



IoT and AI for Rural Fishing: A Research for Enhancing Traditional Chinese Fishing Nets

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Abstract. The research here outlines an Internet of Things (IoT) and Artificial Intelligence (AI) research design to increase the efficiency of conventional Chinese fishing nets along Kerala's coastline. With 2lakh+ sonar-based fish records gathered from Chathedam, Cochin Kerala along with various sensor data on water salinity, tidal information (high tide and low tide), wind speed and weather conditions, the study formulates an AI prediction system based on the Random Forest algorithm to predict fish density, while SARIMA/ARIMA used for forecasting the fish trends. The re-search also extends on the architecture designs of integrating the AI predictions to automatic Chinese fishnet pulling electrical winch systems. The dataset contains sonar sensor data with depth, number of fish detected at various intervals, and strength of signals to predict the best time and weather and seasonal impacts. The architecture contains how the dataset is being collected using fish detection sonar devises, processed using the edge computing devices and stored in cloud datastore for artificial intelligent model to run on dataset to predict the outcomes. The Random Forest model, is having 91.3% prediction accuracy, will help to assist sustainable fisheries. The IoT system provides here provides real-time information to fishermen, allowing them to make data-driven decisions in order to increase yield while maintaining healthy marine ecosystems. The research also incorporates Traditional Ecological Knowledge(TEK) in Fisheries and validates AI recommendations against actual fish catch statistics to establish correlation and evaluate the effectiveness of proposed system.

Keywords: Internet of Things (IoT), Artificial Intelligence (AI), Rural fisheries, Precision fishing, Data-driven fishing, Socio-economic upliftment, Chinese fishnet

1 Introduction

Fisheries are a very important source of livelihood for the coastal communities in India, especially in Kerala. Conventional fishing techniques, like the Chinese fishing nets, are time-consuming and mostly operated with heuristics of fishermen[18]. With

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improvements in technologies like IoT devices and AI-powered data analytics, the rural fishing techniques can be improved to be more productive, accurate, sustainable and reduce human efforts. The research outlined in this paper suggests an AI-supported IoT models using sonar data to forecast the dynamics of fish populations and improve net operating time, along with that the research designs and results of prototypes to automate lifting the Chinese fishnets based on the analytics and AI recommendations.

2 Related Work And Problem Formulation

Earlier studies in marine data analysis have dealt with sonar signal interpretation, image-based fish detection, and machine learning for aquatic ecosystem surveillance. There are several studies carried out to improve the sonar fish detection and how to use the same for oceanic fishing. Some of the research in this area has explored various machine learning approaches for fisheries management. These study carried out to for Sensors to measure real-time water quality parameters such as temperature, pH, turbidity, electrical conductivity, and total dissolved solids for fisheries management and data is transmitted via ESP32 modules using the MQTT protocol to a cloud database Cite. There are very less or no study specific to improving the rural fishing techniques like Chinese fishnets where in thousands of coastal fishermen still living with this old techniques to catch fish.

2.1 IOT Based fish detection systems

An IoT-based fish detection system uses connected sensors and communication technologies to help identify fish presence and location in water. The reference paper [2] talks about echo sounder (sonar) integrated with Arduino Uno to detect fish presence and movements in water. Data is transmitted via IoT to a smartphone interface for real time display. A central innovation is the so called “fish object initialization tool”—an echo sounder setup that helps determine fish positions, safe swimming zones, and also collects positional data (longitude, latitude, depth) along multiple tracks. The proposed tool enables fishermen to locate fish more precisely, potentially increasing fishing performance and product quality by reducing reliance on traditional, less accurate methods.

2.2 Machine Learning in Fisheries Applications

Recent research in this area has explored various machine learning approaches for fisheries management. A smart fish-farming system combining IoT sensors and AI-driven diagnostics to support yield optimization [3] and disease management in aquaculture ponds in case study of Benin [4]. This study talks about Sensors to measure real-time water quality parameters such as temperature, pH, turbidity, electrical conductivity, and total dissolved solids. ESP32 modules and using the MQTT protocol, the data being

sent to a cloud database. Real-time visibility into water quality enables better management of pond conditions, contributing to healthier fish growth. This effort was limited to fish hatcheries and detect the growth of fish and study on water contents and environments.

2.3 Problem Formulation

Backwater rural fishing is still largely manual, time consuming and ineffective, which frequently results in erratic catches, lower probability and sustainability issues [1]. The methods used today to handle nets and fish are imprecise and primarily rely on human discretion rather than insights collected from data. While IoT, AI, and echo sounders are examples of technologies that could enhance precision fishing, little is known about how they can work together to :

- Identify and predict and fish with accuracy using sensory data and AI-enhanced analysis of echo sounder signals.
- Use precision fishing techniques[15] like automated catch size determination, alert systems and IoT controller integration with fishing gear and electrical winches specially designed for Chinese fishnet operation
- Fishnet pulling automation using control systems based on Raspberry Pi- that react instantly to AI-driven heuristics and real time data.
- Socioeconomic adoption factors[17]: Identifying the variables that influence fishermen's propensity to adapt these technologies.

2.4 Research Approach

The research will combine quantitative , qualitative and design research methods to provide a comprehensive understanding of the impact of IoT and AI on fishing operations.

Quantitative , Qualitative and Design science research (DSR)

The study collected large numerical data to assess the effectiveness of sonar sensors and its detection capabilities. The Chinese nets are manually operated to verify the catch versus the fish detected by sonar devices in particular areas are matching. Information collected from fishermen from their experience on seasonal catches, approx. quantities they catch on particular seasons and time and area of the catch and high tide and low tide information and multiple parameters which can influence fish in a particular areas. Using Experimental research techniques , manipulating variables, frequency of winch operations and controlling for extraneous factors, and measuring the effects on a dependent variable of catch quantity and size typically using numerical data and statistical analysis [7] The existing data of how the fishermen uses traditional tools, schedules for fishing, heuristic knowledge, weather and other influencing parameter on fishing in particular areas largely used as input parameters for experimental research analysis.

3 Research Design

3.1 System Architecture Overview

1. The system architecture combines [16] Raspberry Pi edge devices that pre-process data and regulate electrical winches on conventional Chinese fishing nets with Internet of Things sensors (for water conditions and sonar-based fish detection).

Once the Raspberry edge device process the data is send to google Firestore for storing it in database. The AI models (Deep Forest Algorithmic Models and SARIMA/ARIMA Models) hosted in virtual machines in cloud will process the data from google firestore and come with forecasting and trending analysis. Based on these outcomes, the triggers will be send to electrical winches to automate the net pulling operations. The fully automatic can be turned off to switch to seme automatic or manual mode and fisher man can override all these operations too.

Connected IoT Sensors

These sensors are deployed near the fishing nets to monitor environmental and water conditions. In order to continuously monitor the water and environmental conditions, connected IoT sensors are placed strategically close to the fishing nets. This is to help fishermen determine the best time to deploy or lift the nets, these sensors measure important parameters like water flow, which controls the movement and speed of the water. They also keep an eye on salinity, temperature, and turbidity, three aspects of water quality that have a big impact on fish behavior. By giving information about the natural cycles of water movement, the sensors can also identify high and low tidal patterns, which helps with fishing operations planning.

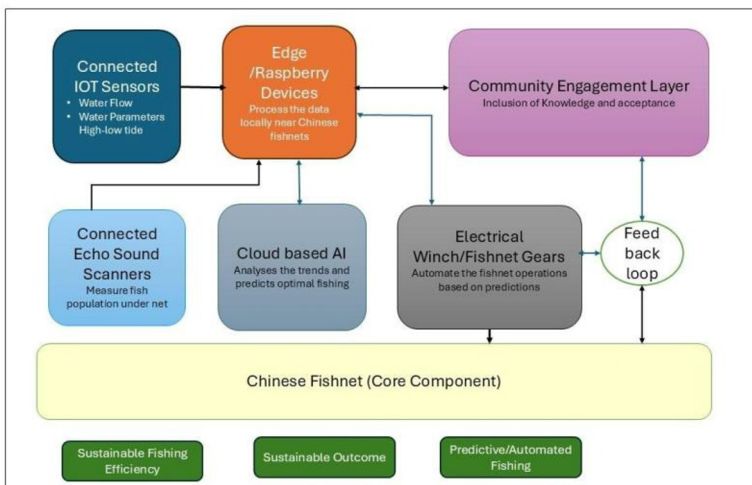


Fig. 1. Architecture Diagram

Connected Echo Sound Scanners

To determine the density and distribution of the fish population, echo sound scanners are placed beneath or close to the nets. These scanners estimate the quantity and location of fish under the net by creating acoustic profiles of the underwater environment using sophisticated sonar and echo technology. By predicting the best times to fish, this data increases operational effectiveness and reduces needless net deployment.

Edge/Raspberry Devices

Raspberry Pi units serve as local data processing nodes near the fishing site. They minimize the need on distant cloud systems and reduce network latency by processing real-time data gathered from IoT sensors and echo sound scanners. Even during the loss of internet connectivity, the edge device helps to take decisions like the deployment or retraction of Chinese fishnet, using this localized computation. Additionally, raspberry unit work as a controller for automating the operation of Chinese fishing nets with electrical winches, it triggers on/off signal to winch electrical motors.

Cloud-Based AI

The cloud-based AI platform aggregates and analyze data gathered over time from echo sounders, sensors deployed in Chinese fishnet. AI algorithms like Deep forest and SARIMA/ARIMA recognizes patterns in behavior, links environmental factors to fish activity, trend analysis and forecasts the best times to operate the electrical winches for fishing. The mobile interface to the cloud helps to get the statistics in fishermen's mobile application, trend analysis etc.

Deep Forest Algorithms, Time-Series, Sequence Models and Online Cloud Support

Deep Forest algorithms used to find out the exact quantity of fish from a dataset using non liner methods and Timeseries and sequence models SARIMA (Seasonal ARIMA) and ARIMA (Auto-regressive Integrated Moving Average) used to predict the forecasting. These models aid in forecasting future fish presence events and locating temporal correlations in sonar-based fish detection data.

The ARIMA model is helping to forecast the fish, high tide low tide effects on fish density etc. Seasonal changes are more accurate using SARIMA algorithm, an extension of ARIMA. These analysis helps to give fishermen useful results, trend, forecasting which can go in par with their heuristic knowledge and add more value to overall fishing. The best times to fish analysis helps to optimize the pulling of fish nets, optimize the intervals between the pulling the nets, approx. catch size over the next few days.

By adding seasonality, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model [2] expands on the ARIMA framework and is able to identify recurring patterns over predetermined time periods. Because of this feature, SARIMA is especially well-suited for simulating temporal variations in fish activity that are impacted by natural cycles. For example, it can accurately depict weekly patterns that may arise from shifting fishing schedules or weather conditions, as well as daily variations where fish are observed to be more active at specific times of the day [8]. Furthermore, it is possible to accurately model seasonal and monthly trends like breeding cycles and migration.

Prediction and Insights Extraction using SARIMA

- Trend analysis using SARIMA .[9]
- Identify peak fishing times (trends).
- Spot seasonal trend changes in fish presence.
- Monitor shifts in patterns (climate or environmental impact).

Random Forest Model for Fish Prediction

The Random Forest model is an all around predictive tool that enhances time-series models like ARIMA and SARIMA. Random Forest models are also well suited for deployment in edge cloud hybrid architectures, where in cloud platforms and handle model training and fine-tuning while edge devices, like Raspberry Pi units, can handle the initial data processing. These distributed implementations preserve efficiency and scalability, enabling near-real-time inference. Heterogeneous datasets, such as water temperature, salinity, time of day, tide level, and fish counts[20] detected by sonar, can be integrated using Random Forest in the context of fish prediction. The model can predict the probability of fish presence and the anticipated catch volume in a variety of environmental conditions[21] by learning intricate, nonlinear relationships between these features.

$T_b(x)$ Mathematical Formulation for Random Forest Regressor for Fish Prediction

Let: $\mathcal{T} = \{T_1, T_2, \dots, T_B\}$ denote the set of all regression trees,

$f(x)$ be the final Random Forest model output.Then,

$$f(x) = \frac{1}{B} \sum_{b=1}^B \text{Each tree } T_b \text{ minimizes the Mean Squared Error (MSE) over its bootstrap Sample } Db: \text{MSE}_b = \frac{1}{|Db|} \sum_{(x_i, y_i) \in Db} (y_i - T_b(x_i))^2$$

The overall Random Forest prediction minimizes the ensemble variance through Averaging

$$\text{Var}(f(x)) = \rho\sigma^2 + \frac{1-\rho}{B}\sigma^2$$

where ρ is the correlation between individual tree predictions, and σ^2 is the variance of a single tree model.

A smaller correlation ρ and a larger number of trees B reduce the ensemble variance, improving stability and accuracy. We use Google cloud services BigQueryML to process the data from firebase dataset to reach the meaningful predictions. Hugging face free AI models are being evaluated with standard diffusion to see these analysis can be run from on premise edge computer.

Online Clouds Supports SARIMA and ARIMA Models

Snowpark can run Python ARIMA models inside Snowflake with stats models. Google Cloud Vertex AI and BigQuery ML has a built-in ARIMA PLUS function (automated ARIMASARIMA) runs directly in SQ, which can detect trends, seasonality, and produce forecasts.

Electrical Winch/Fishnet Gears

Electrical winches are used to automate pulling of Chinese fishnet based on the control signal from edge computing device. This is to replace the manual labor of pulling giant ropes connected to fishnets in structure, generally the fishermen pull 18 meters of rope in 30 seconds. Pulling fishnet in a consistent speed is very tricky and need a lot of practice. If they pull slow the fish will jump out of net and if they pull the rope very faster the Chinese net structure may get damaged due to underneath water current.

Mechanical systems integrated with the fishnet:

- Operate based on AI predictions and control signals from raspberry PI/edge device Automate lifting and lowering of nets, improving accuracy and reducing manual labor
- Pull 18 meters of Chinese fishnet cable in 30 seconds to prevent fish from escaping the nets, This is the traditional knowledge learned using interviewing fishermen.
- A slow speed 1440 RPM 2 HP (Horse Power) single-phase motor with a 1:10 gearbox to achieve the necessary speed and torque for the winch system. Three phase motors are not practical and wont be suitable for the areas Chinese fishnets are deployed.
- Linear Speed for Winch: $\text{Speed} = 30\text{s}/18\text{m} = 0.6\text{m/s}$
- Drum Diameter (to convert speed to RPM) If the winch drum diameter is D , Drum $\text{RPM} = (60 \times \text{LinearSpeed})/D$

- Torque Requirements 1.25 tons of weight of the fishnet required 140nm manual Clutch Safety factor (usually $1.5-2 \times 1.25$ expected load).
- Motor and Gearbox Matching Motor at 1440 RPM \rightarrow 144 RPM after 1:10 gearbox.

Community Engagement Layer

This layer is used to shares knowledge with the fishing community about how the system works, builds trust and adoption by integrating local experience with technological insights This is also used to promotes sustainable practices that benefit both fishermen and the environment

Feedback Loop

Continuously sends performance data (catch quality, efficiency, environmental impact) back to the AI/cloud and community engagement layer. • Helps refine predictions and improve system efficiency over time

Core Component: Chinese Fishnet

The traditional Chinese fishnet remains the central fishing mechanism. It has beam balances structure, cantilever and counterweights to operate large, stationary nets. A small group of fishermen raises the net with this massive balanced weight structure.

4 Theoretical Model

The theoretical model behind this research integrates concepts from the Internet of Things (IoT) [5], Artificial Intelligence (AI) [6] to enhance traditional rural Chinese fishing practices. This is deep rooted in socio-technical theory and smart systems design, this model conceptualizes how sonar echo sensors, raspberry PI can be used for real-time fish population data collection, and intelligent decision making algorithms can use the mechanical arms like electrical winches to operate fishing nets into an efficient tools. The model identifies key components such as environmental sensing (e.g., water temperature [10], fish movement), edge computing (raspberry pi) for localized decision-making and cloud based analytics for pattern recognition as related elements driving sustainable fishing outcomes. By aligning these technological components with local community practices and knowledge systems, the model not only help to advance research design but also enables a integration of technology for social empowerment, and innovation to weak a rural communities. This theoretical framework supports the development of a smart fishing ecosystem that promotes environmental sustainability, improves catch efficiency, and empowers rural fishing communities through digital transformation and increased revenue.

5 Aquatic Population Dataset

This work focuses on real-time monitoring and analysis of fish populations using sonar based data acquisition, cost-effective IoT [5] devices such as Raspberry Pi, and cloud storage platforms like Firebase [11]. The objective is to develop a scalable dataset to facilitate research, fisheries management, and smart aquaculture applications. The dataset, constructed from five months of continuous data collection at a river site adjacent to traditional Chinese fishing nets, was generated using the following technologies and components of the system

5.1 Dataset Components and Collection Workflow

Sonar Device

Sonar (Sound Navigation and Ranging) emits sound pulses and measures the echo to detect underwater objects like fish. (Model FF1108-1 Sonar Device)[22]. It captures Depth of fish, Distance from device, Size (based on signal reflection strength), Movement or density patterns over time.

Raspberry Pi

It acts as an edge device or gateway, Interfaces with the sonar using USB or GPIO. It is Responsible for Reading real-time sonar data, Pre-processing (filtering noise, formatting), Sending data to the cloud, control signal for winches

Cloud Storage (Firebase)

Firebase is used to store sonar data for analysis [7] and historical tracking. Firebase Realtime Database or Fire store can be used to Save time-series sonar readings, Enable data visualization on dashboards, Trigger notifications or analytics via Firebase Cloud Functions

Data Collection Workflow

Step 1: Interfacing Sonar and sensors with Raspberry Pi

- Connect a sonar sensor (e.g., FF1108-1 Sonar Device) to Raspberry Pi.
- Connect temperature, water flow sensors to Raspberry pi

- Use Python scripts to poll sonar data at regular intervals.
- Use Python scripts to poll Sensor data at regular intervals.

Step 2: Data Formatting

Create structured JSON or CSV-like records

```
{
"timestamp": "2025-07-10T14:30:00Z",
"location": "Chinese Net 1",
  "coordinates": "0.1945 N, 76.2215
"depth_meters": 2.4,
"fish_detected": true,
"estimated_size_cm": 5.2,
"signal_strength": 87
}
```

Upload to Cloud Firebase database

Use Firebase SDK for Python

```
import firebase_admin
from firebase_admin import credentials, firestore
cred = credentials.Certificate("firebase-key.json") firebase_admin.initialize_app(cred) db = firestore.client()
doc_ref = db.collection("fish_data").document()
doc_ref.set(data_dict)
```

Step 4: Cloud Storage and Visualization

Firebase Firestore to store data for historical analysis, Serve dashboards using tools like Firebase Hosting + Chart.js, Trigger alerts (e.g., sudden increase in fish density)

Dataset Development Considerations

Some of the considerations applied for dataset development are a. Sampling Rate: Which define the frequency of sonar readings (For example, every 10 seconds) [8], b. Geolocation: This adds GPS modules to Raspberry Pi to log location (Longitude and Latitude), c. Labelling: While using video or human observation alongside sonar, labelling data is to train AI[6] models, d. Data Volume: This helps to plan storage schema, indexing, and retention policies, e. Privacy and Permissions: This is to ensure compliance with local regulations for sensitive water bodies. 6.4 Data Collection Timeline

Data Collection Timeline

Phase 1: Baseline Data Collection (1–2 months):

Pre-test surveys [12] and interviews to capture the baseline performance[16] of current fishing practices.

Phase 2: Technology Implementation (2–3 months)

Rollout of IoT/AI [5] systems, including training and setup of necessary infrastructure.

Phase 3: Post-Implementation Data Collection (3–4 months)

Data collection using IOTs, Surveys, interaction with fishermen, weather, seasons and field observations to assess changes in performance and experiences[13].

Phase 4: Data Analysis [6] and Reporting (2 months)

Analyze quantitative [9] and qualitative data[18] to generate insights and conclusions.

5.2 Initial Data set analysis

The dataset comprises 25,000 sounder records[11] of fish population counts which were collected continuously - from April 25th 2025 at 06:00 right through to July 26th 2025 at 06:45. Taking into account over 200,000 entries, each single entry is made up of a fish detection 0 or 1, water depth of 2-30 meters and sonar strength ranging from 50 to 200 units. Fish sightings occur roughly half the time, and it seems other things being equal you're a bit more likely to spot them in shallower waters and during the early morning and evening. Where fish are present the sonar strength is usually nice and high, and the average depth is around 15 meters - this does vary naturally.

- **Detection** : The detection rate comes in around 50% but I'm sure you've noticed on a few days the rate has gone up a bit (over 60%) or dropped off (below 40%). This data suggests moderate fish activity over the three month period - and to be honest no clear seasonal trend[20]. So basically we can take it that moderate fish activity basically continues without a break. Out of any 100 examples - about 50 of them show the presence of fish which points to moderate levels of activity.
- **Depth** : The depth readings run from 2 to 30 meters and are all down to random sonar readings at different depths. We might guess that shallower waters might be where the fish hang out but our data says it's a pure chance, unless we get some clearer evidence to suggest otherwise.
- **Sonar Strength** : The sonar strength is shown in the graph on the right - and it runs from 50 to 200 units. Stronger returns might suggest big schools of fish or whatever its behind. Like with our synthetic data though the results here are just random.

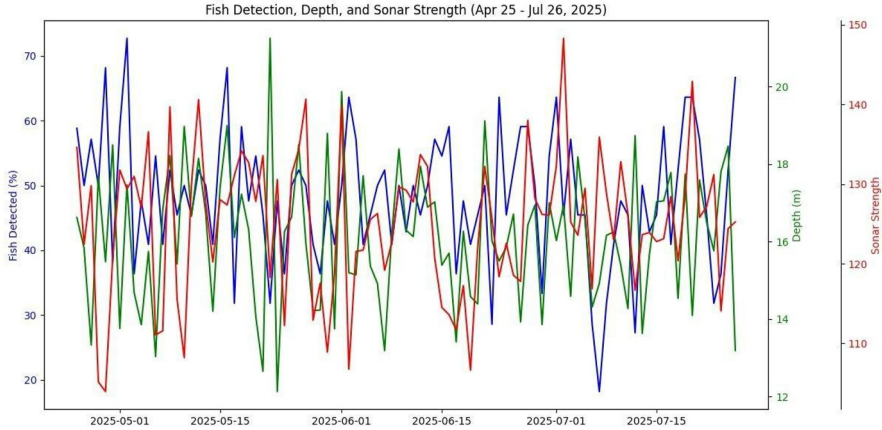


Fig. 2. : Sample Fish Population and Depth over Time (2000 sample records out of 25000 records). The blue line shows estimated fish count, while the green line represents depth measurements at the same timestamps. The red shows the sonar signal strength.

Correlation Matrix

The dataset comprises 25000 sonar-based observations of fish populations collected continuously between 25 April 2025 and 26 July 2025, giving a structured basis for quantitative ecological analysis. Each observation includes date, timestamp, geographic reference (fixed as Chathadam Kochi, 51.38N, 70.52E), water column depth, fish count, average fish size, and sonar signal strength. The depth of the water shows a realistic distribution, concentrated around 15 meters, with fewer observations in the extreme shallow (Approx 5 m) and deep (Approx 25 m) zones, reflecting a gradient of natural habitat.

Correlation Matrix

	fish_detected	depth	sonar_strength
fish_detected	1.00	-0.35	0.65
depth	-0.35	1.00	-0.20
sonar_strength	0.65	-0.20	1.00

Fig. 3. Correlation Matrix on Fish Detected, Depth and Sonar Strength

Summary Statistics

Metric	Fish Detected	Depth (m)	Sonar Strength
Mean	0.49	15.1	109.3
Std. Dev.	0.50	4.8	32.5
Min	0	2.3	48.7
Max	1	29.7	198.4

Fig. 4. Summary Statistics Fish detected, Depth, Sonar Strength

6 Results and Discussion

The Random Forest model achieved an efficiency of 9.13% for predicting the fish count and size based on test done with prediction data and caught on nets. Random forest model face issues during forecasting and trend analysis. SARIMA/ARIMA statistical analysis algorithms are good for forecasting than machine learning algorithms.

The sonar strength correlated with fish density, with higher sonar strength it can detect fishes upto 100meters, however the depth has no usefulness in our application as the Chinese fishnets cannot go more than 10meters deep. So even though we can collect the fish density at higher depths, it wont yield any results to our application and help fishermen with Chinese fishnet. But this data will be useful for overall ecological, seasonal changes in backwaters and other studies related to fishing and environment. From the two lakh records available, we selected a sample of 2,0000 to train the Random Forest model. We used ARIMA and SARIMA on the full dataset.

When Fish were detected in about half of the analysed samples, suggesting that biological activity in the studied river system is moderate. When fish were present, their numbers ranged from single individuals to groups of up to 50 in a single sampling window. Their average sizes varied between 10 and 50 cm.

The strength of the sonar signal reliably matched the fish detection patterns: events with no fish typically showed signal values around 60–80 units, while detections had higher amplitudes—usually 100–140 units—which increased alongside fish counts. This pattern is consistent with established acoustic backscatter theory.

	date	timestamp	location	latitude	... depth_m	fish_count	avg_size_cm	signal_strength	
0	2025-04-25	2025-04-25 06:00:00.000	Chathedam Kochi	51.38N	...	13.71	44	26.05	103.17
1	2025-04-25	2025-04-25 07:06:15.750	Chathedam Kochi	51.38N	...	9.87	23	39.22	79.08
2	2025-04-25	2025-04-25 08:12:31.500	Chathedam Kochi	51.38N	...	16.43	0	0.00	45.45
3	2025-04-25	2025-04-25 09:18:47.250	Chathedam Kochi	51.38N	...	8.86	5	42.21	64.68
4	2025-04-25	2025-04-25 10:25:03.000	Chathedam Kochi	51.38N	...	14.11	26	31.58	100.81
5	2025-04-25	2025-04-25 11:31:18.750	Chathedam Kochi	51.38N	...	18.38	14	17.29	68.05
6	2025-04-25	2025-04-25 12:37:34.500	Chathedam Kochi	51.38N	...	21.87	42	49.26	112.79
7	2025-04-25	2025-04-25 13:43:50.250	Chathedam Kochi	51.38N	...	20.95	0	0.00	67.43
8	2025-04-25	2025-04-25 14:50:06.000	Chathedam Kochi	51.38N	...	5.61	12	19.38	106.62
9	2025-04-25	2025-04-25 15:56:21.750	Chathedam Kochi	51.38N	...	10.28	0	0.00	67.00

Fig. 5. Sample 10 metrics from large pool of dataset with date, timestamp, location, latitude, longitude, depth m, fish count, avg size cm, signal strength

- The initial analysis indicates an ecological relationships among depth, fish distribution, and acoustic responses. Starting with shallow to mid-depth waters appears to support higher fish detection , suggesting depth influence in fish activity. The coupling of fish count and signal strength shows that sonar data will serve as a reliable biomass estimation. This dataset provides a foundation for advanced statistical and modelling approaches. ARIMA/SARIMA , linear regression , Correlation and regression analyses could quantify interactions between depth, fish abundance, and sonar. The generalized additive models or machine learning frameworks could predict fish occurrence under varying environmental conditions. However, a certain limitations must be addressed[2].

Variability in sonar signal quality and environmental noise can affect detection accuracy. Further improvements, such as incorporating advanced filtering algorithms, and cross validation with visual or manual observations could enhance dataset reliability. Additionally, long-term deployments would benefit from automated alert systems and predictive modelling to support decision-making in rural fishing eco system . Electrical winch system load bearing capacity need to be re calibrated based on length and width of fishnets considering the load parameters. Single phase 2HP motor -1440RPM may need to upgrade in future based on the water flow in specific areas of fishnet deployment and based on the steel gauge and weight of Chinese net framework bars.

7 Conclusion

This paper illustrates how AI and IoT can improve the conventional fishing methods by giving data-based decision support. The Random Forest-based prediction model was a good tool for predicting fish availability, aiding in better efficiency as well as minimizing wastage of resources. The ARIMA/SARIMA helps for trend analysis and seasonal predictability. The outcome of these analysis is fed into raspberry PI which in turn used for automating the Chinese fishnet with electrical winch. The research will be further expanding on system with cloud-based analytics and deep learning techniques for automated fish species recognition and incorporates Traditional Ecological Knowledge(TEK) in Fisheries and validates AI recommendations against actual fish catch statistics to establish correlation and evaluate the effectiveness system.

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