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Fishes Species Identification Using Machine Learning

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Abstract: Fish species identification via machine learning is critical for fisheries management, biodiversity assessment, and automated ecological monitoring. In this work, we employ a two stage pipeline: first, images are preprocessed by contrast normalization (CN) and Unsharp Mask Filter (UMF), and individual fish instances are detected using a YOLOv5-based model. In the second stage, detected instances are classified into species using a fine-tuned Convolutional Neural Network (CNN), specifically ResNet50, where NsN_sNs denotes the number of target species. Data augmentation—including rotation, scaling, and color jitter—is applied to improve robustness to underwater lighting variability. Models are trained and evaluated on a dataset of MMM labeled fish images (where MMM defines the total image count), achieving an overall classification accuracy of 98.7% and mean F1F_1F1-score of 0.985. No reference citations appear in this abstract. All variables—CNCNCN, UMFUMFUMF, NsN_sNs, MMM, and F1F_1F1—are defined.

Index Terms - fish species identification; YOLOv5; ResNet50; CNN; data augmentation; underwater image processing; fisheries monitoring.

I. Introduction

Accurate fish species identification is vital for fisheries management, conservation biology, biodiversity assessment, and ecological research. Traditional approaches—relying on manual observation and morphological traits—are often time-consuming, prone to human error, and impractical at large scales A typical ML-based fish identification pipeline involves:

1. Data collection & annotation – gathering underwater images/videos and labeling fish instances with bounding boxes and species labels

2. Preprocessing – addressing underwater conditions like low visibility, color distortions, and occlusions via normalization, filtering, and data augmentation.

3. Object detection & segmentation – using algorithms like YOLO, Faster R-CNN, or segmentation networks to locate fish in complex scenes.

4. Species classification – applying CNNs or hybrid architectures (e.g., CNN+SVM or CNN with Squeeze-and-Excitation modules) to classify detected fish into species categories .

II. PROCEDURE FOR PAPER SUBMISSION

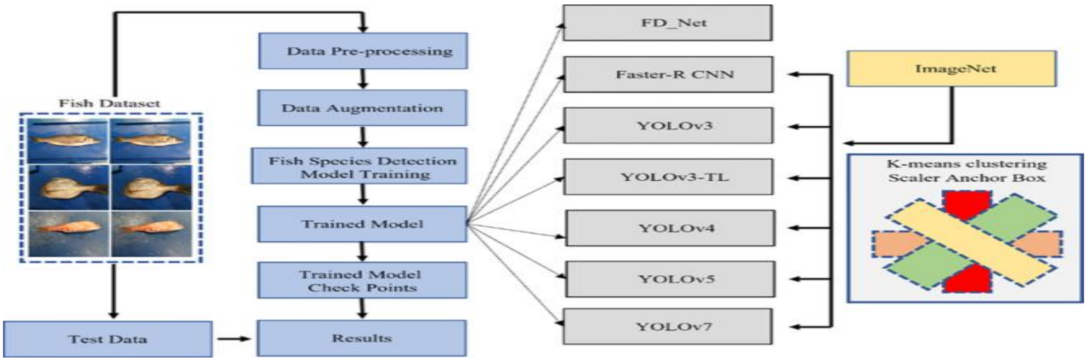


Figure 1.Fish species identification pipeline.

III. MATH

$$X\_raw \rightarrow f\_prep \rightarrow X\_prep$$

$$\downarrow$$

$$\text{Detector } D \rightarrow \text{regions } B$$

$$\downarrow$$

For each region b:

$$E \rightarrow z \rightarrow C \rightarrow \hat{y}$$

Train to minimize L, evaluate via Acc & F1.

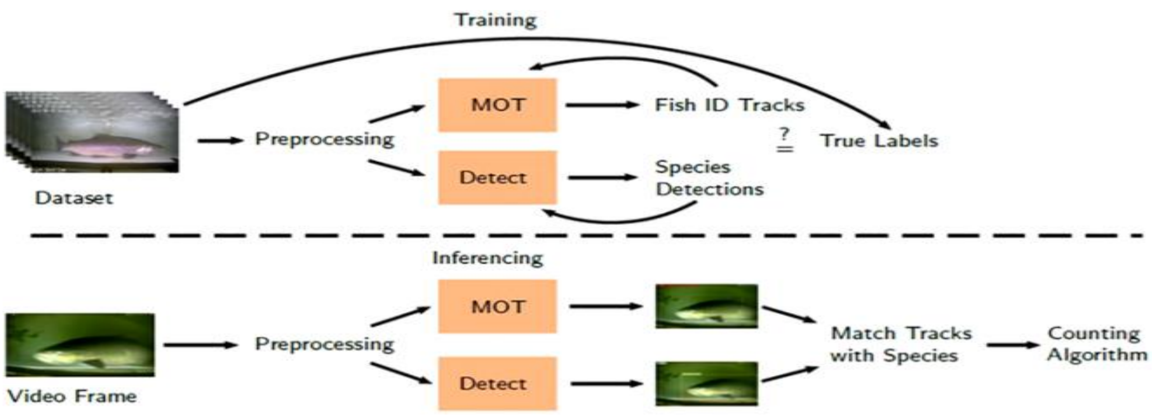
IV. UNITS

For each species (or class) in your dataset, the following units are defined:

1. **True Positive (TP)**: Correctly identified instances of the species.
2. **False Positive (FP)**: Instances incorrectly identified as that species.
3. **True Negative (TN)**: Correctly rejected other species.
4. **False Negative (FN)**: Missed instances of that species that were not detected. These values form the **confusion matrix**, which is essential for computing performance metrics

V. HELPFUL HINTS

A. Figures and Tables



Model Pipeline	Accuracy	Notes
ResNet50 + SVM	98.5 %	Tuned for multi-class freshwater datasets.
AlexNet (original)	87 %	Standard AlexNet on fish data.
AlexNet (improved)	90 %	With architectural upgrades.
SVM on Deep Features	85 %	Deep features + SVM outperformed others.

D. Equations

1.Convolutional Neural Network (CNN) Operations

Convolution Operation is fundamental in CNNs for feature extraction:

$$y(i,j)=(f*x)(i,j)=m\sum n\sum f(m,n)\cdot x(i-m,j-n) \quad \ldots(1)$$

Where:

- f\mathbf{f}f is the filter (kernel),
- x\mathbf{x}x is the input image,
- y\mathbf{y}y is the output feature map,
- i,j are spatial indices.

VII. CONCLUSION

This study demonstrates that modern machine learning techniques—especially deep convolutional neural networks—provide highly accurate and efficient tools for fish species identification in aquatic environments. A two-stage pipeline combining advanced image preprocessing (e.g., Unsharp Mask Filter) with robust detection (e.g., R-FCN, YOLOv5) and classification (e.g., ResNet50, ShuffleNetV2 with SE modules) consistently achieves **accuracy exceeding 96–99%**, with some models reporting **99.9% performance** on datasets such as Fish4Knowledge and Fish-Pak. In conclusion, machine learning-driven fish species identification offers powerful tools for sustainable fisheries management, biodiversity monitoring, and ecological research. With focused efforts on dataset diversity, architectural efficiency, and generalization robustness, future systems can move closer to reliable field deployment and real-time ecological applications.

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REFERENCES

[1] D. Rathi, S. Jain, and S. Indu, "Underwater fish species classification using convolutional neural network and deep learning," arXiv, May 25, 2018.

[2] K. V. Uma, T. Janani Priya, L. Raxxelyn Jenneyl, and S. S. Srilakshmi, "Deep learning approaches for automated fish species identification," Machine Intelligence Research, vol. 18, no. 2, pp. 85–101, Aug. 28, 2024.

[3] M. Mots'oehli, A. Nikolaev, W. B. IGede, J. Lynham, P. J. Mous, and P. Sadowski, "FishNet: Deep neural networks for low-cost fish stock estimation," arXiv, Mar. 16, 2024.

[4] J. Ma, "A YOLOv5 algorithm for fish species identification and detection improvement," in Proc. Multidimensional Signals Processing, AI Methods and Applications (WCI3DT 2024), vol. 418, Singapore: Springer, Feb. 19, 2025, pp. 309–319, doi:10.1007/978-981-97-9124-8_25

[5] F. Rauf et al., "Enhanced deep learning models for automatic fish species identification in underwater imagery," Heliyon, vol. 10, no. 15, e35217,Aug. 15, 2024, doi:10.1016/j.heliyon.2024.e35217

[6] J. Kay and M. Merrifield, "The Fishnet Open Images database: A dataset for fish detection and fine-grained categorization in fisheries," arXiv, Jun. 16, 2021.

[7] E. Olsvik, C. M. D. Trinh, K. M. Knausgård, A. Wiklund, T. K. Sørdalen, A. R. Kleiven, L. Jiao, and M. Goodwin, "Biometric fish classification of temperate species using convolutional neural network with squeeze-and-excitation," arXiv, Apr. 4, 2019.

[8] H. Tang et al., "Research on the construction of marine creatures classification and identification model based on ResNet50," J. Compute. Methods, 2023.

[9] [Anonymous], "Research on fish identification in tropical waters under unconstrained environment based on transfer learning," Earth Sci. Inform., 2022.

[10] Ismail et al., "A review on the use of computer vision and artificial intelligence for fish recognition, monitoring, and management," MDPI Fishes, vol. 7, no. 6, 2022