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Grade and Disease Detection of Dragon Fruit based on Modified VGGNet with Identity Mapping

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Abstract

In the agricultural sector, dragon fruit is one of the most frequently harvested fruits throughout the year, regardless of the season. To ensure optimal quality during the harvest period, fruit monitoring should begin from the immature stage. However, dragon fruit is highly susceptible to various diseases, particularly as it approaches ripeness. Therefore, there is a growing need for an automated system that can classify the quality grade of dragon fruit. In addition, such a system should also be able to detect potential diseases affecting fruit. In this study, we propose a modified VGGNet architecture integrated with Identity Mapping. The original VGGNet serves as the backbone. Identity Mapping is then incorporated into each block to improve training efficiency and computational performance. At the final stage, the fully connected and classification layers are fine-tuned to enhance overall accuracy. The proposed method is evaluated using a dragon fruit dataset collected from Bondowoso. Experimental results demonstrate that the proposed approach achieves superior performance, with 99.9% accuracy, recall, and precision. It also outperforms baseline models, including VGG16, AlexNet, and EfficientNet variants B0–B3 and B5–B6.
Keywords: *VGGNet, Identity Mapping, Dragon Fruits, Classification, Deep Learning.*

1. Introduction

Dragon fruit (Hylocereus spp.) is rich in essential vitamins and minerals that are highly beneficial for health and can thrive in semi-arid conditions [1]. However, the harvesting process is still performed manually [2]. This manual approach often leads to errors, including the harvesting of underripe or overripe fruits. Premature harvesting can compromise fruit quality by diminishing key attributes such as flavor, sweetness, and overall palatability. A decline in product quality not only affects consumer satisfaction but also reduces market demand and value, ultimately resulting in financial losses, elevated labor costs, and decreased profitability for farmers. Traditionally, the ripeness of dragon fruit is assessed using non-invasive methods, such as evaluating physical characteristics including weight, surface texture, and external coloration [3], [4]. However, these methods are subjective and prone to inconsistency. Accurate detection of ripeness, defects, and diseases is critical for maintaining quality standards, minimizing post-harvest losses, and supporting the economic viability of fruit production. In addition, rigorous quality control is essential for enabling compliance with international trade standards and enhancing the competitiveness of agricultural products in global markets [5], [6]. To address these challenges, the integration of computer vision technologies presents a promising avenue for the development of automated harvesting and grading systems. By analyzing images that capture various stages of fruit development, such systems can support farmers in making precise decisions regarding the optimal harvest time. This approach not only improves operational efficiency and reduces dependency on manual labor but also helps to minimize financial risks associated with harvesting errors and post-harvest losses.

The dragon fruit image dataset presented in this study serves as an essential resource for training and evaluating computer vision and deep learning models. This dataset is highly valuable for researchers, serving as a critical asset for the development and evaluation of computer vision [7], machine learning [8], [9], and deep learning [10], [11] technologies. It facilitates the design of automated systems for fruit recognition [12], harvesting optimization [13], freshness prediction [14], [15], and packaging automation [16]. This dataset promotes interdisciplinary collaboration between computer scientists and agricultural experts. Its application also has the potential to generate economic benefits by reducing labor costs and enhancing crop quality, thereby reinforcing its significance in the fields of computer science and precision agriculture.

Moreover, the quality and development of dragon fruit are highly susceptible to various plant diseases, which can significantly impact both yield and marketability. Common bacterial and fungal infections, such as brown spot disease, stem rots (Colletotrichum gloeosporioides), and stem cancer, have a substantial impact on both yields and the overall quality of dragon fruits [17], [18]. Detecting such infections remains a challenge, as symptoms typically require 3 to 7 days to become visually apparent, depending on the fruit's stage of maturity. Nevertheless, early skin and flesh discoloration often signal the onset of infection. Timely and accurate disease detection is therefore essential to facilitate effective intervention strategies that can prevent the spread of infection and minimize economic losses.

Recent advancements in image processing [19], [20], [21], [22] and machine learning techniques [23], [24], [25], [26] have shown promising results in supporting early-stage disease identification. These technologies enable automated analysis of visual cues, allowing for rapid, non-invasive detection that can enhance disease management in dragon fruit cultivation. Several researchers have contributed to advancements in this domain. Tran et al. [19] implemented an image processing technique for automatic dragon fruit counting. Yin-kai et al. [21] integrated machine vision with machine learning to estimate fruit weight. Kulkani et al. [20] applied a Region-Based Convolutional Neural Network (R-CNN) for feature extraction and employed a Support Vector Machine (SVM) for classification. Hoang et al. [22] utilized a transfer learning approach with Convolutional Neural Networks (CNNs) to classify fruit ripeness.

Similarly, Ansari et al. [23] combined wavelet transforms with Support Vector Machines (SVM) to classify various categories of dragon fruit. Prasetyo et al. [24] employed a backpropagation neural network utilizing RGB histogram features to determine ripeness levels. Xiao et al. [25] developed a disease detection model based on Histogram of Oriented Gradients (HOG) combined with machine learning algorithms. Meanwhile, Patil et al. [26] conducted a comparative analysis of Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), and SVM for grading and sorting dragon fruits based on five attributes: shape, size, weight, color, and disease presence.

While these studies demonstrate the effectiveness of machine learning for dragon fruit classification, recent state-of-the-art approaches favor end-to-end models that integrate feature extraction and classification within a single architecture using CNNs. These models utilize convolutional layers for hierarchical feature extraction and fully connected layers for classification tasks.

For instance, Risdin et al. [27] employed a basic CNN model for general fruit type classification. Khatun et al. [28] applied ResNet50 to detect ripeness levels and perform quality grading of dragon fruits. Although ResNet50 achieved strong performance, its deep architecture results in longer training times, making it less suitable for real-time applications. In contrast, CNN models such as AlexNet [29], and VGGNet [30] offer simpler and more computationally efficient alternatives. VGGNet is widely recognized for its balanced performance and faster training capabilities; however, its basic architecture may struggle to accurately detect subtle differences in fruit grades and disease patterns.

To overcome these limitations, this study proposes a modified VGGNet architecture enhanced with Identity Mapping. VGGNet serves as the backbone network, while identity mapping is incorporated into each convolutional block to improve gradient flow, accelerate convergence, and reduce training complexity. Additionally, the fully connected and classification layers are fine-tuned to optimize prediction accuracy.

The structure of our paper is as follows: Section 2 outlines the materials and methods used in the study, including dataset acquisition, class labeling, architectural design of the proposed model, and the evaluation metrics applied. Section 3 presents the experimental results. Section 4 discusses the findings and provides a comparative analysis with existing approaches. And the last section concludes the paper by summarizing the key contributions and potential directions for future research.

2. Materials and Methods

2.1. Dragon Fruits Datasets

In this study, we evaluate a modified VGGNet architecture enhanced with Identity Mapping using a dragon fruit image dataset collected from agricultural regions in Indonesia. The dataset was acquired from two major production areas in East Java Province, Bondowoso. Representative samples from the data collection process are illustrated in Figure 1.

The dataset comprises three distinct classes: two representing different quality grades of dragon fruit (Grade A and Grade B), and one representing fruit affected by disease. Each image has a high resolution of 2848×4272 pixels and is stored in JPG format. Images were captured using a Vivo Y12 smartphone equipped with a 13-megapixel rear camera. During the image acquisition process, the average distance between the camera and the fruit object was maintained at approximately 50 cm to ensure consistent image quality and scale. The distribution of images across the three classes used in this study is summarized in Table 1.

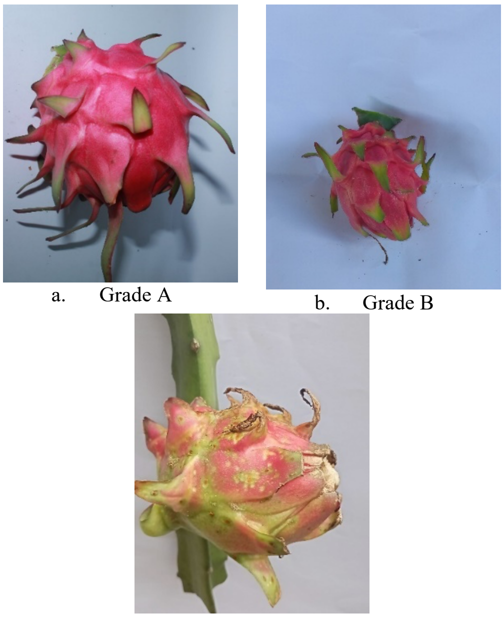
Ideally, dragon fruit image datasets are collected under natural farm or outdoor conditions to reflect real-world scenarios. However, in this study, image acquisition was conducted in an indoor environment due to several practical and technical considerations. Indoor settings allowed for controlled and consistent lighting conditions, which helped minimize shadows and reduce variability caused by changes in natural sunlight. Moreover, challenges such as unfavorable weather, limited access to farm locations, and the unavailability of field workers made outdoor data collection less feasible. The indoor environment also offered greater flexibility for scheduling and repeating image acquisition sessions.

Based on findings from previous studies, the grading of dragon fruit is generally determined by considering the fruit's weight parameter [21]. All dataset labels in this study were initially assigned directly by experienced dragon fruit farmers during the harvesting process and subsequently validated by plant biology experts from Universitas Indonesia. Grade A (High Quality): Fruits that are uniformly red in color, have smooth skin without scratches, no visible bruises, and fully mature at harvest. The fruit size ranges between 350–500 gram, consistent with Indonesian National Standard (SNI 01-3164-1992) and similar grading references in horticultural export quality guidelines [37].

Grade B (Moderate Quality): Fruits with minor surface defects such as small scars, uneven coloration, or slightly smaller size (250–300 gram). These fruits are still suitable for consumption and local sales but do not meet export criteria. Disease: Fruits showing visible symptoms of common dragon fruit diseases such as stem canker, anthracnose, or soft rot. The symptoms include brown or black lesions, discoloration, and in some cases, fungal growth. Meanwhile, dragon fruits identified as diseased are not subjected to the harvesting process but are instead left in the field to subsequently function as organic fertilizer.

Table 1. Total of the dataset image.

Type	Total Images
Grade A	284
Grade B	343
With Disease	192



a. Grade A

b. Grade B

c. Dragon fruits with disease

Figure 1. Classes of dragon fruits.

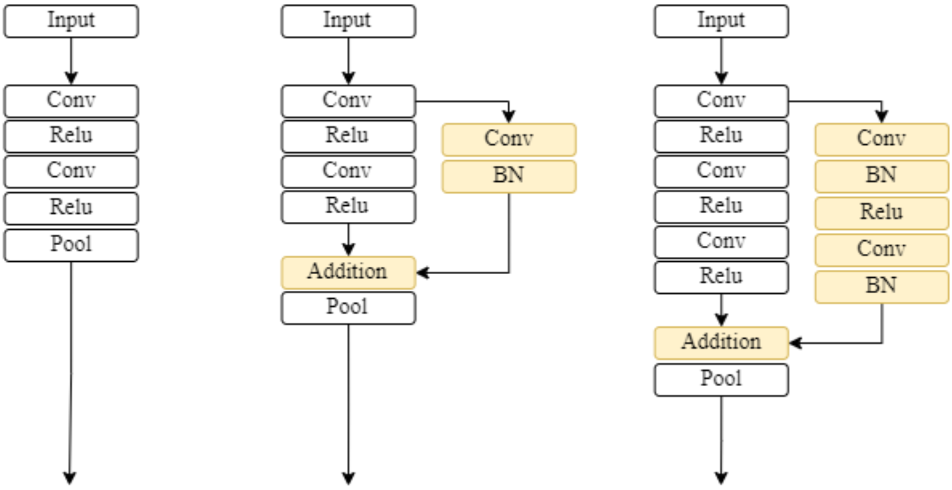
2.2. VGGNet

VGGNet utilizes input images with a resolution of 224 × 224 pixels and three RGB color channels. This network architecture employs small convolutional filter sizes, specifically 3 × 3 filters, in each convolutional layer [31]. The use of a small receptive field enables the stacking of multiple convolutional layers without requiring a pooling layer in between. This design enhances feature extraction capability while maintaining computational efficiency.

By employing 3 × 3 filters, VGGNet achieves significant improvement over its previous configurations, such as VGGNet-16 and VGGNet-19, in terms of both performance and parameter efficiency. The smaller filter size contributes to a reduction in the total number of trainable parameters. For example, assuming the same number of input and output channels (denoted by A), three stacked convolutional layers with 3 × 3 filters require approximately $3 \times (3^2 \times A^2) = 27A^2$, where A denotes the number of input channels. In contrast, a single convolutional layer with a 7 × 7 filter would require $7^2 \times A^2 = 49A^2$ parameters. This comparison reveals that the use of three stacked 3 × 3 filters reduces the number of parameters by approximately 81% compared to a single 7 × 7 filter. Consequently, VGGNet offers a more parameter-efficient design that enables effective feature extraction during training [30].

2.3. Identity Mapping

VGGNet has a deeper network architecture, which can increase the performance of the deep



a. Plain VGGNet

b. VGGNet with identity mapping block 1 and 2

c. VGGNet with identity mapping in block 3,4, and 5

Figure 2. Comparison architecture.

learning network. The other side has a deeper network architecture, causing overfitting and degradation during the training process. To overcome the problems in deep residual networks, a repeating block of the residual network is used. This architecture network was proposed by He et al. [32]. The residual network is obtained from the result of adding the identity mapping or skip connection $h(x)$ and the residual functions $F(x)$. The feature input x_l, sets the weight and bias W_l associated with the l-th unit. The output of l-th unit is x_{l+1} after calculating the ReLU activation function $f(r)$. The identity mapping in the residual network is given in equations (1) and (2).

$$r_l = h(x_l) + F(x_l, W_l) \quad (1)$$

$$x_{l+1} = f(r_l) \quad (2)$$

The identity mapping or skip connection can achieve the fastest error reduction and lowest training loss in the residual architecture network. The skip connection consists of ReLU activation and batch normalization as pre-activation. This point makes the residual network much easier to train and generalizes better than the original ResNet [33].

2.4. VGGNet with Identity Mapping

In this study, we proposed VGGNet with Identity Mapping. VGGNet architecture networks have a small kernel size in convolutional layers, which can cause VGGNet to have small parameters during the training process, and the identity mapping networks can reduce errors and have fast-computing time. The combination of VGGNet and Identity mapping can reduce the number of training parameters, thus allowing training with few parameters but achieving an appropriate result in the classification. Figure 3(a) is a plain VGGNet that consists of convolutional layers followed by ReLU and so on, then followed by a pooling layer to reduce the size of the feature maps. Figure 3(b) is a VGGNet with identity mapping that is used in block 1 and 2 in VGGNet architecture. Figure 3(c) is a VGGNet with identity mapping that is used in block 3, 4, and 5 in VGGNet architecture. The number of convolution and batch normalization layers in identity mapping follow the number of convolution and ReLU layers in plain VGGNet.

The VGGNet concept is like deep residual networks. The proposed architecture network $\boldsymbol{G}$ is obtained by adding the result from the identity mapping function $h(x)$ with the VGGNet block unit function $V(x)$. The x_l, W_l are featuring input and set weight with bias respectively, that is associated with the l-th unit. The x_{l+1} is the output of the l-th unit. Then followed by an activation function $f(G)$ using ReLU activation. The function is calculated using equations (3) and (4).

$$G_l = h(x_l) + V(x_l, W_l) \quad (3)$$

$$x_{l+1} = f(G_l) \quad (4)$$

The proposed architecture has 5 blocks of plain VGGNet with Identity mapping for feature extraction. The first and second block have 3 convolutional layers where the output of the convolution layer is added in the addition layer. The third, fourth, and fifth block have 5 convolutional layers respectively. The architecture network is shown in Figure 2. Each convolutional layer uses a stride with size 1 × 1 and the fully connected layer, then the last layer is a

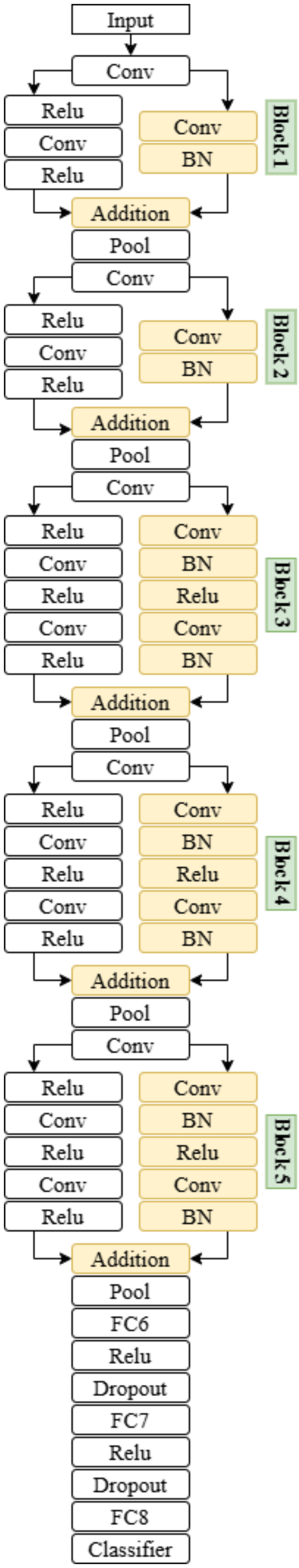


Figure 3. Proposed architecture network VGGNet with Identity Mapping.

classification layer to classify the class of dragon fruit. The total number of convolutional layers is 21 layers. The details of the convolutional layers are described in Table 2.

The input image size that we use in this proposed architecture is 224 × 224 × 3, the three channels in the input image are obtained from an RGB colour image.

2.5. Evaluation Metrics

In this study, we use accuracy, recall, and precision to evaluate the performance of the modified architecture using VGGNet and Identity Mapping. The evaluation metrics are calculated based on a confusion matrix that consists of true positive (TP), true negative (TN), false positive (FP), and false negative (FN). The evaluation metrics are given in equations (5), (6), and (7).

We use the F1 score to evaluate the performance of the architecture because of the imbalance in the dragon fruit dataset. F1 score is suitable for multiclass cases because that can balance the value of precision and recall, evaluate performance in each class, and avoid overfitting. The evaluation metric is given in equation (8).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (8)$$

3. Experiments and Results

The proposed architecture network is compared with Alexnet, the original VGGNet16, and VGG19. We modified the two versions of VGGNet using identity mapping. Before the training process, we employed various augmentation techniques, including shearing, random rotation, horizontal flipping, adjustments to width and height, zooming, and modifications to brightness. To enhance the diversity and robustness of the dataset. Data augmentation has a crucial role in deep learning models, especially in the context of visual object classification. Augmenting the training dataset by generating new images based on existing ones can improve model generalization and reduce overfitting.

The proposed method uses the dragon fruit dataset that we collected from East Java and West Java. The dataset was divided into training, validation, and testing. In the input of architecture VGGNet, we use an input size of 224 x 224 x 3, where the 3 comes from the color channels red, green, and blue. In the Alexnet architecture, we use an input size of 227 x 227 x 3. The percentage of training and testing images is 90% and 10% of the total images. After that, the training data was augmented seven times, resulting in 1.792 samples for grade A, 2.163 for grade B, and 1.209 for disease.

Since the number of test data is relatively small, we also performed augmentation on the testing images to increase data variation and reduce the possibility of evaluation bias. This augmentation technique aims to ensure that the model is tested not only on the original data, but also on image variations that represent real-world conditions, such as changes in lighting, rotation, or scale. After data augmentation, the number of testing data resulted in 560 for class A, 680 for class B, and 384 for class C.

Deep learning architecture training requires many hyperparameters. We apply an optimized loss function using the SGDM optimizer with momentum 0.9 and a learning rate value of 0.05. We set the epoch in our training to be 50 and the mini batch size to 1 and 10 cross validations to evaluate architecture performance and overcome overfitting. For the multiple classes in deep learning architecture, we use cross-entropy in the classification layer. The size input of testing images is 224 x 224 x 3 for the proposed VGGNet architecture, and 227 x 227 x 3 for the Alexnet architecture.

Table 2. The details of the convolution layer from the proposed architecture.

Block Level	Conv Layer	Filter and Stride	Output Size
Input			224×224×3
Block 1	Conv 1	3×3 / 1	224×224×64
	Conv 2	3×3 / 1	224×224×64
	Conv 3	3×3 / 1	224×224×64
Block 2	Conv 4	3×3 / 1	112×112×128
	Conv 5	3×3 / 1	112×112×128
	Conv 6	3×3 / 1	112×112×128
Block 3	Conv 7	3×3 / 1	56×56×256
	Conv 8	3×3 / 1	56×56×256
	Conv 9	3×3 / 1	56×56×256
	Conv 10	3×3 / 1	56×56×256
	Conv 11	3×3 / 1	56×56×256
Block 4	Conv 12	3×3 / 1	28×28×512
	Conv 13	3×3 / 1	28×28×512
	Conv 14	3×3 / 1	28×28×512
	Conv 15	3×3 / 1	28×28×512
	Conv 16	3×3 / 1	28×28×512
Block 5	Conv 17	3×3 / 1	14×14×512
	Conv 18	3×3 / 1	14×14×512
	Conv 19	3×3 / 1	14×14×512
	Conv 20	3×3 / 1	14×14×512
	Conv 21	3×3 / 1	14×14×512

3.1. Comparison with Baseline Architecture

In this section, we compared the proposed architecture with baseline architectures like Alexnet, EfficientNet type B0 until type B7 [34] on a publicly available dataset with three classes. The classes are dragon fruit with grade A, grade B, and disease around the fruit. Alexnet Architecture has a simple layer, which is different from EfficientNet, which has a very complex architecture. Even though EfficientNet has a very complex architecture, it is quite stable in different input images. The results of the evaluation metrics comparison are shown in Table 3. We added the F1 score performance evaluation because of the multiclass case.

The best performance is highlighted in bold. Based on Table 3, our proposed method can reach the best accuracy with an accuracy of 99.9% on the dataset. Our proposed method has the same accuracy as the EfficientNet architecture type 4. However, in terms of computing time, our proposed method is quite a bit faster than EfficientNet type 4. This shows our method is faster in computing time and has a high level of accuracy.

Based on Table 3, EfficientNet type 0 has an input image with a size of 224 x 224 with an accuracy of 99.4%, EfficientNet type 1 has an input image with a size of 240 x 240 with an accuracy reach 99.6% until EfficientNet type 6 with an input image size of 600 x 600 and can reach an accuracy of 99.3%. Table 3 shows that the EfficientNet architecture is stable on changes in the input image, because EfficientNet still has almost the same level of accuracy from type 0 to type 6.

Based on Table 3, the best performance was obtained by the proposed method, surpassing all other F1 scores of 99.9%. As the F1 score is the harmonic mean of precision and recall, the evaluation is suitable for an imbalanced dataset, which was used in our dataset. AlexNet and VGGNet achieved an F1 score of 99.2%, which indicates that the networks performed slightly lower on the imbalanced dataset. Similarly, the EfficientNet variants B1-B5 also achieved 99.6%. However, EfficientNet B4 achieved a slightly higher F1 score of 99.8%, indicating better performance in both precision and recall. Likewise, the proposed architecture was more optimal in the F1 score compared to other architectures. From the F1 score results, it can be concluded that our proposed architecture is not only accurate but also highly effective on the imbalanced dataset.

Time computation refers to the duration required by each architecture network to complete the testing image. Networks with deeper and complex architectures, such as EfficientNet, tend to require

Table 4. Misclassified image examples.

Input Image			
Ground Truth	Dragon fruit with disease	Grade A	Grade B
Alexnet	Grade A ✗	Dragon fruit with disease ✗	Grade B ✓
VGGNet 16	Grade B ✗	Dragon fruit with disease ✗	Grade B ✓
EfficientNet B0	Grade A ✗	Dragon fruit with disease ✗	Grade A ✗
EfficientNet B1	Grade A ✗	Dragon fruit with disease ✗	Grade B ✓
EfficientNet B2	Grade A ✗	Dragon fruit with disease ✗	Grade B ✓
EfficientNet B3	Grade A ✗	Dragon fruit with disease ✗	Grade B ✓
EfficientNet B4	Grade A ✗	Grade A ✓	Grade B ✓
EfficientNet B5	Grade A ✗	Dragon fruit with disease ✗	Grade B ✓
EfficientNet B6	Grade A ✗	Dragon fruit with disease ✗	Grade A ✗
Proposed Method	Dragon fruit with disease ✓	Grade A ✓	Grade B ✓

longer computation times. In contrast, the proposed method and VGGNet with identity mapping architecture acieved faster computation and high-performance metrics, making them more efficient and practical for deployment.

3.2. Evaluation Misclassified Image

Table 4 presents the misclassified dragon fruit images by the proposed method compared with various existing CNN architectures. The table highlights three samples testing images that represent different classes of dragon fruit with disease, grade A, and grade B. The examples of misclassified images were selected to evaluate the robustness of the proposed method compared with existing architecture methods.

The misclassified of "dragon fruits with disease" in the testing image distinguishes between color and texture from disease and natural skin. The AlexNet and VGGNet16 misclassified the testing image as "Grade A" and "Grade B" respectively, indicating the architecture has limited capture of disease specific features. Similarly, with the EfficientNet type B0-B5, the architecture misclassified the disease testing images as "Grade A", only the proposed method succeeded in detecting the testing image correctly.

In the case of "Grade A" only the EfficientNet type B4 and proposed method can detect the class correctly. Because the texture, color, and size are almost similar between "Dragon fruit with disease" and "Grade A" causing other architectures to fail to detect the class. In the case of "Grade B" almost all architecture can identify this class correctly. However, only EfficientNet type B0 is misclassified as a "Grade A".

Based on the example of misclassified images, it indicated that the proposed method achieved correct detection from the three testing images, showing robustness in identifying not only the disease texture but also the quality grades.

Figure 4 (a) presents the confusion matrix, which demonstrates the excellent performance of the proposed classification method namely VGGNet using Identity Mapping, as also reflected in the evaluation metrics such as accuracy, precision, recall, and F1-score. Out of a total of 1,624 testing images after augmentation, the model correctly classified 1,623 testing images, yielding a high accuracy of 99.9%. For the Grade A and With Disease classes, both precision and recall reached 100%, as no misclassifications occurred for these categories. In contrast, for the Grade B class, precision and recall slightly decreased due to a single misclassification, achieving 99.9% and 99.9%, respectively. In terms of the F1-score, which represents the harmonic mean between precision and recall, the results are also remarkably high.

The Grade A and With Disease classes obtained high F1-scores of 100%, while the Grade B class achieved a nearly ideal value of approximately 99.9%. The overall average F1-score of the model is 99.9%, indicating an optimal balance between the model's ability to correctly identify positive samples and to minimize misclassifications. Thus, the relationship between the confusion matrix and these evaluation metrics confirms that the model is both highly reliable and consistent in classifying the data.

Despite the seemingly small margin of 0.03% between the proposed method and VGGNet, as shown in the confusion matrix in Figure 4, this difference holds substantial importance in the agricultural context, since an incorrect grade classification of even a single fruit may reduce its commercial value and consequently lead to financial losses for farmers. Moreover, even a seemingly small difference of 0.03% may represent a considerable 3% misclassification rate, which is significant. In Indonesia, the average market price of dragon fruit is approximately IDR 8,000 per kilogram for Grade B and IDR 18,000 per kilogram for Grade A. This indicates a price gap of around IDR 10,000 [47], meaning that any misclassification of fruit grade could result in substantial economic losses for farmers.

4. Discussion

In this section, we discuss the comparison of the performance of our proposed architecture with baseline networks such as Alexnet, VGG16, and VGG19. The result of competitive comparison is shown in Table 3, and Figure 4 shows the confusion matrix from the results of our proposed architecture.

Based on Table 3, we highlighted the best performance in precision, recall, accuracy, and F1 score. The proposed method has the best performance in precision, recall, accuracy, and F1 score compared with Alexnet, VGGNet16, and VGGNet19. However, based on the computation time, the Alexnet Architecture has the fastest computation time for training and testing. Alexnet has the fastest computation time when training and testing because the architecture structure is so simple. However, our computation time is slightly more competitive compared with Alexnet architecture, although the total depth of our architecture is deeper than Alexnet architecture.

The deep learning method has many advantages, especially in image processing for classification, segmentation, and detection. This method can achieve classification results of almost 100%. However, this method has limitations that do not fit all datasets, requires a large amount of training data, and imbalanced datasets. To enrich the small amount of training datasets, this study used a data augmentation method or a synthetic dataset [35]. In this research, we prefer using data augmentation to overcome the small amount of the dataset instead of synthetic data, because the image has a diseased area. With synthetic data, synthetic image results can occur where the diseased area can be in the background area.

The proposed architecture network in all convolutional layers uses a small kernel size of 3 x 3. Small kernel size plays an important role in getting information from the input image. The small kernel size has led to better information and low computational cost based on research conducted by Chen et al. [36]. We use a stride size of 2 to make computational time faster. The activation function uses the ReLU activation function to overcome degradation and non-linearity from the network. The architecture combines the VGGNet backbone and Identity mapping or skip connection from the Residual Network. The identity mapping is used to overcome the vanishing gradient, speed up convergence during the training processes, and enrich the feature to get better results in accuracy.

We analyze VGGNet with a focus when creating direct path information for propagating features and information in the input image. In our derivations based on Eq. 3 and Eq. 4, if $h(x_l)$ and $f(G_l)$ are skip connections or identity mappings, the features can be directly propagated from one stack to another stack in identity mapping layers. In the training process, the architecture network becomes easier even if the architecture is close to the conditions.

We analyze and compare VGGNet with skip connections and the original VGGNet to understand the role of skip connections. Based on the paper on skip connections, we find that the identity mappings with full pre-activation $h(x_l)$ chosen in each residual network can achieve the best and fastest error reduction, lowest training loss, and better degradation during training [32], [33].

5. Conclusion and Future Work

The deep learning method is the state-of-the-art method currently, and the grading of dragon fruit is still a challenge for researchers because dragon fruit is a higher commodity for Indonesian agriculture. The process of grading dragon fruit uses a deep learning method based on image processing and automated classification. In this paper, we proposed VGGNet with Identity mapping to classify the grade and disease of dragon fruit. We use identity mapping to overcome time computation and can achieve the best performance in accuracy.

We conduct our experiment using our dataset that we collect from Bondowoso, East Java, Indonesia, and a publicly available dataset from India to compare our method with baseline architectures. Based on the experimental results, our proposed method can reach better accuracy than other architectures and can reach quite fast in time computation. Our dataset only uses datasets obtained from limited areas. Further research is needed to get a more varied dataset and more classes on the disease of dragon fruit.

Further work in our research is to add classes to dragon fruit diseases, both on the stem and fruit of dragon fruit.

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