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Classification of Tempeh Maturity Using Decision Tree and Three Texture Features

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***Abstract*— Tempeh is an average food from Indonesia, eaten in Indonesia. Even today, *tempe* is around the world, and vegans around the world use tempeh as a meat substitute. This study plans to work on the accuracy of *tempe* characterization by utilizing the three-element extraction technique and the choice tree arrangement strategy. This research uses a decision tree method with three texture features in its classification. The results obtained indicate that this method has the highest Gabor channel level, including extraction, which is 71% accuracy, the split proportion is 10;90 and the lowest is 60% with parted balance of 90:10. The most important level value of GCLM extraction precision is 86% with a split proportion of 90;10 and the lowest price level and 60% level with a split ratio of 10;90 for Wavelet including the highest extraction rate price is 77%. It can be said that from the extraction of three elements, GLCM is the element extraction with the highest value from Gabor and Wavelet, including extraction at a split proportion of 10:90 by 86%. The test shows the Featured Tree highlight designation. The extraction technique was superior to different strategies for interaction characterization of *tempe* development quality. In the next research, improve the accuracy performance so that it can reach 100% using the CNN deep learning method. Then you can also add Support Vector Machine (SVM) and Naive Bayes methods based on the GLCM Extraction feature.**

***Keywords*—GLCM; classification; decision tree; extraction.**

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I. INTRODUCTION

Tempeh is a typical food from Indonesia which is very much consumed. In Indonesia, tempeh is now worldwide; many vegetarians worldwide use tempeh as a substitute for meat [1]. In the development of tempeh, many products can now be produced from tempeh [2]. A product must have an advantage in the business process by paying attention to product quality as a top priority to compete with products made from tempeh [3]. Therefore, a company always maintains quality in tempeh maturity [4]. The maturity level of tempeh is the main factor in influencing consumer interest to increase the selling price and increase the amount of market demand. Indonesia is the country that can produce. The largest tempeh today. The quality made in processing tempeh is currently for producers abroad as much as 50% in exports. Today's daily consumption in Indonesia is 6.45 kg, so the importance of the tempeh maturity classification process is needed [5], [6]. The selection process of tempeh must be by the standards determined by the level of good tempeh quality to increase the expected taste. The temperature of the maturity level of tempeh is also very influential; the aroma produced can also be known until the color of the tempeh is dark [7]. Choosing good quality tempeh with a level of maturity and density according to the maturity classification takes a long time if using a manual process.

In previous studies, the process of Classification of Ripeness of Citrus Fruits Based on Color Features Using the SVM Method has been carried out [8], [9]. This study discusses ripe and unripe citrus fruits designed using the system. The dataset is divided into 20 testing data and 80 training data. This feature uses three levels of color features that influence the maturity value of citrus fruits, namely R, G, and B [10]. From the color features used, the research was conducted to test for the fruit maturity classification process—oranges using the SVM method [11], [12]. After testing and classification, the matching accuracy is obtained with 80% of 100 orange images. However, in the classification process, only color features are used [13]. The subsequent research is Defect Coffee Detection in Single Green Beans Image Using Ensemble Decision Tree Method. This research aims to perform image processing in the form of segmentation [14] of the image of green coffee beans using thresholding. This research was conducted to analyze the texture feature level using a grey-level co-occurrence and continued with the classification modeling algorithm C.45 method [15]. From this research, the process in the coffee detection segmentation still uses a manual process by using the texture features of each coffee and is still said to be low in the test.

Then, previous studies identified soybean seed types that were also carried out using the GLCM level as the testing method [16], [17]. The study describes and identifies soybean seeds using digital images in the tests carried out using feature extraction features to identify the soybean seeds [18]. Four parameters are used in the trial: energy, contrast, homogeneity, and correlation in identifying soybean seeds [2], [19]. The results obtained in the test received an accuracy rate of 47%. from a total of 198 image samples that have been tested [20].

Therefore, the researcher proposes Temperament Image Classification Using a GLCM-Based Decision Tree. This study aims to classify the image of tempeh maturity with the texture features of GLCM, Wavelet, and Gabor. This research also aims to make it easier for ordinary people just starting in the MSME business made from tempeh.

II. Materials and Methods

This research method has several stages that must be passed to classify the image of tempeh maturity—starting with pre-processing with two sets of training, namely training data and testing with data testing. Then in the test, various types of tempeh will be used with three levels raw, ripe and rotten—data collection for training and testing data using the Redmi 7 smartphone camera. Data collection was also carried out in several micro, small and medium enterprises (MSMEs) in the Pasuruan and Malang areas.

The information acquired for the picture arrangement of tempeh development is 369 test information with a correlation between preparing and testing knowledge. Tempeh picture grouping additionally utilizes a split proportion with a proportion of 10% preparation information and 90% testing information and 90% preparation information, and 10% testing information in each test. Then, at that point, the following stage is the division interaction, where this cycle takes the attributes of the tempeh picture utilizing 3 degrees of element extraction. After that, the next process is the image classification process of tempeh maturity using the Decision Tree and Artificial Neural Network (ANN) method. Evaluation is used to determine the final value and accuracy level corresponding to each parameter, as shown in Fig. 1.

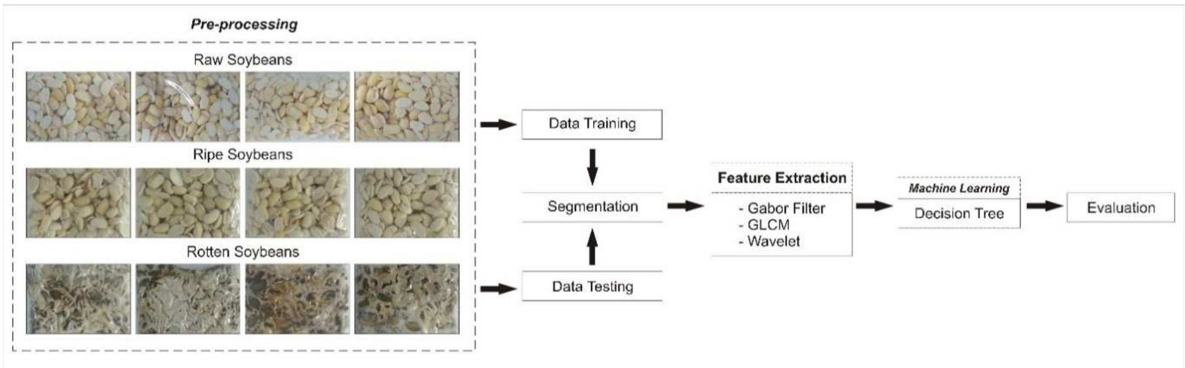

Fig. 1 Tempeh Maturity Classification System Using Decision Tree

A. Extraction Feature

This feature extraction process collects data on each image's overall characteristics from tempeh for testing. This feature extraction also uses three levels of feature extraction, namely Gabor filter, GLCM, and Wavelet, in the testing process. In each feature extraction, a testing process also uses a training and testing process to be processed using machine learning. I am taking the characteristics of tempeh based on the level of maturity produced to facilitate the process of testing and training in machine learning.

B. Gabor Filter

Gabor Filters is a group of wavelets in the form of analytical tools that can be used to present data with functions and operators into different components. Furthermore, handling every part with a goal suitable to its scale, every Wavelet catches energy at a specific recurrence and in a particular course. The surface elements can then be disengaged from this gathering of energy appropriations.

The Gabor channel's scale and direction properties are discernible accordingly, making them extremely valuable for surface investigation focused on equation 1.

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

In formula 1 it can be explained that the value of i is the root of (-1) in other words, the value of i is the initial value used. At you is the recurrence of the sinusoidal wave. Then, at that point, on is the control of the direction of the Gabor work, which in this formula will know the image value of the resulting classification. The 2D filter is formed at the Gabor level with two components, namely the Gaussian Envelope and the Sinusoidal wave in the complex form referred to in formulas 2 and 3.

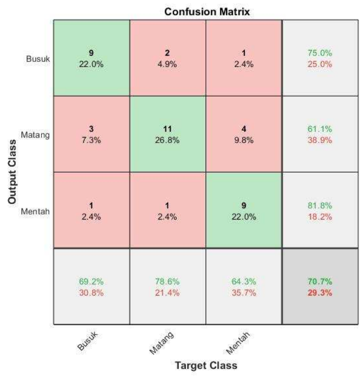

Fig. 2 Results of Matrix Confusion Gabor Filter Split Ratio Testing 10:90

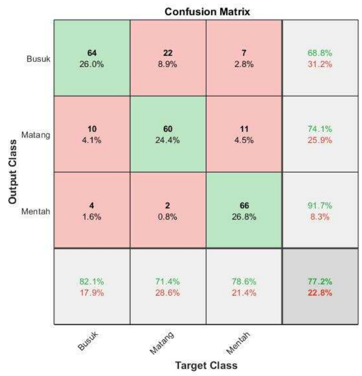

Fig. 3 Results of Matrix Confusion Gabor Filter Split Ratio Testing 20:80

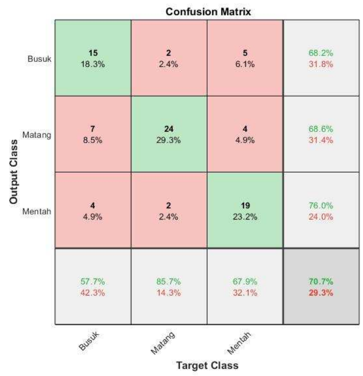

Fig. 4 Results of Matrix Confusion Gabor Filter Split Ratio Testing 30:70

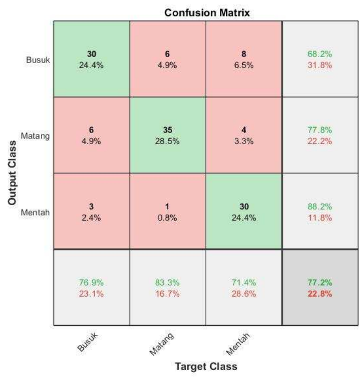

Fig. 5 Results of Matrix Confusion Gabor Filter Split Ratio Testing 40:60

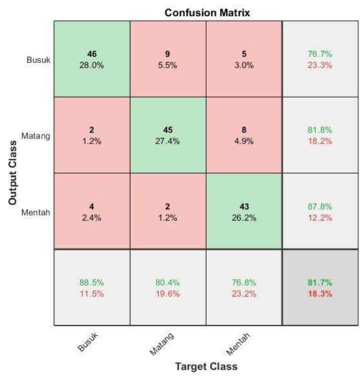

Fig. 6 Results of Matrix Confusion Gabor Filter Split Ratio Testing 50:50

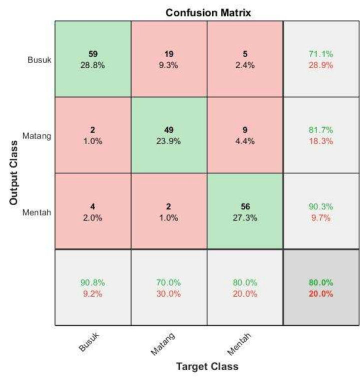

Fig. 7 Results of Matrix Confusion Gabor Filter Split Ratio Testing 60:40

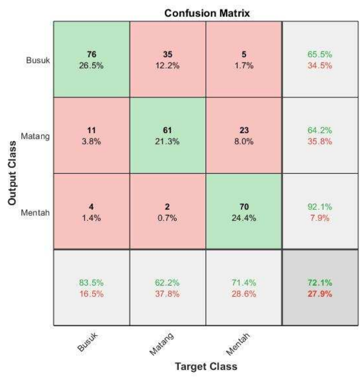

Fig. 8 Results of Matrix Confusion Gabor Filter Split Ratio Testing 70:30

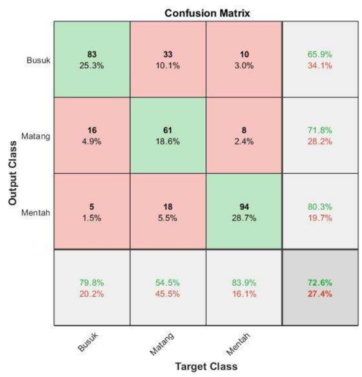

Fig. 9 Results of Matrix Confusion Gabor Filter Split Ratio Testing 80:20

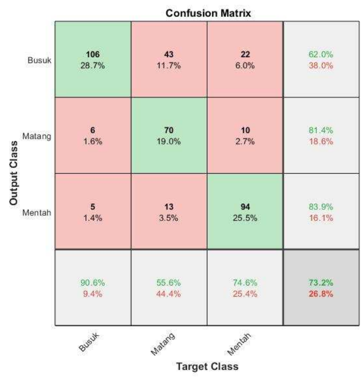

Fig. 10 Results of Matrix Confusion Gabor Filter Split Ratio Testing 90:10

In formulas 2 and 3, it can be explained that the frequency used is the value of u with 5 values 0, 1, 2, 3, 4, and s as the angle. There are eight orientations used, namely at e with values of 0.1,2,3,4,5,6, and 7. So it produces 40 Gabor Response (Magnitude Response).

C. GLCM (Gray Level Co-Occurrence Matrix)

In GLCM (Gray Level Co Event Grid), perceiving surface examples is a strategy utilized as a picture surface examination device to include extraction. GLCM is a bunch of Grid that shows the recurrence of a couple of two pixels. Each value generated by the pixel has a distance and direction of the angle. Initialization distance in degrees with pixels and angles. Data retrieval is formed using different angles, namely 0°, 45°, 90°, and 135°, as well as the space between the two. Multiply pixels by 1 pixel. The GLCM stage of the calculation process results from a calculation between two pairs of original image pixels. For example, f(x, y) is an image with size Nx and Ny has the highest gray level pixels (Level L). The sum is the vector for the direction of the spatial offset referred to in formulas 3 through 7.

$$s(x,y) = \exp\left(i(2.\ \pi\ (u\ .x\ .\ \cos\theta + u.y.\sin\theta)\right) \tag{2}$$

$$\textstyle\sum_k k^2\ [\Sigma i \Sigma j(i,j)] \tag{3}$$

$$\sum i,\ \frac{(i-\mu i)(j-\mu j)\,\mathrm{p(i,j)}}{\sigma i \sigma j} \tag{4}$$

$$\sum i,j\ p(i,j)\ 2 \tag{5}$$

$$\sum i,j\ \frac{p(i,j)}{1+|\mathrm{i}-\mathrm{j}|} \tag{6}$$

$$-\sum i,j\ P\ (i,j)\ log\ P\ (i,j) \tag{7}$$

In recipes 2 to 6, it is realized that the p esteem is a potential worth that is zero to one. The images demonstrate portions of the force near one another, corresponding to the line numbers

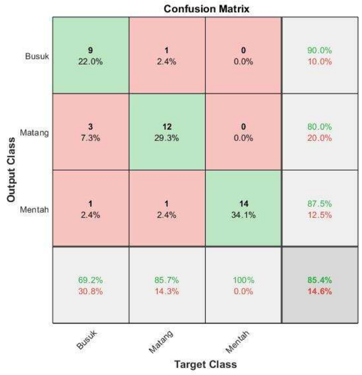

Fig. 11 Results of Matrix Confusion GLCM Filter Split Ratio 10:90

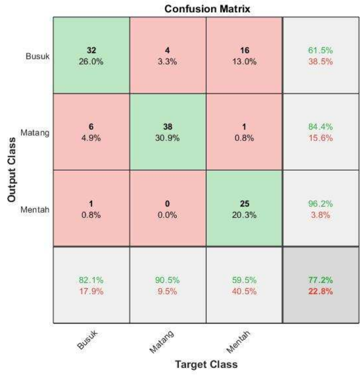

Fig. 12 Results of Matrix Confusion GLCM Filter Split Ratio Testing 20:80

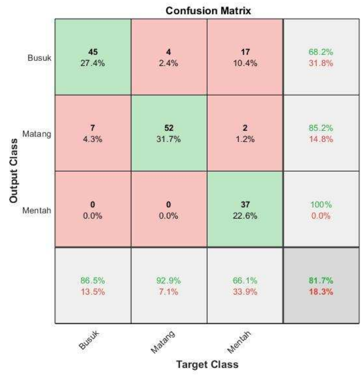

Fig. 13 Results of Matrix Confusion GLCM Filter Split Ratio Testing 30:70

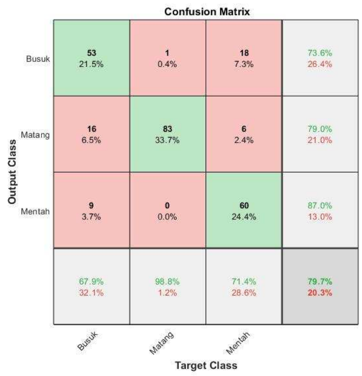

Fig. 14 Results of Matrix Confusion GLCM Filter Split Ratio Testing 40:60

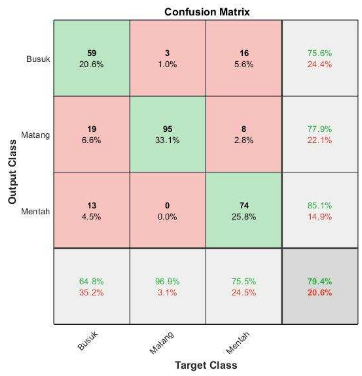

Fig. 15 Results of Matrix Confusion GLCM Filter Split Ratio Testing 50:50

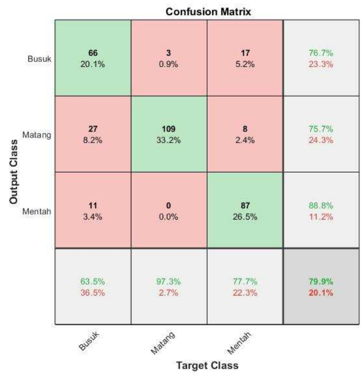

Fig. 16 Results of Matrix Confusion GLCM Filter Split Ratio Testing 60:40

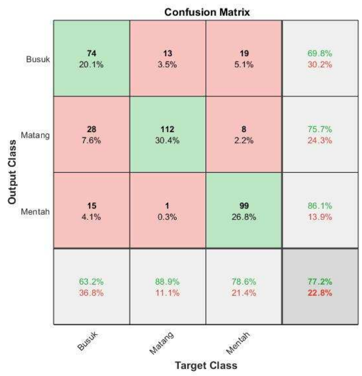

Fig. 17 Results of Matrix Confusion GLCM Filter Split Ratio Testing 70:30

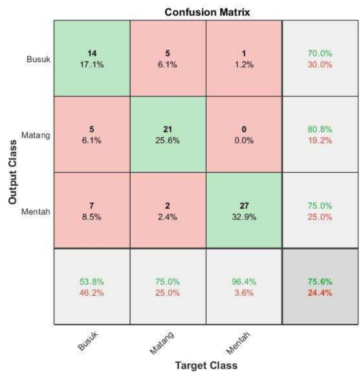

Fig. 18 Results of Matrix Confusion GLCM Filter Split Ratio Testing 80:20

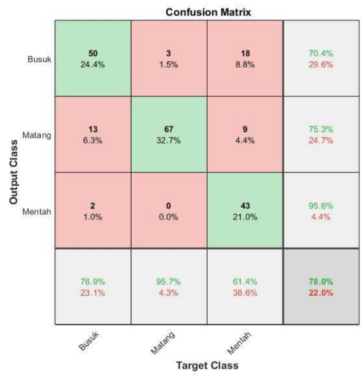

Fig. 19 Results of Matrix Confusion GLCM Filter Split Ratio Testing 90:10

and section numbers found from the aftereffects of the tempeh development characterization test. The parts of the intensity which are the descriptions in the matrix also play an important role in finding a value from the overall data used.'

D. Wavelet

Wavelet is a mathematical function of the data or a function of the frequency component. The difference is that the advantage of a wavelet is that it is a physical Fourier analysis where the signal is discontinuous and sharp. Shortwave location change time analysis Signal duration, and same Shortwave expansion change frequency analysis. The mathematical formula for signal representation is called wave transformation. Definition of wave, as a short wave (or Impact wave), the energy is concentrated in the physical domain (space or time), commonly called a wavelet. The primary purpose of the Gabor Wavelet is to display the specific features of the image in the kernel. A set of kernel coefficients for several corner frequencies in one image pixel is called a jet. These are small chunks of the grey value in the core-rendered image around the pixels.

E. Decision Tree

Wavelet is a mathematical function of the data or a function of the frequency component. The difference is that the advantage of a wavelet is that it is a physical Fourier analysis where the signal is discontinuous and sharp. Shortwave location change time analysis Signal duration, the mathematical formula for signal representation is called a wave transformation. Definition of wave, as a short wave (or Impact wave), the energy is concentrated in the physical domain, commonly called a wavelet. The primary purpose of the Gabor Wavelet is to display the specific features of the image in the kernel.

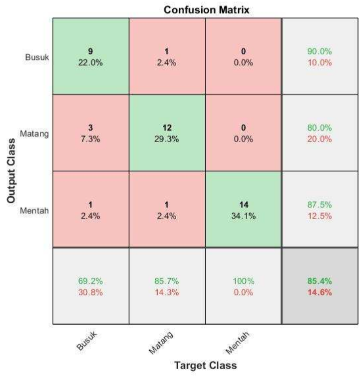

Fig. 20 Results of Matrix Confusion Wavelet Filter Testing Split Ratio 10:90

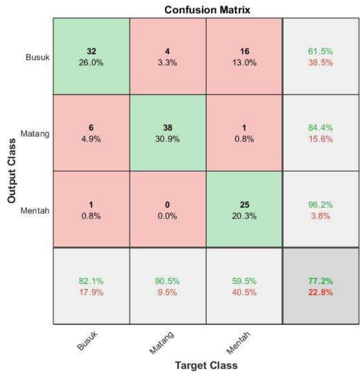

Fig. 21 Results of Matrix Confusion Wavelet Filter Testing Split Ratio 20:80

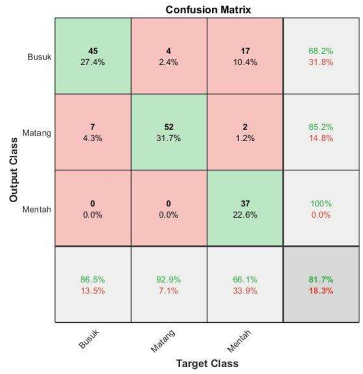

Fig. 22 Results of Matrix Confusion Wavelet Filter Testing Split Ratio 30:70

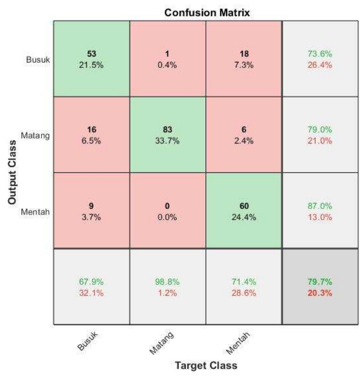

Fig. 23 Results of Matrix Confusion Wavelet Filter Testing Split Ratio 40:60

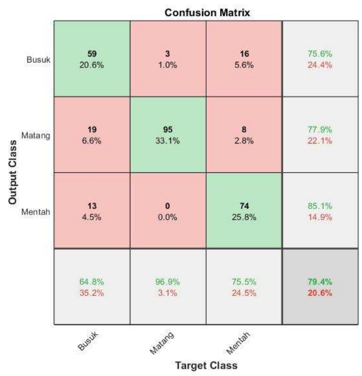

Fig. 24 Results of Matrix Confusion Wavelet Filter Testing Split Ratio 50:50

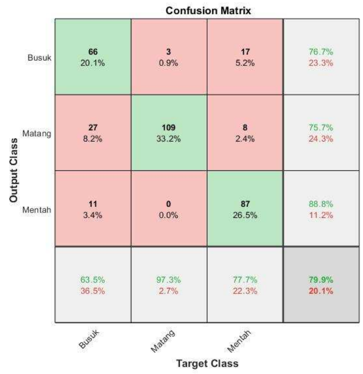

Fig. 25 Results of Matrix Confusion Wavelet Filter Testing Split Ratio 60:40

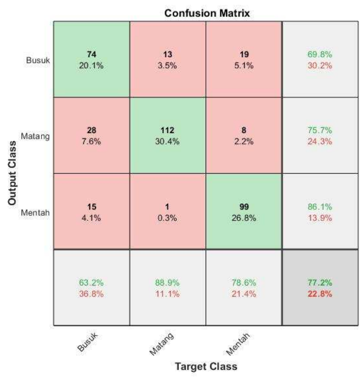

Fig. 26 Results of Matrix Confusion Wavelet Filter Testing Split Ratio 70:30

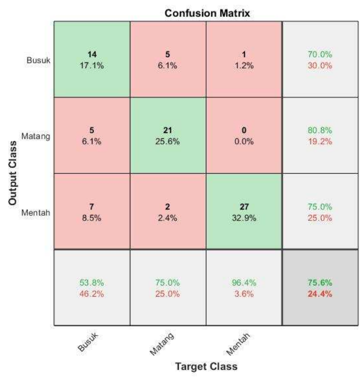

Fig. 27 Results of Matrix Confusion Wavelet Filter Testing Split Ratio 80:20

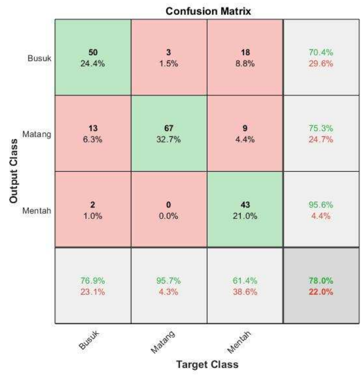

Fig. 28 Results of Matrix Confusion Wavelet Filter Testing Split Ratio 90:10

A set of kernel coefficients for several corner frequencies in one image pixel is called a jet. These are small chunks of the grey value in the core-rendered image around the pixels. A Decision Tree is one of the classification methods used for alternative problem-solving. Its representation is in the form of a tree structure that shows alternative results from decisions accompanied by estimates of the final decision results according to the role of this decision tree as a Decision Support Tool to help humans make a decision. The Decision Tree function breaks down the decision-making process, making decisions easy [21]. Making the Decision Tree itself usually uses a supervised learning method where new data is classified based on training samples or existing data. The Decision Tree has three parts: Root Node, a tree with several notes above [22]. Then at the Internal Node level is a branching. There is only one input with two outputs and Leaf Node, which contains one information, has no work. Each note will be given a class label in the decision tree, including the root node and internal node. It will contain test data or test samples to separate data information with different characteristics. With these advantages, it can handle optimally, and it is also hoped for this algorithm to get the highest accuracy value, which is aimed at formula 8.

$$Gain\ (S, A) = Entropy(S) - \sum * Entropy(Si) \qquad (8)$$

Formula 8 is a decision tree-solving procedure; predictions are formed using several if-then conditions similar to controls in various programming languages. It would help if you also determined an object to be classified in predicting the shape you want. The data mining output nodes, branches, and leaf nodes. Each branch node represents a condition in some input attribute, there is an interim each chapter selects output based on the situation & each leaf node has a class label.

F. Evaluation

The evaluation stage has three parameters: accuracy, precision, and recall. The evaluation process for accuracy, precision, and recall is used to measure the performance of the system results. Moreover, in the evaluation stage, there are parameters in each process, which are aimed at the formula 9-11.

$$Precision=\frac{TG}{TG+FG} \quad (9)$$

$$Recall=\frac{TG}{TG+FG} \quad (10)$$

$$Accuracy=\frac{TG+TN}{TG+FG+TN+FN} \quad (11)$$

Based on formulas 9 to 11, it is known that in measuring using a confusion matrix. From the explanation of formulas 9 to 11, it is known that the TG parameter to predict positive values is total, and the TN parameter, which is a negative value, amounts to incorrect prediction results. Then the FG parameter, which is a false negative, when mispredicted, turns out that the matter is positive

III. RESULT AND DISCUSSION

In the results and discussion, several values are classified into nine classes of split ratio, ranging from a split ratio of 10 to 90. Each feature extraction method uses accuracy, precision, and recall parameters. As well as with the tests carried out also used three kinds of test features, namely the Gabor Filter, GLCM, and Wavelet features, which are shown in Table 1.

TABLE I
TEST RESULTS USING THE GABOR FILTER FEATURE

split ratio	accuracy	precision	recall
10:90	71%	52.65 %	53.31%
20:80	67%	56.11%	50.48%
30:70	66%	57.22%	49.87%
40:60	63%	63.20%	45.73%
50:50	59%	31%	39.67%
60:40	69%	59.25%	53.07%
70:30	63,14%	53.06%	44.81%
80:20	64,23%	50.62%	46.06%
90:10	60,98%	42.56%	41.03%

Table 1 is the consequence of testing utilizing the Gabor Channel, including the development level of tempeh pictures. The experimental outcomes started with the most noteworthy exactness esteem at a parted proportion of 10:90 with 71%. Then, at that point, in the accuracy boundary, the most remarkable worth is in the 40:60 parted proportion with 63.20%. The highest elevated esteem in the review boundary is 53.31%, with a proportion of 10:90.

Table 2 is the consequence of testing utilizing the GLCM, include on the order of the development level of tempeh pictures. The experimental outcomes acquired to start with the highest precision esteem is at a parted proportion of 90:10 with 86.99%. Then, at that point, the accuracy boundary has the most elevated outcome, with a correlation between 90:10 with a worth of 81.41%. The most remarkable effect on the review boundary is 80.22%, with a correlation of 90:10 preparation and testing information.

Table 3 is the consequence of testing utilizing the Wavelet, including the order of the development level of tempeh pictures. This wavelet highlight grouping process uses a split proportion of 10:90 to 90:10 from preparing information to testing information. The experimental outcomes started with the highest precision at 90:10 with 77.24%. Then, at that point, the accuracy boundary has the most noteworthy worth in the 40:60 split proportion, with 75.75%. The most elevated outcome on the review boundary is 66.67%, with a parted proportion of 90:10 for preparing and testing information.

TABLE II
TEST RESULTS USING THE GLCM FILTER FEATURE

split ratio	accuracy	precision	recall
10:90	71%	52.65 %	53.31%
20:80	67%	56.11%	50.48%
30:70	66%	57.22%	49.87%
40:60	63%	63.20%	45.73%
50:50	59%	31%	39.67%
60:40	69%	59.25%	53.07%
70:30	63.14%	53.06%	44.81%
80:20	64.23%	50.62%	46.06%
90:10	60.98%	42.56%	41.03%

TABLE IIII
TEST RESULTS USING THE WAVELET FILTER FEATURE

split ratio	accuracy	precision	recall
10:90	71%	52.65 %	53.31%
20:80	67%	56.11%	50.48%
30:70	66%	57.22%	49.87%
40:60	63%	63.20%	45.73%
50:50	59%	31%	39.67%
60:40	69%	59.25%	53.07%
70:30	63,14%	53.06%	44.81%
80:20	64,23%	50.62%	46.06%
90:10	60,98%	42.56%	41.03%

Then in the training and testing feature, there will be feature extraction; there are three classes that are tested, namely raw, ripe and rotten, and some of the parameters used for the Gabor Filter method are phase and magnitude. The way of Gabor Filter is a meticulous process of taking the test. While GLCM uses 4 parameters. The Wavelet method combines horizontal and vertical lines in feature extraction. The combination of these lines will be classified using the Decision Tree method, such as using several confusion matrices in describing the highest classification graph. Then in this classification, there are 3 features used in each extraction in the testing process.

IV. CONCLUSIONS

Based on the results of digital image processing research, the identification of the maturity level of tempeh using the Gabor filter feature extraction and two comparison feature extractions, Glcm and Wavelet, can be concluded as starting from the extraction feature of the Gabor filter feature using phase and magnitude parameters where tempeh would be measured by the size of the texture and density. Wavelet extraction uses vertical and horizontal line parameters of the image. Then the data from feature extraction will then be trained and tested with a decision tree identification system that produces some of the highest percentage values of Gabor filter feature extraction, namely an accuracy of 71%, with a split ratio of 10;90. the highest percentage value of GLCM feature extraction is 86% accuracy with a split ratio of 90;10 and the lowest percentage value and 60% percentage value with a split ratio of 10;90, while the wavelet feature extraction has the highest percentage value of 77% accuracy with a split ratio of 90;10 and the lowest percentage value is 57% of the split ratio of 10;90 . It can be concluded that from the three feature extractions, GLCM is a feature extraction that shows the highest percentage value between Gabor and Wavelet feature extraction at a split ratio of 10:90 by 86%.

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