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Classification Of the Maturity Level of Fermented Glutinous Rice Using Convolutional Neural Network Model

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ABSTRACT

Fermented glutinous rice is a popular snack in Indonesia. One of the main benefits of eating white cheddar rice is to trigger the digestive system. Excessive consumption can result in a decrease in sweetness and inappropriate texture. Therefore, it is necessary to classify the maturity level of the tape, so that there is no excessive maturity that results in adverse effects on the body and the quality of the tapes. The study aims to test the accuracy of the white tape maturity classification program as well as design and implement a classification system using the Convolutional Neural Network (CNN) method with the VGG16 architecture. The white tape image data set was obtained with the iPhone X camera in jpg format, covering three maturity classes: raw, ripe, and rotten, each consisting of 400 images. The data set is divided into 768 training data, 192 validation data, and 240 test data, then processed through preprocessing stages including resize, augmentation, and rescale. The CNN model was implemented with the VGG16 architecture and tested on various Epochs, producing an accuracy of 0.98 on Epochs 20 and 30, and reaching 0.99 on the 40th. The results of the research showed that the CNN method with VGG-16 architecture was effective in classifying the maturity level of the tape, achieving high accuration and significant consistency as the number of Epochs increased. This implementation is expected to preserve the quality of the tapes and extend the application of modern technology in traditional industries.

1. INTRODUCTION

Indonesia possesses abundant natural resources, including white glutinous rice (Oryza sativa glutinosa), which is widely used in the preparation of traditional foods such as tape Ketan [1]. Tape Ketan is a fermented food made from glutinous rice and yeast, known for its sweet flavour, strong alcoholic aroma, and soft texture [2], [3]. Besides its sensory appeal, tape Ketan is nutritionally valuable, containing essential nutrients like calcium, phosphorus, and vitamin B1, which provide various health benefits [4]. The cultural and nutritional significance of this traditional product makes its quality a critical factor in consumer acceptance and satisfaction [5].

One of the key determinants of tape Ketan quality is its level of maturity, which affects both taste and texture [6]. Over-fermented tape can result in undesirable changes, such as excessive alcohol production, altered taste, or compromised texture. Since the visual appearance of the fermented rice reflects its fermentation stage, accurate classification based on visual cues is essential to ensure product consistency. Manual inspection, however, is prone to subjectivity and inefficiency, especially in large-scale production. This challenge calls for an automated and objective method of maturity classification to maintain high quality standards [7].

To address this issue, deep learning technologies, particularly Convolutional Neural Networks (CNNs), present a highly effective solution [8]. CNNs emulate the human visual recognition system and have demonstrated remarkable success in a wide range of image classification tasks [9]. The study utilizes the VGG16 architecture within the CNN framework due to its proven ability to extract detailed image features through its deep yet straightforward structure. This architecture has been successfully applied in previous research areas, including fruit ripeness classification, medical imaging for brain tumour detection, and skin cancer identification [10],[11],[12].

Building on this foundation, the current study applies CNN with the VGG16 model to develop an accurate system for classifying tape Ketan maturity [13]. By implementing this approach, the study aims not only to enhance the consistency and quality of the final product but also to encourage the adoption of modern technologies in traditional food industries. Integrating AI-based solutions into the fermentation process supports innovation in local food production, preserving cultural heritage while advancing technological capabilities in Indonesia's agro-food sector.

2. RELATED WORK

Convolutional Neural Networks (CNN) have been widely adopted in recent years for various image classification tasks, offering significant advantages in accuracy and efficiency. These networks are particularly powerful in extracting complex visual features and have demonstrated high performance across different domains. Their success forms a solid basis for applying CNN in traditional food quality assessment, particularly for products like tape Ketan, which depend heavily on visual cues for maturity classification.

Saputro et al. [14] utilized the VGG16 architecture, a well-known CNN model, to differentiate plant varieties based on leaf images. The study achieved a classification accuracy of 79% and a validation accuracy of 82%, with computation completed in just 71 seconds. These results highlight CNN's potential in identifying subtle visual differences that are often difficult to distinguish through manual observation. The effectiveness of VGG16 in this context supports its relevance in other visual-based classification tasks, including the assessment of fermentation levels in food products.

Another notable application was conducted by Kholik [15], who used CNN to categorize screenshots of Instagram pages. The research achieved 91% accuracy, 93% recall, and an F1 score of 91%, underscoring CNN's robustness in processing and categorizing complex digital imagery within a social media context. Similarly, Ersyad et al. investigated hand movement recognition using various sensing techniques, including computer vision. While glove-based methods were fast and accurate, the study highlighted that camera-based image recognition though more computationally intensive offered broader usability. These findings further affirm the adaptability of CNNs across different technological environments.

Research by [16], [17] evaluated several CNN architectures VGG16, MobileNetV2, and InceptionV3 for automatic mask detection. The study found that MobileNetV2 performed best in terms of accuracy and consistency, achieving a confidence level of 100% under specific test conditions. This reinforces the view that CNN models, including VGG16, offer high adaptability and precision. Based on these precedents, the current study leverages VGG16 to classify the maturity stages of tape fermentation. This approach is expected to improve product quality through accurate and consistent classification, while also promoting the application of modern artificial intelligence solutions within traditional food processing industries.

3. METHODOLOGY

In this study, the Convolutional Neural Network (CNN) algorithm was utilized to classify the maturity level of fermented tape Ketan based on image data. The methodological steps implemented are illustrated in Figure 1, which outlines the overall research framework. The process begins with dataset collection, followed by image preprocessing to enhance data quality for model training. Subsequently, the VGG16 architecture, a deep learning model known for its high performance in image classification tasks, is employed. The model is then subjected to a testing phase to evaluate its prediction capabilities. Finally, the accuracy of the model is assessed, and the findings are synthesized in the conclusion stage to determine the effectiveness of the approach in supporting traditional food quality assessment with modern artificial intelligence techniques.

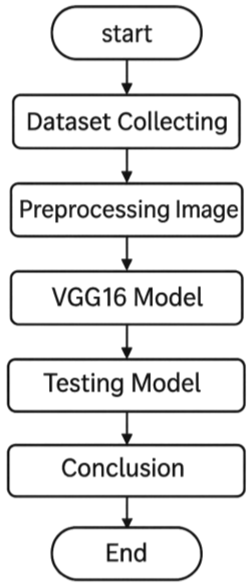

FIGURE 1. RESEARCH METHODOLOGY

3.1 Dataset & Preprocessing

In the collection of data sets in this study, data sets were taken in the form of white tape images. The process of taking images is done directly using the camera of the mobile phone, iPhone X in jpg format. The processing of these data sets is divided into three classes: raw, ripe, and rotten. Each class consists of 400 image datasets with a total of 1200 white tape image data.

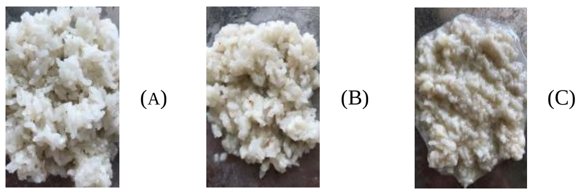

FIGURE 2. (A) RAW TAPE, (B) RIPE TAPE, (C) ROTTEN TAPE

The entire data set will go into the preprocessing process, this step will be done with a resize of 224x224x3, then an augmentation with a rotation of 20 degrees as well as 30 degrees, and a rescale of 1/255 and a horizontal flipping. Before the data is augmented, the entire data set will be divided into training data of 768 image data, validation data of 192 image data and test data of 240 image data. The result of the data set that has been preprocessed will be processed with the CNN model with the VGG16 architecture and will be tested until the accuracy of the program is obtained.

3.2 Architecture VGG16

In this research model with the CNN model using the Visual Geometry Group Network (VGGNet) 16 [18] [19]. The VGG16 model corrected the shortcomings of the previous model and focused on better accuracy with high efficiency. The layers involved in this proposed VGG16 architecture are 16 layers including 13 convoluted layers plus a maximum combined layer and 3 fully connected layers. The main advantage of the VGG16 architecture is the use of smaller overlapping filters than one large filter. The VGG-16 architecture includes convulsive layers, maximum pooling layers and fully connected layers. Below is an overview of the VGG16 architecture that will be used in this study.

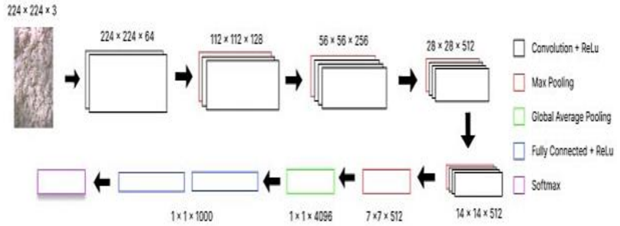

FIGURE 3. ARCHITECTURE VGG16

The VGG16 architecture is the architecture chosen to conduct classifications at the maturity level of the fermentation of the tapes because it has proven to be able to perform processes on image data well and efficiently.

4. RESULT AND DISCUSSION

In this section we will discuss the process and results of this research, here are some images of the datasets that will be processed on the CNN model.

FIGURE 4. DATASET SAMPEL

Figure 4 has successfully displayed a sample of a data set of 50 images with their respective labels before the data augmentation. Then we go into the data augmentation, where there are several processes that are rotated 20 degrees and 30 degrees. On both rotating processes such yields the same accuracy. That doesn't change the accuracy of the classification of the maturity of the fermentation of the cutting tape. Then rescale with 1/255, which is used to normalize the pixel value of the image so that it is in the range between 0 and 1. This is a pre-processing step that is commonly done when working with images in deep learning model training, especially on tasks that involve subtle texture or color differences between classes, such as food image classification. After that, a horizontal flipping will be performed which serves to increase the variation of data sets as well as reduce the risk of overfitting.

Here are 5 views of the data augmentation results that have been taken as examples of the result of data visualization that has been processed as follows:

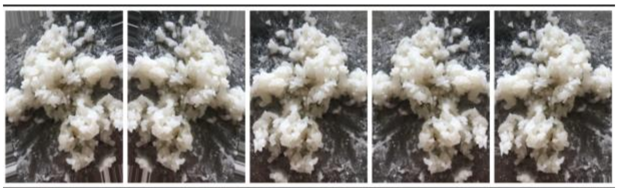

FIGURE 5. AUGMENTATION VISUALIZATION WITH EPOCH 20

On figure 5 is the result of the visualization of an augmentation that has been completed processed with a 20-degree rotation range.

FIGURE 5. AUGMENTATION VISUALIZATION WITH EPOCH 30

On Table 1 presents the results of the visualization process following data augmentation using a 30-degree rotation. Visualizing augmented data is crucial for understanding the variations introduced to the training set and evaluating how effectively the data generator produces diverse input to enhance model generalization. This process plays an important role in reducing overfitting and improving model robustness. Although both 20-degree and 30-degree rotations offer different angular transformations, they yield similar classification accuracy, indicating that minor rotational differences do not significantly impact model performance in this context. Following the augmentation, the next step involves constructing and compiling a Convolutional Neural Network (CNN) model based on the pre-trained VGG16 architecture. To adapt the model for the specific classification task, additional dense layers and a SoftMax activation function were incorporated for multi-class output.

The model was compiled using the Adam optimizer with a learning rate of 0.0001, and the loss function used was `sparse_categorical_crossentropy`, suitable for integer-labeled target classes. Furthermore, the training process was enhanced using the `ModelCheckpoint` callback, which automatically saves the model with the best performance based on validation loss, ensuring that the most optimal model is retained for further evaluation and deployment. This approach helps avoid overfitting by preserving the model with the best generalization capability during training. The outcome of building this VGG16-based CNN model, including its architecture modifications and training configuration, is summarized in the following visualization, which demonstrates how the model was successfully adapted to classify the fermentation maturity of Tape Ketan with high consistency.

TABLE 1. RESULT MODEL

Layer (Type)	Output Shape	Param #
Input_1 (InputLayer)	(None, 224, 224, 3)	0
VGG16 (Functional)	(None, 25088)	14,714,688
Flatten (Flatten)	(None, 25088)	0
Dense (Dense)	(None, 1024)	25,691,136
Dropout (Dropout)	(None, 1024)	0
Main_model (Dense)	(None, 3)	3075

- Model : VGG16
- Total params : 40,408,899
- Trainable Params : 40,408,899
- Non – trainable params : 0

As a result of the above table, it can be concluded that the program displays the VGG16 model where its input layer is (None, 224, 224, 3), which means that this model enters a 224x224 pixel dimension image and 3 color channels (RGB) as well as several parameters of 0 because it is an input Layer and has no weight. VGG16 (Functional) is a pre-trained model loaded with the output dimensions (None, 7, 7, 512) of the total parameters of 14,714,688 because this is a model loading from ImageNet. Then there's a flat layer that is a layer which turns a multi-dimensional tensor into a one-dimension vector with a size of 25088. After that, there is a dense layer, a fully connected layer with 1024 neurons with a total of 25,691,136 parameters. The dense layer itself serves to help models study more complex relationships between features and image features. There's a drop-out layer with a dropout probability of 0 with several parameters of 0 because of the transition layer and has no weight. On the output layer or play model with dense layer 3 neurons corresponds to the number of predicted classes and has a parameter number of 3,075.

Parameters themselves refer to variables whose values are set during the training process. The total parameters of the entire model are 40,408,899. In this case, all parameters are trainable, so the total and trainable of the parameters have the same value. Epoch in model training is an important element in CNN training, because it represents several times the entire dataset seen by the model during the training. Model training is carried out with several epoch experiments namely Epochs 20, Epochs 30, Epochs 40. The results of the training and validation produce a graph that is shown in the following image.

With a total of 40,408,899 trainable parameters, the model demonstrates high learning capacity. The addition of a final dense layer with 3 neurons aligns with the three target classes in the tape maturity classification. The use of different epoch settings (20, 30, and 40) during training further justifies the tuning process to achieve optimal performance, as shown by consistently high validation results.

FIGURE 6. GRAPHICS OF ACCURACY EPOCH 20

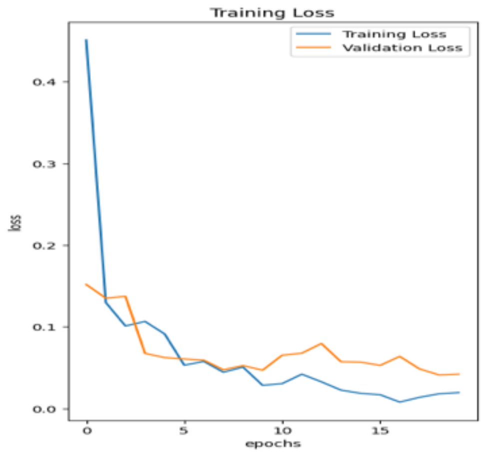

FIGURE 7. GRAPHICS OF LOSS EPOCH 20

On the graph with Epoch 20 can be shown training accuracy and validation accuracy at the beginning, the training precision increased sharply from about 0.825 to more than 0.975 at around epoch 5. The validation accurateness followed a similar pattern, also reached about 0.9775 at the epoch 5. Training Loss and Validation Loss at the start, training loss dropped sharp from 0.4 to about 0.1 at the epoch 5. At the 20th Epoch obtained training precisions 0.9961, validation precision 0.9792, training loss 0.0194, and loss 0.0419. In the graph above with Epoch 20 shows quite good performance in the training process.

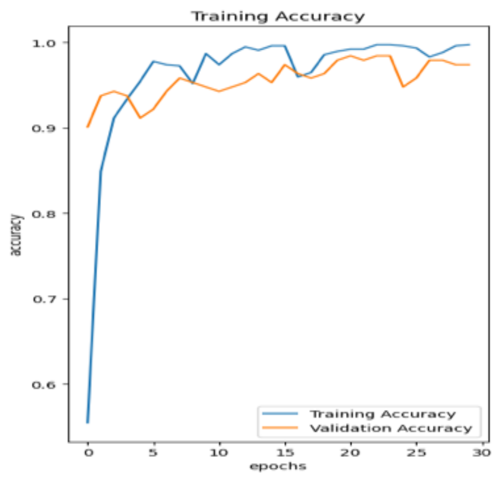

FIGURE 8. GRAPHICS OF ACCURACY EPOCH 30

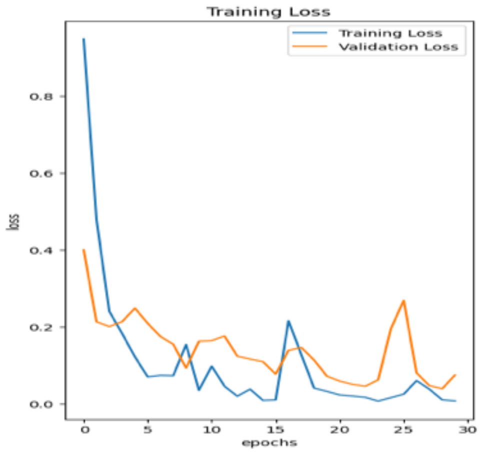

FIGURE 9. GRAPHICS OF LOSS EPOCH 30

On the results of the Epoch 30 graph, training accuracy and validation accuracy indicate an increase in training precision, validation precision also increases with similar patterns. Then on the training loss and validation loss shows that training loss decreases sharply from about 0.8 in the epoch 0 to less than 0.2 in the 5Epoch. In the 30th Epoch, the result of training accurateness is 0.9974, validation accurate is 0.974, training loss is 0.0068, validation loss is 0.074.

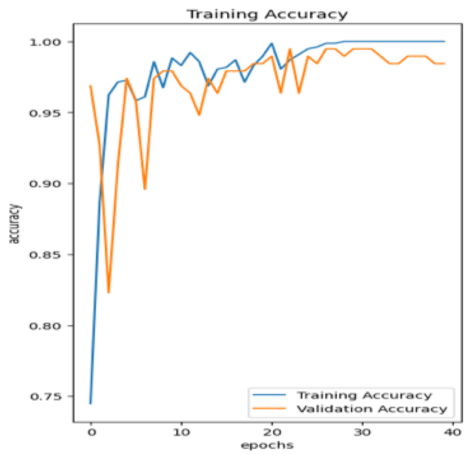

FIGURE 10. GRAPHICS OF ACCURACY EPOCH 40

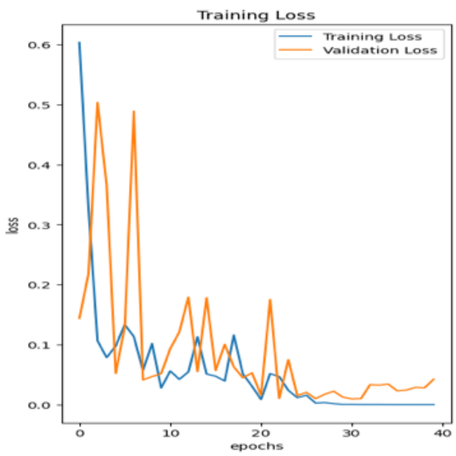

FIGURE 11. GRAPHICS OF LOSS EPOCH 40

The model experienced a significant improvement in accuracy in the early stages of training and then stabilized at a high level of precision. The accuracy and loss curves for training and validation data show similar, indicating no significant overfitting or underfitting. At Epoch 40, the results were obtained from training accuracy of 1,000, validation of precision of 0.9844, training loss of 0.00, and validation for loss of 0.0424. Overall, this graph shows that the model is well trained and produces improved performance on training and validation data.

As for the result of the confusion matrix [20] produced by the program as follows.

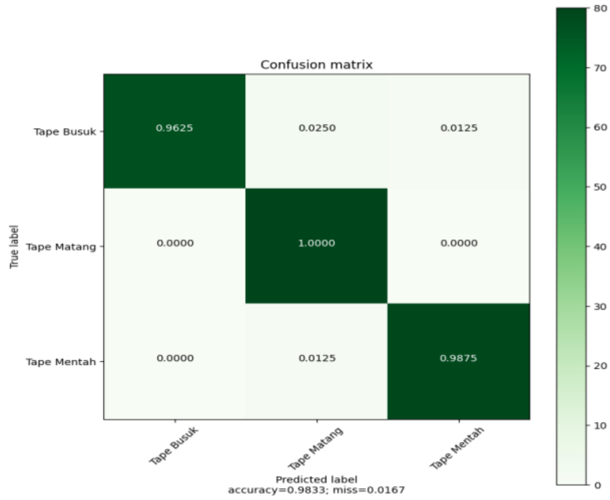

FIGURE 12. CONFUSION MATRIX EPOCH 20

Figure 12 shows the results of the classification of the maturity behavior of the tapes according to their respective classes using the Convolutional Neural Network.

TABLE 2. TEST DATA RESULTS EPOCH 20

Class	Precision	Recall	F1-Score	Support
0	1.00	0.96	0.98	80
1	0.96	1.00	0.98	80
2	0.99	0.99	0.99	80
Macro Avg	0.98	0.98	0.98	240
Accuracy				240

Based on the calculations of the model evaluation matrix in the above table, it can be concluded that precision, recall, and F1-Score for each class 0 = raw tape, 1 = ripe tape, and 2 = rotten tape. Then accuracy is obtained with the Epoch 20 overall model of 0.98 which indicates that the proportion of correct prediction overall is 98%.

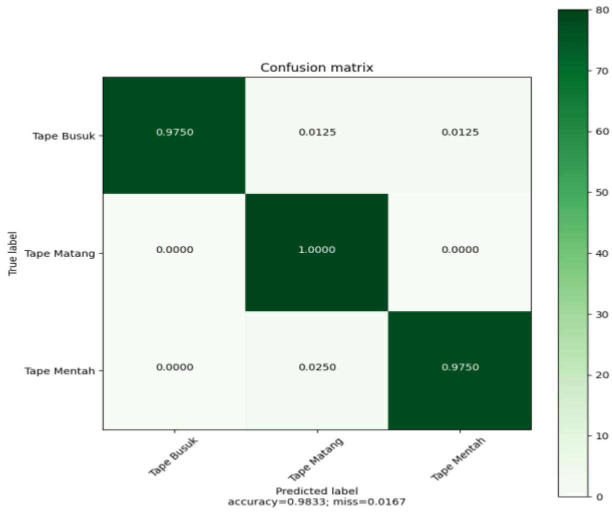

FIGURE 13. CONFUSION MATRIX EPOCH 30

Figure 13 illustrates the classification results of tape fermentation maturity behavior using 30 training epochs. The model demonstrates consistent performance, capturing detailed maturity features and achieving high classification accuracy.

TABLE 3. TEST DATA RESULTS EPOCH 30

Class	Precision	Recall	F1-Score	Support
0	1.00	0.97	0.99	80
1	0.96	1.00	0.98	80
2	0.99	0.97	0.98	80
Macro Avg	0.98	0.98	0.98	240
Accuracy				240

Table 3 presents the accuracy results of the tape maturity classification model, indicating outstanding performance. The precision, recall, and F1 scores were nearly perfect across all classes, with an impressive overall precision of 0.98. These metrics highlight the model's robustness, reliability, and effectiveness in accurately identifying fermentation stages.

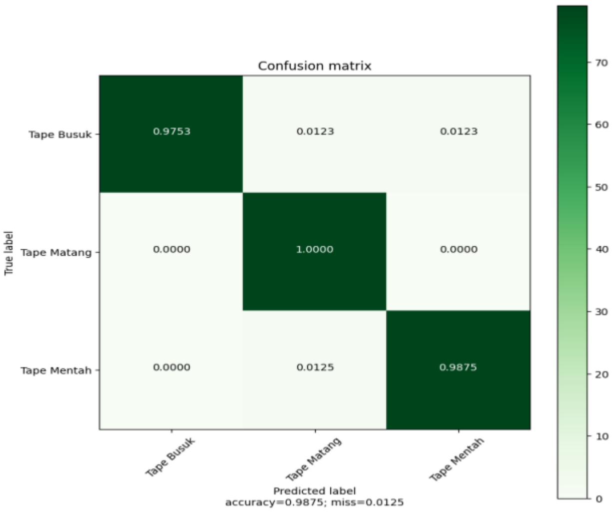

FIGURE 14. CONFUSION MATRIX EPOCH 40

Figure 14 displays the classification results of tape fermentation maturity using 40 training epochs, revealing a highly refined model performance. At this stage, the model demonstrates excellent accuracy and stability in recognizing subtle differences between maturity levels. The increased epoch count contributed to improved feature learning, resulting in more precise classification outcomes and reinforcing the model's capability for reliable, automated maturity detection in real-world applications.

TABLE 4. TEST DATA RESULTS EPOCH 40

Class	Precision	Recall	F1-Score	Support
0	1.00	0.98	0.99	80
1	0.98	0.99	0.99	80
2	0.99	0.99	0.99	80
Macro Avg	0.99	0.99	0.99	240
Weighted	0.99	0.99	0.99	240
Accuracy				240

The results obtained from the test data using 40 training epochs revealed that the classification model for tape fermentation maturity achieved exceptional performance. It demonstrated near-perfect precision, recall, and F1-scores across all classes, alongside an outstanding overall accuracy of 0.99. This high level of accuracy indicates the model's robustness and consistency in capturing complex visual patterns related to maturity levels. Moreover, the results affirm the effectiveness of the deep learning approach in delivering reliable, scalable solutions for automated quality assessment in fermentation-based food processing systems.

5. CONCLUSIONS

Based on the findings, this study concludes that the classification of tape fermentation maturity levels using the Convolutional Neural Network (CNN) method with the VGG16 architecture has been effectively implemented through a systematic preprocessing and training pipeline. The process involved resizing images to 224x224 pixels with RGB channels, applying rescaling (1/255), and utilizing a 20-degree rotation for augmentation. A frozen layer strategy was adopted to retain pretrained weights, while the Adam optimizer with a learning rate of 0.0001 was employed during model compilation. Notably, the number of epochs had a significant impact on classification accuracy, with the model achieving 98% accuracy at 20 and 30 epochs, and reaching 99% accuracy at 40 epochs, demonstrating the high reliability and effectiveness of the proposed deep learning approach in classifying the fermentation maturity of cutting tape. These results highlight the potential of deep learning in agricultural and food processing fields, offering an efficient, consistent, and automated method for assessing product quality in large-scale production environments. The implementation of this model can also reduce subjectivity in manual evaluations, improve decision-making speed, and support scalable production monitoring, making it highly relevant for smart agriculture and industry 4.0 initiatives focused on quality control and automation.

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