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SHAPE AND TEXTURE INTEGRATION FOR JAVA SEA FISH CLASSIFICATION USING K-NEAREST NEIGHBORS ALGORITHM

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Abstract

Manual identification of fish species at fish auction sites (TPI) was often time-consuming and prone to inconsistencies, which affected economic valuation and data recording accuracy. This study proposed an automated fish classification system to address these challenges using the K-Nearest Neighbors (KNN) method. The system was designed to assist the fish identification process in the Java Sea, with a case study conducted at the Karanganyar Fish Auction Site. The proposed approach employed computer vision techniques, beginning with image pre-processing steps such as segmentation and cropping to isolate fish objects. Subsequently, two complementary feature extraction methods were combined to obtain a robust representation of each fish image: Hu Moments for capturing holistic shape features that are invariant to scale and rotation, and Local Binary Pattern (LBP) for extracting detailed surface texture information. This hybrid feature representation provided a comprehensive descriptor for every fish instance. The dataset consisted of 1,000 images categorized into 10 main fish species (e.g., tongkol, bawal, and others). Model training and hyperparameter optimization were performed using a k-fold cross-validation scheme, followed by an 80:20 train-test evaluation. The experimental results demonstrated that the KNN model with the optimal k value achieved an overall classification accuracy of 98.50% on the unseen test set. These findings indicated that the integration of Hu Moments and LBP features was highly effective in distinguishing fish species and showed strong potential for practical implementation as a fast, objective, and reliable identification tool at fish auction sites such as Karanganyar Fish Auction Site.

Keywords: fish classification, k-nearest neighbors, hu moments, local binary pattern, digital image processing

Abstrak

Identifikasi jenis ikan secara manual di Tempat Pelelangan Ikan (TPI) sering kali memakan waktu dan rentan terhadap inkonsistensi, yang dapat memengaruhi nilai ekonomi dan akurasi pencatatan data. Penelitian ini mengusulkan sistem klasifikasi ikan otomatis menggunakan metode K-Nearest Neighbors (KNN) untuk mengatasi permasalahan tersebut. Sistem ini dirancang untuk membantu proses identifikasi ikan di perairan Laut Jawa dengan studi kasus di TPI Karanganyar. Pendekatan yang digunakan berbasis computer vision, diawali dengan tahap pra-pemrosesan citra seperti segmentasi dan cropping untuk mengisolasi objek ikan. Selanjutnya, dua metode ekstraksi fitur dikombinasikan untuk menghasilkan representasi citra yang lebih kuat: Hu Moments digunakan untuk menangkap fitur bentuk yang invarian terhadap skala dan rotasi, sedangkan Local Binary Pattern (LBP) digunakan untuk mengekstraksi fitur tekstur permukaan ikan. Kombinasi kedua fitur ini memberikan deskripsi yang komprehensif terhadap setiap citra ikan. Dataset yang digunakan terdiri atas 1.000 citra yang terbagi ke dalam 10 kelas utama ikan (misalnya, ikan tongkol, ikan bawal, dan lainnya). Pelatihan model dan optimasi hiperparameter dilakukan menggunakan skema k-fold cross-validation, diikuti dengan pengujian pada pembagian data latih dan uji sebesar 80:20. Hasil eksperimen menunjukkan bahwa model KNN dengan nilai k optimal mencapai akurasi klasifikasi keseluruhan sebesar 98,50% pada data uji. Temuan ini menunjukkan bahwa kombinasi fitur Hu Moments dan LBP sangat efektif dalam membedakan jenis ikan dan memiliki potensi kuat untuk diimplementasikan sebagai alat identifikasi otomatis yang cepat, objektif, dan andal di TPI Karanganyar.

Kata kunci: klasifikasi ikan, k-nearest neighbors, hu moments, local binary pattern, pengolahan citra digital

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INTRODUCTION

Fish species identification is a crucial aspect of fisheries management, marine biology, and trade at Fish Auction Sites (TPI). In Indonesia, particularly in Java Sea waters, fish diversity is exceptionally high, presenting challenges in the identification process. The northern Java Sea waters are rich in small pelagic fish and juveniles, dominated by species such as mackerel (Rastrelliger sp.), white sardinella (Sardinella sp.), and splendid ponyfish (Eubleekeria splendens) (Mubarok et al., 2023). These small pelagic fish have high commercial value and serve as an important food source, but they often experience overexploitation that threatens the sustainability of fishery resources (Oktaviani et al., 2020).

At the case study location of Karanganyar Fish Auction Site, located in Karanganyar Village, Kragan District, Rembang Regency, Central Java, the process of fish identification and sorting is still largely conducted manually by experts or experienced fishermen. This manual method has limitations, such as subjectivity, human fatigue, and time-consuming processing. These challenges are further intensified by the generational transition of fishermen and TPI staff, where the new generation has trouble in recognizing the highly diverse fish species in Java Sea waters (Nuralam et al., 2023). These limitations can affect operational efficiency and the economic value of auctioned fish.

The development of computer vision and machine learning technology offers solutions for automating the identification process. Various studies have explored fish classification using digital images with different feature extraction approaches (Khan et al., 2024). Fish detection and classification is a complex task that is important for commercialization and fish farming, but faces challenges such as segmentation errors, noise, and image distortion (Dewan et al., 2022). However, relying on only one type of feature is often inadequate, as many fish species have similar shapes or texture patterns.

The K-Nearest Neighbors (KNN) algorithm is a simple yet effective supervised learning classification method that works based on the distance proximity between data points (B & Gangula, 2024). As a non-parametric algorithm, KNN does not require assumptions about data distribution, making it capable of handling large datasets with high flexibility (Daulay et al., 2023). Previous research by Iman et al. (Iman et al., 2023) used KNN with 2-Dimensional Linear Discriminant Analysis (2D-LDA) features and achieved 93.12% accuracy. Other research by Suwarsito et al. (Suwarsito et al., 2022) achieved 70% accuracy in freshwater fish classification using KNN, while Jannah et al. (Jannah et al., 2023) successfully achieved 100% accuracy in identifying salmon species with a limited dataset. Research by Kusuma et al. (Kusuma et al., 2023) showed that a KNN-based system successfully identified fish freshness levels with 96% accuracy for fresh fish and 84% for spoiled fish, as well as fish species classification with 97.7% accuracy at k=5. However, there is still room for improvement, especially in handling fish variations that have similar shapes but different textures, or vice versa.

This research proposes the combination of two feature extraction methods to improve KNN classification accuracy: Hu Moments and Local Binary Pattern (LBP). Hu Moments are used to extract invariant values that represent object shapes, unaffected by translation, rotation, and scale. On the other hand, LBP is a robust texture descriptor that works by analyzing the relationship of neighboring pixels to the center pixel. The combination of these two methods is expected to capture the unique characteristics of each fish species based on shape variations and texture patterns present on the fish body.

Therefore, this research aims to develop an automated fish classification system for Java Sea species using K-Nearest Neighbors (KNN) algorithm combined with Hu Moments and Local Binary Pattern (LBP) feature extraction methods. The specific objectives are to implement an effective image preprocessing pipeline including segmentation and feature extraction optimized for fish images, to determine the optimal k value in KNN through systematic hyperparameter optimization, and to achieve high classification accuracy exceeding 95% that demonstrates the practical applicability of the system at fish auction sites.

The contribution of this research is to test the effectiveness of combining shape features (Hu Moments) and texture features (LBP) for Java Sea fish species classification using a primary dataset from Karanganyar Fish Auction Site, as well as performing KNN hyperparameter optimization to obtain an accurate and generalizable model. The novelty of this study lies in the integration of Hu Moments and LBP features specifically tailored for Java Sea fish species, which has not been extensively explored in previous studies, the use of a primary dataset collected directly from TPI Karanganyar representing real-world conditions and local fish species diversity, and the

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development of a lightweight classification system that operates without GPU requirements, making it accessible for deployment in resource-constrained fish auction sites. This system is designed to be used without requiring special hardware such as GPUs, so it can be directly applied in the field and support the digitalization of operational activities in the fisheries sector.

RESEARCH METHODS

System Architecture and Workflow

This research is conducted through several main stages illustrated in Figure 1. The research workflow, from user input to classification output, is designed following a modular system architecture. This architecture details the logical stages executed by the system, encompassing five main components: User, Interface, Library, Preprocessing, and KNN Model.

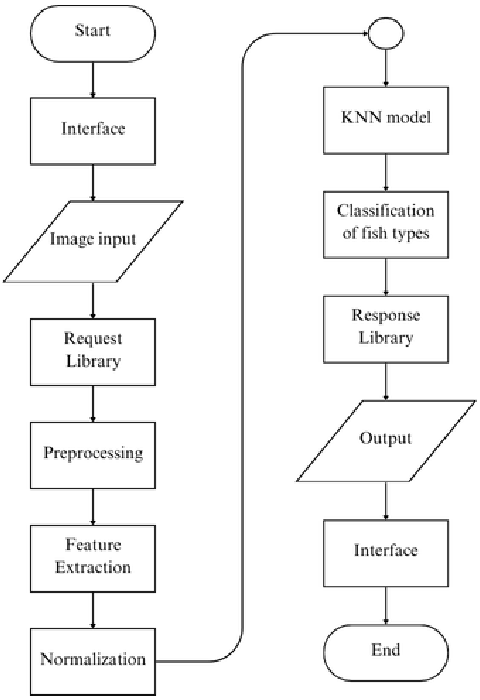

Figure 1. Flowchart of Interface Workflow in the System

The process begins when the user uploads a fish image through the interface. The system then performs a series of preprocessing steps including resize to standardize image dimensions, background segmentation using the rembg library to focus on the main object (fish), and conversion to grayscale to facilitate the feature extraction process. This preprocessing stage is important for simplifying visual information and preparing the image to be analyzed numerically (P, 2024).

After preprocessing, feature extraction is performed using Hu Moments method to capture the global morphological shape of the fish, and LBP to capture local texture patterns from the fish surface. The combination of these two features produces a robust numerical representation of shape and texture differences between fish species. The resulting feature vector is then normalized using MinMaxScaler to equalize the scale between features, so that the KNN model can calculate distances more accurately (Nuraini et al., 2023). This normalization process is crucial because the KNN method, which is sensitive to data scale, can be affected if features have unbalanced value ranges.

The KNN model then calculates the distance of input features to training data to determine the fish class based on the majority label of the k nearest neighbors. The prediction results (output) are then returned to the interface and displayed to the user in the form of fish species name along with preprocessing result visualization.

Dataset

The dataset used in this research is a primary dataset collected manually directly at the case study location, Karanganyar Fish Auction Site. This dataset consists of a total of 1,000 digital images divided equally into 10 fish classes commonly found in these waters, including Kembung Banyar, Barakuda, Semar, Lemuru, Layang, and Tongkol. The selection of these fish species is based on frequently found species with high commercial value in Java Sea waters. The distribution of primary dataset image samples for each fish species can be seen in Table 1.

Table 1. Distribution of Dataset Image Samples per Fish Class

No	Class Name	Number of Images
1	Barakuda	100
2	Bawal	100
3	Kembung Banyar	100
4	Layang	100
5	Lemuru	100
6	Selar Bentong	100
7	Semar	100
8	Tenggiri	100
9	Tengkurungan	100
10	Tongkol	100

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Figure 2 presents sample images from each of the 10 fish classes used in this study. These samples illustrate the visual diversity and morphological characteristics that distinguish each species, including variations in body shape, fin structure, and surface texture patterns. The images were captured under varying lighting conditions and angles to ensure the dataset represents real-world conditions at fish auction sites. Notable morphological differences include the elongated body of Barakuda, the compressed disc-like shape of Bawal, and the fusiform bodies of pelagic species such as Tongkol and Layang. These visual variations, particularly in scale patterns, body proportions, and surface textures, provide the foundation for effective discrimination through Hu Moments (shape) and LBP (texture) feature extraction methods.

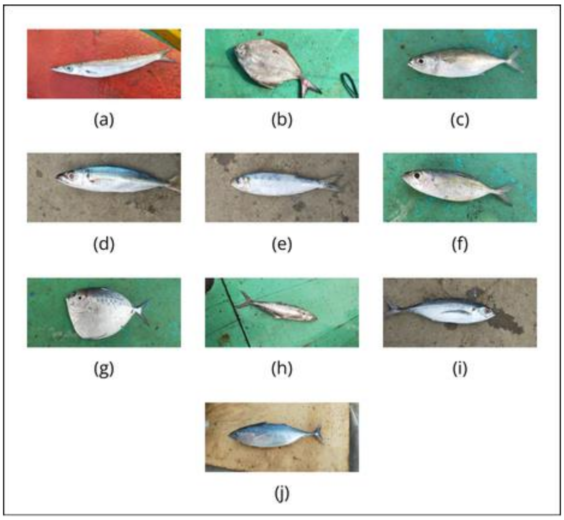

Figure 2. Sample Images from Each Fish Class in the Dataset: (a) Barakuda, (b) Bawal, (c) Kembung Banyar, (d) Layang, (e) Lemuru, (f) Selar Bentong, (g) Semar, (h) Tenggiri, (i) Tengkurungan, (j) Tongkol

Each class is represented by 100 images acquired using a smartphone camera (Oppo A9 2020, 48 MP) over one semester with three data collection sessions. This gradual data collection aims to obtain representative samples with variations in lighting conditions and image capture angles (Khatami et al., 2019). The dataset is divided into 800 training images (80%) and 200 test images (20%) using the train_test_split method with stratify=y parameter to maintain class distribution proportions and random_state=42 for result consistency.

The stratified splitting approach ensures that each fish class is proportionally represented in both training and testing sets, preventing class imbalance issues that could bias model evaluation. This balanced distribution is particularly important for the KNN algorithm, which relies on distance-based classification and can be affected by unequal class representation. The use of a fixed random state guarantees reproducibility of results, enabling fair comparison with future studies and facilitating validation of the proposed methodology by other researchers working with similar fish classification problems.

Image Preprocessing

Before feature extraction, each raw image goes through a preprocessing stage to isolate the fish object from the background and standardize the size. This preprocessing process is a fundamental stage in image processing aimed at enhancing image information for further interpretation. All images are resized to a uniform dimension of 200×200 pixels to ensure consistency across the dataset and optimize computational efficiency during feature extraction and classification. The preprocessing stages include:

1. Segmentation

Image segmentation is a fundamental process aimed at dividing an image into several different regions or segments (Patel, 2024). In this research, images are converted to grayscale, then thresholding (Otsu method or simple binary threshold) is performed to create a binary mask. This segmentation technique is important because it enables high-precision individual fish identification and helps the model network stay focused on the fish body, overcoming disturbances such as complex backgrounds (Zheng et al., 2024).

2. Morphological Operations

Closing and opening operations are applied to the mask to remove noise (small holes or spots) and refine the object shape. These operations help in accurately extracting fish shape features, thus facilitating fish separation from the background (Fajri et al., 2024).

3. Cropping & Padding

The largest contour (assumed to be the fish) is detected using a contour detection algorithm. The bounding box from this contour is used to crop the original image. To ensure that no information is cut off at the edges, the cropped result is then given padding (10 pixels) around it. This process ensures that the fish object is well isolated and ready for the feature extraction stage.

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An example visualization of fish image preprocessing results is displayed in Figure 3. The segmentation mask shown in sub-figure (b) represents the binary mask after applying morphological operations (closing and opening) to remove noise and refine the fish object boundaries.

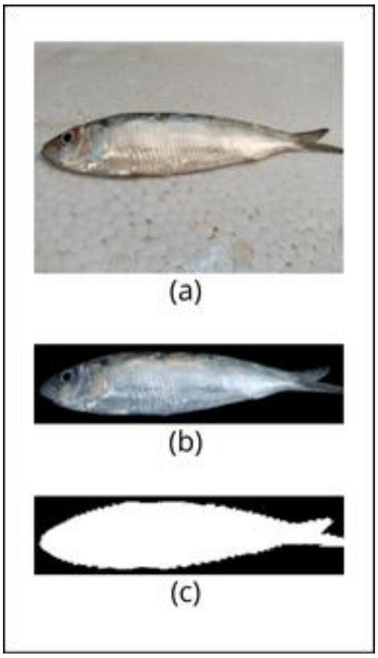

Figure 3. Visualization of Fish Image Preprocessing Results in Interface for "Selar Bentong" species: (a) Original Image, (b) Segmentation Result Mask after Morphological Operations, and (c) Cropped Grayscale Image

Feature Extraction

Feature extraction is the process of identifying important patterns and relationships in data to filter valuable information (Regulwar et al., 2024). In this research, two types of features are extracted from each processed image:

1. Hu Moments

This feature extracts 7 invariant moment values from the object shape. This feature is invariant to translation, scale, and rotation, making it suitable for recognizing fish shapes even though their position and size vary. Hu Moments are derived from geometric moments calculated from image pixel intensity. The first step is to calculate central moments to achieve translation invariance, then the result is normalized to achieve scale invariance. Two of the seven main Hu Moments formulas are:

$$I_1 = (\eta_{20} + \eta_{02}) \tag{1}$$

$$I_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \tag{2}$$

Where η_{ij} are normalized central moments defined as:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{1+\frac{p+q}{2}}} \tag{3}$$

And μ_{ij} are central moments calculated as:

$$\mu_{pq} = \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q f(x, y) \tag{4}$$

These seven values form the first feature vector representing fish shape characteristics generally invariant to geometric changes.

2. Local Binary

This feature extracts surface texture by generating binary codes at each pixel based on the comparison of its intensity value with surrounding pixels. In implementation, uniform LBP with parameters P=24 (number of neighboring points) and R=8 (radius) is used. LBP works by comparing the intensity value of the center pixel (g_p) with its 24 neighbors (g_n). If $g_n \geq g_p$, the value is 1, otherwise 0. This produces a 24-bit binary code that is converted to a decimal value. The histogram of these values is then normalized to form 26 texture features.

The main advantage of LBP is its resistance to lighting changes and its efficiency in representing complex textures. By encoding local pixel intensities into binary patterns, LBP can group textures in fish images into patterns that are easier to analyze. This method is not only capable of capturing the distinctive texture characteristics of various fish species but also remains efficient in image data processing.

The final feature vector is formed by combining these two vectors, producing a total of 33 features (7 from Hu Moments + 26 from LBP) for each image. This combination of shape and texture features provides a robust representation in distinguishing the visual characteristics of diverse fish images.

K-Nearest Neighbors (KNN) Classification

KNN is a lazy learning algorithm that classifies new data based on the majority class of its k nearest neighbors. As a non-parametric algorithm, KNN does not require assumptions about data distribution, making it capable of

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handling large datasets with high flexibility (Li, 2024). Distance between data (feature vectors) is calculated using Euclidean Distance, as in Equation (5):

$$d(p, q) = sqrt(\Sigma(pi - qi)^2) \quad (5)$$

Where d is the distance, p and q are two feature vectors, and i is the feature dimension.

As a simple illustration with 3 features, if there is Test Data p = [0.8, 0.2, 0.5] and Training Data q = [0.7, 0.3, 0.4], then the distance between them is calculated as:

$$d(p, q) = sqrt((0.8 - 0.7)^2 + (0.2 - 0.3)^2 + (0.5 - 0.4)^2) \; d(p, q) = sqrt((0.1)^2 + (-0.1)^2 + (0.1)^2) \; d(p, q) = sqrt(0.01 + 0.01 + 0.01) \; d(p, q) = sqrt(0.03) \approx 0.173 \quad (6)$$

This process is repeated for all 33 features on each training data to find the k nearest neighbors. The algorithm then takes the majority label from these k neighbors as the prediction result. The advantages of KNN are its simplicity, ability to handle non-linear data, and flexibility for small to medium datasets.

Testing Scenarios and Evaluation

To prevent overfitting and find a generalizable model, the following testing scenarios are applied:

1. Feature Scaling

All feature vectors (33 dimensions) are normalized using MinMaxScaler to the range [0, 1]. This is important so that features with large value ranges do not dominate the KNN distance calculation. Feature normalization helps improve model performance by balancing the contribution of each feature in distance calculation (Dhabliya et al., 2024).

2. Dataset Split

The dataset (X, y) is divided into 80% training data (X_train, y_train) and 20% test data (X_test, y_test) using train_test_split with stratify=y to maintain class proportions and random_state=42 for result consistency.

3. Hyperparameter Optimization

The k value is a crucial hyperparameter in KNN. To find the best k, 5-fold cross-validation is performed on training data for odd k ranges (3, 5, 7, 9, and 11). Cross-validation helps measure model stability and ensures the model can work well on unseen data. The k value with the highest average validation accuracy is selected as the optimal parameter.

4. Model Evaluation

The final model is trained on the entire X_train_scaled using the best k, and tested once on X_test_scaled. Performance is measured using Accuracy, Precision, Recall, and F1-Score, presented in a classification report and confusion matrix. These metrics provide a comprehensive overview of the model's performance in classifying each fish class.

This comprehensive evaluation framework addresses multiple dimensions of classification performance. Accuracy measures overall correctness, precision and recall evaluate false positive and false negative rates, while F1-score balances both metrics. The confusion matrix reveals misclassification patterns between species pairs. These metrics ensure thorough assessment of system readiness for deployment at fish auction sites, where both overall accuracy and class-specific reliability are critical.

RESULTS AND DISCUSSION

Feature Extraction Results

Feature extraction was successfully performed on all preprocessed images, generating 33-dimensional feature vectors for each image (7 from Hu Moments and 26 from LBP). The visualization in Figure 3 demonstrates the intermediate results of this process, where the segmentation mask (Figure 3b) is used to compute shape-based Hu Moments features, while the LBP texture visualization would show the texture patterns extracted for classification. These numerical features, after normalization using MinMaxScaler, serve as the input to the KNN classifier. The combination of shape and texture features provides a comprehensive representation that enables the model to distinguish between visually similar fish species effectively.

Hyperparameter Optimization Results

The selection of k value in the KNN algorithm is performed using a 5-fold cross-validation scheme on training data. The k value is tested on several candidates (k = 3, 5, 7, 9, and 11) to find the optimal configuration that provides the best balance between accuracy and model generalization ability. This optimization process is important to ensure that the model does not overfit

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on training data, but remains capable of providing accurate predictions on new, unseen data.

Table 2. Comparison of KNN Performance Across Different K Values

k Value	Accuracy	Macro F1	Weighted F1	CV Accuracy
3	98.50%	98.00%	98.00%	97.25%
5	98.33%	98.00%	98.00%	97.25%
7	97.00%	97.00%	97.00%	97.00%
9	97.50%	97.00%	97.00%	95.88%
11	97.00%	97.00%	97.00%	92.38%

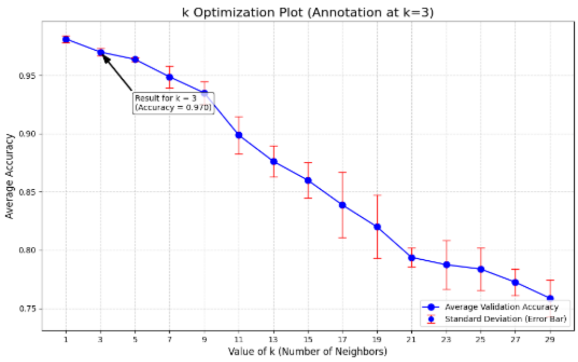

Figure 4. Graph of K Parameter Optimization in KNN Algorithm Based on Average Validation Accuracy with Optimal K Value Marker

The evaluation results show that k = 3 provides the best performance with test data accuracy of 98.50% and cross-validation average accuracy of 97.25%. As shown in Table 2, there is a consistent trend of decreasing accuracy as k increases beyond 3. This value shows high consistency between performance on training data and test data, indicating that the model has good generalization ability. The selection of k = 3 is also supported by optimization graph analysis showing that this value is at the optimal point before performance degradation occurs.

From the k-versus-accuracy graph in Figure 4, the model tends to overfit at k = 1, because it is too sensitive to noise and local variations in data. Conversely, larger k values (≥ 5) tend to gradually decrease accuracy because classification decisions become overly influenced by farther neighbors, which may not be relevant to the test data characteristics. The value k = 3 provides optimal balance, where the model is sensitive enough to capture important local patterns, but not too affected by noise or outliers in the data.

The high cross-validation accuracy (97.25%) approaching test data accuracy (98.50%) shows that the model does not experience significant overfitting. This validates that the combination of Hu Moments and LBP features, together with MinMaxScaler normalization, can produce robust and informative feature representations to distinguish various Java Sea fish species. This performance stability is very important for practical field applications, where image capture conditions and object variations may vary from training data.

Final Model Evaluation Results

The final model is developed using the KNN algorithm with optimal parameter k = 3 obtained from the hyperparameter optimization stage. Training is conducted on 80% training data (800 images) and testing on 20% test data (200 images) that have never been used in the training or validation process, to ensure model generalization ability on new data. Evaluation includes accuracy, precision, recall, and F1-score metrics to comprehensively measure system performance on each fish class.

Test results show that the model can achieve overall accuracy of 98.50% on test data, with precision, recall, and F1-score values consistently high above 0.95 on almost all classes. This confirms that the combination of Hu Moments (shape features) and LBP (texture features), normalized using MinMaxScaler, provides highly effective feature representation for the KNN algorithm in distinguishing the morphology and surface texture of the ten Java Sea fish species studied.

Table 3 shows the model performance distribution on each fish class. It can be observed that six out of ten classes achieve perfect values (1.00) for at least two evaluation metrics, indicating high consistency in classification. Classes with perfect performance include Bawal, Layang, Selar Bentong, Semar, and Tengkurungan, indicating that the shape and texture features of these species are quite distinctive and easily distinguished by the model.

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For classes with slightly lower performance, such as Kembung Banyar, Tenggiri, and Tongkol which have recall of 0.95, the model still shows very good identification ability. This small decrease in recall indicates that there are some samples from these classes that are classified into other classes, possibly due to morphological similarities or surface texture. However, with precision remaining high (0.95-1.00), the model ensures that when a sample is predicted as a certain class, that prediction has a very high confidence level.

The macro average and weighted average values both at 0.99 for precision and 0.985 for recall and F1-score show that the model has balanced performance across all classes, without significant bias toward any class. This is very important in practical applications, as it ensures that the system can be relied upon to identify various fish species with consistent accuracy levels.

Confusion Matrix Analysis

Further evaluation is conducted through confusion matrix analysis to understand classification error patterns and identify class pairs that most frequently experience confusion. The confusion matrix provides clear visualization of how the model performs classification for each combination of actual class and predicted class.

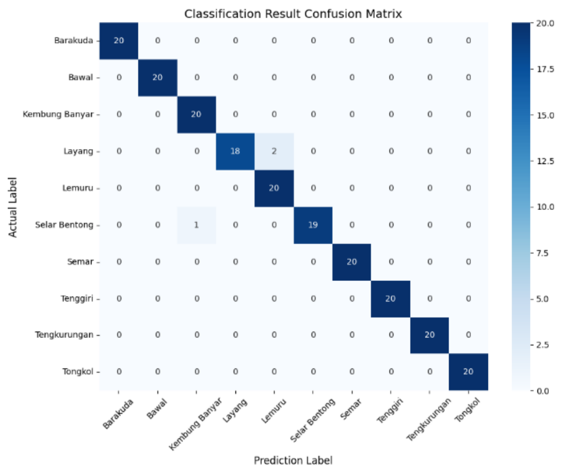

Figure 5. Confusion Matrix of KNN Model Classification Results (k = 3) on Test Data.

From the confusion matrix analysis in Figure 5, most samples are classified correctly, as indicated by high values on the main diagonal of the matrix, confirming model consistency in recognizing unique shape and texture patterns of each fish species. Classification errors, although very limited at only 3 out of 200 samples (1.5%), mainly occur in species pairs with high morphological similarity. For example, one Selar Bentong sample was incorrectly classified as Kembung Banyar, and two Layang samples were incorrectly predicted as Lemuru. This similarity can be explained biologically, as both species pairs have elongated body structures with similar proportions and scale texture patterns that can overlap in feature space.

These misclassification cases indicate that although the extracted features are quite robust, intra-class variations within species caused by factors such as fish size variations, surface conditions (wet/dry), or non-standard image capture angles can cause overlap with other classes. Nevertheless, the very low error rate demonstrates the system's excellent discrimination ability. The combination of Hu Moments capturing geometric invariance and LBP sensitive to local texture patterns proves complementary in distinguishing fish species, even those with high visual similarity, while feature normalization ensures balanced contribution of both feature types in Euclidean distance calculation for the KNN algorithm. This performance validates the effectiveness of the hybrid feature approach for practical fish species identification in real-world auction site conditions.

System Prototype Implementation (PWA)

As proof of concept and practical contribution from this research, the classification model that has been trained and validated is implemented into a ready-to-use application interface prototype. This prototype is designed as an interactive and responsive Progressive Web App (PWA), built using the Flask framework for backend API and HTML/CSS/JavaScript for frontend user interface.

The PWA architecture enables the application to be accessible through standard web browsers with advantages including offline capability after initial caching, direct installation to user devices without app stores, and a smaller footprint compared to conventional mobile applications. These characteristics are particularly suitable for Karanganyar Fish Auction Site, where internet infrastructure may be limited and users require fast and easy access without complicated installation procedures.

The system interface provides intuitive functionality for users, especially TPI officers and fishermen, to upload fish images directly through traditional browse buttons or modern drag-and-drop features. After the image is uploaded, the system automatically executes the complete

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classification pipeline including preprocessing, feature extraction, normalization, and prediction using the deployed KNN model.

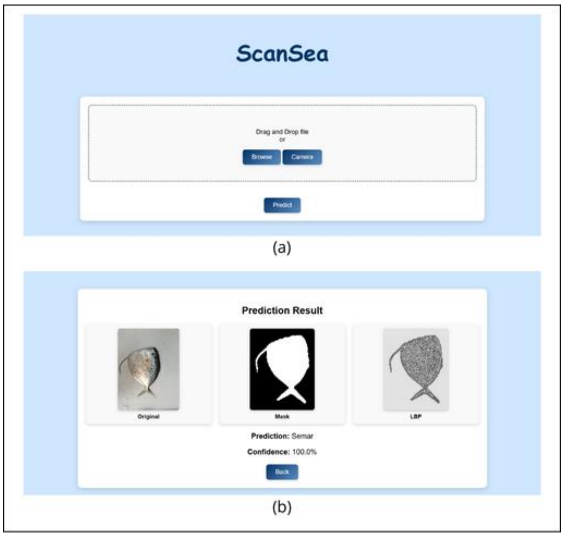

Figure 6. (a) PWA Main Page Interface with Image Input Area, (b) Classification Result Page Interface Displaying "Semar" Fish Species Prediction along with Preprocessing Visualization.

Classification results are displayed in an informative and transparent form. Besides displaying the predicted fish species name with clear and easily readable fonts, the system also presents preprocessing process visualizations including:

1. Cropped Image

Shows the fish object that has been isolated from the background with bounding box and padding, providing visual confirmation that the correct object has been detected.

2. Segmentation Result Mask

Displays a binary image (mask) showing the fish object area (white) vs. background (black), providing transparency about how the system separates objects from the background. This mask is directly used in computing the 7 Hu Moments features that represent the fish's shape characteristics.

3. LBP Texture Visualization

Displays a texture map resulting from LBP extraction in heatmap or grayscale image form, showing local texture patterns used as one of the classification bases. This visualization represents the spatial distribution of the 26 LBP features extracted from the fish surface, which capture scale patterns and skin texture.

These visualizations not only provide transparency but also represent the actual numerical features (33-dimensional vector: 7 Hu Moments + 26 LBP) that are fed into the KNN classifier for species identification.

This visual transparency not only increases user trust in the system but also functions as an educational tool that helps users understand the principles of computer vision technology applied.

In terms of computational performance, the system proves to work responsively and efficiently. Average response time for one complete classification cycle (from image upload to result display) ranges from 1 to 3 seconds, depending on resolution and input image file size. This speed is very adequate for real-time applications at TPI, where identification speed can improve auction and sorting process efficiency.

More importantly, the system can be run on standard computers or laptops without requiring GPUs (Graphics Processing Units) or other special hardware. This is possible because the method used (KNN with classic feature extraction) is relatively light computationally compared to deep learning approaches that require complex neural network inference. This characteristic makes the system very flexible and easy to apply in various environments with infrastructure limitations, including rural areas or TPIs with limited budgets.

The system is also equipped with simple but functional navigation features, including a "Back" button to repeat the classification process with a new image.

Limitations and Future Research Directions

Although the proposed classification model successfully achieves high accuracy of 98.50%, this research has several limitations. First, the system is sensitive to input image quality variations including sharpness, lighting conditions, and noise levels. Second, extreme fish object rotations can affect accuracy despite Hu Moments' theoretical rotation invariance. Third, the dataset is limited to 10 species under relatively controlled conditions, requiring further validation for broader generalization. Additionally, the PWA prototype currently processes single images only and does not support real-time video streaming, limiting its effectiveness during mass auction activities.

For future research, three main directions are recommended. First, exploring deep learning methods such as CNN or transfer learning architectures (MobileNet, EfficientNet) could improve accuracy and system robustness. Second, expanding the dataset with more species, varied

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lighting conditions, and diverse capture angles will enhance generalization capability. Third, implementing active learning mechanisms would enable continuous model improvement from user feedback without extensive retraining.

Table 3. Detailed Classification Results of KNN Model (K=3) on Test Data

class	precision	recall	f1-score	support
Barakuda	0.95	1.00	0.98	20
Bawal	1.00	1.00	1.00	20
Kembung Banyar	0.95	1.00	0.98	20
Layang	1.00	0.95	0.97	20
Lemuru	0.95	1.00	0.98	20
Selar Bentong	1.00	1.00	1.00	20
Semar	1.00	1.00	1.00	20
Tenggiri	1.00	0.95	0.97	20
Tengkurungan	1.00	1.00	1.00	20
Tongkol	1.00	0.95	0.97	20
accuracy			0.98	200
macro avg	0.99	0.98	0.98	200
weighted avg	0.99	0.98	0.98	200

CONCLUSIONS AND SUGGESTIONS

Conclusion

This research successfully developed an automatic classification system for 10 types of Java Sea fish species using the K-Nearest Neighbors (KNN) algorithm with a combination of Hu Moments and Local Binary Pattern (LBP) features. The implemented system encompasses comprehensive image preprocessing stages including segmentation, morphological operations, cropping, and padding, followed by shape and texture feature extraction, normalization using MinMaxScaler, and classification with optimized KNN. The evaluation results demonstrate that the proposed model achieves an overall accuracy of 98.50% on test data, with precision, recall, and F1-score values consistently exceeding 0.95 across almost all classes. Hyperparameter optimization through 5-fold cross-validation identified the optimal k value of 3, which provides the best balance between sensitivity to local patterns and resistance to noise.

Confusion matrix analysis confirms that classification errors predominantly occur in species pairs with high morphological similarity, yet the remarkably low error rate of 1.5% demonstrates the excellent discrimination capability of the proposed feature combination. Compared to previous studies, this research achieves superior performance: our accuracy of 98.50% surpasses the 93.12% achieved by Iman et al. (2023) using 2D-LDA and KNN for sea fish classification, the 70% accuracy reported by Suwarsito et al. (2022) for freshwater fish using KNN, and the 97.7% accuracy obtained by Kusuma et al. (2023) at k=5 for fish species and freshness identification. While Jannah et al. (2023) achieved 100% accuracy in salmon classification, their study was limited to only two salmon types with a much smaller dataset (30 images), whereas our system handles 10 diverse species with 1,000 images under varying real-world conditions.

Suggestion

Based on the findings and limitations identified in this research, several suggestions are proposed for future investigations and practical implementation. Future studies should expand the dataset to include a wider variety of fish species, diverse environmental conditions such as various lighting scenarios, weather conditions, and background complexities, as well as multiple fish orientations to enhance the model's generalization capability and robustness across different operational environments. Researchers are encouraged to explore deep learning approaches such as Convolutional Neural Networks (CNN), transfer learning architectures including MobileNet, EfficientNet, or ResNet, and hybrid models combining classical feature extraction with deep learning, as these methods may potentially capture more complex hierarchical features and improve classification accuracy, particularly for morphologically similar species. Investigation into

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real-time video streaming-based classification systems should be conducted, integrating direct camera input for continuous fish identification during sorting and auction processes, which would significantly enhance practical applicability and operational efficiency. Additionally, developing and integrating active learning mechanisms or human-in-the-loop systems that enable the model to learn continuously from user feedback and corrections would allow adaptive improvement without extensive retraining procedures.

For methodological improvements specific to the KNN-based classification model developed in this study, future research should focus on the following directions. First, investigate alternative distance metrics beyond Euclidean distance, such as Manhattan or Mahalanobis distance, which may better capture the relationships between Hu Moments and LBP features in the 33-dimensional feature space. Second, explore weighted KNN approaches where features can be assigned different importance levels, potentially giving more weight to either shape (Hu Moments) or texture (LBP) features depending on species-specific characteristics. Third, implement feature selection techniques such as Principal Component Analysis (PCA) or feature importance ranking to identify the most discriminative features among the 33 extracted features, which could improve classification speed and reduce model complexity without sacrificing accuracy. Fourth, develop an ensemble approach combining KNN with other lightweight classifiers (such as Random Forest or SVM) to leverage the strengths of multiple algorithms while maintaining the system's ability to run without GPU requirements. Finally, implement incremental learning capabilities that allow the model to be updated with new fish species or additional samples without complete retraining, making the system more adaptable to expanding datasets and emerging classification needs at different fish auction sites.

REFERENCES

B, V., & Gangula, R. (2024). Exploring the Power and Practical Applications of K-Nearest Neighbours (KNN) in Machine Learning. *Journal of Computer Allied Intelligence*, *2*(1), 8–15. https://doi.org/10.69996/jcai.2024002

Daulay, R. S. A., Efendi, S., & Suherman. (2023). Review of Literature on Improving the KNN Algorithm. *Transactions on Machine Learning and Artificial Intelligence*, *11*(3), 63–72. https://doi.org/10.14738/tecs.113.14768

Dewan, J., Gele, A., Fulari, O., Kabade, B., & Joshi, A. (2022). Fish Detection and Classification. *2022 6th International Conference on Computing, Communication, Control and Automation (ICCUBEA*, 1–5. https://doi.org/10.1109/ICCUBEA54992.2022.10010836

Dhabliya, D., Thangarasu, N., Reddy, B., Nirmala, D., Parmar, Y., & Ganesan, S. (2024). Feature Extraction Techniques in Document Image Analysis an Analysis. *2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, 1–6. https://doi.org/10.1109/ICCCNT61001.2024.10724751

Fajri, F. N., Dzikrillah, M., & Khairi, A. (2024). Digital Fish Image Segmentation Using U-Net for Shape Feature Extraction. *JURNAL TEKNOLOGI DAN OPEN SOURCE*, *7*(2), 195–201. https://doi.org/10.36378/jtos.v7i2.3968

Iman, Y. D. Al, Isnanto, R. R., & Nurhayati, O. D. (2023). Klasifikasi Jenis Ikan Laut K-Nearest Neighbor Berdasarkan Ekstraksi Ciri 2-Dimensional Linear Discriminant Analysis. *Jurnal Teknologi Informasi Dan Ilmu Komputer*, *10*(4), 919–926. https://doi.org/10.25126/jtiik.20241046787

Jannah, M., Nababan, A. A., & Ningsi, Y. S. (2023). Penerapan Metode K-Nearest Neighbor dalam Identifikasi Jenis Ikan Salmon yang Dapat Dikomsumsi Untuk Bahan Mpasi Bayi. *J-SISKO TECH (Jurnal Teknologi Sistem Informasi Dan Sistem Komputer TGD)*, *6*(2), 636. https://doi.org/10.53513/jsk.v6i2.8716

Khan, M. A., Jamil, S. A., Vellanki, S., Latha, M., Singh, K. U., & Batra, M. (2024). Creation of Machine Learning-Based Fish Classification Systems Based on Morphometric and Mathematical Transform Data. *J. Electrical Systems*, *20*(5), 2325–2332.

Khatami, A. M., Yonvitner, & Setyobudiandi, I. (2019). Karakteristik Biologi dan Laju Eksploitasi Ikan Pelagis Kecil di Perairan Utara Jawa. *Jurnal Ilmu Dan Teknologi Kelautan Tropis*, *11*(3), 637–651. https://doi.org/10.29244/jitkt.v11i3.19159

Kusuma, F. H., Ms, A. U., Ibadillah, A. F., Nahari, V., Joni, K., & Saputro, A. K. (2023). Sistem Identifikasi Kesegaran dan Jenis Ikan dengan Metode K-Nearest Neighbor Berdasarkan Citra Mata dan Bentuk Ikan. *Jurnal FORTECH*,

The work is distributed under the Creative Commons Attribution-NonCommercial 4.0 International License

4(1), 33–41. https://doi.org/10.56795/fortech.v4i1.383

Li, G. (2024). Machine learning. In *Chemical Theory and Multiscale Simulation in Biomolecules* (pp. 51–80). Elsevier. https://doi.org/10.1016/B978-0-323-95917-9.00004-3

Mubarok, M. I., Sulistyowati, B. I., Perangin-angin, R., & Nurlaela, E. (2023). Composition of The Catch of Mini Purse Seine in The Java Sea. *Coastal and Marine Journal*, *1*(1), 23–28. https://doi.org/10.61548/cmj.v1i1.5

Nuraini, R., Wibowo, A., Warsito, B., Syafei, W. A., & Jaya, I. (2023). Combination of K-NN and PCA Algorithms on Image Classification of Fish Species. *Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi)*, *7*(5), 1026–1032. https://doi.org/10.29207/resti.v7i5.5178

Nuralam, M. M., Hernawati, D., & Agustian, D. (2023). Keanekaragaman dan Potensi Jenis Ikan Hasil Tangkapan Nelayan di Tempat Pelelangan Ikan (TPI) Pamayangsari Kabupaten Tasikmalaya. *Jurnal Biosilampari: Jurnal Biologi*, *5*(2), 154–162. https://doi.org/10.31540/biosilampari.v5i2.2000

Oktaviani, D., Prianto, E., & Nugroho, D. (2020). Length-Weight, Maturity, and Condition Factor of Torpedo Scads (Megalaspis cordyla Linnaeus, 1758) in the Java Sea, Indonesia. *Biodiversitas*, *21*(4), 1527–1534. https://doi.org/10.13057/biodiv/d210433

P, R. K. (2024). Role of Digital Image Processing in Education and Medical Field. *IOSR Journal of Computer Engineering*, *26*(5), 01–08. https://doi.org/10.9790/0661-2605030108

Patel, D. (2024). Computer Vision and Image Segmentation. *International Journal for Research in Applied Science and Engineering Technology*, *12*(2), 915–925. https://doi.org/10.22214/ijraset.2024.58479

Regulwar, G. B., Mahalle, A., Pawar, R., Shamkuwar, S. K., Kakde, P. R., & Tiwari, S. (2024). Big Data Collection, Filtering, and Extraction of Features. In D. Darwish (Ed.), *Big Data Analytics Techniques for Market Intelligence* (pp. 136–158). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-0413-6.ch005

Suwarsito, Mustafidah, H., Pinandita, T., & Purnomo. (2022). Freshwater Fish Classification Based on Image Representation Using K-Nearest Neighbor Method. *JUITA: Jurnal Informatika*, *10*(2), 183.

Zheng, T., Wu, J., Kong, H., Zhao, H., Qu, B., Liu, L., Yu, H., & Zhou, C. (2024). A video object segmentation-based fish individual recognition method for underwater complex environments. *Ecological Informatics*, *82*(1), 102689. https://doi.org/https://doi.org/10.1016/j.ecoinf.2024.102689

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