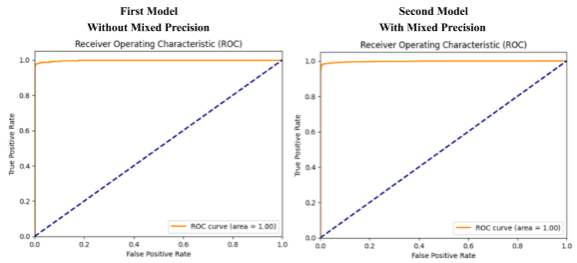

Figure 5. The evaluation metric AUC-ROC for both models

Both models are able to surpass or match 6 out of 8 other studies considered state-of-the-art. However, the models still lag behind compared to the research conducted by Singha and Roy [15], which achieved an accuracy of 98.39% using a combined model of ResNet, VGGNet, and MobileNet. Lastly, the study by Rashid et al. [16] achieved an accuracy of 98.2% using MobileNetV2.

The model without mixed precision had a total training time of 19,603 seconds (326 minutes and 43 seconds). This is calculated based on the duration of training for each epoch. Meanwhile, the model that used mixed precision during training had a total training time of 17,957 seconds (299 minutes and 17 seconds). This is calculated based on the duration of training for each epoch. Table 4 will display the comparison of the training times for the two models.

Table 4. Comparison of Training Time

Epoch	Model 1	Model 2
1	990	911
2	977	902
3	982	892
4	977	896
5	981	901
6	974	902
7	982	908
8	977	893
9	974	904
10	985	891
11	976	895
12	978	891
13	974	894
14	986	894
15	989	899
16	988	901
17	980	901
18	979	901
19	978	897
20	976	884
Total	19.603 seconds	17.957 seconds

The model using mixed precision demonstrates faster training due to the combined use of 16-bit and 32-bit floating-point types. This method optimizes computation by applying 16-bit (half-precision) to parts of the model that don't require full precision, such as certain matrix multiplications or weight updates. Since 16-bit operations require less memory and bandwidth, the GPU can perform more operations in parallel, boosting overall efficiency. This reduces the model's memory footprint, allowing faster processing, which is evident in the observed 9% decrease in training time.

However, using 16-bit precision comes with a slight downside. During forward and backward propagation, lower precision arithmetic can introduce small rounding errors or reduced accuracy in how values are calculated. While these errors are typically minimal and do not significantly affect simpler patterns, they can become more noticeable when the model deals with complex, nuanced tasks, such as distinguishing between benign and malignant lesions in medical images.

In these cases, the small imprecisions can impact how effectively the model fine-tunes its weights, leading to a slight reduction in accuracy. Although the mixed precision model converges more quickly, the trade-off is a small performance drop, such as the 1% decrease in accuracy compared to the full 32-bit model.

This trade-off between speed and precision is a typical characteristic of mixed precision training. While it accelerates computations, it can slightly hinder the model's capacity to capture fine-grained distinctions, resulting in a minor compromise in performance. For many applications, this is an acceptable trade-off, as the increased efficiency often outweighs the slight decrease in model performance. Table 5 is a summary of the performance of the two models:

Table 5. Summary Performance

Metric Evaluation	Model 1	Model 2
Accuracy	98%	97%
Precision	98%	97%
Recall	98%	97%
F1-Score	98%	97%
AUC-ROC	1.0	1.0
Time	19.603 seconds	17.957 seconds

4. Conclusions

Based on the findings of this research, it can be concluded that the convolutional neural network model using MobileNetV3Large with transfer learning and without mixed precision outperforms the model that incorporates mixed precision in terms of accuracy, precision, recall, and F1-score, achieving a value of 98%. In contrast, the model with mixed precision achieves a slightly lower performance, with a value of 97%. The AUC-ROC evaluation metric for both models remains consistent, at a value of 1.0. While the model utilizing mixed precision has a faster training time—being 1,646 seconds (27 minutes and 26 seconds) quicker than the non-mixed precision model, it shows an 8.39% improvement in training speed. This research highlights that while mixed precision can significantly improve computational efficiency, it may come at the expense of a slight reduction in performance. The study contributes to the field by demonstrating how optimization techniques like mixed precision can

accelerate model training, which is particularly useful in clinical applications where time is critical. However, the trade-off between training speed and model accuracy needs to be carefully considered based on the specific use case. For future research, it is recommended to explore additional optimization methods, such as quantization or pruning, to further enhance both performance and efficiency. Additionally, applying these techniques to larger and more diverse datasets could validate the findings and provide insights into the model's generalizability across different clinical contexts. Finally, a detailed analysis of the limitations, such as the dataset size and the potential overfitting due to augmentation and oversampling, should be addressed in subsequent studies to improve robustness.

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