Determination of Zea Mays Plant Fertility Level in Automatic Fodder Systems using Supervised Learning based on GLCM and Physical Feature

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Received: 2 December 2024 | Revised: 2 January 2025 | Accepted: 5 January 2025

 DOI: https://doi.org/10.48084/etasr.9809

ABSTRACT

The problem during the dry season is the availability of animal feed, especially for cattle. One of the efforts made is to use fermented feed and corn fodder. Automated feedstock monitoring and control is one of the technologies that has been developed. This study proposes a method to determine the fertility of Zea May sp plants in automatic fodder using supervised learning based on Self-Organizing Map (SOM), Gray Level Co-occurrence Matrix (GLCM), and physical features. The results showed that the system worked satisfactorily, where both methods achieved an accuracy of 93.5% on 3-day Zea Mays fodder using SOM and the highest on 12-day Zea Mays fodder using both methods with an accuracy of 96%. Although this system has shown good performance using both SOM and K-means, in some conditions, K-means achieved higher performance. These contributions are expected to help farmers provide animal feed.

Keywords-SOM; k Means; zea mays; fodder; GLCM

I. INTRODUCTION

One of the difficult conditions during the dry season is the availability of feed for livestock. This occurs in several areas, including Belu Regency, Nusa Tenggara [1], Gorontalo [2], Bali [3], Semarang [4], and other areas of Indonesia. This is the basis for why the development of technology in this field is very important. The solution to these problems is to provide fermented food to livestock [5-8]. Another solution is to make fodder that can produce livestock feed in a fast time. Several automatic approaches have been presented for fodder, showing that this system can help farmers because it is more efficient [9]. Fodder has also been developed based on IoT [10-11], which can be controlled remotely and automatically. Such systems are not specific to fodder. Fodder research focuses on the design of IoT-based monitoring systems [12], but more developments are needed to facilitate farmers to provide livestock feed. Supervised learning has been widely used in several studies.

Fodder environmental conditioning research has been conducted, but fodder plant growth control is still very limited. Control is required because the fertility of plants must be monitored for health. This monitoring can be achieved using a camera. This study aims to determine Zea May plant fertility in an automatic fodder system using supervised learning based on the Gray Level Co-occurrence Matrix (GLCM) and physical features. This system aims to help farmers monitor the fertility of fodder plants. The originality of this study is monitoring plants in fodder using image processing and artificial intelligence. First, the image is captured by involving healthy and unhealthy plants. Supervised learning is used to obtain weights, which will be used to identify whether the plants are healthy or not. This study can help farmers monitor the health of fodder plants so that they can immediately take action if there is a discrepancy in the growth of Zeay Mays.

II. METHODS

The stages in this study include data collection, division of learning and testing data, learning process, and continued data testing. The supervised method involved K-means and Self-Organizing Map (SOM). Fodder can be harvested on the 14th day of growth, grows every day, and has physical characteristics. Figure 1 shows the scenario of the method. Monitoring was carried out (image capture) on days 3, 6, 9, and 12 using a camera, and then the image was classified to determine whether the plants at that age were fertile or infertile using supervised learning.

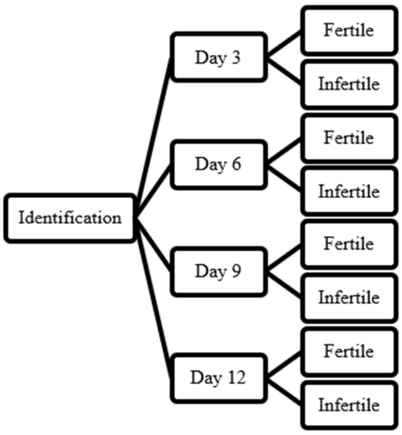

Fig. 1. Research scenario.

Data collection for the third day of growth involved 240 images, which were divided into 40 for the learning process (20 infertile and 20 fertile) and 200 for the testing process (100 infertile and 100 fertile). Data collection was carried out again when Zea Mays' growth was on the 6th day. 240 images were captured, divided into 40 for the learning process (20 infertile and 20 fertile) and 200 for the testing process (100 infertile and 100 fertile). This was also repeated for the 9th and 12th days. The total number of images was 960, consisting of 160 for learning and 800 for the testing process. Figure 2 shows a flowchart that describes the dataset. As this study used machine learning to classify the fertility of Zea Mays, a 20:80 ratio was used for training and testing, which is different from when using deep learning, where usually a ratio of 80:20 is used.

The learning process was carried out 8 times, that is when the growth of Zea Mays was on days 3, 6, 9, and 12 using SOM and K means. The testing process was also carried out 8 times using the weights generated from the learning process of each stage of Zea Mays' growth. Figure 3 shows the growth of the Zea May plants. At the age of 1 day, Zea Mays is still in seedling growth and the height of the plant is still a seed or 1 cm. At the age of 3 days, the seedlings have grown and their height varies from 4-5 cm. At the age of 6 days, the average height is 11 cm, at 9 days it is about 16 cm, at 12 days it is about 19 cm, and on the 14th day, it is around 26 cm. This study combines the texture features produced by the camera and the physical characteristics of the plant, namely its height.

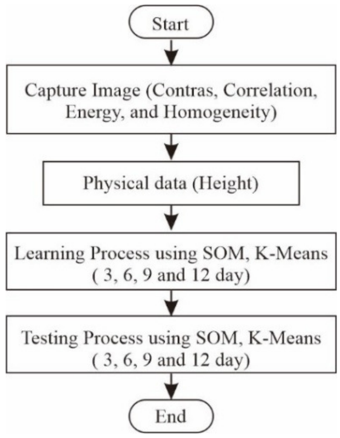

Fig. 2. Flowchart describing the dataset.

Fig. 3. Zea May plant growth: (a) 1 day, (b) 3 days, (c) 6 days, (d) 9 days, (e) 12 days, (f) 14 days.

The image features used are contrast, correlation, energy, and homogeneity. Contrast is the variation of local pixel values of the image in GLCM, correlation is the joint probability occurrence of the specified pixel pairs, energy is the sum of the squared elements (uniformity) of GLCM, and homogeneity is the proximity of the distribution of GLCM elements to the GLCM diagonal [13-15]. The input to the learning system is a 1×5 matrix, where 4 elements represent image features and 1 physical element of the plant (plant height) obtained from the ultrasonic sensor. Figure 4 describes the input features.

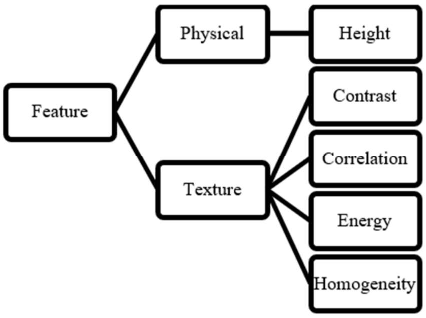

Fig. 4. Input features.

The learning was carried out in four stages (age: 3, 6, 9, and 12 days), where each stage has two experiments, namely, using K-means and SOM. Figure 5 depicts the research stages. This method begins with data collection and feature extraction, continues with data normalization, learning using SOM, testing using SOM, learning using K means, testing using K means, and analysis of the results. The SOM and K-means were chosen because they have been successfully implemented in various fields [16-21].

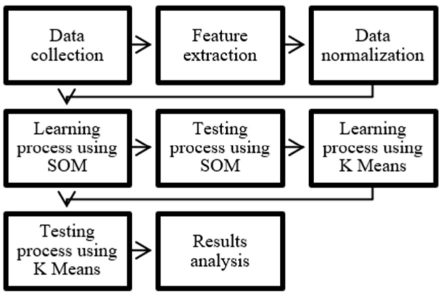

Fig. 5. Research stages.

System performance analysis was performed using the accuracy, precision, recall, and F1 score values of each machine learning model built. Accuracy, precision, recall, and F1 score values were calculated using:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1\ score = \frac{2 \times Precision\ x\ Recall}{Precision + Recall} \quad (4)$$

III. RESULTS AND DISCUSSION

Data collection was carried out following the design where the data obtained was sourced from the image and physical data from the Zea May Sp plants. The image data were searched for its GLCM features and the physical data is the height data of the plant obtained from the ultrasonic sensor. Feature extraction for plant image texture features was carried out by searching for contrast, correlation, energy, and homogeneity. The formulas for contrast, correlation, energy, and homogeneity are shown in (5)-(8). Before feature extraction, the image dimensions were normalized to anticipate that the image dimensions to be processed were following the standard (all images have the same dimensions). The average results of the GLCM feature values and the height of the plant are explained in Table I.

$$Contrast = \sum_{i,j=0}^{N-1} (i-j)^2 p(i,j) \quad (5)$$

$$Correlation = \sum_{i,j=0}^{N-1} \frac{(i-\mu_i)(j-\mu_j)\, p(i,j)}{\sigma_i \sigma_j} \quad (6)$$

where:

$$\mu_i = \sum_{i,j=0}^{N-1} i(p(i,j)),$$

$$\mu_j = \sum_{i,j=0}^{N-1} j(p(i,j)),$$

$$\sigma_i = \sqrt{\sum_{i,j=0}^{N-1} p(i,j)(i-\mu_i)^2},$$

$$\sigma_j = \sqrt{\sum_{i,j=0}^{N-1} p(i,j)(j-\mu_j)^2}.$$

$$Energy = \sum_{i,j=0}^{N-1} p(i,j)^2 \quad (7)$$

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{p(i,j)}{1+(i-j)^2} \quad (8)$$

TABLE I. GLCM PHYSICAL FEATURES OF ZEA MAYS SP

Age (days)	Condition	Contrast	Corre-lation	Energy	Homo-geneity	Height (cm)
3	Fertile	0.784	0.248	0.356	0.645	4
	Infertile	0.701	0.138	0.245	0.512	<4
6	Fertile	0.634	0.576	0.456	0.812	11
	Infertile	0.641	0.238	0.395	0.634	<11
9	Fertile	0.693	0.432	0.534	0.811	16
	Infertile	0.745	0.335	0.356	0.621	<16
12	Fertile	0.622	0.411	0.567	0.956	19
	Infertile	0.792	0.358	0.328	0.523	<19

The next stage involved data normalization to standardize the value of all data and avoid values that are too high or too low. Normalization involved dividing the value by the highest value in each dataset so that the existing data were between 0 and 1. Table II shows an example of the normalization results.

TABLE II. EXAMPLE OF NORMALIZED GLCM AND PHYSICAL FEATURE DATA OF ZEA MAYS SP

Age (days)	Condition	Contrast	Corre-lation	Energy	Homoge-neity	Height (cm)
3	Fertile	0.786	0.250	0.358	0.647	0.200
	Infertile	0.703	0.140	0.247	0.515	0.117
6	Fertile	0.632	0.578	0.458	0.815	0.550
	Infertile	0.639	0.240	0.397	0.637	0.262
9	Fertile	0.692	0.431	0.533	0.814	0.800
	Infertile	0.743	0.337	0.355	0.624	0.512
12	Fertile	0.620	0.413	0.566	0.959	0.950
	Infertile	0.790	0.360	0.330	0.526	0.723

The learning process used a learning rate of 0.1 and was carried out for 1000 epochs. This learning process provided the weights that would be used in the testing process. The SOM algorithm was used as follows:

- Determine the target of each input.

- Determine the initial weight (gold standard) for each cluster.
- Determine the learning rate value where the value is between 0.1 and 0.9.
- The training process begins with learning data.
- Find the shortest distance from each cluster using the Euclidian distance formula (9). This process seeks the lowest distance which is then called the winning neuron.

$$d = arc \min\left(\sum_{x=1}^{x=i}(x_i - c_i\right) \quad (9)$$

- Compare the results of the shortest distance to each cluster. If the calculated cluster is in accordance with the specified target, the weight remains the same. If it is different, a new weight calculation is carried out using:

$$w_{ij}(t + 1) = w_{ij}(t) + \propto (t)\left[x_{ij} - w_{ij}(t)\right] \quad (10)$$

- Weight update process.
- Save new weight.

The testing process using SOM was carried out and the results of the confusion matrix, accuracy, precision, recall, and F1 score values were obtained. Testing was only carried out on learning data for each age group of Zea Mays plants (at ages 3, 6, 9, and 12 days). The confusion matrices of the different ages are shown in Tables III-VI.

TABLE III. CONFUSION MATRIX USING SOM ON ZEA MAYS (3 DAYS AGE)

	Fertile	Infertile
Fertile	93	7
Infertile	4	96

TABLE IV. CONFUSION MATRIX USING SOM ON ZEA MAYS (6 DAYS AGE)

	Fertile	Infertile
Fertile	94	6
Infertile	5	95

TABLE V. CONFUSION MATRIX USING SOM ON ZEA MAYS (9 DAYS AGE)

	Fertile	Infertile
Fertile	94	6
Infertile	5	95

TABLE VI. CONFUSION MATRIX USING SOM ON ZEA MAYS (12 DAYS AGE)

	Fertile	Infertile
Fertile	96	4
Infertile	4	96

Table VII shows the accuracy, precision, recall, and F1 score values using SOM. The highest accuracy in the testing results was using SOM on Zea Mays aged 12 days. This is because the difference between fertile and infertile plants aged 12 days is very significant.

The next training process was carried out using K-means on Zea Mays at the same ages as in the learning process using SOM. The learning process used a learning rate of 0.1 and learning was carried out for 1000 epochs. Similar to the previous procedure, the weights obtained from this training process were used for the testing process. The K-means algorithm used is as follows:

- Determine the number of clusters (K) along with the cluster center of each cluster.
- Calculate the distance of each data to the cluster center.
- Group the data into clusters with the shortest distance.
- Calculate the cluster center.
- Repeat the previous two steps until no data move to other clusters.

TABLE VII. EVALUATION METRICS USING SOM

Performance	Value
Precision Fertile (3 days)	0.92
Precision Infertile (3 days)	0.95
Precision (3 days)	0.935
Precision Fertile (6 days)	0.94
Precision Infertile (6 days)	0.95
Precision (6 days)	0.945
Precision Fertile (9 days)	0.96
Precision Infertile (9 days)	0.96
Precision (9 days)	0.96
Precision Fertile (12 days)	0.96
Precision Infertile (12 days)	0.97
Precision (12 days)	0.965
Recall/sensitivity Fertile (3 days)	0.92
Recall/sensitivity Infertile (3 days)	0.95
Recall/sensitivity (3 days)	0.935
Recall/sensitivity Fertile (6 days)	0.94
Recall/sensitivity Infertile (6 days)	0.95
Recall/sensitivity (6 days)	0.945
Recall/sensitivity Fertile (9 days)	0.96
Recall/sensitivity Infertile (9 days)	0.96
Recall/sensitivity (9 days)	0.96
Recall/sensitivity Fertile (12 days)	0.96
Recall/sensitivity Infertile (12 days)	0.97
Recall/sensitivity (12 days)	0.965
Accuracy (3 days)	0.935
Accuracy (6 days)	0.945
Accuracy (9 days)	0.945
Accuracy (12 days)	0.96
F1 score (3 days)	0.935
F1 score (6 days)	0.945
F1 score (9 days)	0.96
F1 score (12 days)	0.965

The testing process using K Means was carried out and the results of the confusion matrix [22, 23], accuracy, precision, recall, and F1 score were obtained. Tables VII-XI show the confusion matrices for ages of 3, 6, 9, and 12 days.

TABLE VIII. CONFUSION MATRIX USING K MEANS ON ZEA MAYS AGED 3 DAYS

	Fertile	Infertile
Fertile	93	7
Infertile	5	95

TABLE IX. CONFUSION MATRIX USING K MEANS ON ZEA MAYS AGED 6 DAYS

	Fertile	**Infertile**
Fertile	94	5
Infertile	5	95

TABLE X. CONFUSION MATRIX USING K MEANS ON ZEA MAYS AGED 9 DAYS

	Fertile	**Infertile**
Fertile	94	5
Infertile	5	95

TABLE XI. CONFUSION MATRIX USING K MEANS ON ZEA MAYS AGED 12 DAYS

	Fertile	**Infertile**
Fertile	96	4
Infertile	4	96

Table XII shows the evaluation results for K means.

TABLE XII. EVALUATION RESULTS USING K MEANS

Performance	**Value**
Precision Fertile (3 days)	0.93
Precision Infertile (3 days)	0.95
Precision (3 days)	0.94
Precision Fertile (6 days)	0.94
Precision Infertile (6 days)	0.95
Precision (6 days)	0.945
Precision Fertile (9 days)	0.96
Precision Infertile (9 days)	0.96
Precision (9 days)	0.96
Precision Fertile (12 days)	0.96
Precision Infertile (12 days)	0.97
Precision (12 days)	0.965
Recall/sensitivity Fertile (3 days)	0.93
Recall/sensitivity Infertile (3 days)	0.95
Recall/sensitivity (3 days)	0.94
Recall/sensitivity Fertile (6 days)	0.94
Recall/sensitivity Infertile (6 days)	0.95
Recall/sensitivity (6 days)	0.945
Recall/sensitivity Fertile (9 days)	0.96
Recall/sensitivity Infertile (9 days)	0.96
Recall/sensitivity (9 days)	0.96
Recall/sensitivity Fertile (12 days)	0.96
Recall/sensitivity Infertile (12 days)	0.97
Recall/sensitivity (12 days)	0.965
Accuracy (3 days)	0.94
Accuracy (6 days)	0.945
Accuracy (9 days)	0.945
Accuracy (12 days)	0.96
F1 score (3 days)	0.94
F1 score (6 days)	0.945
F1 score (9 days)	0.96
F1 score (12 days)	0.965

Table XII shows that the highest accuracy in testing was achieved using K means on Zea Mays aged 12 days, which is the same as using SOM. This is also because the difference between fertile and infertile plants aged 12 days is very significant, unlike those aged 3 days, where infertile and fertile plants have differences that are not too significant. One of the visible differences is the height of the plant. Both SOM and K-means achieved similar results. Their only difference in accuracy was for Zea Mays aged three days, where K-means slightly better accuracy (94%) than SOM (93.5%).

The application of artificial intelligence in the agricultural sector is very helpful for farmers as it facilitates their work and provides several other benefits. However, several consequences must be faced, such as response time, accuracy, implementation, and high costs during the initial phase of implementation [24, 25].

IV. CONCLUSION

This study proposed a method for determining the fertility fodder of the Zea May Sp plant using supervised learning based on GLCM and physical characteristics. The results show that the system worked well, where SOM and K-means achieved the lowest accuracy on 3-day Zea Mays fodder and the highest on 12-day Zea Mays fodder. This system showed good performance using both methods. However, on day 3, K-means achieved slightly higher performance. The originality of this study is that it reveals in detail the growth of Zea Mays in each growth period, namely at the ages of 3, 6, 9, and 12 days. Previous studies have discussed the health of this plant in general, whereas each growth age has its own characteristics. The significance of this study is that it is important to monitor the growth of Zea Mays to help farmers provide animal feed during the dry season. Future research can increase the input parameters to the system, which can cause the system to become more complex but can increase its accuracy.

ACKNOWLEDGMENT

The authors would like to thank the Directorate General of Higher Education (Ditjen Dikti) which is one of the main units of the Ministry of Education and Culture of the Republic of Indonesia that has provided funding for this research, with contract number 101/E5/PG.02.00.PL/2024. The authors also like to thank the Faculty of Engineering, Trunojoyo University, Madura, which provided facilities and infrastructure during this research.

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