Comparison of Deep Convolutional Neural Network Architectures for Fruit Categorization

Original Scientific Paper

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Abstract *– In general, there are so many types of fruit images that it is difficult for humans to differentiate them based on their visual characteristics alone. This research focuses on identifying and recognizing images of fruit from 23 different classes or types. Fruit varieties consist of 13 apple classes, 1 orange class, and 9 tomato classes, totaling 15,987 images. Fruit image data were collected from various sources, including the internet, magazines, and direct capture with a digital camera. The process of identifying and recognizing fruit images involves the classification of fruit images using a deep learning algorithm. Several CNN models, which are derivatives of deep learning, are used to achieve high accuracy and robustness in recognizing various types of apples and tomatoes. To evaluate the performance of each model, the apple data were trained on a large and diverse set of apple images using several CNN models such as ResNet50V2, InceptionV3, InceptionResNetV2, VGG16, VGG19, MobileNetV2, and EfficientNet. Performance is assessed using metrics such as accuracy, precision, recall, and F1 score. To achieve optimal performance in the image recognition process, it consists of preprocessing strategies, data augmentation, feature extraction, and classification supported by optimization, all of which have a significant impact on increasing accuracy performance. Experimental results show that certain CNN model architectures outperform other model architectures in terms of time efficiency and accuracy in recognizing fruit types/classes. However, to get more optimal results regarding the performance of the CNN model architecture for fruit categorization, two optimizers will be used, namely Adam and Adagrad, and will be compared. Based on Adam's optimizer experiments, the EfficientNet model produces the highest average accuracy of up to 99%, followed using the VGG 16 and ResNet V2 50 models, which achieve 98% and 97% accuracy. Meanwhile, the use of the Adagrad optimizer with the VGG 16 model produces the highest average accuracy of up to 95%, followed using the VGG 19 and EfficientNet models, which achieve accuracy of up to 93% and 91%. Overall, this experiment produced very good accuracy because it produced an average of above 90%. However, there is still room for improvement in recognizing fruits of different shapes, textures, and colors.*

Keywords*:* *fruit, identification, recognition, CNN, categorization, apple, tomato*

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1. INTRODUCTION

There are numerous types of fruits, which makes it difficult for humans to distinguish between them solely based on their characteristics. Additionally, there is a lack of user knowledge in differentiating between types of fruits and vegetables among various horticultural products in agriculture fields, particularly apples and tomatoes. This lack of knowledge makes it challenging for users to easily identify and select apples and tomatoes that are readily available in the market and are easily consumable [1]. To address this issue, it is important to provide users with information that will help them easily identify and select apples and tomatoes that are readily consumable. In general, identifying fruit objects through images is very useful because there are many types of fruit that exist and can be carried out. Fruit categorization has benefited greatly from deep learning techniques [2]. Accurate and efficient fruit categorization is crucial in agriculture, quality control, and automated fruit sorting systems Traditional methods of grading and sorting fruit by humans are slow, labor-intensive, error-prone, and tedious [3]. Therefore, there is a need for intelligent fruit grading systems. To address the challenges posed by differences in fruit appearance, shape, size, and orientation, researchers have developed a deep learning-based fruit categorization system [4]. The findings of this study contribute to the advancement of fruit classification systems and have practical implications in various fields, such as agriculture, the food industry, and automated fruit sorting [5]. In other studies architectures leverage deep learning techniques to eliminate the need for hard-coding specific features related to a fruit's shape, color, or other attributes. This method has the potential to enhance the accuracy and efficiency of fruit categorization operations, enabling automated and reliable fruit quality evaluation [6]. In conclusion, deep learning-based fruit categorization systems have proven to be effective in accurately classifying different varieties of fruits. These systems offer advantages such as non-contact operation, improved efficiency, and reliable fruit quality evaluation. They have practical applications in agriculture, the food industry, and automated fruit sorting systems [7].

The goal of the study was to create a robust and reliable model capable of accurately classifying different varieties of fruits. To achieve this, various deep learning models were employed, including ResNet50V2, InceptionV3, InceptionResNetV2, VGG16, VGG19, and EfficientNet. These models have demonstrated exceptional performance in picture classification tasks and are known for their ability to capture nuanced features and patterns. The research also involved extensive testing of different optimizers. Optimizers play a crucial role in deep learning models as they determine how the model learns and updates its parameters during training. Different optimizers have been shown to yield varying performance in terms of accuracy, precision, recall, and F1-score. However, specific details about the optimizers used in the study are not provided in the given information.

2. RELATED STUDY

Various types of evaluations and analyses were conducted on various classification models to identify citrus fruit diseases. This paper discusses concepts related to image acquisition processes, digital image processing, feature extraction, and classification approaches. Each concept is discussed separately [8]. It is crucial to employ image annotation techniques that are fast, simple, and highly effective. This research focuses on the agricultural sector and implements automatic image annotation to classify the ripeness of oil palm fruit and to identify different types of fruit. This approach aids farmers in improving fruit classification methods and increasing their production [9]. The fruit industry faces a common challenge: the lack of an automated system for classifying dates. Recent advancements in machine learning techniques have opened new opportunities for automating fruit classification and sorting tasks, traditionally handled by human experts [10].

This study explores the performance of various deep learning models and the impact of different parameters on the accuracy and efficiency of fruit classification systems using convolutional neural networks (CNNs) with various approaches [11]. This article highlights the application of AI in the food industry, maximizing resource utilization by reducing human error. Artificial intelligence, coupled with data science, can enhance the quality of restaurants, cafes, online food delivery chains, hotels, and food outlets by increasing production using different pairing algorithms for sales prediction [12]. In conducting the experiments using a dataset comprising images of 30 different fruit classes. The researchers employed prominent deep learning architectures, such as VGG16 and ResNet50, as the foundation for their classification system. They evaluated the models' performance based on accuracy, precision, recall, and F1-score. Their findings yielded 86% and 85% accuracy from the public dataset and 99% and 98% accuracy from their custom dataset [13].

By utilizing the Fruit-360 dataset, we ensure the dataset's reliability, backed by the success of previous research using this dataset. This research emphasizes the application of AI in the food industry, recommending significant capital savings through resource optimization, including human error reduction. This experiment employed a GPU as the primary processing power, achieving 177x acceleration on training data and 175x on test data [14]. In another study, a wider variety of fruits were used. The experiment was conducted using 24 classes of fruit comprising 3,924 images. The authors preprocessed the data by applying augmentation techniques. They implemented CNN, which trained the data with a batch size of 16 and 100 epochs, resulting in 95.5% accuracy for their test [15]. The comparison research used various kinds of apples, such as Granny Smith, Braeburn, Golden Delicious, and Cripps Pink, and other fruits, such as mandarin, lemon, and orange. It indicated that the average accuracy values for training and test datasets were 100% and 73%, respectively [16]. The advantages of artificial intelligence, deep learning-based computer vision can support various agricultural activities can be carried out automatically with maximum precision, making smart agriculture a reality [17].

Computer vision techniques, together with the ability to acquire high-quality images using remote cameras, enable non-contact and efficient technology-based solutions in agriculture [18, 19]. In another study, sea buckthorn fruits were used to quickly identify the moisture content range by collecting images of the appearance and morphology changes during the drying process [20]. Machine learning approaches for fruit classification have been proposed in the past, but deep learning, with its improved recognition and classification capabilities, can be a powerful engine for producing actionable results [21]. The classification of fruits can be divided into classes for edible and non-edible fruits, which is an important aspect in the industry. For example, one research project classified four fruits (Banana, Papaya, Mango, and Guava) into three stages: raw, ripe, and overripe [22].

Another study used a Convolutional Neural Network (CNN) to identify and classify different varieties of peanuts. Based on the deep learning technology, this paper improved the deep convolutional neural network VGG16 and applied the improved VGG16 to the identification and classification task of 12 varieties of peanuts [23]. In yet another study, a 13-layer CNN was designed, and various data augmentation methods were used, such as image rotation, Gamma correction, and noise injection. The researchers also compared maximum pooling with average pooling and used stochastic gradient descent with momentum to train the CNN [24]. The comparison table with existing studies can be seen in Table 1.

Table 1. The Comparison of some table with existing studies

Ref.	Tittle	Fruit Image used Method	Accuracy
6	Computerized Classification of Fruits using Convolution Neural Network	This research detect disease in fruit using a digital basis. Early detection of disease protects against damage to the entire plant using CNN	90%
9	Enhancing Image Annotation Technique of Fruit Classification Using a Deep Learning Approach	This research is about automatic image annotation which is repeated to classify the ripeness of oil palm fruit and recognize fruit varieties with Yolo based on Deep learning	98.7%
13	Fruits Classification and Detection Application Using Deep Learning	This paper is for an automatic fruit classification and detection system that has been developed using deep learning algorithms, namely Yolo and ResnetV2 or VGG16	85% and 98%
14	Analysis of artificial intelligence-based image classification techniques	This research is about an artificial intelligence-based image classification system for quickly identifying vegetables and fruits by looking through the camera billing process.	93%
17	Fruit image classification model based on MobileNetV2 with deep transfer learning technique	This research requires an automatic system to classify various types of fruit without the help of human labor using the modified version of MobileNetV2	99%
21	Fruit Classification Using Deep Learning	In this research about the importance of fruit classification for people who have dietary needs including to help them choose the right fruit category on a digital basis Using CNN Model	94.3%

Table 1. provides information about the comparison of several research references related to fruit image classification, including the model/algorithm used and the resulting accuracy of the model used in each reference. In the proposed system there are four classified fruits, namely Banana, Papaya, Mango, and Guava which are divided into three stages, namely unripe, ripe, and overripe fruit using a Convolutional Neural Network [25]. The fruit research process involves several steps, including fruit classification methodology, pre-processing, and the implementation of fruit classification using appropriate software and hardware. Preprocessing includes background removal and segmentation techniques to extract fruit areas.

3. PROOSED METHOD

In this classification research, the workflow is done based on this research method diagram in Fig. 1.

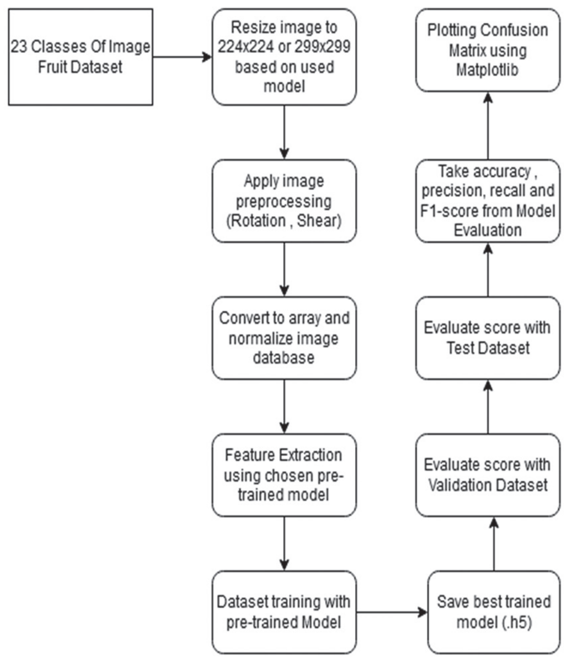


Fig. 1. Research diagram for "Fruit Image Classification Using Various Pre-Trained Models

The aim of experiment is to find the CNN model that yields optimal accuracy values. Two optimizer methods would be employed to support the classification performance in this experiment. To conduct this experiment, the images will undergo changes in pixel size and rotation. These modified images will then be converted into array values during the normalization process, which will be applied to all the images in the dataset. The array values would be processed to extract image characteristics based on the selected CNN model, both for training and testing data. A comparison process performed between the trained images and the testing images to determine the accuracy and performance of the classification. In summary, the stages involved in the classification of fruit images can be described as follows:

1. Data Preparation of Fruit Image Dataset

This research utilized the dataset obtained from Kaggle.com, specifically the Fruits-360 dataset. The dataset comprises 15,987 fruit images, covering 23 different fruit classes, with a primary focus on various types of apples and tomatoes. This diverse collection facilitates training and testing of CNN models, leading to improved classification accuracy. Additionally, these modifications have an impact on other accuracy measures during the experiment. An example of an apple can be seen in Fig. 2.

Fig. 2. Inform the Apple Braeburn class dataset which has undergone changes in rotation and focus

Meanwhile, the number of fruit classes in this study can be seen in Fig. 3.

Fig. 3. Dataset Images from each Classes

Fig. 3 present the fruit dataset studied which consists of 13 classes of apples studied, 1 class of citrus fruit and 9 classes or types of tomatoes. They are apple Braeburn, Apple Crimson Snow, Apple Golden 1, Apple Golden 2, Apple Golden 3, Apple Granny Smith, Apple Pink Lady, Apple Red1, Apple Red2, Apple Red3, Apple Red Delicious, Apple Red Yellow, Apple Red Yellow2, Orange, Tomato1, Tomato2, Tomato3, Tomato cherry Red, Tomato Heart, Tomato Marcon, Tomato Not Ripened, Tomato Yellow.

2. Fruit Data Image Preprocessing (Resize, Rotation)

The fruit image data is pre-processed before being used for the dataset training process with a pre-trained model. Before, training the models, the fruit data images undergo preprocessing steps such as resizing and rotation. These steps help standardize the input images and ensure the models be able to handle variations in size and orientation. The following steps are taken for pre-processing the fruit image data:

1. Resizing: Fruit Image presents a full-frame fruit with different rotations and orientations. The dataset also includes resized fruit images with pixel sizes of 224 x 224 and 299 x 299. Each image is resized to either 299x299 or 224x224, depending on the model being used. The InceptionResNetV2, InceptionV3, and ResNet50V2 models require the image size to be 299x299, while the VGG16, VGG19, MobileNetV2, and EfficientNet models require the image size to be 224x224.
2. Rotation: After resizing the image, the entire dataset is reprocessed by applying different scale and shear rotations to each image. Moreover, each image undergoes rotation changes of 15 and 20 degrees, as well as shifts to ideal positions, enhancing recognition ease. These modifications aim to ensure equalized sizes within the fruit image dataset.
3. Selection of Pre-trained Models

To leverage the power of deep learning, pre-trained models are used in this study. Pre-trained models are neural network models that have been trained on large-scale datasets, such as ImageNet, and have learned to extract meaningful features from images. By using pre-trained models, researchers can benefit from the knowledge and representations learned by these models, saving time and computational resources.

3. Configuration and Optimization of Models

Configuring and optimizing the models involves setting up all the necessary parameters for processing the training data. This includes defining the architecture of the CNN models, specifying activation functions, kernel initializers, padding, input shape, and other relevant parameters. The models are then compiled and trained using the specified optimizers. The entire process of configuring and optimizing the models can be visualized through the output, which provides a comprehensive overview of the experiment.These resources are specifically tailored to configuring and optimizing the models for the task of fruit classification. This involves fine-tuning the models, adjusting hyperparameters, and selecting suitable optimization algorithms to achieve the best performance.

4. Training Dataset

The prepared data set is used to train the selected model. During the training process, the models learn to recognize and classify various types of fruits based on pre-prepared images and labels. The training data set is essential for the model to learn patterns and features that differentiate one class of fruit from another. For this training process, experiments have been carried out with several epochs of 10 and 50. As well as dividing the amount of fruit data used as training, testing and validation data.

5. Evaluation of Models on the Dataset

Once the models are trained, they are evaluated on a separate dataset to assess their performance. This evaluation dataset contains images that the models have not seen during training. By evaluating the models on unseen data, researchers can measure their generalization ability and determine how well they can classify fruits in real-world scenarios. The dataset consists of a total of 15,987 images with different rotations and orientations, including 9,600 training datasets, 2,386 validation datasets, and 4,001 testing datasets.

6. Comparative Analysis of CNN Models

A comparative analysis is conducted to compare the performance of the different CNN models used in this study. This analysis helps to identify the strengths and weaknesses of each model and provides insights into which models are most effective for fruit classification. Overall, this study focuses on the image processing of apples and tomatoes, utilizing deep learning algorithms and optimizations to achieve optimal classification accuracy. The experimental implementation is divided into several stages, including data preparation, image preprocessing, model selection, configuration and optimization, training, evaluation, and comparative analysis of CNN models.

4. EXPERIMENTAL RESULTS

In this experiment on fruit image classification, the model trained the image as many as 10 and 50 epochs of the given test time. However, it based on the test results on the fruit images obtained the accuracy results of the tests that have been carried out quite satisfactory and convincing, as well as being able to draw conclusions regarding the success of this research. The result of training showed with Matplotlib for better understanding of each training process. All the results shown in Fig. 4.

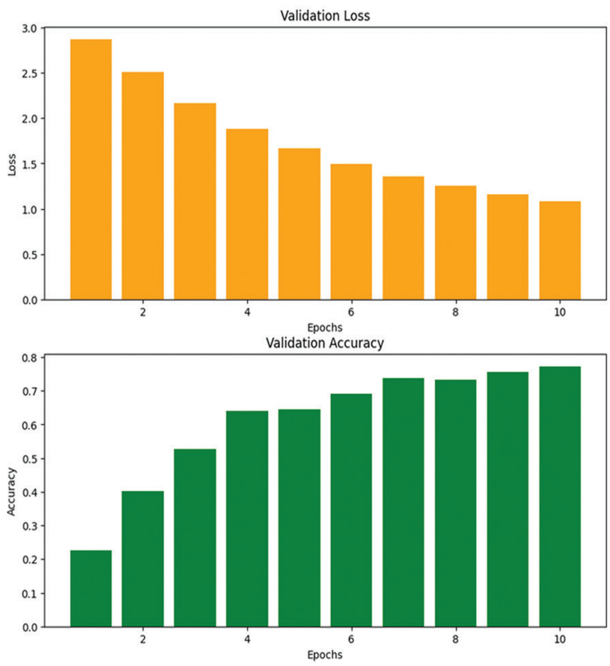


Fig. 4. Validation Dataset Accuracy and Loss on InceptionV3 through 10 Epochs using Adagrad optimizer

In Fig. 4, the experiment focused on comparing the performance of the Adagrad optimizer. The initial accuracy of the Adagrad optimizer was not as high as that of the Adam optimizer. However, the experiment showed that the Adagrad optimizer consistently improved over time throughout the epochs. Although it did not achieve the same level of accuracy as Adam in this test.

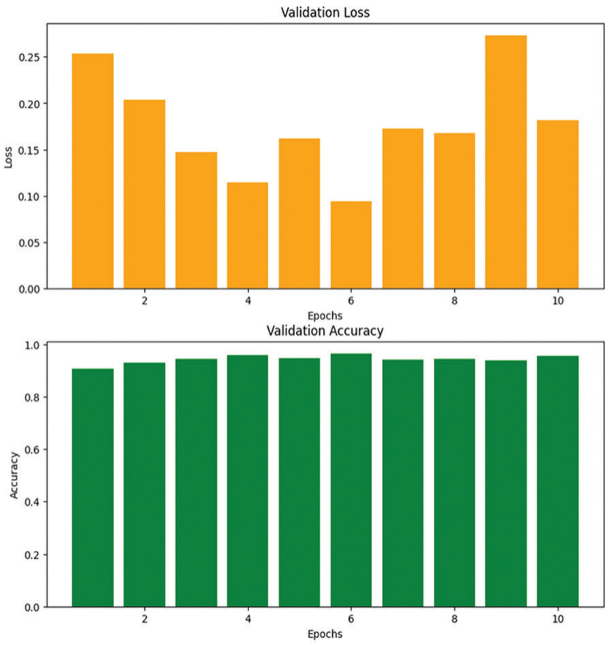
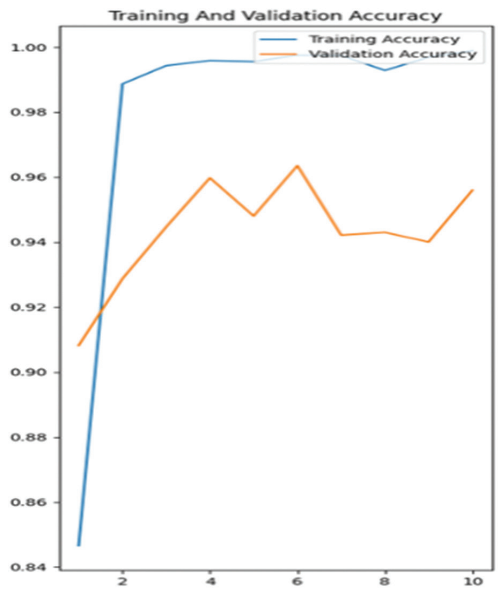
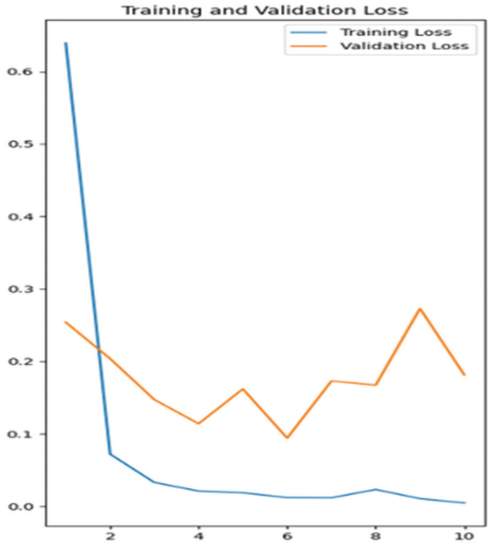


Fig. 5. Validation Dataset Accuracy and Loss on InceptionV3 through 10 Epochs using Adam optimizer

In Fig. 5 inform about the experiment of image classification used Adam optimizer and then the accuracy from the beginning was already high but the accuracy and losses seems to fluctuate a lot although the difference wasn't much with the numbers fluctuate around 0,1 between the fluctuation.



a) Training and Validation Accuracy Curves using Adam Optimizer on ResNet50V2

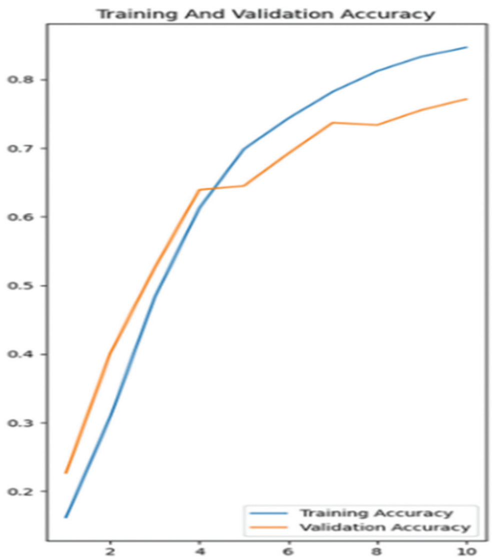


(b) Training and Validation Loss Curves using Adam Optimizer on ResNet50V2

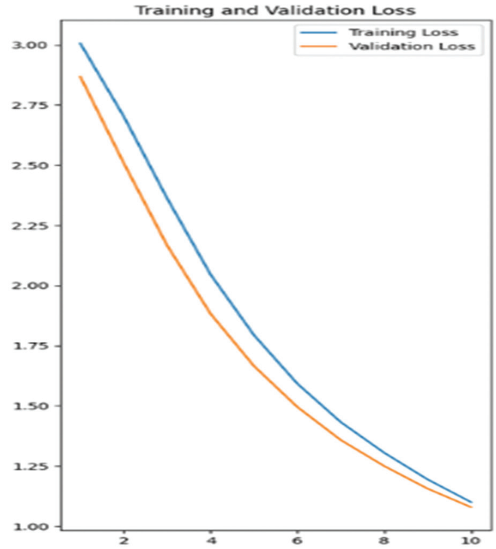
Fig. 6. Training and Validation Accuracy include Loss Curves using Adam Optimizer on ResNet50V2

In Fig. 6 present the training and validation accuracy dataset, as well as the increase in loss during training. The experiment used ResNet50V2 and Adam optimizer shows high accuracy up to an average of 90%, indicating good fluctuations in the training process.

In Fig. 7 present the training and validation accuracy include loss process used Adagrad optimizer starts with an accuracy more of 86% but shows consistency during training. In-depth analysis, the experiment extends the model training to 50 epochs. In this experiment, the EfficientNet model was used with the Adam optimizer, achieving an average accuracy of 97%. When using the Adagrad optimizer, the accuracy reached 92%. Additionally, the training loss with the Adam optimizer was smaller than with Adagrad.



(a) Training and Validation Accuracy Curves using Adagard Optimizer on ResNet50V2



(b) Training and Validation Loss Curves using Adagard Optimizer on ResNet50V2

Fig. 7. Training and Validation Accuracy include Loss Curves using Adagard Optimizer on ResNet50V2

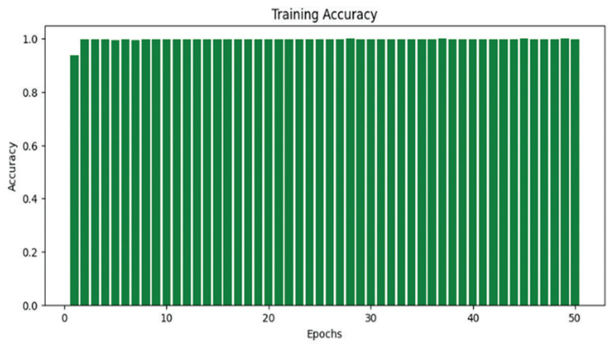


Fig. 8. Training accuracy used EfficientNet model and Adam Optimizer

Fig. 9. Training loss used EfficientNet model and Adam Optimizer

Fig. 8 and Fig. 9 present the training accuracy and loss process results using the EfficientNet model by carrying out a 50-iteration. The image obtained shows that the accuracy using the Adam optimizer has an accuracy of almost 100% and however, Fig. 10 and Fig. 11 present the training accuracy and loss process results used Adagard optimizer which had an accuracy of 80 - 90% results. In this experiment present confusion matrices for all models on the test dataset to provide a detailed of model performance.

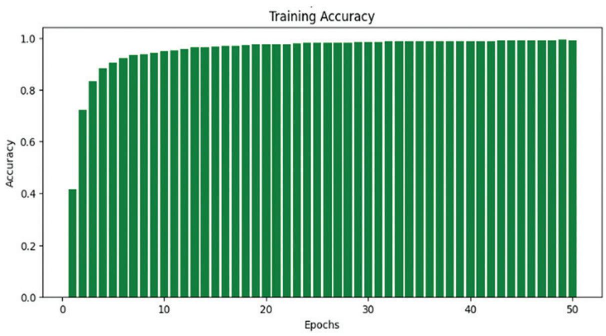


Fig. 10. Training accuracy used EfficientNet model and Adagard Optimizer

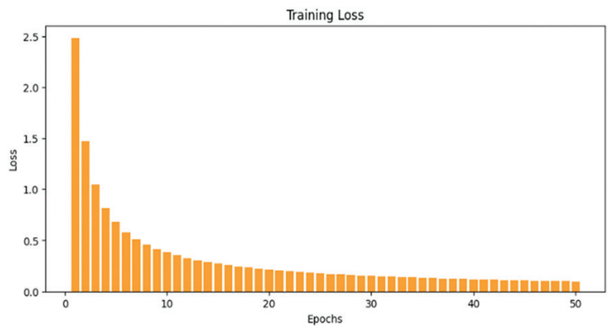


Fig. 11. Training loss used EfficientNet model and Adagard Optimizer

In Fig. 12 and Fig. 13 inform the confusion matrix graph shows that the overall performance evaluation in classifying fruit image data shows that the prediction results of the CNN model with the Adam optimizer produce better accuracy than Adagard. In this experiment, the EfficientNet model was used which produced prediction performance accuracy between 98 - 100%. whereas with Adagard only a few of fruits images can be detected properly.

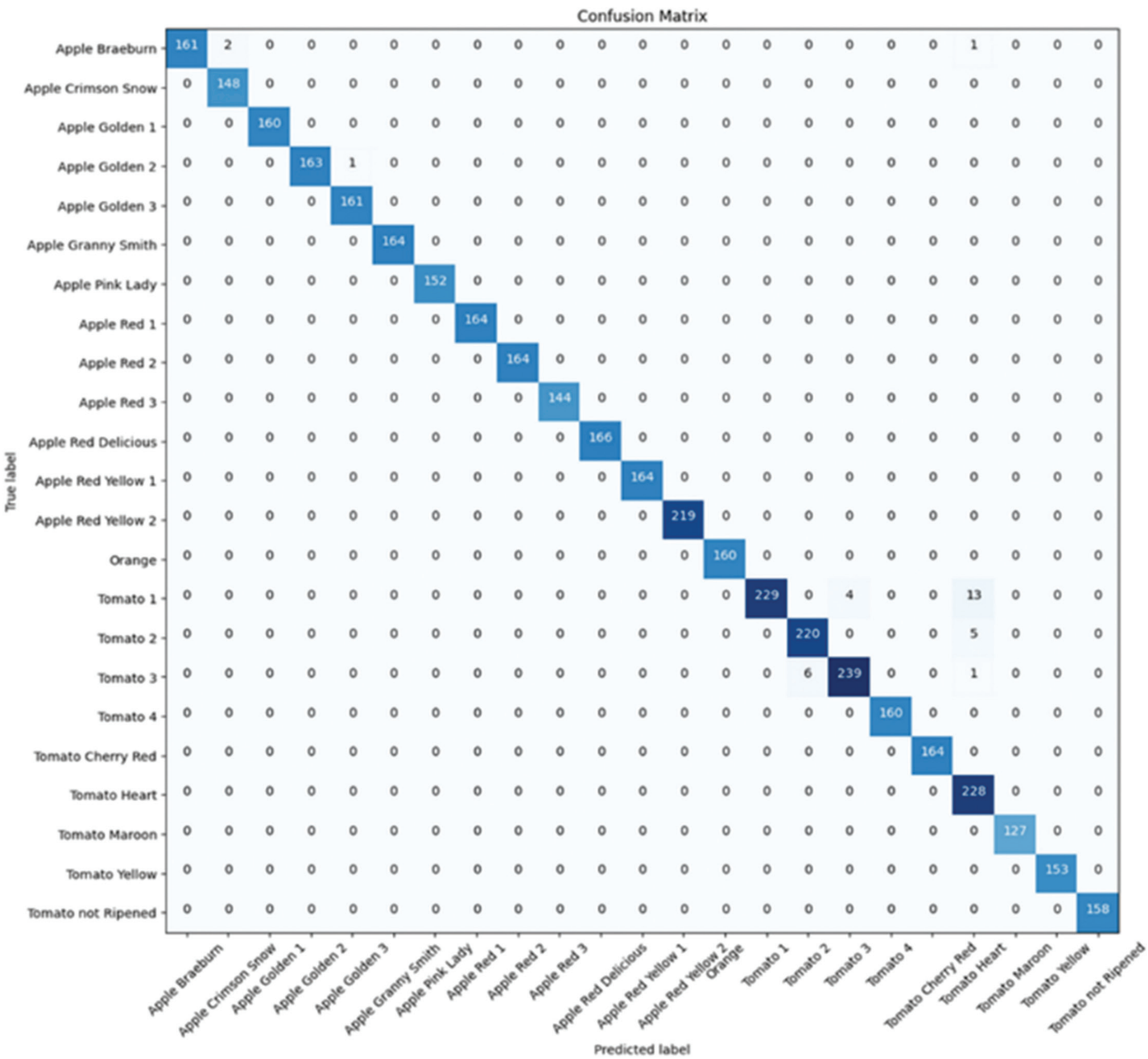


Fig.12. The confusion matrices used EfficientNet model and Adam Optimizer

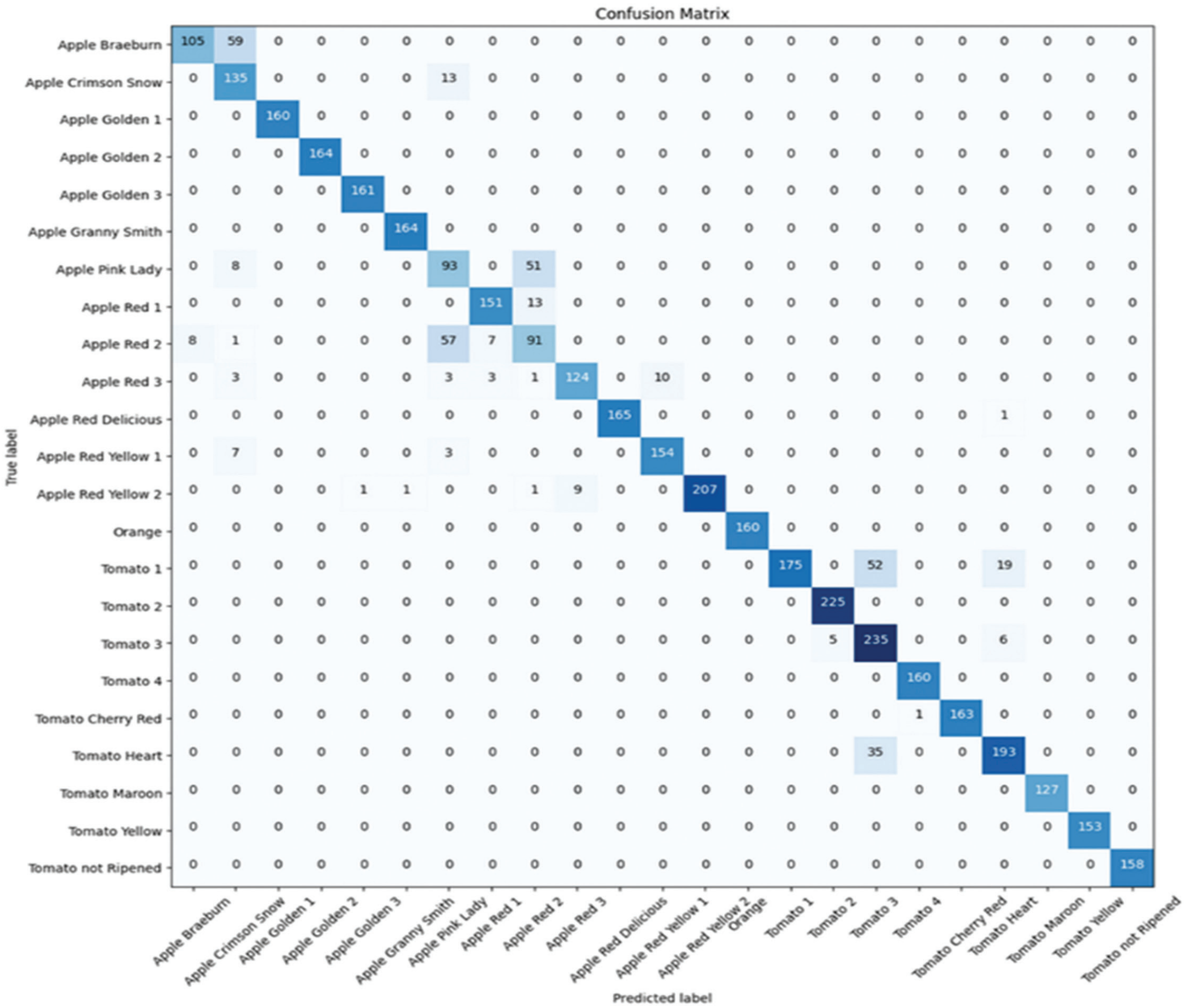


Fig.13. The confusion matrices used EfficientNet model and Adagard Optimizer

After doing the training and testing the fruit image dataset, the next step is to evaluate and test the model using test dataset for every model which supported with Optimizers. In this section, we presented the results of our tests using 7 pre-trained models and 2 optimizers. It is important to mention that we have tested 1 Orange dataset, which achieved 100% accuracy, so we will not provide further details about it in this description.

a) InceptionV3

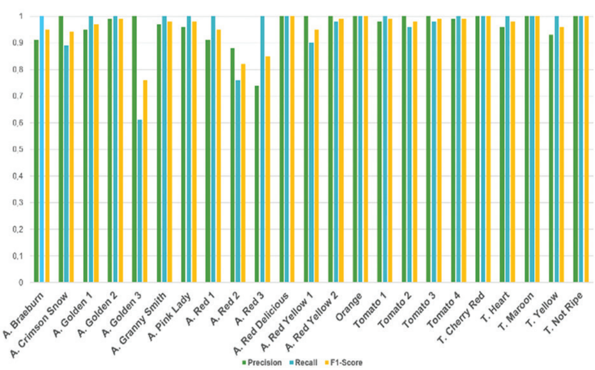


Fig. 14. Accuracy Classification using InceptionV3 and the Adam optimizer

Fig. 14 shows the results of experiments using InceptionV3 and the Adam optimizer. The classes of tomatoes, namely Red Delicious, Orange, Cherry Red, Maroon, and Note Ripe, achieved an accuracy of 100%. Additionally, the average accuracy of this experiment reached 96%. The experiment also yielded accuracy results of 100% for several other tomato classes.

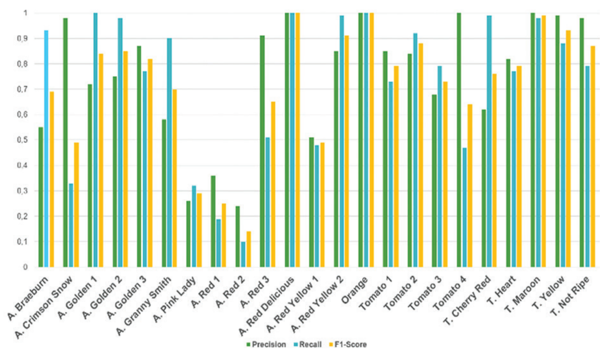


Fig. 15. Accuracy Classification using InceptionV3 and the Adagrad optimizer

In Fig. 15, the experiment results are shown using the InceptionV3 model and the Adagrad optimizer. It is observed that Orange and A. Red Delicious achieved 100% accuracy.

The dataset experiment overall achieved an average accuracy of 74%. However, the accuracy results for Apple Red 1 and 2, including pink lady, were significantly lower with an average accuracy of only 16% in this experiment.

b) InceptionResNetV2

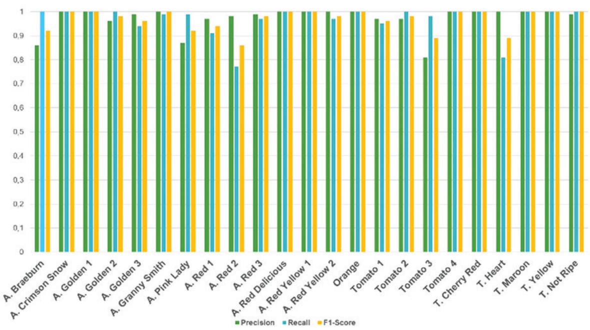


Fig.16. Accuracy Classification using InceptionResNetV2 and the Adam optimizer

In Fig. 16 the results of the experiment using the InceptionResNetV2 and Adam optimizer are reported. The following fruits achieved 100% accuracy: Crimson Snow, Golden 1, Red Delicious, Red Yellow1, Tomato 4, Cherry Red, Maroon, Yellow, and Not Ripe. The dataset experiment achieved an average accuracy of 74%. However, when using this CNN model, 10 types of fruit can be recognized with 100% accuracy, while the accuracy for other types of fruit can reach up to 80%.

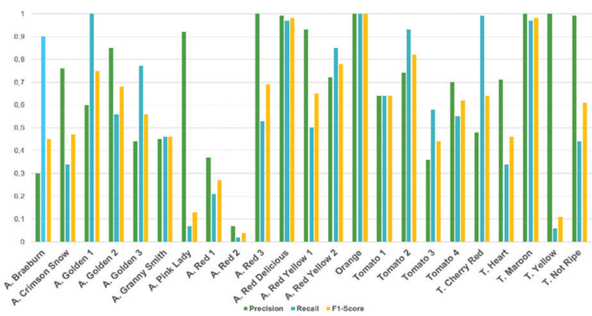


Fig.17. Accuracy Classification using InceptionResNetV2 and the Adagrad optimizer

In Fig. 17, the results of the experiment using the InceptionResnetV2 model and the Adagrad optimizer are presented. It is observed that the Orange class achieved 100% accuracy. Other types of fruits, such as Red Delicious and Maroon, achieved an accuracy rate above 95%. However, in this experiment, both Pink Lady and Red 2 showed low accuracy, with an average of less than 10%.

c) ResNet50V2

In Fig.18, the results of the experiment using the ResNetV2-50 model and the Adam optimizer are presented. According to this experiment, around 12 fruits achieved 100% accuracy, including Golden 1 and 2, Red Yellow, Orange, Red Delicious, and others. The dataset experiment achieved an average accuracy of 88% using this model.

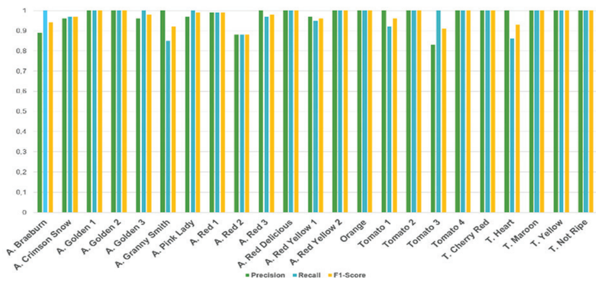


Fig. 18. Accuracy Classification ResNet50V2 using the Adam optimizer

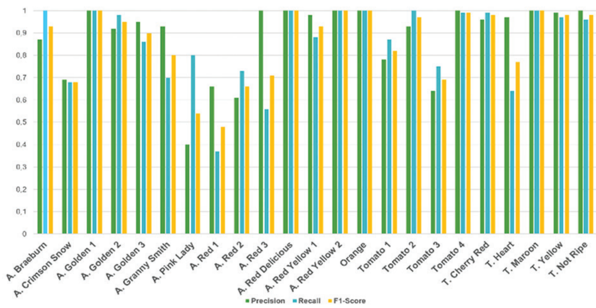


Fig. 19. Accuracy Classification using ResNetV2 and the Adagrad optimizer

In Fig. 19 present the experiment results using the ResNetV2-50 model and the Adagrad optimizer show that Orange and A. Red Delicious have 100% accuracy. The dataset experiment achieved an average accuracy of 74%. However, the accuracy results for Apple Red 1 and 2, including Pink Lady, were low, with an average accuracy of only 16% in this experiment.

d) VGG16

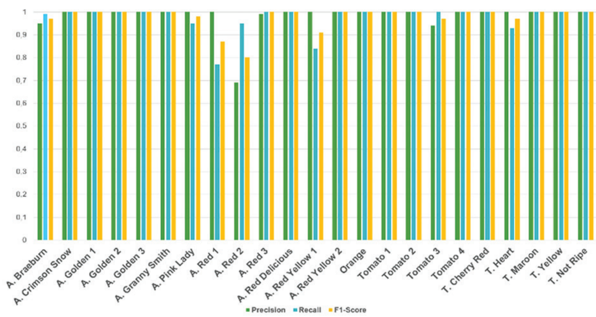


Fig. 20. Accuracy Classification on VGG16 using the Adam optimizer

In Fig. 20 present the experiment result using the VGG 16 and the Adam optimizer. In this experiment around 15 Fruits have achieved 100% accuracy such as A. Golden 1 and 2, A. Red Yellow, Orange, Tomato and A. Red Delicious and others. The experiment achieved the average more than 94% accuracy using this model. Based on this result can be concluded using this model has the best accuracy results.

In Fig. 21 present the experimental results using the VGG16 model and the Adagrad optimizer. In this experiment, around 10 fruits have achieved 100% accuracy, including Golden 1, Red Delicious, Red Yellow2, Orange, Tomato1, and other tomato varieties. The dataset experiment achieved an average accuracy of over 87% using this model. The lowest accuracy observed with the VGG16 was approximately 60%.

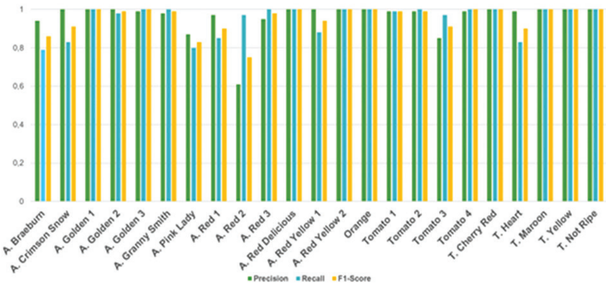


Fig. 21. Accuracy Classification using VGG16 and the Adagrad optimizer

e) MobileNetV2

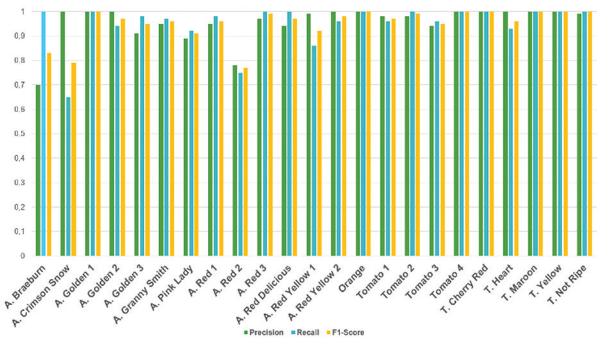


Fig. 22. Accuracy Classification using MobileNetV2 and the Adam optimizer

In Fig. 22 present the experiment results using the MobileNetV2 model and the Adam optimizer are presented. In this experiment, around 6 fruits have achieved 100% accuracy, including Golden 1 Orange, as well as various other kinds of tomatoes. The dataset experiment has achieved an average accuracy of over 82% using this model. The lowest accuracy achieved using the MobileNetV2 model was approximately 68%.

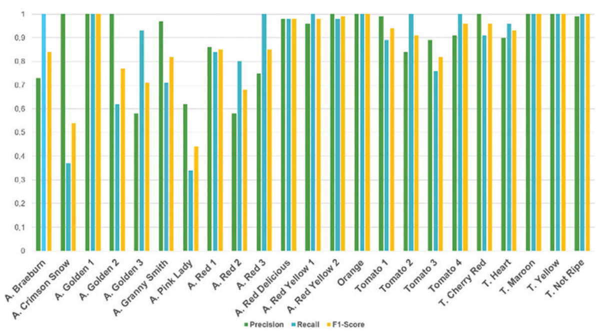


Fig. 23. Accuracy Classification on MobileNetV2 using the Adagrad optimizer

In Figure 23, the experiment results using the MobileNetV2 model and Adam optimizer are presented. In this experiment, around 5 fruits achieved 100% accuracy, including Golden 1 Orange and various types of tomatoes. The dataset experiment achieved an average accuracy of over 82% using this model. The lowest accuracy was observed with the MobileNetV2 model, which was about 64%.

f) EfficientNet

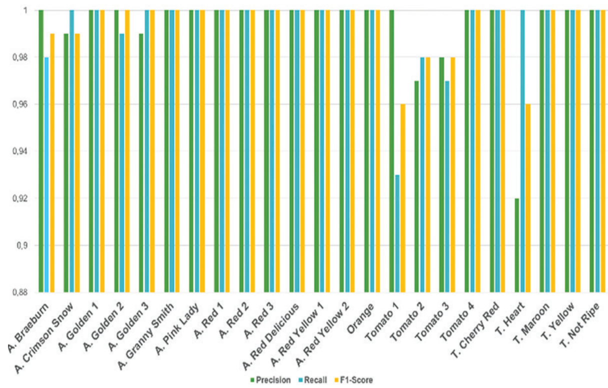


Fig. 24. Accuracy Classification on EfficientNet using the Adam optimizer

In Fig. 24, the experiment results using the EfficientNet and Adam optimizer are presented. In this experiment, around 15 fruits achieved 100% accuracy, including A. Golden 1, A. Granny Smith, A. Pink Lady, and apple varieties, as well as tomato varieties. The experiment achieved an average accuracy of more than 92% using this model. EfficientNet and Adam Optimizer emerged as the most successful among the 7 models tested with Adam optimizer. Interestingly, EfficientNet exhibited a different behaviour compared to the other models. While the models struggled to identify Apple Red, EfficientNet had the lowest accuracy in identifying Tomato Heart, but it still achieved 90% accuracy.

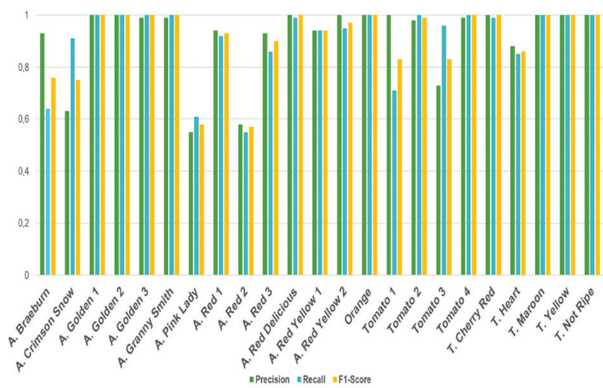


Fig. 25. Accuracy Classification on EfficientNet using the Adagrad optimizer

In Fig. 25 present the experiment results using the EfficientNet and Adagrad optimizer are presented. In this experiment, approximately six fruits achieved 100% accuracy, including A. Golden 1, A. Golden 2, Orange, and other types of tomato fruits. The experiment achieved an average accuracy of 73% using this model.

5. EVALUATION AND DISCUSSION

Based on the results from the testing dataset, we have concluded that the experiment conducted using the Adam Optimizer performed better than the one using the Adagrad Optimizer. When conducting the experiment with the Adam Optimizer, the image fruit dataset achieved an average accuracy of approximately 96.85% with a loss of only 0.85%. On the other hand, when the Adagrad optimizer was used, the dataset had an average accuracy of about 85.5% with a significantly higher average loss of 60%. The results of all the experiments are presented in Figs. 22 and 23.

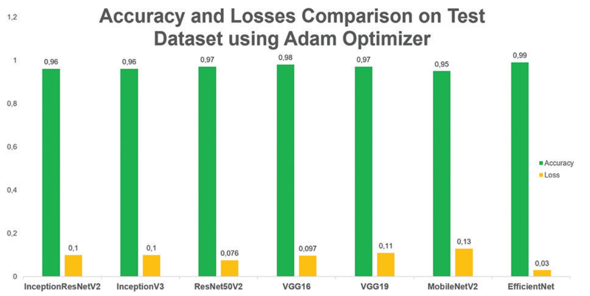


Fig. 26. Average Results of Accuracy and Losses after Testing Using Test Dataset and the Adam Optimizer

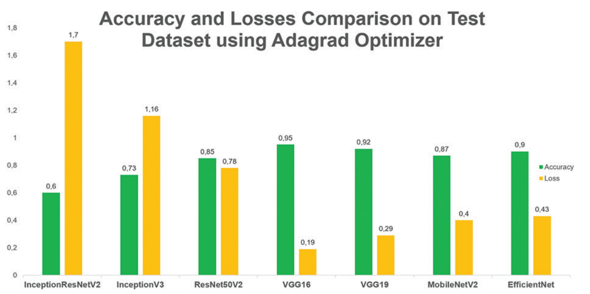


Fig. 27. Average Model Accuracy and Losses after testing using Test Dataset using the Adagrad Optimizer

In Fig. 26 dan Fig. 27 present on several experiments on recognizing types of fruit that have been carried out using several CNN models and optimizers. The results can be seen in Fig. 24 and Fig. 25.

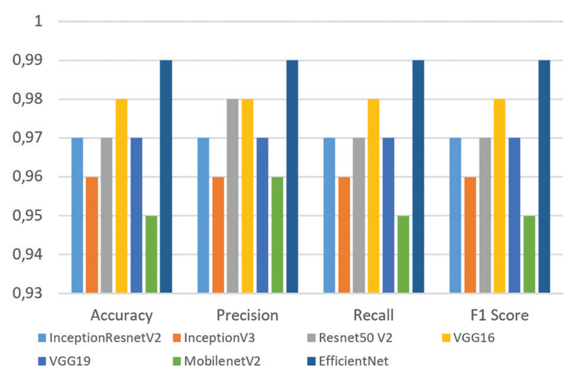


Fig. 28. Average accuracy results, precision, recall, and F1 Score, on several CNN models supported by Adam Optimizer

Fig. 28 presents the highest accuracy, precision, recall and F1 Score results with several CNN models in banana fruit classification with the EfficientNet, VGG 16, and VGG 19 models supported by Adam Optimizers with performance of 99%, 98% and 97%. However, if you experiment using the Adagard optimizer can be seen in Fig. 25.

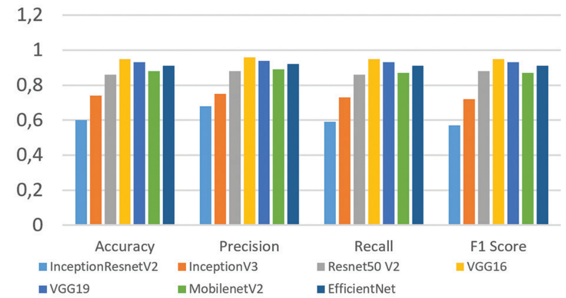


Fig. 29. Average accuracy results, precision, recall, and F1 Score, on several CNN models supported by Adagard Optimizer

Fig. 29 presents the highest accuracy, precision, recall and F1 Score results with several CNN models in banana fruit classification with the VGG 16, VGG 19 and EfficientNet models supported by Adam Optimizers with performance of 95%, 93% and 91%.

In recognition process is optimal because in the extracting image characteristics, it is divided into 3 values height, weight, and dimension. The experimental process using 2 optimizers and 7 CNN models. The conclusion got from the experiment using this dataset where The Adam optimizer is better when it comes to training and classifying fruit image dataset. Adagrad optimizer does not perform well in the model accuracy in such small epochs used but from our observations, Adagrad have a good consistency when it comes to training model. Meanwhile Adam optimizer already have a good accuracy starting from early epochs, but the accuracy and losses fluctuate a lot, so it creates inconsistencies. However, Adagrad in the other hand have a bad accuracy and losses in such small epochs but showed steady improvement over training. Extended research using the shape characteristic is needed to prove the hypothesis of this theory.

6. CONCLUSIONS

In conclusion, this research used the fruit dataset and made several key findings:

1. The feature extraction process in this research involved using a library to process images with three dimensions: height, width, and channel. Additionally, a value of 1 was added to indicate whether the elaboration process was completed for each image.
2. The research utilized CNN algorithms, employing seven different models: ResNet50V2, InceptionResNetV2, InceptionV3, VGG16, VGG19, MobileNetV2, and EfficientNet.

3. Among these models, VGG16 demonstrated the best performance, achieving 98% accuracy with the Adam optimizer and 95% accuracy with the Adagrad optimizer.
4. The Adam optimizer proved to be a superior option for fruit classification research. In contrast, the Adagrad optimizer resulted in poor accuracy and high losses during training, which negatively impacted the experiment's outcome. It is worth noting that the number of epochs used may have influenced Adagrad's poor performance.
5. Notably, the Apple Red 2 dataset consistently exhibited the lowest accuracy across all tests. This discrepancy may be attributed to the fact that apples themselves can have different colors depending on their orientation.

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