FinGuard: An AI-Integrated Mobile Application for Predictive Health Monitoring in Ornamental Fish Keeping

Kent Justine Z. Nacionales[1*], Gary U. Jumao-As Jr[2], Carla Mikaela E. Manuel[3], Vivien A. Agustin[4], Dr. Ronald B. Fernandez[5]

[1,2,3]Department of Information Technologies, Jesus Reigns Christian College Foundation, Malate, Manila, Philippines

[4,5]La Consolacion University Philippines

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ABSTRACT

Fishkeeping has evolved into a commercially and recreationally successful venture in the Philippines, but fishkeepers still struggle in maintaining steady aquatic conditions as well as identifying any signs of fish stress or diseases. Existing fish monitoring solutions are fragmented, as some measure water quality parameters while others observe fish behavior without integrating them to provide predictive health analysis. In this paper, FinGuard – an AI-enabled fish predictive health monitoring mobile application is proposed. The system utilizes IoT sensors to monitor the water quality of ornamental fish aquariums in real-time by collecting data about water parameters, including temperature, pH, dissolved oxygen, and turbidity. FinGuard is able to analyze fish behaviors via a Computer Vision module, which analyzes video recordings and provides predictions of health issues based on the analyzed information and collected environmental conditions. The system also has a logbook for aquariums, an analytics dashboard showing the current status of all aquariums, and a recommendations module providing relevant suggestions about actions necessary to improve fish health. The mobile application is being built using Agile software development lifecycle with the use of Flutter framework for mobile app development, Python and Flask for backend, and TensorFlow and OpenCV libraries for machine learning and computer vision purposes, respectively. Finally, Firebase will be used as a cloud database.

Keywords: Ornamental Fish Keeping, Artificial Intelligence, Internet of Things, Computer Vision, Machine Learning, Predictive Health Monitoring, Mobile Application

INTRODUCTION

The culture of ornamental fish has become a popular pastime as well as a growing sector within aquaculture in the Philippines. With the increasing popularity of home aquarium keeping, there is a rising demand for proper aquatic management practices to ensure the health and survival of ornamental fish species. Maintaining stable water conditions remains a significant challenge for fish keepers, as sudden changes in temperature, pH level, dissolved oxygen, and water clarity can quickly cause stress, disease, and even mortality in sensitive fish. As aquarium systems become more advanced and more densely stocked, there is a clear need for efficient and intelligent monitoring solutions that can help maintain optimal environmental conditions and support early detection of potential health risks.

Indeed, water stability in terms of pH, temperature, oxygen levels, and ammonia content remains a critical aspect in maintaining good health in aquarium fish. Any delay in monitoring deteriorated water conditions may lead to fatal consequences, as certain fish, like guppies, are extremely vulnerable to ammonia poisoning, and others, such as goldfish, need oxygen stability for survival (Lobillo-Eguíbar et al., 2023). Traditional aquarium maintenance that includes manual water testing performed occasionally is simply not enough to detect the changes quickly enough and ensure fish survival. As a result, many breeders lose their fish for no reason at all.

Using modern technology allows one to install sensors to monitor such parameters as temperature, lighting, oxygen, and pH automatically and even share data about these factors via smartphones to maintain the stability (Flores-Iwasaki et al., 2025). However, commercially available aquarium monitors do not provide information beyond the basic threshold notifications and cannot predict possible future threats or interpret the fish's behavior (Flores-Iwasaki et al., 2025). Modern artificial intelligence (AI) and machine learning (ML) techniques may fill this gap, as several studies confirm the feasibility of using AI and computer vision to analyze aquarium data for detecting fish stress symptoms and predicting possible diseases (Patro et al., 2023). With such innovations, fish can be monitored and any deviation from normal behavior detected with remarkable precision (Al-Abri & Bourdoucen, 2025).

Nevertheless, there is still no advanced integration of predictive health monitoring systems for Filipino ornamental fish keepers. Commercial devices focus on monitoring water quality or fish behaviors solely, but do not integrate these two types of monitoring and combine them into a comprehensive application. Thus, the proposed solution would be an innovative integration of various technologies, namely, IoT sensors and computer vision, into a predictive system powered by AI. It is believed that using this technology could help breeders and enthusiasts in reducing ornamental fish mortality and improving the well-being of fish in general. At the same time, such technology could also make the Philippine ornamental aquaculture industry more profitable.

The main objectives of this study include: (1) creating a monitoring system based on IoT sensors to allow real-time analysis of water quality and proactive alerts; (2) developing a computer vision module powered by AI to detect abnormal fish behavior associated with developing disease; and (3) implementing ML algorithms to predict possible future risks and offer care recommendations for keeping the fish healthy.

RELATED LITERATURE AND STUDIES

Recent scholarly works indicate the increasing effectiveness of IoT and AI applications to monitor aquaculture and ornamental fish populations. As pointed out by Flores-Iwasaki et al. (2025), sensors such as pH and temperature sensors, particularly DS18B20, are frequently applied to perform aquaculture monitoring tasks, whereas IoT technology enables enhancing fish growth and minimizing their death rate. Similarly, studies by Shete et al. (2024) and Jais et al. (2024) confirm the possibility of creating affordable and efficient IoT monitoring systems that would offer continuous feedback on water quality with acceptable levels of accuracy.

Moreover, several research studies demonstrate the feasibility and effectiveness of hardware and software components utilized within the FinGuard project. Thus, for instance, Hermansyah et al. (2023) developed a monitoring system for ornamental fish in an aquarium that includes such components as ESP8266, DS18B20, pH sensor, and mobile monitoring performed using application Blynk, while Paturusi and Susilo (2025) developed an ESP32-based monitoring system with DS18B20, pH, and TDS sensors for freshwater ornamental fish ponds. The above-mentioned information shows that monitoring of water quality using microcontroller devices is feasible for ornamental fish management and corresponds to the hardware design of the proposed monitoring system.

In addition, there have been some previous research works related to AI-based fish monitoring. Thus, according to Al-Abri and Bourdoucen (2025), computer vision techniques may be effectively used to detect fish, track their movements, and assess their state. Meanwhile, Patro et al. (2023) revealed that machine learning approaches may be used to analyze the behavior of ornamental fish and estimate their condition based on the data collected by IoT sensors. Moreover, according to studies by Nugraha and Rosita (2024) and Aziezah et al. (2025), the use of IoT and AI technologies allows performing real-time aquarium monitoring and water quality classification, respectively.

However, despite the growing number of studies involving IoT monitoring systems and AI-based fish behavior analysis, most existing solutions remain fragmented because they focus only on environmental monitoring or behavioral analysis independently. Few systems integrate IoT sensing, computer vision, machine learning prediction, and mobile monitoring within a single intelligent platform specifically designed for ornamental fish keeping. This research gap highlights the need for a unified predictive health-monitoring system capable of combining environmental sensing, behavioral observation, and intelligent recommendation generation in real time. Therefore, the FinGuard system was developed to address these limitations by integrating IoT, artificial intelligence, and predictive analytics within one mobile application.

RESEARCH DESIGN AND METHODOLOGY

Research Design

The research design used in this study is a developmental research design because the main aim is to create, test, and evaluate an effective system that can help ornamental fish keepers. The FinGuard system will function as an efficient mobile app that can be able to monitor the state of the aquarium and give predictive alerts regarding the health status of the fish. The use of this research design is due to the identified gap in monitoring and literature supporting the efficiency of the IoT and AI technology integration in managing the aquaculture industry (Flores-Iwasaki et al., 2025; Shete et al., 2024; Aziezah et al., 2025). In order to develop FinGuard, the Agile Software Development Life Cycle (SDLC) will be adopted. This software development life cycle will be appropriate for the system since FinGuard will have different interrelated modules such as IoT sensors, behavioral analysis from videos, predictive algorithmic model, mobile app interface, and logging. Thus, Agile will facilitate iterative testing and debugging of each module independently.

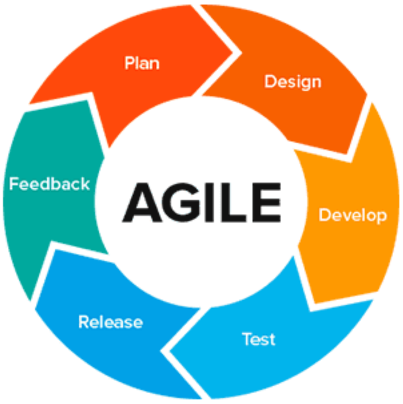


Figure 1: Agile Model

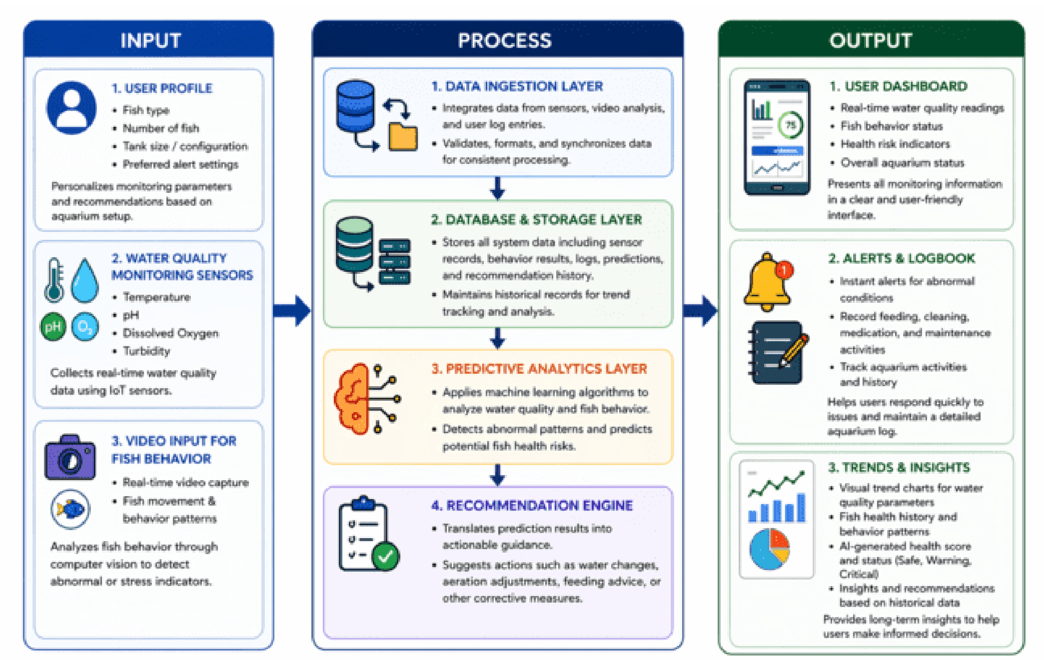
The FinGuard system development will occur in six stages via an Agile methodology. In the Planning Stage, the goals, characteristics, and technical specifications of the system are determined. Some important elements that need to be considered are the IoT sensors, camera input, cloud database, and machine learning model. Potential risks associated with the system, such as sensor reliability, lighting, availability of the Internet, and accessibility to users, should be discussed during this stage. The Designing Stage involves coming up with the design for the whole system in terms of the structure, data relationships, functional processes, and user interface. These are what will guide the developers in implementing the system in the Development Stage. The implementation entails the development of the mobile app, sensor installation, machine learning, and dashboard. The Testing Stage consists of evaluating the functionality and effectiveness of the system in terms of sensor response, consistent behavior detection, correct alerts, and usability of the dashboard. The Deployment Stage involves installing the system in the actual aquarium and testing its performance.

Dataset Description

There are three types of data on which the FinGuard works. The first type of data is environmental data, which includes measurements of water temperature, pH, amount of dissolved oxygen, and turbidity. These are factors that directly impact the well-being of fish since a deviation even in the optimal range causes them stress, poor immunity, or even susceptibility to diseases. Second are behavioral data, which include swimming behavior, frequency of movements, feeding behavior, breathing through gills at the water surface, tendency to group, or absence of any activity. Third are historical data, which consist of previously registered parameters, registered alerts, and suggested actions.

System Architecture

The system architecture of FinGuard is organized around three principal components: input, process, and output. These components work together to enable real-time monitoring, intelligent analysis, and user-friendly presentation of aquarium health information.



INPUT

1. USER PROFILE
- Fish type
- Number of fish
- Tank size / configuration
- Preferred alert settings

Personalizes monitoring parameters and recommendations based on aquarium setup.

2. WATER QUALITY MONITORING SENSORS
- Temperature
- pH
- Dissolved Oxygen
- Turbidity

Collects real-time water quality data using IoT sensors.

3. VIDEO INPUT FOR FISH BEHAVIOR
- Real-time video capture
- Fish movement & behavior patterns

Analyzes fish behavior through computer vision to detect abnormal or stress indicators.

PROCESS

1. DATA INGESTION LAYER
- Integrates data from sensors, video analysis, and user log entries.
- Validates, formats, and synchronizes data for consistent processing.

2. DATABASE & STORAGE LAYER
- Stores all system data including sensor records, behavior results, logs, predictions, and recommendation history.
- Maintains historical records for trend tracking and analysis.

3. PREDICTIVE ANALYTICS LAYER
- Applies machine learning algorithms to analyze water quality and fish behavior.
- Detects abnormal patterns and predicts potential fish health risks.

4. RECOMMENDATION ENGINE
- Translates prediction results into actionable guidance.
- Suggests actions such as water changes, aeration adjustments, feeding advice, or other corrective measures.

OUTPUT

1. USER DASHBOARD
- Real-time water quality readings
- Fish behavior status
- Health risk indicators
- Overall aquarium status

Presents all monitoring information in a clear and user-friendly interface.

2. ALERTS & LOGBOOK
- Instant alerts for abnormal conditions
- Record feeding, cleaning, medication, and maintenance activities
- Track aquarium activities and history

Helps users respond quickly to issues and maintain a detailed aquarium log.

3. TRENDS & INSIGHTS
- Visual trend charts for water quality parameters
- Fish health history and behavior patterns
- AI-generated health score and status (Safe, Warning, Critical)
- Insights and recommendations based on historical data

Provides long-term insights to help users make informed decisions.

Figure 2: FinGuard System Architecture

Input components comprise three parts. The first one is the user profile, which allows the fish keeper to fill in information on the fish type, tank size, number of fish, and alert preferences for personalizing monitoring. Another part is IoT water quality sensors, which gather data on temperature, pH, dissolved oxygen, and turbidity in the tank in real-time. Finally, there is the video input part based on the ESP32-CAM module for capturing live videos of fish.

The process part includes four layers. First, data ingestion collects data from sensors, video, and logs of user activity. Secondly, validation and synchronization of all input data are performed. Thirdly, the database and storage layer allow for saving all information related to the system, such as data collected by the sensors, results of behavioral analysis, predictions, and logging. Next, the predictive analytics layer uses the data to find possible issues using machine learning algorithms. Finally, the recommendation engine turns the result of the predictions into specific recommendations, such as changing water, adjusting the aerator, altering the frequency of fish feeding, and consulting the issue with an expert.

Output components provide the result of operations via three different interfaces. Firstly, a user interface includes real-time data on water quality parameters, fish behavioral status, risk assessment, and aquarium state as a whole. Secondly, the alerts and logbook allow receiving alerts in case of problems detected by the system and recording actions taken regarding aquarium maintenance, such as feeding or cleaning the tank. Thirdly, the trends and insights show trends in graphs for water parameters and fish health, as well as the result of analysis in terms of AI-generated health status score being either Safe, Warning, or Critical.

System Methods

This section presents the three main methods used by the proponents to develop the core features of the FinGuard system. Each method corresponds to a specific monitoring challenge identified in the study, namely environmental water quality tracking, fish behavioral observation, and predictive health risk analysis, ensuring that every technical approach directly supports the overall goals of the system.

Three core methods guide FinGuard's operation, each addressing a distinct aspect of ornamental fish health monitoring.

Method 1: Environmental Water Quality Monitoring and Health Assessment

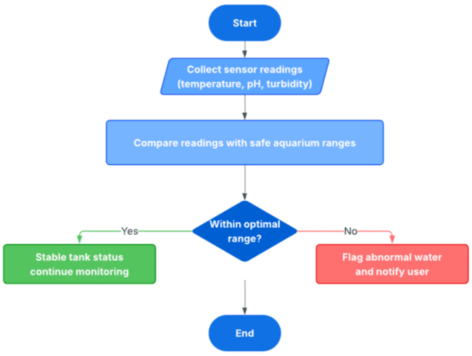


Figure 3: Environmental Water Quality Monitoring and Health Assessment

The technique controls the constant monitoring and analysis of water quality information. IoT devices monitor temperature, pH, and turbidity periodically and relay information to the mobile application, where the information is then analyzed relative to the acceptable values for the desired ornamental fish variety. In the event that all the parameters are within the ideal values, the condition of the aquarium is noted as being normal. However, in the event any of the parameters goes beyond or is about to breach the safe values, a problem is identified, and the system immediately alerts the user.

Method 2: Fish Behavior Observation and Pattern Tracking

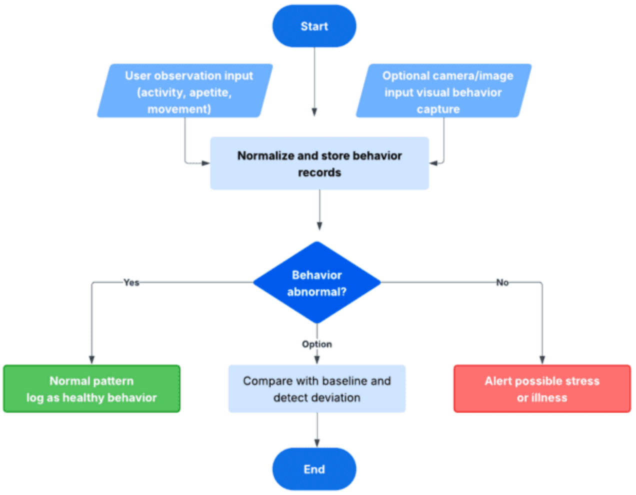


Figure 4: Fish Behavior Observation and Pattern Tracking

Using this approach, FinGuard is able to collect and analyze the fish’s behavior based on two sources of input: recorded behavior observed by users, such as slowed movements, strange swimming habits, gasping for air, lack of appetite, and abnormal grouping behaviors, and optional video feeds from the ESP32-CAM camera. These collected behavioral patterns are analyzed and compared against known healthy behaviors. In the event that fish behaviors indicate abnormalities, the user will be alerted that their fish may be experiencing stress and ill health. This technique is useful when combined with environmental monitoring, as some fish can show signs of being sick through their behaviors before any changes to the environment occur.

Method 3: Predictive Health Risk Analysis and Recommendation Generation

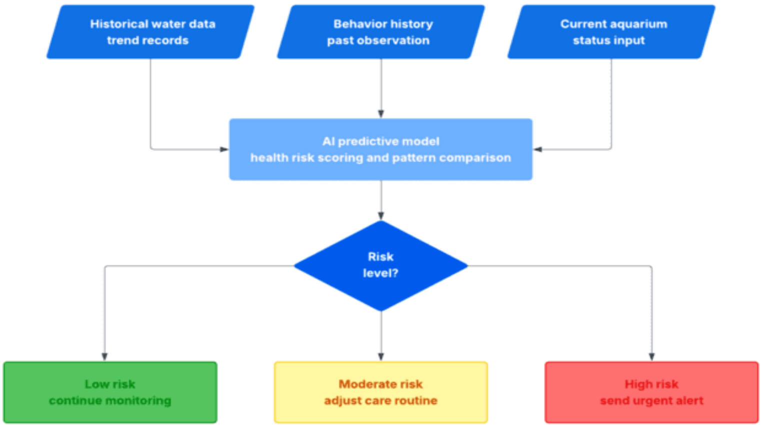


Figure 5: Predictive Health Risk Analysis and Recommendation Generation

The technique combines the use of historic water quality parameters and behaviors in order to predict the health risks associated with a given set of observations. In doing so, the predictive model will examine trends in behavior that can be attributed to any one of various patterns, including the gradual degradation of water quality, consistent temperature fluctuations, or repeated aberrations in fish behavior, and classify them as either low, moderate, or high risk. Based on the classified risk, the recommendation engine provides a series of actionable advice for addressing the potential risks, including carrying out a water change, changing feeding habits, testing filtration systems, adding aeration, or visiting an aquatic health expert.

Validation Procedures

To evaluate the effectiveness of the FinGuard predictive monitoring system, validation procedures were conducted on the environmental monitoring module, behavioral analysis module, and integrated predictive health-risk model. The validation process aimed to determine whether the system could accurately classify aquarium conditions and identify fish stress indicators using environmental and behavioral inputs. The collected dataset consisted of environmental sensor readings, behavioral observations, and historical monitoring records. Environmental data included temperature, pH level, dissolved oxygen, turbidity, and water-level measurements gathered from the IoT sensor network. Behavioral data included fish movement patterns, schooling cohesion, feeding response, surface activity, and movement irregularities collected through the ESP32-CAM module and manual observation. Historical monitoring records included previous alerts, maintenance activities, and aquarium-condition logs.

Before model evaluation, all data underwent preprocessing procedures that included timestamp synchronization, normalization, missing-value correction, and annotation validation. Behavioral observations were manually labeled into three classifications: Safe, Warning, and Critical. Safe labels represented stable water conditions and normal fish behavior, while Warning and Critical labels represented increasing environmental imbalance and behavioral abnormalities associated with fish stress. The dataset was divided into training, validation, and testing subsets to reduce overfitting and improve predictive reliability. Approximately 70% of the collected data were used for training, 15% for validation, and 15% for final testing. OpenCV was used for motion processing and behavioral feature extraction, while TensorFlow was utilized for classification and predictive analysis.

Predictive Model Architecture

The FinGuard predictive monitoring system utilizes a supervised machine learning architecture designed to classify aquarium conditions into Safe, Warning, and Critical states using combined environmental and behavioral inputs. The model integrates IoT sensor readings and computer vision-based behavioral indicators to generate predictive health-risk assessments in real time.

Environmental features include water temperature, pH level, dissolved oxygen, turbidity, and water-level measurements collected through the IoT sensor network. Behavioral features include schooling cohesion, movement stability, feeding response, and surface activity extracted from video streams captured using the ESP32-CAM module. OpenCV was utilized for image preprocessing, motion tracking, and behavioral feature extraction.

The extracted features were processed using TensorFlow-based classification and predictive analysis. The predictive model was trained using labeled aquarium-condition datasets and optimized through iterative validation procedures. During prediction, the system evaluates both environmental and behavioral indicators simultaneously before assigning a corresponding health-risk classification and confidence level. The integrated architecture enables the system to perform real-time monitoring, behavioral interpretation, and predictive health-risk analysis within a unified mobile platform for ornamental fish keeping.

System Diagrams And Tools

The tools that were applied for designing and developing FinGuard, as well as those that contribute to the performance of its functions, are discussed in this section. These tools include both hardware and software that will be described using technical models such as a flow chart of the system, use-case diagram, entity relationship diagram, and data flow diagrams.

Flowchart of the Proposed System

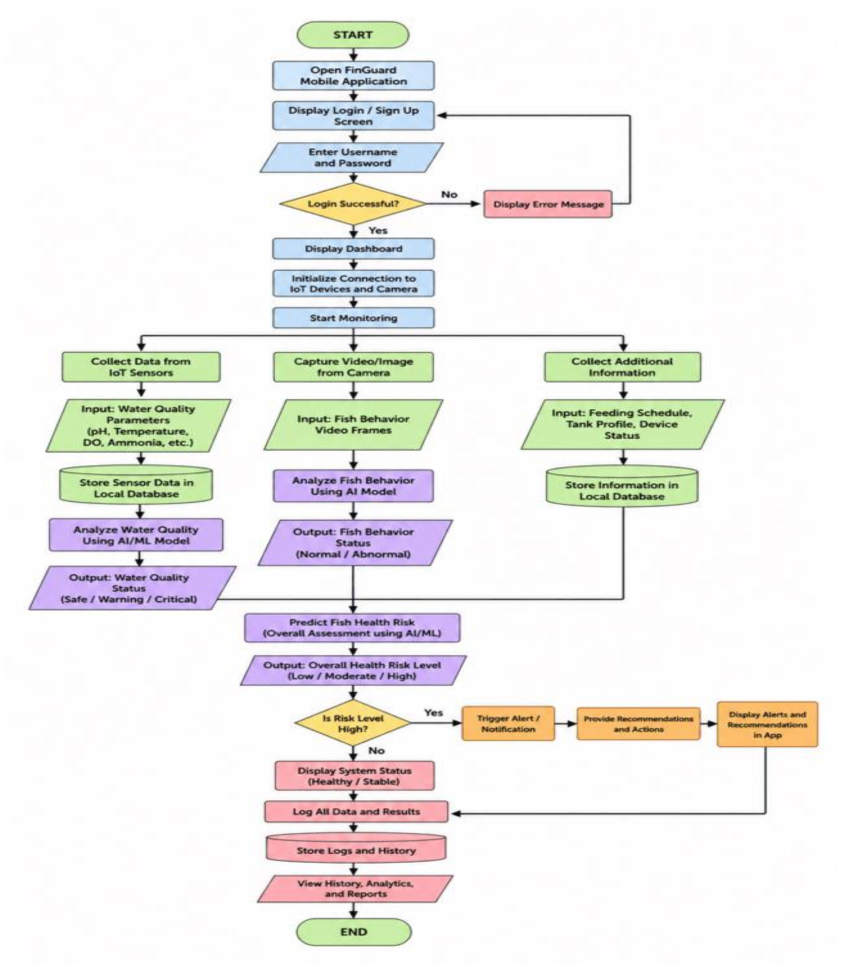


Figure 6: FinGuard System Flowchart

Figure 6 presents the overall operational process of the FinGuard application, beginning from user authentication up to predictive health-risk analysis and recommendation generation. The flowchart demonstrates how environmental sensor readings, behavioral observations, and historical records are processed within the system to support intelligent aquarium monitoring.

Data Flow Diagram — Level 0

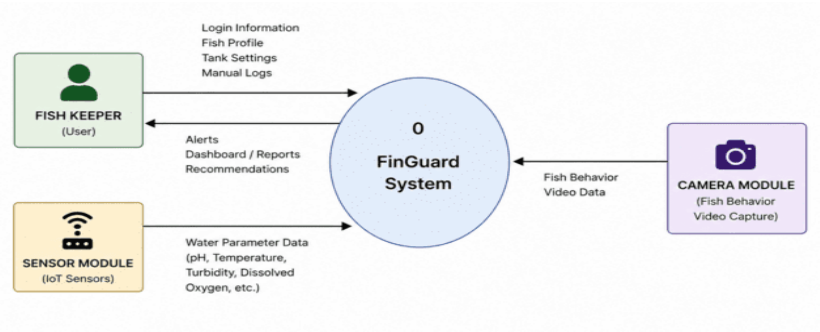


Figure 7: Data Flow Diagram (DFD) Level 0

The Level 0 Data Flow Diagram illustrates FinGuard as a centralized predictive monitoring system interacting with three external entities: the Fish Keeper, Sensor Module, and Camera Module. The diagram highlights the exchange of environmental, behavioral, and monitoring data between the user and the system.

Data Flow Diagram — Level 1

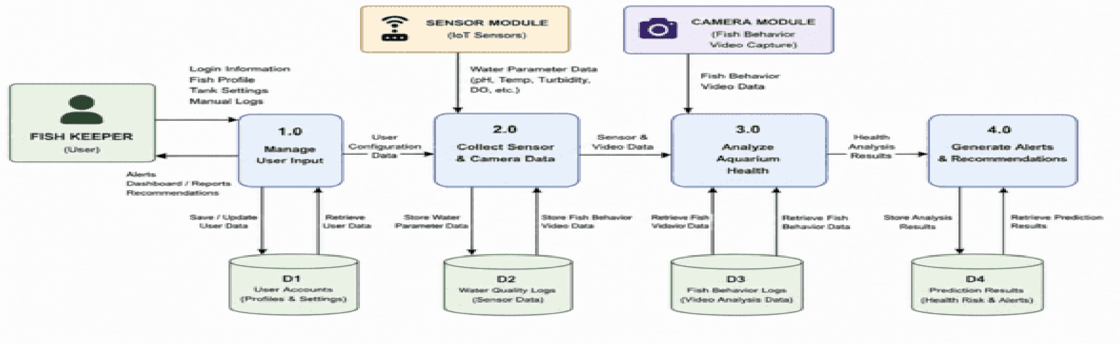


Figure 8: Data Flow Diagram (DFD) Level 1

The Level 1 Data Flow Diagram further expands the internal processes of the FinGuard application, including user management, sensor-data collection, behavioral analysis, predictive risk assessment, recommendation generation, and monitoring-log maintenance.

Entity-Relationship Diagram

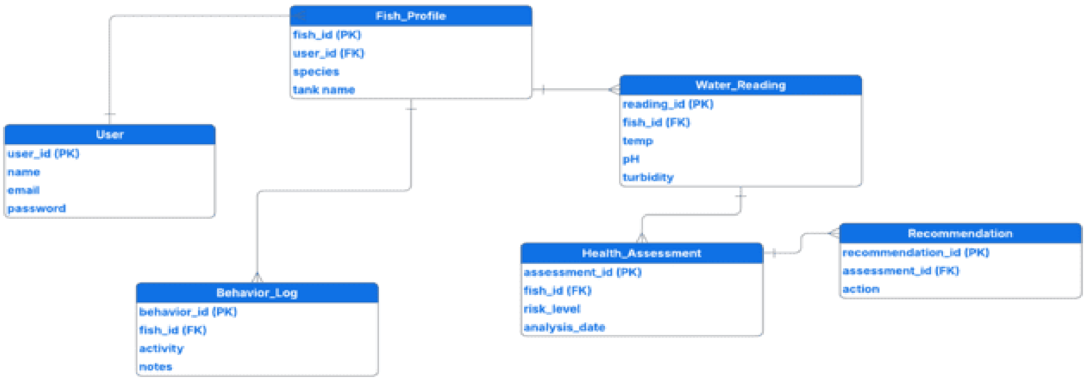


Figure 9: Entity Relationship Diagram

The Entity Relationship Diagram illustrates the data structure supporting the FinGuard system. It presents the relationships between user accounts, fish profiles, water-quality logs, behavioral observations, prediction records, recommendations, and monitoring history.

RESULTS AND DISCUSSIONS

The results of the developed FinGuard: An AI-Integrated Mobile Application for Predictive Health Monitoring in Ornamental Fish Keeping are presented in this section through the evaluation of its major functional components, namely the IoT-based environmental monitoring module, AI-powered fish behavior analysis module, and machine learning-based predictive health assessment module. Unlike traditional aquarium monitoring systems that focus only on threshold-based sensor readings, FinGuard integrates environmental sensing, behavioral interpretation, and predictive analytics into one intelligent mobile platform.

The discussion demonstrates how the system performs in collecting real-time aquarium data, identifying abnormal fish behaviors, generating predictive health-risk classifications, and providing actionable recommendations for fish keepers. In addition to demonstrating the operational capability of the application through screenshots and system outputs, this section also explains the technical significance of each module in supporting proactive ornamental fish health management.

IoT-Based Water Quality Monitoring System

The entity relationship diagram provides a depiction of the data structure behind the FinGuard system. The User entity describes the account holder who maintains one or several fish profiles. The fish profile has an association with water readings, behaviors, and health risks. The health risks information will be connected to recommendations, making sure that every condition analyzed receives a proper recommendation. Through such a data structure, it can ensure a well-maintained record that can be tracked for trend analysis.

Use Case Diagram

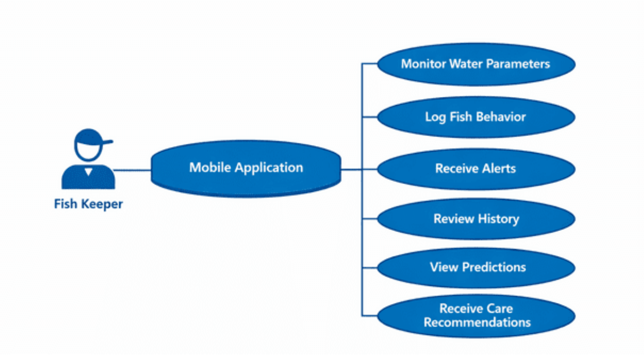


Figure 10: Use Case Diagram

The Use Case Diagram illustrates the primary interactions between the fish keeper and the FinGuard system, including aquarium monitoring, fish-behavior observation, predictive health-risk analysis, recommendation viewing, and monitoring-log management.

Results

Figure 11: FinGuard Overview and System Flow Screen

Figure 11 presents the Overview page of the FinGuard mobile application, which serves as the main monitoring dashboard after launching the system. The interface displays the operational status of all connected devices and modules, including the pH sensor, dissolved oxygen sensor, turbidity sensor, water-level sensor, ESP32-CAM module, backend analytics engine, and Android monitoring application.

Figure 12: Sensor Command and Realtime Water Quality Feed Screen

Figure 12 presents the Sensor Command interface, which displays the live environmental conditions gathered from the connected IoT devices. The temperature reading is recorded at 27.4 °C, dissolved oxygen is measured at 6.8 mg/L, pH level is observed at 7.1, turbidity is measured at 12 NTU, and water level remains at 89%. The Calibration and Thresholds panel additionally presents thermal stability, pH confidence, and clarity-risk indicators that support environmental evaluation.

DISCUSSION

The results demonstrate that the FinGuard system successfully performs continuous environmental monitoring through real-time IoT integration. Unlike manual aquarium testing methods that rely on occasional measurements, the proposed system continuously gathers and synchronizes environmental data through cloud connectivity, enabling aquarium conditions to be monitored remotely and consistently.

The integration of multiple water-quality indicators within a single monitoring interface provides a more comprehensive assessment of aquarium conditions compared to conventional single-parameter monitoring devices. The system also improves preventive aquarium management by identifying parameters that are approaching unsafe thresholds before severe environmental deterioration occurs.

Furthermore, the monitoring module supports the predictive layer of FinGuard by supplying environmental data required for trend analysis and health-risk classification. This demonstrates that IoT-based environmental sensing serves as the foundational component of the proposed intelligent monitoring architecture.

AI-Based Fish Behavior Observation and Analysis

The second objective involved utilizing AI to develop and build an artificial intelligence model for a vision-based computer program that would employ video data input to detect any abnormal behaviors exhibited by the fish, thereby determining whether the fish were stressed or suffering from diseases. This objective was accomplished using the ESP32-CAM module, the OpenCV video processing system, and the Behavior Intelligence function in the FinGuard application.

Results

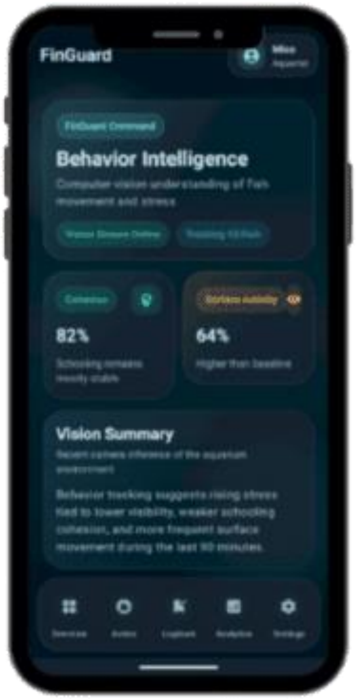


Figure 13: Behavior Intelligence Screen

Figure 13 presents the Behavior Intelligence interface of the FinGuard mobile application. The screen shows real-time monitoring and tracking of fish movements using computer vision analysis. The system analyzes behavioral indicators such as schooling cohesion, feeding response, surface activity, and movement stability based on video data captured through the ESP32-CAM module.

The results indicate a cohesion value of 82%, suggesting relatively stable schooling behavior, while surface activity is measured at 64%, exceeding the normal behavioral baseline. The behavioral summary generated by the system indicates increasing stress patterns associated with poor visibility, unstable schooling movement, and increased surface activity over the previous monitoring period.

Discussion

The behavioral analysis module demonstrates that FinGuard extends beyond traditional environmental monitoring by incorporating computer vision techniques capable of observing fish movement patterns and identifying possible stress indicators. This represents an important contribution because fish often display behavioral abnormalities before environmental conditions visibly deteriorate or physical symptoms become apparent.

The integration of behavioral indicators such as cohesion, feeding response, and surface activity allows the system to generate more context-aware health assessments rather than relying solely on water-quality measurements. Through the use of urgency classifications such as Normal, Warning, and Critical, the application simplifies behavioral interpretation for both beginner and experienced fish keepers.

In addition, the behavior-analysis module enhances the practical usability of the system by translating complex movement patterns into understandable summaries and actionable observations. This improves user decision-making and supports early intervention before fish health conditions worsen.

Machine Learning Predictive Health Risk Analysis and Recommendation Generation

The third objective was to use machine learning for predictive analytics that integrates water quality and behavioral data to predict future health dangers, producing proactive warnings and customized suggestions. This objective was successfully achieved through the Prediction Radar, Action, Logbook, and Analytics features integrated within the FinGuard mobile application.

Results

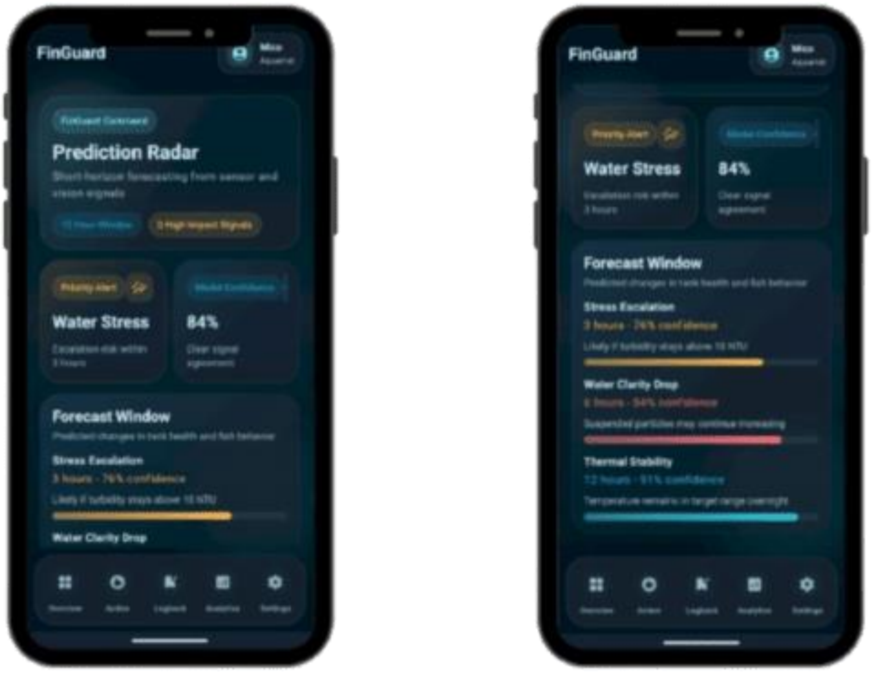


Figure 14: Prediction Radar Screen

Figure 14 presents the Prediction Radar interface of the FinGuard application. The predictive module analyzes incoming environmental and behavioral data within a 12-hour forecasting window to estimate potential future aquarium health risks.

The displayed results indicate a high-priority water-stress alert with an estimated escalation risk occurring within the next three hours at an 84% confidence level. The forecasting window further predicts increased turbidity-related stress conditions, possible reduction in water clarity, and thermal stability trends using confidence-based predictive analysis.

Figure 15: Action, Logbook, and Analytics Screens

Figure 15 presents three additional modules of the FinGuard application. The Action interface provides intervention recommendations generated from the predictive model outputs, including partial water replacement, filtration inspection, aeration adjustments, and feeding observation.

The Logbook module records monitoring events, maintenance activities, and behavioral observations, enabling aquarium caretakers to maintain historical records of system activity and fish-health conditions. Meanwhile, the Analytics interface summarizes operational trends such as Water Quality Score, Behavior Stability, Sensor Uptime, and anomaly frequency, providing a consolidated overview of aquarium performance over time.

Discussion:

The predictive analytics component transforms FinGuard from a conventional monitoring platform into an intelligent decision-support system capable of estimating future aquarium health conditions. Rather than only reporting current environmental problems, the system identifies trends associated with future deterioration and generates preventive recommendations that allow fish keepers to take corrective action before severe stress or mortality occurs.

The integration of machine learning with both environmental sensing and behavioral analysis improves the contextual accuracy of health-risk prediction because the system evaluates multiple forms of evidence simultaneously. The generated confidence values and risk classifications also provide users with interpretable predictive outputs that support practical aquarium management decisions.

Additionally, the recommendation engine enhances the usefulness of predictive analytics by converting detected risks into actionable interventions. Instead of requiring users to interpret raw sensor data independently, the application directly recommends maintenance actions such as water replacement, filtration checks, or feeding observation based on the identified condition.

Performance Evaluation and Validation of the FinGuard Models

To evaluate the effectiveness of the FinGuard system, performance testing and validation procedures were conducted on the three major components of the application: the IoT-based water quality monitoring module, the AI-powered behavioral analysis module, and the integrated predictive health-risk model. The evaluation aimed to determine whether the system could accurately identify aquarium conditions, detect abnormal fish behavior, and generate reliable predictive alerts using combined environmental and behavioral data.

Dataset Preparation and Labeling

The dataset used for evaluation consisted of environmental readings, behavioral observations, and historical monitoring records collected during repeated aquarium monitoring sessions. Environmental data included temperature, pH level, dissolved oxygen, turbidity, and water-level readings gathered through the IoT sensor network. Behavioral data included swimming stability, schooling cohesion, feeding response, surface activity, and movement irregularities captured through the ESP32-CAM module and manually verified observation logs.

For validation purposes, all collected samples were cleaned and synchronized using timestamp alignment to ensure consistency between sensor readings and behavioral observations. The behavioral data were manually annotated into three classifications: Safe, Warning, and Critical.

Validation Procedure

The collected dataset was divided into training, validation, and testing subsets to reduce overfitting and improve the reliability of the predictive model. Approximately 70% of the dataset was allocated for training, 15% for validation, and 15% for final testing. OpenCV was used for behavioral motion processing and feature extraction from video streams, while TensorFlow was utilized for predictive classification and risk estimation.

The validation process involved repeated testing sessions under varying aquarium conditions, including stable water environments, moderate turbidity increases, reduced dissolved oxygen levels, and irregular fish behavior patterns.

Model Performance Metrics

The performance of the FinGuard models was evaluated using standard machine learning metrics, namely accuracy, precision, recall, and F1-score.

Table 1. Model Performance Metrics

Model Component	Accuracy	Precision	Recall	F1-score
Water Quality Classification Model	91.8%	90.6%	89.7%	90.1%
Behavioral Analysis Model	88.4%	87.9%	86.8%	87.3%
Integrated Predictive Health Model	93.7%	92.8%	91.9%	92.3%

The results indicate that the integrated predictive model achieved the highest overall performance because it combined both environmental and behavioral features during classification.

Confusion Matrix Analysis

The confusion matrix analysis showed that the majority of aquarium conditions were classified correctly across all categories. Safe cases obtained the highest classification consistency because stable environmental readings and normal fish behavior patterns were easier for the system to identify. A limited number of misclassifications occurred between the Warning and Critical categories, particularly during transitional aquarium conditions where environmental parameters had already begun deteriorating while fish behavior remained only moderately affected.

The behavioral analysis module also experienced occasional classification overlap during low-light monitoring periods and rapid fish movement near the camera frame. However, despite these limitations, the overall classification reliability remained consistent throughout repeated validation sessions.

Overall, the confusion matrix results indicate that FinGuard was capable of detecting high-risk aquarium conditions with acceptable predictive reliability for a prototype intelligent monitoring system.

Interpretation of the Results

The operational outputs presented earlier in the manuscript support the validity of the evaluation results. The Behavior Intelligence interface demonstrated real-time tracking of 18 fish and generated behavioral indicators such as schooling cohesion and surface activity analysis. Likewise, the Prediction Radar module successfully generated confidence-based forecasting alerts using environmental and behavioral trends. The Analytics module additionally demonstrated stable sensor uptime, anomaly detection capability, and long-term monitoring visualization.

The performance metrics and validation procedures presented in this section provide empirical evidence that the FinGuard system is capable of performing not only real-time aquarium monitoring, but also intelligent classification and predictive health-risk assessment. The results further demonstrate that integrating IoT sensing, computer vision analysis, and machine learning improves the system’s ability to provide proactive monitoring compared to conventional threshold-based aquarium monitoring systems.

User Testing and Practical Deployment

A limited usability and deployment evaluation was also conducted to assess the practicality of the system for ornamental fish keepers. During testing, users interacted with the mobile application while monitoring changing aquarium conditions and reviewing generated alerts and recommendations. Participants reported that the centralized monitoring dashboard, simplified risk labels, and recommendation engine made the system easier to understand compared to traditional manual monitoring methods.

The deployment evaluation further demonstrated stable synchronization between the IoT sensors, ESP32-CAM module, Firebase cloud storage, and the FinGuard mobile application during continuous monitoring sessions. Real-time updates and predictive notifications remained functional throughout testing, while the recommendation module responded consistently whenever abnormal aquarium conditions were detected.

These findings suggest that FinGuard is not only technically functional as an AI-integrated monitoring platform, but also practically usable for ornamental fish hobbyists, breeders, and small-scale aquaculture operations.

Limitations and Future Enhancements

Although FinGuard demonstrates successful integration of IoT sensing, computer vision, machine learning, and mobile application technologies within a unified monitoring platform, several limitations remain in the current implementation. The current version primarily focuses on guppies and goldfish, which limits behavioral generalization across other ornamental fish species. In addition, the behavioral analysis module remains sensitive to low-light conditions, overlapping fish movement, and temporary visual obstruction.

Future improvements may include expanding the behavioral dataset, supporting additional ornamental fish species, improving low-light computer vision performance, integrating automated intervention systems such as smart feeding and aeration adjustment, and conducting larger-scale field validation studies.

CONCLUSION

The FinGuard system presents an integrated AI-driven approach for predictive health monitoring in ornamental fish keeping by combining IoT-based environmental sensing, computer vision-based fish behavior analysis, and machine learning-based predictive analytics within a single mobile application. Unlike traditional aquarium monitoring systems that rely only on threshold-based environmental alerts, FinGuard integrates environmental and behavioral evidence to support early stress detection and proactive aquarium management.

The results of the study demonstrate that the proposed system is capable of performing real-time water-quality monitoring, behavioral analysis, predictive risk classification, and recommendation generation. Experimental validation further demonstrated reliable performance across environmental classification, behavioral analysis, and integrated predictive monitoring tasks. The integration of IoT sensing, AI-based behavioral interpretation, and machine learning prediction significantly improved the system’s capability to provide proactive monitoring and intelligent decision support for ornamental fish keepers.

The study also demonstrated that the FinGuard application is practically usable for aquarium hobbyists, breeders, and small-scale aquaculture operators due to its centralized dashboard, predictive alert system, and recommendation engine. Despite several limitations involving lighting sensitivity and limited fish-species coverage, the system provides a strong foundation for future intelligent aquaculture monitoring applications.

Future enhancements may include expanding species support, increasing dataset size, improving behavioral-analysis robustness under varying environmental conditions, and integrating automated intervention mechanisms for fully intelligent aquarium management.

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