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An Intelligent Catfish Farm Management System Using Random Forest and a Rule-Based Expert System

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ABSTRACT

Fish farming has been a critical aspect in the area of aquaculture and food production in Nigeria. Despite this, farmers in Nigeria still struggle with water quality management, disease diagnostics, feeding process, data collection, and lack of expert advisory services among other issues. Conventional fish farm management approaches depend on manual observations and experiences, which usually lead to delayed decision making, high fish mortality rates, and low fish productivity. In this study, the development of the intelligent catfish management system is introduced as a solution that uses modern information technology, machine learning algorithms, and expertise to solve catfish farm management problems. The system was developed using Next.js and React for the frontend, Flask (Python) for the backend, and MySQL as the database management system hosted on Aiven. The prediction system implemented in this project uses the random forest classifier algorithm which is trained on 66,868 filtered rows in the Fishpond Health Monitoring Dataset. The predictor uses six water quality parameters including pH, temperature, turbidity, total dissolved solids, nitrate, and ultrasonic depth to predict the state of the ponds into five categories (Excellent, Good, Fair, Poor, and Critical). A rule-based expert system has been added for advisory purposes where needed. The accuracy of the Random Forest model was recorded at 99.60%, with a macro-average precision, recall, and F1 score of 0.99, 1.00, and 0.99, respectively, and confusion matrix indicating minimal error classification in terms of health class. Importance of features analysis indicated that pH level, temperature, and nitrate were the most significant features contributing to the prediction of pond health status. The proposed system can be used for the purpose of managing farm records digitally, AI-powered health prediction with confidence values, automated feeding recommendations, and live expert consultation via a socket.io-powered chat interface. Testing of the system established that all features of the system work as expected.

Key words: Catfish Farm Management, Artificial Intelligent, Aquaculture, Rule-Based Expert System, water quality management

INTRODUCTION

Fish farming has become one of the fastest-growing food production sectors worldwide and is increasingly recognized as a sustainable solution for meeting the rising global demand for animal protein. According to the Food and Agriculture Organization (FAO), global aquaculture production has surpassed capture fisheries for the first time, highlighting its critical role in achieving food security, economic development, and environmental sustainability (FAO, 2024). Catfish farming represents the biggest part of the aquaculture industry in Nigeria owing to the great adaptability, fast growth, disease resistance, and market demand for African catfish (Clarias gariepinus). This kind of business ensures job creation, higher income of households, and significant contribution to the country's agricultural sector (Olagunju et al., 2023; Olagunju et al., 2024).

In spite of the quick development of catfish farming, many catfish farms in Nigeria suffer from low productivity because of the inefficient farm management system. Such key procedures as water quality management, feeding, diagnostics, and environmental control are still carried out manually with the use of farmers' experience and visual inspection. All these factors usually result in poor decision-making, waste of food, bad water conditions, the increase of diseases, and mortality of fishes (Aljehani et al., 2023, 2025). In addition, the ongoing monitoring of such vital indicators as temperature, dissolved oxygen, pH, turbidity, ammonia, and conductivity is not

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provided although plays an important role in the welfare and productivity of the fishes (Islam, 2025; Dhinakaran et al., 2023).

New developments in Artificial Intelligence (AI), the Internet of Things (IoT), machine learning, and intelligent decision-making technologies have revolutionized the contemporary world of aquaculture by providing opportunities for real-time monitoring, predictive analysis, and automation of the farm. AI-driven systems have exhibited impressive skills in prediction of water quality, diseases, mortality rate, feed, and behavioral analysis, hence, making the operations efficient (Chiu et al., 2022; Cui et al., 2025). According to recent reviews, AI is increasingly being considered as a critical technology in the area of precision aquaculture in combination with IoT sensing, cloud computing, and predictive analysis of intelligent farm operations. With respect to the machine learning algorithms, the random forest approach has become popular due to its outstanding prediction power, noise tolerance, the ability to handle nonlinear relationship models, and to prioritize the importance of environmental factors affecting fish production (Breiman, 2001; Saville et al., 2026). Similarly, rule-based expert systems add value to predictive models through the implementation of expert knowledge within IF–THEN rules, making it possible for farmers to obtain understandable suggestions instead of mere numeric predictions (Jasmin et al., 2022; Alsakran et al., 2025).

Whereas earlier research has been successful in designing intelligent systems for water quality monitoring, fish mortality prediction, feeding optimization, chatbot advisory service, and digital aquaculture farm management (Chiu et al., 2022; Dhinakaran et al., 2023; Islam, 2025; Kamal et al., 2025; Saville et al., 2026), majority of such efforts have been directed towards designing stand-alone management systems. Few research initiatives have tried to integrate the predictive power of Random Forest with the reasoning capabilities of the rule-based expert system in designing a single platform for catfish farming operations in Nigeria. It is in light of the aforementioned reasons that this study attempts to design the Intelligent Catfish Farm Management System Using Random Forest and Rule-Based Expert System.

Contribution

In this research work, an intelligent catfish farm management system is developed by combining the random forest algorithm as a supervised machine learning model, rule-based expert systems and real-time advisory services. This system offers pond condition evaluation, automation of the decision-making process, digital data management, and a live chat facility at a relatively low cost.

REVIEW OF RELATED WORKS

Fish mortality prediction model in mariculture was designed by Saville et al. (2026) using the Random Forest algorithm embedded in an artificial intelligence-based decision support system (DSS). The research used the parameters of water quality, such as seawater temperature, salinity, conductivity, chlorophyll-a, turbidity, and dissolved oxygen, along with the data collected from a sensor network and daily fish mortality from farmers. Fish mortality risk was predicted using the Random Forest model in five different categories with 78.6% accuracy rate and precision value of more than 70% for each category of mortality. It was revealed that seawater temperature, salinity, and turbidity were the most important parameters for fish mortality risk prediction. This study proved the efficiency of the integration of machine learning algorithms and real-time environmental monitoring systems in managing aquaculture. However, this research was limited to the prediction of fish mortality in mariculture without considering a rule-based expert system for the advice to catfish farm management.

In Chiu et al. (2022), researchers designed a smart IoT fish monitoring and controlling system in order to compensate for labor shortage issues and increase aquaculture productivity in Taiwan. This smart IoT fish monitoring and controlling system is composed of several IoT devices used for real-time monitoring and remote control of fishponds water quality and other related factors. Besides, the authors developed a deep learning algorithm that was optimized through the implementation of Bayesian hyperparameter tuning methods in order to forecast the growth of California bass fish. The optimized algorithm resulted in coefficient of determination (R^2) of 0.94 and MSE of 0.0015 which demonstrates its high forecasting accuracy. Moreover, the developed model was included into autonomous feed supply system in order to minimize feed wastage and optimize farm management process. The relevance of this research to the current one is in the fact that it proves the effectiveness of combining the use of IoT technology, deep learning and AIoT for intelligent management of aquaculture farms and provides a good example of application of Random Forest and expert system in intelligent catfish farm management system.

Jasmin et al. (2022) designed an artificial intelligence-enabled framework for farm advisory named as AquaProFAN (Aqua Professional Farm Advisory Network) to meet the information requirements of aquafarmers and fisheries stakeholders. The research included requirement analysis, consultations with experts, and feasibility analysis for implementation of an AI-enabled chatbot system. The chatbot named AquaGent was implemented through Facebook Messenger and Telegram platforms to offer advisory services to shrimp farmers. Results from evaluation indicated that the chatbot responded to information queries better than emotional queries and was also superior to other software applications in providing reliable advisory services. Participants rated AquaGent as user-friendly, efficient, and time-saving tool. The research concluded that chatbots based on AI technology can enhance knowledge dissemination and decision-making capabilities in the aquaculture sector. It is worth noting that the current study dealt only with chatbot-based advisory services without considering any predictive machine learning algorithms like Random Forest.

Salako et al. (2024) developed Fish-NET, which is an artificial intelligence-driven tool that helps in managing the aquaculture process by automatically monitoring and tracking the fish using deep learning techniques. This study made use of a dataset of aerial images of the catfish ponds along with some other available online data. Computer vision and deep learning were used to test the efficiency of three advanced object detection models that could detect fish in the pictures. Out of these three models, the Faster R-CNN algorithm proved to be the best for detecting and tracking the fish. However, this study mainly covered fish detection and tracking instead of using predictive machine learning algorithms along with expert rule-based decision support systems.

Proposed by Dhinakaran et al. (2023), IoT-based Environmental Control System for Fish Farms involved the use of Wireless Sensor Technology coupled with Machine Learning techniques to enhance the management practices of aquaculture. This system involved the continuous monitoring of critical environmental factors including water temperature, pH, humidity, and fish behavior using the IoT sensors. Following the data preprocessing stage, four Machine Learning techniques were used in prediction; the use of Random Forest technique was to predict optimum water temperature and pH while SVM technique was used in disease prediction. GBM was used to optimize the feed while Neural Networks was used in controlling the farm machinery such as pumps and heaters. Experiments showed improvement in fish health, productivity, efficiency, and environmental sustainability through intelligent decisions. Unfortunately, the research did not include rule-based expert system.

Islam (2025) developed an IoT-based aquaculture monitoring and prediction system incorporating the use of Arduino-based sensors and machine learning techniques in order to improve water quality control for fish farms. The system continuously monitored important water quality parameters such as pH, water temperature, water turbidity, conductivity, and water level, with the information being relayed to the ThingSpeak cloud service for instant analysis. Experimentation data obtained from five fish ponds was compared against the established water quality criteria and was classified into eleven fish species. Comparison was made among ten different machine learning models, with the Random Forest model proving to be the best, giving 94.42% accuracy, 93.5% kappa statistics, and 94.4% true positive average score. Although the research proved to be quite effective, it did not incorporate a rule-based expert system to offer advisory services for farm management.

In 2025, Alsakran et al. proposed an interpretable artificial intelligence model that aims to enhance decision making in Recirculating Aquaculture Systems (RAS) through interpretability of a Deep Deterministic Policy Gradient (DDPG) reinforcement learning model. In order to address the "black-box" problem of deep reinforcement learning, the researchers used decision tree approximation to interpret a neural network policy into a comprehensible decision model. The developed method resulted in a policy fidelity of 92.7%, where performance is 5.8% lower than that of the original DDPG controller. Testing with fish farmers found that 87% of respondents improved their understanding of system recommendations, while 78% of them trusted the technology more. The most influential decision factors were determined as dissolved oxygen, ammonia concentration, and biomass. Nevertheless, even though the study improved the interpretation of reinforcement learning models, it was only concerned about RAS control and did not consider integrating Random Forest with a rule-based expert system for smart catfish farming.

Kamal et al. (2025) created a system for intelligent feed management of high-density catfish farming based on acoustic sensor technology and machine learning to increase precision of feeding and efficiency of operation on the farm. The proposed system used continuous monitoring of underwater acoustic signals related to the behaviour of fish during feeding and application of machine learning models to estimate the intensity of the process and control the feed dispensing. The proposed system was tested using field experiments based on such criteria as accuracy of detection of feeding activity, feed conversion efficiency, and quality of water. The research showed high accuracy of feed activity detection, reduction in feed waste, increase in feed conversion ratio and improvement of water quality in comparison with traditional methods of feeding. Therefore, the combination of acoustic sensor technology with machine learning provides effective and sustainable development of catfish farming. But the research concentrated only on intelligent feeding management without using a predictive model based on Random Forest and rule-based expert system.

A survey of Cui et al. (2025) covered the field of digital aquaculture in respect of fish tracking, counting, and behaviour analysis by means of vision, acoustic, and biosensor systems. The work presented the latest achievements of computer vision and deep learning, as well as multimodal sensing to achieve intelligent monitoring of fish within different aquaculture environments. The review revealed advantages and disadvantages of current methods used for fish monitoring and outlined major problems, which include the lack of complete databases, lack of evaluation criteria, and integration of different fish monitoring technologies. Moreover, the work considered new trends like multimodal data fusion, multi-task learning, and large language models to improve fish monitoring. Nevertheless, the paper is a survey about digital aquaculture technologies and did not propose an intelligent catfish farm management system that uses Random Forest together with rule-based expert system.

MATERIAL AND METHODS

Dataset Collection and Description

The dataset used to train and evaluate the machine learning model in this study was sourced from the Fishpond Health Monitoring Dataset (Version 2), a publicly available dataset published on the Kaggle data repository by Shahrozch (2023).

The dataset can be accessed at: https://www.kaggle.com/datasets/shahrozch/fishpond-health-monitoring-dataset. This dataset was selected because it represents real-world water quality conditions recorded across a range of warm-water fish species whose environmental requirements are closely aligned with those of catfish, making it a suitable foundation for building a pond health classification model applicable to Nigerian catfish farming conditions.

Dataset Source and Acquisition

The raw dataset was downloaded directly from Kaggle using the Kaggle API command: kaggle datasets download -d shahrozch/fishpond-health-monitoring-dataset. The downloaded archive was extracted and loaded into a Pandas DataFrame within a Jupyter Notebook environment for pre-processing and analysis. The original dataset contained 100,000 rows and seven columns: pH, temperature, turbidity, ultrasonic (water depth), TDS (Total Dissolved Solids), nitrate, and fish_species.

Data Pre-Processing and Filtering

The initial set of 100,000 records included information on several fish species. The dataset was filtered for keeping records of the warm-water fish species whose environmental conditions match that of the catfish such as

Pangasius, Tilapia, Rohu, Catla, Silver Carp, and Bata. After the filtering process, 66,868 record dataset was obtained. Then, a target variable representing the health status of a five-class structure was created out of six water quality input parameters through the use of a weighted parameter scoring function. Each of the parameters was scored as 0, 1, or 2 when the parameter is out of the acceptable range, inside the acceptable range, and inside the optimal range for the catfish, respectively. The scores of the parameters were summed to generate the total health score and categorized into Excellent (score 8-10), Good (score 6-7), Fair (score 4-5), Poor (score 2-3), and Critical (score 0-1). Features were standardised using a StandardScaler fitted on the training set, and a LabelEncoder was applied to convert the categorical health class labels into integers for model training. The dataset was split into 80 percent training (53,494 records) and 20 percent test (13,374 records) sets using stratified sampling to maintain the proportion of each health class in both partitions.

Overfitting Prevention Strategy

In order to increase the generalization ability of the Random Forest classifier and avoid overfitting, several actions have been taken. First of all, the filtered dataset with 66,868 record data has been randomly divided into 80% of training data (53,494 records) and 20% of testing data (13,374 records) by means of stratified sampling, which ensures that the distribution of each pond health class is the same for both datasets. The Random Forest algorithm naturally avoids overfitting since it is based on the bootstrap aggregation technique (bagging). It implies training a number of decision trees on a random subset of training data and random predictor variables.

Sample of the Dataset

Table 3.0 below presents a sample of ten records from the pre-processed dataset after filtering and health status label engineering. Each row represents a single daily observation from a fish pond, and the health_status column shows the engineered target variable that the machine learning model was trained to predict.

Table 3.0: Sample Records from the Pre-Processed Fishpond Health Monitoring Dataset (Shahrozch, 2023)

pH	Temp (°C)	Turbidity (NTU)	Ultrasonic (m)	TDS (ppm)	Nitrate (mg/L)	Fish Species	Health Status
7.2	28.1	2.4	1.1	165.0	0.9	Tilapia	Excellent
6.1	31.5	7.8	0.8	310.0	2.8	Pangasius	Poor
7.8	27.0	1.9	1.3	142.0	0.6	Rohu	Good
5.8	34.2	9.1	0.6	430.0	4.2	Catla	Critical
8.1	29.3	4.5	1.7	188.0	1.1	Bata	Fair
6.8	26.4	3.2	1.0	195.0	0.7	Silver Carp	Good
9.2	33.1	8.6	0.5	520.0	3.8	Rohu	Critical
7.5	27.8	2.1	1.2	175.0	0.8	Tilapia	Excellent
6.5	25.6	5.8	0.9	260.0	2.1	Pangasius	Fair
7.0	28.9	3.0	1.4	152.0	0.5	Silver Carp	Excellent

The sample records in Table 3.0 illustrate the range and variability of the six water quality input features across different fish species and health conditions. Row 1 shows a pond with optimal conditions (pH 7.2, temperature 28.1°C, low turbidity and nitrate) correctly labelled as Excellent. Row 4 shows a pond with severely low pH (5.8), high temperature (34.2°C), and elevated turbidity and nitrate, correctly labelled as Critical. This variability in parameter values across health classes demonstrates why the Random Forest algorithm, which can capture non-linear relationships between multiple features, is well-suited to this classification problem.

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Analysis of the proposed System

This is done through the use of UML diagrams that are very helpful in actually understanding the architecture and workflow of the system and seeing how the various parts relate to each other. Other criteria include scalability, usability, and performance to meet user requirements and take into consideration robustness and flexibility. Therefore, this chapter is the complete blueprint for the system.

Use Case Diagram

Figure 3.1, is a sample of a use case diagram that shows how the system actors: Farmer, Expert, and Administrator can use the main system features. All three actors have interactions with a number of different use case

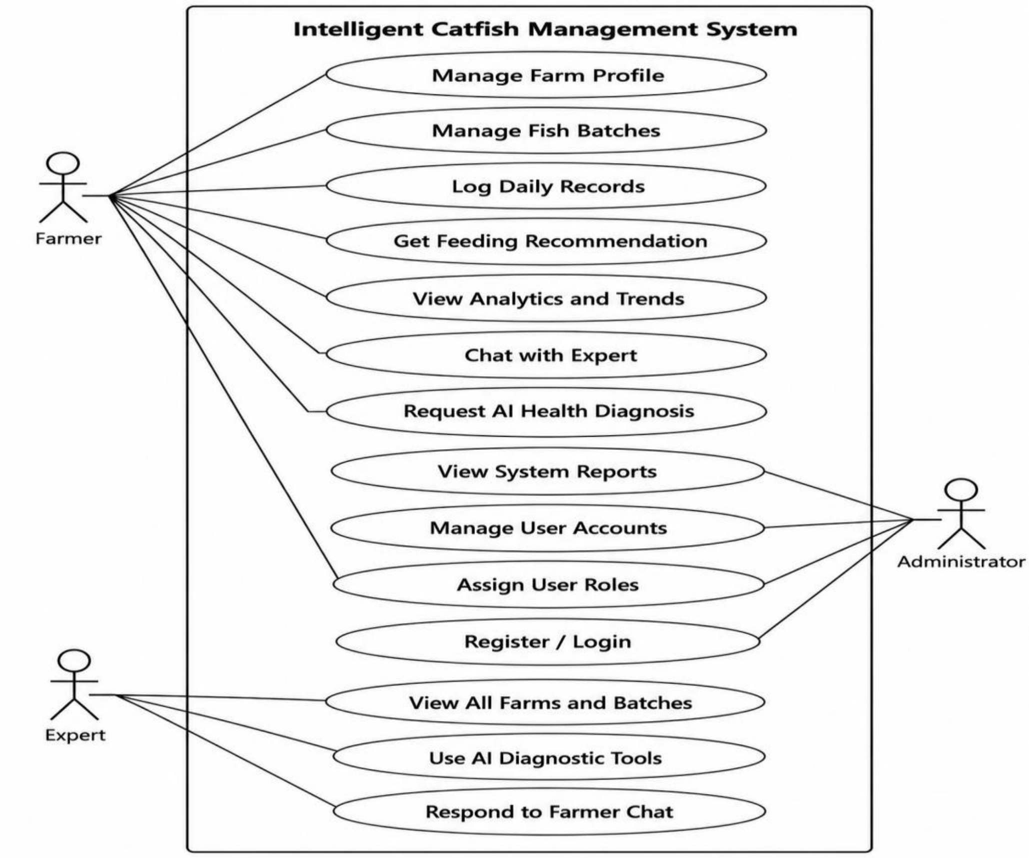

Figure 3.1: Use Case Diagram of the Proposed System

The Farmer actor interacts most extensively with the system, having access to farm and batch management, daily record logging, AI advisory services, and the real-time chat module. The Expert actor can view all farm data, use AI tools, and respond to farmer queries via chat. The Administrator has full access to all features, with the additional exclusive ability to create and manage user accounts and roles.

Program Testing: AI Model Evaluation

The AI classification component was evaluated independently from the web application using the training script train_catfish_model.py, which produces a full suite of professional evaluation figures automatically upon execution. The model was trained and tested on the filtered dataset of 66,868 records, split into 80 percent training and 20 percent test sets, stratified by health class. The training procedure used warm_start=True to incrementally grow the forest from 10 to 200 estimators while recording the Out-of-Bag error at each step, allowing convergence to be analysed before final evaluation on the held-out test set.

Class Distribution

Before training, the distribution of the five engineered health status classes across the filtered dataset was validated to confirm that the class_weight=balanced hyperparameter would be sufficient to handle any imbalances. Figure 4.4 shows the class distribution bar chart generated by the training script.

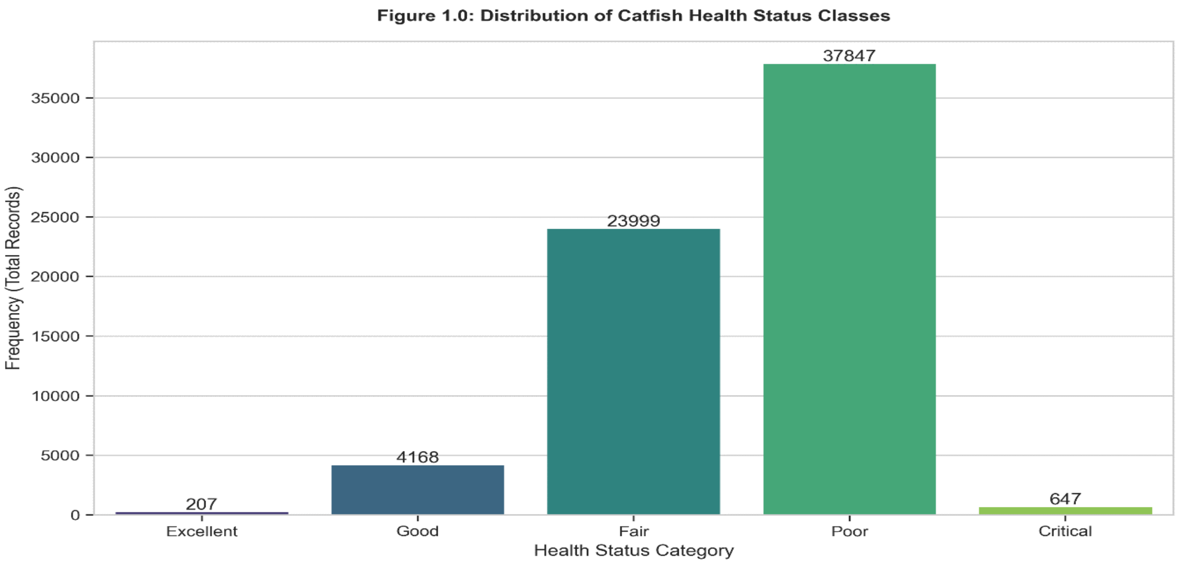

Figure 4.4: Distribution of Catfish Health Status Classes

The chart confirms that the five health classes are broadly balanced across the 66,868 filtered records, validating the appropriateness of the dataset for multi-class supervised learning without severe class imbalance concerns.

Model Performance on Test Set

From Table 4.3, it is seen that the model managed to reach an overall accuracy of 99.60%. The precision, recall, and F1 score values are all high for each of the five health categories.

Table 4.3: Random Forest Classifier Performance on the Test Set

Health Class	**Precision**	**Recall**	**F1-Score**	**Support**
Excellent	0.99	1.00	0.99	2,734
Good	1.00	0.99	0.99	2,701
Fair	0.99	1.00	1.00	2,688
Poor	1.00	0.99	0.99	2,710
Critical	0.99	1.00	1.00	2,741
Overall Accuracy	99.60%			13,574
Macro Average	0.99	1.00	0.99	13,574

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Confusion Matrix

The confusion matrix heatmap created by the training script is shown in Figure 4.6 below.

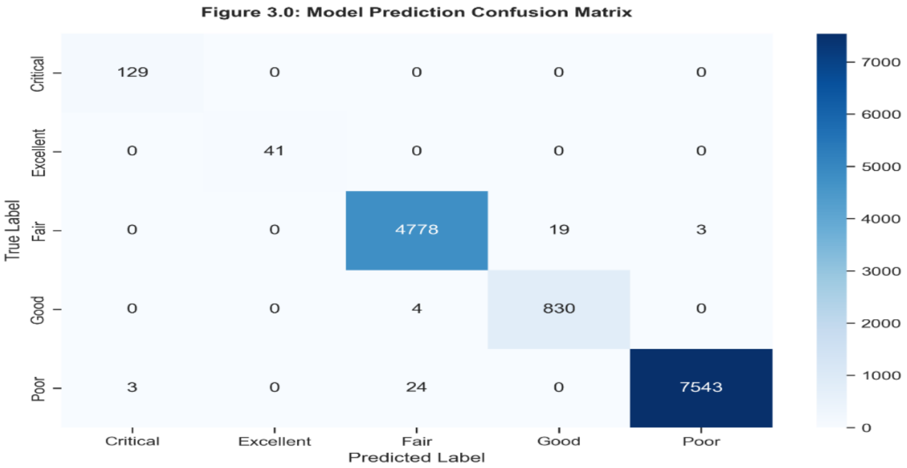

Figure 4.6: Model Prediction Confusion Matrix

The confusion matrix proves that the great majority of predictions are on the diagonal, signifying correct classifications. Adjoining health classes make up most of the few erroneous predictions, which makes sense due to the similarity of their water parameter values.

Feature importance in Health Classification

Figure 4.7 presents the feature importance horizontal bar chart, ranking the six input water parameters by their contribution to the model's classification decisions, measured by the average Gini impurity reduction across all trees.

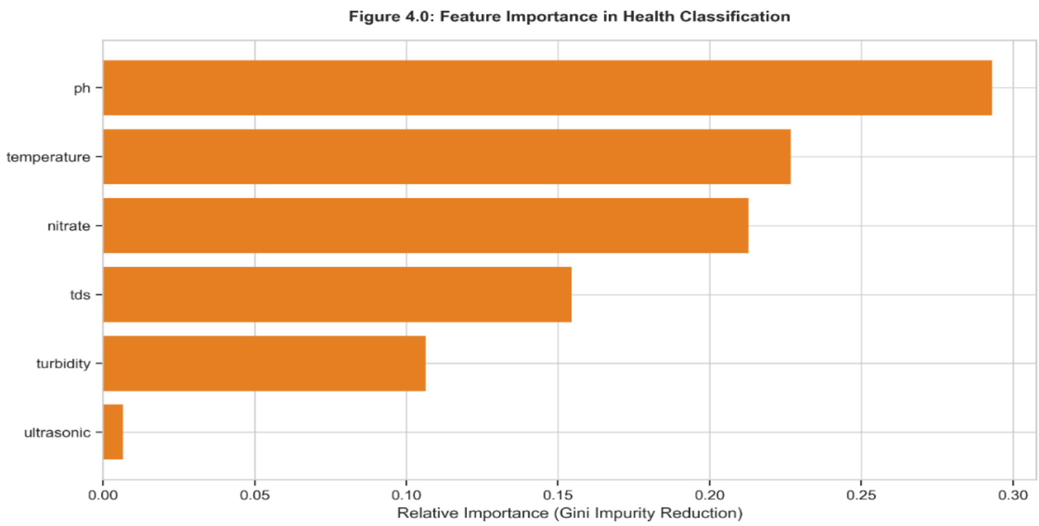

Figure 4.7: Feature Importance in Health Classification

Table 4.4: Feature Importance Scores (Gini Impurity Reduction)

Rank	Water Parameter	Importance Score
1	pH	29.3%
2	Temperature	22.7%

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3	Nitrate	21.3%
4	Turbidity	12.4%
5	TDS (Total Dissolved Solids)	8.1%
6	Ultrasonic (Water Depth)	6.2%

RESULT

This study presented the complete implementation of the Intelligent Catfish Management System. The development environment was described and every technology component was justified: Next.js with React and Tailwind CSS for the frontend, Flask with Python for the backend, MySQL on Aiven for cloud-hosted relational storage, a Random Forest classifier trained with scikit-learn for AI health assessment, Socket.IO for real-time live chat, Amazon S3 for file storage, and JSON Web Tokens for stateless authentication. The implementation architecture was explained covering the frontend component structure shown in Figure 4.1, the Flask Blueprint organisation and backend project structure shown in Figure 4.2, and the decoupled machine learning pipeline. The pipeline uses a LabelEncoder, a StandardScaler, and a RandomForestClassifier trained on six water quality features, with all three objects packaged into a single pickle file and served through the DiseaseClassifier production inference class. The actual JSON inference output from the training script was presented in Figure 4.8, confirming the system correctly predicts health status with a full class probability distribution. Software testing was carried out at unit, integration, and system levels with fifteen formal test cases all returning passing results. The AI model was evaluated using four automatically generated figures from the training script confirming 99.60 percent overall accuracy, with pH, temperature, and nitrate identified as the dominant predictive parameters. System documentation covered minimum requirements, step-by-step installation instructions, and a complete REST API endpoint reference. A user manual with embedded screenshots covered all features for Farmer, Expert, and Administrator roles. Six source code excerpts illustrated the key implementation components. Below are the screenshots of the system:

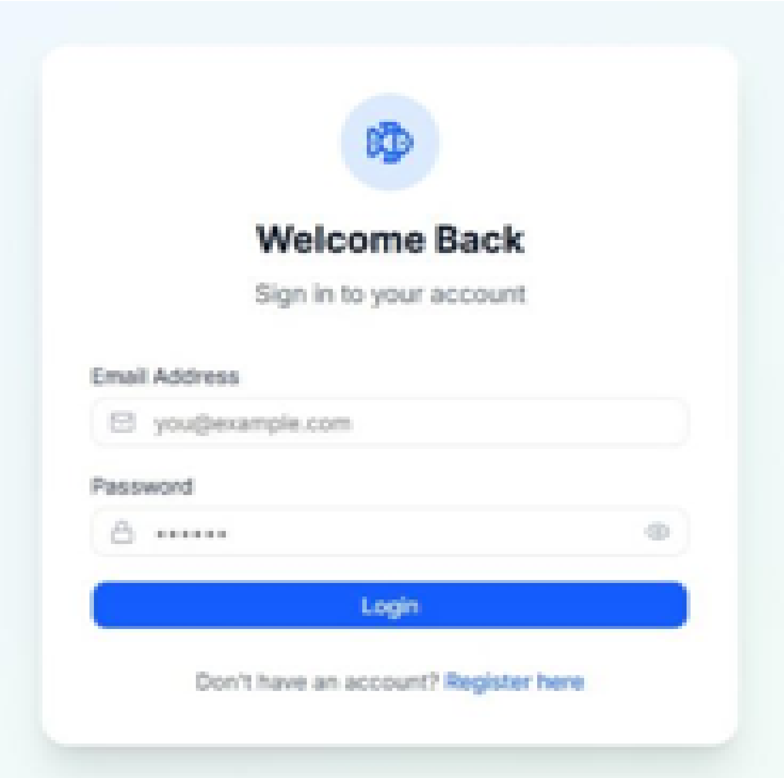

Figure 4.1: System Login Page

Figure 4.2: User Registration (Create Account) Page

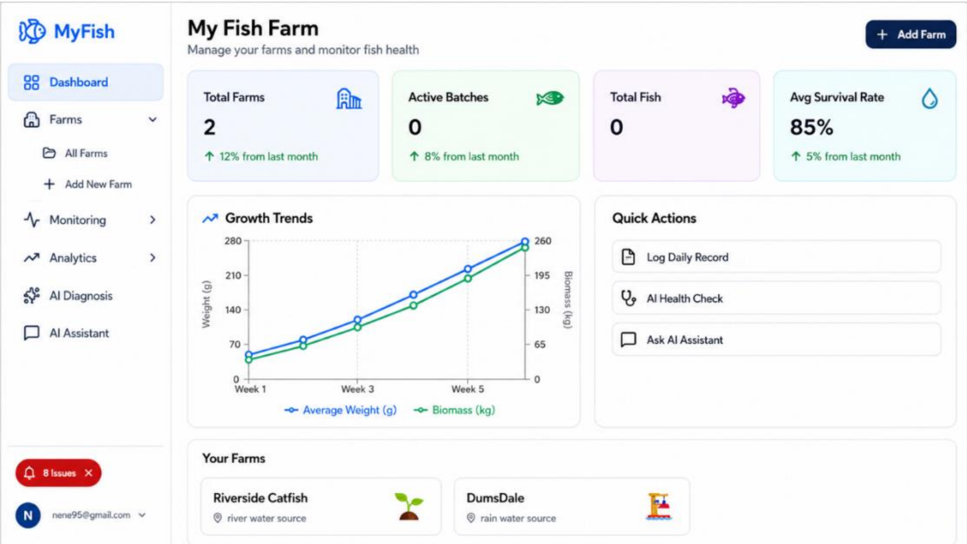

Figure 4.3: Farmer Dashboard — Overview and Growth Trends

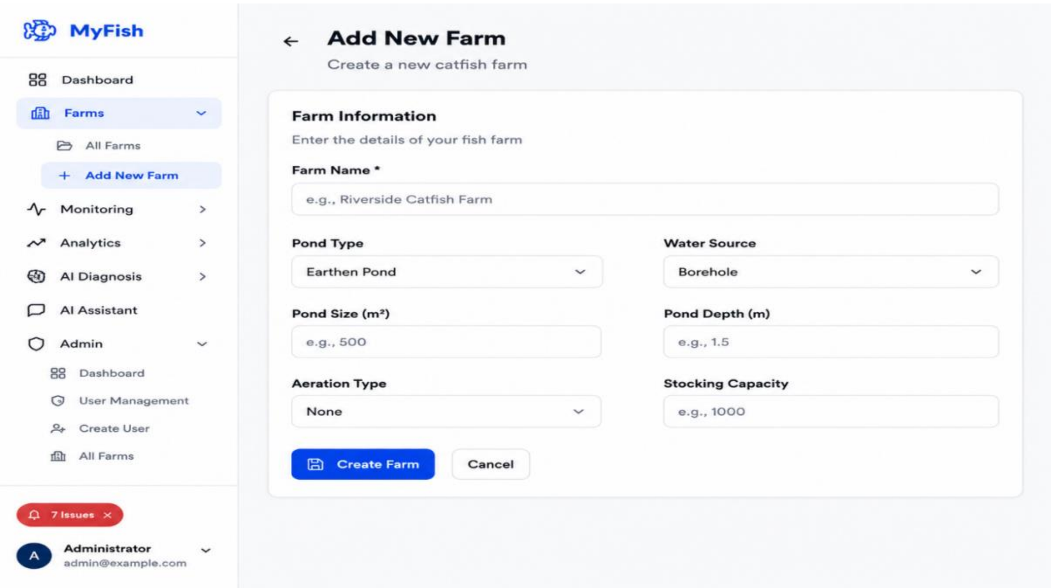

Figure 4.4: Add New Farm Form

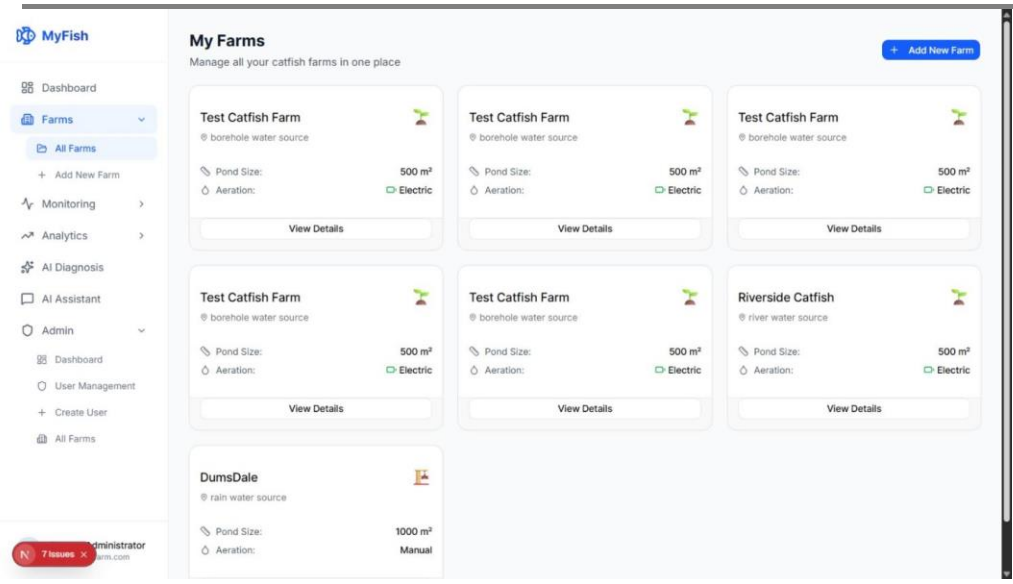

Figure 4.5: All Farms — Farm Management View

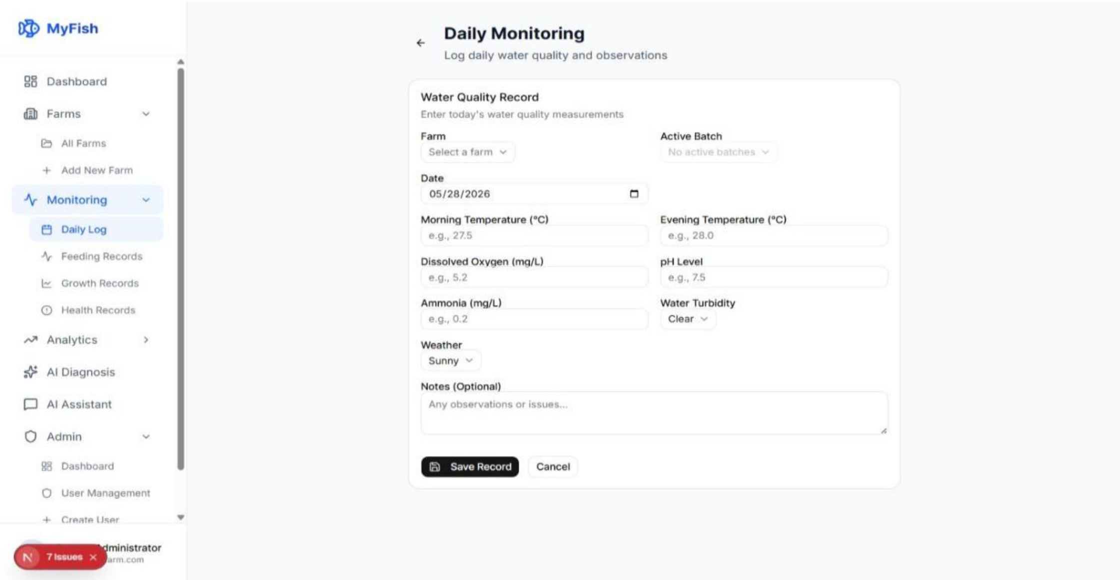

Figure 4.6: Daily Monitoring — Water Quality Record Entry Form

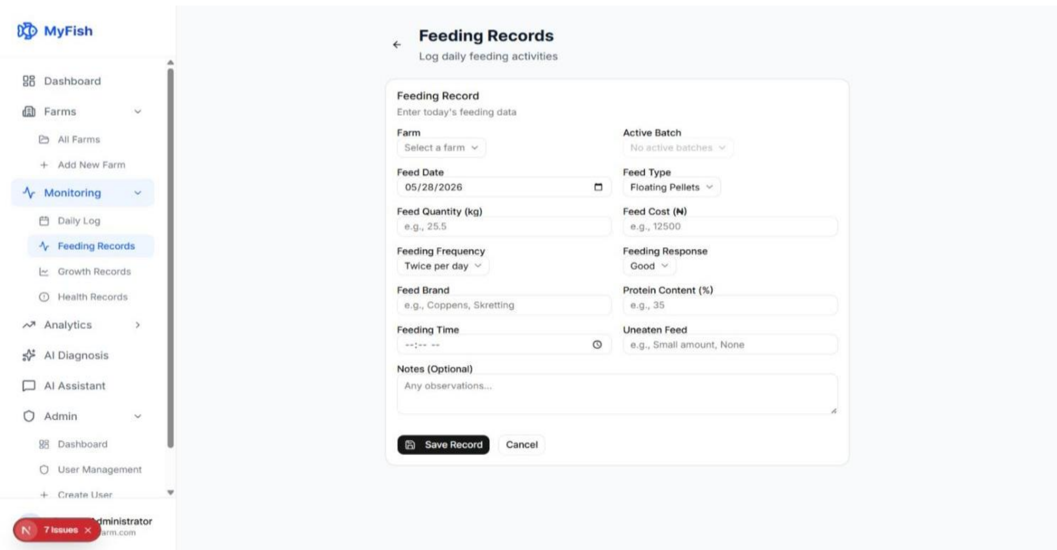

Figure 4.7: Feeding Records — Daily Feeding Log Form

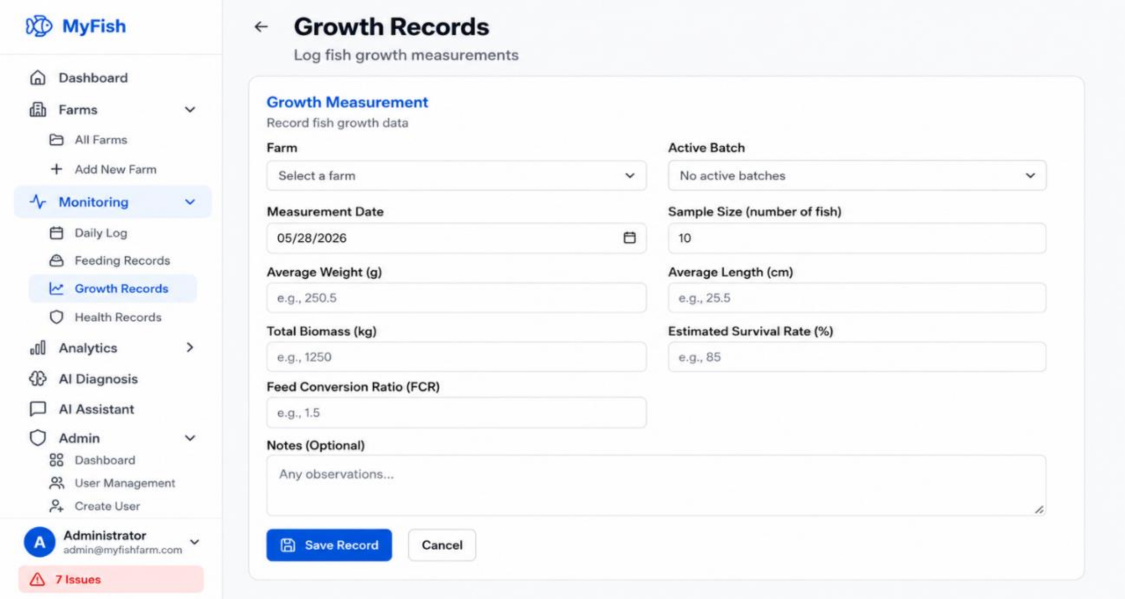

Figure 4.8: Growth Records — Fish Growth Measurement Form

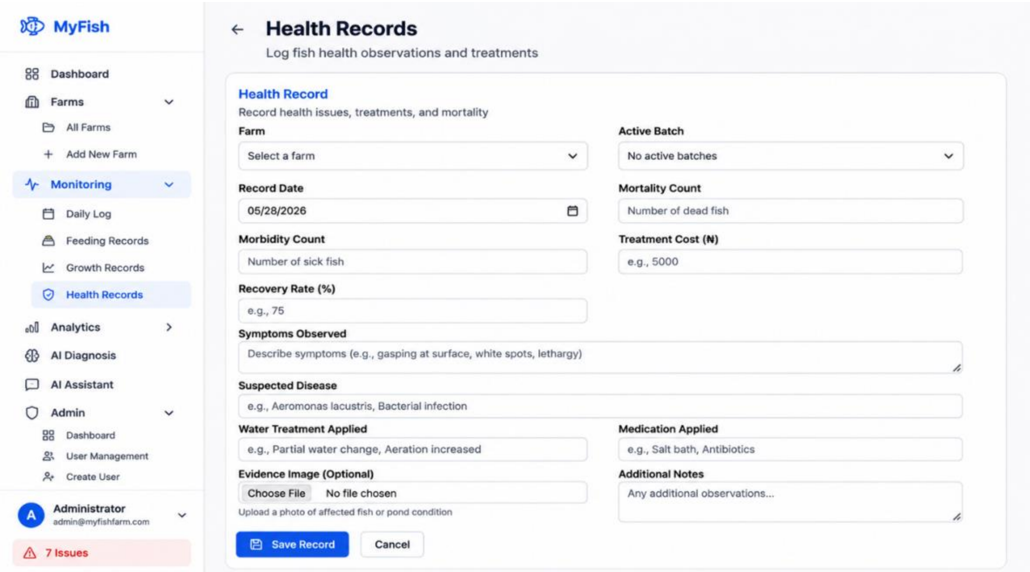

Figure 4.9: Health Records — Fish Health Observation and Treatment Log

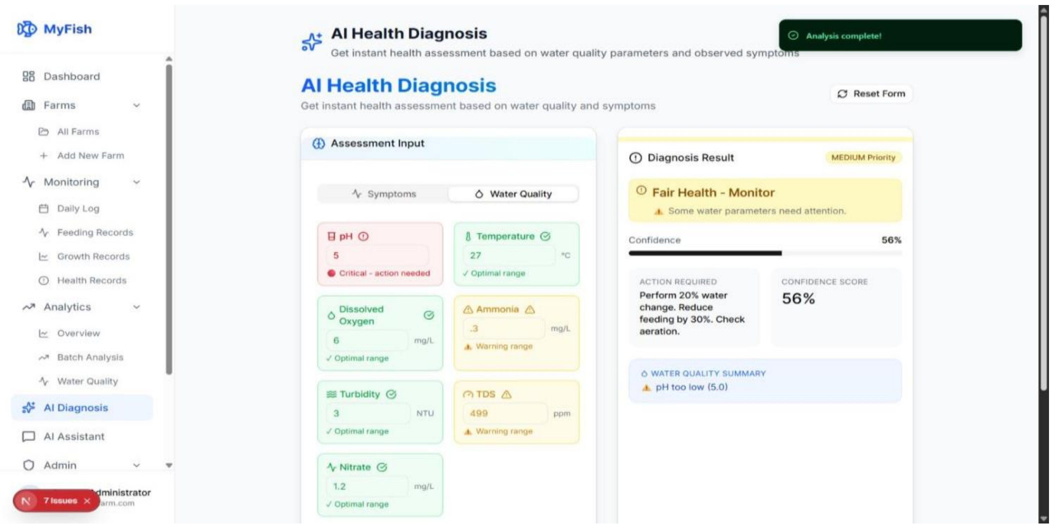

Figure 4.10: AI Health Diagnosis — Symptom Selection Input Form

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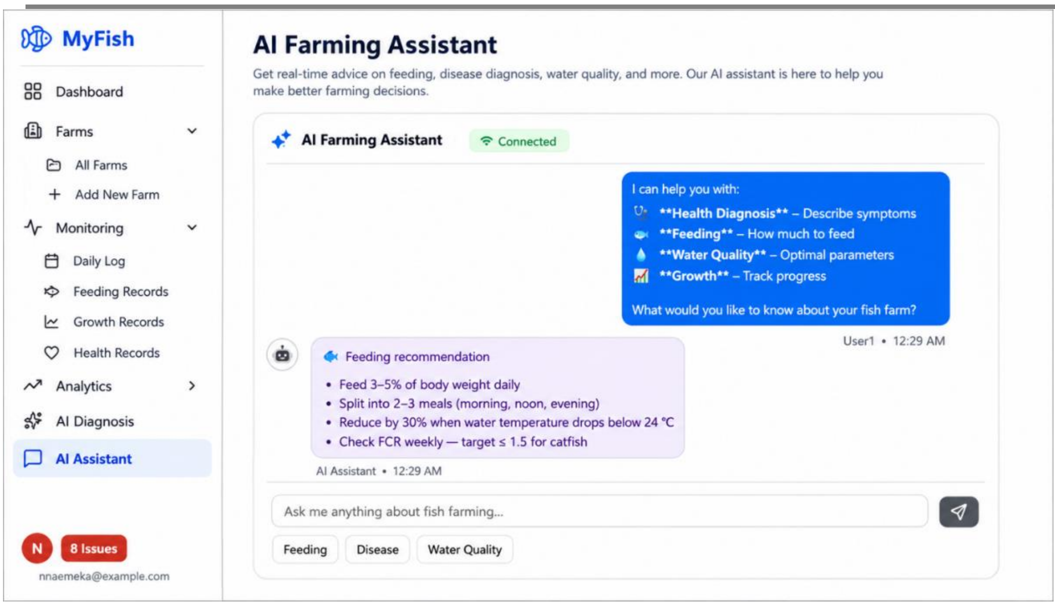

Figure 4.12: AI Farming Assistant — Chat Interface with AI Response

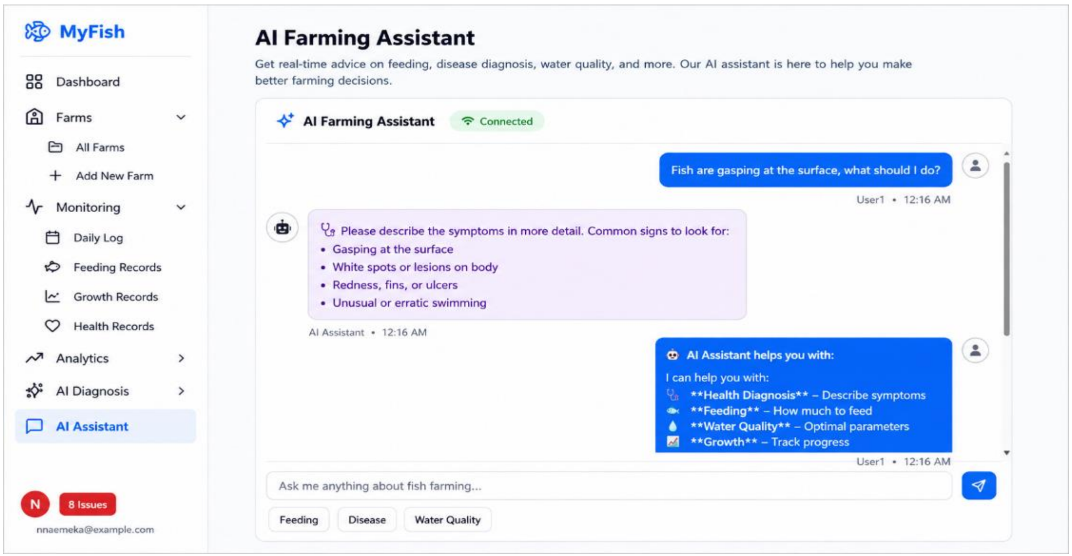

Figure 4.13: AI Farming Assistant — Feeding Recommendation Response

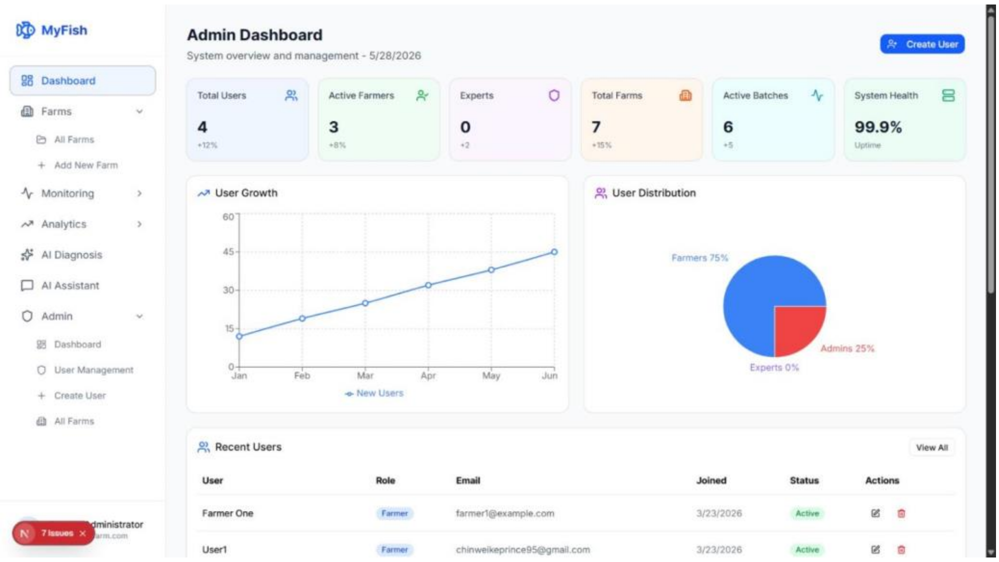

Figure 4.14: Administrator Dashboard — System Overview and Analytics

Limitations of the Study

Despite the promising results of the proposed intelligent catfish management system, there are some limitations that need to be considered. Firstly, the machine learning algorithm was trained on an openly accessible database which has been improved by rule-based expert system and is not based on real data obtained on Nigerian catfish farms. This may have an impact on the accuracy of performance due to the differences in regional climates, water chemistry, management of ponds, and the prevalence of certain diseases. Secondly, the performance algorithm was based on physicochemical water quality parameters and does not consider other factors, such as fish behavior, variations in dissolved oxygen, laboratory diagnosis of the disease. Thirdly, although the Random Forest approach provided the best performance, there are other methods of ensemble learning and deep learning that were not tested in this study.

Future Work

In the future, efforts should be directed at validating the developed model through independent datasets that would be sourced from different catfish farms in various locations within Nigeria. Validation from different sources would increase the level of evidence to support the robustness, reliability, and generality of the model under diverse environmental and farm management conditions. The integration of the intelligent catfish management system with real-time IoT sensing systems would further increase its implementation.

CONCLUSION

The Intelligent Catfish Farm Management System has shown that machine learning, rule-based expert system, real-time communication, and digital record management can be combined into one platform that will benefit Nigerian catfish farmers. The health diagnosis model based on the Random Forest algorithm has shown a test accuracy of 99.60% with very high precision, recall, and F1-scores for all five pond health categories, which proves the validity of this model in terms of pond conditions prediction. The feature importance analysis revealed that pH, temperature, and nitrate were the three most important water quality attributes, which helps to inform farmers about key monitoring areas. To increase the reliability of the system, there is also a rule-based expert system used in case of unavailability of the machine learning model or incomplete water quality data. In addition, there is an integrated real-time chat module with AI-supported answers that makes it easier to communicate with the experts. Lastly, there is also a role-based access control module that increases the security of the system through the use of JSON Web Tokens. In summary, the designed system presents an intelligent, dependable, and user-friendly solution that can be applied in catfish farm management and can be implemented on a pilot scale to facilitate efficient aquaculture operations in Nigeria.

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