Combination of Feature Extraction Methods for Identification of Diseases in Corn Leaves

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***Abstract*—This research develops a classification model that is effective in detecting diseases on corn leaves using the Corn or Maize Leaf Disease dataset from Kaggle. The preprocessing process includes image augmentation, such as horizontal rotation and flipping, increasing data variation and preventing overfitting. The image size is standardized to 150x150 pixels, and color segmentation with HSV color space is used to separate relevant objects. The feature extraction methods used are Hu Moments, Haralick, and Histogram, which collectively provide a rich and informative feature representation. Of the various classification algorithms tested, Support Vector Machine (SVM) showed the best performance with an accuracy of 98.53% and an error rate of 0.10%. Logistic Regression (LR) and Linear Discriminant Analysis (LDA) also performed well, but were not as superior as SVM, while Naïve Bayes (NB) had the lowest performance. Evaluation with the confusion matrix shows a very low error rate in the classification of various disease classes. With an overall accuracy of 98%, this model shows a good balance between precision and recall, indicating its ability to consistently identify corn leaf diseases and healthy conditions with high accuracy. This research is expected to increase the productivity and health of corn plants through faster and more accurate disease detection.**

Keywords—Corn Leaf, Disease, Ekstraction, Classification, Images Augumentation

I. Introduction

Agriculture has a strategic role in the economy and people's lives, especially in countries with a dominant agricultural sector such as Indonesia [1]. Corn, as one of the main agricultural commodities, contributes significantly to food, animal feed and industrial needs [2]. However, the main challenge in cultivating corn is disease attacks which can reduce the quantity and quality of crop yields [2], [3]. In the era of rapidly developing information technology [4], automatic identification of diseases in corn plants through digital image processing offers an effective solution [5]. Processing by machines increases the accuracy of the information provided, thereby making it more convincing for the recipients [6]. Feature extraction from corn leaf images plays a key role in disease identification [7] with the main challenge being the need for a combination of methods to handle complex variations in disease symptoms [8].

Feature extraction is an important technique in image processing which aims to identify and isolate various important characteristics of objects in images, such as shape, size and orientation [9]. This technique is very useful in template matching algorithms, which compare images with predetermined templates to recognize and classify objects. In practice, feature extraction involves taking data from the image to be recognized and comparing it with data from a template image that has been stored in a database [10]. One of the advantages of this method is its ability to simplify and speed up the process of object identification by focusing only on essential characteristics. Algorithms such as Hu-Moments, Haralick, and Histogram are some examples used in feature extraction, each with its own unique way of addressing certain aspects of image analysis. Hu-Moments is effective for shape recognition, Haralick focuses on texture, while Histogram handles the distribution of color intensity or brightness in the image [11].

This research was designed to answer how a combination of feature extraction methods can increase accuracy in identifying diseases in corn leaves, what feature extraction methods are most effective, and the effect of this combination on the efficiency and accuracy of disease identification [8]. The aim is to develop a disease identification system that can support farmers and practitioners in early detection, as well as contribute to knowledge of digital image processing in agriculture [12]. This research has the potential to provide benefits in improving the quality and productivity of corn cultivation through better disease detection, contributing new knowledge, and becoming a reference for further studies [13].

Research limitations include a focus on downy mildew, leaf rust, and leaf blight, the use of certain digital image data, and limitations on combinations of feature extraction methods that have been proven effective in the literature, for focused results and appropriate interpretation in the context of disease identification on maize leaves by using feature extraction for image recognition identification.

II. Literature Review

Research on corn leaf disease by [3] proposed the use of a simple Convolutional Neural Network (CNN) based Deep Learning (DL) model to classify the severity of gray leaf spot on corn leaves into five different severity levels, considering the importance of effective detection of common and dangerous diseases such as CGLS, common rust, and leaf blight in corn plants. The model achieved an impressive detection accuracy of 95.33% on high-risk images, demonstrating superior performance on these images compared to other severity levels. These results highlight the effectiveness of CNN-based DL models in disease classification and open opportunities for further development, including experiments with hybrid DL approaches or applications at higher severity levels for more accurate results, expanding the potential applications of this technology in modern agriculture. However, this study does not provide details on how this model performs on images with lower severity levels, so for validity, it is important to test this model consistently across all severity levels.

Furthermore, research by [8] on the classification of corn leaf diseases, this study proposes the use of a corn disease classification method using Random Forest, Neural Network, and Naive Bayes techniques on a dataset of corn leaf images collected from the Madura region, Indonesia, with a focus on four main classes : healthy, gray leaf spot, blight, and common rust. The test results show that the Neural Network method, especially with HOG feature extraction, provides superior performance compared to other methods, with AUC values reaching 90.09%, classification accuracy 74.44%, F1 score 72.01%, precision 74.14% , and recall 74.43%. This conclusion confirms that Neural Networks are effective for digital image classification of corn plants, promising to increase efficiency in identifying the health conditions of corn plants and helping increase production in the agricultural sector.

In the same case, research on disease classification on corn leaves using a fuzzy method approach concluded that image processing to obtain a good and accurate model often requires a lot of training data, which ca`n result in high computational costs. To overcome this, this research proposes the use of CUDA and MPI in image pre-processing to increase efficiency and reduce processing time with load distribution and parallel processing methods. The results of this approach show increased accuracy and precision, as well as time savings. In addition, this research also compares the Fuzzy C-Means and RNN algorithms in detecting disease on corn plant leaves, with recommendations for further research in developing and testing both methods to improve disease detection performance [13].

III. RESEARCH METHODS

In order to support research so that it is focused and structured, a research method was created to describe the flow of this research. The following is figure 1 of the flow of the research.

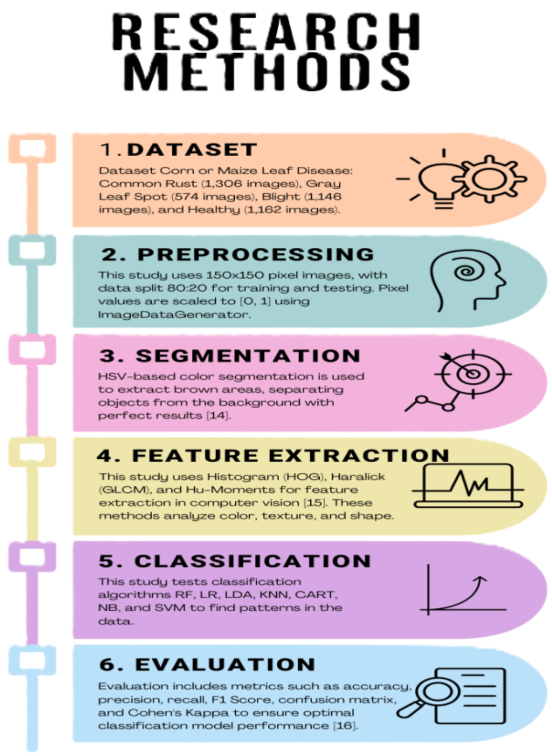


Fig. 1. Research Methods

A. Dataset

In this research, the dataset to be studied was selected through a process of collecting, understanding and identifying the data held. The dataset used is stored in the directory specified by train_path. This is the path to the dataset stored in Google Drive for use in Google Colab. The dataset source was taken from Kaggle public data regarding the classification of corn leaf diseases [14].

B. Preprocessing

The image size used was set at a scale of 150 x 150 pixels, as determined by the PixImag size variable [15]. Data division does not show an explicit separation between training, validation, and testing data, but the data is divided with a ratio of 80:20 for training and testing data. Image scale is not set explicitly, but in general, ImageDataGenerator scales image pixel values into the range [0, 1] by multiplying the original pixel value (0-255) by a factor of 1/255 [5], [16].

C. Segmentation

Segmentation in this code is carried out with a color-based approach using the HSV color space. The purpose of segmentation is to extract brown areas of the image. Color segmentation is one of the segmentation methods in digital image processing which is used to separate objects from the background in a digital image [13]. The method used is HSV segmentation, where this segmentation process is combined to determine the object that will be separated from all objects in the digital image [17]. The final result shows that the objects can be separated perfectly [18].

D. Feature Extraction

The feature extraction stage is an important step in computer vision which is widely used to analyze color, texture and shape. This research was carried out with the following feature extraction stages [19].

1. Histogram
   Histogram of Oriented Gradients (HOG) is a type of feature extraction that functions as a graphic representation of the distribution of tones in a digital image. This plots the number of pixels for each note value. By looking at the histogram for a particular image,

viewers can assess the overall distribution of color tones at a glance [20].

2. Haralick
   The Haralick texture feature method is a set of features used to analyze texture in images, based on the Gray-Level Co-occurrence Matrix (GLCM) which describes the frequency with which pairs of pixels with specific intensity values occur in a defined spatial relationship [21].

3. Hu-Moments
   Hu-Moments is a widely used feature extraction method in pattern recognition tasks like shape recognition and object retrieval[19]. hey are often applied in handwriting recognition, medical object detection, and satellite image analysis because they provide stable and consistent shape descriptions, improving classification accuracy and performance [22].

E. *Model Classification*

At this stage, an algorithm is selected with optimal parameter values to achieve a computational representation of the observation results, which aims to look for patterns in the data. This research tested several classification algorithms, including Random Forest Classifier (RF), Logistic Regression (LR), Linear Discriminant Analysis (LDA), K-Nearest Neighbors (KNN), Decision Tree Classifier (CART), Gaussian Naive Bayes (NB), and Support Vector Machine (SVM). Each of these algorithms is evaluated to determine the best performance in classifying data [23].

F. *Evaluation of Results*

The The evaluation results in this study include important metrics such as accuracy, precision, recall, F1 Score, confusion matrix, and Cohen's Kappa. Accuracy measures the ratio of correct predictions, precision measures the accuracy of positive predictions, recall measures the ability to detect all positive cases, and F1 Score provides a balance between precision and recall. The confusion matrix shows the number of correct and incorrect predictions, while Cohen's Kappa measures the agreement between model predictions and actual values, including chance agreements. These metrics ensure the optimal performance of the model in data classification. [24], [25].

IV. RESULTS AND DISCUSSION

The results of this discussion explain in detail the steps taken in the research, from the initial to the final stages, to achieve the best algorithm classification results on corn leaf disease images. The results of this research are as follows.

4.1.Dataset

The Corn or Maize Leaf Disease dataset comes from the Kaggle repository and is a collection of images created using the popular PlantVillage and PlantDoc datasets. This dataset has four classes: Common Rust (1,306 images), Gray Leaf Spot (574 images), Blight (1,146 images), and Healthy (1,162 images). This dataset is used to classify diseases on corn leaves, assisting in the development of corn leaf disease classification models. The use of this dataset in academic research is expected to make a significant contribution to increasing the productivity and health of corn plants.

4.2. Preprocessing

The preprocessing process is carried out using various calculations with Python tools. The first step is to enter the image to be studied. Next, the selected image is processed by determining the pixel size and data according to the label you want to examine. In this research, the image used has a size of 150x150 pixels, in accordance with established standards.

At this stage, the process includes grouping images by class, determining image size, and dividing the data into training and testing paths to prepare the data to be tested according to the predetermined class labels. The distribution of data for each class is as shown in the following table.

TABLE I. NUMBER OF DATASETS FOR EACH CLASS

Class Name	Number of Image	Image Result
Common Rust	1306	
Gray Leaf Spot	574	
Blight	1146	
Healthy	11662	

To increase data variation and avoid overfitting, image augmentation is carried out. This augmentation aims to make the number of images in each class more balanced. Augmentation techniques used include rotation, width and height shift, tilt change, zoom, and horizontal flip.

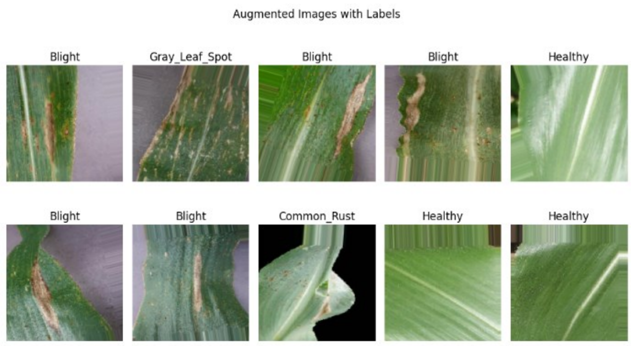


Fig. 2. Image augmentation process

With this augmentation, the dataset becomes more varied, which helps the machine learning model in learning important features from images more effectively, and reduces the risk of overfitting during training.

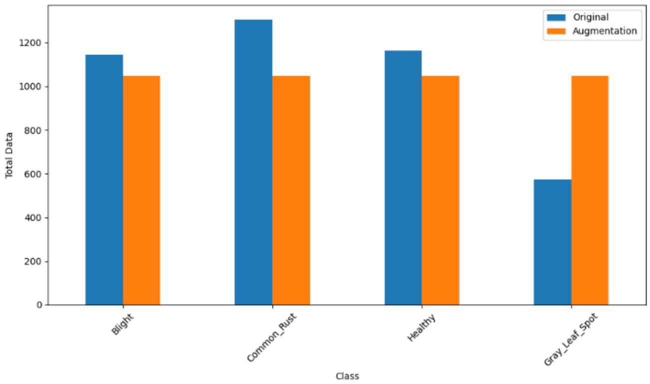


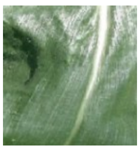
Fig. 3. Image augmentation results

4.3. Segmentation

At this stage, color segmentation is used to separate certain objects from the image background based on their color. This process begins by generating a batch of images, where one of the images from the batch is converted to the `uint8` data type to ensure compatibility with OpenCV operations. The original image in RGB format is then converted to HSV (Hue, Saturation, Value) color space using the `cv2.cvtColor` function, because HSV color space is more suitable for color segmentation, separating color information (hue) from intensity (saturation and value).

Next, the brown color range to be segmented is defined in HSV format, by setting two boundary values: `lower_brown` and `upper_brown`. A filter is then created for this brown color range using the `cv2.inRange` function, which produces a binary image where pixels that fall into the brown color range are assigned a value of 255 (white) and other pixels are assigned a value of 0 (black).

TABLE II. HSV IMAGE SEGMENTATION RESULTS

Class	Original	Segmentation
Blight		
Common Rust		
Gray Leaf		
Healty		

The resulting filter is applied to the original image using the `cv2.bitwise_and` function. This function retains the pixels that match the filter (brown color) and changes the remaining pixels to black, resulting in a segmented image. This segmentation process allows the isolation of brown objects in the image, which is useful for further analysis.

This segmentation process allows the isolation of brown objects in the image, which is useful for further analysis such as disease detection or object classification based on specific colors. This color segmentation is an important step in digital image processing because it helps separate relevant objects from the background, facilitating deeper and more accurate analysis.

4.4. Feature Extraction

The feature extraction process is carried out with the aim of extracting important information from images that can be used in the classification process. Each class must be included when performing feature extraction to get good accuracy results as desired. The following is an explanation of the three feature extraction methods used:

1. Hu Moments

   Hu Moments are seven values that remain unchanged under image translation, scaling, and rotation, used for shape recognition. These values are derived from image moments that measure pixel intensity distribution and are very useful in pattern recognition as they provide shape descriptions that are robust to geometric transformations.

2. Haralick

   Haralick features, generated from the Gray-Level Co-occurrence Matrix (GLCM), calculate the frequency of pixel pairs with specific intensity values at certain distances and orientations. From GLCM, we can extract texture features such as contrast, homogeneity, energy, and entropy, providing information about the texture structure in the image for texture analysis and pattern recognition.

3. Histogram

   An image histogram is a graphical representation of the intensity or color distribution in an image. A histogram counts the number of pixels for each intensity or color value. In the context of a color histogram, it plots the distribution of colors in various channels. Histograms provide information about the overall color composition of an image and can be used for color analysis, image segmentation, and image matching.

By using these feature extraction methods, important information from images can be isolated and used in classification algorithms to improve model accuracy and performance.

4.5. Classification Algorithms

The classification process utilizes the results from the feature extraction stage, followed by model evaluation using processed data that has undergone feature extraction and classifier training. The algorithms tested include Logistic Regression (LR), Linear Discriminant Analysis (LDA), K-Neighbors Classifier (KNN), Decision Tree Classifier (CART), Random Forest Classifier (RF), Gaussian Naive Bayes (NB), and Support Vector Machine (SVM).

TABLE III. RESULT CLASSIFICATION ALGORITHM

No	Classification	Accuracy	Error Rate
1	Linear Discriminant Analysis	0.951153	0.006845
2	Logistic Regression	0.96123	0.005377
3	Classification and Regression Tree	0.932115	0.002349
4	Naïve Bayes	0.672969	0.011894
5	K-Nearest Neighbors	0.938613	0.001283
6	**Support Vector Machine**	**0.985313**	**0.00096**
7	Random Forest	0.938613	0.001055

Evaluation was conducted to assess the performance of algorithms in classifying data based on extracted features, aiming for the best accuracy. Support Vector Machine (SVM) showed the best performance with an accuracy of 98.53% and an error rate of 0.10%, followed by Logistic Regression (LR) with an accuracy of 96.12% and an error rate of 0.54%, and Linear Discriminant Analysis (LDA) with an accuracy of 95.12% and an error rate of 0.68%. Naïve Bayes (NB) had the lowest performance with an accuracy of 67.30% and an error rate of 1.19%. Models with high accuracy and low error rates are considered more effective in correctly classifying data.

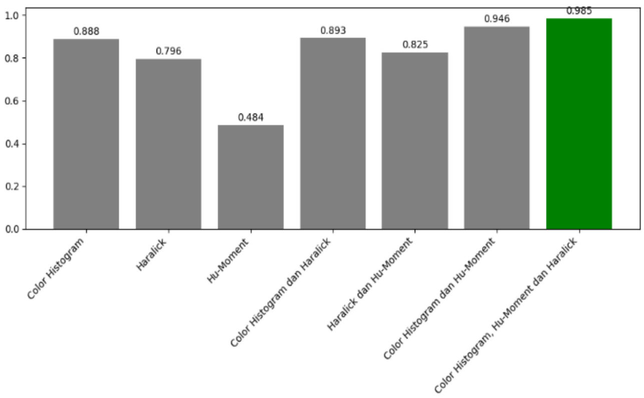


Fig. 4. Accuracy results from feature extraction

The evaluation results show significant variations in accuracy between the various feature extraction methods used for image classification of corn leaf diseases. Combining various feature extraction methods, especially Color Histogram, Hu-Moment, and Haralick, provides the best results with the highest accuracy of 98.54%. This combination successfully leverages the strengths of each method, namely color distribution (Color Histogram), texture (Haralick), and shape (Hu-Moment), to provide a richer and more informative feature representation. This combination method improves the model's ability to perform accurate classification, reduces errors, and ensures that the model has good generalization on corn leaf disease datasets..

4.6. Model Evaluation

This study evaluated feature extraction methods and classification algorithms for classifying corn leaf diseases, finding that the combination of Color Histogram, Hu-Moment, and Haralick feature extraction methods provided the best results with an accuracy of 98.54%. Support Vector Machine (SVM) proved to be the best classification algorithm with an accuracy of 98.53% and the lowest error rate of 0.10%. These results demonstrate that the integration of these methods can provide rich and informative feature representations and highly effective classification performance.

TABLE IV. CONFUSION MATRIX

Actual / Predicted	Blight	Common Rust	Gray Leaf Spot	Healthy
Blight	60	2	1	1
Common Rust	0	20	0	0
Gray Leaf Spot	0	0	20	0
Healthy	0	0	0	181

The table provided is a confusion matrix that is used to evaluate the performance of classification models in machine learning. Each row in the table represents an actual class, and each column represents a predicted class..

1. Blight: Of the total of 64 samples that actually belonged to the Blight class, the model correctly predicted 60 samples as Blight, but predicted 2 samples as Common Rust, 1 sample as Gray Leaf Spot, and 1 sample as Healthy.
2. Common Rust: Of the 20 samples that actually fall into the Common Rust class, the model correctly predicts all of them as Common Rust.
3. Gray Leaf Spot: Of the 20 samples that actually fall into the Gray Leaf Spot class, the model correctly predicts all of them as Gray Leaf Spot.
4. Healthy: Of the 181 samples that actually belonged to the Healthy class, the model correctly predicted all of them as Healthy.

TABLE V. MATRIX EVALUATION SVM METHOD

	Precision	Recall	F1-Score	Support
0	1	0.93	0.97	64
1	0.91	1	0.95	20
2	0.95	1	0.97	20
3	0.99	1	0.99	181
accuracy			0.98	285
macro avg	0.96	0.98	0.97	285
weighted avg	0.98	0.98	0.98	285

The table above presents the evaluation results of the classification model used to detect corn leaf diseases. Out of a total of 285 samples, this model successfully classified 98% correctly, including 60 out of 64 Blight samples, all 20 Common Rust samples, all 20 Gray Leaf Spot samples, and all 181 Healthy samples. With an accuracy of 0.98, these results indicate that the classification model has excellent performance, with a good balance between precision and recall across various classes. This model is highly effective in identifying corn leaf diseases and healthy conditions with a very low error rate, making it a highly reliable tool for detecting corn leaf diseases.

V. CONCLUSION

This study concludes that the developed corn leaf disease classification model performs exceptionally well, with an accuracy of 98.53%. The model utilizes the Corn or Maize Leaf Disease dataset from Kaggle, processed with image augmentation techniques such as rotation, shift, and horizontal flip, and standardized to a size of 150x150 pixels to increase data variation and prevent overfitting. Color segmentation using the HSV color space proved effective in separating relevant objects from the image background, while feature extraction methods such as Hu Moments, Haralick, and Histogram provided rich and informative feature representations. Among the various algorithms tested, the

Support Vector Machine (SVM) demonstrated the best performance, followed by Logistic Regression (LR) and Linear Discriminant Analysis (LDA), with Naïve Bayes (NB) showing the lowest performance. Evaluation using a confusion matrix showed that this model has a very low error rate and a good balance between precision and recall across all disease classes. Overall, the combination of image augmentation techniques, color segmentation, and feature extraction methods used successfully produced an effective and accurate classification model for detecting corn leaf diseases, which is expected to enhance corn plant productivity and health through faster and more accurate disease detection.

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