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CLASSIFICATION OF MANGO FRUIT MATURITY USING SUPPORT VECTOR MACHINE (SVM) AND CONVOLUTION NEURAL NETWORK (CNN)

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ABSTRACT

Mango ripeness is one of the main indicators of fruit quality, which is generally still assessed subjectively through visual observation. Therefore, an accurate and objective automatic classification system is needed. This study aims to classify the ripeness level of mangoes based on digital images using a Convolutional Neural Network (CNN) and a combination of CNN–Support Vector Machine (SVM). The dataset used consists of 198 colored (RGB) mango images divided into three classes, namely unripe mangoes, ripe mangoes, and rotten mangoes. The pre-processing stage includes changing the image size to 128×128 pixels and normalizing the pixel values. CNN is used to extract visual features as well as an initial classifier. Next, the features extracted by CNN were used as input to the SVM model with a Radial Basis Function (RBF) kernel to improve classification performance. Evaluation was performed using accuracy, confusion matrix, and precision, recall, and f1-score values. The test results showed that the CNN model achieved a training accuracy of 96.38% and a validation accuracy of 97.47%. The CNN–SVM approach provided better results with a classification accuracy of 99% and a very low error rate across all classes. Based on these results, it can be concluded that the combination of CNN and SVM is effective for classifying the ripeness of mangoes and has the potential to be applied to automatic fruit sorting systems.

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1. INTRODUCTION

Mangoes are tropical fruits that are very popular in Indonesia, which is also one of the world's largest mango producers. This fruit is known for its distinctive sweet taste and comes in many varieties found across various regions, such as Arumanis, Golek, Manalagi, and Kweni mangoes. In addition to their appealing taste, mangoes also have significant economic value and are among the leading commodities in the agricultural sector (Budi, Chan, Alda, Arif, & Idris, 2024). The ripeness of mangoes significantly affects their quality, which is directly related to their texture, taste, and shelf life (Mutmainnah Muchtar, n.d.). Therefore, determining the ripeness level of mangoes is crucial to ensuring optimal product quality in the market. Traditionally, determining the ripeness of mangoes is done manually by visual inspection of the fruit's color, texture, and aroma. However, this method is often subjective and can lead to inconsistencies in assessing fruit ripeness, as well as requiring a long time to complete the process (Mutmainnah Muchtar, n.d.). Digital image processing technology offers a more efficient and accurate solution to replace this manual method. One widely used technique for image classification is Convolutional Neural Networks (CNNs), a deep learning method that can extract visual features from images with high accuracy (Setiawan, Nursafitri, & Afnarista, 2022).

Previous research has shown that CNNs are highly effective at classifying fruit ripeness from images. Several studies have reported that CNNs can achieve excellent results even under varying lighting conditions and complex image backgrounds (Hidayat, n.d.). However, most previous studies remain limited to small datasets and have not accounted for more complex real world variations, such as differences in lighting, image backgrounds, and fruit conditions that are not always uniform (Roza et al., n.d.). Therefore, it is necessary to develop a more robust classification system capable of handling larger, more varied datasets.

In addition to CNN, another widely used method for image classification is Support Vector Machine (SVM). SVM has proven effective at handling data with complex distributions and is widely used in image classification applications, including mango classification (Manajemen, Dan, & Mdp, 2018). SVM has the advantage of separating data classes with maximum margin, allowing better classification of data that cannot be linearly separated, such as mango images (Mutmainnah Muchtar, n.d.). The HSV (Hue, Saturation, Value) color space is also often used in fruit image processing due to its ability to separate color information more clearly, which is very useful for classifying fruit by ripeness level (Mutmainnah Muchtar, n.d.).Research by Parhan Daulay et al. (2024) compares the performance of SVM and K-Nearest Neighbors (KNN) in classifying mangoes using HSV color images. Their results show that SVM outperforms KNN in terms of precision and recall, especially on datasets with complex, non-linearly separable features (Hidayat, n.d.). Thus, although both CNN and SVM have their own advantages, this study will integrate both methods to improve accuracy and efficiency in mango ripeness classification.

This research aims to develop a classification system that is not only effective but also practically implementable in real-world conditions, where variations in lighting, image background, and fruit condition can affect classification results. This research will involve converting mango images to the HSV color space, extracting color features, and training models using two methods: CNNs and SVMs. The dataset will include various types of mangoes at different stages of ripeness, sourced from various sources. With an automated system that accurately and efficiently classifies mango ripeness, it is hoped that it will help farmers and fruit traders determine the optimal harvest time, improve the quality of marketed fruit, and reduce waste from fruit that is not fully ripe.

2. METHOD

2.1. Research Dataset

The dataset used in this study consists of digital images of colored mangoes (RGB) that visually represent variations in mango ripeness levels. The dataset was obtained from direct image capture and/or secondary image collection used in previous studies on digital image-based mango classification (Arkadia, Damayanti, & Prasvita, 2021). The ripeness classification was divided into three main classes: unripe, semi-ripe, and ripe mangoes. This classification is based on changes in fruit skin color during ripening, with green dominant in unripe mangoes, a combination of green and yellow in semi-ripe mangoes, and bright yellow to orange in ripe mangoes (Manajemen et al., 2018). These color changes are directly related to the physiological ripening of mangoes and are often used as the primary visual indicator in image-based research (Arkadia et al., 2021).The dataset is organized in a directory structure by ripeness class, then divided into training, validation, and test sets. This division aims to ensure that the developed model learns optimally and generalizes well to new data that has never been seen before (Hidayat, 2022).

2.2. Data Preprocessing

The preprocessing stage is carried out to improve image quality and standardize inputs before they are used in the model training process. All mango images are resized to 128 × 128 pixels to ensure uniform dimensions and compatibility with the CNN architecture used (Arkadia et al., 2021).In addition, pixel values were normalized by changing the image intensity range from [0,255] to [0,1]. This normalization aims to stabilize the training process and improve model learning efficiency, as applied in previous CNN-based fruit and plant classification studies (Hidayat, 2022). Each class label is represented as one-hot encoding to support multi-class classification, as used in CNN-based research on agricultural object classification (Roza et al., n.d.).

2.3. Development of the Convolutional Neural Network (CNN) Method

A Convolutional Neural Network (CNN) is used as the main model to directly classify mango ripeness levels. CNNs were chosen for their ability to automatically extract visual features from raw images without requiring manual feature extraction (Arkadia et al., 2021). The CNN architecture used consists of several convolutional layers that capture local visual patterns, such as surface texture, color gradients, and object edges, in mango skin. Each convolutional layer is followed by a max pooling layer to reduce feature dimensions and increase the model's robustness to small variations in object position (Hidayat, 2022).

A fully connected layer maps the extracted features into the ripeness class space, while the output layer uses a softmax activation function to generate probabilities for each class (Arkadia et al., 2021).The CNN model was trained using the Adam optimizer and the categorical cross-entropy loss function, which are commonly used in CNN-based multi-class image classification research in agriculture (Roza et al., n.d.). The training process was carried out for a specified number of epochs, using validation data to monitor model performance and avoid overfitting (Hidayat, 2022).

2.4. CNN-Based Feature Extraction

After the CNN is trained, the model is not only used as a classifier but also as a feature extractor. Feature extraction is performed by taking the output of the last dense layer before the classification layer, which represents the high-level visual features learned by the CNN (Arkadia et al., 2021) . This approach allows the use of rich, discriminative feature representations from the CNN for other classification methods. The extracted features are represented as high-dimensional numerical vectors that capture the visual characteristics of mango ripeness more comprehensively than manual features (Hidayat, 2022).

2.5. Development of the Support Vector Machine (SVM) Method

A Support Vector Machine (SVM) is used as an advanced classification method that utilizes the extracted CNN features. SVM was chosen because it can form an optimal decision boundary with a maximum margin, thereby producing stable and accurate classification (Manajemen et al., 2018). The Radial Basis Function (RBF) kernel is used because it is effective at handling nonlinear data and capable of modeling complex relationships among features extracted by CNNs. The SVM is trained on features from the training data, and the test data is used to evaluate the model's generalization ability for classifying mango ripeness levels. This CNN–SVM hybrid approach aims to combine the advantages of CNNs for automatic feature extraction and SVMs for margin-based classification (Roza et al., n.d.).

2.6. Model Performance Evaluation and Analysis

The performance of the CNN and CNN–SVM models was evaluated using accuracy, precision, recall, and F1-score metrics. In addition, a confusion matrix was used to analyze the distribution of classification errors across each mango ripeness class (Arkadia et al., 2021). The evaluation results of both methods were compared to assess differences in classification performance and the models' ability to distinguish between maturity classes with similar visual characteristics. This analysis served as the basis for determining the most effective and applicable classification approach for developing a digital image based mango ripeness sorting system (Hidayat, 2022).

3. Results and Discussion

3.1 Research Results

3.1.1 Dataset and Class Distribution

The dataset used in this study comprises 198 mango images divided into three maturity classes: rotten, ripe, and unripe. This classification is based on visual characteristics arising from physiological changes during mango ripening, particularly changes in skin color, brightness level, and indications of fruit surface texture (Arkadia et al., 2021). The relatively balanced distribution of data across classes provides favorable conditions for the model's learning process, as it reduces the potential for bias toward certain classes and allows the model to learn each class's visual patterns proportionally (Manajemen et al., 2018). This condition is important in multi-class classification, especially for mango images that exhibit gradual visual differences across ripeness levels (Hidayat, 2022).

Table 1 Mango Classification

Rotten Mangoes	198
Ripe Mangoes	198
Young Mangoes	198

Based on the table, all images were successfully loaded and classified according to their class labels. This indicates that the dataset has been well prepared and is suitable for training and testing machine learning-based classification models (Arkadia et al., 2021).

3.1.2 Architecture and Training Process of the CNN Model

The Convolutional Neural Network (CNN) model used in this study consisted of three convolutional layers, each with 32, 64, and 128 filters. This multi-layered approach allows the model to extract visual features hierarchically, from simple patterns such as edges and color gradations to more complex ones, including combinations of texture and color on the surface of mango fruit (Hidayat, 2022). The CNN model has 3,305,027 trainable parameters, reflecting its capacity to learn visual representations of mango fruit ripeness. This number of parameters is considered adequate for a medium-sized dataset, as it is large enough to capture data variation while still manageable to reduce the risk of overfitting (Roza et al., n.d.).

Table 2 Model Architecture

Layer (type)	Output Shape	Param #
Conv2d_6 (Conv2D)	(None, 126, 126, 32)	896
Max_pooling2d_6 (MaxPooling2D)	(None, 63, 63, 32)	0
Conv2d_7 (Conv2D)	(None, 61, 61, 64)	18,496
Max_pooling2d_7 (MaxPooling2D)	(None, 30, 30, 64)	0
Conv2d_8 (Conv2D)	(None, 28, 28, 128)	73,856
Max_pooling2d_8 (MaxPooling2D)	(None, 14, 14, 128)	0
Flatten_3 (Flatten)	(None, 25088)	0
Dense_6 (Dense)	(None, 128)	3,211,392
Dense_7 (Dense)	(None, 3)	387

The CNN was trained for 10 epochs using both training and validation data. The training results showed a consistent increase in accuracy and a decrease in loss across both the training and validation data.

```
Epoch 1/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 80s 6s/step - accuracy: 0.3799 - loss: 1.3972 - val_accuracy: 0.5960 - val_loss: 1.0769
Epoch 2/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 15s 1s/step - accuracy: 0.4958 - loss: 1.0608 - val_accuracy: 0.4192 - val_loss: 1.0997
Epoch 3/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 24s 1s/step - accuracy: 0.4948 - loss: 0.9754 - val_accuracy: 0.5859 - val_loss: 0.9020
Epoch 4/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 13s 1s/step - accuracy: 0.5808 - loss: 0.8407 - val_accuracy: 0.7172 - val_loss: 0.6872
Epoch 5/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 13s 1s/step - accuracy: 0.6972 - loss: 0.6954 - val_accuracy: 0.7929 - val_loss: 0.5928
Epoch 6/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 13s 1s/step - accuracy: 0.7392 - loss: 0.6413 - val_accuracy: 0.9040 - val_loss: 0.4624
Epoch 7/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 15s 1s/step - accuracy: 0.8375 - loss: 0.4524 - val_accuracy: 0.9444 - val_loss: 0.2843
Epoch 8/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 18s 1s/step - accuracy: 0.9024 - loss: 0.3219 - val_accuracy: 0.9192 - val_loss: 0.2276
Epoch 9/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 13s 1s/step - accuracy: 0.8609 - loss: 0.2881 - val_accuracy: 0.9798 - val_loss: 0.1558
Epoch 10/10
13/13 ━━━━━━━━━━━━━━━━━━━━ 13s 1s/step - accuracy: 0.9638 - loss: 0.1595 - val_accuracy: 0.9747 - val_loss: 0.1112
```

Figure 1 Training Progress per Epoch

Based on the figure above, the model shows a gradual increase in classification accuracy, reaching 96.38% on the training set and 97.47% on the validation set. The small difference in accuracy between the training and validation data indicates that the model has good generalization ability and does not exhibit significant overfitting (Hidayat, 2022).

3.1.3 Classification Results Using the SVM–CNN Approach

After CNN training was complete, the model was used as a feature extractor, taking the dense layer output before the classification layer. This approach allows the use of high-level visual features learned by CNNs, which are more discriminative than manually extracted features (Arkadia et al., 2021). The extracted features were then classified using a Support Vector Machine (SVM) with Radial Basis Function (RBF) kernel. This kernel was chosen because it is effective at handling nonlinear data and can form optimal decision boundaries in high dimensional feature spaces (Roza et al., n.d.). The test results show that the SVM–CNN approach produces an overall accuracy of 99%, reflecting very high classification performance.

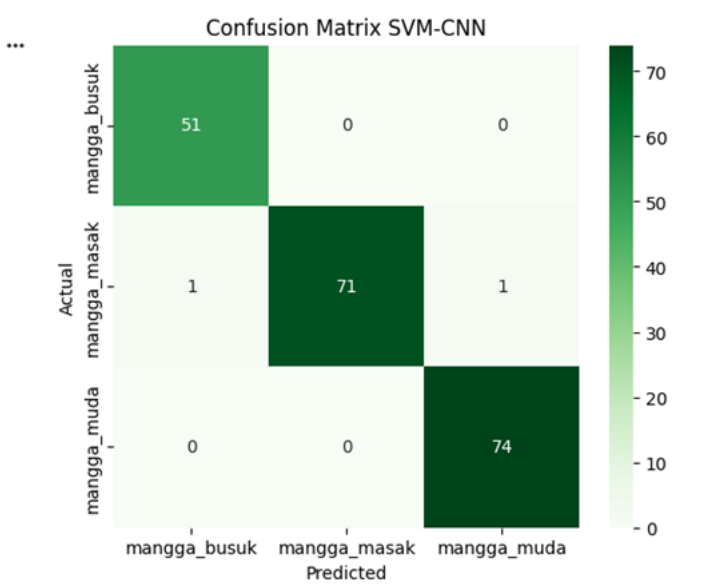

Figure 2: Confusion Matrix for SVM-CNN

	precision	recall	f1-score	support
mangga_busuk	0.98	1.00	0.99	51
mangga_masak	1.00	0.97	0.99	73
mangga_muda	0.99	1.00	0.99	74
accuracy			0.99	198
macro avg	0.99	0.99	0.99	198
weighted avg	0.99	0.99	0.99	198

Figure 3 Classification Report

Based on the image above, almost all images in each class were classified correctly. The mangga_busuk and mangga_muda classes show perfect classification results, while the mangga_masak class only experienced one classification error. Precision, recall, and F1-score values in the range of 0.98–1.00 indicate that the model has a very high level of accuracy and consistency (Arkadia et al., 2021).

3.2 Discussion (Revised Source & Year)

3.2.1 Analysis of CNN Performance in Mango Ripeness Classification

The results of the CNN training show that the architecture used is capable of effectively learning the visual patterns of mango ripeness levels. The CNN's ability to recognize changes in skin color and surface texture is a major factor in distinguishing ripeness classes, as shown in previous CNN-based mango classification studies (Arkadia et al., 2021). The stable increase in accuracy and decrease in loss values during the training process indicate that the CNN architecture configuration, image input size, and pre-processing strategy used are appropriate for the characteristics of the research dataset (Hidayat, 2022).

3.2.2 Advantages of the Hybrid SVM–CNN Approach

The SVM–CNN hybrid approach shows superior performance compared to CNN as a direct classifier. This indicates that the high-level features extracted by CNN are highly representative, enabling SVM to form more optimal decision boundaries between mango ripeness classes (Manajemen et al., 2018). The main advantage of this approach lies in the combination of CNNs' ability to extract complex features and SVMs' ability to produce maximum-margin classification. This approach is particularly effective on relatively limited datasets, as demonstrated in research on CNN–SVM-based agricultural image classification (Roza et al., n.d.).

3.2.3 Implications and Potential Applications of the System

The results of this study indicate that the CNN–SVM-based mango ripeness classification system has great potential for application in automatic fruit sorting systems. The high level of accuracy and minimal classification errors allow this system to improve efficiency, consistency, and objectivity in assessing mango quality in the agricultural and post-harvest industries (Hidayat, 2022).

4. CONCLUSION

Based on the research and discussions conducted, it can be concluded that classifying mango ripeness levels from digital images using a Convolutional Neural Network (CNN) and a combination of CNN–Support Vector Machine (SVM) provides excellent classification performance. CNNs have proven effective at extracting important visual features that represent changes in color, brightness, and texture of mango skin, serving as key indicators of ripeness. The CNN training results show a consistent improvement in accuracy on the training and validation data, with relatively small differences in performance. This indicates that the model generalizes well and does not overfit. Given the architecture, the CNN can learn a hierarchical, effective visual representation of mango ripeness.

Using a CNN as a feature extractor combined with the Support Vector Machine (SVM) yields better classification performance. The CNN–SVM hybrid approach achieves a very high accuracy of 99%, with precision, recall, and F1 scores that are close to perfect across all maturity classes. This shows that the high-level features extracted by the CNN are highly discriminative and can be optimally utilized by the SVM to form decision boundaries between classes. Minimal classification errors, particularly in the ripe mango class, indicate that the model successfully captured most of the visual differences between classes, although challenges remain in classes with closely related visual characteristics. Nevertheless, overall, the system demonstrated a high level of reliability and stability.Thus, it can be concluded that the CNN–SVM approach is an effective and promising method for application in an automated mango ripeness sorting system. This method has great potential to support the development of smart agricultural technology, particularly in improving the efficiency, consistency, and objectivity of mango quality assessment in the post-harvest stage.

REFERENCES

Arkadia, A., Damayanti, S. A., & Prasvita, D. S. (2021). *Classification of Badami Mangoes to Determine Ripeness Levels Using the CNN Method*. (September), 158–165.

Buah, J., Berdasarkan, M., & Hsv, C. (2024). *Multidisciplinary Computer Journal*. *7*(12), 72–79.

Budi, E. S., Chan, A. N., Alda, P. P., Arif, M., & Idris, F. (2024). *Optimization of Machine Learning Models for Image Classification and Prediction Using the Convolutional Neural Network Algorithm*. *4*(5), 502–509.

Management, A., Dan, I., & Mdp, K. (2018). *Caltex Riau Polytechnic Journal*. *4*(1), 50–61.

Mutmainnah Muchtar, Rafiqah A. Muchtar. (n.d.). *Muchtar.pdf*.

Ngii, K. A., Isnansyah, G., & Saputra, R. A. (2023). *CLASSIFICATION OF MANGO LEAF IMAGES USING THE SUPPORT VECTOR MACHINE ALGORITHM*. *07*(03), 80–83.

Prasetya, W. A. (2024). *THESIS PROPOSAL USING THE CONVOLUTIONAL NEURAL NETWORK (CNN) METHOD*. 1–8.

Roza, Y. B., Salim, D. A., Ramadhanu, A., Informatika, M. T., Putra, U., & Yptk, I. (n.d.). *Optimization of Mango Quality and Ripeness Through Image Processing Using Median Filter*. *5*(4), 5589–5598.

Setiawan, A., Nursafitri, A., & Afnarista, E. V. (2022). *Classification of Mango Plant Diseases Using the CNN Algorithm on Leaf Images*.

Turnandes, Y., Abiyus, W., Irwanda, A. A., & Juliani, F. (2024). Penerapan metode Monte Carlo dalam memprediksi jumlah pengunjung perpustakaan Universitas Lancang Kuning. ZONAsi: Jurnal Sistem Informasi, 6(1), 136–143. https://doi.org/10.31849/zn.v6i1.17317

Yunefri, Y., Sutejo, Y. E., Fadrial, K. A., Ramadhani, M., & Hardianto, R. (2022). Implementation of object detection with you only look once algorithm in limited face-to-face times in pandemic. *Journal of Applied Engineering and Technological Science*, *4*(1), 400-404.