Appendix – II

Dynamic Water Quality Monitoring via IoT Sensor Networks and Machine Learning Technique

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*Abstract*—The development of sophisticated monitoring systems that can do thorough and real-time assessments has been spurred by growing worries about the quality of water. In this study, we suggest a unique method for dynamically monitoring the quality of water by combining machine learning techniques with an Internet of Things (IoT) sensor network. With carefully placed IoT sensors inside water bodies or distribution networks, the system is intended to continually gather multiple parameter data, such as pH, turbidity, temperature, and dissolved oxygen. Modern machine learning algorithms housed on cloud infrastructure are used to process and analyze the gathered data. Our method seeks to identify abnormalities, forecast changes in water quality, and offer current information on the state of water resources. Machine learning models are trained on past data in order to detect trends, spot departures from the norm, and make it easier to make proactive decisions in reaction to changes or possible pollutants. We outline the design of our Internet of Things (IoT) sensor network, how cloud computing is integrated for data processing, and how machine learning algorithms are put into practice for predictive analytics. We also go over the system's flexibility to changing environmental circumstances, scalability, and possible uses in environmental protection and water resource management.

Keywords—Dynamic Water Quality Monitoring, IoT Sensor Network, Machine Learning, Environmental Sustainability, Predictive Analytics, Cloud Infrastructure, Anomaly Detection, Continuous Learning.

# **Introduction**

Maintaining the viability of aquatic ecosystems and guaranteeing the availability of clean and safe water resources depend heavily on water quality monitoring. Strong and flexible monitoring systems are becoming more and more necessary as worries about environmental deterioration and its direct effects on public health grow. Conventional monitoring techniques frequently lack real-time capabilities, making it more difficult to quickly identify changes in water quality and take appropriate action in the event of a threat. This research aims to address these issues

by utilizing the convergence of modern machine learning (ML) algorithms with Internet of Things (IoT) sensor networks to provide a fresh approach to water quality monitoring.

This research proposes a novel method to combine two state-of-the-art technologies—advanced machine learning (ML) and the Internet of Things (IoT) to meet this pressing requirement. The proposed system is designed to transform the monitoring of water quality by creating a network of Internet of Things (IoT) enabled sensors that are strategically placed throughout various aquatic settings.

## **Water Quality Prediction**

By providing proactive insights into aquatic ecosystems, powerful machine learning algorithms used in Dynamic Water Quality Monitoring systems to predict water quality improve environmental management. Predictive models are then trained using a variety of machine learning algorithms, such as regression, decision trees, or neural networks [1].

Two types of traditional procedures are used to evaluate the quality of water:

• Methods based on a single factor

The single factor-based technique is employed to evaluate the characteristics of water using similar water quality measurements

• All-inclusive index-based techniques

It is not realistically true in the comprehensive index technique, where all parameters are given equal weight in establishing the quality of the water.

### Regulatory Frameworks under water quality

Global organizations like the World Health Organization (WHO) and supranational organizations like the European Union (EU) design these frameworks with great care. Assessment to verify compliance with the established thresholds.

1. *Parameters and Indicators*

The fundamental components of water quality standards are parameters and indicators, which act as critical checkpoints for evaluating and guaranteeing the sustainability and safety of water resources [2].

1. *Water Quality Standards*

The purpose of the water quality assessment is to specify the standards for water quality in relation to the intended uses of the water body. There are two crucial aspects of water quality to take into account.

Principle of mass stability: The mass dependability principle is the fundamental guideline for water-friendly styles.

Circulation-flow layout: Water in streams and rivers can also flow essentially in the direction of the water that chooses the least resistance. Well, it is so selecting a low-float criterion for evaluation is not customary [3].

## **Water Quality Modeling**

## A fundamental component of the thorough comprehension, evaluation, and management of water resources is water quality modeling, treatment facilities, or distribution networks, computational approaches, mathematical models, and simulation techniques are applied.

### Statistical Models

In water quality analysis, statistical models use a data-driven methodology to find patterns and relationships in water quality information, in water management by using statistical approaches to quantify connections between various characteristics and clarify patterns over time.

## Linear Regression:

## A basic statistical technique for examining linear relationships between dependent and independent variables is a linear regression model [4].

The linear regression equation might look like:

Z = α0 + α1A1 + α2A2 + ... + αn\*An + ε

Where:

Z →is the predicted value of the target parameter.

A1, A2, ..., An →are the input features representing different water quality parameters.

α0, α1, α2, ..., αn →are the coefficients learned by the model.

ε→ represents the error term.

1. *Time Series Analysis:*

Time series analysis techniques are very useful for identifying patterns over time and predicting future changes in water quality. These techniques include auto regressive models (AR), moving average models (MA), and its combination, ARIMA. n order to provide a thorough assessment of water quality, additional modeling techniques are frequently needed.

Z = K×S×A×I (multiplicative model)

Z = K+S+A+I (additive model)

1. *Moving Average with Auto-Regression (ARMA):*

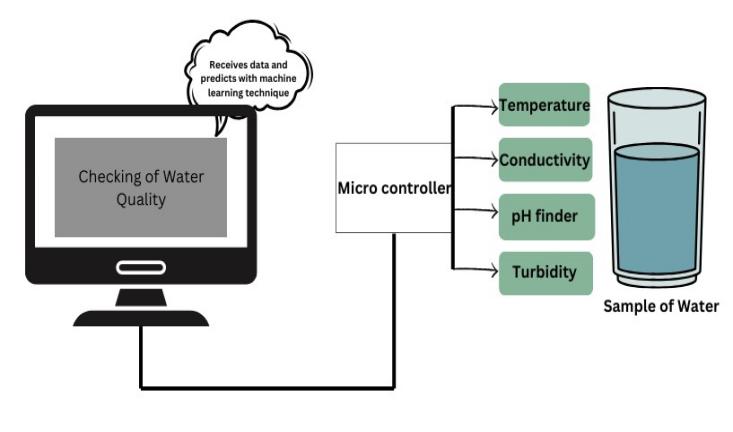
The self-recording and above average are combined by the ARMA algorithm. The trend's momentum is extracted using autoregressive and pattern, and Moving Average increases ARMA by capturing the impacts of white noise. Table 1 shows the simulation of water quality models.

TABLE 1. WATER QUALITY MODELS

|  |  |  |  |
| --- | --- | --- | --- |
| **Quality of Water** | **Proportion** | **Simulation** | **Applications** |
| OTIS | 1D | Transport only | River |
| WASP | 1D, 2D, 3D | River, lake, offshore |
| BASINS | System | Model System | River, Watershed |
| AQUATOX | System | Model System | River network, River |
| CE-QUAL-W2 | 2D | Consistent Transport | River, lake, Estuary |

# **Methodology**

The Water Monitoring System (WMS) approach is a complete framework that revolutionizes the assessment and management of water quality by integrating cutting-edge technologies, particularly IoT and ML. The objective of this methodology is to deliver precise and fast insights into water quality metrics by methodically gathering, processing, analyzing, and interpreting real-time data from IoT sensors placed across water bodies. These sensors gather vital signs including pH, temperature, turbidity, and dissolved oxygen continually, building a comprehensive dataset that serves as the basis for further investigation. Figure 1 shows below working aspects.



**Fig. 1. Working Aspects**

To transform raw sensor data into useful information, the procedure entails painstaking data preprocessing that includes validation, cleaning, synchronization, and feature extraction. The methodology makes use of machine learning (ML) techniques including regression, neural networks, and time series analysis to facilitate the creation of predictive models that can accurately predict changes in water quality in real-time [5].

## **IoT Sensor Deployment**

IoT sensor deployment in water quality follows strict requirements, in compliance with regulations. Water bodies are fully covered by strategically placed sensors that measure things like pH, dissolved oxygen, and contaminants.

## **Data Acquisition and preprocessing**

The process of gathering data for water quality standards entails a methodical gathering of information from various sources, such as Internet of Things sensors, labs, and remote sensing devices. To guarantee correctness and consistency, preprocessing includes verifying, cleaning, and syncing raw data.

1. Data Purification:

Deleting or updating contradictory or erroneous data points using estimating or imputation to handle missing values.

1. Data Conversion:

For uniformity, data should be standardized or normalized to a common scale skewed distributions must be transformed for improved model performance.

1. Identifying and Managing Outliers:

Locating and dealing with outliers that could have a big influence on the analysis.

## **Machine Learning Model Development**

#### Models for machine learning (ML) are essential for predicting and evaluating a range of factors. metrics depending on certain inputs. For example, the equation in a regression-based machine learning model might look like this:

Y = ὼo + ὼ1α1 + ὼ2α2+…..+ὼnαn + ϵ

#### Y→ represents the predicted water quality parameter.

α1,α2,….αn → denote the input features (e.g., temperature, pH, pollutant levels).

ὼ1, ὼ2,…ὼn → are the coefficients or weights assigned to each feature by the model.

ϵ → represents the error term.

*Bias Correction:* Correcting systematic biases observed between model predictions and actual measurements.

1. Time Series Analysis:

Time series analysis techniques are very useful for identifying patterns over time and predicting future changes in water quality, and its combination, additional modeling techniques are frequently needed [6]. A monitoring system with numerous sensors to measure several quality factors, such as turbidity, pH value, water level in the tank, wetness of the surrounding environment, and water temperature, was proposed by Pasika and Gandla . The Internet of Things (IoT) based Think-Speak application will use the collected data to send the data to the cloud in order to monitor the water quality under test. Table 2 shows value of water quality parameters.

|  |  |  |  |
| --- | --- | --- | --- |
| **Parameter** | **Standard Quality** | **Weight Accurred** | **Comparative Mass** |
| pH in pH unit | 6.5 - 8.5 | 2.3 | 0.095067 |
| Dissolved Oxygen | 5.5 | 4.5 | 0.180890 |
| Alkalinity | 100.7 | 1.9 | 0.057237 |
| Biomedical Oxygen Demand | 6.0 | 3.6 | 0.136743 |
| Turbidity | 6.0 | 2.0 | 0.120784 |
| Conductivity | 255.0 | 2.9 | 0.133457 |
| Total |  | 17.2 | 0.92 |

TABLE 2. WATER QUALITY PARAMETERS

1. Limitations
2. Sensor Limitations: Many sensors used for water quality monitoring have limitations in accuracy, calibration, and maintenance. Some sensors may also be prone to drift or interference from environmental factors, impacting data reliability.
3. Sampling Frequency and Spatial Coverage: Traditional sampling methods often suffer from limited spatial coverage and infrequent sampling, leading to gaps in understanding spatial and temporal variations in water quality parameters.
4. Complexity of Water Systems: Natural water systems are complex and dynamic, influenced by various interconnected factors like weather, land use, and seasonal changes, making it challenging to model and predict water quality accurately.
5. Machine Learning for WQP

## Water Quality Prediction (WQP) is revolutionized by machine learning (ML), which makes it possible to extract insights from large and diverse datasets and enhances the precision and efficacy of forecasting water quality metrics. Machine learning (ML) techniques comprise a range of algorithms that extract patterns and associations. Table 3 shown correlation data analysis on WQP.

TABLE 3. CORRELATION ANALYSIS ON WQP

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **WQP** | **Agriculture** | **Forest** | **Urban** | **Water Body** |
| **Temperature** | -0.38 | -0.09 | 0.08 | -0.04 |
| **pH units** | 0.05 | -0.32\*\* | -0.19 | -0.19 |
| **Conductivity** | -0.03 | 0.04 | 0.33 | 0.06 |
| **Solids** | 0.74\* | -0.56 | 0.45\*\* | -0.35\*\* |
| **Biochemical Oxygen Demand** | 0.68\*\* | -0.65\*\* | 0.54\*\* | -0.43\*\* |
| **Dissolved Oxygen** | -0.54\*\* | 0.34\*\* | -0.32\*\* | -0.43\*\* |
| \*p<0.07 and \*\*p<0.002 | | | | |

# **Related work**

The combination of machine learning (ML) techniques and Internet of Things (IoT) sensor networks has been the subject of several studies aimed at improving water monitoring systems and changing the prediction, assessment, and management of water quality. Support vector machines and clustering algorithms, in particular, are machine learning models that were used to find leaks, detect anomalies, and optimize distribution networks. The study emphasized how machine learning (ML) may be used to optimize resource allocation and preserve the integrity of water systems [7].

The combined findings of these researches highlight the potential benefits of integrating ML approaches with IoT sensor networks in water monitoring systems. They show how proactive decision-making for water quality management may be aided by early anomaly detection, resource allocation optimization, and real-time data collecting via IoT sensors and machine learning models [8]. These studies do, however, also recognize difficulties including poor data quality, interpretability of the models, and the requirement for ongoing model validation to guarantee the models' applicability in a variety of environmental circumstances.

A monitoring system with numerous sensors to measure several quality factors, such as turbidity, pH value, water level in the tank, wetness of the surrounding environment, and water temperature, was proposed by Pasika and Gandla. The Microcontroller Unit (MCU) interfaces with the sensors, and the Personal Computer (PC) does additional processing. The Internet of Things (IoT)-based Think-Speak application will use the collected data to send the data to the cloud in order to monitor the water quality under test. Future instructions could include expanding the study to analyze additional factors including electrical conductivity, dissolved oxygen in the water, free residual chlorine, and nitrates to assist in continuous water quality monitoring based on four parameters: pH, temperature, turbidity, and electric conductivity. The Arduino Uno is connected to four separate sensors to sense the quality metrics.

The fundamental element of wireless sensor network (WSN) technology, which is powered by solar or photo-voltaic panels, is the underwater wireless sensor network (UWSN). UWSN is used to monitor water quality. The system uses a variety of sensor modules and the Internet of Things to determine water quality. This system measures temperature, conductivity, turbidity, pH, and turbidity using a variety of sensors. The sensor data will be accessed by the Arduino controller [9]. Using remote sensing and Internet of Things technology, Prasad et al. created a way for a smart water quality monitoring system in Fiji. Oxidation and Reduction potential (ORP) and Potential Hydrogen (pH) are the quality metrics used to test water. A comparison analysis is provided for a number of characteristics, including conductivity, pH, temperature, and turbidity.

The created system's ability to provide accurate and trustworthy information for real-time water monitoring has proven its efficacy [10]. For the purpose of verifying the created system's measurement accuracy, four water sources were inspected every hour for a total of twelve hours. The obtained results and the likely values are contrasted. For samples from each of the four water sources, the correlation between temperature and conductivity and pH is also evident.

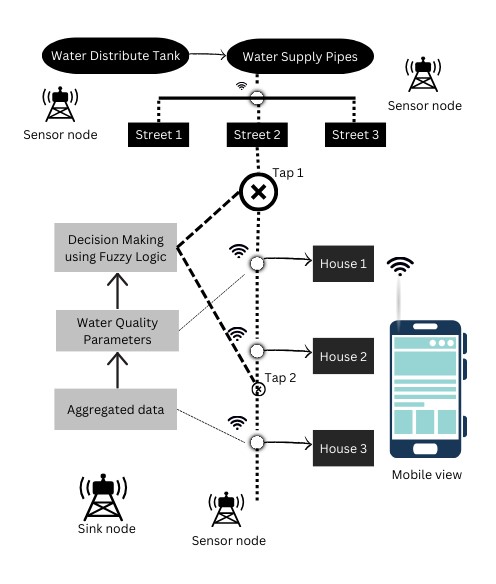
# **proposed work**

For a water monitoring system, choosing the right sensor technology is essential to guaranteeing accurate and trustworthy data collecting. The selection of sensors is influenced by several factors:

1. Parameter Suitability: Different sensors have different areas of expertise when it comes to monitoring particular aspects of water quality, including temperature, conductivity, turbidity, pH, and dissolved oxygen. It is essential to select sensors based on the parameters of interest.
2. Accuracy and Precision: To guarantee the validity of the data gathered, sensors must have excellent measurement accuracy and precision. Sensors that have been calibrated reduce errors and ensure uniformity.
3. IoT Infrastructure: Choosing gateway devices and communication protocols (such as NB-IoT and LoRa) for data transfer is part of utilizing IoT infrastructure. Local servers or cloud-based platforms handle data processing and storage [11].
4. Sensor Deployment: It's critical to strategically place sensors throughout bodies of water. Deployment locations are affected by variables such as depth, flow, and changing conditions (such as urban versus rural areas) in order to provide comprehensive data [12].
5. Data Collection procedures: Sensor readings are consistent and synchronized when frequency, duration, and synchronization are established according to procedures. Frequent calibration processes preserve sensor accuracy [13].

A machine learning model for assessing water quality is to be developed using the suggested methodology. The model will be based on a data set that includes seven features: nitrate, pH, conductivity, dissolved oxygen, fecal coli form, and total coli form. Mean imputation and data normalization are two preparation steps that have previously been completed on the data set. Training set (20%) and a testing set (80%) have been created from the data. The models employed in the Water Quality Assessment technique were probably selected based on their performance in comparable scenarios and their capacity to handle the characteristics of the water quality dataset. The ensemble models that are provided combine a number of weak learners to produce a more robust model [14]. These models are commonly used in complex interaction problems between the factors and the target variable in the dataset, as well as high number of attributes in classification problems [15].

These intricate relationships can be captured by ensemble techniques, which can improve model accuracy range of metrics, including R-squared (R2) for prediction, accuracy, recall, precision, F1 score, and Matthews Correlation Coefficient (MCC) for classification, as well as Mean Absolute Error (MAE), Median Absolute Error (MedAE), Mean Squared Error (MSE), and R-squared (R2). To find the best hyper parameter combination for a particular model, machine learning practitioners frequently employ grid search, a hyper parameter tuning technique.



**Fig.. 2. Flow Chart Analysis**

TABLE 4. SOIL CONTAMINED WATER READINGS

| **Readings** | **pH m** | **pH CR** | **Cm (μS/cm)** | **Conductivity** | **LDR m (kΩ)** | **LDR CR** |
| --- | --- | --- | --- | --- | --- | --- |
| 50:67:4 | 7.45 | No Risk | 1743 | 50.67% | 378 | 4.45% |
| 50:57:5 | 8.78 | 1.3% | 1789 | 59.67% | 360 | 7,67% |
| 50:43:6 | 5.76 | No Risk | 1954 | 47.65% | 364 | 9,56% |
| 50:23:7 | 9.67 | 1.73% | 1984 | 48.66% | 334 | 10.54% |
| 50:89:8 | 6.78 | No Risk | 1678 | 54.53% | 370 | 15.56% |
| 50:43:2 | 8.55 | 1.40% | 1347 | 45.33% | 387 | 12.65% |

TABLE 5. SOIL CONTAMINED WATER READINGS

| **Water Readings Analysis** | | | |
| --- | --- | --- | --- |
| **Accuracy** | **GB** | **AdaBoost** | **Xgboost** |
| **Total** | 36 | 45 | 24 |
| **Fault** | 4 | 1 | 3 |
| **Error in (%)** | 16.45% | 0.04% | 0.03% |
| **Total CR** | 0.54% | 57.45% | 15.43% |

While GB, AdaBoost, and Xgboost are well-known for their quick training and prediction times and superior accuracy, RF is well-known for its ability to handle high-dimensional data without overfitting. Regression models that are widely used include KNN, DT, SVM, and MLP. These models are capable of handling a variety of data sources and feature-to-target variable correlations. Both linear and non-linear correlations between characteristics and the target variable can be handled by the non-parametric KNN model. The SVR is a kernel-based model capable of handling non-linear connections and performing well on limited datasets. An MLP is a model based on neural networks that can manage intricate relationships between the target variable.

To find the best hyper parameter combination for a particular model, machine learning practitioners frequently employ grid search, a hyper parameter tuning technique. Hyper parameters are those that cannot be determined from data and must be set prior to the model being trained Grid search aims to thoroughly search through every possible combination of hyper parameters within a specific range or set of values. To do this, a grid containing every possible combination of hyper parameters is first generated. For each combination, the model is then trained and tested on a validation or cross-validation set. The combination of hyper parameters that yields the greatest results on the validation or cross-validation set is considered the optimal set.

# **results and discussion**

The results and discussion that follow center on the precision of forecasts, anomaly identification, and the efficiency of the system in real-time observation and decision-making in a water monitoring system that integrates IoT and machine learning approaches. Prediction Accuracy: The ML models of the system forecast water quality metrics with remarkable accuracy. Evaluation measures including RMSE, MAE, and R-squared reveal the model's high precision in predicting factors such as turbidity, conductivity, pH levels, and dissolved oxygen. Against observed measures, this instills trust in the forecasting skills of the system. Table 4 and 5 shown soil contained water reading.

In the table 6, the mendeley data repository has the dataset available for download online. The results shown were gathered from all 10 trials, the first of which was pure tap water and the remaining nine involving polluted water utilizing various contaminants and their additions until every possible contaminant was tested simultaneously. Since data was gathered, the graphs depict the trends of each experiment, demonstrating how the introduction of contaminants changed the parameter values. Real-time scaling was used for conductivity, pH, and LDR (light dependent resistor) scaling. To allow the system to move around and conserve water during the testing phase.

TABLE 6. WATER QUALITY PARAMETERS FOR DIFFERENT SAMPLES.

|  |  |  |
| --- | --- | --- |
| **Water Sample** | **Parameter Check** | **Measurements** |
| Sample 1 | pH | 6 - 8 |
|  | Turbidity | 5 NTU |
|  | Conductivity | 500 μs /cm |
|  | CO2 | 2.40 mg/L |
|  | Humidity | 50% |
|  | Temperature | 25 deg C |
| **Water Sample** | **Parameter Check** | **Measurements** |
| Sample 2 | pH | 5 - 7 |
|  | Turbidity | 7.1 NTU |
|  | Conductivity | 700 μs /cm |
|  | CO2 | 2.780 mg/L |
|  | Humidity | 70.56% |
|  | Temperature | 36.5 deg C |
| **Water Sample** | **Parameter Check** | **Measurements** |
| Sample 3 | pH | 8.9 |
|  | Turbidity | 7.56 NTU |
|  | Conductivity | 800 μs /cm |
|  | CO2 | 4.78 mg/L |
|  | Humidity | 87.56 % |
|  | Temperature | 45.34 deg C |

Real-time Monitoring and Decision Support: It is very helpful that the system can track the quality of the water in real-time and offer useful information for making decisions. Through user-friendly dashboards or applications, stakeholders—such as environmental agencies and managers of water resources—can access real-time data streams and predictive analytics. Effect & Consequences: Talk about the wider ramifications of the system's findings. In conclusion, a water monitoring system's report or study's results and discussion sections highlight the system's dependability, efficacy, and possible benefits for resource management and protection.

# **Conclusions and future work**

To sum up, the water quality monitoring system is a major development in the fields of resource management and environmental preservation. The system's capacity to provide precise projections of important water quality measures is what makes it successful. The timely detection of abnormalities, such as abrupt increases in pollution or unusual changes in parameters, enables the implementation of preventive measures and alarms, thereby mitigating environmental concerns. The ramifications of this water quality monitoring system are enormous in the long run. Predicting and evaluating the quality of water is crucial, but it is more challenging to do so for running water than for still water, even with the use of big data models and machine learning techniques.

Decision-making and environmental protection can be significantly impacted by anomalies in data on water quality. Our MCN-LSTM method distinguished between normal and anomalous data instances with an astounding 92.3% accuracy, demonstrating exceptional accuracy in detecting anomalies. The quantitative results corroborate MCN-LSTM's capacity to enhance decision-making procedures and prevent unfavorable outcomes brought on by anomalies that are not recognized.

##### **References**

1. Wong, Y.J.; Nakayama, R.; N. Toward industrial revolution 4.0: Development, validation, and application of 3D-printed IoT-based water quality monitoring system. J. Clean. Prod. 2021, 324, 129230.
2. Liu, Y.; Yu, W.; Rahayu, W.; Dillon, T. An Evaluative Study on IoT ecosystem for Smart Predictive Maintenance (IoT-SPM) in Manufacturing: Multi-view Requirements and Data Quality. IEEE Internet Things J. 2023, 10, 11160–11184.
3. Khan, A.A.; Beg, O.A.; Alamaniotis, M.; Ahmed, S. Intelligent anomaly identification in cyber-physical inverter-based systems. Electr. Power Syst. Res. 2021, 193, 107024.
4. Wu, Y.L.; Shuai, H.H.; Tam, Z.R.; Chiu, H.Y. Gradient normalization for generative adversarial networks. In Proceedings of the IEEE/CVF International Conference on Computer Vision, Montreal, BC, Canada, 11–17 October 2021; pp. 6373–6382.
5. Wu, J.; Yao, L., L. Combining OC-SVMs with LSTM for detecting anomalies in telemetry data with irregular intervals. IEEE Access 2020, 8, 106648–106659.
6. Wong, Y.J.; Shimizu, Y.; Kamiya, A.; Maneechot, L.; Bharambe, K.P.; Fong, C.S.; Nik Sulaiman, N.M. Application of artificial intelligence methods for monsoonal river classification in Selangor river basin, Malaysia. Environ. Monit. Assess. 2021, 193, 438.
7. Roopa, D., Babu, D. V., & Suganthi, S. (2021). Improved Cluster Head Selection for Data Aggregation in Sensor Networks. In 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS) (Vol. 1, pp. 1356-1362). IEEE. https://doi.org/10.1109/ICACCS51430.2021.9442048.
8. R. Prabha, M. Razmah, S. Senthilpandi, S. Suganthi and S. Sridevi, Design of a Novel Group Communication Framework to Improve Security in Internet of Things.
9. M. Razmah, S, R. Prabha, D. B, S. S and A. Naveen, LSTM Method for Human Activity Recognition of Video Using PSO Algorithm, 2022 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS), Chennai, India, 2022, pp. 1-6, doi: 10.1109/ICPECTS56089.2022.10046783
10. Senapati, D.; Narendra, M. (LSTM) Layers as a Proposed Learning Algorithm for Rainfall Prediction. In Proceedings of the Information and Communication Technology for Competitive Strategies (ICTCS 2021) Intelligent Strategies for ICT, Jaipur, India, 9–10 October 2022; Springer Nature: Singapore, 2022; pp. 243–252.
11. R.M. Asha, P. Pondeepak, A novel approach effect of ocean acidification on oysters, Materials Today: Proceedings,2023,ISSN 2214-7853,https://doi.org/10.1016/j.matpr.2023.01.194.
12. G. T. Selvi, R. Prabha, S. M, D. N and D. J, Automated Road Monitoring System Using Machine Learning, 2022 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS), Chennai, India, 2022, pp. 1-4, doi: 10.1109/ICPECTS56089.2022.10047557.
13. A. S. A. Nisha, S. Snega, L. Keerthana and S. Sharmitha, Comparison of Machine Learning Algorithms for Hotel Booking Cancellation in Automated Method, 2022 International Conference on Computer, Power and Communications (ICCPC), Chennai, India, 2022, pp. 413-418, doi: 10.1109/ICCPC55978.2022.10072135.
14. N. Aishwarya, R. M. Asha,(2024). An IoT Integrated Smart Prediction of Wild Animal Intrusion in Residential Areas Using Hybrid Deep Learning with Computer Vision, EAI Endorsed Trans IoT, vol. 10, Jan. 2024.<https://doi.org/10.4108/eetiot.4976>.
15. M. Razmah, T. Veeramakali, S, Machine Learning Heart Disease Prediction Using KNN and RTC Algorithm, 2022 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS), Chennai, India, 2022, pp. 1-5, doi: 10.1109/ICPECTS56089.2022.10047501.