Jurnal Ilmu Komputer dan Informasi (Journal of Computer Science and Information)
15/1 (2022), xx-xx. DOI: http://dx.doi.org/10.21609/jiki.v15i1.xxx

Classification of Koi Fish Types Using Gray-Level Co-Occurrence Matrix and Color Feature Extraction with the K-Nearest Neighbor Algorithm

Shafirkan[1], Duwi Cahya Putri Buani[2*]

[1,2]Informatika, Faculty of Information Technology, Universitas Nusa Mandiri, Jakarta, Indonesia

E-mail: firkannn1203@gmail.com, duwi.dcp@nusamandiri.ac.id

Abstract

Koi fish classification is an important process for distinguishing various koi fish types that have highly similar color patterns and visual appearances. This study aims to develop an automatic classification system using the Gray Level Co-Occurrence Matrix (GLCM) and color features for feature extraction, as well as the K-Nearest Neighbor (KNN) algorithm for classification. The dataset consists of 1,500 koi fish images representing 15 classes, with 100 images for each class, obtained from Kaggle and divided into 1,200 training images (80%) and 300 testing images (20%). The preprocessing stage includes resizing the images to 256 × 256 pixels, removing the background, cropping the object region, converting the images to grayscale, and enhancing image quality using Contrast Limited Adaptive Histogram Equalization (CLAHE). Texture features are extracted using GLCM, including Contrast, Dissimilarity, Correlation, Homogeneity, Energy, and Angular Second Moment (ASM) with distances of 1, 3, and 5 and angles of 0°, 45°, 90°, and 135°, while color features are extracted from the HSV and RGB color spaces. All features are normalized using StandardScaler before being classified using the KNN algorithm (K = 3). Experimental results show that images with backgrounds achieved an accuracy of 70.00%, precision of 70.92%, recall of 70.00%, and an F1-score of 69.71%, whereas background-removed images achieved an accuracy of 95.33%, precision of 95.54%, recall of 95.33%, and an F1-score of 95.27%. These results demonstrate that the combination of GLCM, color features, and the KNN algorithm effectively classifies koi fish types, while background removal significantly improves classification performance.

Keywords: Koi fish, Gray Level Co-Occurrence Matrix, Color features, K-Nearest Neighbor, Image classification.

1. Introduction

Koi (Cyprinus carpio), which originate from Japan, are widely known as freshwater ornamental fish that symbolize love and friendship[1]. The main appeal of koi lies in the beauty of their patterns and colors, making them highly sought after as ornamental fish however, most members of the general public still find it difficult to identify and distinguish between different types of koi due to the wide variety of patterns and colors among the different types, which are often very similar[2].

In addition to their aesthetic value, the diversity of koi's visual characteristics also has implications for the identification and trade of ornamental fish. Koi variety identification is generally based on color, pattern, body shape, and the distribution of markings on the fish's body. Similarities in these characteristics can lead to misidentification, especially when the identification process is conducted visually by individuals who lack specific experience or knowledge regarding koi varieties. This situation highlights the need for an automated approach that can facilitate the identification of koi varieties in a more objective, consistent, and efficient manner[3], [4], [5], [6].

Advances in computer vision and digital image processing offer opportunities to address these issues. Fish images can be represented based on visual characteristics such as color and texture, which are then converted into numerical features for the classification process. For fish objects, color characteristics can be important information because each species or variety may have different color patterns, while texture characteristics can be used to represent the surface

patterns of the objects. Research on image-based fish classification also shows that a combination of color and texture features can be used to improve the system's ability to distinguish between fish objects that have similar visual characteristics [7].

Previous research by Hanggara et al. applied the Content-Based Image Retrieval (CBIR) method to identify four types of koi using 80 images, achieving a highest accuracy of 65% for the Ki Utsuri variety and a lowest accuracy of 50% for the Taisho Sanke variety [8].

These results indicate that identifying koi fish species remains a challenging problem, primarily due to the similarity in visual characteristics among species. Furthermore, previous studies have relied on a relatively limited number of classes and images. Therefore, further research is needed with a larger number of classes and a larger dataset to test the classification methods' ability to handle the diversity of koi fish visual characteristics.

Another aspect to consider in koi fish image classification is the presence of the background. The background in an image may contain visual information not directly related to the fish object, which could potentially affect the extracted color and texture features. Research on image classification shows that models can utilize background information as part of the decision-making process, including features that are spurious or not directly related to the main object [9]. This issue is also particularly evident in fish image classification, where a complex background can act as background noise and interfere with the process of recognizing fish objects [10]. Conversely, removing or masking the background can help the model focus more on the characteristics of the main object and improve the robustness of the classification against background variations[11]. Therefore, comparing images with backgrounds to those without backgrounds is important for determining how image conditions affect the performance of koi fish classification.

Based on these issues, this study aims to design and test a classification system for 15 types of koi fish using GLCM and color (HSV and RGB) feature extraction with the KNN algorithm, and then compare the accuracy levels of images with and without backgrounds. The dataset consists of 1,500 images, with 100 images for each species, obtained from Kaggle [12]. The results of this study are expected to serve as a reference for the classification of koi species with a reasonably high degree of accuracy.

Based on the above discussion, there is a research gap in that there is still a limited number of studies that specifically evaluate multi-class classification of koi fish by combining GLCM texture features with HSV and RGB color features using KNN, while also analyzing the effect of background presence on classification results. This study addresses this gap by using 15 types of koi and 1,500 images, resulting in a more complex classification scenario compared to previous studies. A comparison between images with and without backgrounds was also conducted to determine the most appropriate preprocessing conditions for generating features that are representative of koi characteristics.

Thus, the contribution of this study lies not only in the development of a classification model for koi fish varieties, but also in the evaluation of combinations of color and texture features, as well as the analysis of the impact of preprocessing on classification performance. The results of this study are expected to serve as a reference for the development of ornamental fish identification systems based on digital image processing and to provide a foundation for future research using machine learning and deep learning approaches in the classification of koi fish varieties.

2. Materials and Methods

The research stages include dataset collection, image preprocessing, feature extraction, the classification process, and evaluation of the results using a confusion matrix.



Figure 1. Research Phases

Figure 1 illustrates the research workflow, which begins with loading a dataset of koi fish images consisting of 15 species with a total of 1,500 images. Next, the images undergo a preprocessing stage that includes resizing, cropping, grayscaling, and CLAHE. Once the images are ready, feature extraction is performed using GLCM to obtain texture characteristics and HSV and RGB color features to determine the fish's color characteristics. These two sets of features were then combined into 120 features and normalized using StandardScaler. Next, the features were used as input for the K-Nearest Neighbor (KNN) algorithm to determine the koi fish species based on the nearest neighbors. The classification results were then evaluated using accuracy, precision, recall, F1-score, and a confusion matrix to assess the model's performance.

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP+TN}}{\boldsymbol{TP+TN+FP+FN}} \boldsymbol{x}\ \mathbf{100\%} \quad (1)$$

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}} \boldsymbol{x}\ \mathbf{100\%} \quad (2)$$

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \boldsymbol{x}\ \mathbf{100\%} \quad (3)$$

$$\boldsymbol{F1-Score} = \frac{\boldsymbol{2\ x\ Precision\ x\ Recall}}{\boldsymbol{Precision+Recall}} \boldsymbol{x}\ \mathbf{100\%} \quad (4)$$

a. Dataset

The dataset used was obtained from Kaggle under the name "Koi Image Dataset" [12], and consists of 15 types of koi fish (asagi, bekko, doitsu hariwake, kinginrin, kohaku, matsuba, ogon, sanke, showa, shusui, tancho, and usuritmono), with a total of 1,500 images, each class containing 100 images. The dataset was split in an 80:20 ratio, with 1,200 images used for training and 300 images for testing.

b. Data Preprocessing

During the data preprocessing stage, images of koi fish are prepared before entering the feature extraction and classification stages. This stage aims to standardize image sizes, separate the fish objects from the background, and convert color images to grayscale so they can be optimally processed during feature extraction. Preprocessing is performed to reduce the influence of irrelevant information, such as differences in image size and background, so that the feature extraction process can yield more representative texture information. The result of this stage is an image ready for use in the feature extraction process using the Gray Level Co-Occurrence Matrix (GLCM) and color methods. This process is illustrated in Figure 2.

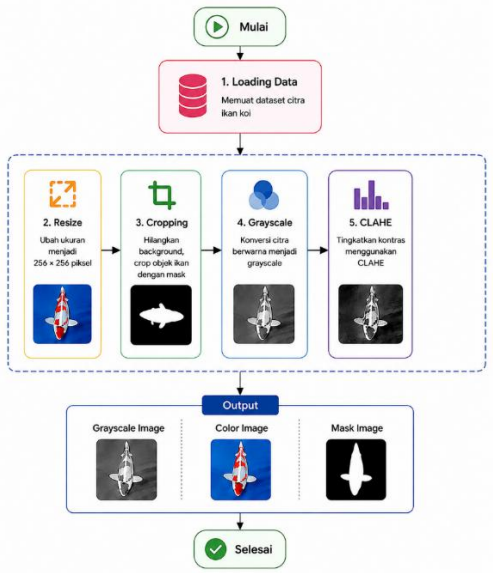


Figure 2. Stages of data processing

The preprocessing stage is performed to prepare the koi fish images before proceeding to the GLCM and color feature extraction stages. The main objectives are to standardize the image dimensions, separate the fish objects from the background, improve the quality of the grayscale images, and reduce the influence of the background on the feature extraction process.

The Gray Level Co-Occurrence Matrix (GLCM) is a method used to analyze the relationships between pixels in a digital image based on frequently occurring gray levels. It calculates the frequency of occurrence of pairs of pixel values at specific distances and angles, making it useful for analyzing image texture based on pixel intensity. GLCM is a statistical feature extraction method in which feature information is derived from the matrix of relationships between pixels that form specific patterns in an image [13].

c. Feature Extraction

Texture features were extracted using the GLCM method with six properties: Contrast, Correlation, Inverse Difference Moment (IDM), Angular Second Moment (ASM), Energy, and Dissimilarity. These were then calculated at 3 pixel distances (d = 1, 3, 5) and 4 orientation angles (0°, 45°, 90°, and 135°), resulting in 72 texture features.

Color features were calculated from the HSV and RGB color spaces as the mean and standard deviation of each channel, computed both globally and across 3 image regions (head, body, and tail) to capture the spatial distribution of color, resulting in 48 color features. All 120 features (72 texture features and 48 color features) were then combined and normalized using StandardScaler

before being used as input for the classification model, so that features with a wide range of values would not dominate the distance calculations in the KNN algorithm.

Table 1. Feature Extraction Parameters

Jenis fitur	Parameter	Jumlah
GLCM	6 properties × 3 distances × 4 angles	72
(HSV&RGB)	Mean and Standard Deviation for the Global and 3 Regions	48
		120

d. Classification

Classification is performed using the K-Nearest Neighbor algorithm with the Euclidean distance metric. The system calculates the distance between the test data and all training data, sorts them from closest to farthest, and then determines the class based on the majority of the K nearest neighbors. The training and testing processes were conducted on two data scenarios—images with backgrounds and images without backgrounds—to determine the effect of the presence of a background on classification accuracy.

K-Nearest Neighbor (KNN) is a method for classifying objects based on training data. KNN is a supervised learning algorithm in machine learning that is simple in concept, easy to implement, and frequently used to solve data classification problems [14]. If the majority of neighbors belong to the positive class, the data point is classified as positive. Meanwhile, when k = 6, the classification is determined based on the six nearest neighbors, so the classification results may differ. Therefore, the choice of the k value significantly affects the accuracy of the KNN algorithm [15].

e. Model Evaluation

Model performance was evaluated on the test set using the metrics accuracy, precision, recall, and F1-score, which were calculated using the `classification_report()` function from scikit-learn, and further analyzed using a confusion matrix. The entire evaluation process runs automatically after the "Start Training" button is clicked in the "Model Training" menu.

3. Results and Discussion

Testing was conducted on 15 classes of koi fish using two test data scenarios: images with backgrounds and images without backgrounds, each using 300 test images (20 images per class).

Table 1. Results of the Model Evaluation with K = 3

Metrik	Dengan Background	Tanpa Background
Accuracy	70,00%	95,33%
Precision	70,92%	95,54%
Recall	70,00%	95,33%
F1-Score	69,71%	95,27%

In the image scenario with a background, the model achieved an accuracy of 70.00%. The shusui class achieved the highest F1-score (0.85), followed by asagi and kohaku (0.84), and matsuba (0.83), indicating that the visual characteristics of these classes are relatively easy to recognize even though the background still affects texture feature extraction. Conversely, the kinginrin class achieved the lowest performance, with precision, recall, and F1-score of 0.45 each, making it the class most difficult for the model to distinguish. The class pairs most frequently misclassified in this scenario were kawarimono predicted as kinginrin (4 cases), as well as bekko–utsurimono, goromo–showa, kinginrin–showa, and tancho–kinginrin/utsurimono (3 cases each).

In the image scenario without a background, the model's accuracy increased significantly to 95.33%, a rise of 25 percentage points compared to the scenario with a background. Four classes—bekko, doitsu hariwake, kawarimono, and kohaku—were successfully classified with perfect precision, recall, and F1-score (1.00). The class with the lowest performance in this scenario was matsuba, with an F1-score of 0.86. The number of misclassifications between pairs of the same class also decreased sharply; for example, the number of misclassifications for the kawarimono–kinginrin pair dropped from 4 to 2 cases.

Background removal demonstrates that the presence of a background in an image significantly affects the quality of GLCM texture features, as the background texture is included in the co-occurrence matrix and obscures the actual texture patterns of the fish scales. Furthermore, separating the fish objects from the background ensures that the HSV and RGB color features are calculated purely from the pixels of the fish's body, rather than from the color of the water or other background elements, thereby preserving the distinctive color characteristics of each type of koi fish. These results are consistent with previous GLCM- and KNN-based classification studies, which also demonstrated the importance of input image quality on classification accuracy.

4. Conclusion

This study successfully developed a classification system for 15 types of koi fish using GLCM and color (HSV and RGB) feature extraction with the K-Nearest Neighbor algorithm, which was implemented in a Streamlit-based application encompassing the stages of dataset loading, preprocessing, feature extraction, model training, and prediction. The model tested on images without a background achieved an accuracy of 95.33%, significantly better than the model tested on images with a background, which achieved only 70.00% accuracy; thus, it can be concluded that the background removal stage contributes significantly to improved classification performance. Future research is recommended to use datasets with more consistent image quality and lighting conditions, as well as to develop more accurate automatic background removal methods so that the process of separating fish objects from the background can be performed consistently without manual intervention.

References

[1] Fariz Prasetya Putra, "Klasifikasi Jenis Ikan Koi Menggunakan Metode Support Vector Machine Dengan Fitur Hog Dan Hsv Oleh : Fariz Prasetya Putra Program Studi Informatika Fakultas Ilmu Komputer Dan Rekayasa Universitas Multi Data Palembang Palembang," 2023.

[2] S. S. Asmoro *et al.*, "Rancang Bangun Aplikasi Mobile Untuk Klasifikasi Jenis Ikan Koi Menggunakan Algoritma Convolutional Neural Network," vol. 3, pp. 270–277, 2024.

[3] E. Alfonsius, P. Korespondensi, S. Kawulusan, and W. D. Ch Weku, "Sistem Identifikasi Varietas Koi Berdasarkan Pola Corak dan Warna Menggunakan YOLOv8," *CHAIN: Journal of Computer Technology, Computer Engineering, and Informatics*, vol. 4, no. 4, pp. 520–529, Oct. 2026, doi: 10.58602/CHAIN.V4I4.359.

[4] H. Syarif and P. N. Andono, "Content Based Image Retrieval Berbasis Color Histogram Untuk Pengklasifikasian Ikan Koi Jenis Kohaku," *JIPI (Jurnal Ilmiah Penelitian dan Pembelajaran Informatika)*, vol. 8, no. 2, pp. 616–626, May 2023, doi: 10.29100/JIPI.V8I2.3612.

[5] L. David *et al.*, "Aspects of red and black color inheritance in the Japanese ornamental (Koi) carp (Cyprinus carpio L.)," *Aquaculture*, vol. 233, no. 1–4, pp. 129–147, Apr. 2004, doi: 10.1016/J.AQUACULTURE.2003.10.033.

[6] J. Hu, D. Li, Q. Duan, Y. Han, G. Chen, and X. Si, "Fish species classification by color, texture and multi-class support vector machine using computer vision," *Comput. Electron. Agric.*, vol. 88, pp. 133–140, Oct. 2012, doi: 10.1016/J.COMPAG.2012.07.008.

[7] S. Kaharuddin, E. W. Sholeha, T. P. Lunak, and T. Informasi, "Classification of Fish Species with Image Data Using K-Nearest Neighbor," *International Journal of Computer and Information System (IJCIS)*, vol. 2, no. 2, pp. 54–58, May 2021, doi: 10.29040/IJCIS.V2I2.33.

[8] N. R. Hanggara, R. K. Niswatin, and P. Kasih, "Penerapan Content Based Image Retrieval Untuk Pengenalan Jenis Ikan Koi," 2021.

[9] M. Moayeri, P. Pope, Y. Balaji, and S. Feizi, "A Comprehensive Study of Image Classification Model Sensitivity to Foregrounds, Backgrounds, and Visual Attributes," 2022.

[10] Q. Yan, X. Du, C. Li, and X. Tian, "CLIB: Contrastive learning of ignoring background for underwater fish image classification," *Front. Neurorobot.*, vol. 18, p. 1423848, Jul. 2024, doi: 10.3389/FNBOT.2024.1423848/TEXT.

[11] A. Aniraj, C. F. Dantas, D. Ienco, and D. Marcos, "Masking Strategies for Background Bias Removal in Computer Vision Models," 2023.

[12] Rayhannnn, "Koi Image Dataset," Kaggle. Accessed: May 05, 2026. [Online]. Available: https://www.kaggle.com/datasets/rayhannnn/koi-image-dataset/data

[13] G. Dan and K. N. Knn, "Klasifikasi Jenis Jamur Menggunakan Ekstraksi Fitur Glcm Dan K-Nearest Neighbor (KNN) Frencis," vol. 4, no. 3, pp. 286–290, 2022.

[14] A. Prabowo, D. Erwanto, and P. N. Rahayu, "Klasifikasi Kesegaran Daging Sapi Menggunakan Metode Ekstraksi Tekstur GLCM dan KNN Freshness Classification of Beef Using GLCM Texture Extraction Method and KNN," vol. 7, no. 1, 2021.

[15] Rina, "Algoritma K-Nearest Neighbor (KNN): Penjelasan dan Implementasi untuk Klasifikasi Kanker." Accessed: May 20, 2026. [Online]. Available: https://esairina.medium.com/algoritma-k-

nearest-neighbor-knn-penjelasan-dan-implementasi-untuk-klasifikasi-kanker-ff9b7fbe0a4