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Comparative Analysis of CNN, SVM, Decision Tree, Random Forest, and KNN for Maize Leaf Disease Detection Using Color and Texture Feature Extraction

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Abstract

Corn (Zea mays L.) is an important agricultural commodity in Indonesia, serving as the second staple food after rice and playing a crucial role in supporting national food security. However, corn production is frequently threatened by sudden outbreaks of pests and diseases, making accurate early detection essential to maintaining yield stability. This study aims to detect maize leaf diseases using five classification algorithms: Support Vector Machine (SVM), Decision Tree, K-Nearest Neighbors (KNN), Random Forest, and Convolutional Neural Network (CNN). These algorithms were tested using a combination of texture and color features, including Gray Level Co-occurrence Matrix (GLCM), Local Binary Pattern (LBP), Hue-Saturation-Value (HSV), and L*a*b*. The dataset used consists of 2,048 maize leaf images classified into four categories: Blight, Common Rust, Gray Leaf Spot, and Healthy, with 512 images per class. Each class was divided into training and testing sets to train and evaluate the classification models. The results show that CNN achieved the highest accuracy of 93.93% when using a complete combination of color and texture features. Meanwhile, SVM also demonstrated high performance, achieving the same accuracy (93.93%) using only the combination of color features (HSV and Lab*). Random Forest and Decision Tree performed best when using color features alone, with accuracies of 89.81% and 87.14%, respectively. These findings indicate that color features have a dominant influence on classification accuracy, and that combining color and texture features can significantly enhance model performance, particularly in CNN architectures. This study contributes to the development of early disease detection systems in precision agriculture.

Keywords : *CNN, Corn Leaf Diseases, Decision Tree, KNN, Random Forest, SVM.*

1. INTRODUCTION

Corn (Zea mays L.) is one of the primary agricultural commodities widely cultivated in Indonesia. As the second staple food after rice, corn plays a vital role in supporting national food security [1]. Additionally, corn serves multiple functions in the national economy, including its use as animal feed and as a raw material in various industries [2]. Prior to the 1970s, local corn was even used as a staple food by parts of the Indonesian population [1]. However, corn production frequently faces numerous challenges, one of which is the sudden onset of pest and disease attacks. To this day, various efforts continue to be made to prevent and control pests and diseases that affect corn crops [3]. Accurate early detection of plant diseases is key to effective prevention and control efforts, thereby supporting the stability of national corn production.

The advancement of Artificial Intelligence (AI) and Machine Learning (ML) technologies offers innovative solutions in agriculture, particularly in the early and accurate detection of plant diseases. Image classification methods such as Support Vector Machine (SVM), Decision Tree, Random Forest, and Convolutional Neural Network (CNN) have been widely applied in plant disease detection systems based on digital imagery [4–6]. Singh et al applies the AlexNet Deep Learning model for automatic

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detection of maize leaf diseases. Using the PlantVillage dataset with two disease categories (Cercospora/Gray leaf spot and Common rust), the model achieved 99.16% accuracy. The results demonstrate the effectiveness of CNN in image feature extraction and its practical potential for early disease detection in maize plants [7]. Masood proposes MaizeNet, a Faster-RCNN model with ResNet-50 and spatial-channel attention, to detect four maize leaf diseases: Gray Leaf Spot, Northern Leaf Blight, Northern Leaf Spot, and Grey Leaf Spot. Tested on the Corn Disease and Severity dataset, the model achieved 97.89% accuracy and 0.94 mAP, showing high effectiveness under complex backgrounds and image distortions [8]. Kale et al developed an image-based plant disease detection system involving preprocessing, segmentation using K-Means, feature extraction, and classification with SVM, KNN, and Random Forest. The system classifies crop images into four categories: Leaf Scab, Leaf Black Rot, Leaf Cedar Rust, and Healthy Leaf. Evaluation results show that SVM outperformed the others with a precision of 0.86, recall of 0.85, and F1 score of 0.84. These findings indicate that SVM is the most accurate and consistent method for crop disease classification in this study [9]. This study aims to classify diseases and pests in corn plants using a Decision Tree model enhanced with fuzzy membership functions. The three identified diseases are Leaf Rust Disease, Downy Mildew Disease, and Leaf Blight Disease, while the three types of pest infestations include Locusta Pests, Spodoptera frugiperda Pests, and Heliotis armigera Pests. The integration of fuzzy curves such as S-growth, triangle, and S-shrinkage effectively addresses ambiguity in predictor variable discretization. The fuzzy model shows improved performance compared to the conventional Decision Tree, with the highest improvements observed in kappa (12.16%), recall (11.8%), and F1-score (9.71%) [10]. This study developed and compared Decision Tree and K-Nearest Neighbors (KNN) models for classifying coffee leaf diseases, using a dataset with four classes: No Disease, Miner, Phoma, and Rust. Cross-validation was used for training and testing. The Decision Tree outperformed KNN, achieving 98.20% accuracy, AUC 0.9879, and F1-score 0.9819, while KNN achieved 75.01% accuracy and F1-score 0.7485. These results indicate that Decision Tree is more effective for detecting coffee leaf diseases, though KNN may still be relevant depending on application needs [11]. Singh et al presents a novel approach for detecting maize diseases using Convolutional Neural Networks (CNNs) for feature extraction and Random Forest for classification. The model targets major maize diseases such as Maize Dwarf Mosaic Virus, Northern Corn Leaf Blight, Gibberella Ear Rot, and Grey Leaf Spot, which significantly reduce crop yields. A heterogeneous dataset of healthy and infected maize leaf images was augmented and preprocessed through zooming, rotation, and translation to enhance quality. Experimental results show that the combined CNN-Random Forest model effectively classifies multiple disease types, offering a reliable tool for early diagnosis and contributing to improved maize productivity [12]. This study classified three maize leaf diseases Leaf Blight, Common Rust, and Leaf Spot along with healthy leaves using a Convolutional Neural Network (CNN) model built with Keras on TensorFlow. Without requiring preprocessing or explicit feature extraction, the model processes 224×224 pixel images and achieved an accuracy of 98.56%. These results demonstrate the potential of CNNs to assist farmers and plant pathologists in accurately and efficiently diagnosing plant diseases, reducing the time and errors associated with manual detection [13].

However, although various studies have explored different classification algorithms and feature extraction techniques, there has been no research comparing the CNN classification method results with the GLCM, HSV, and L*a*b* features individually, or the combination of two features such as HSV and L*a*b*, GLCM and HSV, and GLCM and L*a*b* for disease detection in corn. Most studies focus on a single feature, so there is no comprehensive study that compares and combines multiple features, particularly in the context of disease detection in corn. Additionally, while deep learning models such as CNN have been used in several studies, the use of transfer learning and the combination of GLCM, HSV, and L*a*b* feature extraction for corn disease detection remains limited. Therefore, this research

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focuses on a comparative exploration of GLCM, HSV, and L*a*b* feature extraction, and how these three features can improve the accuracy of disease detection in corn, particularly for Blight, Common Rust, and Gray Spot diseases. This study uniquely addresses the gap by comparing combined color and texture features across multiple classifiers for maize disease detection.

2. METHOD

This study aims to classify diseases in corn leaves using five classification algorithms: Convolutional Neural Network (CNN), Support Vector Machine (SVM), Random Forest, K-Nearest Neighbors (KNN), and Decision Tree. The selection of these five algorithms is intended to allow a comprehensive comparison in terms of accuracy and performance. The corn leaf images used in this study first undergo preprocessing steps, such as image resizing and color conversion. Following this, features are extracted from the images using four main methods: Gray Level Co-Occurrence Matrix (GLCM) to capture texture characteristics, HSV (Hue, Saturation, Value) and Lab* to extract color information from two different color spaces, and Local Binary Pattern (LBP) to capture micro-texture patterns on the leaf surface. These four feature extraction methods are applied both individually and in combination to assess the impact of feature types on classification accuracy. The extracted features are then input into each classification model for performance evaluation. CNN is utilized due to its capability in processing image data deeply, while SVM, KNN, Decision Tree, and Random Forest serve as benchmarks representing more traditional machine learning approaches. Each algorithm has distinct characteristics, making them worthy of further analysis in the context of corn leaf disease detection.

All processing and implementation are carried out using Python 3.11, supported by libraries such as TensorFlow, scikit-learn, OpenCV, and NumPy. The objective of this study is to determine the optimal combination of feature extraction methods and classification algorithms that yields the best performance in detecting and classifying corn leaf diseases. Evaluation is conducted using a confusion matrix and performance metrics including accuracy, precision, recall, and F1-score, to ensure the resulting model is reliable and applicable for supporting automated detection systems in agriculture. The methodological steps implemented in this study are illustrated in Figure 1 below.

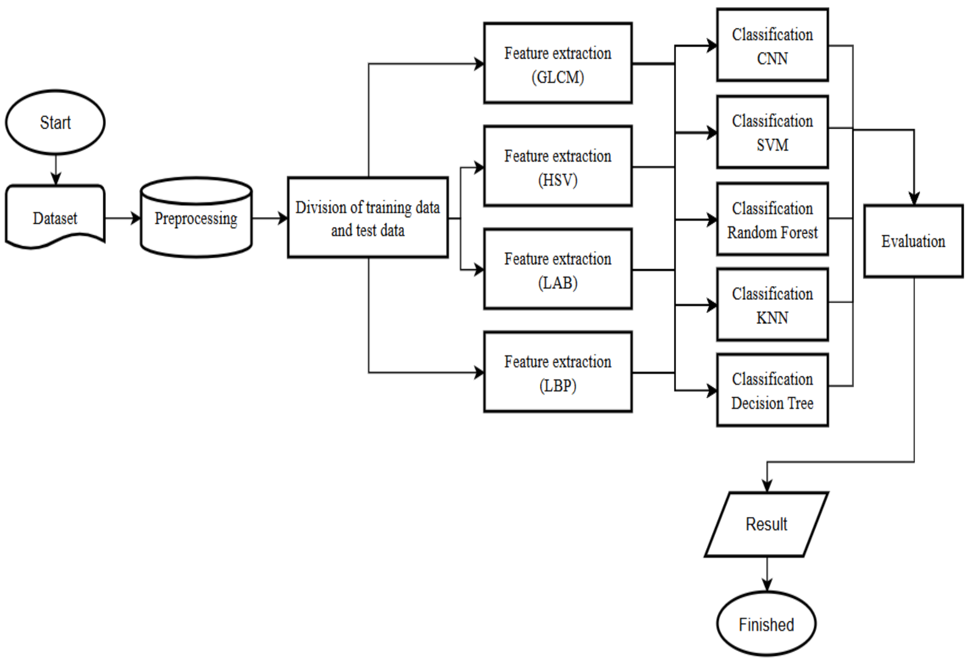

Figure 1. Methodological Framework of the Study

The methodological approach adopted in this study is described in detail as follows:

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2.1. Data Collection

In this study, a total of 2,048 corn leaf images were used, categorized into four classes: Blight, Common Rust, Gray Leaf Spot, and Healthy, with each class consisting of 512 images. The data in each class were then divided into training and testing sets. A total of 409 images were used to train the model, while 103 images were used to evaluate the model's performance. This data split is intended to enable the model to better recognize patterns and characteristics of each disease type as well as healthy leaf conditions. Sample images from each category are shown in Figure 2 below.

Blight Common Rust Gray spot Healthy

Figure 2. Representative examples from each category

2.2 Preprocessing

At the pre-processing stage, the original images were resized and their dimensions standardized. Resize is the process of changing the original image size, either by reducing or enlarging its scale, so that all images have uniform dimensions [14]. To ensure more efficient classification, the images were resized to 256 x 256 pixels [15]. The purpose of this resizing is to standardize the image dimensions, thereby facilitating subsequent processing steps such as feature extraction and model training. With consistent image sizes, the algorithms can operate more effectively, resulting in improved classification accuracy. The preprocessing process was applied uniformly across all models to maintain the validity of the comparison.

2.2. Feature Extraction

In the feature extraction stage of this study, four different methods were used to analyze the texture and color of corn leaf images, namely Gray Level Co-Occurrence Matrix (GLCM), Hue Saturation Value (HSV), Lab*, and Local Binary Pattern (LBP). Each method employs a distinct approach to capture characteristic features of the leaves related to diseases. After extracting features using these four methods, the results were evaluated with five classification algorithms: Convolutional Neural Network (CNN), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, and Random Forest. The objective was to compare the performance of these algorithms in accurately recognizing and classifying corn leaf diseases based on the extracted features.

2.2.1. GLCM (Gray Level Co-Occurrence Matrix)

The Gray Level Co-Occurrence Matrix (GLCM) is an analytical method used to extract texture information from an image by evaluating the spatial relationships between neighboring pixels [16]. This method is employed to describe the patterns and structural textures within an image. The following is a description of several features derived from the GLCM method that are utilized in this study [17].

a. Contrast: To assess the extent of variation and differences in gray levels between the reference pixel and its surrounding pixels. The equation used for this calculation is as follows:

$$\sum_{n=0}^{n_g-1}|i-j|^2 * \left\{\sum_{i=0}^{n_g-1}\sum_{j=0}^{n_g} p_{d,\theta}(i,j)\right\} \quad (1)$$

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b. Dissimilarity: To evaluate the level of texture irregularity in the image. The value will be high if the texture pattern is random, and low if the pattern is uniform or consistent. The dissimilarity is computed using the formula below:

$$\sum_{i,j=0}^{n-1} p_{i,j} |i-j| \qquad (2)$$

c. Homogeneity: To assess how uniform or consistent the texture is in a local area of an image.

$$\sum_{i=0}^{n_g-1} \sum_{j=0}^{n_g-1} \left(\frac{1}{1+(i-j)^2}\right) * (p_{d,\theta}\,(i,j)) \qquad (3)$$

d. Energy: To assess the level of pixel value similarity across the entire image. Calculation is carried out using the equation below:

$$\sum_{i=0}^{n_g-1} \sum_{j=0}^{n_g-1} p_{d,\theta}\,(i,j)^2 \qquad (4)$$

e. Correlation: Indicates the linear relationship between the gray level of the reference pixel and the surrounding pixels within the image matrix. This calculation is carried out using the following formula:

$$\sum_{i=0}^{n_g-1} \sum_{j=0}^{n_g} p_{d,\theta}\,(i,j) * \frac{(i-\mu_x)(i-\mu_y)}{\sigma_x \sigma_y} \qquad (5)$$

Illustrative values for each feature are shown in Table 1:

Table 1. Sample Results of GLCM Feature Extraction using angle 0°

Class	contrast	dissimilarity	homogeneity	energy	correlation
Blight	348.5590699	11.87833725	0.206099549	0.000272102	11822.40819
Common Rust	561.1637376	11.04805916	0.537029611	0.21269989	9261.566972
Gray Spot	551.0223761	16.91094062	0.144116113	0.000190132	11329.16513
Health	129.4918028	7.809531868	0.236306835	0.000468967	19960.08934

2.2.2. HSV (Hue, Saturation, Value)

The HSV (Hue, Saturation, Value) color space is a color representation model widely utilized in image processing and computer vision tasks, especially in agricultural applications such as plant disease detection. It comprises three key components: Hue, which indicates the color type and is typically measured in degrees from 0 to 360; Saturation, which represents the color's purity or intensity, where higher saturation corresponds to more vivid and distinct colors; and Value, which measures the brightness or luminance of a color, indicating how light or dark it appears. Compared to the traditional RGB model, HSV offers a more intuitive representation of color, closely aligned with human visual perception, making it particularly suitable for visual analysis tasks. In the context of identifying diseased areas on plant leaves, the original RGB images are converted into HSV color space to enhance the contrast between healthy and infected regions. This transformation facilitates more effective extraction, segmentation, and analysis of image features relevant to disease symptoms such as discoloration or spotting. Consequently, the HSV model plays a critical role in improving the accuracy and efficiency of automated plant disease detection systems. The conversion process from RGB to HSV can be calculated using the following formulas below [18].

$$r = \frac{R}{(R+G+B)}, \quad g = \frac{G}{(R+G+B)}, \quad b = \frac{B}{(R+G+B)} \qquad (6)$$

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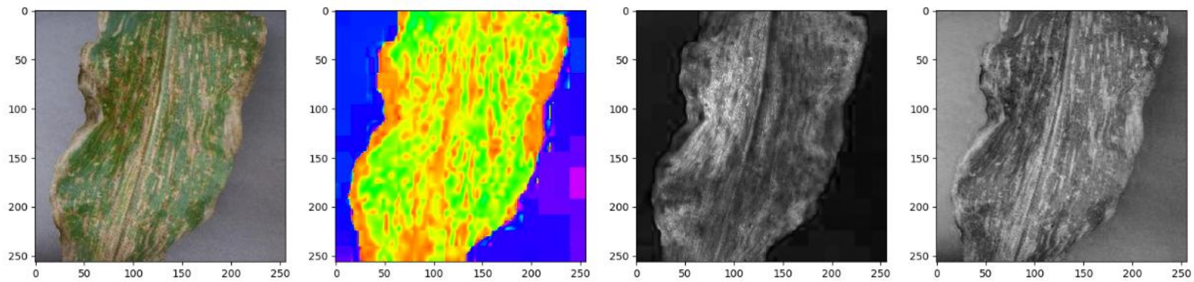
$$V = \max\ (r, g, b) \tag{7}$$

$$S = \begin{cases} 0 & , if\ V = 0 \\ v - \frac{\min(r,g,b)}{V}, & if\ V > 0 \end{cases} \tag{8}$$

$$f(x) = \begin{cases} 0, & if\ S = 0 \\ \left(\frac{60 * g - b}{S * V}\right), & if\ V = r \\ 60 * \left(2 + \frac{b - r}{S * V}\right), & if\ V = g \\ 60 * \left(4 + \frac{r - g}{S * V}\right), & if\ V = b \end{cases} \tag{9}$$

$$H = H + 360\ jika\ H < 0 \tag{10}$$

An illustration of the RGB image of corn leaves after conversion to the HSV color space is presented in Figure 3 below:

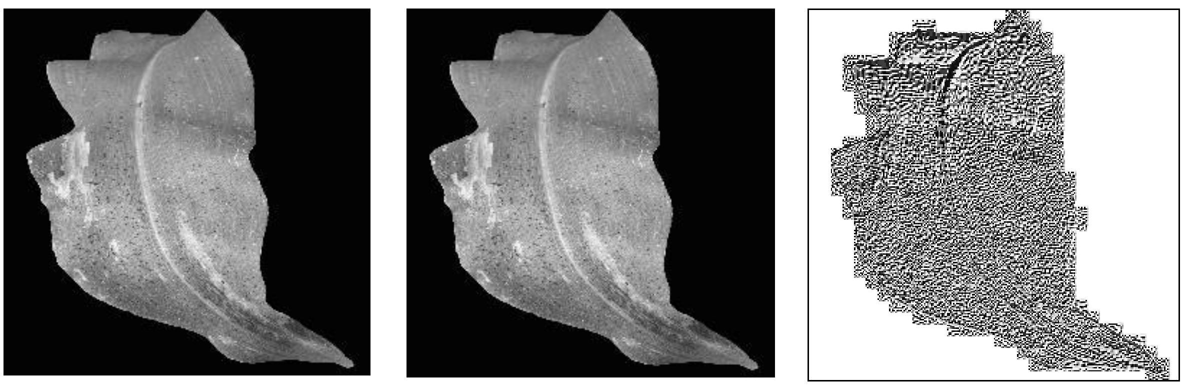


RGB Image Hue Saturation Value

Figure 3. Transformation of RGB Images into HSV Color Space for Feature Extraction.

2.2.3. LBP (Local Binary Pattern)

Local Binary Pattern (LBP) is one of the methods used to recognize texture patterns on infected leaves. This method has been proven effective in extracting texture features and demonstrates strong robustness against variations in lighting and image noise [19]. The Local Binary Pattern (LBP) feature produces numerical values ranging from 0 to 255 for each pixel in the image. By utilizing an LBP histogram with 256 bins, the final feature takes the form of a vector with 256 columns, where each column represents the frequency of occurrence of a specific LBP pattern within the image.



Grayscale Resize LBP

Figure 4. Grayscale to LBP Conversion Process for Enhanced Feature Extraction

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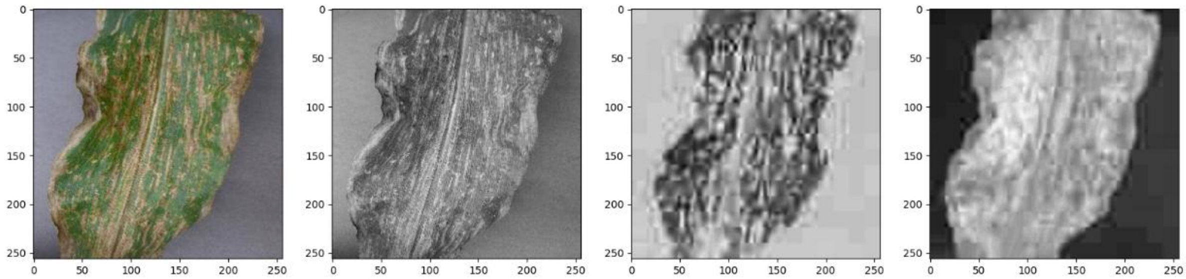
2.2.4. L*a*b*

The L*a*b* color space is a perceptually uniform color model commonly used in digital image analysis, comprising three components: L*, which represents luminance or brightness; a*, which encodes the chromaticity between red and green; and b*, which captures the chromaticity between yellow and blue. The a*and b* components are positioned as opposing axes within the color spectrum, allowing for a more accurate representation of color differences [20]. In the present study, a total of nine color features were extracted from the Lab* space, including the mean, standard deviation, and skewness of each individual channel (L*, a*, and b*). These statistical features are employed to capture comprehensive color information that is robust to lighting variations, thereby enhancing the reliability of the disease classification process in corn leaf analysis. The transformation of an RGB image of corn leaves into the L*a*b* color space is depicted in Figure 5:



RGB Image L* a* b*

Figure 5. Extraction of Color Features via RGB to L*a*b* Image Conversion

2.3. Classification

This study, five widely recognized and effective classification algorithms in the field of image processing were employed for the detection of diseases in corn leaves. Each method offers unique strengths and utilizes different approaches in feature processing and class determination. A brief overview of the five classification techniques implemented in this research is presented below:

2.3.1. CNN (Convolutional Neural Netrwork)

Convolutional Neural Network (CNN) is a type of artificial neural network specifically designed to recognize visual patterns and effectively process image data. The main structure of CNN consists of several key layers, including convolutional layers, pooling layers, activation function layers, and fully connected layers. Each layer plays a specific role in feature extraction, dimensionality reduction, introducing non-linearity, and connecting the extracted features to the final classification process comprehensively diseases [21]. In this study, a CNN model with three consecutive convolutional layers accompanied by pooling layers was used to extract features from corn leaf image data reshaped into a (6,1) format. The extracted features were then processed through several dense layers with ReLU activation functions and dropout to reduce overfitting, followed by a softmax output layer for classification into four disease classes. The model was compiled using the Adam optimizer and sparse categorical cross-entropy loss function, trained for up to 50 epochs with EarlyStopping and ModelCheckpoint techniques applied to achieve optimal performance. Evaluation results demonstrated high accuracy in classifying corn leaf

2.3.2. SVM (Support Vector Machine)

Support Vector Machine (SVM) is a classification method frequently applied in pattern recognition for images. SVM belongs to the supervised learning algorithms capable of grouping data into two classes (binary classification) or more than two classes (multiclass classification) [22]. It is a

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machine learning technique based on the principle of Structural Risk Minimization (SRM), aiming to find the optimal hyperplane that maximally separates two classes in the input space. SVM determines the optimal hyperplane by utilizing support vectors from each class, thereby achieving maximum separation between the classes. In this study, the SVM model employs a Radial Basis Function (RBF) kernel with parameters C = 1, gamma = 'scale', and applies feature standardization using StandardScaler to enhance the model's performance.

2.3.3. KNN (K-Nearest Neighbors)

K-Nearest Neighbor (KNN) is an algorithm used to classify or predict the value of new data by assessing its similarity to existing data points. The algorithm identifies a set number of closest neighbors (K) to the new data based on a distance metric, then assigns a class or value based on the majority among those neighbors. KNN is a simple yet effective method, especially useful in pattern recognition and data analysis [23]. To calculate the proximity between data points, the K-Nearest Neighbor (K-NN) algorithm uses the Euclidean Distance formula, which is defined as follows:

$$Euclidean\ Distance = d_{(x,y)} = \sqrt{\sum_{i=1}^{p}(x_i - y_i)^2} (11)$$

2.3.4. Decision Tree

Decision Tree is a widely used algorithm for both classification and prediction tasks, where decisions and their possible outcomes are represented in a tree-like structure. Each node contains a decision rule based on feature values, and branches represent the outcomes of these rules, allowing the model to recursively split the data into increasingly homogeneous subsets. This method is easy to understand, effective for various types of data, and capable of producing accurate predictions through a simple and interpretable analysis process [24]. In this study, the Decision Tree model was applied to classify corn leaf diseases, with the max_depth parameter set to 6. This depth limit was determined through a trial and error process to achieve the optimal balance between model complexity and generalization capability. Setting an appropriate tree depth is crucial, as a tree that is too shallow may underfit the data, while one that is too deep may lead to overfitting. The use of max_depth = 6 in this study ensured sufficient model depth to capture meaningful patterns in the data while maintaining robustness and avoiding over-complexity.

2.3.5. Random Forest

Random Forest Classifier is a supervised learning algorithm that can be applied to both classification and regression tasks. It operates by constructing multiple decision trees, and the more trees it builds, the stronger and more reliable the model becomes. One of its main advantages is the ability to minimize the risk of overfitting and to achieve high prediction accuracy, even when dealing with missing values in the dataset [25]. In general, Random Forest operates by constructing a collection of decision trees to perform classification or regression tasks. The algorithm begins by generating multiple random samples from the original dataset using bootstrap sampling (sampling with replacement). For each tree, only a random subset of features is considered when determining the best split at each node. This randomness results in diverse tree structures within the forest. During prediction, each tree makes an individual prediction, and the final output is determined by majority voting (for classification) or averaging (for regression). By aggregating the predictions of multiple trees, Random Forest effectively reduces overfitting, improves accuracy, and produces more robust and reliable results compared to a single decision tree. In this study, the number of trees parameter (n_estimators) was tested with values of 50 and 100 through a trial-and-error process. The best results were achieved when using 100 trees, and therefore, this value was selected for the final model.

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2.4. Model Evaluation

To evaluate the performance of the classification models in this study, several standard evaluation metrics were employed, namely accuracy, precision, recall, and the F1-Score. These metrics collectively provide a comprehensive assessment of the model's ability to accurately classify corn leaf diseases. The formula for accuracy is presented in Equation 11, while precision is calculated as shown in Equation 12. The computation of recall is detailed in Equation 13, and the formula for the F1-Score is provided in Equation 14 [26].

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{12}$$

$$precision = \frac{TP}{TP+FP} \tag{13}$$

$$recall = \frac{TP}{TP+FN} \tag{14}$$

$$F1 - Score = 2x\frac{Precision\ x\ Recall}{Precision+\ Recall} \tag{15}$$

True Positives (TP) represent instances where the model correctly predicts the positive class. True Negatives (TN) refer to cases where the model accurately identifies the negative class. In contrast, False Positives (FP) occur when the model incorrectly classifies a negative instance as positive, while False Negatives (FN) arise when a positive instance is mistakenly predicted as negative[28].

3. RESULT

This study aims to evaluate and compare the performance of five classification algorithms Support Vector Machine (SVM), Decision Tree, K-Nearest Neighbors (KNN), Random Forest, and Convolutional Neural Network (CNN) in detecting and classifying maize leaf diseases. The evaluation is based on four metrics: accuracy, precision, recall, and F1-score. All five algorithms are tested using a combination of texture features (GLCM and LBP) and color features (HSV and L*a*b*) to determine the effect of feature combination on classification performance. The following are the results of testing using the CNN method with a combination of features

Table 2. CNN classification results using various features

Feature	Accuracy	Precision	Recall	F1-Score
GLCM 0°	77.91	0.8079	0.7791	0.7932
HSV	90.05	0.9023	0.9005	0.8994
LBP	85.44	0.8559	0.8544	0.8552
L*a*b*	92.23	0.9228	0.9223	0.9217
HSV + LAB	90.78	0.9074	0.9078	0.9076
GLCM 0° + LBP	88.83	0.9016	0.8884	0.8876
GLCM 0° + HSV + LAB + LBP	93.93	0.9403	0.9393	0.9390

Based on the results presented in Table 2, the performance of the Convolutional Neural Network (CNN) in classifying maize leaf diseases varies significantly depending on the type of features used. Color features demonstrate superior performance compared to texture features. Among the individual features, the L*a*b* color space yields the highest accuracy of 92.23%, followed by HSV with an accuracy of 90.05%. In contrast, texture features such as LBP and GLCM 0° achieve lower accuracies of 85.44% and 77.91%, respectively. However, when features are combined, the classification performance improves notably. The combination of HSV and L*a*b* increases accuracy to 90.78%,

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while the combination of GLCM 0° and LBP achieves 88.83%, indicating that merging texture descriptors can enhance classification accuracy compared to using them individually. The highest performance is attained through the comprehensive combination of GLCM 0°, HSV, L*a*b*, and LBP, resulting in an accuracy of 93.93%, precision of 0.9403, recall of 0.9393, and an F1-score of 0.9390. These findings indicate that integrating both color and texture features provides complementary information, significantly enhancing the CNN model's ability to accurately classify maize leaf diseases.The classification performance of the SVM algorithm with different feature sets is presented in Table 3 below.

Table 3. SVM classification outcomes based on various features

Feature	Accuracy	Precision	Recall	F1-Score
GLCM 0°	79.13	0.8128	0.7913	0.8019
HSV	91.26	0.9124	0.9126	0.9125
LBP	84.95	0.8521	0.8495	0.8508
L*a*b*	92.48	0.9256	0.9248	0.9252
HSV + LAB	93.93	0.9391	0.9393	0.9392
GLCM 0° + LBP	89.81	0.9013	0.8981	0.8997
GLCM 0° + HSV + LAB + LBP	92.23	0.9255	0.9223	0.9239

Table 3 presents the classification results of the Support Vector Machine (SVM) algorithm using various feature sets. Color features, particularly L*a*b*, achieve the highest accuracy among individual features at 92.48%, followed by HSV with an accuracy of 91.26%. In contrast, texture features such as LBP and GLCM 0° yield lower accuracies of 84.95% and 79.13%, respectively. Combining features generally improves classification performance, with the HSV + L*a*b* combination achieving the highest overall accuracy of 93.93%. The texture feature combination GLCM 0° + LBP also shows improvement, reaching an accuracy of 89.81%. However, the full combination of texture and color features (GLCM 0°, HSV, L*a*b*, and LBP) results in an accuracy of 92.23%, slightly lower than the color-only combination but still maintaining high precision, recall, and F1-score values. This indicates that while feature combination can enhance performance, adding too many features does not always guarantee the best results for SVM classification.

The following table illustrates how the Decision Tree performs with different types of features.

Table 4. Classification results of the Decision Tree algorithm using different feature sets

Feature	Accuracy	Precision	Recall	F1-Score
GLCM 0°	76.21	0.7705	0.7621	0.7663
HSV	80.58	0.8144	0.8058	0.8101
LBP	76.46	0.7746	0.7646	0.7696
L*a*b*	80.1	0.8275	0.801	0.814
HSV + LAB	86.65	0.8682	0.8665	0.8673
GLCM 0° + LBP	81.31	0.8277	0.8131	0.8203
GLCM 0° + HSV + LAB + LBP	87.14	0.8735	0.8714	0.8724

The classification results of the Decision Tree algorithm, as presented in Table 4, demonstrate varying performance depending on the types of features used. Among the individual features, the HSV and L*a*b* color spaces yield moderate accuracies of 80.58% and 80.10%, respectively, while texture-based features such as GLCM 0° and LBP result in slightly lower accuracies of 76.21% and 76.46%. Combining features significantly enhances the classification performance. The fusion of HSV and

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L*a*b* features leads to an improved accuracy of 86.65%, indicating the benefit of combining complementary color features. Similarly, the combination of GLCM 0° and LBP two texture descriptors achieves an accuracy of 81.31%, outperforming the individual texture features. The best performance is observed when all features are integrated (GLCM 0°, HSV, L*a*b*, and LBP), resulting in an accuracy of 87.14%, along with high precision 0.8735, recall 0.8714, and F1-score 0.8724. These results suggest that combining both color and texture features enhances the discriminatory power of the Decision Tree classifier, enabling it to better capture the characteristics of the data and improve overall classification performance.

The performance of the Random Forest classifier using multiple feature sets is detailed in Table 5.

Table 5. Analysis of Random Forest classification results across distinct feature sets

Feature	Accuracy	Precision	Recall	F1-Score
GLCM 0°	79.37	0.7925	0.7937	0.7931
HSV	87.86	0.8782	0.8786	0.8784
LBP	82.77	0.8268	0.8277	0.8272
L*a*b*	89.81	0.8975	0.8981	0.8978
HSV + LAB	89.81	0.8975	0.8981	0.8978
GLCM 0° + LBP	81.8	0.8169	0.818	0.8174
GLCM 0° + HSV + LAB + LBP	89.56	0.8956	0.8956	0.8956

Table 5 demonstrates that the Random Forest algorithm achieves its highest classification performance when using color features, particularly L*a*b* and HSV, both yielding an accuracy of 89.81% with consistently high precision, recall, and F1-score. In contrast, texture features such as GLCM 0° and LBP result in lower accuracies of 79.37% and 82.77%, respectively. The combination of HSV + L*a*b* maintains strong performance, indicating that combining complementary color features can be beneficial. However, the full feature combination (GLCM 0°, HSV, L*a*b*, and LBP) slightly reduces accuracy to 89.56%, suggesting that the addition of certain texture features may not significantly enhance, and may even slightly dilute, the model's effectiveness. Overall, these results confirm that Random Forest performs better with color-based features than with texture-based ones, and that careful feature selection is crucial for optimal classification performance.

4. DISCUSSIONS

This study evaluated the performance of five classification algorithms—Support Vector Machine (SVM), Decision Tree, K-Nearest Neighbors (KNN), Random Forest, and Convolutional Neural Network (CNN)—in detecting maize leaf diseases. Using a combination of texture features (GLCM, LBP) and color features (HSV, Lab*), the results clearly indicate that classification accuracy is highly dependent on the choice of both features and classifiers. Among individual feature sets, color-based features consistently outperformed texture-based features across all algorithms. Specifically, the Lab* color space achieved the highest accuracy, reaching up to 92.48% with SVM, followed by HSV features. Texture features such as GLCM and LBP, while achieving lower accuracy individually approximately 77%–85%, contributed positively when combined with color features. The combination of all features (GLCM, HSV, Lab*, and LBP) produced the best overall results for CNN with an accuracy of 93.93%, and similarly strong metrics for SVM (93.93% accuracy with HSV + Lab*). The CNN model consistently achieved the highest accuracy across feature combinations, highlighting its strength in automatic feature extraction and complex pattern recognition. SVM also performed very well, especially when using combined color features, whereas Decision Tree and Random Forest showed moderate

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improvements with feature fusion but remained less accurate compared to CNN and SVM. KNN lagged behind all other models, confirming its limitations in handling complex feature spaces in this context.

Compared to previous studies, these findings align with reported trends and further expand the understanding of the impact of features on disease classification. Singh et al. [7] reported a 99.16% accuracy using AlexNet CNN for maize diseases, slightly higher but comparable to our CNN results. Their focus on the end-to-end learning capability of CNNs is supported by our findings that CNN excels when combining multiple complementary features. Masood's MaizeNet [8], using Faster-RCNN with advanced attention mechanisms, achieved 97.89% accuracy, again demonstrating CNN's power in complex real-world scenarios. Our study confirms these results while providing additional insight into the relative importance of texture versus color features. Kale et al. [9] highlighted the effectiveness of SVM for crop disease detection with precision and recall around 0.85–0.86, which closely corresponds to our SVM performance, particularly when using combined color features. This study advances the field by systematically evaluating multiple feature sets and their combinations, demonstrating that color features (HSV, Lab*) contribute more significantly to classification success than texture features alone, though integrating texture descriptors further improves performance. Furthermore, the moderate performance of Decision Tree and Random Forest classifiers contrasts somewhat with previous works that found these methods competitive under certain conditions [10][11]. This suggests that classifier effectiveness may strongly depend on dataset characteristics and feature representation. Our results imply that while Decision Tree and Random Forest benefit from feature fusion, CNN and SVM remain more robust choices for maize disease detection.

Overall, the comparative analysis underscores the superiority of CNN and SVM classifiers in maize leaf disease detection when combining color and texture features. The highest classification accuracy was achieved by CNN at 93.93% (with combined features), closely followed by SVM at 93.93% (HSV + Lab*). Color features play a dominant role, but texture features enhance model sensitivity and specificity when integrated. These outcomes validate the importance of hybrid feature extraction strategies in developing precise and reliable automated plant disease diagnostic tools. This study fills a research gap by explicitly comparing multiple feature sets and classifiers on a common dataset, providing a comprehensive foundation for future crop disease monitoring systems. Its practical implications support the development of early and accurate disease detection applications to improve crop management and food security.

Nevertheless, this study has several limitations. First, the size and diversity of the dataset are still limited to 2,048 images with a balanced proportion for each class, which does not fully represent the variability of maize leaf conditions in real-world environments, such as differences in lighting, background, plant varieties, and growth stages. This limitation may affect the model's ability to generalize its performance when applied in the field. Second, the Convolutional Neural Network (CNN) model used in this study carries the potential risk of overfitting, especially when trained on a relatively small and homogeneous dataset without the application of advanced regularization techniques such as dropout, batch normalization, or diverse data augmentation strategies. This risk may result in high performance on similar test data but significantly reduced accuracy when encountering new, unseen data. Therefore, a more holistic approach is needed in future model development, including dataset expansion, diversification of data sources, and the application of more robust training techniques to improve model generalization.

5. CONCLUSION

The results of this study indicate that the Convolutional Neural Network (CNN) algorithm achieved the best classification performance in detecting and classifying maize leaf diseases, with the highest accuracy of 93.93%, precision of 0.9403, recall of 0.9393, and F1-score of 0.9390. This optimal result was obtained using a complete combination of color features (HSV and L*a*b*) and texture features (GLCM 0° and LBP), demonstrating that integrating both types of features significantly enhances model performance.

In addition, the Support Vector Machine (SVM) also showed high performance, achieving the same accuracy of 93.93% when using only the combination of HSV and L*a*b* features, even without texture features. Meanwhile, the Random Forest and Decision Tree algorithms performed best with color features alone, reaching maximum accuracies of 89.81% and 87.14%, respectively.

Overall, color features contributed more significantly to classification accuracy than texture features. However, the combination of both especially when implemented in CNN produced the highest performance, making CNN the most effective algorithm for maize leaf disease classification based on the dataset and feature configurations used in this study. Future studies may incorporate real-time deployment in agricultural fields or explore lightweight CNN models for mobile applications

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