Neural Network method is considered small in terms of the results obtained [29], [30].

Bird classification has also been carried out for small UAVs and birds with micro-Doppler signatures [31]. The research is looking for a sound from a bird, which will later be known as the type of bird. This research is still classified as very rare because the sound of a bird is very much and almost similar [32]. The sounds of birds used in this study were 20 bird sounds. Each bird sound will be filtered to reduce noise from other sounds [33]. The results in sound extraction will be feature extraction using the Naïve Bayes method. This research provides a result in speech recognition using the naïve Bayes method, which is obtained by 70%. This research using naïve Bayes is still said to be low because the results are still below 80%. The study captured the original sound in a filter to remove noise. This reduces the authentic sound of each bird [34], [35].

Research on Classification of Bird Species from Image Using VGG-16 [36]. In this study, data were obtained from taking pictures that had been collected. The bird images used in this study will later be subjected to a feature extraction process from various types of birds [37]. The number of birds used in the study was 15 [38]. Each bird will later undergo a feature extraction process. This process identifies each bird by taking various characteristics of the color, texture, and shape of each bird [31]. After recognizing a pattern for each type of bird, the results of this introduction will be classified using the support vector machine (SVM) and random forest methods [39]. The results of this study show that SVM has an accuracy of 65% in recognizing these birds. However, the random forest method has an accuracy of 73% in bird recognition. The random forest method is indeed the highest in this study, but the results in this classification are still said to be low because the results are still less than 80% [40].

Based on this brief explanation, the researcher proposes to improve the classification of starlings' images with Gabor and Wavelet Artificial Neural Network-based. They are enhancing the variety of starling images to increase the accuracy in the category of starlings. In this case, classifying starlings will also make it easier for people to select the type of starling using machine learning Artificial Neural Networks. Another goal in society is to make it easier for lovers and ordinary people who want to do starling cultivation to recognize expensive and cheap starlings, who wish to make it more accessible from the economic field, to acknowledge the benefits and loss by knowing the type of starlings.

II. Material and Methods

The design structure in the research method is used in artificial neural networks. The stages in this research are carried out in phases with the process flow that has been designed, as shown in Figure 1. They start with the data training and testing stage, where the data that has been determined will be trained according to the tests to be carried out. Then, in classifying starlings, a data testing process is also carried out, where, in this case, the data from the training results are tested to find the accuracy value. The manual segmentation method aims to remove the background or background in the starling image data. This process is to facilitate the testing in the classification of starlings. The next step in classifying starling species is the feature extraction process. In this feature extraction procedure, three features are used in the test. The features used in this extraction are GLCM, Gabor, and Wavelet. The next stage is the testing process using Artificial Neural. Network, where in this process to test the accuracy value is based on three features carried out. The last process in the classification of starlings is the evaluation of the test results. The assessment uses an accuracy parameter, which will later know the best accuracy value based on the features used.

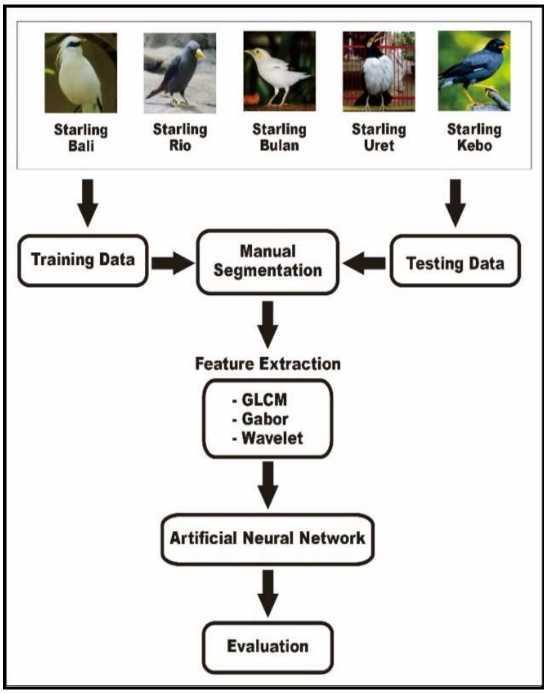

Fig. 1 Starling Image Classification System Using Texture Feature-Based Artificial Neural Networks

A. Data For Both Training and Testing

The feature extraction process is the following step in classifying starling species. In this feature extraction procedure, three extractions The test takes advantage of features. The features used in this extraction are GLCM, Gabor, and Wavelet. The data used in this test uses five types of starlings, including Bali Starling, Rio Starling, Moon Starling, Uret Starling, and Kebo Starling. The total in the overall picture of starlings is 500 datasets with 100 images each. The photos used were taken using a cellphone camera with standard quality. The next stage is the testing process using Artificial Neural Network, where this process tests the accuracy value based on three features carried out. The last process in the classification of starlings is the evaluation of the test results. The assessment uses the accuracy parameter, which will later know the best accuracy value based on the features used.

B. Manual Segmentation

In this manual segmentation process, the most common way is to remove the background image taken for use in the test. In the idea of the starlings, the background will be changed and removed to be done by the analyst physically. Moreover, during this time spent eliminating this foundation, his party intends to make it more precise in testing the order of symbolism of the starlings.

C. GLCM

Testing the classification of starlings will later use the GLCM extraction feature to recognize an image object. The results in identifying the characteristics of the starlings will be studied in a structured manner. Retrieval parts that require grey values from the image use Gray Level Co-occurrence Matrix (GLCM). There are several steps taken in taking texture features, namely the color changed to grayscale, then the RGB value is changed to grey using equation 1.

$$\text{Gray} = 0.2989{*}R + 0.5870{*}G + 0.1140{*}B \quad (1)$$

$$\textstyle\sum_k k^2\left[\sum_i \sum_j p(i,j)\right] \quad (2)$$

$$\sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i \sigma_j} \quad (3)$$

$$\textstyle\sum_{i,j} p(i,j)^2 \quad (4)$$

$$\sum_{i,j} \frac{p(i,j)}{1+|i-j|} \quad (5)$$

$$-\textstyle\sum_{i,j} P\,(i,j)\,log\,P\,(i,j) \quad (6)$$

It starts with meeting 1 with red patterned elastic R, green patterned Gram, and blue patterned B. Next, at meetings 2 to 6, the variable p is a value that allows empty values up to 1. The variable is a co-occurrence matrix result, and the variable I with j is the value adjacent to the row and column results in an image.

D. Gabor

Gabor filters are waveforms that can help us see different parts of a data set more clearly. In extending the signal power using this base, a local frequency description is provided to capture the signal's local/energy features. The texture features can then be extracted from this power distribution class. The ratio and direction of the fundamental nature of the filter Gabor make it very useful for compositional analysis focused on equation 7.

$$G\,(x,y,\theta,u,\sigma) = \frac{1}{2\pi\sigma^2} - \exp\left\{\frac{x^2+y^2}{2\sigma^2}\right\} \quad (7)$$

In equation 7, i is the initial value used, the root of (-1). This tells us the importance of I, which is the root of (-1). The frequency of the sinusoidal wave, u, is controlled by the variable on, and the resulting image value of the classification is found by the control of the orientation of the Gabor function, which is described in this Equation.

E. Wavelet

Wavelet is a data function used for Fourier analysis of discontinuous and sharp signals. Wave transformation approximates the shortwave signal to analyze the signal frequency. Shortwave location change time analysis looks at the time change of shortwave movements. Signal duration Analysis looks at how long a specific shortwave signal lasts, and the same Shortwave expansion change frequency analysis looks at how the frequency of a shortwave signal changes over time.

$$G\,(x,y) = \frac{1}{2\pi\sigma^2}\exp\left\{-\frac{x^2+y^2}{2\sigma^2}\right\} \quad (8)$$

In equation 8, the frequency is your value with five different weights. These values represent the angle (s) used in the Gabor response. Eight different orientations (e) are used, each with an additional discount for s. This results in a total of 40 Gabor responses.

F. Artificial Neural Network

This technique is used in Artificial Neural Networks to categorize photos of starlings. In this method, the next day, we would try to test and get the accuracy number based on three types of features. The test is tried by looking for between 0.1 and 0.9 as the learning rate to produce the best accuracy number. Numerous Artificial Neural Network Algorithm forms exist, such as input, hidden, and output layers. In this form, tomorrow, we would carry out calculations in dividing numbers using the method on each feature.

G. Evaluation

This last step is the assessment method, where this method will identify the accuracy numbers that have been tried. The test method that has been tried for this number the next day will be positive and minus, where the positive number is the result of the correct amount estimate and the minus number the result of the wrong number estimate, which is aimed at Equation 9.

$$Accuracy = \frac{AC+AN}{AC+AN+FC+FN} \quad (9)$$

This last step is the assessment method, where this method will identify the accuracy numbers that have been tried. This test method will be the number of accuracies in classifying the starling view. The test method that has been tried for this number the next day will be positive and minus, where the positive number is the result of the correct number of estimates and the minus number is the result of the wrong number of assessments aimed at the Equation. 9.

III. Results and Discussion

The tests carried out to classify starling species give 6 test results based on each feature. The results in this test are carried out with the learning rate (LR) or parameters in a trial in calculating the value of the classification of starling species. Table 2 shows the test results in classifying starlings using the GLCM feature.

TABLE I
CONFIGURATION OF ARTIFICIAL NEURAL NETWORK

Feature	Layer Input	Layer Hidden	Layer Output	Level
GLCM	4	5	5	
Gabor	2	4	5	1
Wavelet	4	5	5	
GLCM +Gabor	6	6	5	
Gabor + Wavelet	6	6	5	2
GLCM +Wavelet	8	7	5	

TABLE II
GLCM FEATURES STARTING CLASSIFICATION TEST

Feature	LR	Accuracy
	0.1	38%
	0.2	41%
	0.3	53%
	0.4	49%
GLCM	**0.5**	**68%**
	0.6	45%
	0.7	50%
	0.8	45%
	0.9	35%

Table 2 is the process of classifying starling species using the GLCM feature. The results in the test, starting with LR 0.1, have a value for accuracy of 38%. The test for classifying starling species with LR 0.5 has an accuracy value of 68%. The results in the tests on the LR 0.5 are the highest results produced on the GLCM feature. The results in the classification process at LR 0.8 have an accuracy value of 45%, and at LR 0.9, they have a deal accuracy of 35% from testing classification starlings using the GLCM feature. Stages starting from LR 0.1 to LR 0.9. Further testing was conducted to classify starling species using the Gabor feature, as shown in Table 3.

TABLE III
GABOR FEATURES CLASSIFICATION TESTING

Feature	LR	Accuracy
	0.1	56%
	0.2	55%
	0.3	44%
	0.4	49%
Gabor	0.5	49%
	0.6	**57%**
	0.7	50%
	0.8	56%
	0.9	55%

TABLE IV
CLASSIFICATION OF STARING WAVELET FEATURES

Feature	LR	Accuracy
	0.1	60%
	0.2	60%
	0.3	64%
	0.4	66%
Wavelet	0.5	70%
	0.6	73%
	0.7	74%
	0.8	69%
	0.9	**75%**

Table 3 is the process of classifying starling species using the Gabor feature. The results in the test, starting with LR 0.1, have an accuracy value of 56%. Furthermore, testing the classification of starling species was conducted at LR 0.6, with an accuracy of 57%. The tests on LR 0.6 produce the highest results on the Gabor feature. The process of testing the classification of starling species at LR 0.7 has an accuracy value of up to 50%. The results in the classification process at LR 0.8 have an accuracy value of 56%, and at LR 0.9 have a deal accuracy of 55%. The highest result for testing classification of starlings using the Gabor feature is at LR 0.6, with a maximum accuracy value of 57%. The results of this test are carried out in stages starting from LR 0.1 to LR 0.9. Furthermore, testing is carried out to classify starling species using the wavelet feature, as shown in Table 4.

Table 4 is the process of classifying starling species using the wavelet feature. The results in the test, starting with LR 0.1, have an accuracy value of 60%. Furthermore, the classification of starlings at LR 0.2 has a deal accuracy of 60%. The outcomes of the type of starlings with wavelet features at LR 0.3 has an accuracy value of 64%, and LR 0.4 reaches 66%. The test for classifying starling species with LR 0.5 has an accuracy value of 70%. Furthermore, starlings were classified at LR 0.6 with an accuracy value of 73%, and LR 0.7 reached 74%. The LR 0.8 has an accuracy value of 69%, and the LR 0.9 has an accuracy value of 75%.

The results in the test on LR 0.6 are the highest results generated on the wavelet feature. Based on testing the classification of starlings using the wavelet feature. The highest impact is at LR 0.6, with a maximum accuracy value of 75%. The results carried out in this test are carried out in stages. We were starting from LR 0.1 to LR 0.9. Further testing was conducted to classify starling species using the GLCM and Gabor features, as shown in Table 5. Table 5 classifies starling species using the GLCM and Gabor features. The results of the test, starting with LR 0.1,

TABLE V
GLCM AND GABOR FEATURES CLASSIFICATION TESTING

Feature	LR	Accuracy
	0.1	56%
	0.2	59%
	0.3	61%
GLCM	0.4	64%
+	0.5	64%
Gabor	0.6	61%
	0.7	69%
	0.8	**70%**
	0.9	65%

TABLE VI
GABOR AND WAVELET FEATURES CLASSIFICATION TESTING

Feature	LR	Accuracy
	0.1	56%
	0.2	59%
	0.3	61%
Gabor	0.4	64%
+	0.5	64%
Wavelet	0.6	61%
	0.7	69%
	0.8	**70%**
	0.9	65%

It has an accuracy value of 56%. Furthermore, the classification of starlings at LR 0.2 has an accuracy value of 59%. The results of the type of starlings with GLCM and Gabor features at LR 0.3 have an accuracy value of 61%. Testing the classification of starling species with LR 0.4 and LR 0.5 has an accuracy value of 64%.

Furthermore, starlings testing was carried out on LR 0.6, which had an accuracy value of 61%, and LR 0.7 had an accuracy value of 69%. The results in the classification process at LR 0.8 have an accuracy value of 70%. The results in the tests on LR 0.8 are the highest results produced on the GLCM and Gabor features. The last test of the classification of starling species with LR 0.9 has an accuracy value of 65%.

Based on testing the classification of starlings using the GLCM and Gabor features. The highest result is at LR 0.6, with a maximum accuracy value of 75%. The results of this test are carried out in stages starting from LR 0.1 to LR 0.9. Further testing was conducted to classify starling species using the Gabor and Wavelet features, as shown in Table 6.

Table 6 classifies starling species using Gabor and Wavelet features. The results in the test, starting with LR 0.1, have an accuracy value of 65%. Furthermore, the classification of starlings at LR 0.2 has an accuracy value of 56%. The outcomes of the type of starlings with Gabor and Wavelet features at LR 0.3 have an accuracy value of 61%. They are testing the classification of starling species with LR 0.4. The results in the classification process at LR 0.8 have an accuracy value of 70%. The results in the test on LR 0.8 are the highest results produced on the Gabor and Wavelet features. The last test of the classification of starling species with LR 0.9, a value for accuracy of 65%. Based on testing the type of starlings using the Gabor and Wavelet features. The highest result was at LR 0.6, with a maximum accuracy value of 75%. The results of this test are carried out in stages starting from LR 0.1 to LR 0.9. To determine which starling species is which, scientists used a machine to measure how noisy the birds are and how they move. Then, they compared the results to what's in a table.

TABLE VII
GLCM AND WAVELET FEATURES CLASSIFICATION TESTING

Feature	LR	Accuracy
	0.1	73%
	0.2	69%
	0.3	71%
GLCM	0.4	70%
+	0.5	75%
Wavelet	0.6	72%
	0.7	72%
	0.8	73%
	0.9	**83%**

TABLE VIII
COMPARISON OF PROPOSED RESEARCH WITH PREVIOUS RESEARCH

Article	Feature	Machine Learning	Learning Rate	Evaluation Accuracy
[23]	GLCM Texture	Decision Tree	-	50%
[21]	GLCM Texture	Artificial Neural Network	0.5	68%
Our Proposed	GLCM+ Wavelet Texture	Artificial Neural Network	0,9	83%

Table 7 classifies starling species using GLCM and Wavelet features. The results in the test, starting with LR 0.1, have a value for accuracy of 73%. The outcomes of classification starlings with GLCM and Wavelet features at LR 0.3 have an accuracy value of 71%. Testing the classification of starling species with LR 0.4 has an accuracy value of 70%, and LR 0.5 gets an accuracy of 75%. Furthermore, starling testing was carried out at LR 0.6 and LR 0.7, which had an accuracy value of 72%. The results in the classification process at LR 0.8 have an accuracy value of 73%. The last test of starling species classification with LR 0.9 has an accuracy value of 83%. The results in the tests on LR 0.9 are the highest results produced on the GLCM and Wavelet features.

Based on the tests carried out, GLCM testing is the lowest compared to the others. Improving accuracy requires an increase in the learning rate. However, if learning is faster, the accuracy decreases. The results for a learning rate of 0.3 are 53%, and a learning rate of 0.4 is 49%. The highest accuracy value for the GLCM feature is when the learning rate is set to 0.5. That means the accuracy in this setting is 68%. Then, the learning rate of 0.6 has an accuracy rate of 45%, followed by a learning rate of 0.7 with an accuracy value of 50%. The learning rate of 0.8 has the same accuracy value as the learning rate of 0.6, which can only reach 45%. In the last learning rate, namely the learning rate of 0.9, the resulting accuracy value is meager compared to other learning. The accuracy results are at a learning rate of 0.9, only 35%.

Figure 3 results from the highest accuracy of the GLCM + wavelet feature. The value of accuracy and precision in classification is very accurate compared to other parts. In this case, it can be explained that the learning rate 01 produces an accuracy value of 73%. Furthermore, a learning rate of 0.2 has an accuracy value of 69%. The next test is to use a learning rate of 0.3; the result is an accuracy of 71%, and a learning rate of 0.4 is 70%. Accuracy results at a learning rate of 0.5 reached 75%, followed by 72% at a learning rate of 0.6 and 0.7. Furthermore, the learning rate of 0.8 is 73%, and the highest accuracy of the others is at a learning rate of 0.9 of 83%.

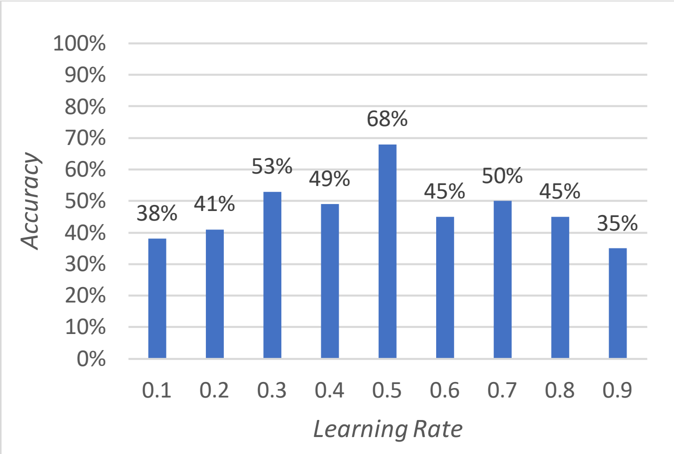

Fig. 2 Lowest Accuracy Results

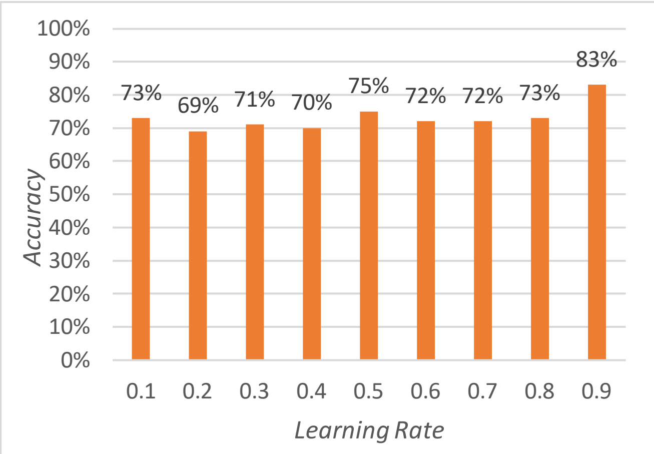

Fig. 3 Highest Accuracy Results

The results in the test on LR 0.6 are the highest results generated on the wavelet feature. Based on testing the classification of starlings using the wavelet feature. The results in this test are carried out in stages starting from LR 0.1 to LR 0.9. the trial, beginning with LR 0.1, has an accuracy value of 56%. The results of the classification of starlings with GLCM and Gabor features at LR 0.3 have an accuracy value of 61%. Testing the type of starling species with LR 0.4 and LR 0.5 has an accuracy value of 64%.

Furthermore, starlings testing was carried out on LR 0.6, which had an accuracy value of 61%, and LR 0.7 had an accuracy value of 69%. The results in the classification process at LR 0.8 have an accuracy value of 70%. The results in the tests on LR 0.8 are the highest results produced on the GLCM and Gabor features. The last test of the classification of starling species with LR 0.9 has an accuracy value of 65%.

After researching the image classification of starlings using an Artificial neural network on the GLCM+Wavelet texture features shown in Table VIII. Researchers compare the results that have been done with previous research. Table VIII is a comparison of research that has been done before. Research [23] showed that starlings were classified using a decision tree with GLCM texture features. The results of the research have an accuracy value of 50%. In this previous study, no learning rate was used in the following analysis [21], namely, using ANN as machine learning with GLCM texture features. The research results show that the highest learning rate is at 0.5 with 68% accuracy. What has been done shows that the results are still below 70%. Therefore, further development is needed to improve the results of the previous evaluation. In previous studies, the researchers proposed using ANN on GLCM and Wavelet features. The highest results were carried out in the research conducted, namely at a learning rate of 0.9 with an accuracy value of 83%

IV. Conclusions

In explaining the starling classification test using the GLCM, Gabor, and Wavelet features, the highest degree of precision can be drawn to conclude that results are at the GLCM and Wavelet feature levels. The GLCM and Wavelet level accuracy results reached 83% at a rate of 0.9. In the experiments that have been done, the GLCM and Wavelet levels can increase accuracy using artificial neural networks. The classification method of this type of starling also shows that the computational time in testing is much faster to produce accurate values. In addition, the precise accuracy during the testing and identification of starlings also increases. The weaknesses in this study result in the grouping of starling species being still below 90%. For further research, it is possible to develop a process for classifying starlings using three levels of features that can produce better accuracy values based on the types of existing features.

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