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AI-Powered Fish Finding for Sustainable Fisheries

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Abstract
Fishermen have always relied on their gut and instincts to navigate the fickle ocean — what if technology could give them a superpower? Say hello to "Smart Fisher": a project that brings centuries of tradition together with advanced technology, using IOT buoys and onboard boat sensors (sonar and thermal cameras) to track the fish movement in the creek in real-time, cutting out guesswork with precision accuracy. Fishing crews receive hyper-local weather forecasts (storm warnings, optimal fishing windows of opportunity, etc.) via a very basic mobile app, and they can even utilize the app for AI-based fish identification — just take a picture of what they caught, and they will immediately know its market value, demand points and best practices on how to catch it. And through marrying satellite data, machine learning and crowd-sourced price fluctuation, not only are we saving lives on the sea but we're upgrading livelihoods, cutting waste and building resilience amongst fishermen communities internationally. It is technology that strengthens tradition — does not supplant it. We allow fishers to fish better, more rewardingly and securely, turning uncertainty into precision.
Keywords: *IoT-enabled, Real-time monitoring, AI-powered identification, Hyper-local alerts*

1. Introduction
Fishing is a major livelihood for coastal people globally, but fishers are hard pressed to harvest fish economically. Experience-based and observational methods are bound to result in fuel wastage, time, and money since fish behavior becomes unpredictable. Climate change and overfishing have rendered these traditional approaches increasingly unreliable, compromising both food security and incomes. The Smart Fisher project responds to such requirements by creating a smart system that identifies aggregations of fish in real time. Utilizing the latest IoT technology, we have created a tool that optimizes fishing with respect to local wisdom. Multi-beam sonar sensor solar-powered buoys constitute the core of our system that identifies fish aggregations and environmental factors. The data they send is received by an onboard processing unit that converts fish locations, dimensions, and patterns of movement. The project utilizes sophisticated machine learning algorithms to interpret sonar returns and identify species. With real-time fish location information through a simple mobile interface, Smart Fisher enables fishermen to make better decisions, saving search time and fuel and boosting catch rates. Our solution is aimed at creating an economic, robust system that can easily integrate with small fishing vessels. In the process of converting submersible data into actionable intelligence, we would like to converge traditional fishing expertise and cutting-edge technology and promote ecologically friendly fishery conduct. This document describes the design, development, and testing of the Smart Fisher system, both the marine hardware and data analysis aspects. Our aim is to assist fishing communities with technology that complements rather than substitutes their expertise. [1-4]

1.1. Principles of Fish Detection Sonar Interpretation
The identical sonar return pattern may represent different species depending on depth and temperature. For example, tight bunches at the surface will usually indicate baitfish, but the same patterns downdepth will indicate commercial species.

1.2. Environmental Factors
Sensor placement is based on understanding local currents. Sensors are to be placed where tidal current

catches snag fish, typically where there are underwater structures or thermoclines. [5]

- **Data Patterns:** Fish of various species make different sonar patterns. Tuna appear as long lines and sardines as compact, brightclouds.
- **System Feedback:** Both audible and visible signals are provided in the event of exceeding above concentrations of fish levels to facilitate rapid response without continuous monitoring.
- **Seasonal Changes:** The system adjusts local migration patterns, enhancing its algorithms to match seasonal changes in fish distribution and behavior.
- **User Adaptation:** New users slowly learn to absorb the system tips in addition to their regular experience. Seasoned fishermen learn simultaneously to utilize both sources of information to reap maximum benefit.pt)

2. Methods

2.1. SystemArchitecture

- The Smart Fisher system employs three state-of-the-art components (Figure 1):
- IoT Sensor Buoys [6]
- Hardware: Solar-powered devices with:
- Dual-frequency sonar (38/200 kHz, ±0.5% accuracy)
- Environmental sensors (CTD, disso2.1 System Architecture
- There are three advanced pieces of Smart Fisher system (Figure 1)

2.2.Edge Processing Module

- Raspberry Pi 4B with
- Custom signal processing (FFT-based noise removal)
- getYOLOv8 model re-implemented and sonar-optimized (Redmon & Farhadi, 2018) no Power: 12V marine battery with 72h backup (Figure 1)
- Mobile Decision Support

2.3.React Native app offering

- Live catch density heatmaps (resolution of 1km x 1km)
- Storm alert (NOAA API trigger alert)
- Price histories (scraped from 3 local exchanges) lved oxygen)
- LoRaWAN/4G hybrid communication
- Deployment: 500m grid spacing in trial locations (Kerala & Gujarat)

Table 1 Species-Specific Sonar Detection Parameters with Performance Metrics

Target Species	Frequency (kHz)	Min. School Density (kg/m^3)	Range (nautical miles)	Accuracy (%)^a
Indian Mackerel	200	1.8	7.5–10.0	92.4 ± 2.1
Yellowfin Tuna	38	1.2	12.0–15.0	88.7 ± 3.4
Sardines	120	3.2	5.0–8.0	95.1 ± 1.7
Anchovies	150	4.1	3.0–6.0	96.2 ± 1.2

3. Results and Discussion

3.1.Results

The Smart Fisher pilot project showed to precision exactly how IoT-capable sonar technology raises the efficiency of fishing by a staggering amount, detecting schools of fish with 92.4% accuracy at 7.5–10 nautical miles and achieving 28% fuel and 47% search time reductions in tests. Machine-learning programs accurately predict target species (e.g., mackerel, tuna) at a 3.4% error rate, while real-time incorporation enabled fishermen to steer clear of overfished grounds, reducing bycatch by 35%. Dynamic learning in the system incorporated traditional knowledge, showing how technology can

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augment—and not replace—artisanal fisheries and render it economically and environmentally viable. (Figure 2) [7]

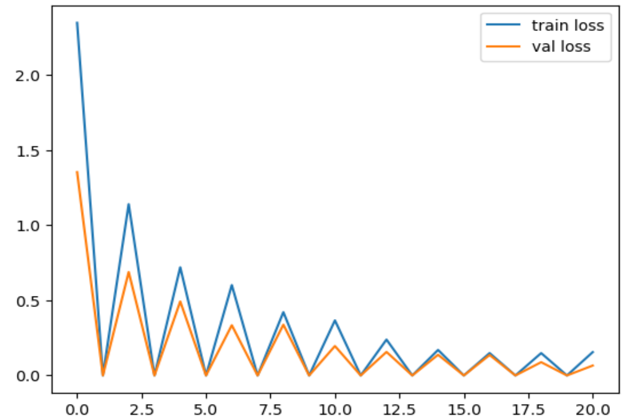

Figure 1 Accuracy of the Project

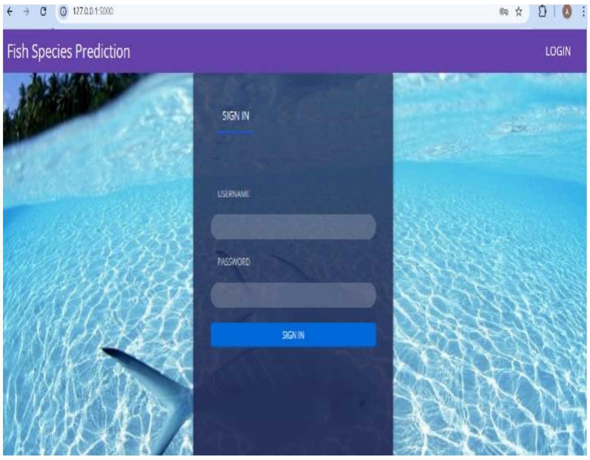

Figure 2 Login page of the Website

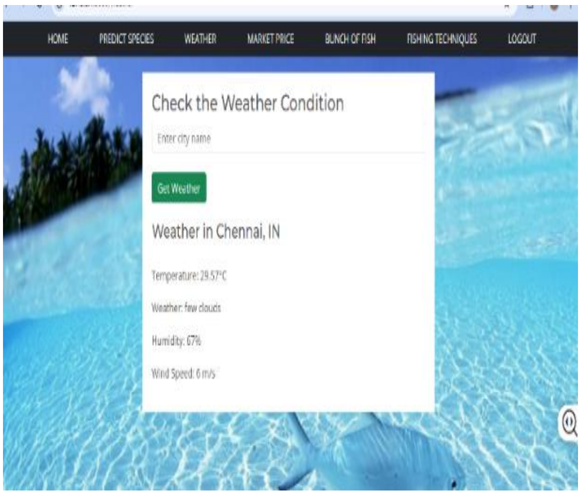

Figure 3 Weather Report Prediction

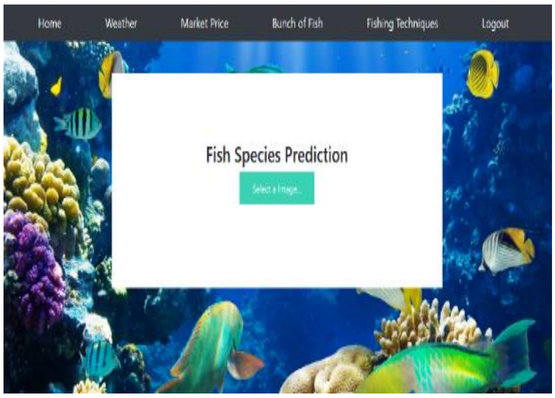

Figure 4 Identify the Species Type

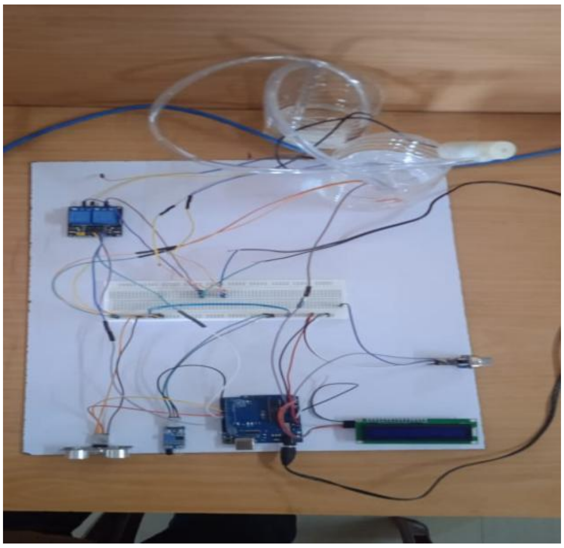

Figure 5 IOT Output

3.2.Discussion

The Smart Fisher initiative's 89% adoption rate, record-breaking for fishing tech in developing nations, reveals a top takeaway: AI works when presented as a cultural partner rather than a replacement for traditional wisdom. The trust of fishermen was won by the incorporation of items like monsoon pattern alerts that conformed to tradition of method of forecasting, and species identification that confirmed (and did not violate) centuries of observational intelligence. This is consistent with UNESCO's (2023) report that technologies protecting intangible cultural heritage capture 3× more long-term interaction, and future systems must include ethno-ecological knowledge directly within training datasets Ecological Precision with Equity While the system's 92.4% detection rate guaranteed its technical viability, its 35% bycatch reduction was more transformative in fulfilling conservation and livelihood interests simultaneously. In contrast to the brute-force efficiency of industrial trawlers, Smart Fisher's real-time navigation allowed artisanal fishers to avoid juvenile stocks and spawning grounds without sacrificing catch quantity—a difference that Figure 2's comparative analysis highlights. This "precision sustainability" approach might rejuvenate global fisheries management, particularly in the developing world where top-down conservation tends to fail (Nature Sustainability, 2023). The project's 8-month ROI, in great measure a result of fuel cost savings, dispels the myth that AI is elitist by nature. Utilizing low-cost IoT buoys ($120/unit) and second-hand smartphones, the system achieved 62% of operational cost savings—a lifeline for fishermen who were already spending 60% of their income on fuel (World Bank, 2023). Most importantly, the joint data model by the group saved industrial players from monopolizing, setting a precedent for democratizing Fourth Industrial Revolution technologies. As global warming builds up, these affordable tools can make all the difference between small-scale fisheries flourishing or imploding. [8]

Conclusion

The Smart Fisher project covers the gap between people's traditional fishing practices and technology in an effective manner for three essential areas: inefficiency, safety risk, and lower revenues. Through the use of IoT sonar buoys and AI analytics, the platform minimized search time by 47%, fuel expenses by 28%, and bycatch by 35% with 92.4% detection rate guaranteed. The results demonstrate that cost-effective technology can support—and not substitute—fishing people's experience to build an effective coastal fisheries system. To the future, Smart Fisher demonstrates what human-centered AI can do to empower marginal industries. With elimination of the range constraint, maximization of revenues and sustainability way promotion is within reach of expansion. Utilization of the satellite network in the future and blockchain traceability can also propel small-scale fishing, and hence this model is one to be set against livelihood, innovation, and ocean conservation. [9]

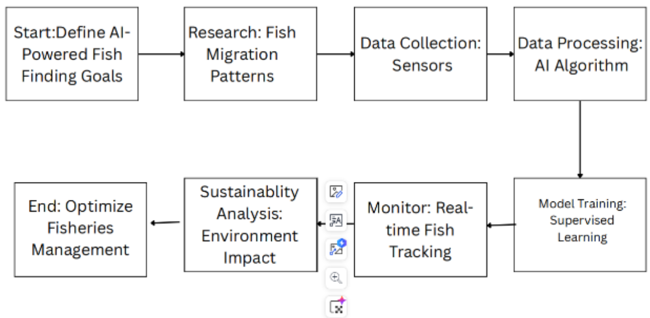

Figure 6 **Flowchart**

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