

IoT-Based Automated Solution for Carp Fish Farming Using Sensor Networks and the Biochemical Parameters

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Abstract - Since fish, like many other living organisms, have a certain tolerance range for a variety of environmental factors, fish farming of particular types of fish species demands the fulfilment of a number of requirements. The people who work in the fish farming ponds must be active all day long to maintain the ecosystem for living fish. Therefore, the primary goal of this research is to monitor and take action to preserve the habitat's sustainable environment for carp fish species inside fishing ponds via distributed machine-to-machine communication, which will reduce the time required for some simple operations. Fish aquaculture, there are three major aquaculture types. The first one is marine aquaculture, the second one is brackish water aquaculture and the third one is Freshwater aquaculture also known as inland aquaculture. In this project, we mainly focused on problems that faced inland aquaculture. One of the major challenges of inland fish framing is maintaining the water quality to have healthy fish and get maximum output of fish- based products to local and foreign markets. As per NAQDA databases, the most popular inland farm fish is carp fish. So we chose carp fish as our main research object. The proposed system for fish feeding in aquaculture utilizes IoT technology to automate the feeding process according to the monitored behaviors of carp fish. The system uses sensors (Ph, Temperature, Turbidity) to gather data on environmental parameters, including water, temperature and fish feeding behaviors, which are then analyzed to improve feeding and overall fish health. By using the gathered sensor data, we will do the machine learning predictions and display the output using a React Native mobile application and a web-based dashboard.

Keywords: IoT, aquaculture, carp fish, monitoring, Ph, esp32, Sensor, microcontroller, fisheries, common carp.

I. INTRODUCTION

Research in aquaculture has led to the creation of production systems that have enhanced the quality in recent years due to advancements in monitoring and automation technology.

Improvement and increased fish yield because of the fish farming ponds. A fish farming pond is an artificial man-made environment, and at its most basic level, there are two main types of ponds: those that grow fish for human food and those that rear tropical species for use as pets and are more commonly referred to as aquariums than ponds. This research focuses on the ponds that produce fish for human consumption. These ponds are normally constructed and maintained in isolated, environmentally sound locations close to water springs, and any environmental stress from the outside will have a detrimental effect on fish productivity.

This is because fish are cold-blooded creatures that directly depend on their surroundings to control their body temperature. As a result, maintaining this ecosystem is a problem comprised of several smaller issues that are interconnected and constantly interacting. Their interaction is a complicated process that requires humans to devote a lot of time, effort, and knowledge to manage and sustain it.

As a result, along with other significant aspects like light intensity, pond water level and others. Temperature is one of the crucial characteristics that must be checked.

As per World Food and Agriculture Organization (FAO) [1], within the decade 2050, there will be more than 9 billion people on the planet and developing nations like Sri Lanka are anticipated to have similar demographic growth. Finding solutions to feed the vast human population will therefore be the major task for FAO research in the future. Additionally, according to the FAO, sea catches will stop increasing at 85 to 90 million tons annually, and aquaculture will be required to meet all demands. When compared to other industries, the

aquaculture sector has emerged as an effective global catalyst for the production of fish food. With an average annual growth rate of 11% since 1984, aquaculture has been the primary form of food production to maintain the present per capita consumption. In the future, it is anticipated that aquaculture would expand quickly and replace other food and protein sources.

Sri Lankan aquaculture industry is developing rapidly these days. Because there is a plan to double the current aquaculture production. This objective will be accomplished through the growth of a sustainable aquaculture industry.

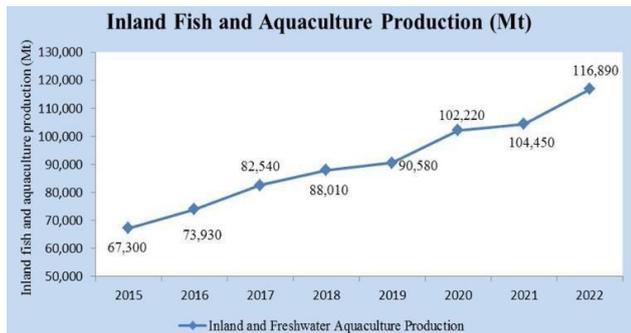


Figure 1: Total Inland aquaculture production between 2015 to 2022 [2]

To maintain sustainability and maximize food outcomes, farmers need to overcome the issues that they are facing in the current days. To overcome those issues, they need new technologies that they can use to optimize the fish harvest and reduce the problems. So before picking a research topic we had some meetings with an officer who works in the National Aquaculture Development Authority (NAQDA). So we learned that there are three main aquaculture types. One is saltwater aquaculture, the next one is brackish water aquaculture and the last one is freshwater aquaculture also known as inland aquaculture.

Sri Lankas Annual fish production by different sub sectors

Year	Off-shore Marine Fish Catch	Coastal	Inland and Aquaculture	Total	% share of Inland
1999	76,500	171950	31,450	279,900	11.24
2000	84,400	163,300	36,700	284,400	12.06
2001	87,300	167,300	38,970	293,570	10.49
2002	96,510	176,250	28,130	300,890	9.29
2003	90,830	163,350	30,200	284,380	10.63
2004	98,720	154,470	33,100	286,290	11.59
2005	66,710	63,690	32,830	163,230	20.10
2006	94,820	121,360	35,290	251,470	14.09
2007	102,560	150,110	38,490	291,160	13.2
2008	109,310	165,320	44,490	319,120	13.9
2009	112,760	180,410	48,560	339,730	13.7
2010	129,840	202,400	52,410	384,650	13.6
2011	160,270	229,990	59,560	449,820	13.5
2012	159,680	257,540	68,950	486,170	14.2
2013	177,950	267,980	66,910	512,840	13.0
2014	190,450	278,850	75,750	539,050	14.2
2015	183,870	269,020	87,300	530,190	15.9
2016	182,800	274,660	73,930	531,390	15.9
2017	189,720	259,720	82,540	531,980	15.5
2018	190,350	249,020	88,010	527,380	16.7
2019	172,910	242,580	90,580	506,070	17.9
2020	144,370	182,560	102,220	429,150	23.9
2021	152,825	179,260	104,450	436,535	23.9

Figure 2: Annual fish production by different sub-sectors

We found that in Sri Lanka inland aquaculture farms mainly use carp varieties as farming fish species. After the discussion, we found some major problems that Sri Lankan

freshwater fish farmers face. One of the major challenges of this fish farming is to maintain the water quality to have healthy fish and get maximum output of fish-based products to local and foreign markets [3]. As per the data we gathered from the NAQDA farmers the main reason for water quality problems is providing fish pellets and other feeding items more than the fish needed. (Simply overfeeding and fish wastage). So, because of overfeeding and fish wastage, the water parameters of fish tank/pond Container become unlivable for Carp fish. Decreased oxygen levels can lead to stress and death of fish. Toxicants can harm fish health, prevent them from growing well, and produce an environment that is favorable to growth diseases. Creating pathogens that can cause illness outbreaks in carp fish. The proposed automated system is a machine learning engaged web solution which will help carp fish farmers to identify is there any risk in their farms that can affect their fish production. The system will provide efficient and accurate communication between farmers. To remotely monitor and manage the system, a mobile application has been created. As a result, the most elite and competitive aquaculture sector could emerge. Fish farming changes could be influenced by financial benefits. Using smart management technologies, farmers can collect data in real-time, optimize fishing performance, and revive the metabolic processes connected to limiting fisheries.

II. LITERATURE REVIEW

In Sri Lanka, people use fish as their main protein food resource. Sri Lanka has a total of 1700 kilometres of coastline, with a estimated 121,000 hectares of lagoons and estuaries [1] But we can see that saltwater fish prices are very high these days. So lots of people in Sri Lanka didn't buy fish products because of the high cost and they couldn't afford to spend that much of money because the economic crisis. They didn't have to way to get protein to their day-to-day meals. So the government and NAQDA now have an eye on developing inland aquaculture. Previously in inland fish industry farmers sold the wild-caught that they caught from natural ponds. So only the village-based families got a chance to eat those freshwater fish species. But now the government and NAQDA have built inland aquaculture fish farms all around the country so that lots of people can get freshwater fish species as their food resource. Carp fish species are the main species that Sri Lankan farmers use to breed on their farms. We identified that one of the major problems in those farms is managing and detecting water quality after a fish feeding. In NAQDA farms they use larger ponds, medium ponds, small ponds and tanks for fish breeding. One of the major challenges of this fish farming is maintaining the water quality to have healthy fish and get maximum output of fish- based products to local and foreign markets.[3] As per data we gathered from the NAQDA farmers the main reason for water quality problems is

providing fish pallets and other feeding items more than the fish needed. (Simply overfeeding and fish wastage). So, because of overfeeding and fish wastage the water parameters of fish tank/pond Container become unlivable for Carp fish. Decreased oxygen levels can lead to stress and death of fish. Toxicity can damage their health and fish may not grow well in those conditions and also can create an environment that is conducive to the growth of disease. Causing pathogens which can lead to outbreaks of disease to carp fish.

Argulus, Tricodina, Aerominia, columnaris, gnteric, redmouth disease carp edma virus, spring viraemia of card are some carp fish diseases that spread because of bad water quality conditions.

Still, the farmers did not have a way to identify these diseases early. So, they can start taking necessary actions when the fish has started to show symptoms. So, at that time it would be too late, and they can lose their entire fish aquaculture [3]. As per gathered details still the farmers use manual ways to measure the water quality parameters. So, there can be inaccurate monitoring and inaccurate prevention methods. Deluge responses increase the rich of diseases when using manual ways. According to research papers that we read and the studies, there are not many applications to identify 2fish disease in its early stages. Specially could not find a system that was specially developed for Carp fish aquaculture farms. There are some mobile-based devices that identify fish diseases using image processing. But those devices only analyze the dead fish images. Farmers can only find the disease when fish are dead. So to overcome this problem our system will give early predictions and risk alerts before the disease spreads among all the ponds and tanks And also, there are some automated feeding systems, but we are going to identify the fish's hungry behaviors and control the feeding according to that data.

Min, Wei, Showkat and Nen-Fu[7] developed a smart aquaculture management system using IoT and AI-based surrogate models. Sensors built into the system is managed by an Arduino Mega2560. They link the various feeding system parameters using a deep learning model to forecast Californian bass fish development. To remotely monitor and manage the system, a mobile application has been created. To determine the input and output variables with the greatest influence on the model's ability to forecast the future, a correlation study was carried out.

Nocheski and Prof Naumoski [9] developed an IoT device that communicates to end-users using sound and RGB LED lights and a messaging system that shows the output on an LCD screen. This project was an enhancement of a currently developed IoT system. To enhance the system they

use a Wivity module. The authors of [10] have developed an automated Internet of Things (IoT) system for the automated fish farming in which the water temperature, pH, and level are monitored using a Wi-Fi remote connection. This could be problematic for systems that are installed in remote locations without access to cellular or other types of internet connections. The authors in [11] suggested a GSM type of notice by sending SMS messages to the end user in order to solve this issue. This proposed system's procedure of notifying the end user after certain intervals or when a predetermined parameter value is reached is one drawback. In the sense of real-time monitoring, this can be overcome.

III. METHODOLOGY

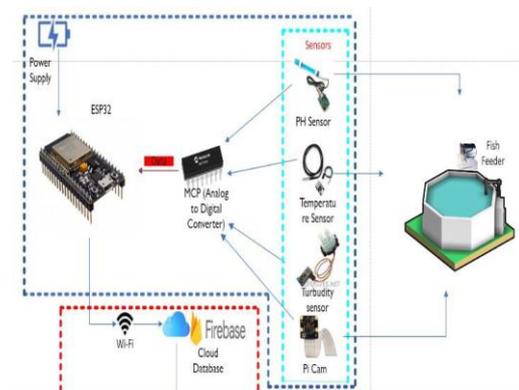


Figure 3: System Diagram

The proposed solution provides a smart approach for fish farmers, researchers, and industry specialists to detect water quality conditions and identify the risk of diseases. As shown in Fig. 3 the device contains an ESP32 module, pH sensor, and turbidity sensor. All functions in the fishpond are driven by the water's temperature. It's controlling the oxygen level in the water as well as the growth and development of the pond's vegetation and other animals. When it comes to fish that dwell in rivers, like trout, the ideal temperature is around 14°C. For tropical fish, the ideal temperature is 25°C with a 2°C allowable fluctuation. The optimum water temperature for carp fish growth and propagation is 20-25°C. [12]

In the developed system we used ESP32 Microcontroller as our main board. It's a low-cost and low-power chip microcontroller that has integrated Wi-Fi and Bluetooth.[15]



Figure 4: ESP32

To monitor the water temperature, we used the DS18B20 Temperature probe. It communicates over one wire bus and needs a power supply between 3.0V to 5.5V. operating temperature range is -55°C to +125°C and accuracy +/-0.5 °C (between the range -10°C to 85°C)[13].



Figure 5: DS18B20 Temperature probe

The turbidity sensor is operating in 5V DC. The operating current is 40mA and the response time is <500ms. It gives both Analog output 0 – 4.5V and Digital Output. It operates between 5°C ~ 90°C and the adapter dimensions are 38mm*28mm*10mm/1.5inches *1.1inches*0.4inches [14].



Figure 6: Turbidity sensor

To measure the pH value used a pH probe sensor. The module power is 5.00V, size 43mmx32mm, measuring range 0-14pH and temperature range is 0-60°C accuracy is ± 0.1pH (25 °C) and the response time is ≤ 1min.



Figure 7: pH sensor

To measure the pH value used a pH probe sensor. The module power is 5.00V, size 43mmx32mm, measuring range

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A) Carp fish disease risk identification and future disease prediction

The purpose of this component is to identify the disease risks in the ponds or tanks before the disease spreads to all the ponds on the farm. If the farmers can get an early alert about disease risks, they can start the prevention methods early. after the field visit to the Kurumegala NAQDA aquaculture farm our research team identified four main diseases that spread in Sri Lankan carp fish farming. The diseases are

- Aeromonas
- Columnaris
- Whitespots
- Spring viraemia of carp (SVC)

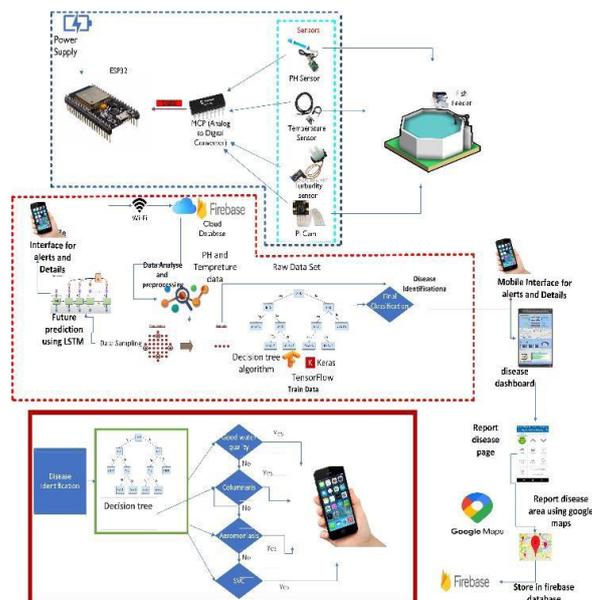


Figure 8: Overall system diagram of the disease identification solution

The mentioned diseases are viruses and bacterial infections. Each disease-spreading virus and bacteria have an optimal level of pH and temperature ranges that they can incubate and start spreading the disease in the carp fish farms. So develop the disease risk detection system by using pH values and temperature values as inputs.

Aeromonas Hydrophila is well-known bacteria that cause diseases in carp fish and reptiles. Lots of cultured fish types are vulnerable to this disease [16]. The optimal growth pH value of the bacteria is between 6.5 to 7.2 and the temperature range is between 28°C to 35°C. [17]

Columnaris is also known as cottonmouth disease. Bacteria named Flavobacterium columnaris is the reason for this disease. Although oral mucosa can occasionally be disturbed,

pathological alterations are often restricted to the gills, skin, and fins. Internal lesions and systemic infections are infrequent and typically develop after the tissues on the outside have been damaged. Depending on the circumstances of the outbreak, the species of fish, and the virulence of the strain involved, a disease may be acute, subacute, or chronic.

Mortality rates can be very high, with a typical range of 60% to 90%. The optimal growth pH value of the bacteria is between 7.0 – 7.5 [18] and the temperature range is between 20°C to 25°C [19].

Carp fish white spot is a disease infected because of the protozoan name *Ichthyophthirius multifiliis*. The optimal growth pH value range is 8.0 – 10.0 [20] and the temperature range is 24°C to 27°C [21].

Rhabdovirus carpio is the disease cause agent of spring viremia of carp (SVC). Clinical signs of SVC include lethargy, enteritis, peritonitis, oedema, exophthalmia, thickening of the swim bladder, and petechial haemorrhages in internal organs, skin, and muscle. The optimum growth pH value of the virus is 7.3 – 7.6 [22]. The optimum temperature value is 10°C – 17°C [23]. For the ML predictions and the time forecasting, we used given pH ranges and temperature ranges.

1) Data collection and processing

Machine learning (ML) models were trained using the sensor-based data gathered from the carp fishponds. For disease identification, got a time series dataset nearly three months long. The data set has five columns. Date and Time, Temperature, pH, turbidity, and a Disease column. The data was divided into 80% training and 20% testing. Table 1 summarizes the data collection process.

To reduce the complexity and to improve the accuracy of the data set used preprocessing techniques such as data cleaning and encoding. For the future prediction of diseases in the fish tank or pond chose ML time series models. There are a lot of time series models that we can choose to develop a future prediction model. Here the prediction is a singular value, so according to the previously published research the best model for this kind of scenario is a global univariate model. LSTM and Tree-Based method is used to test the accuracy of the time series data model.

2) Training the disease detection models

Table I: Summary of data samples

Disease	Purpose	Data
Optimal	The optimal value for the carp fish	5102
Aeromonas	Aeromonas disease Risk	1245

	identification	
Columnaris	Columnaris disease Risk identification	825
Whitespot	White spots disease Risk identification	561
SVC	Spring Viraemia disease Risk Identification	501
Total		8234

To detect the risk levels of the carp fish tank or pond we tried the linear algorithm, decision tree algorithm, random forest algorithm and the lasso algorithm. Table 2 summarizes the Accuracy of the disease prediction ML algorithms.

After training the models, the highest accuracy rate for disease risk identification was given by the decision tree algorithm. Because of the disease risk identification part choose decision tree algorithm as the ML model. The dataset is divided into a training set and a testing set to assess the precision of a decision tree model created to predict disease based on pH and temperature variables. The decision tree algorithm, which learns patterns and develops decision rules based on the pH and temperature values, is trained using the training set. The model is used to make predictions on the testing set after it has been trained.

Table II: Tested machine learning models for disease prediction

ML model	ML model accuracy
Linear Regression	0.5825336522110698
Lasso	0.14452075974874334
Decision Tree Regression	0.9995596358686958
Random Forest Regression	0.9984790263268883

According to accuracy levels choose the Decision Tree algorithm to continue the disease risk identification process.

For disease future forecasting, we trained the data using several models to check the highest accuracy model.

As the first model, we used oversampling applied to test the data. Used the Long Short-Term Memory (LSTM) model using TensorFlow/Keras to predict diseases based on time series data. with over-sampling techniques adapted for the preprocessing of data produces a test accuracy of 23% The LSTM model is created using the Sequential API from TensorFlow/Keras.

It consists of an LSTM layer with 64 units and 'relu' activation function, designed to process the time series data. The output layer is a Dense layer with the number of units equal to the number of disease classes ('len(label_encoder.classes_)') and a 'softmax' activation function to provide probabilities for each class.

The model is compiled with the 'adam' optimizer and 'categorical_crossentropy' loss function, suitable for multi-class classification problems. The accuracy metric is used to evaluate the model's performance during training.

The second method is under sampling applied. Random Undersampling is applied on the training data using the 'imblearn' library to balance all disease classes equally. LSTM model is created using the Sequential API from TensorFlow/Keras. It consists of an LSTM layer with 128 units and a 'relu' activation function, designed to process the time series data. The output layer is a Dense layer with the number of units equal to the number of disease classes ('len(label_encoder.classes_)') and a 'softmax' activation function to provide probabilities for each class.

The model is compiled with the 'adam' optimizer and 'categorical_crossentropy' loss function, suitable for multi-class classification problems. The accuracy metric is used to evaluate the model's performance during training. Test accuracy reducing to 12% with a huge data loss with the reshaping of the data. For the third method we used Long Short-Term Memory (LSTM) neural network which is a type of recurrent neural network (RNN) designed for processing sequential data with test accuracy of 95% and trained accuracy of 97%. Thus avoids the possibility of the data overfitting and underfitting as both test and train set accuracies are present in the same range. Predicting diseases based on time series data with input features like Date and Time, Temperature, pH, and Turbidity (NTU). The data is preprocessed by performing one-hot encoding on the target variable ('Disease') and scaling the input data. Random under sampling with shuffling is applied to balance the class distribution. The LSTM model consists of an LSTM layer with 128 units and a 'relu' activation function, followed by a dropout layer with a dropout rate of 0.2, and finally, a dense output layer with a 'softmax' activation function to provide class probabilities.

The model is compiled with the 'adam' optimizer and 'categorical_crossentropy' loss function, and accuracy is used as the evaluation metric. The model is trained with 20 epochs and a batch size of 32.

Table III: Tested machine learning models for disease forecasting

Model Name	Accuracy
Oversampling applied	0.23707865178585052
Under-sampling applied	0.12743902206420898
LSTM	0.9736481308937073

The highest accuracy level was given by the Long Short-Term Memory (LSTM) neural network model. Because of that, we choose this module for our future disease prediction part.

B) Smart system for carp fish farming and response with real-time data

The proposed system provides a convenient approach to stakeholders facilitating the management of carp fish aquaculture farms. The proposed system has an IoT device that transfers real-time data to the Firebase database and also a React native android application that can read the real-time sensor data and by using the data app can perform predictions like the water quality of the carp fish farm and disease risk identifications. And also it has a future disease prediction system that farmers can identify future disease risks according to past disease data.

IV. RESULTS AND DISCUSSION

The models for disease risk detection and forecasting was trained using several machine learning models (Table 2). The best module for the solution was selected among them by considering the accuracy.

Three sensors temperature, turbidity and pH sensor were used to get the real-time data. We've also created a mobile app for React Native that allows farmers to keep an eye on the relevant water quality metrics detected by smart ponds or tank sensors. The monitored data is directly stored in a cloud database and the app reads the data and shows the real-time data on a dashboard. The main purpose of the system is to predict future water conditions, diseases and future diseases and notify the carp fish farmers. The results of the developed machine learning models learning process highlight its prediction accuracy.

Temperature, turbidity, and pH sensor were used to get the real-time data. We've also created a mobile app for React Native that allows farmers to monitor the relevant water quality metrics detected by smart ponds or tank sensors. The program reads the monitored data from a cloud database and displays the real-time information on a dashboard.

The main purpose of the system is to predict future water conditions, diseases and future diseases and notify the carp fish farmers. The results of the developed machine learning models learning process highlight its prediction accuracy.

Using real-time farm information allows you to identify problems before they occur because the prediction is founded on the most recent information. The evolution of one parameter and the evolution of external factors might be related. We have utilised the ML model to forecast the most important parameters impacting the growth of the smart fish pond based on the real-time observations of a variety of data. Numerous studies have shown that water temperature is one of the most crucial factors affecting water dissolved oxygen

levels. Several factors, including the kind of aquaculture, have a significant impact on the dissolved oxygen levels in aquaculture systems. Depending on the nature of production, these factors' impact varies. The majority, however, may be measured and taken into account by an Internet of Things-based prediction model.

V. CONCLUSION AND FUTURE WORK

In this research, we used cutting-edge technologies like Machine Learning, and time series forecasting technologies used to identify the disease risks and other prediction functions. Decision tree, random forest, SARIMAX, oversampling, under sampling, long short-term memory neural network and Tree-based method. For those overall accuracy is between 89%-99%. Google Maps and expo libraries were used to correctly share the disease locations with researchers and fish farm officers. The proposed system has a three-sensor IoT device and a mobile application for viewing the machine learning predicted outcomes. In the future researchers can add more sensors (dissolved oxygen etc.) to the IoT device and increase the accuracy of the disease risk detection and other sensor-based functionalities and, it should be developed to identify more diseases and other problems that carp fish aquaculture farms already have.

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Citation of this Article:

Sachin Dileepa, P.P.S Amarasinghe, H.K.A.D Sandamini, N.H Manimendra, Sathira Hettiarachchi, Suranjini Silva, "IoT-Based Automated Solution for Carp Fish Farming Using Sensor Networks and the Biochemical Parameters" Published in *International Research Journal of Innovations in Engineering and Technology - IRJIET*, Volume 7, Issue 10, pp 274-281, October 2023. Article DOI <https://doi.org/10.47001/IRJIET/2023.710035>
