CHAPTER 48

Intelligent Fish Farming: CNN-Based Real-Time Species Recognition and Feeding Decision Support

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ABSTRACT

This work presented a real-time, image-based framework for fish species identification, classification, biomass estimation, and feeding-decision support, integrated with vernacular, video-based information delivery through a custom-developed Android application. The system combined image processing, convolutional neural networks (CNN), and cloud computing to enhance aquaculture practices by providing automated, accurate, and user-friendly insights. State-of-the-art algorithms from recent literature were reviewed and benchmarked against the proposed CNN-based approach, which processed high-dimensional and nonlinear image data to deliver high-accuracy predictions. Computationally intensive tasks were executed on cloud infrastructure, reducing hardware costs and resource requirements for end-users. The Android app served as an intuitive interface, allowing fish farmers to upload images and receive species classification, biomass estimation, and feeding recommendations in their native language via video format. The framework demonstrated the ability to effectively process high-dimensional, nonlinear image data and achieve superior accuracy. Offloading computationally intensive tasks to cloud infrastructure significantly reduced hardware costs and user-side resource requirements. Experimental evaluation confirmed the system's high prediction accuracy, reduced processing latency, and enhanced usability, thereby offering a scalable and practical solution to improve aquaculture practices.

Keywords: Fish species identification; Convolutional neural networks; Image processing; Artificial intelligence.

1.0 Introduction

The aquaculture sector is central to food security and rural livelihoods, yet conventional fish farming still depends on manual species identification and biomass

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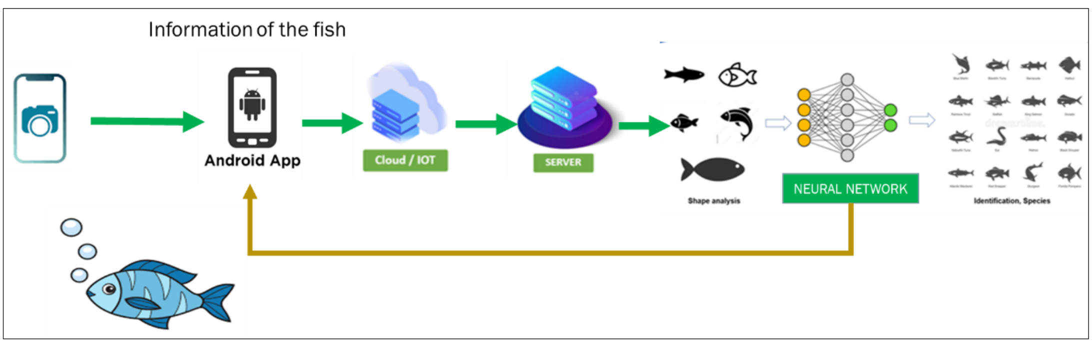
measurement, which are often unreliable. Recent research highlights the use of Convolutional Neural Networks (CNNs) to automate classification tasks by extracting image features directly [1]. While CNN-based models for fish classification have been studied [2], their integration into mobile tools accessible to vernacular-speaking farmers remains limited. Existing IoT-based monitoring systems [3] often demand costly hardware, making them unsuitable for small-scale farmers. Likewise, mobile apps in fisheries [4] focus on basic data collection without incorporating real-time AI-driven prediction. To address this, the proposed framework combines lightweight CNNs, a vernacular Android interface, and IoT-based storage in MongoDB [5]. The contributions are: (i) development of a CNN optimized for edge devices with high accuracy and low latency and (ii) a video-based interface for non-English-speaking farmers. This integrated approach not only provides a cost-effective, real-time solution but also bridges accessibility challenges in rural aquaculture.

2.0 Literature Review

Recent research highlights how deep learning, particularly Convolutional Neural Networks (CNNs), has transformed fish species identification by extracting features directly from images. Early studies emphasized CNN optimization for marine species using controlled datasets [6], showing improved accuracy over traditional methods [7]. Yet, such models required heavy computation and advanced hardware, limiting their use in small-scale aquaculture. To overcome this, lightweight models like MobileNet and EfficientNet were developed, offering reduced complexity and faster inference while retaining accuracy [8]. These architectures enabled deployment on smartphones but were often evaluated only on classification, with little focus on farmer-oriented decision support.

Figure 1: Workflow of the Intelligent Fish Farming Framework for Real-Time Species Identification and Decision Support



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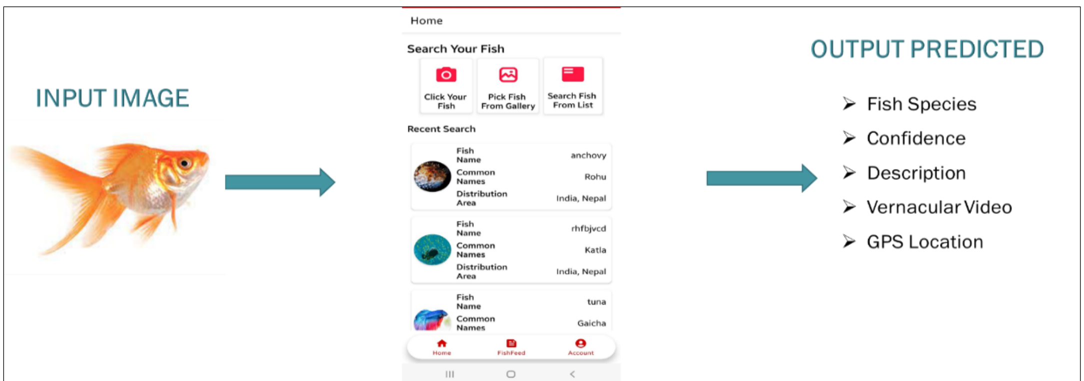
In parallel, mobile marine informatics advanced through IoT-integrated systems. For instance, [9] used underwater cameras and cloud-based CNNs, but dependence on reliable internet made rural deployment difficult. On-device inference reduced this issue but faced trade-offs in accuracy [10]. Beyond classification, CNNs were also applied to biomass estimation, essential for feeding and yield prediction. A method linking fish size to image pixels showed promise [11], but open-water trials faced challenges like poor lighting and occlusion. Recent approaches combined CNNs with multi-modal data, though often with costly sensors [12]. Despite these advances, vernacular interfaces remain underexplored. Studies stress their role in adoption [14], yet no system has unified CNN-based identification with localized, video-based farmer interaction [13].

3.0 Methodology

Figure 1 presents a complete workflow for an intelligent fish farming system that combines image processing, cloud computing, and deep learning to support farmers in real time. The process begins with something as simple as a farmer taking a photo of fish using a smartphone. This ease of use ensures that even those with little technical knowledge can participate. The image is then transferred to a dedicated Android application, which not only serves as the farmer's main interface but also ensures secure transmission of data to the cloud. Importantly, the app presents the results in accessible formats, such as vernacular video instructions, breaking language and literacy barriers.

Figure 2: Input–Output Flow of the Mobile Application for Fish Species Identification



Once the image reaches the cloud, it undergoes pre-processing, where shape and contour analysis help isolate the fish from the background. These refined features are then

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passed into a Convolutional Neural Network (CNN), which identifies the fish species and estimates biomass, considering details like scales, body patterns, and fin shapes. The outputs—species, size, and feeding advice—are immediately sent back to the farmer's phone. This creates a feedback loop that allows farmers to adjust feeding strategies, reduce waste, and optimize resources. In essence, the pipeline transforms a simple photo into actionable insights, merging advanced AI with everyday aquaculture practices in a practical, farmer-friendly way.

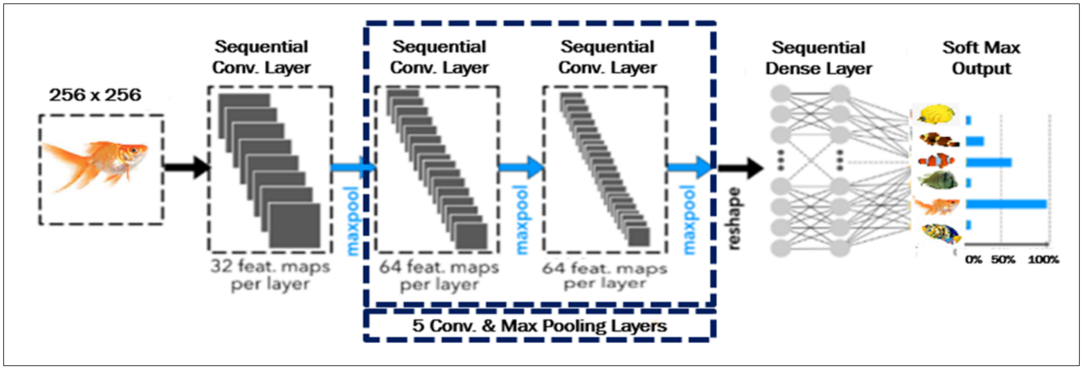
3.1 Application interface

Figure 2 illustrates how the Android-based mobile application works within the intelligent fish farming system. A farmer can begin by taking a new photo of a fish, selecting one from the gallery, or choosing from a pre-set list in the app. This image is then sent to the server, where a Convolutional Neural Network (CNN) analyzes key features such as body shape, fins, and color to identify the species. The results, including species name, confidence score, description, vernacular video, and GPS location, are presented back to the user.

3.2 Convolutional neural network architecture

The proposed Convolutional Neural Network (CNN) architecture (Figure 3) is designed to classify fish species from raw images with high accuracy, making it suitable for aquaculture applications. The workflow begins with image acquisition, where each input is resized to 256×256 pixels. This preprocessing step ensures consistency across the dataset and enables efficient training. Each pixel carries RGB intensity values that preserve color, texture, and shape details essential for classification.

Figure 3: Proposed CNN Architecture for Fish Species Classification with Softmax Output



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At the core of the architecture lie convolutional layers, which apply kernels across the input image to extract local features such as edges, contours, and scale patterns. The convolution operation is mathematically represented as:

$$f_{i,j} = \sum_{m=1}^{M} \sum_{n=1}^{N} I_{i+m,j+n} \cdot K_{m,n} \qquad \text{...1}$$

where I is the input image, K is the kernel, and $f_{i,j}$ represents the output feature map. To introduce non-linearity and enable the network to learn complex decision boundaries, each convolution is followed by a Rectified Linear Unit (ReLU) activation defined as:

$$f(x) = \max(0, x) \qquad \text{...2}$$

After convolution, max-pooling layers reduce dimensionality while keeping dominant features. This is expressed as

$$P_{i,j} = \max_{(m,n) \in R} f_{i+m,j+n} \qquad \text{...3}$$

which selects the maximum value within a defined region R. Stacking five convolution and pooling layers allows the network to gradually progress from detecting edges and colors in early layers to species-specific traits such as scale patterns and body morphology in deeper layers. The extracted features are then reshaped into a single vector and passed through dense layers for high-level integration. The dense layer applies

$$y = f(Wx + b) \qquad \text{...4}$$

where x is the flattened feature vector, W and b represent weights and biases, and f is the activation function. The final classification is performed using the softmax function, which generates probabilities across species:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}} \qquad \text{...5}$$

where z_i is the raw score for class i and N is the total number of classes. Training the model involves minimizing the cross-entropy loss, defined as

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \qquad \text{...6}$$

ensuring the predicted probabilities align with true labels. Together, these stages transform raw images into accurate predictions with confidence scores, making the CNN framework highly suitable for real-time aquaculture applications.

3.3 App development and MongoDB integration

Figure 4 illustrates the integration of the Android application with backend services for real-time fish recognition. Once an image is uploaded, it is securely stored on Amazon S3 using presigned URLs, after which the URL is passed to the prediction model. The Node.js server coordinates communication, while a Python script loads the pretrained CNN model, analyzes the image, and returns the predicted species along with confidence scores,

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descriptions, and GPS data. Results are stored in MongoDB, a flexible and scalable NoSQL database that maintains records such as species name, confidence, timestamps, and image URLs. This ensures users can access their recent searches quickly and administrators can track prediction histories. By combining lightweight app design with secure cloud integration and efficient data storage, the system provides farmers with real-time, accessible, and reliable aquaculture decision support.

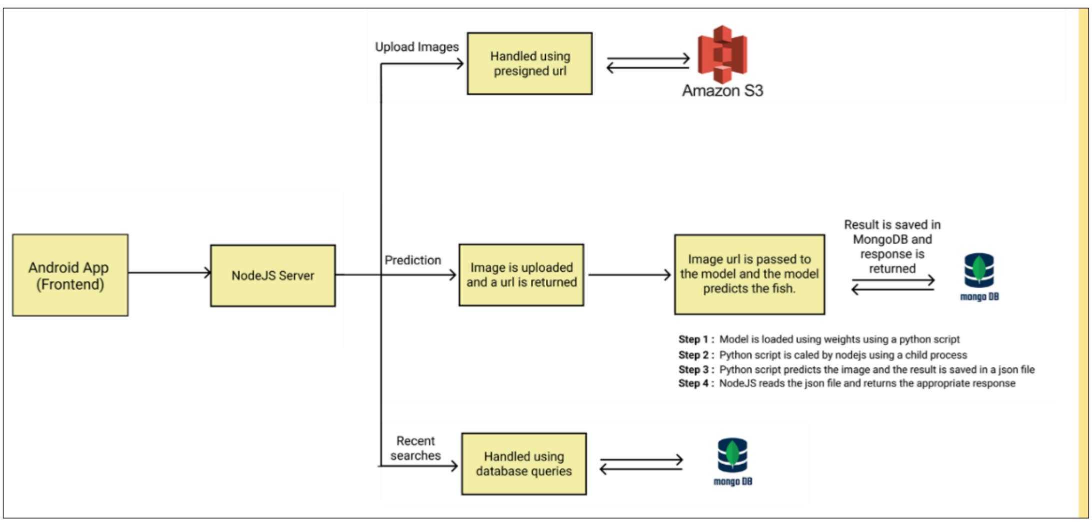
Table 1: Description of the Dataset

Name of Dataset	Number of Fish Species	Total Fish Images	Images after Pre-Processing			
			Total	Training	Testing	Validation
Bihar	15	360	637	509	63	63
Kaggle	8	1280	8000	6400	800	800
Saline Water	18	232	7074	5660	707	707

4.0 Experimental Results

The system was evaluated using three datasets representing diverse aquaculture environments (Table 1). Overall, the datasets ensured the model was tested across freshwater and marine conditions, small and large species groups, and varying image qualities. Such diversity enhanced the reliability and generalization of the CNN framework.

Figure 4: Android Application Workflow with Node.js, Amazon S3, and MongoDB Integration



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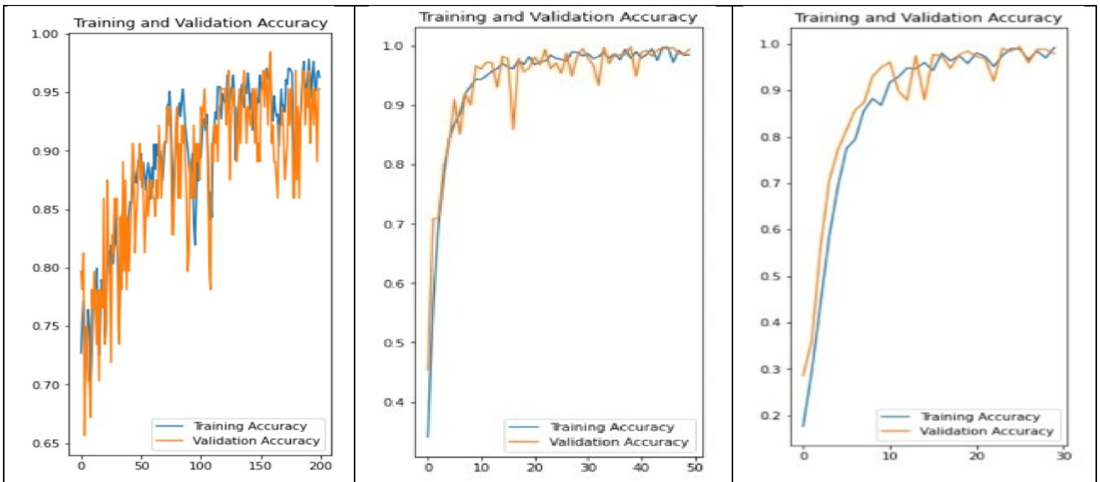
4.1 Training and validation accuracy

Figure 5 present the training and validation accuracy curves of the CNN model designed for fish species classification across different epochs. In each case, the model shows rapid learning during the initial epochs, with accuracy increasing steeply. By around 10–15 epochs, training and validation accuracies stabilize above 90%, showing that the network captures essential fish features effectively. In longer runs, such as 200 epochs, the model continues to refine its performance, eventually converging between 96–99%. The close alignment of training and validation curves demonstrates strong generalization, with little sign of overfitting, as the validation accuracy consistently tracks the training performance. Although slight oscillations are visible, particularly in validation accuracy, they are natural due to dataset complexity and sample variations. Overall, the results indicate fast convergence, high accuracy, and robustness of the CNN, confirming its reliability for real-time fish recognition and decision support in aquaculture environments.

Figure 5: Training and Validation Accuracy Curves of CNN Model for Fish Species Classification (a) Bihar Fish Dataset (b) Kaggle Dataset, and (c) Saline Water Dataset



a	b	c

4.2 Qualitative analysis of the proposed algorithm

Figure 6 depict how the system handles four common situations that arise when farmers use the app. First, it filters out non-target images so accidental uploads don't mislead the workflow: a sea turtle photo is rejected as "not processed" with 99.94% confidence and a human face is flagged as not fish with 100%, which keeps spurious inputs from influencing feeding or record keeping. Second, it judges utility when the image does contain a marine organism. A jellyfish is classified as non-consumable at 100% confidence,

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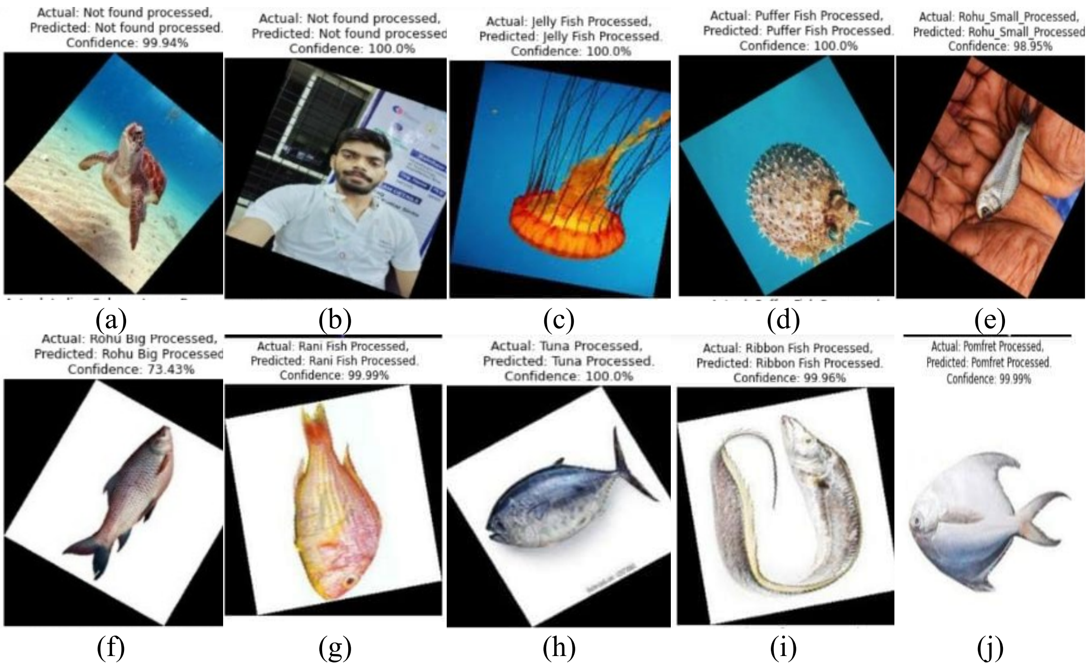
and a puffer fish is labeled non-preferred/dangerous with 100% confidence, preventing these from being treated as culture species or entering stock logs. Third, it grades size within a species for biomass planning and ration calculations.

Figure 6: CNN Outcomes: (a), (b) Non-Fish Filtering, (c), (d) Utility Tagging, (e), (f) Size Grading, and (g) to (j) Premium Saline Species Recognition



A small Rohu is identified with 98.95% confidence, indicating a juvenile class that typically needs higher frequency, lower quantity feed; a large Rohu is recognized with 73.43% confidence—slightly lower due to pose or orientation—but still sufficient to place it in the marketable or near-harvest band. Finally, it recognizes premium saline species with very high certainty, supporting pricing and dispatch decisions: Rani at 99.99%, Tuna at 100%, Ribbon fish at 99.96%, and Pomfret at 99.99%. These outputs appear in the app with species labels, confidence values, and associated metadata, allowing field users to accept or retake images, adjust feed amounts, update pond inventories, and tag catches for sale without needing specialist knowledge or additional hardware.

4.3 Memory consumption of the application

The figure shows the storage analysis of the Fish Detection mobile application, highlighting its lightweight design. The application occupies only 4.40 MB of device memory, with no additional storage required for data or cache. Such minimal memory consumption demonstrates the application's efficiency and compatibility with low-end smartphones commonly used by farmers. The cloud-based design ensures that computationally intensive CNN tasks are performed on external servers, reducing device load. This lightweight footprint not only enhances accessibility for resource-limited users but also enables seamless installation, faster performance, and reduced battery consumption, making the app highly practical for real-world aquaculture deployment.

5.0 Conclusion

This work develops a practical, end-to-end system that helps fish farmers make decisions from a simple phone photo. At its core is a Convolutional Neural Network that recognizes 41 species with about 98% accuracy, robust across sizes and image conditions by learning visual cues like scales, shapes, and fin patterns. Farmers use a lightweight Android app to snap or upload images and get results in real time; heavy computation runs on cloud servers via an IoT link, so even low-cost phones stay responsive. The app's vernacular video interface presents species IDs, biomass cues, and feeding suggestions in the farmer's own language, lowering literacy barriers. The system also checks whether a photo actually contains fish, records GPS with each capture to support mapping and management, and separates small from large fish of the same species for biomass estimation, feeding schedules, harvest planning, and pricing. Each prediction includes a confidence score so users can judge reliability. For oversight and improvement, an admin console allows data extraction, quality review, and dataset growth.

References

1. Ghose, Bishwajit. "Fisheries and Aquaculture in Bangladesh: Challenges and Opportunities." Annals of Aquaculture and Research 1(1) (2014): 1001.
2. Håstein, T., B. Hjeltnes, A. Lillehaug, J. Utne Skåre, M. Berntssen, and A.-K. Lundebye. "Food safety hazards that occur during the production stage: challenges for fish farming and the fishing industry." Revue Scientifique et Technique (OIE) 25(2) (2006): 607–625.
3. Allken, Vaneeda, Nils Olav Handegard, Shale Rosen, Tiffanie Schreyeck, Thomas Mahiout, and Ketil Malde. "Fish species identification using a convolutional neural network trained on synthetic data." ICES Journal of Marine Science 76(1) (2019): 342–349.

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4. Rani, S. V. J., I. Ioannou, R. Swetha, R. M. D. Lakshmi, et al. "A novel automated approach for fish biomass estimation in turbid environments through deep learning, object detection, and regression." Ecological Informatics 79 (2024): 102632.
5. Li, X., J. Li, Y. Wang, L. Fu, Y. Fu, B. Li, and B. Jiao. "Aquaculture Industry in China: Current State, Challenges, and Outlook." Reviews in Fisheries Science 19(3) (2011): 187–200.
6. Ahamed, N. Nasurudeen, and Amreen Ayesha. "Marine Resources: Identification, Restoring, and Monitoring of Fisheries Food Resources Using Deep Learning and Image Processing." In: Artificial Intelligence and Edge Computing for Sustainable Ocean Health (Springer Series in Applied Machine Learning) (2024): 101–121.
7. Moga, L. M. "Cloud computing based solutions for monitoring the supply chain of fish and fishery products." Proceedings of the 2017 8th International Conference on Intelligent Computing and Information Systems (ICICIS) (2017): 33–38.
8. Kiranmayi, D., A. Sharma, K. P. Prasad, and R. Sharma. "Development of an Android-Based Application System for Fish Farmers." Agricultural Research 11(3) (2021): 443–457.
9. Roy, Souvik, Sayak Mondal, Shreyashree Sarkar, Sumit K. Banerjee, Suman Bhattacharya, and Mahamuda Sultana. "AI Based Framework for Fish Species Identification and Classification." International Journal of Computer Sciences and Engineering 11(Special Issue 1) (2023): 81–88.
10. Aftab, Kashif, Pascal Zeller, Bruno Pasini, Bilal Khan, et al. "Intelligent fisheries: Cognitive solutions for improving aquaculture commercial efficiency through enhanced biomass estimation and early disease detection." Cognitive Computation 16(5) (2024): 2241–2263.
11. Peddina, K., and A. K. Mandava. "The intelligent object detection framework for detecting fish from underwater images." International Journal of Communication Networks and Distributed Systems 31(1/2) (2025): 63–88.
12. Nawaz, Umer, Muhammad Zeeshan Zaheer, Faisal Shahzad Khan, Hisham Cholakkal, et al. "AI in Agriculture: A Survey of Deep Learning Techniques for Crops, Fisheries and Livestock." arXiv preprint arXiv:2507.22101 (2025).
13. Hu, Zhenhua, Ran Li, Xianzhong Xia, Chaoyang Yu, Xue Fan, and Yihua Zhao. "A method overview in smart aquaculture." Environmental Monitoring and Assessment 192(8) (2020): 493.
14. Dalal, R., S. Kadam, and D. M. Shinde. "Fish Farm Monitoring and Controlled System Using LoRaWAN Network." In: Proceedings of the 5th International Conference on Recent Trends in Machine Learning, IoT, Smart Cities and Applications (Springer) (2025): 83–92.

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