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Research Article

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Smart Prediction of Water Quality System for Aquaculture Using Machine Learning Algorithms

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Abstract

Intelligent and Smart aquaculture is nowadays one of the most important latest development trends in the field of the aquaculture industry to overcome the problems of the farmers due to water quality monitoring, food feeding, temperature imbalance, and recycling of water. Smart water quality prediction in the real-time environment using intelligent machine learning models and IoT sensors establishes the basis for the evaluation, planning, and intelligent regulation of the aquaculture environment. The purpose of this study is to propose an intelligent Machine learning and IoT-based Biofloc system that enhances the efficiency, production, water recycling system, and automatic food feeding system. This paper proposed a system that collects process data from sensors, stores data in the cloud, and analyses it using different latest machine learning models such as a Decision tree classification model, and Random Forest Model to predict the water quality and provides real-time monitoring through an android app. The article presented a system that collects data using sensors, analyzes them using a machine learning model, generates decisions with the help of Artificial Intelligence (AI), and sends notifications to the user. The proposed linear regression, Random Forest, and other ML models have been implemented and tested to validate and achieve a satisfactory result. A performance comparative analysis of the different ML algorithms has been conducted based on a few metrics such as accuracy, recall, precision, and F1-score. Random Forest Classifier has surpassed all the other models in terms of accuracy, recall, precision, and F1 score. Random Forest Classifier has exhibited an accuracy of 73.76%, recall, precision, and F1-score of 90%, 75%, and 82% respectively.

Keywords: Aquaculture, Machine Learning, water quality prediction, IoT, Sensor, Random Forest classifier, Decision Regression Tree, Biofloc.

1. Introduction

Nowadays the quality of water is one of the major problems in the world as it is getting contaminated due to human activities. Quality of water and cultivating freshwater under controlled conditions are very important for the effective and efficient farming of aquatic organisms such as fish in the field of Aquaculture [1,2]. With the advanced technological development of the Internet of Things (IoT), big data, and artificial intelligence (AI), aquaculture is progressively becoming more intensive, precise, and intelligent. In the field of high-density intensive aquaculture, continuous monitoring and predicting water quality trends (that is, forecasting the trends of water quality parameters such as dissolved oxygen, pH, temperature, and turbidity) in real-time is of great significance for averting the water quality from deteriorating and for avoiding the outbreak of disease.

An intelligent IoT based Aquaculture system can help the farmers by measuring the water parameters continuously using modern IoT sensors in order to monitor and maintain the quality of water, Hence, measuring all the water parameters for the bio floc aquaculture and also a water quality prediction model for the dynamic changes in water parameters are essential [3]. The IoT sensors measure and collect water parameters accurately and transmit them to the base station host computer. Remote monitoring of fish farming is possible based on the sensor data. Then collected data sets are used by farm managers for decision-making purposes.

The article presented a system that collects data using sensors and analyzes them using different latest machine learning models like Decision trees, Random Forest, Logistic Regression, and Support Vector Machines to predict the water quality, and generate decisions with the help of Artificial Intelligence (AI), and sends notifications to the user when the predicted water quality appears to exceed the critical conditions. It also provides real-time monitoring through an Android app from remote mode.

Thus, it will be easier to monitor the water quality and maintain the ecology in biofloc aquaculture.

This article focuses on the importance of the continuous collection of water parameters data from the sensors and also the prediction of water quality using the latest different Machine learning algorithms like Logistic Regression, Random Forest, Support Vector Machine, Decision Tree, K-nearest Neighbour, XGBoost, Gradient Boosting, and Naive Bayes.

These Machine learning models are implemented and tested to validate and achieve a satisfactory result of water quality prediction in terms of different attributes like pH, hardness, Solids, Chloramines, Sulfate, Conductivity, organic carbon, trihalomethanes, Turbidity, and portability.

This paper also focuses on the importance of water quality suitable for aquaculture. It helps aqua farmers to produce brilliant fish, which in turn helps the economy of the agricultural sector. Machine learning model helps to enhance better, more accurate, and faster forecasts of water quality based on accumulated data.

2. Related Work

A lot of research work has been done in the field of Artificial Intelligence (AI), Machine Learning (ML), and IoT-based Smart Water Quality Prediction in the field of Aquaculture.

A. A. Nayan et al. have worked on River water quality for agriculture and fishing applications and identified fish diseases due to the changes in water quality using Machine learning [4,5]. He measured the water quality in terms of pH, DO, BOD, COD, TSS, TDS, EC, PO43-, NO3-N, and NH3-N and predicted the output using a boosting technique. However, he has not suggested any intelligent solutions for small water resources. Juntao Liu et al worked on an accurate and automated system for water quality prediction using the Simple Recurrent Unit (SRU) [6]. It mainly concentrates on predicting water quality in terms of pH and temperature. Finally, the SRU model is presented and it is compared with the RNN model which proves that SRU has high accuracy.

A smooth Support Vector Machine (SSVM) based prediction model was proposed by Wijayanti Nurul Khotimah to predict the quality of water [7]. SSVM is proved to be an effective model for the prediction of water quality with a 0.0275 RMSE value.

J. Wang et al. investigate the characteristics of strong interactions with the correction of water quality parameter information and the disappearance of gradient and gradient Kiranbabu T S, ManojChalla 323 explosions caused by data training of the traditional RNN network model, etc [8]. The structure is shown on this page. Dong Yao, Lei Cheng, QiuXuan Wu, Gong Zhang, Bei Wu, and YuQing He investigate how to analyze and predict the quality of fishing using an electrochemical sensor array such as melted oxygen, pH ammonia, and nitrogen carried by an unauthorized air vehicle [9].

Encinas et al. worked on a ZigBee-based wireless sensor network for a water quality prediction system in the field of Aquaculture using a temperature sensor, pH sensor, and Dissolved Oxygen sensor [10]. However, the performance of water parameter management was not satisfactory.

Liu et al. worked on the Recirculating Aquaculture System (RAS) to conduct an experiment on "RasCarpio" [11]. In 2011, RAS was a better solution for aquaculture in a pond. The water parameters were checked continuously, and if any parameter crossed the specific value, then the water automatically recirculated. WATT TriOMatic, WATT Sensolyt, and WATT Tri oxyTherm type sensors were used to sense dissolved oxygen, pH, and temperature.

3. Dataset

The dataset has been sourced from Kaggle. It is comprised of 3276 entries stretched across 10 columns. A brief description of all the columns is listed below:

3.1. pH value

• pH is an important parameter that is responsible for indicating the acidic or basic nature of the water. A pH value greater than 7 indicates it is basic in nature, a value less than 7 indicates it is acidic in nature and a value equal to 7 means it is neutral in nature. Distilled water has a pH value of 7.

3.2. Hardness

• The hardness of water is mainly caused due to the presence of calcium, magnesium, and iron salts.
• Solids (Total dissolved solids - TDS)
• The presence of minerals in the water, such as potassium, calcium, sodium, bicarbonates, chlorides, magnesium, sulfates, etc. leads to a high TDS value. The permissible TDS value for drinking water is 500 mg/L to 1000mg/L.

3.3. Chloramines

• For the disinfection of water, the widely used chemicals are chlorine and chloramines. The permissible range of chloramines that can be dissolved in water is up to 4 mg/L.

• Sulfate

• Sulfates are found in minerals, soil, and rocks. However, its application is mainly in the chemical industry. The sulfates are either found naturally or are discharged by the chemical industry in our waterbodies. Sulfate levels are almost 2.8 g/L in seawater and 3 to 30 mg/L in freshwater bodies.

• Conductivity

• The presence of ions leads to electrical conductivity (EC) in water. Pure water or distilled water does not conduct electricity. World Health Organization (WHO) has set standards that for drinking water, the EC value should not exceed 400 µS/cm.

3.4. Organic_Carbon (Total Organic Compund - TOC)

• TOC is a measure of the total amount of carbon from organic compounds found in water. Carbon is found in water because of decaying natural organic matter (NOM). It should be less than 2mg/L for drinking water.

• Trihalomethanes - THM

• The concentration of THM varies according to the level of organic compounds present. THM level up to 80 ppm is considered safe for drinking purposes.

3.5. Turbidity

• It is a measure of solid particles suspended in the liquid. The permissible value if 5 NTU, recommended by WHO.

• Portability

• This indicates whether the water is safe for drinking or not. Potability value 1 indicates it is Potable (safe for consumption) and 0 indicates Not Potable (not safe for consumption).

3.6. State-of-The-Art Machine Learning Algorithms

In this section, some of the modern ML algorithms that can be used for the prediction of water quality in Aquaculture have been discussed. Support Vector Machine (SVM) is a supervised Machine learning used for classification and regression. The primary objective of the SVM is to search for a hyperplane that distinctly classifies the data points [12].

Logistic Regression is a supervised Machine Learning algorithm mainly used for classification problems. The important intention of logistic regression is to discover the best-fitting model to describe the relationship between the consequence and a set of predictor variables [13]. K-Nearest Neighbors (KNN) is a very simple supervised ML algorithm that can be used for the solution of classification and regression problems. It predicts whether a particular data point belongs to a particular class or the other based on the calculated distance between the particular data point and the other points [14]. The particular data point pertains to that class whose data points are nearest to it. Naïve Bayes (NB) classification algorithm is a probabilistic classifier. It is based on probability models that incorporate strong independence assumptions [15]. A Decision Tree (DT) is a supervised learning algorithm. The primary objective of using DT is to create a training model that can predict the class or value of the target variable by learning simple decision rules based on prior data [16]. Random Forest is a supervised ML algorithm used for classification and regression problems [17]. It builds decision trees on different samples and takes their vote for classification and average in case of regression. Over-fitting of data can be escaped by this model. Stochastic Gradient Descent (SGD) is an iterative method for optimizing an objective function with suitable smoothness properties [18]. It is also regarded as a stochastic approximation of gradient descent optimization. Extreme Gradient Boosting, XGBoost is a member of the family of boosting algorithms. It is a scalable distributed gradient-boosted decision tree machine learning library. It provides parallel tree boosting. It is an ensemble ML approach and uses a gradient-boosting framework for prediction [19]. It combines predictors with low accuracy and converts them into a model with an elevated accuracy [20,21].

4. Methodology

The methodology has been described in this section and the proposed workflow has been illustrated in Figure1

In this section, the details of the methodology are presented that has been used to forecast water quality, regulate the situation, and process-wise decisions.

The dataset which is measured and collected from IoT sensors, has been used for Machine learning model training and validation comprised of the following attributes [22]:

pH, hardness, Solids, Chloramines, Sulfate, Conductivity, organic carbon, trihalomethanes, Turbidity, and potability. The dataset is stored in a CSV file. Out of the 10 attributes, potability is considered the target variable while the remaining nine attributes are considered the predictor variables. The size of the dataset is (3276 x 10). The dataset that has been used has undergone thorough pre-processing prior to the implementation of the ML models. At first, the dataset was checked for null values and when found discarded. Then the dataset has been inspected to detect the presence of any outliers. The Interquartile Range (IQR) method has been used for the detection and subsequent dropping of outliers. After dropping the null values and outliers from the original dataset, the remaining dataset in hand has been split into training data and testing data. A test size of 15% has been considered. Then Standard Scaling was used to transform all the attributes within the same range.

FLOWCHART OF METHODOLOGY PROPOSED

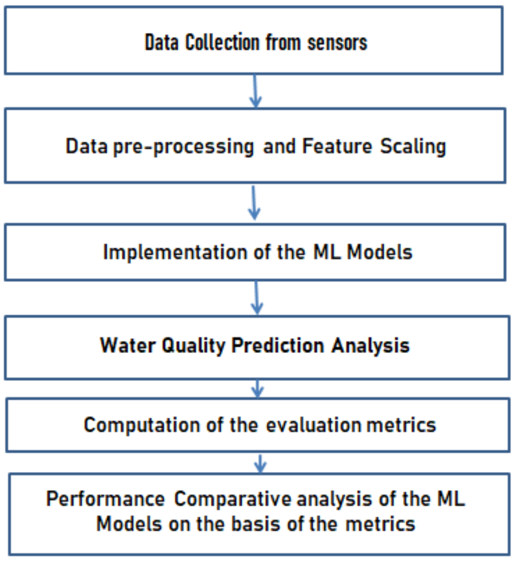

Figure 1: Flowchart of Methodology proposed

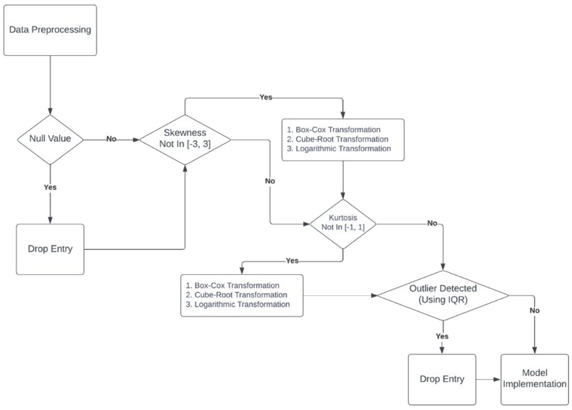

Figure 2: Flowchart of Data Preprocessing proposed

In Figure 2, the Data Preprocessing steps are shown for visualization purposes.

In Figure 3, the distribution plot of the 9 attributes is shown before any sort of data processing steps. This will help in understanding how the distribution changes after data preprocessing.

In Figure 4, the distribution plot of the 9 attributes after data preprocessing is performed. On close inspection, one can notice the change in the distribution of the Turbidity attribute after the processing step.

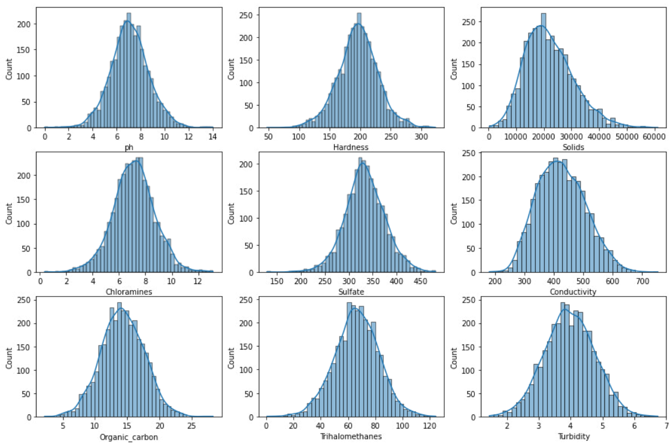

Figure 3: Distribution plot of 9 attributes before data preprocessing

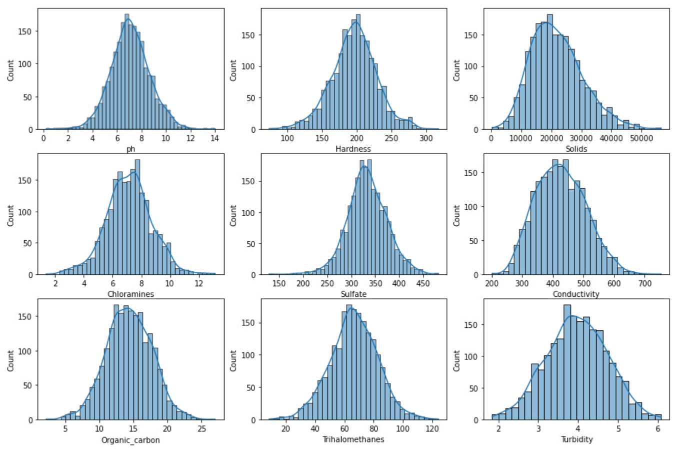

Figure 4: Distribution plot of 9 attributes after data preprocessing

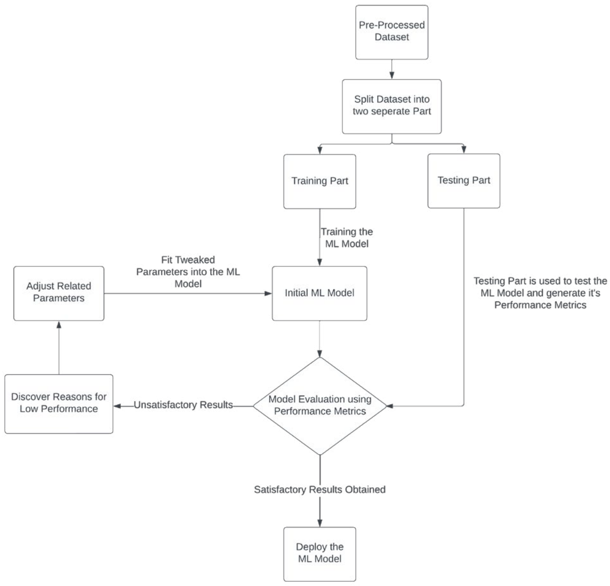

Figure 5: Flowchart of ML Model implementation

In Figure 5, the proposed ML Model implementation is shown after the data preprocessing stage.

5. Experimental Results and Discussion

A comparative analysis of the nine algorithms has been done based on the following Performance metrics:

- *Accuracy*
- *Recall*
- *Precision*
- *F1 score*
- *Area Under Curve – Receiver Operating Characteristics (AUC-ROC) Curve*

For the evaluation of the accuracy, recall, precision, and F1 score, the following 4 attributes have been used in the measurement:

- *True Positive (TP)*
- *True Negative (TN)*
- *False Positive (FP)*
- *False Negative (FN)*

The above-mentioned attributes for each of the eight machine-learning models have been enlisted in Table 1.

Model	TP	FP	FN	TN
RFC	121	13	40	28
SVM	107	25	33	37
XGBC	94	36	42	30
DTC	117	7	54	24
KNN	121	13	40	28
GBC	94	36	28	44
NBC	109	21	59	13
LR	132	0	70	0

Table 1: Attributes for The Calculation of Performance Metrics among the Proposed Ml Algorithms

The performance comparison among the proposed Machine Learning algorithms has been demonstrated in Table 2.

Model	Accuracy	Recall	Precision	F1-score
RFC	0.7376	0.90	0.75	0.82
SVM	0.7129	0.81	0.76	0.79
XGBC	0.7029	0.80	0.75	0.77
DTC	0.698	0.94	0.68	0.79
KNN	0.698	0.73	0.78	0.76
GBC	0.6832	0.72	0.77	0.75
NBC	0.6732	0.89	0.70	0.78
LR	0.6534	0.9967	0.65	0.79

Table 2: Comparison of The Performance Metrics Using Different Ml Algorithms

A comparison of the prediction time for the proposed Machine Learning algorithms has been demonstrated in Table 3.

Model	Prediction Time
RFC	0.054 s
SVM	0.016 s
XGBC	1.206 s
DTC	0.032 s
KNN	0.054 s
GBC	0.008 s
NBC	0.087 s
LR	0.029 s

Table 3: Comparison of The Performance Metrics Using Different Ml Algorithms

The AUC-ROC curves of all the implemented Machine Learning Models are shown in Figures 6, 7, 8, 9, 10, 11, 12, and 13 respectively [23].

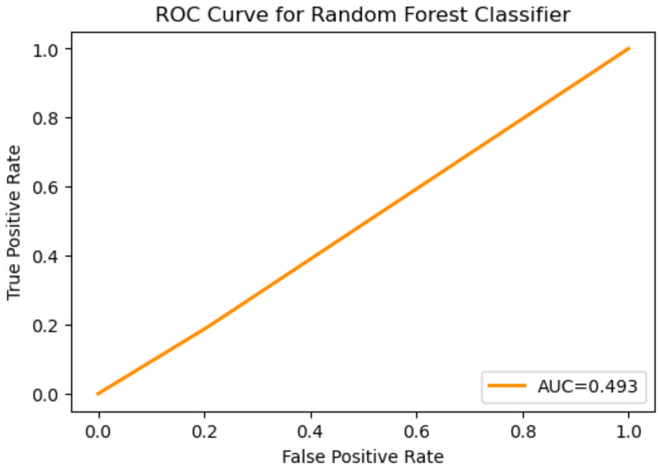

Figure 6: AUC-ROC Curve of Random Forest Classifier (RFC)

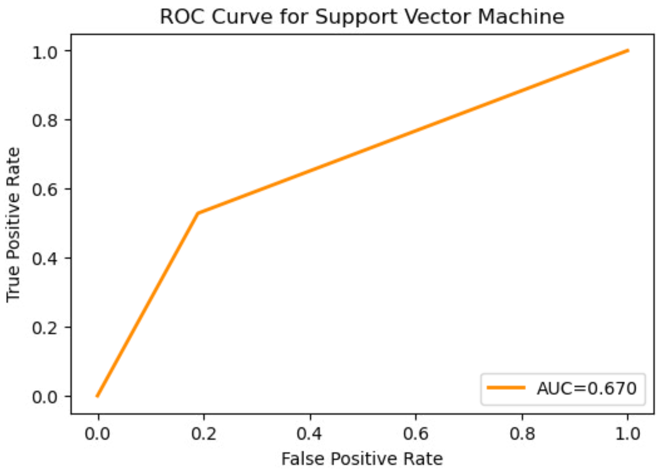

Figure 7: AUC-ROC Curve of Support Vector Machine (SVM)

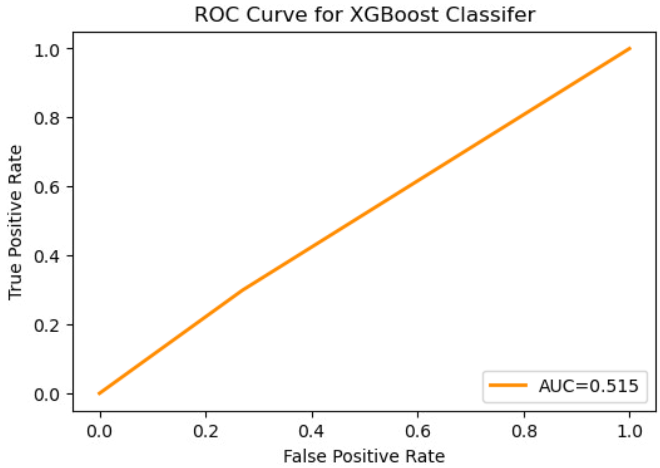

Figure 8: AUC-ROC Curve of XGBoost Classifier (XGBC)

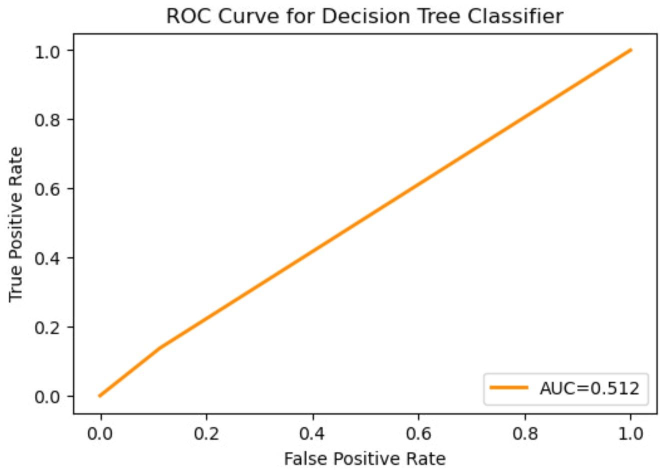

Figure 9: AUC-ROC Curve of Decision Tree Classifier (DTC)

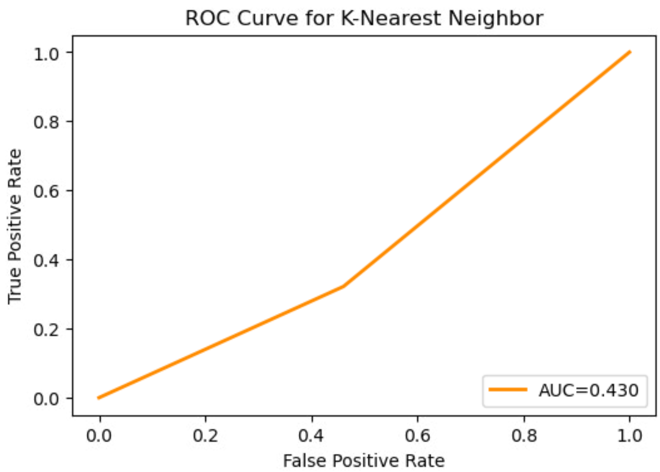

Figure 10: AUC-ROC Curve of K-Nearest Neighbor (KNN)

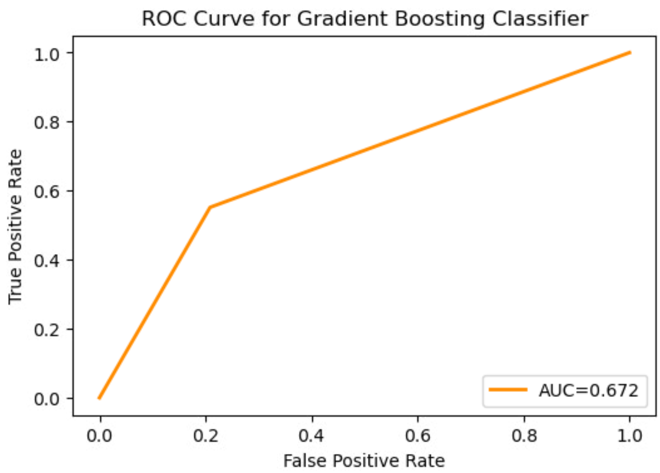

Figure 11: AUC-ROC Curve of Gradient Boosting Classifier (GBC)

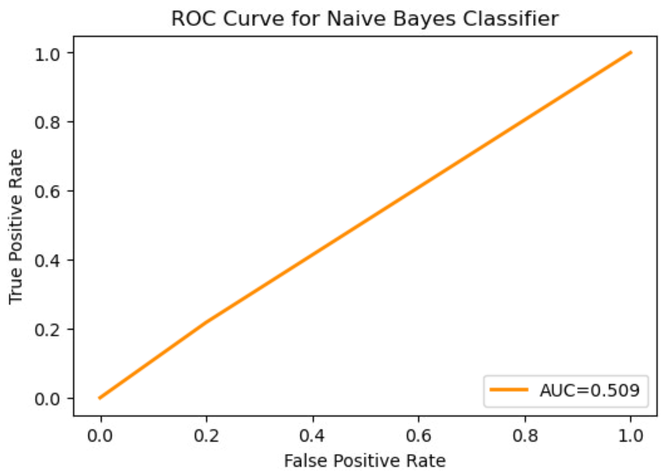

Figure 12: AUC-ROC Curve of Naïve Bayes Classifier (NBC)

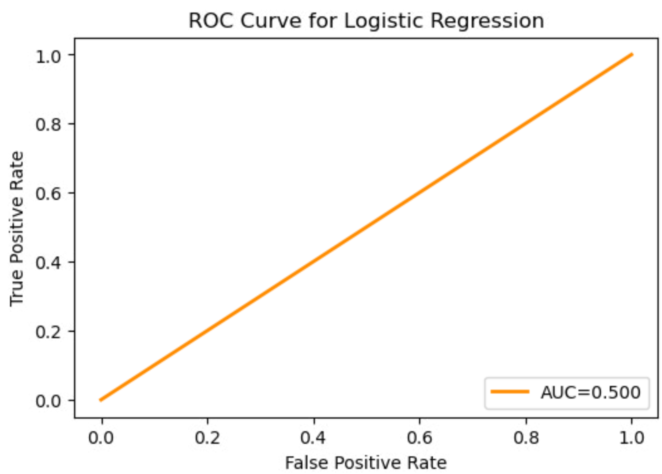

Figure 13: AUC-ROC Curve of Logistic Regression (LR)

In Table 4, the AUC-ROC values of the proposed Machine Learning Algorithms are portrayed for a single glance.

Classifier	AUC-ROC Value
RFC	0.493
SVM	0.670
XGBC	0.515
DTC	0.512
KNN	0.430
GBC	0.672
NBC	0.509
LR	0.500

Table 4: Comparison of The Ml Models Using Auc-Roc Value

The AUC-PR curves of all the implemented Machine Learning Models are shown in Figures 14, 15, 16, 17,18,19, 20, and 21 respectively [24].

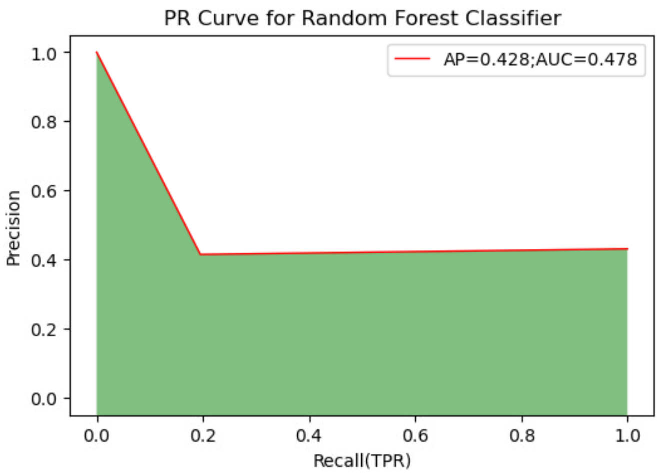

Figure 14: AUC-PR Curve of Random Forest Classifier (RFC)

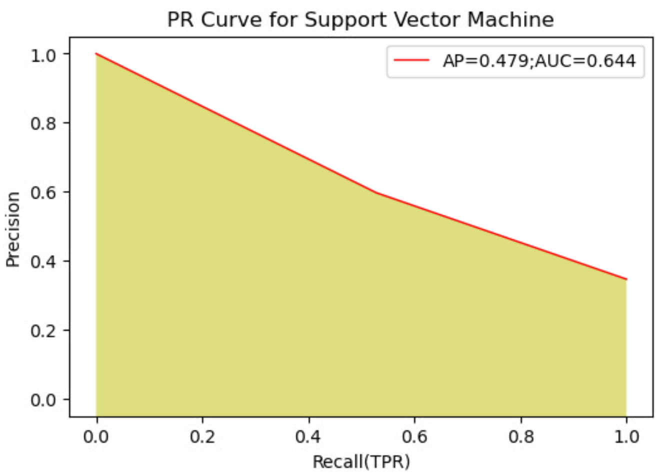

Figure 15: AUC-PR Curve of Support Vector Machine (SVM)

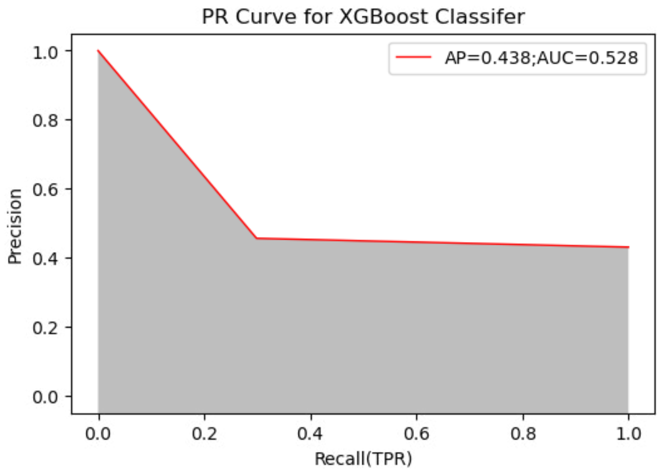

Figure 16: AUC-PR Curve of XGBoost Classifier (XGBC)

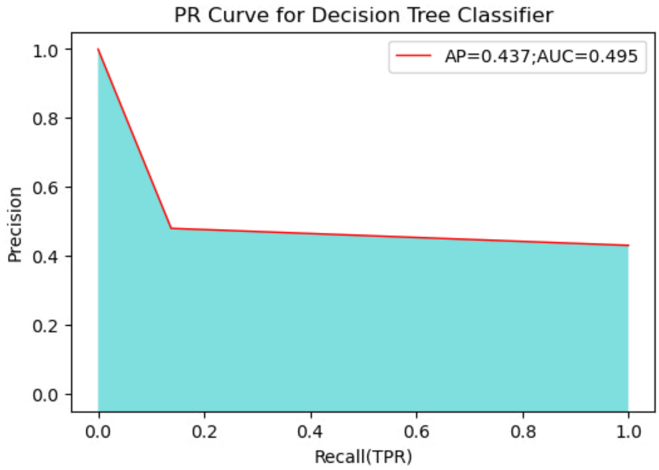

Figure 17: AUC-PR Curve of Decision Tree Classifier (DTC)

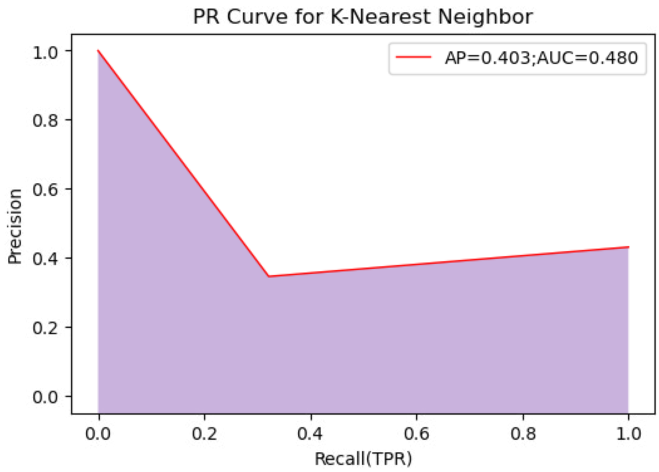

Figure 18: AUC-PR Curve of K-Nearest Neighbor (KNN)

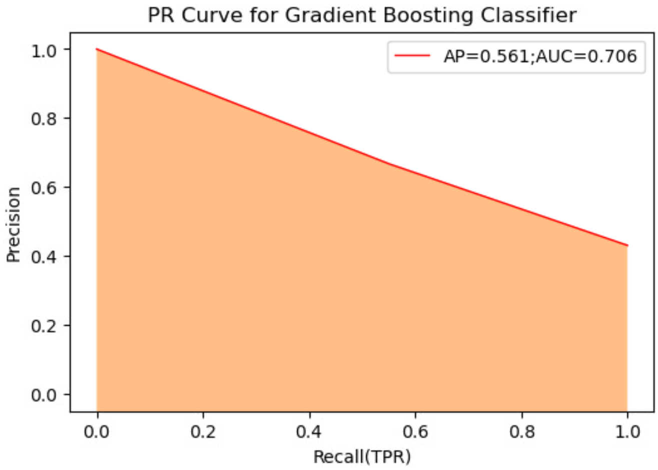

Figure 19: AUC-PR Curve of Gradient Boosting Classifier (GBC)

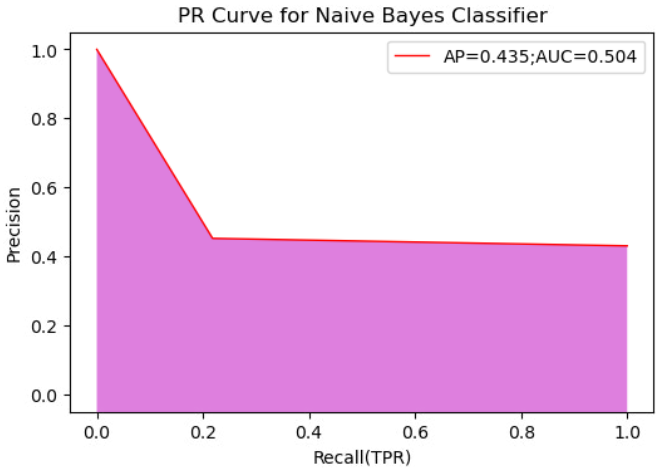

Figure 20: AUC-PR Curve of Naïve Bayes Classifier (NBC)

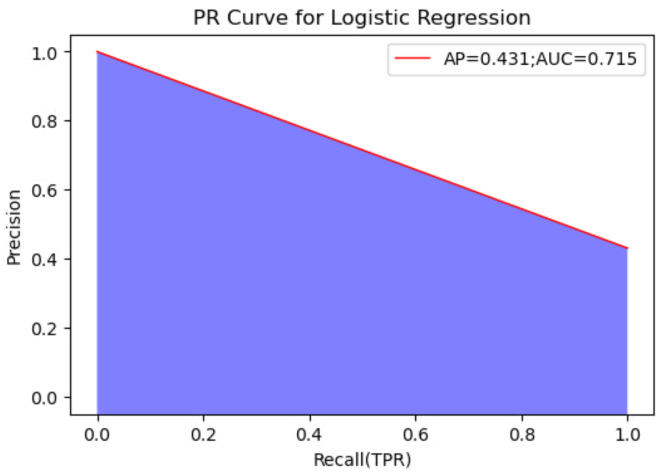

Figure 21: AUC-PR Curve of Logistic Regression (LR)

In Table 5, the AUC-PR values of the proposed Machine Learning Algorithms are portrayed for a single glance.

Classifier	AUC-PR Value
RFC	0.428
SVC	0.479
fXGBC	0.438
DTC	0.437
KNN	0.403
GBC	0.561
NBC	0.435
LR	0.431

Table 5: Comparison of The Ml Models Using Auc-Pr Value

From the results shown in Table 2, the performance of both the Random Forest Classifier and Support Vector Machine has been praiseworthy. The values of the evaluation metrics of both these classifiers have been too close to conclude which of the two classifiers is the best. Random Forest Classifier has surpassed all the other models in terms of accuracy, recall, precision, and F1 score. Random Forest Classifier has exhibited an accuracy of 73.76%, recall, precision, and F1-score of 90%, 75%, and 82% respectively whereas Support Vector Machine has exhibited an accuracy of 71.29%, recall, precision, and F1- score of 81%, 76%, and 79% respectively.

The prediction time of each of the eight ML algorithms has been tabulated in Table 3. Random Forest Classifier which has exhibited the highest accuracy has a prediction time of 0.054 sec. Hence, it can be deciphered that not only does the Random Forest Classifier have higher accuracy in comparison to other algorithms, but it also predicts the water quality (potability) from the dataset under consideration in a time that is less than a second. Not only, Random Forest, but all the other classifiers are also exceptionally fast in predicting the outcome like the Gradient Boosting Classifier having the least prediction time of 0.008 sec. The fact that these algorithms are so fast in predicting the results makes them extremely suitable for real-time application and producing results instantaneously.

6. Conclusion

Water quality monitoring is an important factor for aquaculture. In this paper different latest Machine Learning models like Logistic Regression, Random Forest, Support Vector Machine, Decision Tree, K-nearest Neighbors, XGBoost, Gradient Boosting and Naive Bayes are developed to predict the value of pH, hardness, Solids, Chloramines, Sulfate, Conductivity, organic carbon, trihalomethanes, Turbidity, and portability which are the main parameters for water quality. Based on the predicted value of water quality, it generates decisions with the help of Artificial Intelligence (AI) and sends notifications to the user when the predicted water quality appears to exceed the critical conditions. The IoT-based water quality monitoring system monitors the water quality in real-time and reduces the cost of production, increases efficiency, reduces human dependency, and thus ensures sustainable development economically and socially. The proposed system monitors the water quality in real-time and sends a notification to the user instantly, which reduces the risk. The dataset that has been fed into the proposed machine learning models is the collected information on water quality parameters which are obtained from the Kaggle website. The dataset that has been used for training and validation has undergone pre-processing prior to the implementation of the machine learning models. The dataset has been checked for null values first and when found has been discarded. Then the dataset has been inspected to detect the presence of any outliers and subsequent dropping of it by using the Interquartile Range (IQR) method. The remaining dataset has been split into training data and testing data after dropping the null values and outliers from the original dataset. A test size of 15% and a training size of 85% have been considered. Then Standard Scaling was used to transform all the attributes within the same range.

Here different latest ML models Support Vector Machine, Logistic Regression, KNN, Random Forest Classifier, Decision Tree Classifier, Naive Bayes Classifier, XGBoost, and Gradient Boosting Classifier have been implemented and tested to validate and achieve a satisfactory result. The performance comparative analysis of the different ML algorithms has been conducted based on a few metrics such as accuracy, recall, precision, F1-score, and Prediction time. Then the evaluation metrics were computed in order to perform the comparative analysis of all the ML models Random Forest Classifier surpassed all the other models in terms of accuracy, recall, precision, and F1 score. Random Forest Classifier has exhibited an accuracy of 73.76%, recall, precision, and F1-score of 90%, 75%, and 82% respectively [24-32].

7. Scope of Future Work

In the future, we wish to improve the model to achieve higher accuracy and evaluate the performance in terms of the fish population. Also, the proposed IOT system hardware architecture along with sensor data will be implemented in real-time and will be integrated with Machine Learning models in the future for the automatic data collection from the sensors and the prediction and monitoring of water quality based on the sensor data in the future.

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