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Classification of Corn Diseases and Pests Using Fuzzy Naïve Bayes Method

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ABSTRACT

Corn is an essential dietary source for humans and animals. In addition to being a food source, corn has numerous benefits as a manufacturing commodity. The quality of grain crops must be considered to minimise the likelihood of disease and pest infestations. Therefore, the diseases and pests that attack corn plants must be classified so that farmers can control them during the growth period of corn plants. The fuzzy naive Bayes method is a statistical machine learning method that can be used to classify the diseases and pests of corn crops based on colour space-transformed digital images. This study aims to classify corn plant diseases and pests using the fuzzy naive Bayes method. Digital images of corn plant diseases and pests were transformed into a red, green and blue colour space model. The following seven classes of corn plant diseases and pests were classified: leaf rust disease, downy mildew disease, leaf blight disease, Locusta pest, Heliotis armigera pest, Spodoptera frugiperdita pest and non-pathogenic pest. With this method, the classification model achieves an accuracy of 87.83%, a macro precision of 34.91%, a macro recall of 35.90% and a macro f-score of 33.82%.

Keywords:
Corn disease and pest; discretization, fuzzy naïve Bayes

1. Introduction

Corn is a short-lived plant. After male flowers begin to emerge, the number of leaves is regulated by temperature, duration of light and genotype. Corn is not only useful as food but also for the industry. However, corn plantations often experience financial setbacks and even total crop failure due to infestations of various pests and diseases, including but not limited to, Spodoptera frugiperda pest (SFP), Locusta pest (LP), Heliotis armigera pest (HAP), leaf rust disease (LRD), downy mildew disease (DWD) and leaf blight disease (LBD) [1]. Specifically, S. frugiperda is a pest that recently entered Indonesia in 2019 [2] and has attacks with severity level ranging from 26.50% to 100% [3]. Therefore, corn quality considerations must be incorporated into strategies to meet domestic demand without relying on exports.

Similar to other food crops [4-7], the use of digital images as a dataset for identifying corn plant diseases and pests is expanding rapidly [1, 7-17]. The current price rise can be attributed to the

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technology's lower cost than alternatives such as infrared light [18]. Classification requires the extraction of distinguishing characteristics from digital images, which are critical for identifying corn diseases and pests. Digital image processing using the red, green and blue (RGB) colour space paradigm is the most informative for the identification of diseases and pests in corn crops [16].

Naïve Bayes is a classification model in statistical machine learning that predicts target variables based on the Bayes theorem. The performance of this model can increase significantly if the continuous predictor variables are discretised into valid categories [19-22]. Discretisation can also improve other methods' performance, such as decision tree and random forest [23-26]. In some cases, the result does not provide satisfactory performance [27] possibly due to the ambiguity in discretizing predictor variables. The implementation of fuzzy membership functions into the model to resolve discretisation ambiguity issues is known as fuzzy naïve Bayes [10, 28]. This work aims to classify the diseases and pests of corn plants using the fuzzy naïve Bayes model and show that the model's performance of naïve Bayes can be improved by implementing fuzzy discretisation.

2. Methodology

Images of the pests and diseases of corn plants taken on corn plantations in Ogan Ilir Regency were used as data. The research stages were as follows:

i. Data were collected by capturing images of corn plant diseases and pests in corn plantations around the Universitas Sriwijaya;
ii. The images were cropped to focus only on the pests and diseases of corn plants and then resized to 32×32 pixels so that all images have the same size. The images were extracted into the RGB colour space model using Python programming language via Google Collab. The average image matrix value of each colour (red, green and blue) was determined;
iii. The data were discretised using the concept of crisp sets. If an element of the universal set X is also a member of set A, then it is denoted as $x \in A$ in the crisp set. If x is not a member of A, then it is denoted as $x \notin A$. Therefore, the membership value of x in set A can only be determined by either $\mu_A(x)=1$or $\mu_A(x)=0$ [29];
iv. The fuzzy membership functions were defined, and a fuzzy set was used for discretisation [9]. In the fuzzy set, the membership value x in set A fell within the interval [0,1]. Fuzzy discretisation forms classes by connecting linguistic terms to fuzzy membership functions. In this research, the fuzzy membership function consisted of a shrinkage sigmoid curve, a beta bell curve and a growth sigmoid curve, all which have individual membership functions. β is an inflection point, γ is the centre point of the curve that has an immense membership value, n is the power multiplier value that determines the shape of the curve, α is the smallest element of the domain that has the smallest membership value and c is the most prominent element of the domain that has the smallest membership value;

$$\mu_A(x;\ \alpha,\beta,\gamma) = \begin{cases} 1 & ; x \le \alpha \\ 1-2\left(\frac{x-\alpha}{\gamma-\alpha}\right)^2 & ; \alpha \le x \le \beta \\ 2\left(\frac{\gamma-x}{\gamma-\alpha}\right)^2 & ; \beta \le x \le \gamma \\ 0 & ; x \ge \gamma \end{cases} \tag{1}$$

$$\mu_A(x\colon \gamma,\beta,n) = \begin{cases} 0 & ; x < \alpha \\ \frac{1}{1+(\frac{x-\gamma}{\beta})^{2n}} & ; a \le x \le c \\ 0 & ; x > c \end{cases} \tag{2}$$

$$\mu_A(x;\ \alpha,\beta,\gamma) = \begin{cases} 0 & ; x \leq \alpha \\ 2\left(\frac{x-\alpha}{\gamma-\alpha}\right)^2 & ; \alpha \leq x \leq \beta \\ 1-2\left(\frac{\gamma-x}{\gamma-\alpha}\right)^2 & ; \beta \leq x \leq \gamma \\ 1 & ; x \geq \gamma \end{cases} \tag{3}$$

v. The dataset was divided into 80% training data and 20% test data;
vi. A classification model was built using naïve Bayes and fuzzy naïve Bayes methods by determining the posterior probability values for discretisation. For naive Bayes and fuzzy naïve Bayes, the posterior probability with Laplace smoothing was written as [10]:

$$P(Y_j|X_1,\cdots,X_D) = P(Y_j)\prod_{d=1}^{D}\frac{\sum_k^m n_k(X_d|Y_j)+1}{n(X_d|Y_j)+m} \tag{4}$$

$$P(Y_j|X_1,\cdots,X_D) = P(Y_j)\ \frac{\prod_{d=1}^{D}\sum_{z=1}^{Z}P(x_{f_z}|Y_j)\mu_{\tilde{X}_d}(x_{f_z})+\frac{1}{Z}}{\prod_{d=1}^{D}\sum_{z=1}^{Z}P(x_{f_z})\mu_{\tilde{X}_d}(x_{f_z})+\frac{1}{Z}} \tag{5}$$

where $P(Y_j)$ is the prior probability, and the rest is the likelihood for each model. In the naïve Bayes formula, $n(X_d|Y_j)$ is the number of images related to the j-th class in all variables X, $n_k(X_d|Y_j)$ is the number of images related to the j-th class in a variable X_d with category k and m is the number of categories in the variable X_d. In the fuzzy naïve Bayes formula, $\tilde{X}_d = \{x_{f_1}, x_{f_1} \cdots, x_{f_Z}\}$ is the information space of the fuzzy sample of the predictor variable of X_d, $x_{f_z} \in X$ is the independent event and $\mu_{\tilde{X}_d}(x_{f_z})$ is the fuzzy membership function of X_d with fuzzy sample x_{f_Z};
vii. The test data were classified using the models built with naïve Bayes and fuzzy naïve Bayes methods;
viii. The performance of naïve Bayes and fuzzy naïve Bayes methods was evaluated by calculating the accuracy, precision, recall and f-score values [30, 31]. The confusion matrix for the first class of corn plant diseases and pests is presented in Table 1 [1]. The remaining classes function similarly.
ix. When the values of these metrics increase, the predictive performance of the employed method or model also improves;
x. The results were analysed, and conclusions were drawn.

Table 1
Confusion matrix for the first class of disease and pest of corn plant

		Prediction class					
	j	LRD	DWD	LBD	LP	SFP	HAP
Actual class	LRD	TP	FN	FN	FN	FN	FN
	DWD	FP	TN	TN	TN	TN	TN
	LBD	FP	TN	TN	TN	TN	TN
	LP	FP	TN	TN	TN	TN	TN
	SFP	FP	TN	TN	TN	TN	TN
	HAP	FP	TN	TN	TN	TN	TN

$$\text{Accuracy} = \frac{\sum_{j=1}^{4}\frac{\text{TP}_j+\text{TN}_j}{\text{TP}_j+\text{FP}_j+\text{FN}_j+\text{TN}}}{4} \tag{6}$$

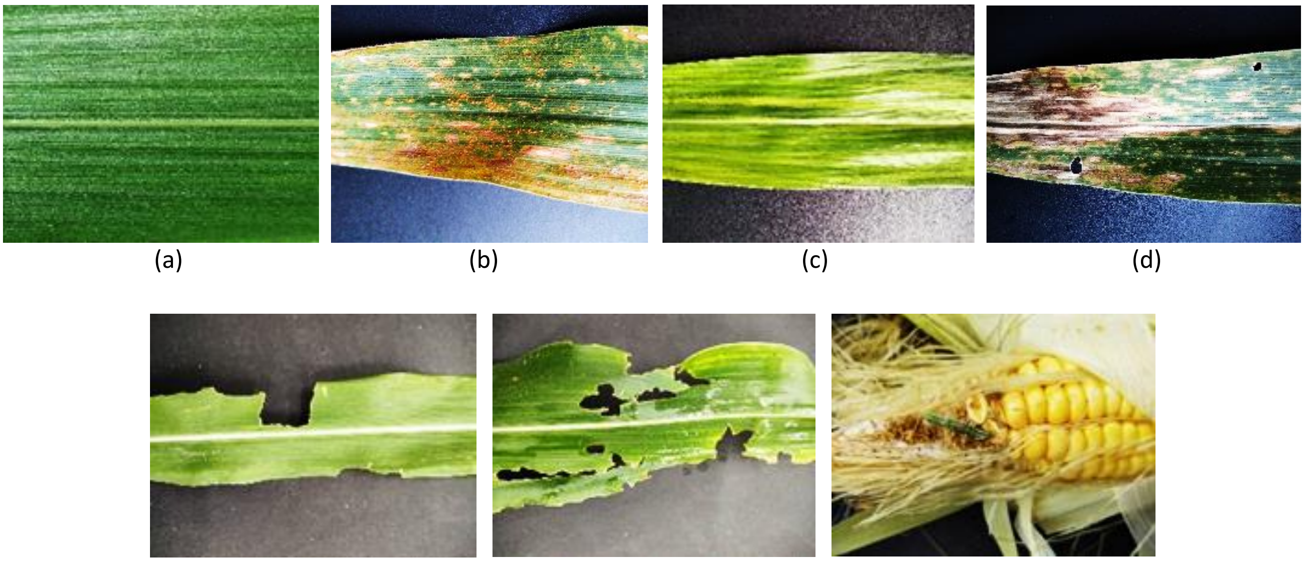
$$\text{Precision} = \frac{\sum_{j=1}^{4}\frac{\text{TP}_j}{\text{TP}_j+\text{FP}_j}}{4} \tag{7}$$

$$\text{Recall} = \frac{\sum_{j=1}^{4}\frac{\text{TP}_j}{\text{TP}_j+\text{FN}_j}}{4} \tag{8}$$

$$\text{F}_1\text{Score} = \frac{2\text{Precision (Recall)}}{(\text{Precision +Recall })} \tag{9}$$

3. Results

Most corn plant pests and diseases attack the leaves. Only the cob borer pest attacks the corn cobs. I this research, digital images of pests and diseases of corn plants and healthy corn plants were collected. Healthy corn plants are characterised by their leaves, and Figure 1 presents their composition. The digital images were taken using a 12-megapixel cell phone camera in Tanjung Pering Village, Tanjung Baru Village and Tanjung Seteko Village and Ogan Ilir Regency.



(a) (b) (c) (d) (e) (f) (g)

Fig.1. Corn plant class composition of non-pathogen, disease, and pest (a) NP (b) LRD (c) DWD (d) LBD (e) LP (f) SFP (g) HAP

A total of 7052 digital images of corn plant pests and diseases were transformed into an RGB colour space model and resized to 32x32 pixels. A statistical summary of each pixel value R, G and B is presented in Table 2.

Table 2
Statistical summary of pixel value

Statistics	Red	Green	Blue
min	27.75	38.69	10.02
q1	102.02	113.82	69.81
median	115.77	127.55	91.52
mean	115.01	130.37	89.46
modus	116.90	128.59	113.71
q3	127.06	149.97	107.56
max	199.43	217.89	196.98

Discretizing each pixel value R, G and B into five categories often leads to satisfactory classification model performance [10, 12]. These pixel values are predictor variables in the classification model. The results of discretisation using the crisp set for each of these variables are as follows.

$$R\begin{cases}\text{Very Dark Red (VDR)} & 27.75 \leq x \leq 62.08\\ \text{Dark Red (DR)} & 62.09 \leq x \leq 96.42\\ \text{Medium Red (MR)} & 96.43 \leq x \leq 130.76\\ \text{Light Red (LR)} & 130.77 \leq x \leq 165.09\\ \text{Very Light Red (VLR)} & 165.10 \leq x \leq 199.43\end{cases} \quad (10)$$

$$G\begin{cases}\text{Very Dark Green (VDG)} & 38.69 \leq x \leq 74.53\\ \text{Dark Green (DG)} & 74.54 \leq x \leq 110.37\\ \text{Medium Green (MG)} & 110.38 \leq x \leq 146.21\\ \text{Light Green (LG)} & 146.22 \leq x \leq 182.05\\ \text{Very Light Green (VLG)} & 182.06 \leq x \leq 217.89\end{cases} \quad (11)$$

$$B\begin{cases}\text{Very Dark Blue (VDB)} & 10.02 \leq x \leq 47.41\\ \text{Dark Blue (DB)} & 47.42 \leq x \leq 84.80\\ \text{Medium Blue (MB)} & 84.81 \leq x \leq 122.19\\ \text{Light Blue (LB)} & 122.20 \leq x \leq 159.59\\ \text{Very Light Blue (VLB)} & 159.60 \leq x \leq 196.98\end{cases} \quad (12)$$

Table 3 presents the likelihood for crisp set-based discretisation with zero likelihood value in several categories in the SFP, LBD and LRD classes. This problem can be solved using Laplace smoothing in Eq. (4).

Table 3
Likelihood for crisp set-based discretisation

Red	Likelihood						
	LP	HAP	SFP	DWD	LBD	LRD	NP
VDR	0.01	0.01	0.00	0.02	0.02	0.02	0.02
DR	0.01	0.02	0.04	0.02	0.17	0.28	0.13
MR	0.16	0.05	0.78	0.02	0.73	0.60	0.38
LR	0.81	0.39	0.18	0.89	0.07	0.09	0.38
VLR	0.01	0.53	0.00	0.04	0.00	0.00	0.10
Green	Likelihood						
	LP	HAP	SFP	DWD	LBD	LRD	NP
VDG	0.01	0.01	0.00	0.02	0.03	0.04	0.01
DG	0.01	0.02	0.01	0.02	0.22	0.34	0.03
MG	0.16	0.26	0.30	0.02	0.72	0.58	0.19
LG	0.81	0.70	0.68	0.89	0.02	0.03	0.53
VLG	0.01	0.01	0.01	0.04	0.00	0.01	0.24
Blue	Likelihood						
	LP	HAP	SFP	DWD	LBD	LRD	NP
VDB	0.05	0.01	0.35	0.02	0.02	0.04	0.02
DB	0.13	0.36	0.39	0.54	0.29	0.40	0.10
MB	0.78	0.60	0.22	0.39	0.66	0.53	0.34
LB	0.02	0.02	0.04	0.02	0.03	0.03	0.45
VLB	0.01	0.01	0.00	0.02	0.00	0.00	0.09

The performance of the naive Bayes classification model using crisp set-based discretisation is presented in Table 4. However, only accuracy has satisfactory performance above 85% [32]. Other performance measures, namely, precision, recall and F-score, are unsatisfactory because their values are below 50%. In terms of accuracy, only the LBD and LRD classes have an accuracy of less than 85%. For precision, only the HAP class has more than 85% and even reach a perfect value (100%). With regards to recall and F-score, no class has reached 85%.

Table 4
Classification performance using the naïve Bayes model

Class	Accuracy	Precision	Recall	F-score
LP	98.58%	0.00%	0.00%	0.00%
HAP	99.15%	100.00%	47.83%	64.71%
SFP	89.79%	78.64%	64.07%	70.61%
DWD	99.43%	0.00%	0.00%	0.00%
LBD	71.93%	48.77%	56.62%	52.40%
LRD	66.55%	51.10%	53.00%	52.03%
NP	88.94%	64.22%	67.12%	65.64%
Average	87.61%	48.96%	41.23%	43.63%

This research implemented discretisation based on a fuzzy set for classification model using the fuzzy naïve Bayes method. The fuzzy membership functions used to discretise the three predictor variables are the shrinkage sigmoid curve for the dark and dark categories, the beta bell curve for the medium category and the growth sigmoid curve for the light and very light categories. The results of discretisation using fuzzy sets for five categories for each variable R, G and B are as follows.

$$R\begin{cases}\text{Very Dark Red (VDR)} & 27.75 \leq x \leq 67.23\\ \text{Dark Red (DR)} & 31.18 \leq x \leq 110.15\\ \text{Medium Red (MR)} & 56.79 \leq x \leq 170.38\\ \text{Light Red (LR)} & 117.02 \leq x \leq 196.00\\ \text{Very Light Red (VLR)} & 159.94 \leq x \leq 199.43\end{cases} \tag{13}$$

$$G\begin{cases}\text{Very Dark Green (VDG)} & 38.69 \leq x \leq 79.90\\ \text{Dark Green (DG)} & 42.27 \leq x \leq 124.70\\ \text{Medium Green (MG)} & 64.14 \leq x \leq 192.43\\ \text{Light Green (LG)} & 131.87 \leq x \leq 214.30\\ \text{Very Light Green (VLG)} & 176.67 \leq x \leq 217.89\end{cases} \tag{14}$$

$$B\begin{cases}\text{Very Dark Blue (VDB)} & 10.02 \leq x \leq 53.02\\ \text{Dark Blue (DB)} & 13.78 \leq x \leq 99.76\\ \text{Medium Blue (MB)} & 51.75 \leq x \leq 155.25\\ \text{Light Blue (LB)} & 107.24 \leq x \leq 193.24\\ \text{Very Light Blue (VLB)} & 153.98 \leq x \leq 196.98\end{cases} \tag{15}$$

Similar to the likelihood for crisp set-based discretisation, several categories in several classes of corn plant pests and diseases, including the NP class, have a zero value in the fuzzy set-based likelihood as presented in Table 5. The solution can be obtained by determining the prior probability based on Laplace smoothing in Eq. (5) for classification using the fuzzy naïve Bayes method.

Table 6 displays the results of the fuzzy naive Bayes classification model when fuzzy set-based discretisation was implemented. According to Aronoff [32], model performance surpassing 85% is considered adequate for accuracy. By contrast, low precision, recall and F-score under 50% indicate unsatisfactory performance levels.

Table 5
Likelihood for fuzzy set-based discretisation

Red	Likelihood						
	LP	HAP	SFP	DWD	LBD	LRD	NP
VDR	0.01	0.01	0.00	0.02	0.00	0.01	0.00
DR	0.01	0.01	0.02	0.02	0.12	0.20	0.08
MR	0.28	0.07	0.89	0.15	0.85	0.74	0.52
LR	0.69	0.79	0.09	0.78	0.02	0.05	0.37
VLR	0.01	0.12	0.00	0.02	0.00	0.00	0.02
Green	Likelihood						
	LP	HAP	SFP	DWD	LBD	LRD	NP
VDG	0.01	0.01	0.00	0.02	0.01	0.01	0.00
DG	0.01	0.01	0.00	0.02	0.15	0.25	0.02
MG	0.58	0.72	0.70	0.13	0.83	0.73	0.34
LG	0.39	0.25	0.29	0.80	0.01	0.02	0.58
VLG	0.01	0.01	0.00	0.02	0.00	0.00	0.06
Blue	Likelihood						
	LP	HAP	SFP	DWD	LBD	LRD	NP
VDB	0.03	0.01	0.12	0.02	0.00	0.01	0.01
DB	0.04	0.22	0.57	0.35	0.21	0.32	0.09
MB	0.90	0.75	0.28	0.59	0.78	0.66	0.45
LB	0.01	0.02	0.03	0.02	0.01	0.01	0.43
VLB	0.01	0.01	0.00	0.02	0.00	0.00	0.02

Table 6
Classification performance using the fuzzy naïve Bayes model

Class	Accuracy	Precision	Recall	F-score
LP	98.58%	0%	0%	0%
HAP	98.37%	0%	0%	0%
SFP	89.51%	73.11%	71.48%	72.28%
DWD	99.43%	0%	0%	0%
LBD	67.75%	44.76%	77.66%	56.79%
LRD	70.02%	63.51%	29.19%	40.00%
NP	89.01%	63.04%	72.97%	67.64%
Average	87.83%	34.92%	35.90%	33.82%

Compared with that of a naïve Bayes model which uses crisp sets, the performance of a fuzzy naïve Bayes model which uses fuzzy sets has better accuracy. However, this premise is not true for other performance measures such as precision, recall and F-score. Discretizing each pixel value R, G and B into five categories leads to satisfactory classification model performance [10, 12]. However, this finding is in contrast to the results of this study which only satisfy the accuracy. Some reports also provided unsatisfactory performance by implementing fuzzy discretisation, such as in the case of predicting heart disease [33], diabetes mellitus and liver disease [34]. Other investigations provided satisfactory performance, such as in the prediction of driver behaviour [26], breast cancer [35] and heart disease [36]. This possibility is related to the choice of fuzzy membership function [9, 12, 37]. Further exploration and analysis are needed to obtain a good performance.

4. Conclusions

This work classifies the pests and diseases of corn plants using the fuzzy naïve Bayes method. The performance of the classification model built on fuzzy discretisation is evaluated and compared with that of a naive Bayes method built on crisp discretisation. The fuzzy naïve Bayes method is generally better than the Naïve Bayes method. However, these two methods have a performance measure of more than 85% in accuracy. Their precision, recall and F-score are below 40%. Additional in-depth analysis is needed to improve the prediction performance of maize disease and pest classification models. For example, investigations must apply statistical learning techniques or multiply the sample sizes.

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