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An Automatic Monitoring System for Dragon Fruit Using Convolutional Neural Networks (CNN) and Internet of Things (IoT)

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ABSTRACT

Plant diseases and pests have led to a decline in the quality of dragon fruit produced in Banyuwangi regency, Indonesia. Infections in dragon fruit cause rot, and farmers struggle to identify the pests responsible. To address this problem, this work proposed two concepts for the classification and monitoring systems of dragon fruit. The classification was done by processing some images of dragon fruits captured by DLSR camera and utilizes a convolutional neural network with three layers for training and testing. The monitoring system is based on the Internet of Things to tracks the status of ripe, raw, and rotten fruits. The application of the dragon fruit classification system to ripe, rotten, and raw fruits has yielded results that increase fold accuracy by 0.976, 0.981, and 0.986, respectively, with 200 training data in each of the three training and testing phases. There is a decrease of 0.024, 0.019, and 0.014 in fold loss accuracy. Meanwhile, the monitoring system's platform integrates the classification of dragon fruit to monitor the condition of ripe, raw, and rotting fruit in real time. With the implementation of the classification and monitoring system, farmers will be better equipped to predict when dragon fruit will ripen and prevent the spread of rot to other fruits.

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1. INTRODUCTION

Banyuwangi is Indonesia's foremost dragon fruit producer (Khoiri, 2020). Dragon fruit farmers there produce 737.5 tons annually (Pupsitasari, 2015). The fruit is known for its nutritional content, antioxidants, bioactive compounds, anti-aging properties, antidotal benefits (Aryanta, 2022), acid-base balance (Meganingtyas & Alauhdin, 2021), and bioethanol production (Ramadhani et al., 2020). The annual production of dragon fruit has surged from 91 tons to 114,335 tons between 2015 and 2022 (Mulyadi et al., 2022). However, the demand for fresh fruit has not kept pace with the increase in dragon fruit production (Isnanda et al., 2017). Challenges in dragon fruit production include seasonal variability, the need for fresh fruit, and the operational costs associated with lighting during the off-season (Indriyani & Hardiyanto, 2019). Addressing these challenges requires artificial intelligence approaches.

Artificial intelligence plays a crucial role in classification. Unfortunately, most fruit detection research on visual systems primarily addresses the identification and location of fruits, which needs to be improved for dragon fruits (Tang et al., 2020). Both deep learning-based and conventional machine vision-based techniques are frequently employed in the fruit identification field(Moreira et al., 2022). Farmers find it less reliable and challenging to use in complex natural environments due to the need for human feature extraction (Zhou et al., 2023). Deep learning-based object detection algorithms have recently gained popularity as promising techniques for fruit detection (Wang et al., 2019).

Deep Learning HSV is employed to identify ripe fruit by color. A camera is used for fruit selection, and after 100 tests, the selection accuracy is 86% with a training duration of 15-22 seconds (Sustiono & Pambudi, 2015). The Naive Bayes Algorithm is applied to determine dragon fruit ripeness, showing an accuracy of 87.37% (Fitri et al., 2022). A Convolutional Neural Network with a smaller VGGNet-like architecture was developed for dragon fruit classification, achieving 91% accuracy with an evaluation of 100 fruit (Wismadi et al., 2020).

Classification of dragon fruit diseases is achieved using a Convolutional Neural Network (CNN) and architecture development in Python. Although farmers are adept at recognizing diseases, this leads to detection failures across different varieties. The CNN recognizes fruit diseases with an accuracy of 85.6% (Hakim et al., 2023). Fruit classification has been enhanced using a CNN with parameter adjustments and data improvement, resulting in classification accuracies ranging from 90.2% to 98.9% (Wu et al., 2020). Visual Grad-Cam has been utilized to improve the accuracy of dragon fruit classification, with findings indicating the presence of rotten fruit (Vo et al., 2023).

Studies have shown that the dragon fruit classification system primarily focuses on rotten fruit (Sustiono & Pambudi, 2015), (Fitri et al., 2022), (Wismadi et al., 2020), diseases (Hakim et al., 2023), and the development of CNN models (Wu et al., 2020). However, the classification of rotten, raw, and ripe fruit must still be completed. The dragon fruit from Banyuwangi varies from other fruits in shape, color, tail, and skin, making it challenging for farmers to classify based on ripeness.

This study proposes using a convolutional neural network to classify dragon fruit and the Internet of Things to track the growth of dragon fruit. The CNN approach classifies the fruit based on its physical shape. At the same time, the monitoring system tracks the fruit at three different ripeness levels, enabling farmers to determine which fruits are ready for harvesting.

2. RESEARCH METHODOLOGY

Dragon fruit samples were captured under various conditions using a DSLR camera to obtain preliminary data. The initial data comprise digital images that are compiled into a dataset. This dataset is split into training and testing sets, which are processed using the VGG-16 Convolutional Neural Network (CNN) method. The dataset includes 200 images, each with a resolution of 224x224 pixels, divided into 100 images for training and 50 for testing. **Figure 1** illustrates the dragon fruit sampling technique (Tanuwijaya & Roseanne, 2021).

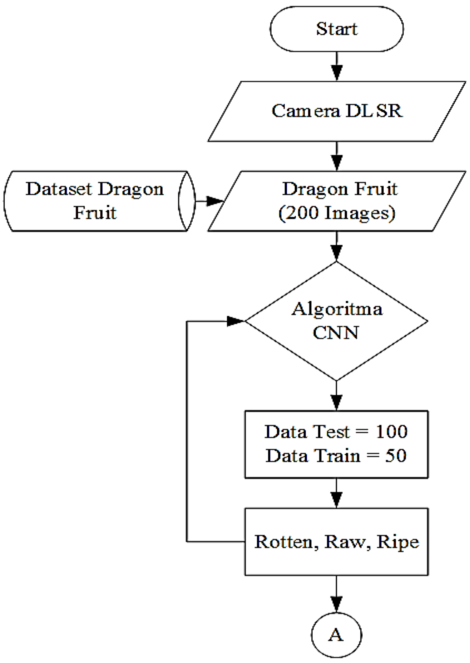

Figure 1. Flowchart classification dragon fruit

The data is analyzed using the CNN algorithm to identify fruit colors based on red, green, and blue (RGB) values. To classify complex hues, RGB colors are converted into a 3x3 matrix. These complex colors are processed using VGG16-DFC to generate image segmentation patterns. Image patterns are detected and retrieved based on similarities and differences in the data patterns, which consist of multiple dimensions (Zhu et al., 2022).

The classification results of dragon fruit are divided into three categories: ripe (A), raw (B), and rotten (C). The data is then evaluated in terms of the dragon fruit's readiness for harvest, and the quality of the dragon fruit is depicted in **Figure 2.** The volume of data processed depends on the color spectrum required to develop fresh dragon fruit samples.

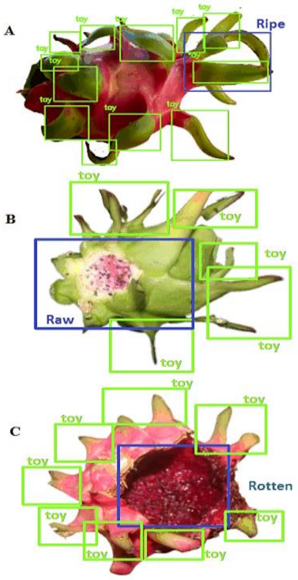

Figure 2. Classification of dragon fruit

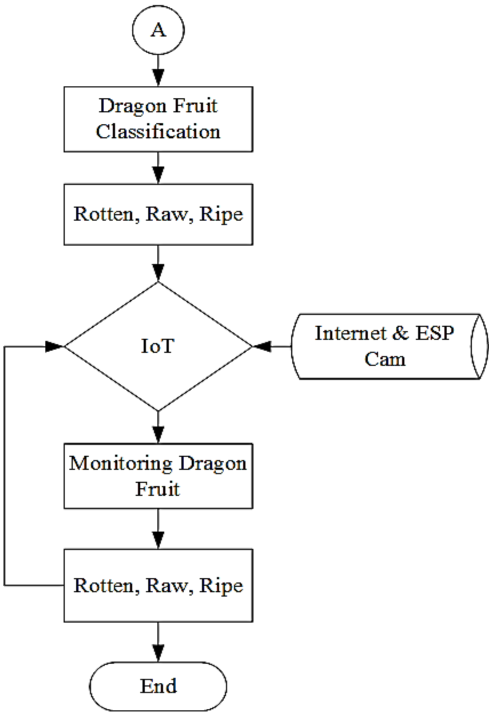

Figure 3. Flowchart monitoring system

The monitoring platform is linked to a GPS receiver, which gathers data based on latitude and longitude coordinates. The Raspberry Pi collects data via Wi-Fi through coordinate information from the MQTT broker. Wi-Fi connectivity extends across 3G and 4G network types. Additionally, the Raspberry Pi acts as an MQTT broker, connecting to the wireless area network (WAN) to receive GPS coordinate data. The monitoring results are displayed on the website as data on dragon fruits that are rotten, raw, or ripe. **Figure 3** shows the flowchart of the monitoring system, and **Figure 4** depicts the dragon fruit monitoring system (Besari, 2019).

Figure 5 demonstrates the application of two systems to dragon fruit. **Figure 5(A)** illustrates classification, while **Figure 5(B)** depicts Internet of Things-based monitoring.

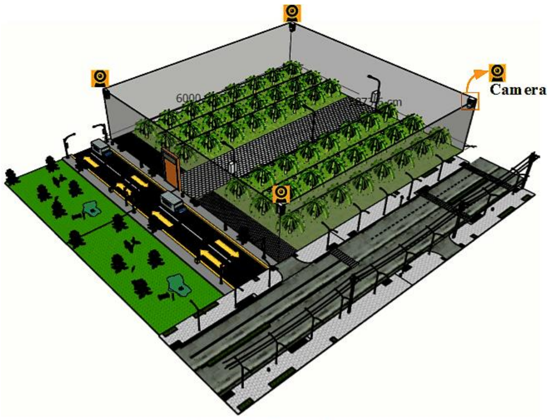

Figure 4. Dragon fruit monitoring system

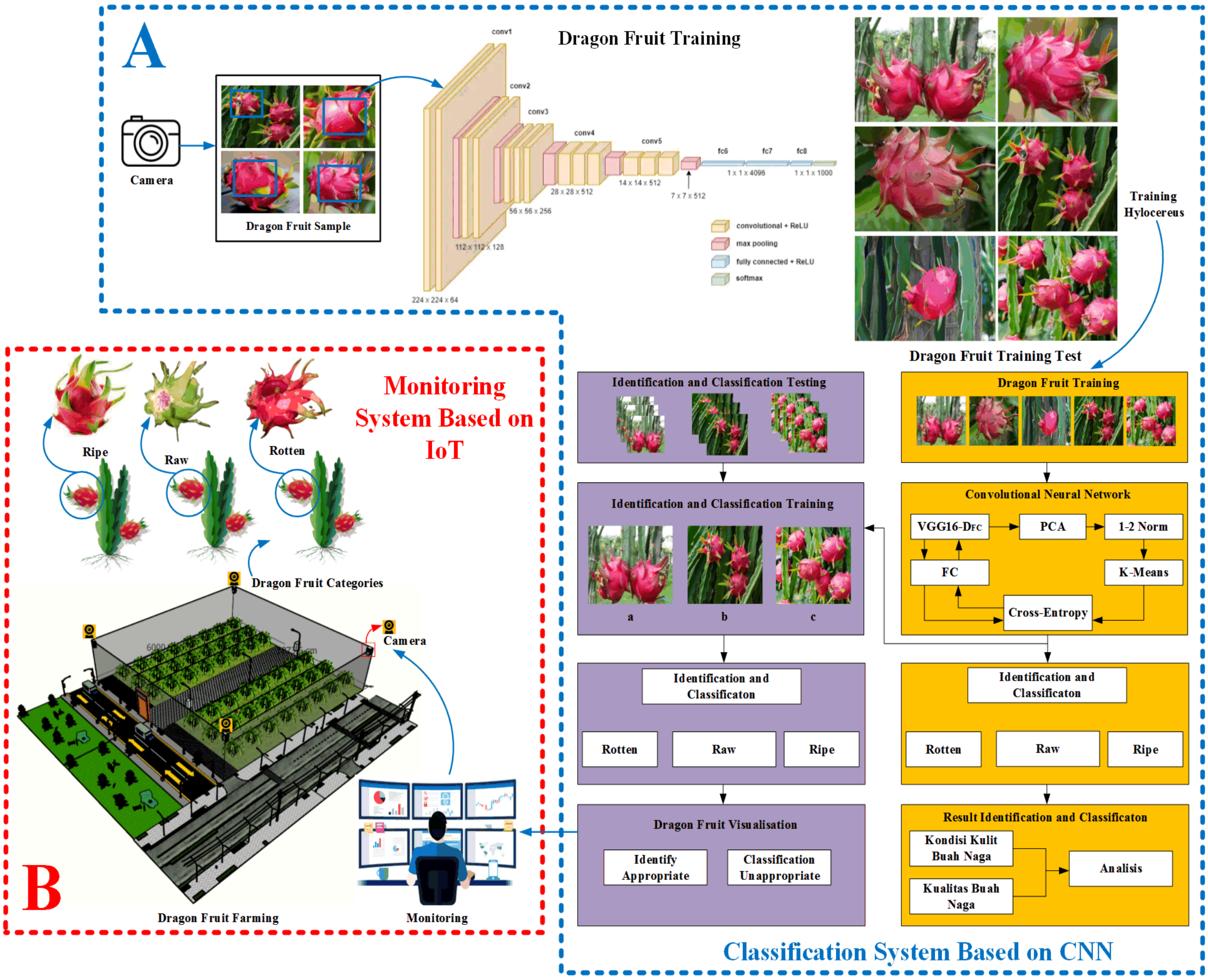

Figure 5. Classification and monitoring system for dragon fruit

3. RESULTS AND DISCUSSION

Figure 6 displays the datasets for classifying dragon fruit in the training and testing phases. Each dataset size of 244×244 pixels is used to import the picture library for training and testing. The classification results are categorized into three groups: raw, ripe, and rotten.

Figure 6. Dragon fruit dataset

In the classification of dragon fruit, three categories are evaluated using a confusion matrix. This matrix represents the prediction data and the accuracy of the Data (Prakosa et al., 2023). The confusion matrix is also used to determine and assess the quality of the CNN model employed for image classification. **Figure 7** depicts the measurement process using a confusion matrix.

The confusion matrix measurement for prediction and accuracy generated classification data for 185 ripe, 196 raw, and 176 rotten dragon fruit. The classification results for 185 ripe dragon fruit predicted 0 raw and 8 rotten fruits; the classification for 196 raw dragon fruit predicted 0 ripe and 3 rotten fruits; and the classification for 176 rotten dragon fruit predicted 6 ripe and 10 raw fruits. The confusion matrix is also utilized for additional calculations, such as determining the accuracy and precision values. This testing data helps ascertain whether a deep learning model functions effectively and accurately. (Rohim et al., 2019).

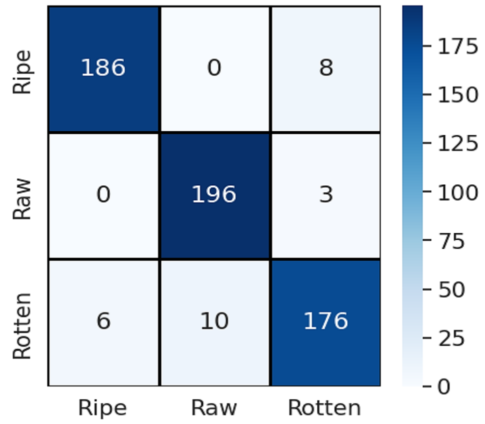

Figure 7. Confusion matrix measurement

Figure 8 explains the accuracy of the dragon fruit classification data. Training was conducted three times to achieve accuracy based on three criteria. The first training session's result was 0.976 accurate, the second training was 0.981 accurate, and the third training was 0.986 accurate.

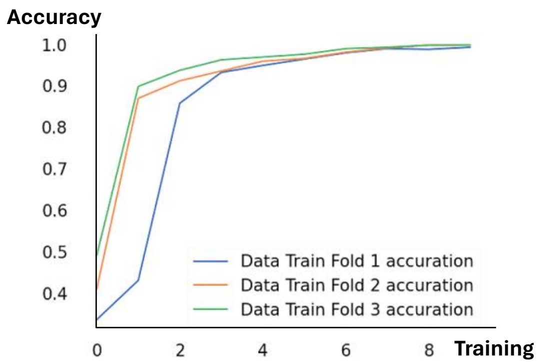

Figure 8. Data fold accuracy of dragon fruit

Each training session lasted 2 minutes per fold of 1, 2, and 3, respectively. Testing also revealed a loss of 0.014. These results indicate that the training and testing data for identifying rotten, raw, and ripe dragon fruits are highly accurate, with minimal loss and quick processing time (Gampur et al., 2022).

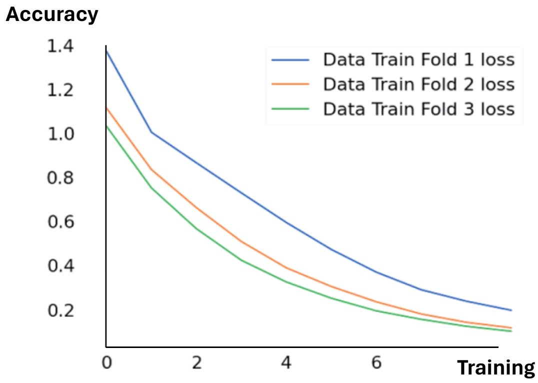

Figure 9. Data fold loss of dragon fruit

Figure 9 illustrates the training data loss for dragon fruit. The first training session yielded a loss of 0.024; the second, 0.019; and the third, 0.014. The training data is evaluated against the accuracy and loss metrics of the dragon fruit classification process. Testing is performed three times, providing data that approximates the color and condition of the dragon fruit as rotten, raw, or ripe.

Figures 8 and **9** show the improvement in training data accuracy and the loss of training data for dragon fruit. **Figures 8** and 9 demonstrate that the accuracy and loss of training data do not indicate overfitting (Chi et al., 2022). This is due to integrating additional accuracy and loss training data while maintaining the same proportion of data (Wen et al., 2021).

The results of classifying dragon fruit from a randomly chosen image dataset into three categories—rotten, raw, and ripe—are displayed in **Figure 10**. There are 200 pictures in the dataset, each size 244 by 244 pixels.

Figure 10. Classification of dragon fruit based on three categories

An Internet of Things platform monitors rotten, raw, ready-to-harvest dragon fruits. This platform consists of testing, training, monitoring, and classification panels. It assists the Dragon Fruit Farmers Group of Banyuwangi Regency in managing the condition of the fruit. Consequently, producers can identify the condition of ripe, raw, and rotting fruits before they spread to other fruits. **Figure 11** categorizes the classification into three groups: ripe, raw, and rotten dragon fruits. The classification data (training and testing) displayed on the bar graph is determined by evaluating the category results. The accuracy of the classification results is verified using the training loss and validation loss data. Subsequently, the data is sent to smartphones to receive remote notifications. Notifications are distributed once every 24 hours on a daily schedule.

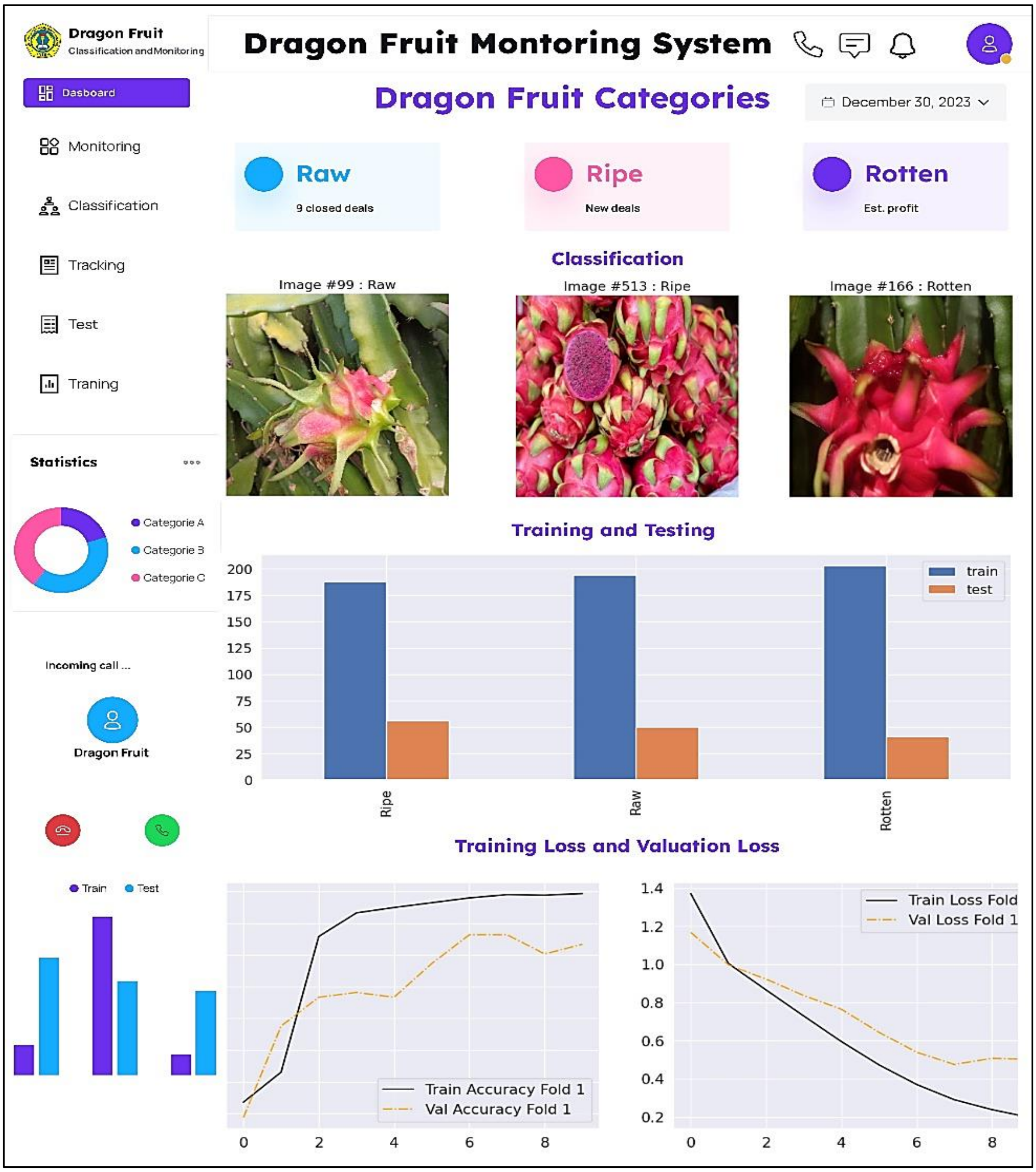

Figure 11. Platform monitoring dragon fruit based on the Internet of Things

The monitoring findings for the classification of dragon fruit are displayed in **Figure 12**. Bar graphs describe the monitoring performance, illustrating the training and testing data. There was a change in the number of ripe fruits between the first training and test, with 186 and 53, respectively. The number of raw fruits during the second test and training was 196 and 50. The ratios of rotting fruit in the second test and training were 30 and 176, respectively. These results are due to the model learning from the image data. The high initial loss value during training indicates that the model is still learning to predict outcomes accurately (Anhar & Putra, 2023).

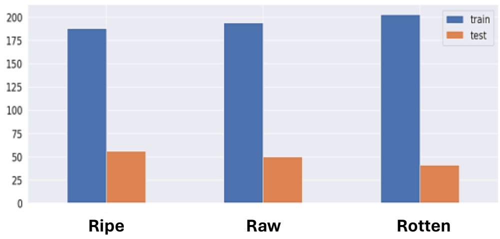

Figure 12. Comparison of train and test

The training accuracy of **Figure 13** and **Figure 14** is 0.055, increasing to 0.088. This occurs when the validation accuracy rises from 0.2 to 0.8 in value. In the meantime, there is a 1.0 to 0.1 decrease in training loss fold 1 and a 1.1 to 0.8 value in validation accuracy loss fold 1.

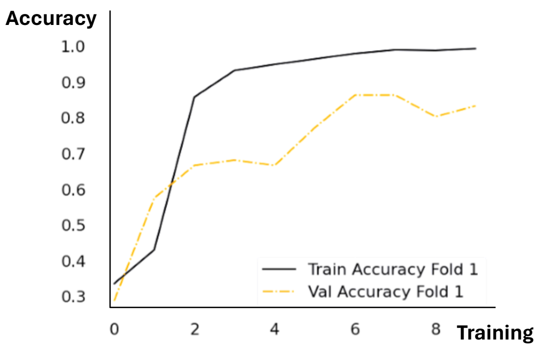

Figure 13. Train accuracy fold 1

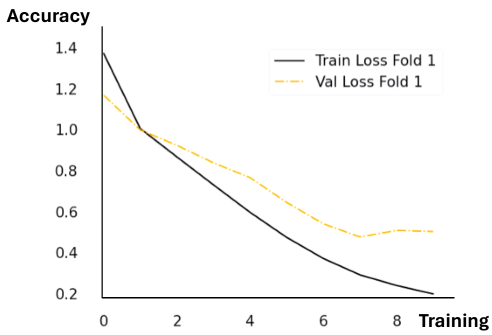

Figure 14. Train loss fold 2

The accuracy of change 1 training improved from 0.061 to 0.9, as seen in **Figure 15** and **Figure 16**. Subsequently, there was an increase in validation accuracy from 0.4 to 0.9. In the meantime, lossfold 1's validation accuracy decreased from 1.2 to 0.039, while its value decreased by 1.0 to 0.1 throughout training.

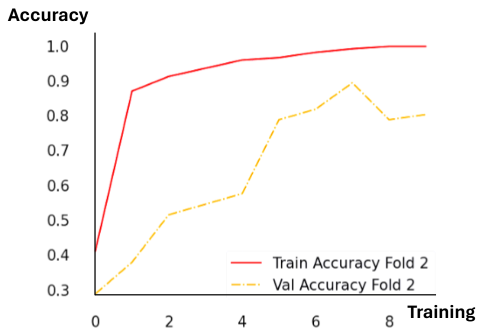

Figure 15. Train accuracy fold 2

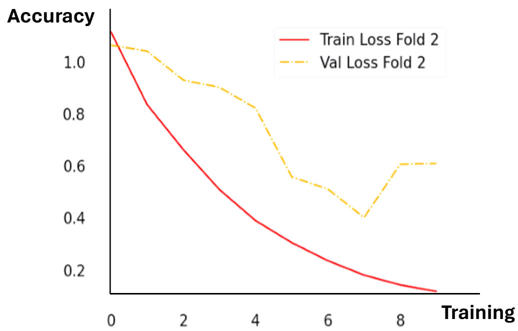

Figure 16. Train loss fold 2

As can be seen in **Figure 17** and **Figure 18**, training accuracy improved from 0.4 to 0.95. There was an improvement in validation accuracy from 0.3 to 0.85. Meanwhile, the accuracy of validation lossfold 1 increased from 1.04 to 1.2 before declining to 0.45, while the accuracy of training loss-fold 1 declined from 1.04 to 0.1.

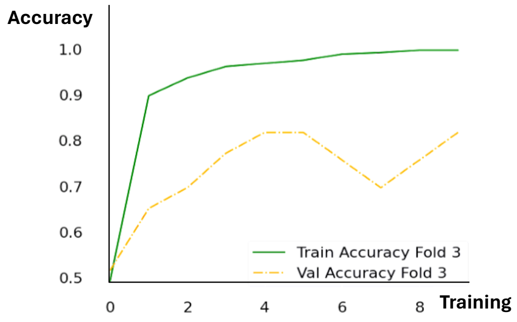

Figure 17. Train accuracy fold 3

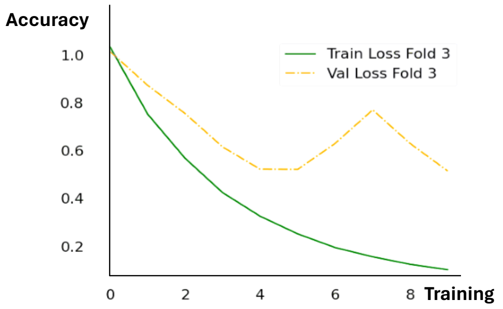

Figure 18. Train loss fold 3

The reported difference between the training accuracy and validation data may be attributed to many non-convergent epochs, leading to under and overfitting. However, augmentation techniques determine the establishment of data in dragon fruit data.

Furthermore, despite a slight decrease, the increase in loss approaches the ideal neural network. The validation accuracy decreases by 0.024, 0.019, and 0.014 (Rahaman et al., 2020), but the average training accuracy increases by 0.976, 0.981, and 0.986 (Maier et al., 2020).

4. CONCLUSION

The convolutional neural network method designed for the monitoring and classification system of dragon fruit, as used by the Dragon Fruit Farmers Group in Banyuwangi Regency, demonstrates that using 200 training data leads to an increase in fold accuracy of 0.976, 0.981, and 0.986. There was a corresponding decrease in fold loss accuracy of 0.024, 0.019, and 0.014. The integrated classification of the monitoring system platform tracks the condition of ripe, raw, and rotting fruit in real time. With the implementation of the classification and monitoring system, farmers can anticipate when dragon fruit will ripen early and prevent the spread of rot to other fruits.

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