Vol. 2, No. 1, March 2025

IJAIS International Journal of Artificial Intelligence and Science

Publsihed By Asosiasi Doktor Sistem Informasi Indonesia

Classification of Aquatic Species in Cultivation Ponds via Image Processing and Machine Learning

Arif Setiawan[1], Angga Wahyu Wibowo[2], Pratomo Setiaji[3], Wiwit Agus Triyanto[4], Muhammad Arifin[6]

[1,3,4,5,6]Department of Information System, Faculty of Engineering, Muria Kudus University, Kudus, Indonesia

[2]Department of Electrical Engineering, Politeknik Negeri Semarang, Semarang, Indonesia

Email: arif.setiawan@umk.ac.id[1], anggawahyuwibowo@polines.ac.id[2], pratomo.setiaji@umk.ac.id[3], at.wiwit@umk.ac.id[4], arifin.m@umk.ac.id[5]

Received: 24 October 2024

Revised: 20 December 2024

Accepted: 1 January 2025

Published: 30 March 2025

Corresponding Author:

Author Name*:

Arif Setiawan

Email*:

arif.setiawan@umk.ac.id

DOI: 10.63158/IJAIS.v2i1.9

Abstract. Fish cultivation is a vital economic activity for coastal communities, yet traditional farming methods often face challenges such as environmental instability, feeding inefficiencies, and water pollution. Effective monitoring of underwater environments is essential to improve fish quality and farming efficiency. A crucial part of this process is the accurate classification of fish and non-fish objects. This study proposes a method for underwater classification using morphometric feature extraction and machine learning techniques. The research process involves six main steps: (1) preparation of Region of Interest (ROI) detection data, (2) extraction of morphometric features—length (L) and width (W), (3) feature computation, (4) data partitioning for training and testing, (5) classification using Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbor (KNN), and (6) evaluation using a confusion matrix. Among all models tested, the Random Forest algorithm yielded the highest accuracy at 93%, with classification results showing True Positive = 349, False Positive = 28, True Negative = 223, and False Negative = 0. The findings highlight RF's potential for enhancing automated fish monitoring in smart aquaculture systems.

Keywords: fish classification, underwater image processing, morphometric features, machine learning, intelligent aquaculture

1. INTRODUCTION

Fish cultivation is more than just a source of food—it plays a pivotal role in enhancing the socio-economic fabric of coastal communities. For many families living near the ocean, fish farming is not merely a business but a lifeline. Studies show that those engaged in aquaculture experience an increase in their economic standing by about 26% to 36% [1]. This is due to the relatively short production cycles in aquaculture, where one harvest typically takes just three months. The speed and profitability of fish farming make it an attractive option for improving livelihoods in areas that depend heavily on marine resources [2].

As global demand for seafood continues to rise, conventional aquaculture practices are being scaled to meet the needs of mass consumption. Saltwater fish production is largely managed using monoculture systems—where a single species is raised in large pond structures. These systems are efficient but require intensive monitoring and care, as the maintenance cycles can range between four to six months depending on species and environmental factors [3]. Despite the scalability, traditional methods are increasingly challenged by environmental instability, disease outbreaks, and high operational costs.

To overcome these challenges, the field of smart fish farming has emerged, merging artificial intelligence (AI), machine learning, and data analytics into traditional aquaculture systems. This technological evolution allows farmers to make data-driven decisions that improve productivity, reduce waste, and promote sustainable practices. However, managing the enormous volume and diversity of data—from sensor readings and video feeds to breeding logs and environmental inputs—presents its own set of complexities. The data come in various forms such as text, image, audio, and video, and originate from multiple sources, including sensors, cameras, and IoT devices embedded in the aquaculture environment [4].

In traditional fish farming, critical parameters like water quality, feeding schedules, and fish growth are often monitored manually, which is time-consuming and prone to human error. Smart systems equipped with cameras and sensors have transformed this landscape by integrating image processing and AI algorithms to automate these processes. These systems not only track fish size and behavior but also optimize feeding and environmental control in real-time [5]. With AI handling the analysis, fish farmers can now access accurate, real-time insights without needing to intervene physically, leading to better stock management and cost savings.

The digital transformation driven by the Fourth Industrial Revolution is placing intelligent aquaculture at the forefront of modern farming practices. Monitoring underwater conditions, particularly identifying and classifying fish, is a foundational task in these systems. Digital image processing, especially through deep learning, has significantly improved the accuracy and efficiency of fish classification. Automated feature extraction of high-dimensional image data has enabled machines to recognize species and assess health conditions more precisely than ever before [6], [7]. This research introduces a novel approach combining advanced feature extraction and machine learning to elevate the capability of underwater fish monitoring, paving the way for more intelligent, responsive, and sustainable aquaculture systems.

2. METHODS

Fish are aquatic animals that reproduce and live entirely in water ecosystems, and they hold immense nutritional value as a primary source of animal-based protein for millions of people around the world [8]. As global demand for seafood continues to surge, fish farming has become a vital industry, offering an efficient way to meet consumption needs while ensuring food security. Among various seafood options, fish is often the most preferred due to its affordability, taste, and rich content of omega-3 fatty acids. However, as fish production scales globally, ensuring the health and quality of farmed fish has become an increasingly complex challenge [9]. One critical step before fish are sent to the market is rigorous quality control, where fish must be accurately classified and inspected according to industry standards to guarantee both safety and market value [1].

To support these objectives, digital technologies such as computer vision and machine learning have been integrated into aquaculture monitoring systems. One of the foundational techniques in these systems is image-based feature extraction. This involves analyzing captured images of fish to extract meaningful visual characteristics. Specifically, features related to colour, texture, and shape are used to differentiate

IJAIS International Journal of Artificial Intelligence and Science
Publsihed By Asosiasi Doktor Sistem Informasi Indonesia

between species and to assess physical health. Of these, morphometric features—quantitative measurements of an organism's form are especially useful for species identification and size estimation. Common morphometric parameters include fish length (L), fish height (H), and fish width (W) [10], [11]. These physical indicators are simple yet powerful tools for classification tasks, offering a way to objectively describe and distinguish aquatic species based on their external appearance [12].

Table 1. Morphometric Features of Fish

Feature	Symbol
Fish Length	L
Fish Height	H
Fish Width	W

In this research, these morphometric features form the core dataset for machine learning algorithms that classify underwater fish objects. The classification process requires robust computational models capable of handling variations in fish size, orientation, lighting, and environmental noise. To achieve this, four widely used machine learning techniques were implemented: Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and K-Nearest Neighbor (KNN).

1) Support Vector Machine (SVM) is a powerful supervised learning algorithm that finds the optimal decision boundary (hyperplane) separating different classes of data. It is particularly effective in high-dimensional spaces and works well even with a limited number of samples. The flexibility of SVM comes from its kernel functions—linear, polynomial, and radial basis function (RBF)—which allow it to model both linear and non-linear relationships between data points [13]. In the context of this study, SVM helps in identifying subtle differences in fish morphology that might otherwise be hard to detect visually.
2) Random Forest (RF) is an ensemble learning method that builds multiple decision trees during training and merges their outputs to improve classification accuracy. RF is highly resistant to overfitting and performs well with large datasets containing noise or missing values. Its effectiveness is directly proportional to the number of trees used in the forest—the more trees, the better the performance in most cases [14], [15]. This makes RF a reliable choice for

IJAIS International Journal of Artificial Intelligence and Science
Publsihed By Asosiasi Doktor Sistem Informasi Indonesia

underwater image data, which can often be noisy due to lighting or water clarity issues.

3) Decision Tree (DT) is one of the simplest yet most intuitive machine learning models. It uses a tree-like graph of decisions and possible consequences to arrive at a final classification. The model splits the dataset based on feature thresholds, making it ideal for problems where interpretability is crucial. DTs also serve as the foundation for more complex models like RF, and they offer fast training and prediction times [16], [17].
4) K-Nearest Neighbor (KNN) is a non-parametric algorithm that classifies new data based on the similarity to its 'K' closest points in the training set. It's particularly useful in recognizing patterns based on visual proximity and works well when class distributions are distinguishable by distance metrics. Although computationally intensive during prediction, KNN delivers strong performance in environments where object shapes and sizes—like those of fish—are distinct [18].

The overall research workflow is broken down into six key stages, as shown in Figure 1. The process begins with the preparation of raw image data obtained from Region of Interest (ROI) detection, where areas containing potential fish objects are identified. Next, the morphometric feature extraction phase involves isolating and measuring the fish's length and height from the detected ROIs. After that, the values of these features are calculated and normalized to ensure consistency across the dataset. The dataset is then split into training and testing sets, allowing the algorithms to learn patterns from one portion and validate them on another.

Once the datasets are ready, machine learning models—SVM, RF, DT, and KNN—are trained using the training data. The model creation phase involves hyperparameter tuning, training iterations, and model validation to ensure optimal performance. In the final stage, the classification performance is evaluated using a confusion matrix, which provides a detailed breakdown of true positives, false positives, true negatives, and false negatives. This evaluation metric is crucial in understanding the accuracy, precision, recall, and F1-score of each algorithm in the fish classification task. The research flow, outlined in Figure 1, presents a comprehensive pipeline from raw data to intelligent decision-making for fish classification in underwater environments.

IJAIS International Journal of Artificial Intelligence and Science
Publsihed By Asosiasi Doktor Sistem Informasi Indonesia

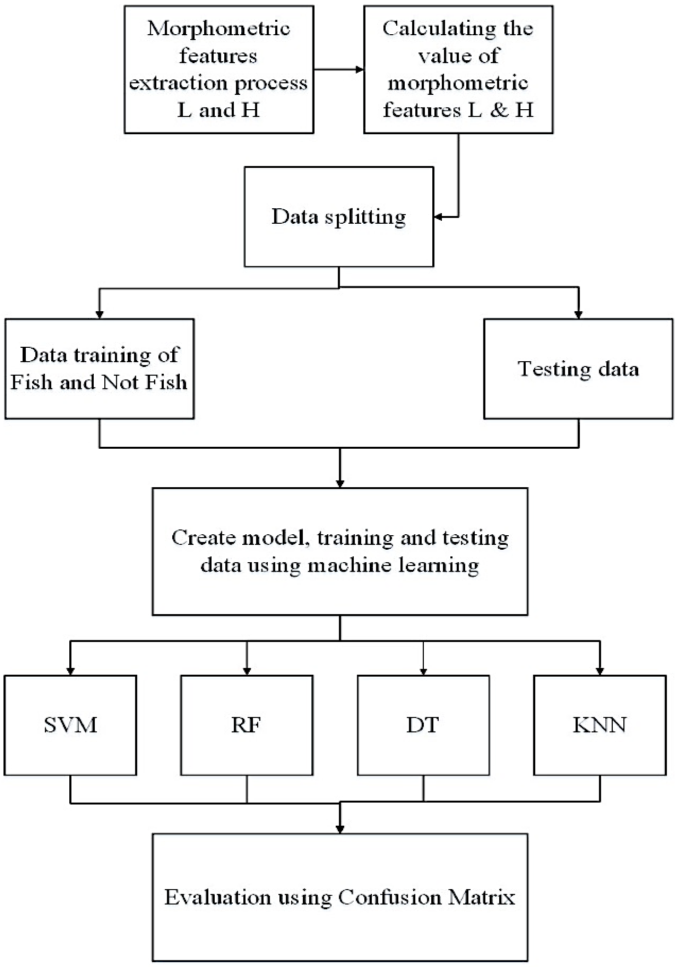

Figure 1. Research flow diagram

3. RESULTS AND DISCUSSION

This research marks the fifth phase in a broader investigation aimed at enhancing intelligent systems in aquaculture environments. Specifically, this phase focuses on developing and evaluating machine learning models that can accurately differentiate between fish and non-fish underwater objects using digital image analysis and morphometric data. The central goal is to establish a reliable, automated method of classification that can support various aquaculture applications—such as stock monitoring, feeding automation, and environmental control. Four prominent machine learning algorithms—Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and K-Nearest Neighbor (KNN)—were employed in this study due to their strong track records in classification tasks involving visual and biometric data [19], [20].

IJAIS International Journal of Artificial Intelligence and Science
Publsihed By Asosiasi Doktor Sistem Informasi Indonesia

3.1. Morphometric Feature Extraction from Underwater Object

The process of fish identification in this study is based on extracting morphometric features from underwater digital images—specifically, the length (L) and height (H) of each object. These features were selected due to their simplicity, computational efficiency, and proven effectiveness in differentiating aquatic species. The measurements were derived using the Euclidean Distance formula, applied to points defined along the contours of the fish or object detected in the image. The dataset used consisted of 2,000 labeled image samples, evenly split between fish and non-fish categories. The non-fish category included various marine elements such as coral fragments, floating debris, aquatic plants, and underwater equipment parts that could be mistakenly classified as fish in low-resolution or noisy environments. The image processing pipeline was essential in isolating these objects effectively.

The workflow for morphometric extraction began with the acquisition of RGB images, which were then converted to grayscale to simplify edge detection. Edge detection algorithms such as Sobel or Canny were applied to identify the object boundaries. Following this, Region of Interest (ROI) detection techniques were used to crop the precise object area for analysis. Finally, the morphometric features (L and H) were extracted by measuring the bounding box dimensions around the detected ROI. Figure 2 illustrates this step-by-step image processing and feature extraction sequence for both fish and non-fish samples. This rigorous preprocessing ensured that the dataset fed into the machine learning models was clean, structured, and uniform in format, which is critical for consistent training and classification outcomes.

3.2. Data Preparation, Training, and Testing

With the morphometric features successfully extracted, the next phase involved organizing the data for machine learning model development. The total of 2,000 samples was split into two subsets: 70% (1,400 samples) for training and 30% (600 samples) for testing. This split ratio balances the need for sufficient data to train the models effectively while also reserving enough samples for a fair evaluation of model performance.

IJAIS International Journal of Artificial Intelligence and Science
Publsihed By Asosiasi Doktor Sistem Informasi Indonesia

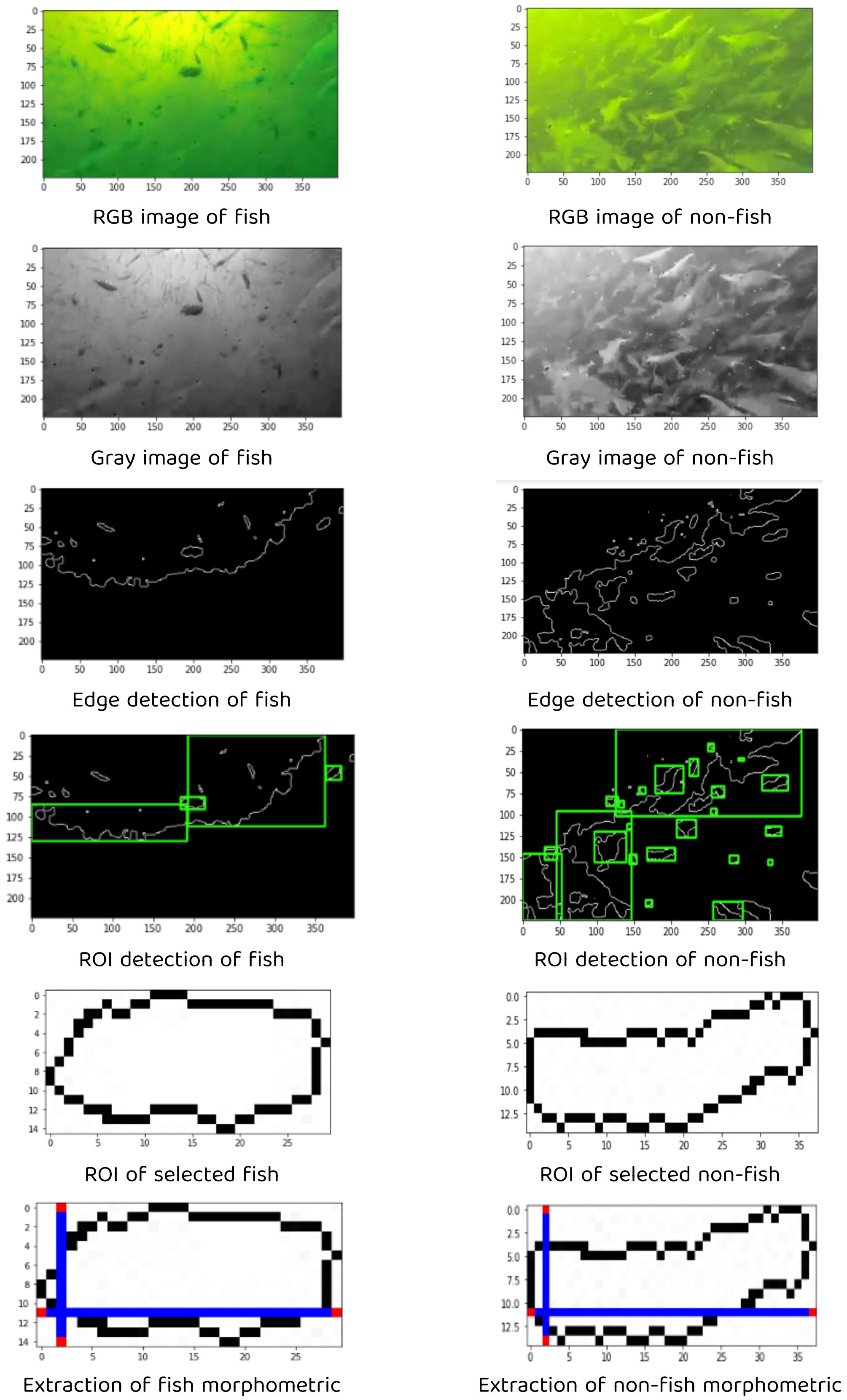

Figure 2. Analysis of digital images of fish and non-fish objects underwater

IJAIS International Journal of Artificial Intelligence and Science
Publsihed By Asosiasi Doktor Sistem Informasi Indonesia

The models were implemented using the Python programming language with support from the Scikit-learn library. The following functions were used for training the classifiers:

1) SVM: SVC.fit(x, y)
2) Random Forest: RandomForestClassifier.fit(x, y)
3) Decision Tree: DecisionTreeClassifier.fit(x, y)
4) KNN: KNeighborsClassifier.fit(x, y)

Each feature vector, consisting of (L, H), was normalized to eliminate scale bias and improve convergence during model training. The training process involved multiple iterations with hyperparameter tuning to optimize model performance. Figure 3 visualizes the distribution of the training and testing datasets along the two morphometric dimensions. This step helped to confirm that the data was balanced across both classes and that there was sufficient variance to challenge and validate the learning capacity of the models.

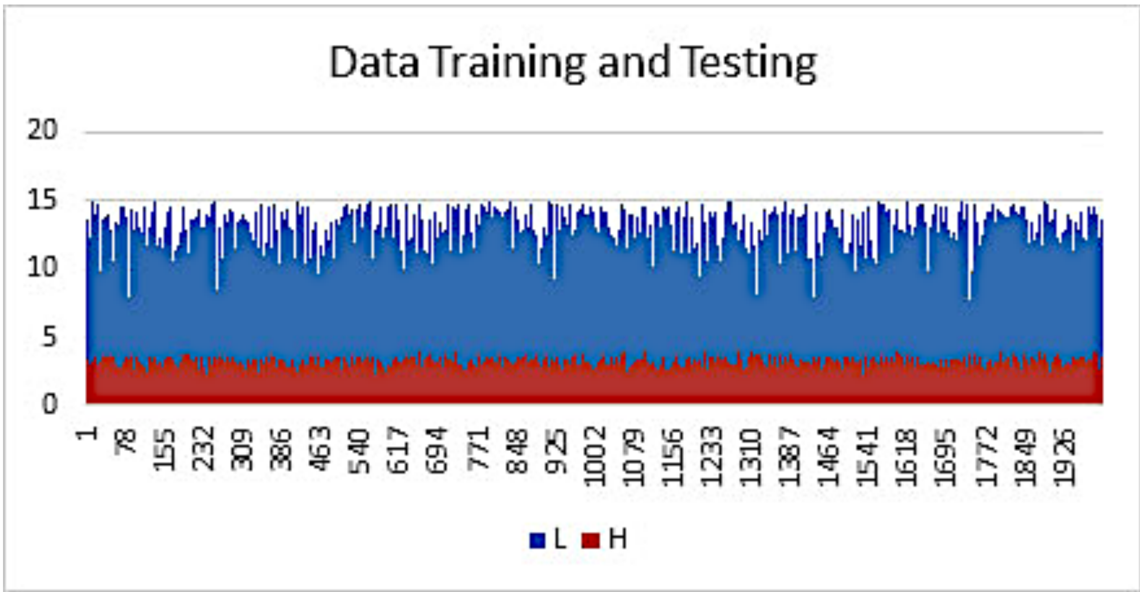

Figure 3. Morphometric features data for classification training and testing

3.3. Classification Performance and Accuracy Results

After completing the training process for each machine learning model, the next critical step was evaluating their performance in correctly classifying underwater objects as either fish or non-fish. The evaluation involved a two-pronged approach. First, confusion

IJAIS International Journal of Artificial Intelligence and Science
Publsihed By Asosiasi Doktor Sistem Informasi Indonesia

matrices were used to provide a detailed breakdown of each model's prediction outcomes. This included four key metrics: True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN). These figures offer granular insights into not just how often a model makes correct predictions, but also the types of errors it tends to make. Second, overall accuracy scores were calculated for a high-level comparison of the models' classification efficiency.

	precision	recall	f1-score	support
fish	0.69	0.60	0.64	251
non-fish	0.73	0.80	0.76	349
accuracy			0.71	600
macro avg	0.71	0.70	0.70	600
weighted avg	0.71	0.71	0.71	600

KNN

	precision	recall	f1-score	support
fish	1.00	0.89	0.94	251
non-fish	0.89	1.00	0.96	349
accuracy			0.95	600
macro avg	0.96	0.94	0.95	600
weighted avg	0.96	0.95	0.95	600

RF

	precision	recall	f1-score	support
fish	1.00	0.37	0.53	251
non-fish	0.68	1.00	0.81	349
accuracy			0.73	600
macro avg	0.84	0.68	0.67	600
weighted avg	0.82	0.73	0.69	600

SVM

	precision	recall	f1-score	support
fish	0.49	1.00	0.54	251
non-fish	1.00	0.38	0.81	349
accuracy			0.61	600
macro avg	0.75	0.69	0.60	600
weighted avg	0.81	0.61	0.59	600

DT

Figure 4. Confusion matrix every classification method

The results for all four classifiers—Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and K-Nearest Neighbor (KNN)—were visually represented using Figure 4, which shows their respective confusion matrices. These matrices illustrate how each model performed when tested on the unseen data, derived from the 30% testing subset of the original 2,000-image dataset. Figure 5 complements this by showing the comparative accuracy of each model, helping to visualize performance disparities clearly.

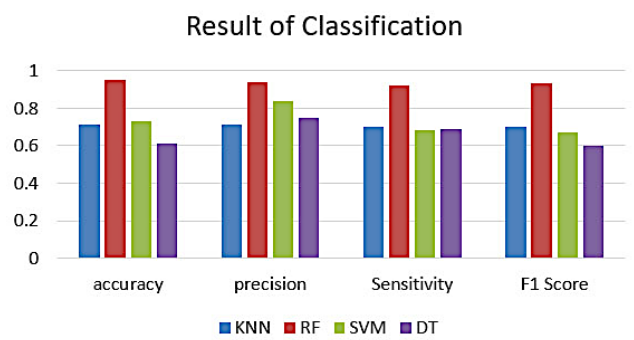

Figure 5. Accuracy results for fish and non-fish classification

IJAIS International Journal of Artificial Intelligence and Science

Publsihed By Asosiasi Doktor Sistem Informasi Indonesia

Among all the classifiers tested, Random Forest (RF) emerged as the top performer. It achieved a remarkable accuracy score of 93%, indicating that it was able to correctly classify a vast majority of the fish and non-fish objects. This result underscores the algorithm's strong generalization ability and robustness in handling the variability often encountered in underwater image data, such as differences in lighting, orientation, and object shape. Delving deeper into RF's performance, Figure 6 presents its confusion matrix in detail. Out of the 600 test samples:

1) True Positives (TP) were 349, meaning 349 fish images were accurately identified as fish.
2) False Positives (FP) totalled 28, which refers to non-fish objects that were incorrectly classified as fish.
3) True Negatives (TN) accounted for 223 samples correctly recognized as non-fish.
4) False Negatives (FN) were 0, meaning no fish images were mistakenly classified as non-fish.

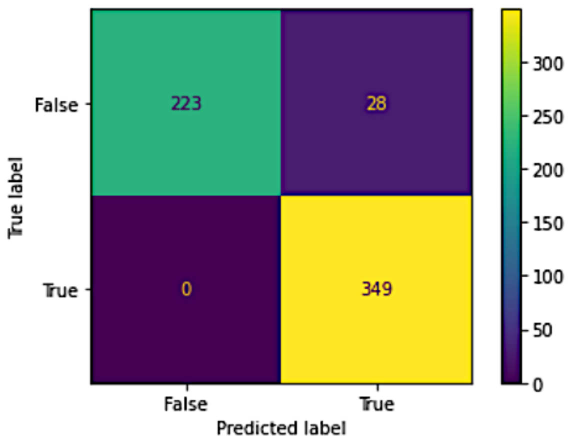

Figure 6. Confusion matrix of Random Forest in the classification process

This absence of false negatives is especially significant. In real-world aquaculture scenarios, missing a fish during automated monitoring could result in that individual being left unfed or unmonitored, leading to growth issues, health decline, or even mortality. The RF model's ability to detect all fish instances without missing any showcases its reliability for high-stakes aquaculture tasks where precision is essential.

The confusion matrix not only confirms RF's overall accuracy but also reflects a well-balanced performance in both sensitivity (ability to detect fish) and specificity (ability to detect non-fish). While 28 false positives represent minor misclassifications, they are far less critical in the context of aquaculture than false negatives. These results validate RF

IJAIS International Journal of Artificial Intelligence and Science
Publsihed By Asosiasi Doktor Sistem Informasi Indonesia

as a powerful and dependable model for underwater object classification, making it an excellent candidate for deployment in smart aquaculture systems where consistent, automated fish detection is vital.

3.4. Discussion

The results obtained from this study underscore the remarkable performance of the Random Forest (RF) algorithm in classifying underwater objects, particularly in distinguishing between fish and non-fish entities. Among the machine learning models tested—Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Decision Tree (DT), and RF—Random Forest delivered the highest accuracy and the most balanced results across all performance metrics. This outcome can be largely attributed to RF's unique approach to learning through ensemble modeling. Rather than relying on a single decision boundary or structure, RF builds multiple decision trees during training and aggregates their predictions using a majority voting mechanism. This strategy significantly reduces the risk of overfitting and makes the model more resilient to noisy or inconsistent data, which are common in underwater imaging scenarios.

A notable strength of Random Forest lies in its use of bagging (bootstrap aggregating). By training each tree on a randomly selected subset of the training data chosen with replacement—RF introduces essential diversity into the learning process. This technique ensures that no single feature or data point dominates the overall model, leading to more generalized and robust predictive behavior. In the context of underwater environments, where image quality can be affected by factors like turbidity, lighting variations, and object occlusion, such robustness is invaluable. RF's ability to adapt to these conditions without significant manual tuning enhances its practical applicability in real-time intelligent aquaculture systems [23], [24].

Furthermore, Random Forest excels at modeling non-linear relationships and high-dimensional feature interactions—an essential capability when dealing with the complex variability found in marine environments. Fish and non-fish objects may share similar shapes or sizes, and only subtle differences in morphology may differentiate them. RF's ability to capture these nuanced patterns, without requiring elaborate feature engineering or complex mathematical transformations, gives it a competitive edge over other algorithms in this application space.

IJAIS International Journal of Artificial Intelligence and Science
Publsihed By Asosiasi Doktor Sistem Informasi Indonesia

When evaluating the performance of the other models, several limitations became apparent. Support Vector Machine (SVM), while known for high accuracy in structured environments, demonstrated sensitivity to outliers and noisy data. It also required precise tuning of kernel parameters to handle non-linear separability, making it less suitable for dynamic or unstructured environments such as underwater classification. K-Nearest Neighbor (KNN), though effective in recognizing local patterns, suffered from computational inefficiency during prediction—particularly with larger datasets—and struggled in cases where class boundaries were not well defined. Decision Tree (DT), while easy to interpret and fast to execute, was prone to overfitting, especially when applied to training data with limited diversity or noise. Without proper pruning, a single decision tree can overly tailor its structure to the training data, leading to diminished performance on unseen samples.

In contrast, Random Forest bridges these gaps by integrating the interpretability of DTs, the pattern recognition strengths of SVM, and the simplicity of KNN—all while addressing their weaknesses. It effectively manages the bias-variance trade-off through its ensemble structure and performs well even when faced with imbalanced datasets, missing values, or inconsistent feature distributions. Another advantage of RF is its ability to rank feature importance, which is especially beneficial in scientific applications. In this study, for instance, understanding the impact of morphometric features like fish length and height on classification decisions provides actionable insights for aquaculture monitoring systems.

Given these advantages, it becomes evident that Random Forest is the most suitable model for deployment in intelligent fish farming systems. Its superior accuracy, adaptability, and resistance to real-world challenges make it a compelling choice for applications requiring continuous monitoring, autonomous decision-making, and minimal human intervention. In conclusion, RF not only achieved the best performance in this research but also demonstrated qualities that align with the operational demands of modern smart aquaculture environments.

IJAIS International Journal of Artificial Intelligence and Science
Publsihed By Asosiasi Doktor Sistem Informasi Indonesia

4. CONCLUSION

This study successfully implemented a machine learning-based approach for classifying underwater objects into fish and non-fish categories, using morphometric feature extraction techniques. The features analyzed—length (L), height (H), and width (W)—proved effective in capturing the physical characteristics necessary for accurate classification. These simple yet informative measurements formed the foundation of the dataset, allowing for efficient model training and analysis. Among the four machine learning algorithms evaluated—Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and K-Nearest Neighbor (KNN)—the Random Forest method achieved the highest performance. It recorded a True Positive (TP) count of 349, a True Negative (TN) of 223, and a relatively low False Positive (FP) rate of 28, with zero False Negatives (FN)—highlighting its exceptional reliability in correctly identifying all fish objects in the dataset.

The ensemble learning capabilities of RF, combined with its robustness against noise and variability in underwater imagery, make it a strong candidate for future applications in intelligent aquaculture. However, to further improve accuracy, scalability, and adaptability in more complex underwater environments, future research should explore the integration of deep learning techniques. Approaches such as Convolutional Neural Networks (CNNs) may offer enhanced feature representation and enable even more precise classification, especially in real-time monitoring systems where automation and accuracy are paramount.

ACKNOWLEDGMENT

The authors gratefully acknowledge the support provided by the Information Systems Study Program, Faculty of Engineering, Muria Kudus University, and the Department of Electrical Engineering, Politeknik Negeri Semarang, Semarang, Indonesia. Their contributions and resources were instrumental in facilitating the successful completion of this research.

IJAIS International Journal of Artificial Intelligence and Science
Publsihed By Asosiasi Doktor Sistem Informasi Indonesia

REFERENCES

[1] S. Ray, P. Mondal, A. K. Paul, S. Iqbal, U. Atique, M. S. Islam, *et al.*, "Role of shrimp farming in socio-economic elevation and professional satisfaction in coastal communities of Southern Bangladesh," *Aquac. Rep.*, vol. 20, Art. no. 100708, Jun. 2021, doi: 10.1016/j.aqrep.2021.100708.

[2] W. C. Valenti, H. P. Barros, P. Moraes-Valenti, G. W. Bueno, R. O. Cavalli, "Aquaculture in Brazil: past, present and future," *Aquac. Rep.*, vol. 19, Art. no. 100611, Jun. 2021, doi: 10.1016/j.aqrep.2021.100611.

[3] X. Yang, S. Zhang, J. Liu, Q. Gao, S. Dong, C. Zhou, "Deep learning for smart fish farming: applications, opportunities and challenges," *Rev. Aquac.*, vol. 13, pp. 66–90, 2021.

[4] I. J. Huang, C. C. Hung, S. R. Kuang, Y. N. Chang, K. Y. Huang, C. R. Tsai, *et al.*, "The Prototype of a smart underwater surveillance system for shrimp farming," in *Proc. 2018 IEEE Int. Conf. Adv. Manuf. (ICAM 2018)*, 2019, pp. 177–180.

[5] Z. Liu, X. Jia, X. Xu, "Study of shrimp recognition methods using smart networks," *Comput. Electron. Agric.*, vol. 165, 2019, Art. no. (jika ada), [halaman jika tersedia].

[6] A. Triantafyllou, D. C. Tsouros, P. Sarigiannidis, S. Bibi, "An architecture model for smart farming," in *Proc. 15th Annu. Int. Conf. Distrib. Comput. Sens. Syst. (DCOSS 2019)*, 2019, pp. 385–392.

[7] H. Liu, T. Liu, Y. Gu, P. Li, F. Zhai, H. Huang, *et al.*, "A high-density fish school segmentation framework for biomass statistics in a deep-sea cage," *Ecol. Inform.*, vol. 64, Jul. 2021, Art. no. 101367, doi: 10.1016/j.ecoinf.2021.101367.

[8] S. Karim, I. Hussain, A. Hussain, K. Hassan, S. Iqbal, "IoT Based Smart Fish Farming Aquaculture Monitoring System," *Int. J. Emerg. Technol.*, vol. 12, no. 2, pp. 45–53, 2021.

[9] H. Do, T. Quoc, "Climate change adaptation strategies and shrimp aquaculture: Empirical evidence from the Mekong Delta of Vietnam," *Ecol. Econ.*, vol. 196, Sep. 2022, Art. no. 107411, doi: 10.1016/j.ecolecon.2022.107411.

[10] J. M. Patel and N. C. Gamit, "A review on feature extraction techniques in content based image retrieval," in *Proc. 2016 Int. Conf. Wireless Commun., Signal Process. Netw. (WiSPNET)*, Chennai, India, 2016, pp. 2259–2263, doi: 10.1109/WiSPNET.2016.7566454.

[11] A. P. Dineshbabu, G. Sasikumar, P. Rohit, S. Thomas, K. M. Rajesh, and P. U. Zacharia, *Methodologies for Studying Finfish and Shellfish Biology*, CMFRI-NICRA Publ. No. 2, Central Marine Fisheries Research Institute, Kochi, India, 2013, 91 pp.

[12] L. Zhang, J. Wang, Q. Duan, "Estimation for fish mass using image analysis and neural network," *Comput. Electron. Agric.*, vol. 173, Apr. 2020, Art. no. 105439, doi: 10.1016/j.compag.2020.105439.

[13] D. Mou, Z. Wang, X. Tan, S. Shi, "A variational inequality approach with SVM optimization algorithm for identifying mineral lithology," *J. Appl. Geophys.*, vol. 204, Dec. 2022, Art. no. 104747, doi: 10.1016/j.jappgeo.2022.104747.

[14] W. Gao, Z. H. Zhou, "Towards convergence rate analysis of random forests for classification," *Adv. Neural Inf. Process. Syst.*, Dec. 2020, Art. no. 103788, doi: 10.1016/j.artint.2022.103788.

[15] Y. G., P. Krecl, A. Créso, "Fine-scale modeling of the urban heat island: A comparison of multiple linear regression and random forest approaches," *Sci. Total Environ.*, vol. 815, 2022.

[16] M. Ghane, M. C. Ang, M. Nilashi, S. Sorooshian, "Enhanced decision tree induction using evolutionary techniques for Parkinson's disease classification," *Biocybern. Biomed. Eng.*, vol. 42, no. 3, pp. 902–920, 2022, doi: 10.1016/j.bbe.2022.07.002.

[17] L. Spirkovska, "Three-dimensional object recognition using similar triangles and decision trees," *Pattern Recognit.*, vol. 26, no. 5, pp. 727–732, 1993.

[18] S. Wang, T. B. Eldred, J. G. Smith, W. Gao, "Ultramicroscopy AutoDisk: Automated diffraction processing and strain mapping in [full title]," *Ultramicroscopy*, vol. 236, Mar. 2022, Art. no. 113513, doi: 10.1016/j.ultramic.2022.113513.

[19] S. K. Singla, R. D. Garg, O. P. Dubey, "Ensemble machine learning methods to estimate the sugarcane yield based on remote sensing information," *Rev. d'Intell. Artif.*, vol. 34, no. 6, pp. 731–743, 2020.

[20] M. G. Uddin, S. Nash, M. Diganta M. T., A. I. Olbert, "Robust machine learning algorithms for predicting coastal water quality index," *J. Environ. Manage.*, vol. 321, Jul. 2022, Art. no. 115923, doi: 10.1016/j.jenvman.2022.115923.

[21] M. Saberioon and P. Císař, "Automated within tank fish mass estimation using infrared reflection system," *Comput. Electron. Agric.*, vol. 150, pp. 484–492, May 2018, doi: 10.1016/j.compag.2018.05.025.

IJAIS International Journal of Artificial Intelligence and Science

Publsihed By Asosiasi Doktor Sistem Informasi Indonesia

[22] I. S. Isa, N. N. Norzrin, S. N. Sulaiman, N. A. Hamzaid, M. I. F. Maruzuki, "CNN Transfer Learning of Shrimp Detection for Underwater Vision System," in *Proc. 1st Int. Conf. Inf. Technol. Adv. Mech. Electr. Eng. (ICITAMEE)*, 2020, pp. 226–231.

[23] S. Giri, Y. Kang, K. MacDonald, M. Tippett, Z. Qiu, R. G. Lathrop, *et al.*, "Revealing the sources of arsenic in private well water using Random Forest Classification and Regression," *Sci. Total Environ.*, vol. 857, Oct. 2023, Art. no. 159360, doi: 10.1016/j.scitotenv.2022.159360.

[24] A. Zermane, M. Z. M. Tohir, H. Zermane, M. R. Baharudin, H. Mohamed Yusoff, "Predicting fatal fall from heights accidents using random forest classification machine learning model," *Saf. Sci.*, vol. 159, Nov. 2023, Art. no. 106023, doi: 10.1016/j.ssci.2022.106023.