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Classification of Diseases on Corn Stalks using a Random Forest based on a Combination of the Feature Extraction (Local Binary Pattern and Color Histogram)

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Abstract. Corn disease has a significant impact on both the food industry and the yield of corn crops since corn serves as a fundamental and essential source of nutrition, especially for vegetarians and vegans. Therefore, ensuring the quality of corn is crucial, and to achieve this, protection against various diseases is necessary. Consequently, there is a pressing demand for an automated method capable of early-stage disease detection and prompt action. However, detecting diseases at an early stage poses a major challenge and is of utmost importance. This research focuses on the development of a classification model for corn stalk images using Random Forest. The model generates fine and coarse features of high quality to capture discriminative, boundary, pattern, and structural information used in the classification process. This research also utilizes the LBP (Local Binary Pattern) method and Color Histogram in the feature extraction process to obtain information related to texture and distinguishing patterns, that are employed in the classification process. Furthermore, the proposed model is evaluated using the corn plant image dataset, which was directly captured by the researcher in Madura, and consists of 3,000 data. The result of this research shows that the utilization of the proposed method can classify and identifying diseases in new data of digital images of corn stalks with an accuracy rate of 99.05%.

1 Introduction

In recent years, various fields such as electronic media, medical, engineering, Défense, and agriculture have undergone revolutionary changes due to the implementation of smart technological advancements and machine learning techniques [1]. Particularly, agriculture has experienced significant development and benefits from these smart technologies [2]. Given that agriculture serves as a major economic source for countries, adopting smart agricultural techniques can have a substantial positive impact on their economies. Certain crops hold significant economic importance, both domestically and through exportation. Among them, corn stands out as a crucial crop in the agricultural sector [3]. Corn serves as a traditional crop with diverse uses, including human food, animal feed, and raw materials for multiple industries [4] and [5]. The quality of corn kernels is closely tied to crop yield and production levels, making it essential to have a fast and effective method for assessing their quality [6].

However, the growth and production of corn are influenced by various biotic (such as variety, pests, diseases, and weeds) and abiotic (climate, soil type, and land conditions) factors, as well as socioeconomic factors [7]. Biotic factors commonly encountered in efforts to increase corn production are attacks by plant pests. Pests and diseases can hinder production stability in tropical and subtropical regions. It is known that Indonesia has about 70 species of insects that cause damage and 100 types of diseases that have been reported to affect corn plants [8]. Diseases frequently found infecting corn stalks include sheath stalk rot, and charcoal stalk rot [9] and [10]. Infections of these stalk rot diseases are influenced by several factors, such as variety resistance, climatic conditions, plant density, suboptimal cultivation practices, high plant population, and the presence of infected residues in the field. These plant stalk diseases have a significant impact on the overall production rate of corn crops. Therefore, precise identification of corn stalk diseases is crucial to maintaining a steady production rate and ensuring a healthy crop yield.

Based on these problems, this research employs the science of digital image classification to address the identification of diseases in corn plants. The main objective is to categorize corn plant leaves into specific classes based on their distinct characteristics. Digital image classification is achieved through the utilization of machine learning techniques, which are currently widely used in this field. Various machine learning methods are available for classifying and analyzing digital images. These techniques offer valuable tools for effectively handling image classification tasks. In 2020, the researchers adopted a method for identifying corn diseases by using the classification of leaf diseases based on a Support Vector Machine (SVM) classifier. Additionally, they conducted a detailed study



on leaf disease segmentation [11]. Moving on to a Convolutional Neural Network (CNN) architecture was implemented for corn leaf disease identification, leading to improved automation and digitalization in agriculture. The CNN architecture enhanced the accuracy of classifying leaf diseases. In, a refined machine learning technique was introduced for detecting crop leaf diseases [12]. Despite these advancements, it should be noted that potential techniques for detecting plant diseases are not yet mature enough for practical applications. Several challenges need to be addressed, such as the precise identification of plant stalk diseases, identifying various factors that can affect crop production and the quality of corn, and developing efficient feature extraction methods for disease type identification.

In this research, a Random Forest classifier is utilized to achieve accurate detection of corn stalk diseases. The process of stalk disease detection is divided into four phases using the proposed Random Forest model. First, the pre-processing phase filters out any noise from the corn stalk images. Second, the feature extraction process is described to extract structure-related information from corn leaf images using LBP and Color Histogram. And the final stage, the obtained features are used for corn stalk classification and disease detection using a Random Forest model.

2 Method

In this section, the definition and working principle of the proposed method in this research will be explained for constructing a classification system on corn stalks.

2.1 Random Forest

Random Forest is a supervised learning algorithm belonging to the ensemble learning category, which employs bagging and random feature selection techniques. The main goal of ensemble learning is to tackle unstable classification issues by combining multiple basic learners to minimize prediction errors. In this approach, a model is created using several decision trees, forming a collection of these trees [13] and [14]. Each tree provides a classification estimate (called a vote), and all the votes from each tree are combined to select the most frequent classification, resulting in an optimal and stable prediction. Here are the steps of the Random Forest algorithm [15]:

The initial step involves creating a random bootstrap sample with a replacement of size n from the dataset.

- 1. A random value m is selected from p predictors, where m << p, to determine the number of predictor variables randomly chosen.
- 2. To predict the response for a given observation, the algorithm combines the results of k trees based on majority voting.
- 3. To determine the majority vote for a tree, the first step is to calculate the entropy value using equations (1) and (2).

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$$entropy(S) = \sum_{i=1}^{c} p_i log_2 p_i$$
(1)

Description:

S : dataset

c : the number of classes

pi: the probability frequency of class-i in the dataset

$$entropy(T,X) = \sum P(c)E(c)$$
 (2)

Description:

(T, X) : T and X feature

P(c) : the probability of feature class

E(c) : entropy result from feature class

2.2 Local Binary Pattern (LBP)

Local Binary Pattern (LBP) was discovered by Ojala and Pietikainen in 1999 as a statistical approach. LBP is one of the texture feature extraction methods that use a simple and efficient operator to describe local image patterns [16]. LBP is a texture measure that remains invariant to changes in grayscale levels. It is computed by analysing a 3x3 local neighborhood surrounding a central pixel. LBP is characterized by a binary code that describes the local texture pattern. This binary code is created by comparing the gray values of the local neighborhood with the gray value of its center pixel. The eight neighboring pixels are labeled using the binary code $\{0, 1\}$, depending on whether their gray values are below or above the gray value of the central pixel. If the tested gray value is lower than the central pixel's value, it is labeled 0; otherwise, it is labeled 1 [17].

$$d_i = \begin{cases} 0 \text{ if } I(x_i, y_i) < I(x_0, y_0) \\ 1 & otherwise \end{cases}$$
(3)

The obtained binary code, denoted as d_i , represents a pattern in the Local Binary Pattern (LBP) calculation. In this technique, d_i is the result of a comparison between the original pixel value, d_i , at position i, and the central pixel value, d_0 . The comparison is done by subtracting d_0 from d_i ; and if the result is positive, d_i becomes 1; otherwise, it becomes 0. Using this process, there are $256 (2^8)$ possible patterns or texture units that can be generated. After obtaining the binary code d_i , it is then multiplied by weights assigned to the corresponding pixels. These weights are given by the value 2⁻¹. To compute the Local Binary Pattern (LBP) measure, the obtained values (d_i multiplied by the weights) are summed together. This sum represents the final LBP value for the particular pattern or texture in the image [17].

$$I_{LBP} = \sum_{l=1}^{8} d_l \ 2^{l-1} \tag{4}$$



2.3 Color Histogram

Color histogram is a tool used to analyze the distribution of color pixels in an image. There are two types of color spaces used in color histograms: RGB (Red, Green, Blue) and HSV (Hue, Saturation, Value). Color Histogram (CH) represents the frequency of occurrence of each color by counting the pixels of the image that have a particular color [18]. Each pixel is grouped into the corresponding histogram bin based on its color, and the similarity or dissimilarity of colors within the same bin is not considered. Since each pixel in the image can be represented by three components in a specific color space (red, green, and blue components in the RGB color space, or hue, saturation, and value in the HSV color space), a histogram can be created for each component by counting the number of pixels that fall into specific categories [19] and [20].

Color descriptors include three parameters: color expectancy, color variance, and color skewness. Color expectancy represents the average color intensity in an image. Color variance indicates the range of color values in the image [21]. Color skewness measures the asymmetry of the probability distribution of the realvalued random variable. Color skewness can be either positive or negative, depending on its direction. By using color histograms and these color descriptors, we can analyse the distribution and characteristics of colors in an image in more depth.

2.4 Hypertuning Parameter using Grid SearchCV

In machine learning, hyperparameters are parameters used to configure the training process of a model, and they are distinct from the model's own internal parameters. Hyperparameter tuning is the process of searching for the optimal combination of hyperparameter values to enhance the model's performance [22]. Grid SearchCV is one of the hyperparameter tuning methods that utilizes crossvalidation techniques. Its operation involves combining various hyperparameter values to be tested and then calculating the average cross-validation score for each combination. The hyperparameter combination with the highest average cross-validation score is selected as the optimal value for the model [23].

In this research, the hyperparameter tuning process using Grid SearchCV is employed to obtain the best parameter values for the Random Forest method to produce a classification model with the highest accuracy. This allows for the fine-tuning of the Random Forest model by systematically searching through different hyperparameter combinations and selecting the one that yields the best performance in terms of accuracy during the cross-validation process.

2.5 Confusion Matrix

The evaluation of the model in research is crucial to understand how well a classification model performs. The evaluation method used in this research is the confusion matrix [24]. The confusion matrix is a technique applied to measure the accuracy or performance of a classification model [25]. It describes the display of the classification model's performance outcomes using a matrix. The matrix showcases four potential results arising from the comparison of predicted and actual classifications, namely: false positives (FP), false negatives (FN), true positives (TP), and true negatives (TN). These outcomes are presented in the table above.

Table 1. Confusion Matrix

| | | Prediction Class | |
|-------|----------|------------------|----------|
| | | Positive | Negative |
| Class | Positive | TP | FP |
| | Negative | FN | TN |

Referred to the table above, when the confusion matrix result falls within the true positive (TP) column, it indicates a correct and positive identification. Conversely, if the result appears in the false positive (FP) column, it means an incorrect and mistaken positive identification. Similarly, if the result is situated in the false negative (FN) column, it represents an erroneous and mistaken negative identification. Lastly, when the result falls into the true negative (TN) column, it signifies a correct and accurate negative identification. In essence, the table allows us to draw conclusions about the correctness of positive and negative identifications made by the model.

From the confusion matrix, we can derive the values of accuracy, recall, precision, and F-measure. The values of accuracy and precision can be obtained using Equation (5) and Equation (6). And, the values of recall and F-measure can be calculated using Equation (7) and Equation (8) [26].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$
(5)

$$cision = \frac{TP}{TP + FP} x \ 100\% \tag{6}$$

$$Recall = \frac{TN}{TN + FN} x \ 100\% \tag{7}$$

$$-measure = 2 x \frac{Recall x Precision}{Recall + Precision} x 100\%$$
(8)

Description:

FP : The instances that are incorrectly classified as positive

FN : The instances that are incorrectly classified as negative

TP : The instances that are correctly classified as positive

TN : The instances that are correctly classified as negative

3 System architecture



In this section, we will explain how the research is conducted using the proposed method as a solution to



the identified problem. The research process will be illustrated through the Input-Process-Output diagram below.

Fig.1. The proposed system diagram, which starts with the input process and ends with the output process.

Based on Figure 1 above, the development of the classification system consists of six stages, namely input process, preprocessing, feature extraction, data validation, data classification, and output process. The explanations for these six stages are as follows:

1. Input Data Process:

The first stage involves collecting a dataset of corn plant images directly taken by the researcher in Madura. The dataset used in this research consists of 3,000 data points, which will be divided into two sets: training data and testing data, with an 80% - 20% split. The training data will account for 80% of the dataset, while the testing data will make up the remaining 20%. The dataset consists of corn plant stem images categorized into three classes. The dataset used can be seen in the following table:

Table 2. Stalk Corn Data Class

| Part of Corn | Class | Quantity |
|--------------|--------------------|----------|
| Plants | | |
| Corn Stalks | Healthy | 1.000 |
| | Sheath stalk rot | 1.000 |
| | Charcoal stalk rot | 1.000 |
| Total | | 3.000 |

2. Preprocessing

The second stage is the preprocessing phase. In this preprocessing stage, the input images will undergo several steps. First, the images will be resized to achieve a uniform pixel size. Then, a contrast stretching process will be applied to enhance the brightness levels. Afterward, the images will undergo segmentation using thresholding techniques to separate objects from the background in the image. In the next steps of



preprocessing, the images will be processed through two methods: LBP preprocessing, which involves converting the color space to grayscale, and Color Histogram preprocessing, which involves converting the color space to HSV image.

3. Feature Extraction

The third stage involves using the results of preprocessing for feature extraction using LBP and Color Histogram methods. Once the feature extraction results are obtained, the features will be combined into one data frame.

4. Data Validate Process

After obtaining the data from the feature extraction results, the data model validation process will then be carried out using the k-fold cross validation method by dividing the k-split model by 10 with the distribution of 80% training data and 20% testing data.

5. Classification Process

The next step is to perform classification using the Random Forest classification method. For each model trained on the training data, the accuracy of the predictions will be evaluated using the testing data.

6. Output

In this final stage, the classification predictions are generated and then their accuracy is calculated using the Confusion Matrix method. For each model, the data validation is performed using kfold cross-validation. The model with the best accuracy results will be saved in a file with the joblib extension, which will be used later for identifying new images of corn plant diseases.

4 Experiment and Result

The focus of the research is to identify diseases in corn plants, which is characterized by various symptoms present on the corn leaves. This is achieved by analyzing several stages of image processing. In this section, scenario testing will be performed on corn plant objects, specifically corn stalks, using feature extraction methods like Local Binary Pattern (LBP) with parameters of neighbourhood (P) and radius (R), and Color Histogram with the HSV color channel, encompassing 3 features: hue, saturation, and value. The best feature extractions from texture and color will be combined, and k-fold cross-validation will be applied to search for the best model for the data.

The testing in this research involves several parameters. For Local Binary Pattern (LBP), the neighborhood (P) is set to 4, 8, and 16, while the radius (R) is set to 1, 2, 3, and 4. The features are then combined from the color channel's hue, saturation, and value (H, S, and V). The classification method used is Random Forest with the following parameters: bootstrap = True, estimators = (10, 30, 50, 70, 90, 100), max depth = (3, 5, 7, 9, 10), min_samples_split = (2, 4, 6), and k-fold = 10. The results of the testing conducted in this research are as follows:

Table 3. Testing Process

| Testing Scenario | Methods | Object |
|---------------------|---|-------------------------------------|
| 1 | Hypertunning parameter random forest of corn stalks image. | |
| 2 | Random Forest classification utilizes a combination of features with data splitting using k-fold cross-validation. | Citra Image of Corn Stalks |
| 3 | Identification of disease images on corn plant stalks. | |

4.1 Hypertuning Parameter

The calculation results of the testing to determine the best parameters for the Random Forest classification using various test parameters are as follows:

| Parameter | Value |
|-------------------|--------------------|
| bootstrap | True |
| n_estimators | 10,30,50,70,90,100 |
| max_depth | 3,5,7,9,10 |
| min_samples_split | 2,4,6 |

Table 4. Testing Parameter

With the use of parameter values as shown in Table 3 above, the result of hyperparameter tuning for the Random Forest method yielded the best parameters for classifying corn plant stalks when the bootstrap parameter is set to True, n_estimators is set to 10, max_depth is set to 7, and min_samples_split is set to 2. The results of running the program can be seen in the figure below.



Fig.2. Running Program Result

4.2 Random Forest Classification

After obtaining the best parameters from the combined feature extraction, they are then applied to the dataset, which will be validated using the k-fold cross-validation method to obtain the best model with



the optimal data arrangement at k = 10. The following table shows the testing results using k-fold cross-validation on corn plant stalks:

| Table 5. Result Accu | racy |
|----------------------|------|
|----------------------|------|

| K-Fold | Accuracy (%) |
|--------|--------------|
| k = 1 | 92,38 |
| k = 2 | 94,29 |
| k = 3 | 99,05 |
| k = 4 | 82,86 |
| k = 5 | 89,52 |
| k = 6 | 88,57 |
| k = 7 | 95,71 |
| k = 8 | 78,57 |
| k = 9 | 90,48 |
| k = 10 | 82,38 |

Table 5 shows the results of the testing for each different value of k-fold, in which there were significant differences in the accuracy obtained for each fold. The best accuracy was achieved when k was set to 3, reaching a value of 99.05%.

4.3 Identification of Corn Stalks Disease

After the classification process is performed, and the best model and accuracy are obtained, the previously saved weight model in a file with the joblib extension will be used to identify new images. The following are the new images that will be identified to determine the type of disease affecting the corn plant stem. The new images of diseased corn plant stalks can be seen in the following picture.



Fig. 3. New Data Image of Stalk Corn

From the selected new images, the images will undergo preprocessing and then feature extraction to determine the feature values of the new images. Subsequently, the feature values will be identified using the weight data model obtained from the previous classification training. The results of the identification process on the new corn plant stem images can be seen in the image below.

Citra Input teridentifikasi berpenyakit : BUSUK PELEPAH

```
Teridentifikasi dengan ciri warna HSV dan tektur LBP dengan nilai:
Hue : 131.77532958984375
Saturation : 241.8036346435547
Value : 157.6562042236328
LBP : 8318.53068295028
```



Fig. 4. Identification Result

Based on the identification results of the new corn plant stem images using the classification model with the best accuracy, the stem images were classified into the category of "Busuk Pelepah" (rotten sheath) based on the Hue, Saturation, Value, and LBP values, as shown in Figure 4 above.

5 Conclusion

Based on the results and discussions conducted to classify diseases on corn plant leaves using the Random Forest algorithm, as well as LBP and Color Histogram feature extraction on a dataset of 3,000 corn plant stem images with 3 target classes (Healthy, Sheath stalk rot, and Charcoal stalk rot), it can be concluded that the three proposed algorithms in this research can classify and identifying diseases in new digital corn plant stem images. The method proposed in this study achieved a very high accuracy of 99.05%.

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