

Comparative Analysis of Machine Learning Techniques for Formalin Fish Classification using Image-based GLCM Feature Extraction

Marlince N. K. Nababan, Muhathir, Reyhan Achmad Rizal, Erwin Panggabean, Mardi Turnip

Abstract—With the maturing of artificial intelligence and machine learning, significant advances are being made by researchers in the mainstream artificial intelligence field and experts in other fields who are using these methods to achieve their own goals. Fish is a food whose quality is very susceptible to decline in shape, texture, taste, and smell. Deterioration This damage occurs due to the activity of enzymes and microbiology. Some fishermen choose a fraudulent method to keep their fish fresh, namely mixing them with formaldehyde, while formalin is poisonous if it enters the body. Considering all the problems and consequences of consuming formaldehyde, the author tried to apply several machine-learning methods to classify images of formaldehyde fish on tilapia fish objects. The methods used were a combination of Support Vector Machine (SVM), Multilayer Perceptron (MLP), Naïve Bayes, K-Nearest Neighbor (KNN), and the J48 Decision Tree method to determine which method was the most effective in classifying fish images. Based on the research results, the Multilayer Perceptron (MLP) method achieved better results compared to the other methods, with an accuracy of 0.667. Compared with previous research on the classification of images of tilapia fish, a better accuracy value was achieved.

Index Terms— Machine Learning, MLP, KNN, SVM.

I. INTRODUCTION

MACHINES are increasingly smart “things”: Facebook can recognize faces in photos, Siri understands sounds, and Google translates websites. Fundamentally, this breakthrough relies as much on statistics as it does on computing. Machine intelligence became possible after researchers stopped approaching the task of intelligence procedurally and began to tackle it empirically. Image recognition algorithms, for example, do not consist of hard-wired rules to scan specific. Combinations of pixels based on a human understanding of what an image is about. Instead, these algorithms use a large data set of photos labeled as having

faces or not to estimate the $f(x)$ function that predicts the presence of y faces from the pixels [1][2]. Machine learning was proposed by Arthur Samuel in 1959 and is now widely applied in computer vision, general gameplay, economics, data mining, and bioinformatics, among other fields. With the maturing of artificial intelligence and machine learning, essential advances have been made by researchers in mainstream artificial intelligence and experts in different fields who use these methods to achieve their own goals. At the beginning of the last century, machine learning was used to detect the solubility of C60 in materials science. It is now used to discover new materials, predict properties of materials and molecules, study quantum chemistry, and design drugs. Because resources and tools for machine learning are abundant and easily accessible, the barriers to entry for implementing machine learning in materials science are lower than ever [3].

Fish quality is crucial in the seafood industry, particularly in ensuring the freshness of marketed products. This study aimed to identify fresh and non-fresh fish using the Self-Organizing Map (SOM) method based on fish eye images. This method was chosen because of its ability to perform clustering and visualize non-linear data efficiently. Fish eye images were selected as the primary parameter due to the significant visual differences between the eyes of fresh and non-fresh fish. The data were analyzed using feature extraction techniques based on texture and color through the Gray Level Co-occurrence Matrix (GLCM) approach. The results indicated that the SOM method could classify fish freshness with an accuracy rate of up to 85%, highlighting its potential for application in automated fish quality inspection systems [4].

Similar research is presented in [5], which used a Naive Bayes classification method and GLCM as feature extraction. It was able to classify fish mixed with formalin with an accuracy of 98.4% and fresh fish with an accuracy of 41.6%, achieving an average accuracy of 70%. These results are satisfactory but do not represent an improvement over the previous study.

In 2021, a similar study [6] was done based on KNN, using a multilayer perceptron and SVM analysis. The fish that were used as research objects were not only tamban fish but also mujair fish. In this study, identification of tamban fish mixed with formalin was more accurate than identification of tilapia fish, with a total accuracy of 63% for tamban fish and 60% for

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tilapia fish.

Subsequent research [7] used MLP and GLCM for feature extraction. The accuracy results were 62%, the error rate was 50%, the recall was 85%, the specification was 39%, the precision was 58%, and the F1 score was 71%.

In 2021, a similar study [8] was carried out on tamban fish images taken using a smartphone with a 480 x 640 pixels resolution. GLCM feature extraction was used on the fish images, and SVM was used to classify them. The results showed that the average accuracy was 0.784, precision was 0.799, recall was 0.784, and the f-measure was 0.781. Although this model did not achieve optimal results, it performed better than the methods in [4] and [5]. However, further method development can be pursued by leveraging deep learning and applying it to smartphones.

II. METHOD

A. Research Stages

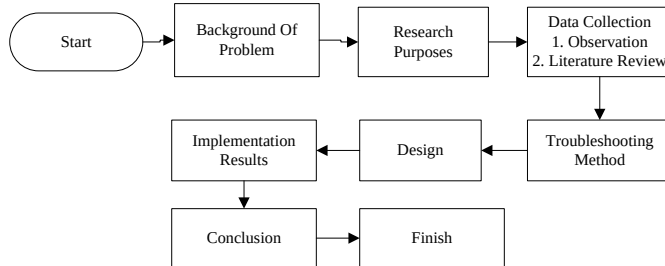


Fig. 1. Research stages.

Fig. 1 above shows the stages or steps used to test machine learning methods in classifying images of formalin fish. This study was carried out in the chemical laboratory of Prima University of Indonesia (UNPRI). The materials used were a pan as a receptacle for the fresh fish mixed with 1 L formalin solution. The fresh fish prepared as study objects were as many as 30 mujair fish and 30 tamban fish. Photos were taken of both fresh fish samples and formalin-treated fish samples. Each fish was placed on a banana leaf, and images were captured from various angles. The formalin-treated samples were prepared by immersing fresh fish samples in a pan with formalin for one hour. After the fish absorbed the formalin, images were taken using the same procedure as the fresh fish samples. The fish samples used in this study are presented in Table 1.

TABLE I
MUJAIR FISH IMAGE DATA

Dataset	Formalin Fish Images	Fresh Fish Images	Training Data	Testing Data
Tilapia	100	100	120	80
Sardine	200	200	237	163

B. System Floating Method

The development method used in this research was the Software Development Life Cycle (SDLC), a well-established compression framework for software development. In this method, the software development process follows a clear life cycle that covers all aspects of the software product from

inception to retirement. SDLC is a systematic approach to efficient system development. Without testing, it is impossible because SDLC informs the system development process to improve its quality, but it does not help find defects in the system. SDLC is a strategy to build or maintain software systems. Software methodologies such as Waterfall, Vee-Methodology, and Rational Unified Process (RUP) are referred to as traditional software development methodologies that are considered heavyweight methodologies [7]. In this study, the method used in solving problems was as follows:

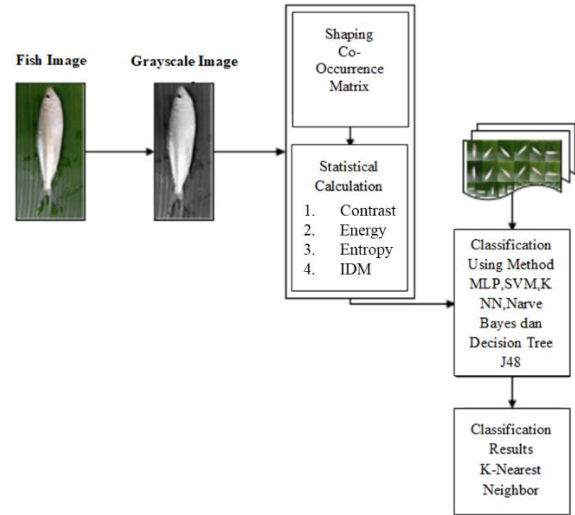


Fig. 2. System procedure.

C. Multilayer Perceptron

Multilayer Perceptron (MLP) is a variant of Artificial Neural Network. It has one or more hidden layers between its input and output layers; the neurons are arranged in layers; connections are always directed from lower to upper layers; neurons in the same layer are not interconnected. MLP is one of the main branches of feed-forward neural networks. MLP consists of a minimum of three layers of nodes. MLP utilizes the backward propagation technique for its training, which is part of the guided learning method. MLP is a subclass of artificial neural networks (ANN), based on a feed-forward architecture. Artificial neural networks are currently widely used to solve classification and regression tasks in cancer recognition [8]. An MLP was used with an input layer, a single hidden layer containing h units (neurons), and an output layer with one unit. The network output due to the vector presentation of the input $x = \{x_1, x_2, \dots, x_n\}$ can be formulated as follows [9]:

$$\hat{f} = \phi(v) = \phi\left(\sum_{s=0}^h w_s \phi\left(\sum_{r=0}^n w_{sr} x_r\right)\right) \quad (1)$$

D. Support Vector Machine

Support Vector Machine (SVM) embodies a number of theoretical machine learning concepts. Initially, SVM was developed with machine learning capacity and control capabilities, using formalization to solve overfitting problems in high-dimensional feature spaces [9]. SVM has been extended to multi-class issues using One-versus-One, One-

versus-Rest, and Directed Acyclic Graph SVM [10] [11]. The purpose of the SVM method is to find a hyperplane defined by the following equation:

$$w\phi(x_i) + b = 0 \quad (2)$$

Where w is the normal to the hyperplane, (x_i) is the mapping function used to map each input vector to the feature space, and b is the bias. The optimization of determining the hyperplane with the largest margin size can be formulated as follows [12]:

$$\min_{w,b,\varepsilon} \quad \frac{1}{2} w^T w + C \sum_{i=1}^k \varepsilon_i \quad (3)$$

$$\text{subject to} \quad y_i(w^T \phi(x_i) + b) \geq 1 - \varepsilon_i \\ \varepsilon_i \geq 0, i = 1, \dots, k$$

Where $\phi(x_i)$ transforms x_i into a higher-dimensional space, $C \geq 0$ is the regularization parameter, and ε_i is a slack variable indicating the extent to which the datum x_i is misclassified.

The KNN classifier is a simple algorithm. The type of instance-based learning is based on similarity measurement (distance function), after which all cases are stored and classified as new cases. On the other hand, based on the majority vote of the neighbors, a case can be classified with cases assigned to the most common class among their nearest neighbors. If $k = 1$, the simple case is transferred to the nearest neighbor class. The KNN algorithm is among the ten best classification algorithms and is in the instance-based group learning category. However, the KNN algorithm has a weakness; namely, when determining the variable at the value of k , the value of the variable must be sought to produce maximum accuracy [13]. The formula for calculating the Euclidean distance is as follows:

$$d_1 = \sqrt{\sum_{i=1}^p (X_{2i} - X_{1i})^2} \quad (4)$$

E. Naive Bayes

Naive Bayes classification has been widely used for text categorization because of its simplicity and efficiency. Naive Bayes (NB) classifiers and their extensions are ubiquitous in data mining, artificial intelligence, and machine learning domains. The Naive Bayes classifier is a probability classifier based on the Bayes hypothesis [14]. The Bayesian hypothesis determines the relationship between the probability of two events, A and B , $P(A)$ and $P(B)$, and the contingent probability of event A being formed by B and the occurrence of B being adapted by A , $P(A|B)$ and $P(B|A)$.

$$P\left(\frac{A}{B}\right) = \frac{P(B|A)}{P(B)} \quad (5)$$

F. Decision Tree J48

The J48 classifier is an implementation of the C4.5 decision tree algorithm. J48 classifies new instances by creating a decision tree from given training sets of attribute values.

When it finds a training set, it recognizes the attributes responsible for categorizing the various examples most accurately. A possible feature value without ambiguity is assigned to the attention branch by stopping it [15]. Classifier J48 is a decision tree classifier. By applying J48, one can predict the class label of a new record in the dataset from a list of dependent and independent variables. The attribute to be expected is known as the dependent variable, while other attributes that help predict it are known as independent variables. The decision tree models the classification process through the symbols of nodes and branches. The tree nodes represent different attributes, the branches represent the separation of the attributes based on their values, and the leaves indicate the class of the dependent variable. Nodes at a certain level are found based on the ratio of the highest information gain obtained on the available attributes, and the same attribute is selected for the next branch. Separation depends on receiving the highest information for the selected node attributes. This creates a decision tree based on attribute values from the available training sets [16].

G. Gray Level Co-Occurrence Matrix

Before classification, the RGB image is first converted to grayscale, after which the contrast, entropy, energy, and IDM values are calculated. This calculation uses the formula for GLCM feature extraction. Gray Level Co-Occurrence Matrix (GLCM) is categorized as texture analysis and is considered the most common and convenient algorithm. It processes the image and reflects the second-order conditional probability value of a combination of pixels (i, j) with a certain angle (θ), distance (d), and different intensities [17][18][19]. GLCM can be defined as a statistical method that reflects a second-order histogram to evaluate the probability of multiple gray-level pixels for single-pixel distances and paths [20][21]. Statistical features are used to correlate minimum and maximum repeated counts:

$$\text{Contrast} = \sum_n n^2 \left\{ \sum_{|i-j|=n} GLCM(i, j) \right\} \quad (6)$$

$$\text{Energy} = \sum_{i=0}^{L-1} [p(i)]^2 \quad (7)$$

$$\text{Entropy} = - \sum_{i=1}^L \sum_{j=1}^L GLCM(i, j) \log(GLCM(i, j)) \quad (8)$$

$$\text{Inverse Different Moment (IDM)} = \sum_{i=1}^L \sum_{j=1}^L \frac{(GLCM(i, j))^2}{1 + GLCM(i - j)^2} \quad (9)$$

H. System planning

In Fig. 3 below, it is explained that the system can be accessed directly without going through a log-in. The system is designed to classify images based on training data that has been previously input.

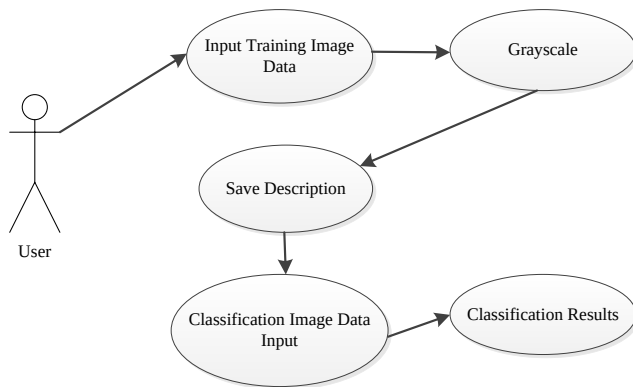


Fig. 3. Use a case diagram.

III. RESULTS AND DISCUSSIONS

Here is the initial page of the formalin-contaminated fish classification system based on fish images.



Fig. 4. System's results using the KNN method.

Before classifying the image using the system, the user must input training data, which is needed to compare the classification image with the training image so that the system can conclude the classified image.

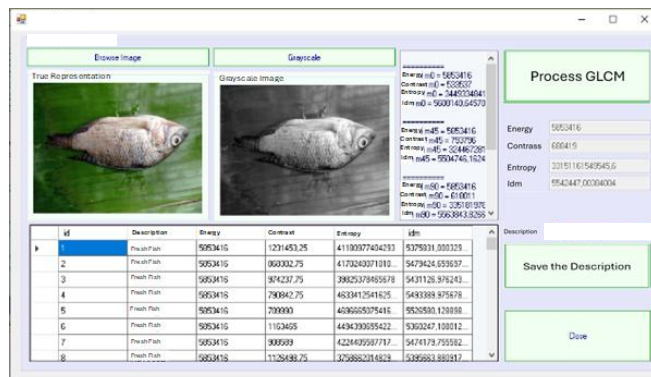


Fig. 5. Training form.

The user can start the fish image classification process when all the training data has been inputted. The system detects the inputted fish image and concludes whether the image represents a formalin fish image or a fresh fish.



Fig. 6. Browse images for classification.

The following are the results of image classification accuracy using the multilayer perceptron (MLP) method.

TABLE II
RESULT OF MULTILAYER PERCEPTRON

Category	Accuracy	Precision	Recall	F1-Score
Fresh Fish	0.833	0.625	0.883	0.714
Formalin Fish	0.5	0.75	0.5	0.6
Average	0.667	0.688	0.692	0.657

Table II shows that the accuracy obtained using the Multilayer Perceptron (MLP) method was 0.667. Using the Support Vector Machine (SVM) method, the accuracy obtained was 0.650. This result was slightly lower than when using the MLP method. The following are the results of classification using the SVM method, which are presented in tabular form.

TABLE III
RESULT OF SVM CLASSIFICATION

Category	Accuracy	Precision	Recall	F1-Score
Fresh Fish	0.4	0.8	0.4	0.533
Formalin Fish	0.9	0.6	0.9	0.72
Average	0.650	0.700	0.650	0.627

Using the MLP and SVM methods, the accuracy results obtained were not much different. The following is the result of image classification using the K-Nearest Neighbors (KNN) method in tabular form.

TABLE IV
RESULT OF KNN CLASSIFICATION

Category	Accuracy	Precision	Recall	F1-Score
Fresh Fish	0.767	0.575	0.767	0.657
Formalin Fish	0.433	0.65	0.433	0.52
Average	0.600	0.613	0.600	0.589

The KNN method result was 0.6, i.e., lower than the MLP and SVM methods. Next is the classification using the Naive Bayes method. The accuracy results were 0.534, i.e., less accurate than MLP, SVM, and KNN.

TABLE V
RESULT OF NAIVE BAYES CLASSIFICATION

Category	Accuracy	Precision	Recall	F1-Score
Fresh Fish	0.3	0.563	0.3	0.391
Formalin Fish	0.767	0.523	0.767	0.622
Average	0.534	0.543	0.534	0.507

The accuracy of the Decision Tree J48 method was 0.55, i.e.,

slightly higher than using the Naïve Bayes method. Table VI shows the results of classification using the J48 Decision Tree method.

TABLE VI
RESULT OF DECISION TREE J48 CLASSIFICATION

Category	Accuracy	Precision	Recall	F1-Score
Fresh Fish	0.967	0.527	0.967	0.682
Formalin Fish	0.133	0.8	0.133	0.229
Average	0.550	0.664	0.550	0.456

A. Discussion

Based on the results of the five different image classification methods tested, the MLP method achieved the best accuracy in classifying images of tilapia fish with formalin. Table VI compares the five methods used in classifying images of tilapia fish with formalin.

TABLE VII
COMPARISON OF CLASSIFICATION RESULTS

Method	Accuracy	Precision	Recall	F1-Score
Multilayer Perceptron	0.667	0.688	0.692	0.657
Support Vector Machine	0.650	0.700	0.650	0.627
Naïve Bayes	0.534	0.543	0.534	0.507
KNN	0.600	0.613	0.600	0.589
Decision Tree J48	0.550	0.664	0.550	0.456

A comparison of the five image classification methods results is presented in graphical form in Fig. 7.

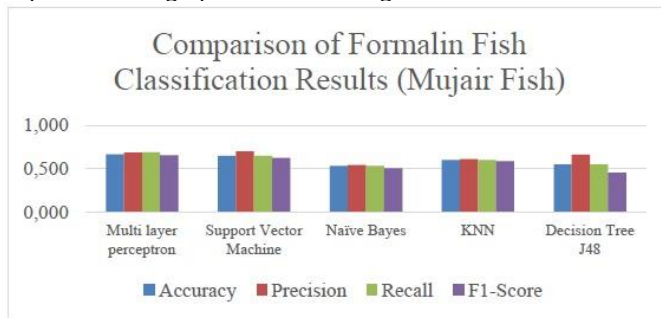


Fig. 7. Graph of classification comparison results.

Previously, image classification was also carried out using various methods on tamban fish objects. Comparing the previous and current research using the same process, namely Naive Bayes, with different image objects, it can be concluded that the Naive Bayes method was more accurate in classifying tamban fish images in previous studies.

TABLE VIII
COMPARISON OF CLASSIFICATION RESULTS WITH PREVIOUS RESEARCH

Fish Type	Method	Accuracy	Precision	Recall	F1-Score
Sardine	Naive Bayes [5]	0.7	0.962963	0.416	0.581006
Tilapia	Naive Bayes	0.534	0.543	0.534	0.507
Sardine	KNN [22]	0.725	0.92	0.661871	0.769874
Tilapia	kNN	0.600	0.613	0.600	0.589
Sardine	MLP [23]	0.62	0.583562	0.852	0.71
Tilapia	MLP	0.667	0.688	0.692	0.657

This is proven by the accuracy results (0.7) compared to those when classifying tilapia fish objects (0.534). Furthermore, compared to previous research using the KNN method on images of fat fish, the current study achieved higher accuracy when classifying tamban fish images, with an accuracy value of 0.725. The classification results for tilapia fish images only

reached 0.6. Using the MLP method, the accuracy obtained was better in the current study than in previous studies for tilapia fish images, with an accuracy ratio of 0.667:0.62.

IV. CONCLUSION

The results were also different; different methods were used to classify tilapia fish images. In this study, the highest accuracy result was achieved using the Multilayer Perceptron (MLP) method, with an accuracy rate of 0.667 compared to other methods. In previous studies using fat fish objects, the MLP method was also the best in classifying fish images, with a ratio of 0.667:0.62. The difference in accuracy of the different methods is not significant. Apart from using various research methods and objects, differences in accuracy can also be caused by differences in image quality and the number of image samples used in the study, which causes this research to be not optimal. This will be addressed in future research.

APPENDIX DECLARATION OF COMPETING INTEREST

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REFERENCES

- [1] S. Mullainathan and J. Spiess, "Machine learning: An applied econometric approach," *J. Econ. Perspect.*, vol. 31, no. 2, pp. 87–106, 2017, doi: 10.1257/jep.31.2.87.
- [2] K. V. Ranjitha and T. P. Pushphavathi, "Analysis on Improved Gaussian-Wiener filtering technique and GLCM based Feature Extraction for Breast Cancer Diagnosis," *Procedia Comput. Sci.*, vol. 235, pp. 2857–2866, 2024, doi: 10.1016/j.procs.2024.04.270.
- [3] J. Wei *et al.*, "Machine learning in materials science," *InfoMat*, vol. 1, no. 3, pp. 338–358, 2019, doi: 10.1002/inf2.12028.
- [4] E. R. Rafafi and E. I. Sela, "Identification of Fresh and Unfresh Fish Based on Eye Image Using The Self-Organizing Maps (SOM) Method," *Int. J. Soc. Serv. Res.*, vol. 3, no. 11, pp. 2826–2833, 2023, doi: 10.46799/ijssr.v3i11.593.
- [5] I. Technology, "Analysis of the Naïve Bayes Method in Classifying Formalized Fish Images Using GLCM Feature Extraction," vol. 1, no. 2, pp. 120–128, 2020, doi: 10.30596/jcositte.v1i2.5171.
- [6] R. Mardiana, L. Lidyawati, and M. Zulfikri, "Identifikasi Formalin Pada Ikan Segar di Pelabuhan Pendaratan Ikan Idi Rayeuk Kabupaten Aceh Timur," *J. Pharm. Heal. Res.*, vol. 1, no. 3, pp. 77–82, 2020, doi: 10.47065/jharma.v1i3.597.
- [7] S. M. Faizi and S. S. M. Rahman, "Choosing the best-fit lifecycle framework while addressing functionality and security issues," *Proc. 34th Int. Conf. Comput. Their Appl. CATA 2019*, vol. 58, pp. 107–116, 2019, doi: 10.29007/cfm3.
- [8] S. Savalia and V. Emamian, "Cardiac arrhythmia classification by multi-layer perceptron and convolution neural networks,"

- Bioengineering*, vol. 5, no. 2, 2018, doi: 10.3390/bioengineering5020035.
- [9] I. Lorencin, N. Anđelić, V. Mrzljak, and Z. Car, "Multilayer perceptron approach to condition-based maintenance of marine CODLAG propulsion system components," *Pomorstvo*, vol. 33, no. 2, pp. 181–190, 2019, doi: 10.31217/p.33.2.8.
 - [10] A. Roy and S. Chakraborty, "Support vector machine in structural reliability analysis: A review," *Reliab. Eng. Syst. Saf.*, vol. 233, no. January, p. 109126, 2023, doi: 10.1016/j.ress.2023.109126.
 - [11] A. Turnip, M. Ilham Rizqywan, D. E. Kusumandari, M. Turnip, and P. Sihombing, "Classification of ECG signal with Support Vector Machine Method for Arrhythmia Detection," *J. Phys. Conf. Ser.*, vol. 970, no. 1, 2018, doi: 10.1088/1742-6596/970/1/012012.
 - [12] T. Hastie, R. Tibshirani, and J. Friedman, *The elements of statistical learning: data mining, inference, and prediction*, 2017.
 - [13] R. A. Saputra, Suharyanto, S. Wasiyanti, D. F. Saefudin, A. Supriyatna, and A. Wibowo, "Rice Leaf Disease Image Classifications Using KNN Based on GLCM Feature Extraction," *J. Phys. Conf. Ser.*, vol. 1641, no. 1, 2020, doi: 10.1088/1742-6596/1641/1/012080.
 - [14] J. Jasmir, D. Z. Abidin, F. Fachruddin, and W. Riyadi, "Experimental of information gain and AdaBoost feature for machine learning classifier in media social data," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 36, no. 2, pp. 1172–1181, 2024, doi: 10.11591/ijeecs.v36.i2.pp1172-1181.
 - [15] S. R. T. Mat, M. F. A. Razak, M. N. M. Kahar, J. M. Arif, and A. Firdaus, "A Bayesian probability model for Android malware detection," *ICT Express*, vol. 8, no. 3, pp. 424–431, 2022, doi: 10.1016/j.icte.2021.09.003.
 - [16] S. Rana and A. Singh, "Comparative analysis of sentiment orientation using SVM and Naive Bayes techniques," *Proc. 2016 2nd Int. Conf. Next Gener. Comput. Technol. NGCT 2016*, no. October, pp. 106–111, 2017, doi: 10.1109/NGCT.2016.7877399.
 - [17] A. Choi, N. Tavabi, and A. Darwiche, "Structured features in naive bayes classification," *30th AAAI Conf. Artif. Intell. AAAI 2016*, pp. 3233–3240, 2016, doi: 10.1609/aaai.v30i1.10427.
 - [18] G. Prasad, G. S. Vijay, and R. Kamath C., "Comparative study on classification of machined surfaces using ML techniques applied to GLCM based image features," *Mater. Today Proc.*, vol. 62, pp. 1440–1445, 2022, doi: 10.1016/j.matpr.2022.01.285.
 - [19] S. Saifullah and R. Drezewski, "Non-Destructive Egg Fertility Detection in Incubation Using SVM Classifier Based on GLCM Parameters," *Procedia Comput. Sci.*, vol. 207, no. Kes, pp. 3248–3257, 2022, doi: 10.1016/j.procs.2022.09.383.
 - [20] C. Nyasulu *et al.*, "A comparative study of Machine Learning-based classification of Tomato fungal diseases: Application of GLCM texture features," *Heliyon*, vol. 9, no. 11, p. e21697, 2023, doi: 10.1016/j.heliyon.2023.e21697.
 - [21] A. Mathew, A. Antony, Y. Mahadeshwar, T. Khan, and A. Kulkarni, "Plant disease detection using GLCM feature extractor and voting classification approach," *Mater. Today Proc.*, vol. 58, pp. 407–415, 2022, doi: 10.1016/j.matpr.2022.02.350.
 - [22] A. Pariyandani, "Klasifikasi Citra Ikan Berformalin Menggunakan Metode K-NN dan GLCM," *Pros. Semin. Nas. Teknol. Inform.*, vol. 2, no. 1, pp. 42–47, 2019. (In Indonesian)
 - [23] J. S. Komputer, E. P. Wanti, P. T. Informatika, F. Teknik, and U. M. Area, "Pengidentifikasian Citra Ikan Berformalin Dengan Menggunakan Metode Multilayer Perceptron," vol. 5, pp. 491–502, 2021. (In Indonesian)