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Comparison of Support Vector Machine (SVM), K-Nearest Neighbor (K-NN), and Stochastic Gradient Descent (SGD) for Classifying Corn Leaf Disease based on Histogram of Oriented Gradients (HOG) Feature Extraction

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ABSTRACT

Image classification involves categorizing an image's pixels into specific classes based on their unique characteristics. It has diverse applications in everyday life. One such application is the classification of diseases on corn leaves. Corn is a widely consumed staple food in Indonesia, and healthy corn plants are crucial for meeting market demands. Currently, disease identification in corn plants relies on manual checks, which are time-consuming and less effective. This research aims to automate disease identification on corn leaves using the Support Vector Machine (SVM), K-Nearest Neighbor (K-NN) with K=2, and Stochastic Gradient Descent (SGD) algorithms. The classification process utilizes the Histogram of Oriented Gradients (HOG) feature extraction method with a dataset of corn leaf images. The classification results achieved an accuracy of 71.44%, AUC of 79.16%, precision of 70.08%, recall of 71.44%, and f1 score of 67.11%. The highest accuracy was obtained by combining HOG feature extraction with the SGD algorithm.

Keywords*:* classification, corn-leaf, disease, HOG, K-NN, SGD, SVM

INTRODUCTION

Corn is a food that is an alternative source of carbohydrates. Besides being needed for food, corn is also used in various industrial raw materials for food processing, animal feed, and bioethanol, so the availability of raw corn materials in consistent quantities is always required [1]. Based on data from the Food Security Agency, Ministry of Agriculture, the estimated domestic corn stock until January 2022 is 2.17 million tons. This amount decreased by 1.52% compared to the corn stock in December 2021 of 2.20 million tons [2].

Several trigger factors can reduce corn production, including pest and disease attacks on corn which can reduce corn production by 26.5% [3]. This disease in corn plants can cause low corn production because, in general, the part that is attacked by bacteria is the leaf which is a place for photosynthesis that inhibits corn's growth [4][5].

Corn-related diseases are generally caused by viruses, parasites, fungi, mycoplasmas, bacteria, and nematodes. Corn disease can occur in seedlings, seeds, stems, leaves, cobs, and post-harvest. Early identification of the presence of diseases in corn by experts can be a solution to maintaining the availability and production of corn. The unbalanced comparison of the availability of experts and the land area becomes an obstacle in the identification process. One alternative that can be used for the automatic identification of corn diseases is to apply machine learning to reduce dependence on the identification process by plant disease experts.

Various studies on identifying diseases in corn have been carried out, some of which J. Chen, in 2021, conducted research using the CNN DenseNet method to classify eight leaf diseases and corn cobs, which resulted in a percentage of accuracy value of 98.5% [6]. Another study by Liu in 2020 used the CNN ResNet method to perform a classification process on eight diseases that attack corn plant leaves and resulted in an accuracy value of 98.52% [7]. The next study in 2020 used the CNN AlexNet method and the Support Vector

Machine to identify three classes of disease in corn plants with an accuracy of 95.08% [8].

The results of the accuracy of some of these studies are, on average more than 95%, with the general method used being various variations of CNN. The use of the CNN method has advantages in terms of high classification accuracy. But the CNN method in addition to requiring a long processing time, is also unable to identify certain parts of the image that indicate disease directly. This study proposes a comparison of the use of methods to reduce the impact of long processing and does not ignore the value of accuracy. The three methods used in this research are Support Vector Machine, K-NN, and Stochastic Gradient Descent (SGD). Application of these three different algorithms is used to classify corn leaf plants as well as to compare the performance of each method.

METHODS

In this study, the classification of corn leaf diseases in the form of digital images will be carried out. This image classification is a process of categorizing the pixels of an image into certain classes where each class has certain characteristics that represent that class. In classifying digital images, there are several stages of the process, starting from data collection, pre-processing, feature extraction, classification process, and evaluation to measure the results of the performance of the built classification model.

Feature extraction is one of the steps needed in classifying images to remove noise in the image to maximize the accuracy of results obtained [9]. In this study, feature extraction was performed using the Histogram of Oriented Gradients (HOG) method and feature extraction at the statistical level.

A. Histogram of Oriented Gradients (HOG)

Histogram of Oriented Gradients or HOG is one method that can be used to extract image features that work by dividing the image into several cells that represent the area to be compared [10]–[12]. The area can be categorized into blocks which will then be normalized. This normalization process aims to obtain nearly the same results for photometric and illumination effects. These blocks are called the Histogram of Oriented Gradients (HOG). The stages of the HOG method are as follows.

1. Determine the size of the block and cell
2. Calculate the value of the gradient. Equations (1) and (2) are used to obtain the gradient value.

$$|G| = \sqrt{lx^2 ly^2} \tag{1}$$

$$\theta = |tan^{-1}((ly)/(lx))| \tag{2}$$

Where:
$|G|$ = big gradient
θ = the measure of the angle
ly = matrix row
lx = column matrix

3. Divide the image into several smaller areas called cells.
4. The next step is to normalize the block using equation (3).

$$Vn = \sqrt{\frac{v}{||v||+\varepsilon}} \tag{3}$$

Where:
Vn = normalized vector value
v = unnormalized vector value
|v| = vector norm v
ε = constant with a small value to avoid division by zero.

The last step is to combine the results of block normalization into one vector to obtain the HOG feature vector.

B. Statistical Feature Extraction

Based on texture analysis, image classification usually requires a feature extraction step, which includes three methods, one of which is a statistical method. This statistical method calculates the histogram distribution by measuring the contrast, granularity, and area roughness of the neighbouring relationship between one pixel and another pixel in the image [13]. This statistical model has unlimited uses, so it fits into the natural texture of the unstructured sub pattern. From the resulting histogram value, several characteristic parameters can be calculated, namely the mean, standard deviation, kurtosis, and skewness. The following is an explanation of some of these characteristic parameters.

1. Mean is a texture feature with histogram, especially at intensity values with high frequency [10]. Calculations are carried out based on equation (4).

$$m = \sum_{i=0}^{L-1} p(i) \quad (4)$$

2. Standard deviation is a texture feature that can provide information about the size of the contrast level of an object [14]. Calculations are carried out based on equation (5).

$$\sigma = \sqrt{\sum_{i=0}^{L-1} (i-m)^2 \; p(i)} \quad (5)$$

3. Kurtosis is a texture feature that shows uniformity where a similar approach is carried out using the probability density function [15]. Calculations are carried out based on equation (6)

$$m_k = \sum_{i=0}^{L-1} (i-\mu f)^k \; p(i) \quad (6)$$

4. Skewness is the imbalance value to the average intensity value. Calculations are carried out based on equation (7).

$$skewness = \sum_{i=0}^{L-1} (i-m)^3 \; p(i) \quad (7)$$

C. Support Vector Machine

Support Vector Machine (SVM) is one method for predicting regression and classification cases [16]. The basic principle of SVM is to use a linear classifier or a linearly separated classification case. Currently, SVM has evolved to be able to work in non-linear cases, namely using the kernel concept in workspaces that have high dimensions. SVM works to find the best hyperplane to separate the distance between two data classes. Hyperplane can be used for high-dimensional space to maximize the distance (margin) between data classes [17][18]. The best hyperplane that can separate two different classes must be found among an infinite number of other hyperplanes. A hyperplane can be the best if it is located right between two sets of objects from two classes. The illustration of the hyperplane in SVM can be seen in Figure 1.

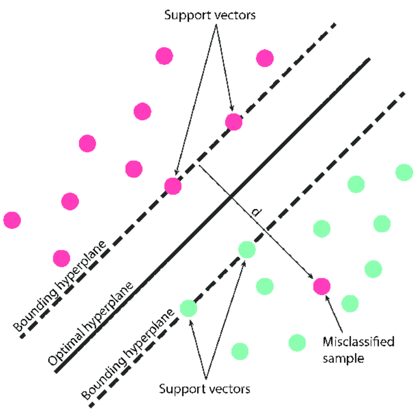

Figure 1. The illustration of the hyperplane in SVM

Figure 1 shows that there are two classes, namely class A, which is marked with a pink pattern, and class B which is marked with a green pattern. In Figure 1, it can be seen that the two classes are separated by a straight line called a hyperplane. In this algorithm, the hyperplane will be optimized to separate two different classes. In addition to solving linear problems, SVM can also solve non-linear problems. Non-linear problems can be solved by using a kernel in a high-dimensional workspace [19]. There are several kernels in SVM, including:

1. Linear Kernel

$$K(x_i, x) = x_i^T x \quad (8)$$

2. Polynomial Kernel

$$\mathrm{K}(x_i, x) = (\gamma x_i^T + r)^p, \gamma > 0 \quad (9)$$

3. Radial Basis Function Kernel

$$\mathrm{K}(x_i, x) = \exp\left(-\gamma ||x - x_i||^2\right) \quad (10)$$

4. Sigmoid Kernel

$$\mathrm{K}(x_i, x) = \tanh(\gamma x_i^T + \mathrm{r}) \quad (11)$$

SVM has several stages in the classification process. These stages, among others.

1. The first step is data input.
2. The second step is to calculate the dot product value with the kernel function.
3. The third step is to calculate the hessian matrix. The hessian matrix is the product of the kernel function and the value of y. The value of y is the vector value worth 1 and -1. The hessian matrix can be calculated using equation (12).

$$D_{ij} = y_{i,}y_j\left(K\left(x_{i,}x_{j,}\right) + \lambda^2\right) \quad (12)$$

Where:
D_{ij} = element of the ij-th hessian matrix
λ = theoretical limit to be derived
y_i = class of i-th data
y_j = class of j-th data

4. The fourth step is to find the error value using equation (13), delta alpha using equation (14), and new alpha using equation (15).

$$E_i = \sum_{i=1}^{l} a_i D_{ij} \quad (13)$$

$$\delta a_i = \min\{\max[\gamma(1 - E_I), -a_i), C - a_i\} \quad (14)$$

$$a_i = a_i \delta a_i \quad (15)$$

Where:
E_i = i-th data error value
α_i = i-th alpha
$\delta\alpha_i$ = i-th alpha delta
C = constant value C

5. The fifth step is to find the bias value using equation (16)

$$b = -\frac{1}{2}(w.x^+ + w.x^-) \quad (16)$$

6. The sixth step is calculating the dot product value between training and testing data (test data).
7. The seventh step is determining the test data class using equation (17).

$$f(x) = \sum_{i=1}^{l} a_i y_i K(x_i, x) + b \quad (17)$$

D. K-NN (K-Nearest Neighbor)

K-Nearest Neighbor, also known as K-NN, is an algorithm whose purpose is to determine the value of a new object based on attributes and training samples. This classification method builds a decision support model where the classification process is determined based on the closest distance [20] [21]. The following are the steps in doing the classification using the K-NN algorithm.

1. The first step is to enter the input data to be analyzed.
2. The second step is to determine the value of k as the number of nearest neighbors.
3. The third step is to calculate the distance between objects using the Euclidean Distance method, which is formulated in equation (18).

$$dist(a, b) = \sqrt{\sum_{i=1}^{n}(ai - bi)^2} \quad (18)$$

Where:
dist(a, b) = Euclidean distance
a = Data 1
b = Data 2
i = Attribute i
n = Number of attributes

4. The fourth step sorts the results from the 2nd stage from the largest to the smallest value.
5. The fifth step is to collect categories from neighboring data based on the value of k.

Then, for the last step, determine the closest neighbor class, the majority, to predict the test data in the testing process.

E. Stochastic Gradient Descent (SGD)

Stochastic Gradient Descent Classifier is a classification method that is a statistically based optimization method that works simply [22]. The purpose of this method is to minimize the possibility of misclassification by minimizing the value of the loss function coefficient (error) on a large scale [23]. If a function with parameters is given, SGD starts by giving the initial parameter value weight, which then in each iteration, will switch to the new weight parameter value which has the smallest point. The process of calculating the smallest or minimum point uses the derivative method to find the line that is closest to the minimum value. For more details, several stages of the SGD method classification process are as follows:

1. The first step is to input the data to be classified.
2. Then, determine the initial value θ by using a search algorithm.
3. Repeating updating the value until the minimum point is found to minimize the function (θ), the new θ value can be calculated using the equation (19), and the calculation of value of J(θ) using equation (20).

$$\theta j = \theta j - \alpha \frac{\partial y}{\partial x} J(\theta) \tag{19}$$

$$J(\theta) = \frac{1}{n}\sum_{i=1}^{n} L(y_i, f(x_i)) + \alpha R(w) \tag{20}$$

Where:
L = loss function
n = number of data
(y_i, x_i)= training data
R = model complexity penalty

F. Evaluation

The system that performs the classification process is expected to classify all data sets correctly, thus requiring system performance evaluation [24]. The confusion matrix is used to measure performance in most cases. A confusion matrix is a tool that can be used to determine the truth of a system [25]. The confusion matrix contains information from the actual and predicted classification results at the time of text classification [26]. The system's performance is evaluated using data in a matrix, as in Figure 2.

X_{jk}		Predicted Class (k)	
		Positive	Negative
Actual Class (j)	Positive	TP	FP
	Negative	FN	TN

Figure 2. Confusion Matrix

Figure 2. shows a confusion matrix used to evaluate the classification process into positive and negative classes. Each matrix cell represents the amount of data from class j whose prediction results go to class k. For example, cell X is the number of data in the positive class that is correctly mapped to the positive class, and Xjk is the data in the positive class that is incorrectly mapped to the negative class. Based on the confusion matrix table, it can be calculated the values of accuracy, precision, recall, f1 score, and AUC using equations 21 to 25 [27].

1. Accuracy

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{21}$$

2. Precision

$$Precision = \frac{TP}{TP+FP} x\ 100\% \tag{22}$$

3. Recall

$$Recall \quad = \frac{TN}{TN+FN} x\ 100\% \tag{23}$$

4. F1 Score

$$F - measure = 2\ x\ \frac{Recall\ x\ Precision}{Recall+Precision} x\ 100\% \tag{24}$$

5. AUC

$$AUC \quad = \frac{1}{2} x\ (\frac{TP}{TP+FN} + \frac{TN}{TN+FP}) \tag{25}$$

Where:
TP = the number of data correctly predicted positive,
TN = the number of data with the original class is positive, but the prediction result is negative,
FN = the number of data correctly predicted negative,
FP = the number of data with the original class is negative, but the prediction result is positive.

RESULT AND DISCUSSION

A. Dataset

The data used in this study is an image dataset of corn leaf disease with a size of 3000 x

4000 pixels obtained from kaggle.com[1] and created by A.R Hasna Azzahra. This dataset is a collection of images of corn leaves taken from farmers' fields in the Madura region with a total of 3500 records with four target classes namely Healthy (1000 records), Gray leaf Spot (500 records), Blight (1000 records), and Common Rush (1000 records).

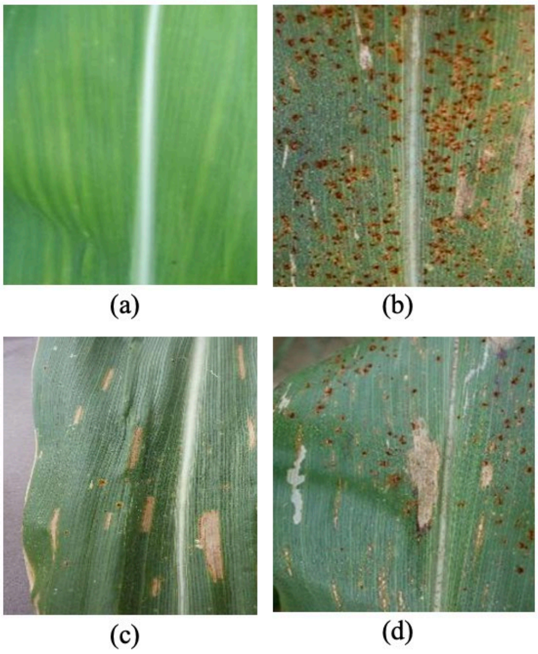

Figure 3. Corn Leave Disease

Figure 3 is an example of the dataset used in this study. Figure 3 shows the four target classes in the corn leaf image. Figure 3(a) is categorized into healthy corn leaf class, Figure 3(b) is corn leaf infected with Gray leaf Spot disease, then Figure 3(c) is corn leaf categorized into Blight class, and Figure 3(d) is a corn leaf with Common Rush. Based on the four classes, the corn leaf was classified to determine whether the corn leaf was healthy or infected with leaf disease.

B. Analysis

The representation of the process flow applied in this study, as shown in Figure 4, has the following stages:

1. Data Input Process
   This process is carried out by entering a dataset of corn leaf image collections taken directly from farmers' fields in the Madura area with as many as 3500 records with four classification target classes.

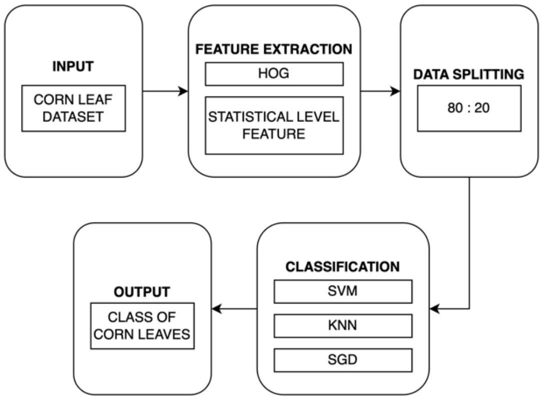

Figure 4. Research flow diagram

2. Feature Extraction
   The feature extraction at this stage uses the Histogram of Oriented Gradients (HOG) method and statistical feature extraction by calculating the results from the histogram that has been obtained with several first-order characteristics, namely mean, standard deviation, kurtosis, and skewness.
3. The Process of Splitting Data
   The third stage is done by splitting the data into training and testing. Training data is used for modelling, and testing data is used for evaluation. The comparison of the distribution of training data and testing data in this study is 80:20.
4. Classification Process
   At this stage, the learning process is carried out to obtain a classification model using three different classification methods, namely SVM, K-NN, and SGD. The results of the accuracy of these three different classification models are compared to identify the classification method that gets the most optimal results in the case of this study.

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1 https://www.kaggle.com/datasets/arhasnaazzahra/cornleavediseasesprehensive

5. Output
   The output of this classification process categorizes corn leaf image data into classes based on the results of modeling and classification that have been carried out and applied to this study.

C. Discussion

Analysis and testing have been conducted to compare the performance results from applying the SVM, K-NN (used K=2), and SGD algorithms. The results of the test can be seen in Table 1:

Table 1 and Table 2 show that, among the three algorithms, K-NN has the best AUC value of 84.85%. However, for the value of accuracy, precision, recall, and f1 score, the best value was obtained when the classification was carried out using the SGD method. Namely, the accuracy value reached 71.44%, precision was 70.08%, the recall was 71.44% and f1 score was 67.11%.

Table 1. Comparative Results of the Three Classification Methods (AUC, CA, and F1)

Model	AUC	CA	F1
SVM	78.35%	56.44%	55.95%
K-NN	**84.85%**	65.86%	65.65%
SGD	79.16%	**71.44%**	**67.11%**

Table 1. Comparative Results of the Three Classification Methods (Precision and Recall)

Model	Precision	Recall
SVM	58.89%	56.44%
K-NN	65.47%	65.86%
SGD	**70.08%**	**71.44%**

Figure 4 proves that the SGD method shows more stable results and has a better accuracy value than the SVM and K-NN methods. The SGD method can minimize the loss function in the data to be tested and minimize errors in classifying data in the testing process to maximize the accuracy value.

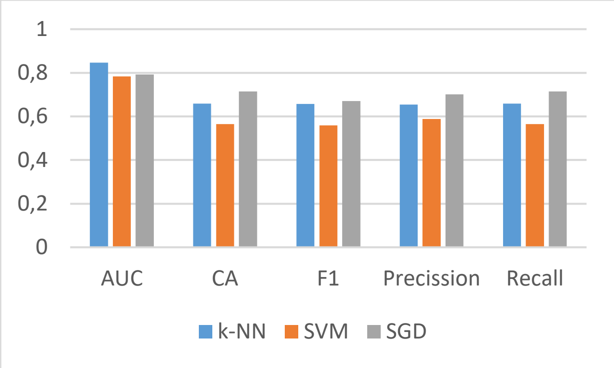

Figure 4. Test results using three classification methods

CONCLUSION

Early identification of diseases in corn by experts can be a solution to maintain the availability and production of corn. An unbalanced comparison between the availability of experts and the land area becomes an obstacle in the identification process. One alternative that can be used to reduce dependence on the process of identifying corn diseases by experts is to identify corn diseases using classification and machine learning methods automatically.

This study has conducted the process of classifying diseases on corn leaves using HOG feature extraction and comparing three classification algorithms, namely Support Vector Machine, K-NN, and Stochastic Gradient Descent (SGD). The corn leaf image dataset used in this study amounted to 3500 records with four target classes namely Healthy, Gray leaf Spot, Blight, and Common Rush.

Based on the results and discussions that have been carried out, it can be concluded that the three algorithms proposed in this study can classify digital images, where the Stochastic Gradient Descent (SGD) algorithm is superior to the other two methods with an accuracy value of 71.44%, AUC of 79.16%, the precision of 70.08%, recall of 71.44% and the value of F1 score of 67.11%

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