© December 2025 | IJIRT | Volume 12 Issue 7 | ISSN: 2349-6002

Fish Species Identification: An AI and Mobile Solution

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***Abstract*—The marine ecosystem is essential for supporting millions of fishermen and coastal communities by providing livelihoods, nutrition, and economic stability. In India, fisheries play a significant role in the national GDP and employment, making timely and accurate species-level catch reporting increasingly important. Even with marine advisory systems like those developed by INCOIS, there are still gaps in real-time data collection and reliable species identification. These gaps often result in incomplete records and limit the effectiveness of fisheries planning, conservation efforts, and policy-making.**

This review looks at a proposed Android-based mobile application that uses Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) to automate fish species identification and digital catch reporting. The system uses the lightweight MobileNetV2 architecture. It is trained on a curated and expert-validated dataset of fish images, and converted to TensorFlow Lite. This allows for fast, offline inference directly on fishermen's smartphones. This makes the solution practical for coastal areas with low connectivity.

The application uses SQLite for offline data storage, allowing fishermen to reliably record catch details even in remote areas without internet access, while Firebase enables secure cloud synchronization once a network is available, ensuring that all data is safely backed up and accessible for analysis. GPS and weather APIs automatically add precise location, time, and environmental conditions to each catch record, providing valuable context for each observation. By combining fish species recognition with detailed contextual information, the system improves the reliability and analytical value of fisheries data, supporting effective ecosystem monitoring and sustainable fisheries management practices at regional and national levels.

***Index Terms*—Fish Species, Machine Learning, Image Classification, Grad-CAM, Artificial Intelligence**

I. INTRODUCTION

A. Background and Context

India's fisheries sector supports over 28 million people and is essential for food security and coastal incomes. However, traditional methods for fish identification and catch reporting still depend on manual observation and handwritten records. This often results in errors and incomplete data. It impacts agencies like INCOIS that need precise species-level information for marine advisories, population assessment, and protecting biodiversity. Since many fishermen operate in remote areas with limited connectivity, there is a pressing need for a straightforward, offline tool that can effectively capture and store data.

B. Motivation for the Project

The project "Fish Species Identification: An AI & Mobile Solution" aims to update traditional fishing practices. It offers fast, automatic, and offline fish identification through an easy-to-use mobile app. The app, built with Kotlin and using a MobileNetV2 model optimized with TensorFlow Lite, identifies fish from a photo and provides a confidence score. It also records GPS location, time, and weather on its own. Data is stored locally in SQLite and synced to Firebase when the internet is available. This makes the system practical for field use and useful for larger analysis.

C. Importance of Accurate Species-Level Data

Species data is crucial for managing fisheries sustainably, tracking stock health, and identifying endangered species. AI-based identification provides consistency and improves the quality of ecological datasets. For fishermen, the app serves as a learning tool and a digital logbook, aiding with daily record-keeping and documentation for schemes or subsidies. Technically, the project uses concepts like CNNs, depth wise separable convolutions, transfer learning, and Grad-CAM for model transparency.

II. LITERATURE REVIEW

Improved YOLOv8n for Fish Detection (Zhang et al., 2024)
Zhang et al. use YOLOv8n tiny to detect fish in natural, unconstrained environments. They apply mosaic, turbidity, motion blur, and scaling augmentations. Their process follows a detection-first pipeline: detect, crop, then classify. They incorporate adaptive NMS and a combined localization/classification loss. The model delivers solid mAP and real-time edge inference. However, it is more complex than single-image classifiers. This modular method works well for images with multiple fish but needs careful compression for mobile use.

Species Identification for Indian Seafood Markets (Gupta et al., 2024)
Gupta et al. present a valuable dataset of Indian fish that includes 8,488 images of eight important species. The images are well-annotated and contain rich metadata. They apply basic preprocessing and test models such as ResNet and MobileNet, reaching good baseline accuracy. The main benefit of this work is its focus on India, making it a solid starting point. However, there is a need for more diverse images taken in the field for real-world applications.

Automated Fish Species Identification using Computer Vision (IEEE Xplore, 2023)
This paper presents a complete CNN approach for classifying fish species. It includes preprocessing steps like denoising, resizing, color correction, and background suppression. The models are trained using transfer learning with either ResNet or custom CNNs. They are evaluated with cross-validation, confusion matrices, and precision/recall for each class. Deep learning clearly performs better than traditional methods. The paper emphasizes solid evaluation practices, but it doesn't address mobile deployment or the use of metadata. Additionally, the study focuses on controlled image datasets, which limits its relevance to real-world fishing settings. The lack of offline or edge-based implementation shows the need for mobile-oriented solutions.

Multi-Classification Deep Neural Networks for Identification (FD_Net, Malik et al., 2023)
FD_Net is a lightweight network designed for small-object feature extraction. It uses preprocessing methods like CLAHE and edge-preserving smoothing. The training process employs class-balanced sampling and focal loss to manage skewed data. Error analysis reveals common mistakes. The authors recommend combining visual predictions with metadata, such as size and shape, to improve accuracy. They provide guidance on integrating information from multiple sources in practical systems.

YOLO-Fish: Robust Fish Detection (Al Muksit et al., 2022)
YOLO-Fish focuses on detecting fish in crowded aquatic images with tuned anchors, multi-scale training, and noise-resistant augmentations. It crops detected fish for classification, which improves recognition in dense scenes. It achieves high detection accuracy (mAP) and decent inference speed. The main challenge is the higher demands on device resources, but techniques like pruning, distillation, and quantization can help. This approach is mainly designed for surveillance or research-grade systems instead of lightweight mobile applications. Its use in low-connectivity or resource-limited fishing environments is still limited.

ICT for India's Small-Scale Fisheries (Rajan et al., 2021)
Rajan et al. highlight the need for inclusive ICT solutions in small-scale fisheries. Surveys reveal challenges such as low digital literacy, poor connectivity, and language barriers. The paper recommends offline-first, simple, multilingual apps. These insights are directly useful for designing user-friendly fish identification tools for local fisherfolk.

MobileNets–V1 for Web-Based Fish Classification (Talenta, 2021)
This study uses MobileNetV1 with transfer learning to classify 10 fish species, with around 300 images for each species. It achieves about 91% training accuracy and roughly 89% validation accuracy. The results indicate that lightweight models work well on small datasets, but web deployment restricts offline use. The paper recommends upgrading to MobileNetV2 or V3 and using TensorFlow Lite for mobile, offline inference.

TABLE I. COMPARATIVE LITERATURE REVIEW

Author / Work	Core Contribut ion	Limitation s Identified	Relevance to Present Work
Zhang et al., 2024 – Improved YOLOv8n	YOLOv8n tiny for natural fish detection; detect→crop→classify; real-time edge inference.	Complex; needs compression for mobile	Guides modular detection→classification for multiple fish on-device.
Gupta et al., 2024	India-specific dataset (8,488 images, 8 species); baseline ResNet/MobileNet.	Limited diversity; needs field images	Dataset for fine-tuning region-specific models.
IEEE Xplore, 2023	End-to-end CNN with preprocessing; robust evaluation	No mobile deployment or metadata.	Shows CNN classification and evaluation best practices.
Malik et al., 2023 – FD_Net	Lightweight small-object network; CLAHE, smoothing; class-balanced/focal loss.	Confusions between classes; needs metadata	Suggests combining predictions with metadata
Al Muksit et al., 2022 – YOLO-Fish	Detection in crowded images; cropped for classification; multi-scale training	High resource demand	Shows detection→classification workflow for edge devices
Rajan et al., 2021	Socio-technical view; offline-first, multilingual apps	Not ML-focused	Guides user-friendly fish ID app design
Talenta, 2021 MobileNetV1	Lightweight CNN for web-based classification (~91% train, ~89% val)	Limited offline use	Supports MobileNetV2/V3 and TensorFlow Lite for mobile

III. RESEARCH GAP

The field of monitoring marine ecosystems and identifying fish species has made significant strides with AI and deep learning. Over the last ten years, CNNs, computer vision, and transfer learning have been widely used to automate fish classification in controlled settings. Models like ResNet, Mobile Net, and Efficient Net can achieve high accuracy, between 90% and 99%, on specially curated underwater or lab datasets.

However, there are still major gaps in real-world applications, particularly in India. Many models depend on limited, region-specific data, need high computational power, and face challenges adapting to changing marine environments. Most research emphasizes static images, which restricts practical applications for daily fish catch reporting or on-site identification.

Studies that focus on accuracy often miss the importance of explainability and user accessibility. CNNs usually do not provide clear insights into their decision-making processes. Additionally, the lack of location, weather, or time-related data diminishes the ecological value of the work. This limits institutions like INCOIS from conducting real-time trend analysis or ecosystem assessments.

Dataset representation is another issue. Global datasets, such as Fish4Knowledge and LifeCLEF, do not focus on Indian fish, making models less effective for local species. There are very few open-access, annotated datasets for Indian fish, which hampers the growth of domain-specific AI applications.

From a deployment standpoint, most systems are web- or cloud-based, which restricts their use in remote areas with poor connectivity. Existing apps, like FishAPP from 2016, use outdated models and cover only a limited number of species, without real-time AI integration. The connection with advisory systems like MFAS is minimal, leading to valuable field data going uncollected and weakening national fishery advisories.

IV. PROPOSED SYSTEM

The proposed system is a mobile AI-based solution. It aims to identify fish species in real-time, capture data, and connect with national fisheries management frameworks like INCOIS. This system tackles major challenges faced by Indian fishermen. These challenges include the absence of tools that work offline, limited data on specific fish species, and the need for useful advisory insights. By using deep learning, capturing metadata, and deploying on mobile devices, the system provides a precise, easy-to-use, and field-ready way to support sustainable fisheries management.

The system is modular and consists of six connected components that work together to ensure reliable identification and reporting. The Image Acquisition and Preprocessing module captures high-quality fish images using a smartphone camera. It also applies real-time preprocessing, including noise reduction, resizing, adjusting color and contrast, and normalizing orientation. This ensures consistent input for AI inference in different field conditions.

The Feature Extraction and Classification module uses MobileNetV2, a lightweight CNN designed for mobile devices, to extract layered visual features like texture, color patterns, fin shapes, and body contours. Fully connected layers with a softmax output generate species probability scores. Grad-CAM visualizations highlight parts of the image that contribute to predictions. This enhances explainability and user trust.

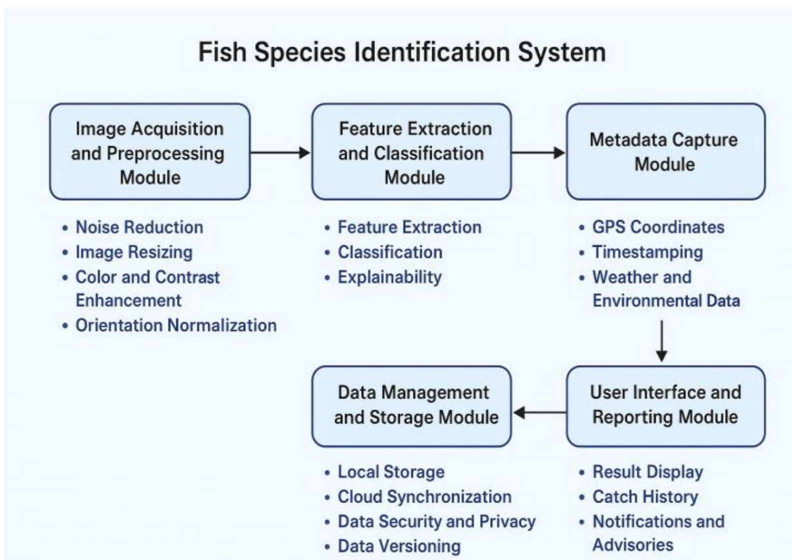

Figure 1. Fish Species Identification System

The model is deployed through TensorFlow Lite to allow low-latency, offline inference. Techniques like quantization and pruning reduce the model's size without losing accuracy.

The Metadata Capture module automatically logs GPS coordinates, timestamps, and environmental conditions like temperature and weather. This provides spatial, temporal, and ecological context for each catch record. The Data Management and Storage module offers reliable local storage using SQLite for offline use and syncs with cloud databases or INCOIS servers when there is connectivity. It uses secure, versioned data handling to keep data safe and prevent conflicts.

V. EXPECTED OUTCOMES

The proposed fish species identification system represents a substantial leap forward compared to existing methods, not just in terms of technology, but also in accessibility and practical usability in real-world scenarios. By leveraging MobileNetV2 directly on smartphones, the system performs real-time fish identification without relying on cloud servers or constant internet connectivity. This feature is particularly valuable for fishermen working in remote coastal regions, where network access is often unreliable, ensuring that the tool remains functional anytime and anywhere.

One of the system's most notable innovations is its carefully curated dataset of Indian marine fish, collected under diverse field conditions. The images include variations in lighting, backgrounds, and fish orientations, making the model robust and capable of accurately recognizing species native to the region. Unlike previous approaches that relied on laboratory images or region-specific datasets, this method reflects the real challenges and variability of natural marine environments, significantly improving the system's accuracy and reliability.

Beyond simple identification, the system is designed as a comprehensive decision-support tool, integrating seamlessly with INCOIS and other advisory services to provide actionable insights. Automated capture of metadata including GPS coordinates, timestamps, and environmental conditions adds significant ecological and analytical value. This feature enables studies on species distribution, seasonal trends, and long-term fisheries planning, turning the application into more than just an identification tool.

Explainability is another key strength of the system. Grad-CAM visualizations highlight the regions of an image that the model relies on for its predictions, fostering transparency and building user trust. Additionally, the lightweight Android application ensures smooth operation even on low-cost devices, making advanced technology accessible to everyday fishermen.

During evaluation, the MobileNetV2 model pretrained on ImageNet was trained on 70% of the dataset, validated on 20%, and tested on 10%. Input images were resized to 224×224 and pre-processed using CLAHE, normalization, and data augmentation techniques such as flips, rotations, and brightness adjustments. The quantized TensorFlow Lite model demonstrated excellent real-time performance, offline functionality, clear user interface, and high user satisfaction, confirming that the system is not only accurate but also practical and user-friendly for deployment in real-world conditions.

TABLE II. INNOVATIONS OF THE PROPOSED METHODOLOGY

Innovation Aspect	Before Fish App	After Fish App
Model Deployment	Cloud-based recognition systems	On-device CNN (MobileNetV2) for offline real-time identification
Dataset	Limited, region-specific datasets	Regionally diverse Indian dataset with real catch images
Integration	Standalone apps	Seamless linkage with INCOIS and advisory feedback systems
Metadata Utilization	Ignored or minimal	Automatic inclusion of GPS, timestamp, and weather context
Explainability	Black-box CNNs	Grad-CAM visualization for model interpretability
Accessibility	High-resource or lab-based systems	Lightweight, Kotlin-based Android app optimized for fishermen
Sustainability	No emphasis on ecological feedback	Promotes responsible fishing and conservation awareness

VI. FUTURE SCOPE

Although the proposed system effectively tries to handle the main challenges of fish species identification and data collection, a number of avenues can still be followed to extend the functionality and, consequently, the impact of such a system. Scaling up, enhancing coverage, and automating future efforts will be done by integrating advanced features and further developing the capabilities of the model.

Direct extensions could include the expansion of the dataset. A larger, open-access dataset of Indian marine fishes can be developed that better captures various coastal species under a variety of lighting and regional conditions. Crowdsourced collection via the mobile application will enrich this dataset constantly and keep the model current for practical use at various locations.

This would also include model enhancement, for example, using newer lightweight architectures such as EfficientNet-Lite or ViT, which may provide better classification accuracies with lower inference times. Lastly, consider ensemble models or hybrid CNN approaches that could further improve performance for species with subtle visual differences.

Such real-time cloud analytics can expand the system from a locally operating identification tool to a general data analysis platform. Future versions of the app are likely to sync data with the cloud, paving the way for large-scale analytics, visualization dashboards, and insights that could be useful for marine authorities in order to support fisheries management and ecological monitoring.

Another promising direction is the integration with IoT devices. In particular, the connection to IoT-enabled sensors or smart fishing gear could allow real-time monitoring of environmental factors like water temperature, salinity, and pollution levels, thus providing additional context to decision-making and ecological studies.

The more essential thing to do is to make AI models explainable and, therefore, regulated. Future work can use techniques related to explainable AI to guarantee more clarity of the algorithm and accountability, thus complying with the principles regarding the use of ethical AI while performing tasks that involve data from ecology and fisheries.

The system has the potential for global applicability and research collaboration. By retraining the models with datasets from other regions, this solution may have applications beyond the waters of India. International marine research institutions could collaborate on developing a common, unified platform for global fish species identification and support scientific exchange and conservation efforts around the world.

TABLE III. FUTURE SCOPE SUMMARY

Future Work Area	Description
Dataset Expansion	Develop a larger, open-access Indian marine fish dataset with diverse species and conditions; use crowd-sourced data.
Real-Time Cloud Analytics	Enable real-time cloud sync for large-scale analysis and visualization for authorities
Voice Assistance & Multilingual Interface	Add regional language and voice commands for accessibility to all users.
Integration with IoT Devices	Connect to sensors for real-time monitoring of water temperature, salinity, and pollution.
Global Applicability & Research Collaboration	Extend to global waters and collaborate with international marine research institutions.

VII. CONCLUSION

1. The proposed AI-based mobile system makes fish species identification faster and more reliable, reducing errors that commonly occur with manual reporting and helping fishermen record accurate catch data even in remote coastal areas.
2. By running entirely on Android devices using an efficient on-device model, the solution remains accessible without continuous internet connectivity, making it practical and inclusive for real-world fishing environments.
3. Automatic collection of location, time, and weather information adds valuable context to each observation, supporting better understanding of marine species behaviour and strengthening data quality for ecological studies.
4. The integration with national institutions such as INCOIS creates mutual benefits by improving marine advisory services while providing fishermen with meaningful, data-driven insights for safer and smarter fishing.
5. With features like interpretable AI visualizations and a modular, upgrade-friendly design, the system builds user trust and lays a strong foundation for future research, conservation efforts, and sustainable fisheries management.

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