**Joinforcs: Journal of informatics and information system**
**Volume 1, (4) 2026, p. 117-128**
**E-ISSN : XXXX-XXXX**
**©2026. The Author(s). This is an open acces article under cc-by-sa**

# Evaluation of CNN And ANN'S Performance In Deep Learning-Based Classification of Fresh And Rotten Fruits

Shafa Nabila Ivana Putri [a,1,*], Suci Muqsithin [a,2], Fauzi Diana Pertiwi [a,3], Ardi Joko Susilo [a,4], Wahyu Maulana Putra [a,5], Arif Darmawan[b,6]

[a] Departement of Informatics, STMIK AMIKOM Surakarta, Indonesia
[b] Departement of Informatics, Universitas Islam Negeri Syarif Hidayatullah Jakarta, Indonesia
[1] shafa.130520@mhs.amikomsolo.ac.id, [2] suci.130539@mhs.amikomsolo.ac.id, [3] fauzi.130532@mhs.amikomsolo.ac.id, [4] ardi.130540@mhs.amikomsolo.ac.id, [5] wahyu.130515@mhs.amikomsolo.ac.id , [6]arif.darmawan22@mhs.uinjkt.ac.id
* correspondent author

**Article Info**

***Article History:***

Received Jul 20, 2026
Revised Jul 27, 2026
Accepted Aug 02, 2026

***Keywords :***
*Artificial Neural Network, Convolutional Neural Network, Deep Learning, Fruit Classification, Image Processing*

*This work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License*

***Abstract***

*This study aims to develop and evaluate a deep learning-based system for classifying fresh and rotten fruits using Convolutional Neural Network (CNN) and Artificial Neural Network (ANN) methods. The CNN architecture is employed to automatically extract visual features such as color, shape, and texture from fruit images, while the ANN performs the final classification based on the extracted feature maps. The dataset used in this study is the Fresh and Rotten Fruits Dataset obtained from the Kaggle platform, consisting of approximately 10.901 fruit images, which were processed through image resizing, normalization, data augmentation, and an 80:20 train-test split prior to model training. The model was trained for 25 epochs and evaluated using accuracy, precision, recall, F1-score, and confusion matrix. The results show that the CNN-ANN model achieved a test accuracy of 93.75%, outperforming the baseline ANN model trained directly on raw pixel features, which achieved a test accuracy of 86.25%. Unlike previous studies that primarily focused on using CNN or ANN as standalone classifiers, this study specifically evaluates the effectiveness of CNN as a feature extractor before ANN classification, resulting in a 7.50% improvement in classification accuracy over the ANN baseline. These findings demonstrate that integrating CNN-based feature extraction with ANN classification is an effective approach for improving the performance of automated fruit freshness classification systems.*

## 1. Introduction

The rapid development of artificial intelligence (AI) technology in the era of digital transformation has reached various sectors, including the optimization of digital image processing. Digital image processing is a field where AI allows computers to recognize objects, analyze images, and perform data classification automatically with a high degree of accuracy. Deep learning is one of the most widely used branches of artificial intelligence in digital image processing [1], [2].

Deep Learning is able to extract features automatically, so that it can improve the performance of the image classification system. Convolutional Neural Network (CNN) is one of the most commonly used Deep Learning techniques in image processing [1], [3]. CNN is a technology specifically designed for digital image processing due to its ability to recognize visual patterns such as the color, shape, and texture of objects in images [4], [5]. CNN technology has been successfully applied to classify the quality and freshness of fruit with excellent accuracy, which shows that Computer Vision technology can support the automatic recognition process of fresh and rotten fruit.

Fruit quality is one of the crucial elements in the field of agriculture and fruit marketing. Fresh fruit has a higher selling price than rotten fruit, because it is more suitable for consumption and has superior quality. However, the fruit sorting process is generally still carried out manually by humans, which takes a long time and is at risk of errors due to fatigue or differences in human judgment in assessing the quality of the fruit [1], [2].

**Joinforcs: Journal of informatics and information system**
**Volume 1, (4) 2026, p. 117-128**
**E-ISSN : XXXX-XXXX**
**©2026. The Author(s). This is an open acces article under cc-by-sa**

Various studies have utilized Convolutional Neural Network (CNN) in the classification of fruit quality. Research conducted by Bahari and Latifa shows that the application of CNN-based Computer Vision techniques is able to identify the quality and freshness level of fruit with high accuracy, so it has the potential to be applied to support the automatic fruit sorting process [4]. Another study conducted by Mushoffah and Nafiiyah compared several CNN architectures with the transfer learning method in fruit quality classification. The results of the study show that the use of modern CNN architecture is able to improve classification performance compared to conventional methods. However, the study still uses CNN as the primary (end-to-end) classification model and has not examined its role as a feature extractor [5].

The study, published in the Journal of Agriculture and Food Research, introduced XAI-FruitNet, a CNN architecture that combines hybrid pooling techniques with Explainable Artificial Intelligence (XAI). This approach is able to produce an accuracy of more than 97% and increase the interpretability of the model in the classification process [6]. In addition, another study developed a ResNet-101 model combined with a Non-local Attention mechanism to detect the freshness level of fruit under complex environmental conditions. The results showed that the application of the attention mechanism could improve the model's ability to recognize changes in color, texture, and decay areas resulting in better performance than the ResNet-50 and VGG-16 architectures [7]. However, both studies are still oriented towards the development of CNN as the primary classification model and have not evaluated the effectiveness of CNN as a feature extractor combined with Artificial Neural Network (ANN).

Another study conducted by Amin et al. in the article Automatic Fruits Freshness Classification Using CNN and Transfer Learning also showed that the use of transfer learning in the CNN model was able to significantly improve the ability to classify fruit freshness. By leveraging the knowledge learned from large-scale datasets, the model is able to produce a better representation of features so that the training process becomes more efficient and classification performance improves. Nevertheless, the study still uses CNN as the primary classification model so it has not evaluated the possible utilization of CNN extracted features by other classification models [8].

In addition, a study published in Current Research in Food Science on Vegetable and Fruit Freshness Detection Based on Deep Features and Principal Component Analysis shows that the quality of feature representation has a great influence on the success of fruit and vegetable freshness classification. The research combines the features of deep learning extraction with Principal Component Analysis (PCA) techniques to reduce the dimensions of the data without losing important information. Meanwhile, the research on the Implementation of CNN's Deep Learning Algorithm for the Classification of Freshness of Fruits and Vegetables also proves that CNN is able to recognize the visual characteristics of objects effectively so that it can be applied as an automated solution in the process of identifying the quality of horticultural products. On the other hand, machine learning-based approaches such as Random Forest have also been used for the classification of fresh and rotten fruits, but it still depends on the quality of the features used so that the performance is greatly influenced by the feature extraction process before the classification stage [9].

The results of the review of previous studies show that most of the research focuses more on efforts to improve CNN performance through architectural modifications, the application of transfer learning, attention mechanisms, and hybrid pooling techniques [5], [6], [7]. On the other hand, studies that specifically examine the use of CNN as a feature extractor before the classification process using Artificial Neural Network (ANN) are still relatively few. In addition, most studies only present an increase in accuracy values without addressing the extent to which the feature representation produced by CNN can improve ANN performance when compared to ANN that is trained directly using image pixel values. This condition shows that there is still a research gap that needs to be further researched.

In an effort to address this research gap, this study proposes an approach that integrates CNN as a feature extractor with ANN as a classifier to classify fresh and rotten fruits using the Fresh and Rotten Fruits Dataset from Kaggle which consists of about 10,901 images. In contrast to previous studies that generally used CNN as the primary classification model, this study focused on evaluating the contribution of the CNN feature extraction process to the improvement of ANN performance through comparison with baseline ANN trained using raw pixel values. The contribution of this study is not only in the form of a

**Joinforcs: Journal of informatics and information system**
**Volume 1, (4) 2026, p. 117-128**
**E-ISSN : XXXX-XXXX**
**©2026. The Author(s). This is an open acces article under cc-by-sa**

comparison of the performance of the two models, but also provides an analysis of the effectiveness of the feature representation produced by CNN in improving the classification ability of ANN based on the accuracy, precision, recall, F1-score, and confusion matrix metrics.

Based on this description, this study aims to develop and evaluate a Deep Learning-based classification system of fresh and rotten fruits by combining CNN and ANN. The results of the research are expected to contribute to the development of image classification methods based on automatic feature extraction and become an effective alternative approach in supporting the automatic fruit sorting process in the agricultural and food industries.

## 2. Research Methodology

This study uses a quantitative experimental approach to build and evaluate a Deep Learning-based model of classification of fresh and rotten fruits. The research was carried out using a personal laptop with the Windows operating system and implemented using the Python programming language in the Kaggle Notebook environment. Model development was done using the TensorFlow framework version 2.9.0 with Keras to build the CNN and ANN architectures. The research stages include problem identification, literature study, dataset collection, data preprocessing, model development, model training, testing, and model performance evaluation. The overall research flow is shown in Figure 1.

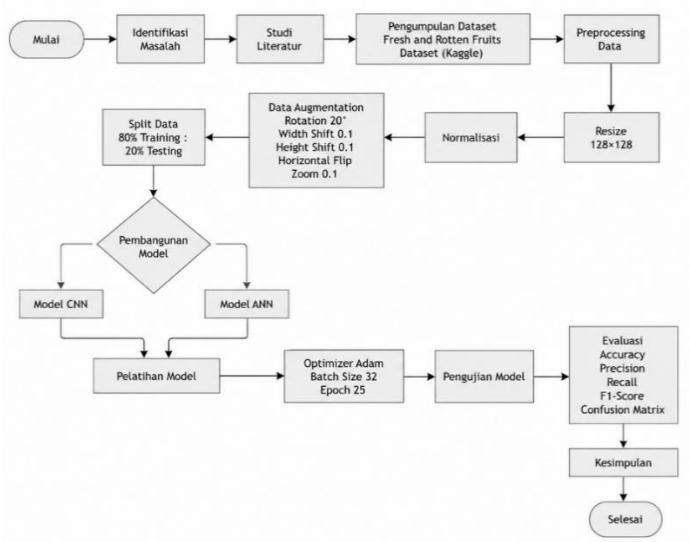



Figure 1. CNN-ANN-Based Fruit Classification Research Flow Chart

This study uses a secondary dataset obtained from the Kaggle platform, namely the Fresh and Rotten Fruits Image Dataset. The dataset consists of 10,901 fruit images divided into six classes, namely freshapples (1,693 images), rottenapples (2,342 images), freshbanana (1,581 images), rottenbanana (2,224 images), freshoranges (1,466 images), and rottenoranges (1,595 images). The six classes represent three types of fruits, namely apples, bananas, and oranges, in two conditions, namely fresh and rotten. Therefore, this study is included in the problem of multiclass image classification.

Before being used for model training, each image goes through several preprocessing stages. First, black background removal was carried out by identifying pixels that have color intensity on all three RGB channels below the 30 threshold, then changing them to white so that the model focuses more on fruit objects. Second, all images were resized (resizing) to uniform dimensions of 128 × 128 pixels with three color channels (RGB). Third, the pixel intensity value is normalized from the range of 0–255 to 0–1 to speed up the convergence process during model training. Fourth, the class labels are converted into one-hot encoding according to the six target categories.

Before the training process, the pre-processing stage is carried out to produce uniform input data so that the quality of the features learned by the model can be improved. Abdullah et al. explained that the initial image processing process, such as standardization of image size and quality, plays an important

**Joinforcs: Journal of informatics and information system**
**Volume 1, (4) 2026, p. 117-128**
**E-ISSN : XXXX-XXXX**
**©2026. The Author(s). This is an open acces article under cc-by-sa**

role in producing a better representation of features so that it can improve the performance of the classification process [10].

Furthermore, the dataset was divided into training data (80%) and test data (20%) using the stratified random split technique with random_state = 42 so that the proportion of each class was maintained in both subsets. The division produced 8,720 images as training data and 2,181 images as test data. The 80:20 split ratio was chosen because it provides a sufficient amount of training data to study patterns in the image, while providing adequate test data to evaluate the model's generalization capabilities.

Specifically in the CNN model training process, on-the-fly data augmentation techniques were applied using ImageDataGenerator, which included random rotation of up to 20°, horizontal and vertical shifts of 10%, horizontal flip, and zoom of 10%. This technique aims to increase the variety of training data so that the model becomes more resilient to changes in the position, orientation, and scale of objects, while helping to reduce the risk of overfitting.

The application of data augmentation aims to improve the model's generalization ability to different data variations. Latifa et al. showed that the CNN model is able to learn the visual characteristics of fruits and vegetables more effectively when trained using data with sufficient variation, so that the risk of overfitting can be minimized [11].

Two Deep Learning architectures, namely CNN and ANN, are built using the same dataset so that performance comparisons are performed under identical experimental conditions. The CNN architecture is designed using three convolutional blocks with a gradually increasing number of filters (32, 64, and 128) to allow the model to learn visual features from simple to complex levels. Meanwhile, the ANN model is used as a comparison by receiving flattened images without the extraction process of spatial features.

The CNN architecture consists of three consecutive convolution blocks with filter counts 32, 64, and 128, each of which uses a kernel of 3 × 3 with a ReLU activation function. Each convolutional block is followed by a 2 × 2 MaxPooling2D layer to reduce spatial dimensions while retaining the most representative features. The output of the last convolutional block is then flattened (Flatten) into a one-dimensional vector and passed to a Dense layer totaling 128 neurons with ReLU activation, followed by a Dropout layer of 0.5 to reduce the risk of overfitting. The output layer uses 6 neurons with a Softmax activation function according to the number of target classes. This architecture has a total of 3,305,414 trainable parameters.

The selection of CNN as a feature extractor is based on its ability to automatically learn visual representations through a cascading convolution process. A similar approach was also applied by Reka et al. in the study of rotten fruit classification and shelf life identification, which showed that CNN was able to effectively recognize the visual characteristics of fruits without the need for manual extraction of features [12].

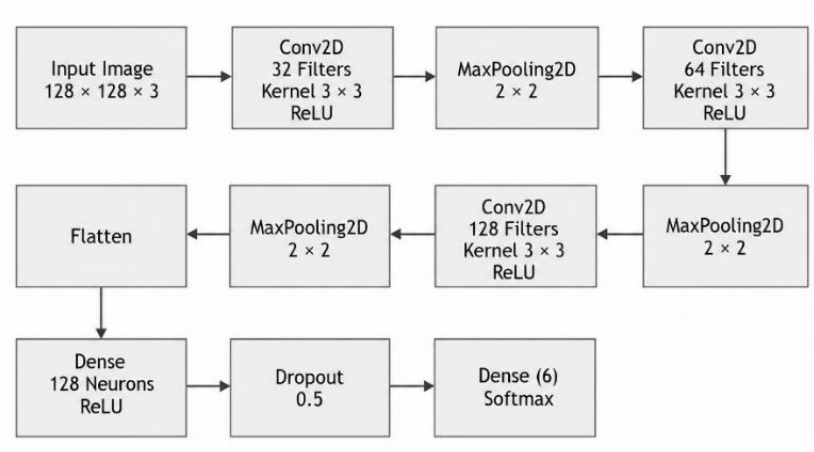



Figure 2. CNN Model Architecture

**Joinforcs: Journal of informatics and information system**
**Volume 1, (4) 2026, p. 117-128**
**E-ISSN : XXXX-XXXX**
**©2026. The Author(s). This is an open acces article under cc-by-sa**

As a comparative model, an Artificial Neural Network (ANN) architecture was built in the form of a Multilayer Perceptron that receives images measuring 128 × 128 × 3 and immediately flattens them (Flatten) into a vector with dimensions of 49,152 without going through the process of extracting spatial features. The vector is passed to three layers of Dense, namely 512 neurons with a Dropout of 0.5, 256 neurons with a Dropout of 0.3, and 128 neurons, all of which use the ReLU activation function. The output layer consists of 6 neurons with a Softmax activation function. In total, the ANN model has 25,331,334 trainable parameters. A much larger number of parameters than CNN suggests that an increase in the number of parameters does not necessarily result in better performance if the model does not have a spatial feature extraction mechanism.

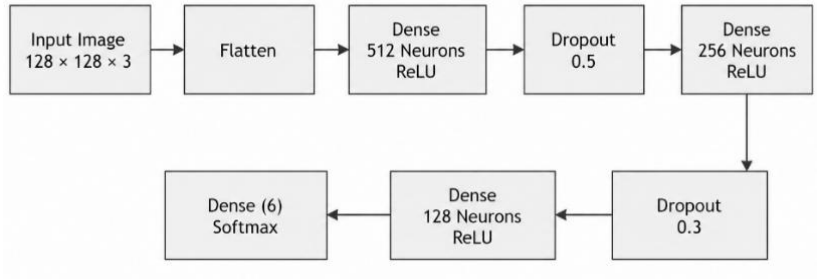



Figure 3. ANN Model Architecture

## 3. Results and Discussion

### 3.1. Model Accuracy and Loss Comparison

The results of the evaluation of the test data consisting of 2,181 images showed that the CNN model obtained an accuracy of 97.20% with a loss value of 0.0679, while the ANN model obtained an accuracy of 21.50% with a loss value of 1.7750. A summary of the results of the evaluation of the two models is presented in Table 1, while a visualization of the accuracy comparison is shown in Figure 4.

Table 1. Comparison of CNN and ANN Model Accuracy and Loss on Test Data

| Model | Accuracy | Loss |
|---|---|---|
| CNN | 0,9720 | 0,0679 |
| ANN | 0,2150 | 1,7750 |

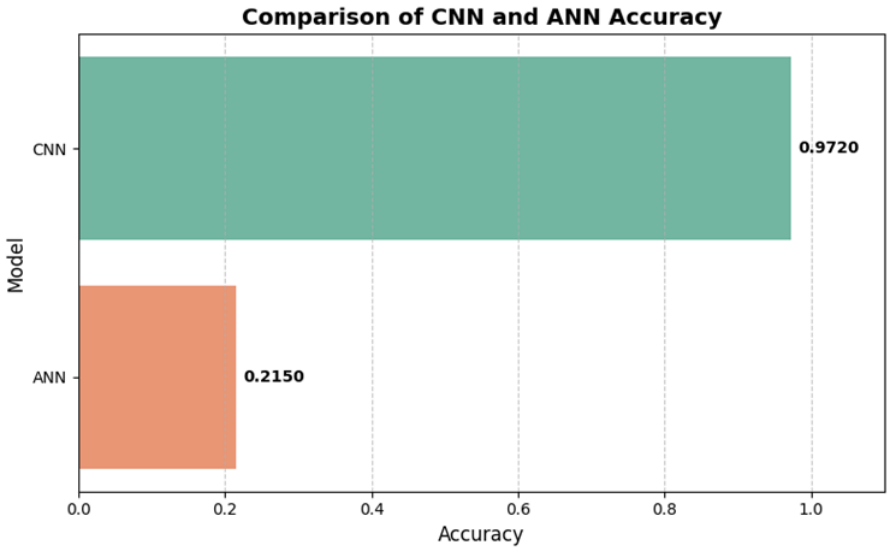



Figure 4. Comparison of CNN and ANN Model Accuracy and Loss on Test Data

**Joinforcs: Journal of informatics and information system**
**Volume 1, (4) 2026, p. 117-128**
**E-ISSN : XXXX-XXXX**
**©2026. The Author(s). This is an open acces article under cc-by-sa**

Based on Table 1, the CNN model shows much better performance than ANN. CNN's high accuracy indicates that the convolutional layer is able to extract visual features such as textures, colors, shapes, and surface patterns of the fruit gradually before the classification process is performed. In contrast, ANN receives images in the form of raw pixels that have been flattened so that the spatial relationships between pixels cannot be maintained. As a result, ANN has difficulty distinguishing visual characteristics between classes, resulting in much lower accuracy.

The difference in accuracy of 75.70 percentage points shows that CNN's feature extraction mechanism has a very significant influence on the success of the classification of fresh and rotten fruit images. These results show that a larger number of parameters in the ANN does not guarantee better performance if the model is not able to learn spatial patterns in the image.

In terms of implementation, the accuracy rate of 97.20% shows that the CNN model has the potential to be applied to the automatic fruit quality identification system. High accuracy can help reduce fruit sorting errors, improve the consistency of the quality control process, and reduce reliance on manual visual inspections that are prone to errors due to fatigue and observer subjectivity. Thus, the use of CNN not only provides a quantitative performance improvement, but also offers practical benefits for the application of fruit classification systems in the agriculture, food industry, and retail sectors.

### 3.2. Classification Report per Kelas

To evaluate the model's ability to classify each category of fruit, an analysis was carried out using a classification report and confusion matrix. The classification report presents the precision, recall, and F1-score values for each class, while the confusion matrix is used to describe the distribution of true and false predictions in each class. The results of the CNN and ANN model evaluations are presented in Table 2, Table 3, and Figure 5.

Table 2. Classification Report Model CNN

| Classes | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| freshapples | 1,00 | 0,94 | 0,97 | 339 |
| Rottenapples | 0,92 | 1,00 | 0,96 | 469 |
| freshbanana | 1,00 | 0,98 | 0,99 | 316 |
| Rottenbanana | 0,99 | 1,00 | 0,99 | 445 |
| freshoranges | 0,96 | 0,98 | 0,97 | 293 |
| rottenoranges | 0,99 | 0,91 | 0,95 | 319 |
| Macro avg | 0,98 | 0,97 | 0,97 | 2181 |
| Weighted avg | 0,97 | 0,97 | 0,97 | 2181 |

Table 3. Classification Report Model ANN

| Classes | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| freshapples | 0,00 | 0,00 | 0,00 | 339 |
| Rottenapples | 0,22 | 1,00 | 0,35 | 469 |
| freshbanana | 0,00 | 0,00 | 0,00 | 316 |
| Rottenbanana | 0,00 | 0,00 | 0,00 | 445 |
| freshoranges | 0,00 | 0,00 | 0,00 | 293 |
| rottenoranges | 0,00 | 0,00 | 0,00 | 319 |
| Macro avg | 0,04 | 0,17 | 0,06 | 2181 |
| Weighted avg | 0,05 | 0,22 | 0,08 | 2181 |

**Joinforcs: Journal of informatics and information system**
**Volume 1, (4) 2026, p. 117-128**
**E-ISSN : XXXX-XXXX**
**©2026. The Author(s). This is an open acces article under cc-by-sa**

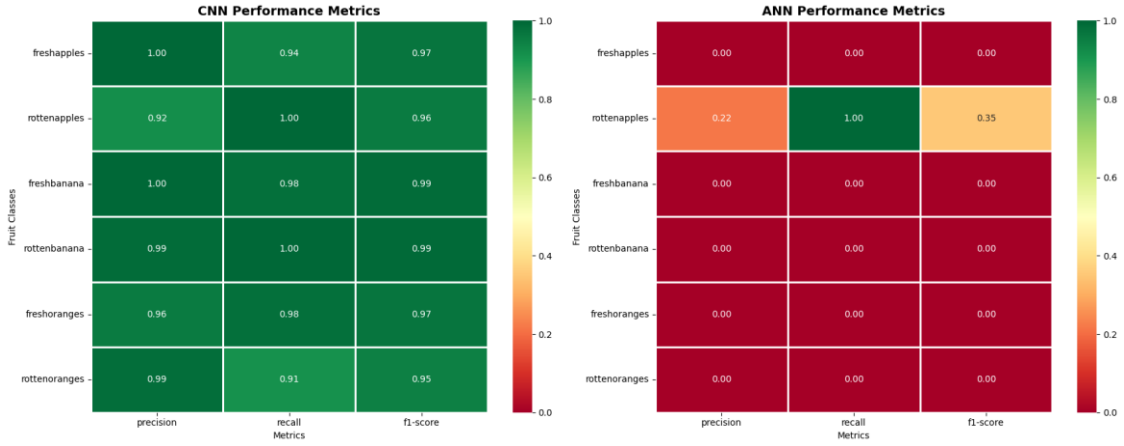



Figure 5. Precision, Recall, and F1-Score Heatmaps of CNN and ANN Models

Table 2 shows that the CNN model provided high and consistent performance across the class, with precision values ranging from 0.92 to 1.00 and recalls ranging from 0.91 to 1.00. These results show that CNN is able to recognize the visual characteristics of each category of fruit, both in fresh and rotten conditions, with a relatively low error rate. In contrast, Table 3 shows that the ANN model is only able to recognize the rottenapples class (recall = 1.00), while the other five classes obtain a precision and recall value of 0.00. The pattern suggests that the ANN model has not been able to learn an adequate representation of features so that predictions tend to be concentrated in one class.

This condition is also seen during the training process. The loss value of the ANN model increased to 9.17 in the first epoch and then remained in the range of 1.77 until the end of the training, while the validation accuracy remained in the range of 0.21–0.22 for 25 epochs. These results show that the model has not managed to significantly improve its classification capabilities even though the training process has been ongoing until the entire epoch is over.

The difference in performance can be explained by the characteristics of the two architectures. CNN performs the feature extraction process through convolutional operations so that it is able to study spatial patterns such as texture, color, and surface shape of the fruit gradually before the classification stage. Instead, ANN receives input in the form of images that have been flattened into 49,152 features without maintaining spatial relationships between pixels. In addition, the ANN model has a much larger number of parameters (25,331,334 parameters) than CNN (3,305,414 parameters), making the optimization process more complex. The combination of high input dimensions and the absence of a feature extraction mechanism makes it difficult for ANN to distinguish visual characteristics between classes, resulting in much lower classification performance than CNN.

### 3.3. Analisis True Positive, False Positive, False Negative, dan True Negative

To obtain a more detailed picture of the pattern of misclassification, an analysis was carried out on the values of True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN) obtained from the multiclass confusion matrix. The results of the analysis are visualized in Figure 6.

**Joinforcs: Journal of informatics and information system**
**Volume 1, (4) 2026, p. 117-128**
**E-ISSN : XXXX-XXXX**
**©2026. The Author(s). This is an open acces article under cc-by-sa**

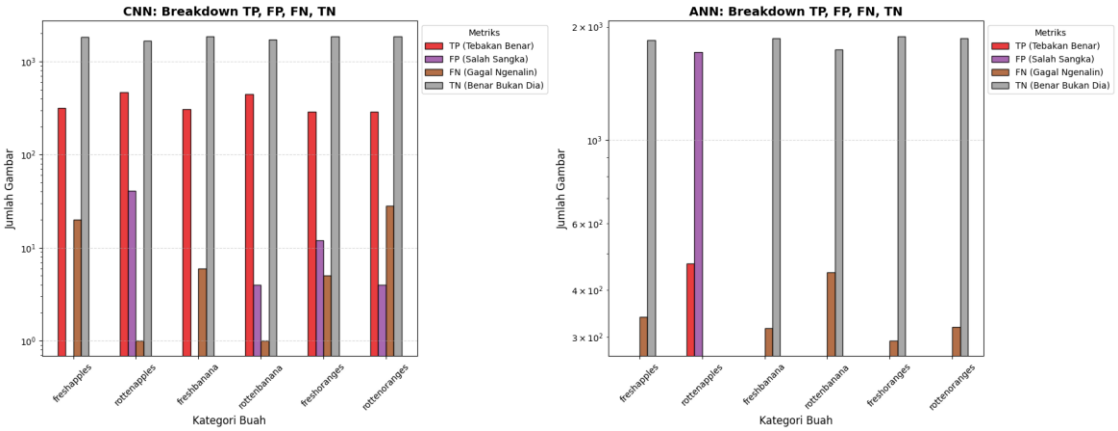



Figure 6. Comparison of TP, FP, FN, and TN Values of CNN (left) and ANN (right) Models in Each Class

Based on Figure 6, the CNN model shows a high number of True Positives (TP) across all classes, while False Positive (FP) and False Negative (FN) values are relatively low. These results show that most of the images are successfully classified into the correct class with a small error rate. The findings are consistent with the high precision, recall, and F1-score values in Table 2, thus showing that the CNN model has good and stable classification capabilities in all fruit categories.

In contrast, the ANN model shows a different pattern. False Negative (FN) values were very high in five classes, namely freshapples, freshbananas, rottenbananas, freshoranges, and rottenoranges, indicating that most of the imagery in those classes failed to be recognized correctly. On the other hand, the False Positive (FP) value is concentrated on the rottenapples class, as the model tends to provide the same predictions to most of the test data without paying attention to the visual characteristics of each class.

This pattern reinforces the results in the previous section that the ANN model has not been able to establish an adequate decision boundary to distinguish six classes of fruits. In contrast, CNN is able to produce more discriminatory feature representations through a convolution-based feature extraction process, thereby reducing the number of misclassifications and improving the model's generalization capabilities to test data. These results further confirm that the use of CNN as the primary architecture is more suitable for image classification tasks than ANN that receives input in the form of raw pixels.

Thus, the analysis of True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN) not only shows the number of correct and false predictions, but also reinforces the results of previous evaluations that CNN has better generalization capabilities than ANN. These results confirm that the use of CNN is more suitable for the classification of fresh and rotten fruit images because it is able to produce more accurate, consistent, and stable predictions across classes.

### 3.4. Qualitative Testing on Test Images

As a complement to the quantitative evaluation, qualitative testing was carried out on several randomly selected images from the test data. The prediction results of the CNN and ANN models along with the probability of Softmax output are shown in Figure 8.

**Joinforcs: Journal of informatics and information system**
**Volume 1, (4) 2026, p. 117-128**
**E-ISSN : XXXX-XXXX**
**©2026. The Author(s). This is an open acces article under cc-by-sa**

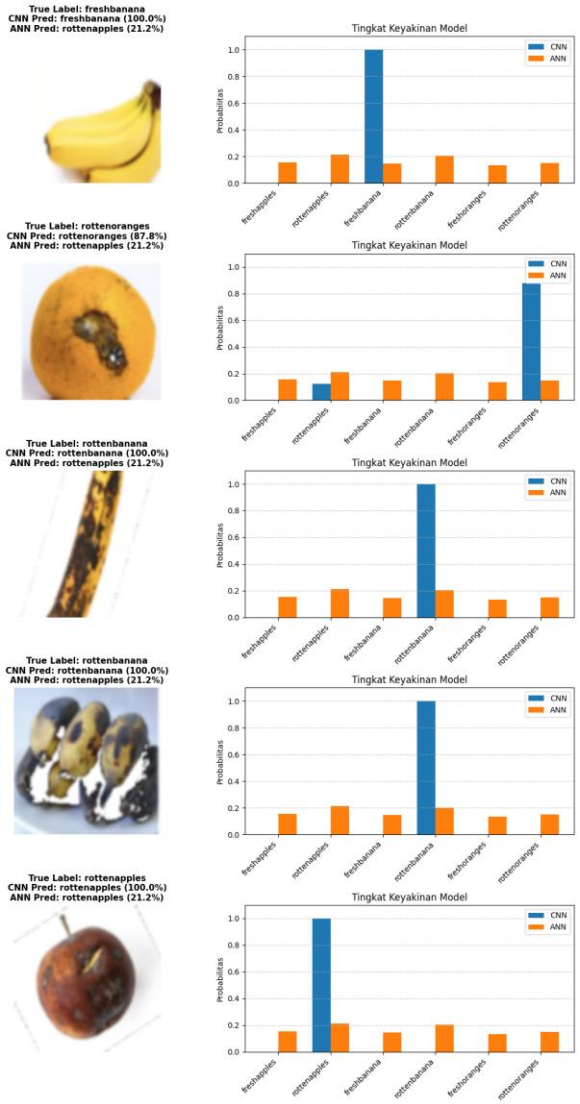



Figure 8. Example of CNN and ANN Predictions on Random Test Imagery with Softmax Probability (Source: Kaggle Experiment Output, 2026)

Based on Figure 8, the CNN model was able to classify most of the test images according to the actual label with a relatively high Softmax probability value in the predicted result class. These results show that the CNN model is able to recognize visual patterns in fruit imagery more consistently, resulting in more accurate predictions.

In contrast, the ANN model still produces some predictions that don't match the actual label and tend to give lower or concentrated probabilities on a particular class. These results are in line with findings in previous quantitative evaluations that showed that ANN had difficulty distinguishing visual characteristics between classes when receiving input in the form of image pixels without a feature extraction process.

The findings of this qualitative test are consistent with the results of the evaluation using accuracy, precision, recall, F1-score, and confusion matrix that have been discussed in the previous section. Thus, both quantitative and qualitative evaluations show that the CNN model has a better ability than the ANN in classifying fresh and rotten fruits.

In terms of implementation, the results of qualitative testing show that the CNN model has the potential to be applied to the automatic fruit quality identification system because it is able to produce accurate predictions with a high level of confidence. This ability can be used to help the fruit sorting

©2026. The Author(s). This is an open acces article under cc-by-sa

process in the agriculture, food industry, and retail sectors so that the inspection process becomes faster, more consistent, and reduces the potential for errors caused by manual visual assessment.

### 3.5. Comparison with Previous Research

The results of this study are in line with the research of Syaharani et al. who reported that CNN was able to classify fresh and rotten fruits with a high level of accuracy [1]. Bahari and Latifa's research also showed that CNN is effective in extracting the visual characteristics of fruits through a computer vision approach so that it produces good classification performance [4].

In contrast to previous studies that generally used CNN as the primary classification model, this study specifically compared CNN and ANN on the same dataset and training configuration. The results of the experiment showed that CNN obtained an accuracy of 97.20%, while ANN only obtained an accuracy of 21.50%. These findings suggest that the ability to extract spatial features is a major factor influencing the success of fruit image classification. In addition, previous research using ANN generally took advantage of the extraction features first before the classification process. In this study, ANN received a raw image measuring 128×128×3 so that the spatial relationship between pixels could not be maintained. These results provide empirical evidence that conventional ANN is not suitable for image classification if it is not preceded by a feature extraction process.

The results of this study also show better performance than the conventional machine learning approach used by Santoso and Hartati in classifying fresh and rotten fruits using the Random Forest algorithm [10]. Unlike Random Forest, which relies heavily on the quality of input features, CNN is able to extract visual features automatically, resulting in a more discriminatory representation of data and improving classification performance [13].

The findings of this study are also in line with the research of Liandaputra and Zahra who applied the deep learning method to the classification of the ripeness level of pineapples [13]. Although the research objects are different, the two studies show that the deep learning model is able to effectively study the visual characteristics of fruits, resulting in high classification performance. This reinforces that the use of deep learning is an effective approach to various image classification problems in the agricultural sector [14].

In addition to the selection of model architecture, the optimization process during training also plays a role in determining model performance. Danuarta and Oktafiani reported that the use of Adam's optimizer was able to produce a more stable convergence process and better classification performance than RMSprop in the Artificial Neural Network model [11]. The findings support the use of the Adam optimizer in this study to optimize the CNN and ANN model training processes [15].

## 4. Conclusion

This research has successfully developed and evaluated a Deep Learning-based fresh and rotten fruit classification model using Convolutional Neural Network (CNN) and Artificial Neural Network (ANN) architectures. The results of the experiment showed that the CNN model obtained an accuracy of 97.20% with a loss value of 0.0679, while the ANN model only achieved an accuracy of 21.50% with a loss of 1.7750. In addition, the results of the classification report, confusion matrix, and True Positive, False Positive, False Negative, and True Negative analysis showed that CNN was able to classify all fruit categories more accurately, consistently, and stably than ANN.

The main contribution of this study is to provide a comprehensive evaluation of the differences in CNN and ANN performance on the dataset as well as the same training conditions for the classification of fresh and rotten fruits. Unlike most previous studies that only focused on improving the CNN architecture or using CNN as the primary classification model, this study directly showed that CNN's spatial feature extraction ability was a major factor that resulted in much better classification performance than ANNs that received input in the form of raw pixels. Thus, this study successfully answered the research gap regarding the limited studies that compared the effectiveness of the two architectures directly on the task of classification fruit images.

**©2026. The Author(s). This is an open acces article under cc-by-sa**

Theoretically, the results of this study reinforce that the convolution-based feature extraction mechanism is able to produce a more discriminatory visual representation thereby improving the model's ability to recognize the characteristics of color, texture, and shape of fruits. In practical terms, the CNN model has the potential to be implemented in automated fruit sorting systems in the agriculture, food industry, and retail sectors because it can improve the consistency of the inspection process, reduce errors due to manual assessment, and support more efficient fruit quality control.

For further research, it is recommended to use datasets with a more diverse amount of data and variations of fruit types so that the generalization ability of the model can be evaluated more comprehensively. In addition, the research can be developed by comparing the performance of modern CNN architectures such as EfficientNet, MobileNet, and ResNet, applying a transfer learning approach, and using evaluation techniques such as k-fold cross-validation to obtain a more robust model and have better performance under various data conditions.

## REFERENCES

[1] M. A. Syaharani *et al.*, "CLASSIFICATION OF FRESH AND ROTTEN FRUITS USING CONVOLUTIONAL NEURAL NETWORK (CNN) ALGORITHMS," 2024. doi: https://doi.org/10.36040/jati.v8i5.11132.

[2] N. Marselina and O. Brilliant Chang, "APPLICATION OF ARTIFICIAL NEURAL NETWORK ALGORITHM FOR CLASSIFICATION OF APPLE QUALITY," vol. 17, p. 26207427, doi: https://doi.org/10.52972/hoaq.vol17no1

[3] R. Faurina, M. J. Gazali, and I. D. A. Herani, "OPTIMIZATION OF DISEASE PREDICTION ACCURACY THROUGH ARTIFICIAL NEURAL NETWORK (ANN) ALGORITHMS IN DIAGNESE APPLICATION," *J. Tek. Inform.*, vol. 5, no. 2, pp. 339–347, Apr. 2024, doi: https://doi.org/10.52436/1.jutif.2024.5.2.1182

[4] U. L. Satrya Darmawan Putra Bahari, "CLASSIFICATION OF FRESH FRUITS USING COMPUTER VISION TECHNIQUES FOR THE DETECTION OF FRUIT QUALITY AND FRESHNESS," vol. 7, no. 3, pp. 1567–1573, 2023, doi: https://doi.org/10.36040/jati.v7i3.6871.

[5] M. Y. M. Sekarwati and N. Nafiiyah, "ARCHITECTURAL ANALYSIS OF CONVOLUTIONAL NEURAL NETWORKS AND TRANSFER LEARNING IN FRUIT QUALITY CLASSIFICATION," *Rabit J. Teknol. and Sist. Inf. Univrab*, vol. 11, no. 1, pp. 67–72, Jan. 2026, doi: https://doi.org/10.36341/rabit.v11i1.6622

[6] S. Sultana, M. A. Moon Tasir, S. M. Nuruzzaman Nobel, M. M. Kabir, and M. F. Mridha, "XAI-FruitNet: An explainable deep model for accurate fruit classification," *J. Agric. Food Res.*, vol. 18, Dec. 2024, doi: https://doi.org/10.1016/j.jafr.2024.101474.

[7] Y. Shu, J. Zhang, Y. Wang, and Y. Wei, "Fruit Freshness Classification and Detection Based on the ResNet-101 Network and Non-Local Attention Mechanism," *Foods*, vol. 14, no. 11, Jun. 2025, doi: https://doi.org/10.3390/foods14111987

[8] U. Amin, M. I. Shahzad, A. Shahzad, M. Shahzad, U. Khan, and Z. Mahmood, "Automatic Fruits Freshness Classification Using CNN and Transfer Learning," *Appl. Sci.*, vol. 13, no. 14, Jul. 2023, doi: https://doi.org/10.3390/app13148087

[9] Y. Yuan and X. Chen, "Vegetable and fruit freshness detection based on deep features and principal component analysis; Vegetable and fruit freshness detection," *Curr. Res. Food Sci.*, vol. 8, Jan. 2024, doi: https://doi.org/10.1016/j.crfs.2023.100656

[10] R. Wariyanto Abdullah, R. Kusumastuti, and Handoko, "Analysis of Image Feature Extraction Processing for Apple Type Classification Using Scikit-Learn with K-Nearest Neighbor Algorithm," *J. Techno. Inf. and Computing Science.*, vol. 12, no. 1, pp. 165–174, Feb. 2025, doi: https://doi.org/10.25126/jtiik.2025129149

[11] A. Latifa, H. Kurniawan, K. Rohmat Hidayat, and N. Larasati, "IMPLEMENTATION OF DEEP LEARNING CONVOLUTIONAL NEURAL NETWORK ALGORITHM FOR THE CLASSIFICATION OF FRESHNESS OF FRUITS AND VEGETABLES," vol. 13, no. 2, pp. 319–328, 2026, doi: https://doi.org/10.25126/jtiik.2026131

[12] S. S. Reka, A. Bagelikar, P. Venugopal, V. Ravi, and H. Devarajan, "Deep Learning-Based Classification of Rotten Fruits and Identification of Shelf Life," *Comput. Mate. Contin.*, vol. 78, no. 1, pp. 781–794, 2024, https://doi.org/10.32604/cmc.2023.043369

**Joinforcs: Journal of informatics and information system**
**Volume 1, (4) 2026, p. 117-128**
**E-ISSN : XXXX-XXXX**
**©2026. The Author(s). This is an open acces article under cc-by-sa**

[13] F. Santoso and E. Hartati, "USE OF RANDOM FOREST ALGORITHM IN THE CLASSIFICATION OF FRESH AND ROTTEN FRUITS," vol. 3, no. 1, pp. 133–140, 2022, doi: https://doi.org/10.35957/algoritme.v3i1.3404

[14] D. Liandaputra and A. Zahra, "Classification of Pineapple Maturity Levels Using Deep Learning Methods," *G-Tech J. Teknol. Apply.*, vol. 8, no. 2, pp. 1091–1103, Apr. 2024, doi: https://doi.org/10.33379/gtech.v8i2.4122

[15] A. Danuarta and D. Oktafiani, "Comparative Analysis of Adam and RMSprop Optimizer on Artificial Neural Network for Clinical Data-Based Classification of Lung Cancer." [Online]. Available: https://joinforcs.iastinsitute.com