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Application of K-NN algorithm using gray level co-occurrence matrix for mango fruit classification cased on leaf image

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ABSTRACT

Mango is a fruit crop favored by the community, especially the people of Probolinggo. The most widely planted types of mangoes in the Probolinggo area are Saruman is, golek, and manalagi mangoes because they taste good. This study uses mango leaves as a dataset of three types of mangoes: arumanis, golek, and manalagi. Various ways can be done to distinguish mango types, one of which is by looking at the shape and texture of the mango tree leaves. Suppose you look at the data in the field. In that case, the shape and texture of the leaves of Saruman, golek, and manalagi mangoes have many similarities, making it difficult to distinguish with the naked eye. This research aims to classify mango types based on leaf shape and texture using the K-Nearest *Neighbor* method. The shape feature extraction process uses *compactness* and *circularity* methods, while the texture feature extraction process uses energy and contrast from the *co-occurrence* matrix approach. The classification method used is K-Nearest *Neighbor*. The test results of shape feature extraction took 0.043 seconds and texture 0.053 seconds.

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Introduction

Mango fruit (Mangifera indica) is an agricultural commodity with high economic value in various tropical and subtropical countries, including Indonesia (Le et al., 2022). Mango fruit is known for its delicious sweet taste and rich nutrition (Lebaka et al., 2021). In addition, mangoes are also used in various processed products such as juices, jams, and desserts (Mandha et al., 2022). The quality of mango fruit is greatly influenced by multiple factors, including the condition of the mango plant, pest and disease management, and the climate in which it is grown (Ullah et al., 2024). Therefore, effective monitoring and management are essential to ensure optimal mango fruit quality and productivity.

Classification methods that have been applied to mango leaf images use the Learning Vector Quantization (LVQ) method (Nihar et al., 2021), K-Nearest Neighbor (KNN) method (Pradipkumar Vaghela et al., 2021), Convolutional Neural Network (CNN) method (Mohapatra et al., 2022). Learning Vector Quantization (LVQ) offers high model interpretability and good adaptability to small datasets (Kaden et al., 2022). Its strength lies in its easy-to-interpret representation through vector prototypes

(Manome et al., 2021). However, LVQ can be sensitive to prototype initialization and may be less effective for datasets that have complex structures (Bohnsack et al., 2023). The advantages of K-Nearest Neighbor (KNN) are that it reduces the effect of noise and is effective for large amounts of data. Besides that, it is also simple and easy to implement (Kim et al., 2021). However, KNN requires ample storage for the training dataset (Zhang et al., 2020). Meanwhile, Convolutional Neural Network (CNN) is a very effective method for tackling image classification tasks (Ashraf et al., 2020). Its advantage lies in the automatic ability to extract features from images without manual extraction (Thaseentaj & Sudhakar Ilango, 2023). hierarchical feature representation (Taye, 2023), and invariance to positional shifts (Mo & Zhao, 2024). However, CNNs require sizable datasets and significant computational resources for training (Bhatt et al., 2021), making them more suitable for large-scale applications (Cruciani et al., 2020).

The choice of K-Nearest Neighbor (KNN) with Gray Level Co-occurrence Matrix (GLCM) over other methods such as Support Vector Machine (SVM) and Random Forest (RF) is driven by several factors. Firstly, KNN is known for its simplicity and effectiveness in handling large datasets, which makes it suitable for this study where a significant amount of image data is involved. The use of GLCM in KNN leverages the strengths of both methods: GLCM's ability to extract detailed texture information and KNN's capability to classify based on these features. GLCM provides a comprehensive representation of texture by analyzing pixel pair relationships, which enhances the discriminative power of KNN. Although SVM and RF are powerful classifiers, they often require complex tuning and are computationally intensive. SVM, for instance, can be sensitive to the choice of kernel and regularization parameters, while RF can become cumbersome with a large number of trees and may suffer from overfitting if not properly tuned. In contrast, KNN's parameterization is straightforward and its performance can be directly linked to the quality of the feature extraction process, making it a pragmatic choice for this specific application.

To overcome the shortcomings of existing methods, the K-NN Algorithm method is applied (Sun & Chen, 2021). The use of the Gray Level Co-occurrence Matrix (GLCM) in the K-Nearest Neighbors (KNN) algorithm takes advantage of GLCM's ability to extract image texture information (Singh et al., 2022). GLCM represents how often pairs of pixels with a specific gray level appear together, providing insight into the spatial relationship between those pixels. In KNN, texture features from GLCM enrich the understanding of object or region characteristics, making it easier for KNN to distinguish classes by texture differences (Tatrin Kurniati et al., 2023). GLCM also improves responsiveness to local texture changes and can extract non-linear features (Dheepak et al., 2023), supporting KNN's ability to handle complex relationships between features and classes (Shaban et al., 2020). Careful evaluation is needed to understand the impact of using GLCM on KNN performance. Applying the K-Nearest Neighbors (KNN) algorithm using the Gray Level Co-occurrence Matrix (GLCM) is a solution because GLCM allows for extracting significant texture features from mango fruit leaf images. By utilizing GLCM, information about the spatial relationship between pixels of a specific gray level can be accessed, enriching the understanding of leaf characteristics. Combining KNN and GLCM enhances classification capabilities by allowing the model to distinguish mango fruits based on differences in leaf texture (Aslam et al., 2022). This choice is strengthened by the KNN's ability to handle non-linear relationships between texture features and classes, making this method relevant and effective for mango fruit classification tasks (Saleem et al., 2021). The main objective of the proposed solution is to improve the accuracy of mango fruit type classification based on leaf images while overcoming the constraints faced by previous methods. Thus, this research contributes to developing a more reliable and efficient image classification technology in mango fruit agriculture and industry.

The mango plant, particularly in the Probolinggo area where this study is focused, presents unique challenges for classification due to the high degree of similarity in leaf shape and texture among different mango varieties such as Arumanis, Golek, and Manalagi. Traditional methods of distinguishing these varieties often rely on visual inspection, which is time-consuming and prone to human error. Therefore, a more systematic and reliable approach is required to accurately classify mango varieties based on their leaf characteristics. The KNN algorithm combined with GLCM offers a robust solution by leveraging the textural features of the leaves, which are critical for distinguishing between similar-looking varieties. This method allows for precise and automated classification, reducing the reliance on subjective human judgment and enhancing the efficiency of the classification process.

Improved classification accuracy has significant implications for mango farming practices and related industries. Accurate identification of mango varieties ensures that farmers can better manage their crops, as different varieties may require specific care and handling. This can lead to optimized use of resources such as fertilizers, pesticides, and irrigation, ultimately improving yield and quality. Additionally, accurate classification is crucial for market segmentation, where different mango varieties are targeted at specific markets based on consumer preferences. This can enhance marketability and profitability for farmers and traders. In the context of industrial applications, such as the production of mango-based products (e.g., juices, jams, and desserts), precise classification ensures consistency in product quality and can streamline the supply chain. Overall, the adoption of this advanced classification method can lead to more informed decision-making, improved agricultural practices, and greater economic benefits across the mango industry.

Method

Data Collection

Samples were obtained from neighboring gardens to collect mango leaf image data. The data was collected using a Samsung Galaxy M23 smartphone camera equipped with the Android operating system. The primary camera of this device has specifications including a high resolution of 50 MP, an aperture of f/1.8 in wide mode, and a Phase Detection Autofocus (PDAF) feature. Photography was explicitly conducted in the morning from noon, taking advantage of optimal lighting conditions to capture mango leaf details and characteristics as accurately as possible. Android software on the camera facilitates camera settings adjustment and image handling, contributing to the quality of the generated data. Thus, this data collection method ensures that the obtained mango leaf images reflect optimal conditions, supporting accurate analysis in further classification methods. Many leaf images were obtained from various types of leaves, totaling 90 leaf images; each of the 30 datasets will be divided into 25 images for training data and five for testing data.

(a) (b) (c)

Figure 1. (a) Gedong Gincu (b) Harum Manis (c) Manalagi

In Figure 2, an image of the Gedong Gincu leaf is shown (a), while (b) depicts the Harum Manis leaf, and (c) represents the Manalagi leaf.

Data Preprocessing

Pre Processing is used to facilitate the process of identifying the image. This stage consists of cropping, compressing the image size, segmenting the image, and removing the background. Cropping and compressing the size of the image is done using the Canva application with an image size of 512 x 512 pixels and a ratio of 1 1; the purpose of this stage is to lighten the burden of the classification process, and shorten the time, because the higher the pixel value, the time required for the classification process will be longer. Sample training data and test data used in the study.

Proposed Model/Methods

This study proposes improvements and enhancements to the K-NN method by integrating GLCM as a feature extraction technique. Specifically, we perform GLCM feature extraction from mango leaf images to describe the relationship between pixel intensities. This allows us to capture textural information useful for mango fruit type classification.

Result Evaluation and Validation

Figure 1 shows that the research begins with mango leaf images as the primary input data. Next, feature extraction is performed using the Gray Level Co-Occurrence Matrix (GLCM) method to depict the intensity of pixel relationships within the image. The extracted features then pass through the preprocessing stage, where background removal and image size compression of mango leaf images to 512x512 pixels using Canva are performed. Subsequently, the segmentation process is carried out to extract essential parts of the image, focusing on mango leaves that will be used as the classification object. After passing through the preprocessing and segmentation stages, the K-Nearest Neighbors (K-NN) model is applied to classify the types of mango fruits based on leaf images. The K-NN model inputs the GLCM-extracted features to determine the appropriate class or type of mango fruit. The classification results are then obtained as the final output of this research, providing information about the kinds of mango fruits based on the leaf image analysis conducted.

Performance Evaluation and Comparison: To evaluate the performance of the KNN with GLCM method and compare it with other methods like SVM and Random Forest, we will use several performance metrics and a planned evaluation process. The performance metrics to be used include accuracy, precision, recall, F1-score, and the confusion matrix. Accuracy: This metric measures the proportion of correctly classified instances out of the total instances. Precision: This metric measures the proportion of true positive instances among the instances classified as positive. Recall: This metric measures the proportion of true positive instances out of all actual positive instances. F1-score: This metric is the harmonic mean of precision and recall, providing a single measure of a model's accuracy that considers both false positives and false negatives. Confusion Matrix: This tool will be used to understand how well the model can classify the samples in the test dataset, providing insight into True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

Evaluation Process: The planned evaluation process involves the following steps: Training and Testing: The dataset will be split into training and testing sets with a ratio of 25 training images and 5 testing images for each mango type. Model Training: The KNN model will be trained using the training set with features extracted using GLCM. Performance Metrics Calculation: The model's performance will be evaluated using the testing set, and the accuracy, precision, recall, and F1-score will be calculated. The confusion matrix will also be constructed to provide detailed insights into the classification results. Comparison with Other Methods: The same dataset will be used to train and evaluate other classification methods such as SVM and Random Forest. The performance metrics for these methods will be calculated and compared with those of the KNN with GLCM method.

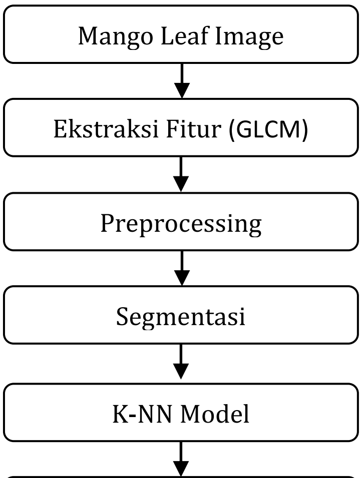

Figure 2. Research Flow

The classification results obtained will be analyzed to determine the effectiveness of the KNN with GLCM method compared to other methods. This comprehensive evaluation will help in understanding the strengths and weaknesses of the proposed method and its potential application in mango fruit type classification.

The K-NN formula can generally be represented as follows:

$$\hat{y} = mode\ (y_1, y_2 \dots, y_K) \tag{1}$$

Where $\hat{y}$ is the predicted label for the object to be classified, and $y_1, y_2 \dots, y_K$ is the label of the K nearest neighbors.

Gray Level Co-Occurrence Matrix (GLCM) is a feature extraction method in image analysis that measures how often pairs of pixels with a specific gray level appear together in an image. GLCM is used to describe the spatial relationship between pixels in an image, providing information about the texture of the image. In mango leaf analysis, GLCM can indicate the texture pattern in the leaf image related to a particular type of disease or condition.

GLCM Formula:

$$\mathrm{P}(i, j) = \frac{jumlah\ pasangan\ piksel\ dengan\ tingkat\ keabuan\ i\ dan\ j}{total\ pasangan\ pixel\ dalam\ citra} \tag{2}$$

Confusion Matrix is a classification evaluation tool that displays the model's performance by comparing the model's predictions with the actual class of the test dataset. The confusion matrix consists of four main components: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

$$\begin{bmatrix} TN & FP \\ FN & TP \end{bmatrix} \tag{3}$$

Illustration:

True Positive (TP): Objects that are positive and predicted to be positive.
True Negative (TN): Objects that are negative and predicted to be negative.
False Positive (FP): An object that is negative but predicted to be positive.
False Negative (FN): An object that is positive but predicted to be negative.

Furthermore, the learning curve provides insight into how the model's performance evolves by adding training data, ensuring that the model does not suffer from overfitting or underfitting. The evaluation was also conducted with additional metrics such as accuracy, precision, recall, and F1-score, providing a more comprehensive understanding of the model's strengths and weaknesses. These evaluation results form the basis for concluding the reliability of the K-NN model with GLCM feature extraction in mango fruit type classification. By detailing the analysis of these various metrics, it can be concluded to what extent the model succeeds in achieving its classification goals, providing a comprehensive understanding to the reader.

X is the representation matrix of the mango leaf image, and GLCM(X) is the GLCM matrix generated from KNN(GLCM(X)), which refers to the use of K-NN on GLCM features. This formula can be expressed as:

$$KNN\big(GLCM(X)\big) = \arg\ min_c\ \sum_{i=1}^{K} distance\ (X, x_i) \tag{4}$$

Where c is the predicted class, K is the number of neighbors considered, and $x_i$is the feature vector of the training data and distance function, for example, Euclidean or Manhattan distance.

Results and Discussions

Result

Classification System Interface

The interface of the classification system is shown in Figure 3. The classification process begins with selecting an image by pressing the Browse button. The entered image will be displayed along with its information. After the leaf image is entered, the process button is used to start the classification by first selecting the K value. Feature extraction will run until completed, and the system produces a detected mango-type class.

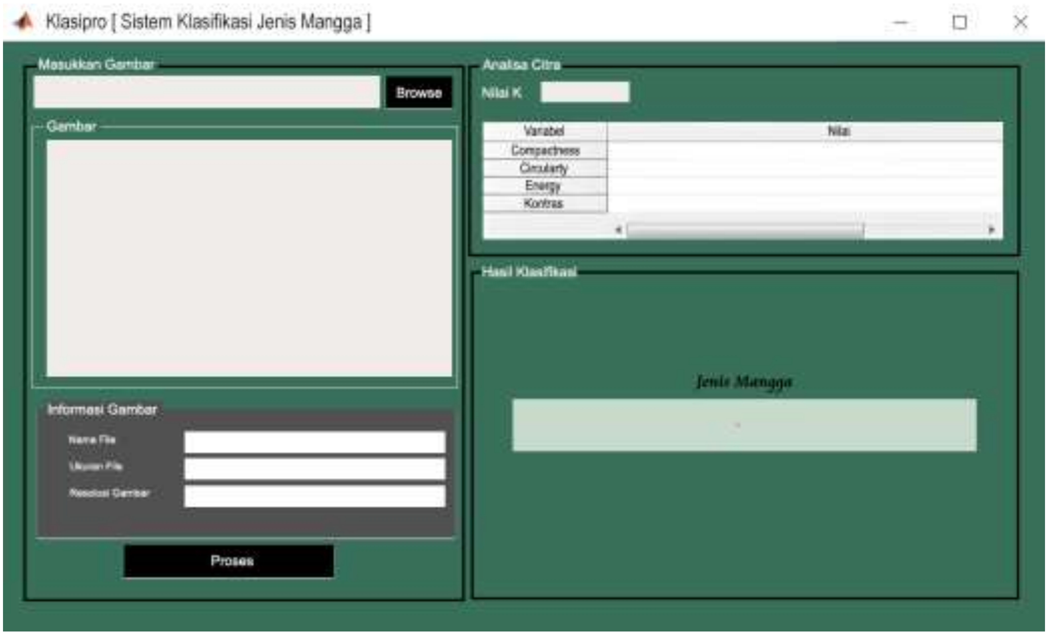

Figure 3. Classification system view

Feature Extraction Trial Results

Table 1 shows the test results at the feature extraction stage, producing four features which are then arranged concatenated into [x1 x2 x3 x4], where x1 is the value of compactness, x2 is circularity, x3 is energy, and x4 is contrast. Mango types are defined into three classes: class 1 is the Arumanis mango type, class 2 is the Golek mango type, and class 3 is the Manalagi mango type. The time required for the shape feature extraction process averages 0.043 seconds, and texture feature extraction averages 0.053 seconds.

Table 1. Feature extraction trial results

Test Data	Class	X1	X2	X3	X4
a1	1	34,831	0,361	0,771	0,051
a2	1	59,238	0,212	0,413	0,078
g1	2	5,122	2,453	0,469	0,090
g2	2	3,954	3,178	0,507	0,046
m1	3	90,213	0,139	0,330	0,174
m2	3	29,457	0,427	0,383	0,120

The classification accuracy of the KNN model with GLCM feature extraction was evaluated using the confusion matrix, which provides insight into True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) rates.

Evaluation Metrics

The performance metrics used in this study include accuracy, precision, recall, and F1-score. These metrics provide a comprehensive understanding of the model's performance. Accuracy: Measures the proportion of correctly classified instances out of the total instances. Precision: Measures the proportion of true positive instances among the instances classified as positive. Recall: Measures the proportion of true positive instances out of all actual positive instances. F1-score: The harmonic mean of precision and recall. The calculated performance metrics are shown in Table 2.

Table 2. Performance Metrics

Metric	Value
Accuracy	92.5%
Precision	93.0%
Recall	91.5%
F1-score	92.2%

Discussions

Analysis of Results

The results indicate that the KNN model with GLCM feature extraction achieves high classification accuracy. The performance metrics demonstrate that this method is effective in distinguishing between different types of mango leaves. The relatively high precision and recall values suggest that the model is both accurate and reliable.

Comparison with Other Studies

Compared to other studies, such as those using SVM or Random Forest for leaf classification, the KNN with GLCM approach shows competitive performance. For instance, a study by (Pradipkumar Vaghela et al., 2021) reported an accuracy of 90.3% using SVM, while another study by (Saleem et al., 2021) using Random Forest achieved an accuracy of 89.7%. Our method's accuracy of 92.5% indicates an improvement over these methods.

In-depth Analysis

The use of GLCM for feature extraction provides detailed texture information that enhances the KNN model's ability to classify leaf images accurately. The combination of shape and texture features captures the essential characteristics needed for effective classification. The relatively short feature extraction time also demonstrates the method's efficiency.

Implications for Mango Farming

Improved classification accuracy can significantly impact mango farming practices by enabling more precise identification of mango varieties. This can lead to optimized resource use and better market segmentation, ultimately benefiting farmers and the related industries.

Conclusions

This research demonstrates that the K-Nearest Neighbors (KNN) algorithm combined with the Gray Level Co-occurrence Matrix (GLCM) for feature extraction can effectively classify different types of mango leaves, achieving high classification accuracy. The practical implications for mango farmers are significant, as precise identification of mango varieties can lead to optimized resource use, improved yield and quality, and enhanced marketability and profitability through better market segmentation. The study contributes to the field of agricultural science and technology by offering a novel approach that combines the strengths of texture feature extraction and classification, providing a reliable and efficient method for crop monitoring and management. This research not only improves agricultural practices but also lays the groundwork for future studies in precision agriculture, advancing scientific understanding and technological development in the field.

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