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Utilizing Deep Learning and the Internet of Things to Monitor the Health of Aquatic Ecosystems to Conserve Biodiversity

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Abstract

The decline in water conditions contributes to the crisis in clean water biodiversity. The interactions between water conditions indicators and the correlations among these variables and taxonomic groupings are intricate in their impact on biodiversity. However, since there are just a few kinds of Internet of Things (IoT) that are accessible to purchase, many chemical and biological measurements still need laboratory studies. The newest progress in Deep Learning and the IoT allows for the use of this method in the real-time surveillance of water quality, therefore contributing to preserving biodiversity. This paper presents a thorough examination of the scientific literature about the water quality factors that have a significant influence on the variety of freshwater ecosystems. It selected the ten most crucial water quality criteria. The connections between the quantifiable and valuable aspects of the IoT are assessed using a Generalized Regression-based Neural Networks (G-RNN)

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framework and a multi-variational polynomial regression framework. These models depend on historical data from the monitoring of water quality. The projected findings in an urbanized river were validated using a combination of traditional field water testing, in-lab studies, and the created IoT-depend water condition management system. The G-RNN effectively differentiates abnormal increases in variables from typical scenarios. The assessment coefficients for the system for degree 8 are as follows: 0.87, 0.73, 0.89, and 0.79 for N-O_3-N, BO-D_5, P-O_4, and N-H_3-N. The suggested methods and prototypes were verified against laboratory findings to assess their efficacy and effectiveness. The general efficacy was deemed suitable, with most forecasting mistakes smaller than 0.3 mg/L. This validation offers valuable insights into IoT methods' usage in pollutants released observation and additional water quality regulating usage, specifically for freshwater biodiversity preservation.

Keywords:

Internet of things, biodiversity, deep learning, aquatic ecosystem.

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Introduction

Water is a precious resource crucial for all living beings' survival and overall health (Scanlon et al., 2023). The escalating population expansion, industrialization, and pollution have greatly jeopardized the quality of water supplies globally (Van Vliet et al., 2021). There is an increasing need for effective and immediate monitoring devices to tackle this urgent problem that can provide precise information on water quality indicators (Fortuna et al., 2023).

The Internet of Things (IoT) have significantly transformed the interaction with the natural environment in the last few decades, providing unparalleled possibilities for tracking and regulating many environmental conditions (Jan et al., 2021; Priyanka et al., 2023). Within this framework, a system for monitoring water quality using the IoT has arisen as a promising resolution, facilitating the ongoing and remote surveillance of water sources (Laith et al., 2023; Muralidharan, 2020; Salam & Salam, 2020).

Providing safe drinking water is a substantial obstacle in Somalia since only 30% of the population can access uncontaminated water sources. The population is susceptible to several potentially fatal illnesses (Nižetić et al., 2020). The absence of adequate access to uncontaminated water also harms the growth and education of kids, particularly females, who are often compelled to spend a significant portion of their day collecting water, resulting in their absence from school. Extracting groundwater is arduous and costly in many parts of the nation due to little precipitation and extensive deep water levels. Most groundwater supplies in the nation exhibit salt levels that exceed the prescribed criteria for potable water (Mazhar et al., 2020). The absence of potable water profoundly impacts both human well-being and the natural surroundings.

Consuming water that is polluted may result in a range of health issues, such as diarrhea, cholera, typhoid, and other diseases transmitted by water. These diseases pose a significant risk to those who are more susceptible, such as children, pregnant women, and individuals with compromised immune systems (Semenza, 2020).

Withdrawing and using water at excessive rates result in water shortages, stress over water, and degradation of freshwater resources. This results in various environmental impacts, such as harm to aquatic environments and decreased biodiversity (Jung et al., 2021). The absence of potable water also results in economic repercussions, such as reduced production and revenue from sickness and the expenses associated with treating waterborne diseases.

The IoT is an interconnected collection of physical items that have transformed into a network of interlinked gadgets, including cell phones, cameras, and other household and vehicular equipment. These devices are all linked, speaking with each other and exchanging information (Hojjati-Najafabadi et al., 2022). Automating manual profiles via sensors as part of IoT tracking has provided several advantages to sectors such as ecological computing and bioinformatics. A sensor is an apparatus that detects a signal (physical, chemical in nature, or behavioral) and transforms it into an electrical output signal, such as electricity or voltage. Due to the laborious and time-consuming nature of profiling techniques and their lack of real-time outputs to prompt proactive action to water contamination, detecting detectors is a possible option for water quality management.

The IoT technology aims to establish connectivity between conventional items and the Internet. It enables them to become intelligent by leveraging detectors, wireless communications, socializing, and cloud-based computing. In 2025, IoT-based services are projected to make a significant contribution of over $2.8 trillion to the global economy on an annual basis. However, monitoring the water's quality in real-time, including various environmental, chemical, and biological characteristics, still needs to be solved. This is mainly because only a few sensors are available on the market. Many compound and natural evaluations still depend on experimental testing, that is both complex and not price-efficient. To tackle issues, this study seeks to accomplish the goals.

1) Determine the essential water condition criteria that impact the variety of freshwater ecosystems.
2) Determine the water condition metrics using existing IoT devices and create a network of IoT devices to monitor these values concurrently.
3) Deep Learning (DL) algorithms estimate characteristics not quantifiable by present IoT sensors, utilizing measurable metrics from a comprehensive historical water supply surveillance dataset.
4) Assess the DL algorithms using a case analysis.

Background and Literature Survey

This section thoroughly examines the context of various data mining techniques in the maritime environment and other situations. It will discuss the existing research accomplishments in oceanic data mining approaches within the IoT context (Robles et al., 2015).

Background

The IoT is a sophisticated interconnected system with several components, including devices, applications, sensors, actuators, and connectivity (Singh & Ahmed, 2021). These components are integrated into physical items such as vehicles, household appliances, and other goods, allowing them to interact with each other and exchange data. The merging of the actual world into computer-aided technologies can significantly boost productivity, offer economic advantages, and minimize human endeavors (Ramachandran et al., 2022). The IoT device serves as a component engaged in collecting data. This information ensures seamless activities, proactive tracking, and data-driven decisions to enhance and optimize a business's overall strategy.

The installation of IoT technology has been completed. The strategic use of IoT devices may facilitate the analysis and evaluation of data in almost real-time, leading to enhanced decision-making skills supported by empirical evidence (Roy et al., 2020). The pervasive integration of intelligent transportation, community infrastructure, shopping practices, eHealth systems, and self-care routines increasingly permeates every aspect of everyday existence. Complex and fast data streams need help managing, analyzing, storing, and securing, resulting in a large volume of information. The IoT sensors and software collect valuable information

(De Camargo et al., 2023). IoT data has a short lifespan, and companies need the resources to use time-sensitive insights effectively. The vast information the IoT creates is a crucial aspect that must be dealt with promptly and within a defined timeframe. Processing this information after a specific date would be futile and useless (Lakshmikantha et al., 2021).

Related Works

Water quality monitoring technologies use sophisticated sensor technology and immediate data processing to evaluate the state of aquatic ecosystems and guarantee the accessibility of safe drinking water. These devices provide precise data on pH, temperatures, oxygen dissolution, and contaminants (Hlordzi et al., 2020; Brahmaiah et al., 2021). Continual progress is required to tackle changing environmental difficulties and safeguard precious water supplies. The section presents an overview of the study conducted by global scholars on monitoring the quality of water technologies.

Arias-Rodriguez et al. suggested using a powerful learning device to combine satellite imagery with the Mexican water supply surveillance system (Arias-Rodriguez et al., 2021). Their system integrates data and field readings from the Mexican national monitoring of the water quality system. However, this data trains deep learning methods, support vector regressions, and linear regressions. These models aim to estimate Chlorophyll-a, Turbidity, Total Suspended matter, and Secchi Disk Depth levels. Remote sensing facilitates monitoring system activities, and as it is progressively included, water quality surveillance initiatives will achieve more excellent quality. Sagan et al. suggested an inexpensive method for monitoring many water quality parameters (Sagan et al., 2020). The equipment consists of cost-effective, user-friendly electrochemical detectors that have a high level of sensitivity. It also includes custom-designed electronics for reading the sensor data and a smartphone application that can connect wirelessly.

The device can identify chemicals at a minimum of ten nM concentrations. It can concurrently measure pH, free chlorine, and temperatures with a sensitivity of 58.5 (mV/pH), 186 (nA/ppm), and 16.9 (mV/°C), correspondingly (Singh et al., 2020). The system provides a versatile platform architecture that facilitates integrating and customizing supplementary water monitoring instruments.

Jerom et al. suggested an IoT-based intelligent system for monitoring water health using cloud technology (Hemdan et al., 2023). The method suggests using the IoT and machine learning techniques to oversee and assess water condition in various water bodies. The technology employs inexpensive sensors to continuously check water quality and transfer the collected information to the cloud for assessment. The system mitigates water pollution by continuously monitoring water quality and guaranteeing reliable access to water from various water bodies and assets.

Maiolo et al. provide research that examines the data from quality water monitoring for drinking delivery systems using multimodal approaches (Elsherbiny et al., 2022). The study considered several chemical-physical data from 2018-2020 for specific water supply systems in the Emilia-Romagna area, Italy. The information was processed, and its dimensionality was lowered using Principal Component Analysis (PCA) and Cluster Analysis (CA) techniques. These approaches assisted in determining the characteristics that had the most significant impact on the subjective condition of the provided water and also helped find clusters.

Proposed Deep Learning Aquatic Ecosystem Monitoring

This section provides an introduction to the research approach. A methodology is suggested for calculating water quality indicators that cannot be directly measured. An advanced water quality monitoring system is introduced using IoT technology. The section demonstrates statistical characteristic evaluation and deep learning algorithms used to predict water quality characteristics that cannot be directly measured.

Problem Evaluation

Following the identification of the top 10 essential water condition variables, a marketplace assessment was carried out to determine the detectors that are now accessible for the development of IoT-based water condition monitoring methods. A total of five distinct sensor types were discovered, namely Totally Dissolved Solids (TDS), pH, temperatures, Dissolved Oxygens (DO), and Electrical Conductance (EC). The parameters ($N\text{-}O_3\text{-}N$, $P\text{-}O_4$, $N\text{-}O_2\text{-}N$, $N\text{-}H_3\text{-}N$, and DO requirement) will be approximated using the following technique since they cannot be directly measured. However, TDS is used since the IoT detector is readily accessible.

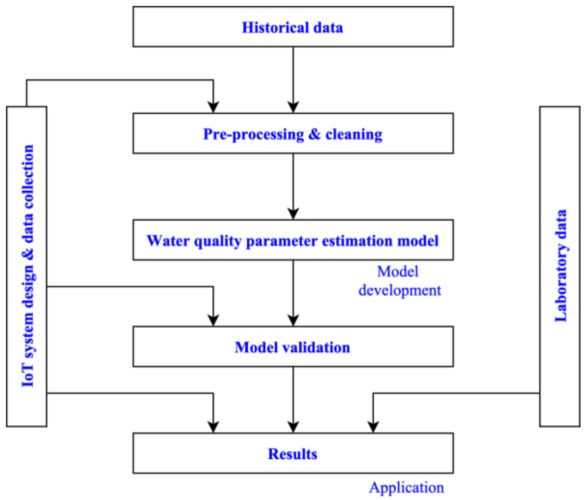

Figure 1. Water quality parameter estimation

A data-driven architecture consisting of three steps is presented in Fig. 1. The parts emphasized are inputs originating from three distinct resources. Initially, the past information is subjected to cleaning and preprocessing. The next phase involves the development of models for estimating variables that cannot be directly measured. The last stage consists of executing the case studies and assessing the suggested models using IoT sensor information and laboratory results.

Generation of the IoT-based Method

Many distinct categories of detectors were found in the marketplace. This IoT system was constructed using the chip, multiplexing, and the sensors above. The Chips is a compact, versatile integrated circuit combining Wi-Fi capabilities with Arduino functionalities. In the IoT structure, the multiplexer serves the purpose of expanding the accessible analog input pins. This is necessary since most detectors only provide analog signals, but the tiny chip only has one analog input line. The IoT webserver is built upon the Things Board commercial version.

The method is integrated inside a monitor to float on the top area. An elastic coating protects it to ensure waterproofing. Once the system's schematic was created and the links were shown, software was constructed in the chip to enable the ongoing and concurrent collection and transmission of five-parameter information to a web server. This data is sent over the access point to a gateway and then uploaded to the website. Fig. 2 shows the network and the control panel correspondingly.

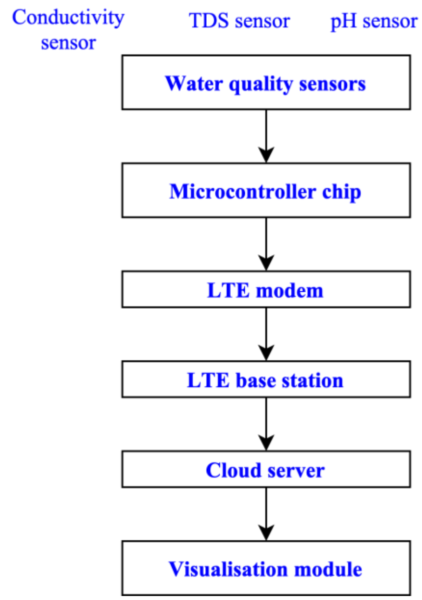

Figure 2. Workflow of the system

Statistical Condition Evaluation

Before the data prototype, the past data's statistical characteristics were analyzed using individual statistics. Apart from the necessary correlation measurement, statistical measures such as number average, standardized deviations, lowest number, highest number, and quartile values are assessed for the initial information set. This data can uncover the links between 10 critical factors, including their central tendency and dispersion. The Pearson correlation factor was used to examine the possible associations between these factors. The Pearson correlation coefficient quantifies the strength of a linear association between two sets of information.

Deep Learning Model

Artificial Neural Network (ANN) models were used to estimate water quality characteristics that could not be directly measured (Jelena & Srđan, 2023; Arora, 2024). The General Regression Neural Network (G-RNN) is a form of feed-forward ANN used in this research because of its efficient training method and high level of accuracy. A drawback of G-RNN is its tendency to increase the size of the concealed layer. The Mean-Squared Error (MSE) is often used as a prominent metric for evaluating the performance of a G-RNN. It has been shown that the G-RNN requires less time for training and achieves greater accuracy than the Backpropagation ANN.

Implementation

This section outlines the fundamental methods and innovations used to get the intended outcome. The section complements the algorithmic criteria by providing software and system engineers with simplified resources and structures to execute the suggested solution.

It illustrates a collection of sensors put into operation to detect and gather data on the surrounding environmental conditions, which are then sent as measures. An actuator regulates the Scientific Instrument Interface Module (SIIM) components regarding voltage, current, frequency, and other parameters. The sensors are implemented using SIIM. SIIM functions as the controller, which is responsible for managing the data from the detectors by packing and delivering it wirelessly. It transfers the data from the sensors to the operating IoT server. The data processing phase is the most critical component of this system for handling and manipulating the information. The loT server receives information gathered from sensors in a predetermined package design, which must be unpacked. Once the data is unpacked, it is instantly delivered to the database's server for safekeeping. Every detector will be preselected by default, but the user can choose any desired sensors to get the information. Following the sensor step, the query executes all the information included in the lists but only within the specified range of parameters. The following query performs the whole list to find the messages corresponding to each inquiry in the list.

Each message discusses the impacts of sensor data, which may be beneficial or detrimental depending on the requirements. The list is organized into categories that provide comprehensive facts about each consequence. The current step involves creating and using databases to generate forecasts using predefined sensor readings.

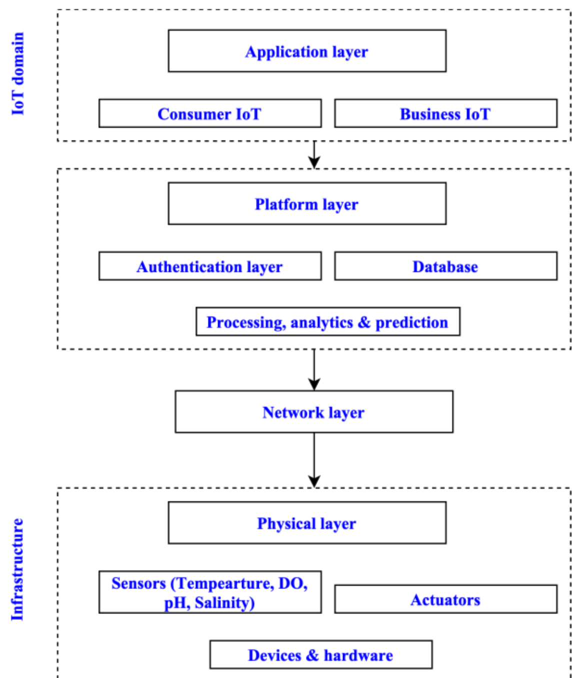

Figure 3. Layered architecture of the proposed model

Fig. 3 displays the suggested architectural structure, separated into many levels. A case study was done to provide the foundation for this proposed framework. The main objective is to provide a set of principles for using methods to comprehend better and improve ocean forecasting methods. The enhanced capabilities would be essential for making decisions, planning maritime operations, and offering vital insights into predicting probable oceanic occurrences.

This structure, along with its extensive array of algorithms, has the potential to be indispensable for the future development of ocean prediction. The system consists of four fundamental layers, with the physical layer being the first. This layer encompasses the hardware components, sensors, and actuation. In the physical layer, information about the seafloor and impressions of the surroundings are collected, organized into an Excel or CSV file for a specific period, and delivered to the loT databases server. The second network layer transmits the information packet from the detectors to the registry servers.

The system consists of three primary layers: the authorization layer, the database layer, and the data handling layer. The microservices Application Programming Interface (API) architecture incorporates the authorization sublayer to authenticate the user's identity independently. The research has implemented a microservices API architecture to enhance authentication and performance. The data collected by the sensors is stored on a storage sub-tier on the loT registry servers. The whole of the data is used to teach the model used for forecasting, resulting in a component of data processing referred to as the model development layer. The stakeholders employ the application layer, the last and fourth layers, to access and see the predictions and suggestions.

Results

According to the correlation study, a correlation result of 0.3 is found among dissolved oxygen and pH among all measurable parameters of the IoT. This refers to the lack of perfect plurality, which indicates no precise but non-random linear connection among every independent factor. Modest convergence did not impact the accuracy of the forecasts and the better performance. It is acceptable to disregard this issue in the proposed system. The methods were calibrated using past information collection. The variable (r^2) is used to assess the model's effectiveness.

$$r^2 = 1 - \frac{SS_r}{SS_t} \tag{1}$$

Where SS_rrepresents the total of the squares of leftovers and SS_t represents the cumulative addition of squares based on each quantity and the average quantity. It employs the coefficient of determination r^2 To determine the degree of fit among each unmeasurable variable and the five quantifiable variables.

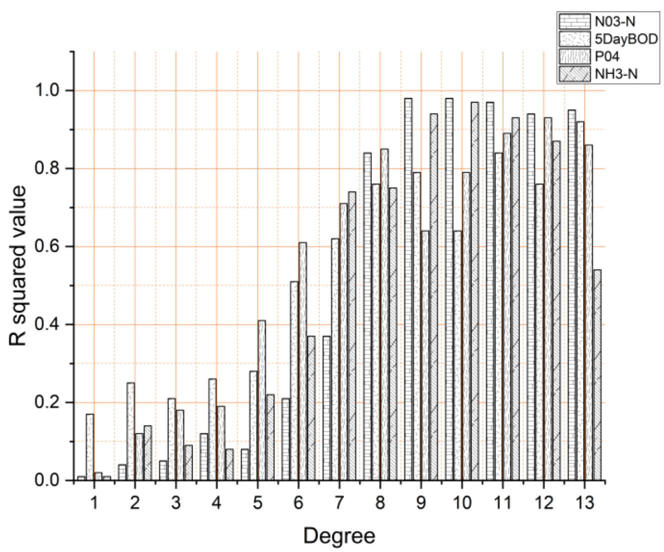

Figure 4. R squared value analysis

Fig. 4 illustrates a steady rise in the coefficient of prediction r^2 as the degree increases. It suggests that the development pattern consists of three distinct phases for the four factors that cannot be measured. 1) There is a consistent and gradual rise in the values before reaching the first five levels. 2) From degrees 6 to 9, the values suddenly and significantly rise. 3) After reaching degree 10, the values stabilize again, which may be attributed to the overfitted value. The variations in P-O_4 and BOD levels after level 10 are attributed to changes in the fitted capability as the level increases. Depending on the level, each variable's response varies according to its unique statistical properties. Overall, the model continues to exhibit an increasing trend in its ability to match the data, as the rising level. The reported rapid increase in r^2 is ascribed to the improving accuracy of the models.

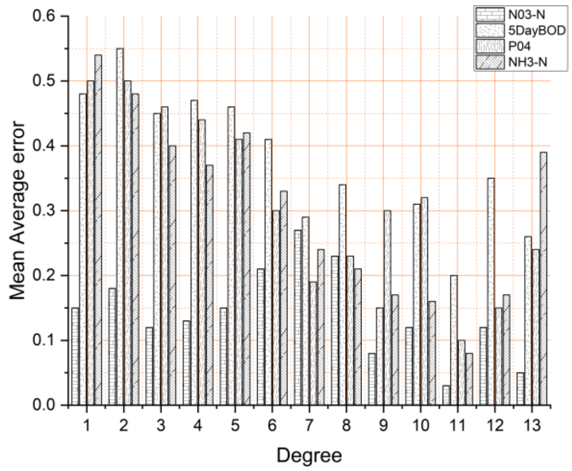

Figure 5. Mean absolute error analysis

Fig. 5 demonstrates that as the level of error increases, the Mean Absolute Errors (MAEs) consistently decline, with occasional fluctuations occurring after 7 level for the three variables, except N-O_3-N. The model degree 1 yields the lowest MAE for N-O_3-N. One potential reason for this unusual outcome might be that N-O_3-N exhibits a very high standard variation, as Fig. 6 shows, and a substantially higher value than its quartile norms. This might result in an even distribution, resulting in a lower MAE when the level of the structure is low. It presents a comparison between the predicted findings and the laboratory findings at four distinct sample locations.

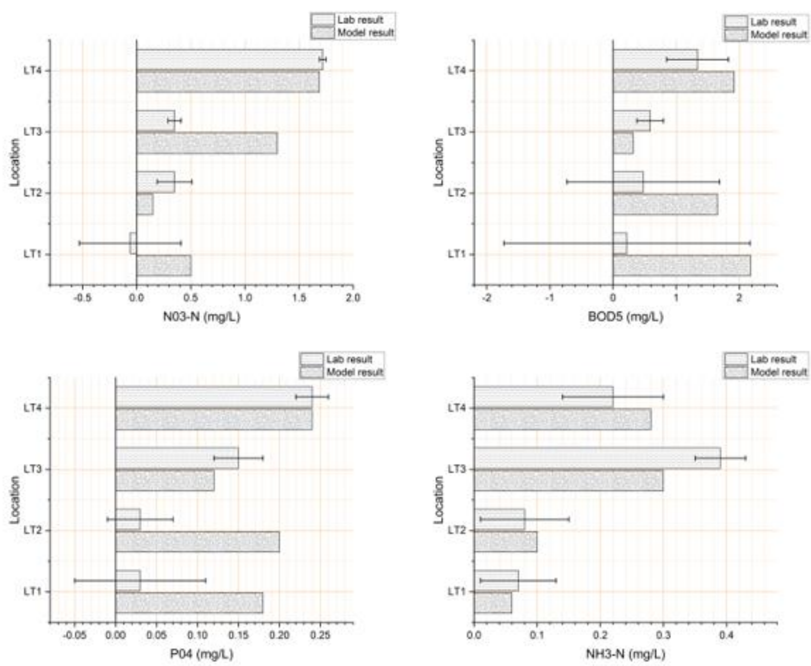

Figure 6. Laboratory and model result comparison

Most errors are less than 0.3 mg/L, indicating the model's adequate value. Significant disparities have been identified in the calculation of BOD5. The inaccuracy is much more important than the other variables, below 0.3 mg/L, except N-O_3-N at the first site. This mismatch may be attributable to the time lapse between collecting and testing the specimen. The faults in LT-3 and LT-4 were comparatively less than those in LT-1 and LT-2. The presence of additional contaminants in the lower part of the river enhances the sensitivity of the

IoT sensors. Most of the information in the historical database utilized in creating the model was gathered from locations more contaminated than LT-1 and LT-2, where the freshwater is much better. The suggested method is more suited for monitoring contaminated river locations.

Conclusion

Utilizing IoT-connected detectors for real-time water quality measuring offers a viable approach to conserving biodiversity in freshwater by monitoring water quality. Monitoring a comprehensive range of characteristics is difficult, primarily because of the restricted variety of sensors now accessible in the marketplace.

The paper established essential water quality metrics from the standpoint of biodiversity protection. Following that, a framework based on data analysis was suggested to estimate water quality characteristics that cannot be directly measured. An IoT system that tracks water quality in real time was created. The research introduced the G-RNN approach and the multivariate polynomial regression algorithm to identify anomalous discharge contaminants and estimate incalculable key water quality variables based on the measured ones via the IoT. The G-RNN method successfully identified anomalous increases in variables compared to typical scenarios.

The proposed algorithm with a level of 8 had coefficient of determination values of 0.87, 0.73, 0.89, and 0.79 for $N\text{-}O_3\text{-}N$, $BO\text{-}D_5$, $P\text{-}O_4$, and $N\text{-}H_3\text{-}N$, correspondingly. The recommended method was evaluated with experimental findings, and their overall efficacy is deemed acceptable and satisfactory. Most error values for estimating $N\text{-}O_3\text{-}N$, $P\text{-}O_4$, and $N\text{-}H_3\text{-}N$ are below 0.3 mg/L. The forecast demonstrates superior performance in river locations characterized by a comparatively elevated concentration of pollutants.

Over time, improving and refining the suggested structure is necessary to achieve a favorable equilibrium between precision and promptness. The research will explore advanced machine learning algorithms to estimate real-time parameters related to water quality. A recurrent neuronal network is utilized to predict consecutive water quality information.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

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