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AI and IoT-Based Water Quality Early Warning System

Atharva Aminbhavi[1]; Yash Nagrale[1]; Sandhya Jaiswal[1]; Aditi Jha[1]; Dr. Pratibha Adkar[2]

[1;2]MCA Department, P. E. S. Modern College of Engineering, Pune, India

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Abstract: Water quality monitoring is important for identifying changes in water conditions and providing timely warnings when unusual measurements occur. Conventional laboratory testing provides accurate results but is not suitable for continuous real-time monitoring. This project proposes an AI- and IoT-based Water Quality Early Warning System that combines water-quality sensors, embedded data acquisition, wireless communication, backend processing, machine learning, and a web dashboard. The system collects sensor readings, validates and processes the data, detects abnormal behaviour, and presents the results through a monitoring interface. The architecture also provides a framework for future pH estimation and water-quality classification using machine-learning models. Since pH is not directly measured in the current hardware, any estimated value must be validated against actual pH measurements before reliable use. The project includes temperature, TDS, and turbidity sensors connected initially to an Arduino Uno R3. An ADS1115 ADC can be used for higher-resolution analog measurements, while an ESP8266 NodeMCU V3 can provide Wi-Fi-based communication. The backend uses Python and FastAPI for data processing, with MQTT proposed for sensor-data transmission. A web dashboard displays live readings, real-time graphs, connection status, range information, and recent readings. The system also provides scope for sensor anomaly detection, pH estimation, and early-warning classification using AI/ML techniques.

Keywords: *Real-Time Monitoring, MQTT Communication, Sensor Fault Detection, Early Warning System, ESP8266, TDS, Turbidity.*

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I. INTRODUCTION

Water is an essential resource for domestic use, agriculture, industry, and environmental systems. Changes in water quality can arise from suspended matter, dissolved substances, temperature variation, chemical contamination, or other environmental factors. Monitoring these changes is therefore important when the objective is to understand the condition of a water source and identify unusual behaviour at an early stage.

Traditional water-quality assessment commonly depends on collecting samples and examining them using laboratory methods. Laboratory analysis can be accurate and informative, but the process may require time, equipment, and manual intervention. It also does not inherently provide a continuous stream of measurements from the monitoring location.

Internet of Things (IoT) technology provides an alternative approach by connecting sensors to a microcontroller and transmitting measurements to a software system. Temperature, TDS, turbidity, and other parameters can then be observed at regular intervals. However, raw sensor readings can contain noise, spikes, drift, communication errors, or other anomalies. A sudden change in a reading does not necessarily mean that the water itself has changed.

Artificial Intelligence and Machine Learning can be introduced after the sensing and communication stages to analyze patterns in the collected data. Such models may assist with sensor-health monitoring, anomaly detection, forecasting, and estimation of parameters that are not directly measured. In this project, the proposed architecture provides a server-side location for pH estimation and water-quality early-warning analysis, while the practical hardware currently focuses on temperature, TDS, and turbidity.

The project follows a staged development approach. Sensor operation is first verified using an Arduino Uno R3. After testing and calibration, the hardware can be migrated to an ESP8266 NodeMCU V3, which adds Wi-Fi connectivity. The resulting data path can then be connected to a backend service and a web-based dashboard for real-time monitoring and session-based graphical visualization.

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II. LITERATURE SURVEY

Sharma et al. (2026) — Sharma and co-authors describe a low-cost, real-time water-quality monitoring system based on ESP32, IoT sensors, cloud integration, and TinyML. The study considers pH, TDS, temperature, and turbidity and reports a quantized neural network deployed on the ESP32 with 99.28% accuracy on a 6,000-point dataset. The work demonstrates the feasibility of edge-based intelligence while also identifying the need for broader evaluation across real-world water sources.

Kushwaha and Pandey (2025) — This study presents an IoT-based water-quality monitoring and predictive-analysis system using ESP32/NodeMCU sensor nodes and a wireless cloud platform. Random Forest, SVM, XGBoost, and LSTM methods are considered for anomaly detection, forecasting, and Water Quality Index computation. The work is relevant to the proposed sensor-to-dashboard architecture, although its evaluation emphasizes predictive performance more than the practical design of an early-warning workflow.

Nie et al. (2025) — Nie and co-authors examine calibration approaches for low-cost IoT turbidity sensors. Linear regression, Random Forest, SVM, and Gaussian-process regression are compared against reference laboratory instruments and evaluated in a water-reuse deployment. The study provides a useful example of how low-cost turbidity measurements can be calibrated against reference data.

Aderemi et al. (2025) — This systematic review examines explainable AI for water-quality monitoring and discusses techniques such as SHAP, LIME, counterfactual explanations, and standardized evaluation measures. The review supports the idea that an alerting system should provide context for a model decision rather than presenting an unexplained contamination message.

Ishikura et al. (2025) — Ishikura and co-authors investigate anomaly detection for drinking-water quality using fluorescent fingerprints and explainable AI. Their experiments use water-quality indicators such as TOC, TN, and EC and report high sensitivity, specificity, and overall accuracy on the studied samples. The authors also identify limitations related to regional, seasonal, and water-matrix coverage.

Shahid et al. (2024) — This work proposes an autonomous IoT framework for real-time water-quality monitoring, prediction, classification, and remote visualization. The study uses parameters including pH, dissolved oxygen, chemical oxygen demand, and ammonia nitrogen, and applies a tuned ensemble machine-learning approach. The reported results are strong on the datasets studied, while the authors also identify the need for additional sensing and broader deployment considerations.

Urbanovičs et al. (2024) — Urbanovičs and co-authors compare machine-learning methods with traditional mathematical approaches for water-contamination detection. The study uses a model water system and simulated contamination conditions and reports substantially better detection with the evaluated machine-learning methods than with the traditional mathematical method. Arduino and Raspberry Pi devices were used for data collection.

Pires and Gomes (2024) — This study presents a low-cost river-water monitoring system using LoRa communication. Temperature, pH, conductivity, and turbidity were measured using multiple sensors, while an Arduino Nano collected and transmitted the readings. The deployment in a Portuguese river demonstrated the feasibility of combining low-cost sensing with long-range wireless communication.

Naloufi et al. (2024) — Naloufi and co-authors evaluate the long-term behaviour of a low-cost IoT water-quality system deployed in urban rivers. The work considers temperature, pH, conductivity, turbidity, and dissolved oxygen together with calibration and maintenance. The reported sensor drift, turbidity instability, and field data loss demonstrate why calibration, cleaning, and long-term sensor-health checks are important in practical deployments.

López-Munoz et al. (2024) — The authors describe a wireless sensor network containing mobile and fixed monitoring stations. The stations measure parameters such as pH, temperature, and salt content, and the mobile unit can be remotely controlled. The system was tested in a campus lagoon and stored measurements for later analysis.

Saeed et al. (2024) — Saeed and co-authors investigate multivariate water-quality forecasting using Long Short-Term Memory networks. Their work demonstrates how historical measurements across multiple variables can be used to model and forecast changes in water conditions.

Jeong et al. (2024) — This study applies machine learning to a biological early-warning system based on behavioural responses of Daphnia magna. Several models were examined, with LightGBM providing the strongest performance among the methods evaluated in the study. The work illustrates another way in which machine learning can support early identification of water-quality changes.

Kartikay Lal et al. (2024) — Lal and co-authors report a low-cost IoT system for monitoring freshwater bodies under changing weather conditions. The system monitored turbidity, TDS, temperature, pH, and dissolved oxygen over deployments lasting several days to weeks. The study highlights the value of continuous monitoring while noting issues such as intermittent connectivity and limitations of prolonged pH-sensor operation.

El-Shafeiy et al. (2023) — El-Shafeiy and co-authors investigate real-time anomaly detection in sensor data using an MCN-LSTM model. The work focuses on recognizing unusual patterns that may indicate abnormal system behaviour or sensor-related problems, supporting the use of machine learning for sensor anomaly detection. The source document does not provide further implementation details in this review.

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Jabbar et al. (2023) — This study develops a portable, solar-powered water-quality monitoring system for rural areas. LoRaWAN is used to transmit parameters including pH, salt content, turbidity, and temperature. Testing in a Malaysian lake showed measurements comparable with traditional laboratory testing and demonstrated the potential of energy-efficient remote monitoring.

Czyczula Rudjord et al. (2022) — The authors develop a laboratory-based AI system for real-time detection of chemical-contamination anomalies using UV absorbance and fluorescence. The experiments examine several representative organic contaminants and show the potential of AI-based anomaly detection under controlled conditions. The study also notes limitations caused by controlled experimental conditions and biofouling.

Mokua, Maina and Kiragu (2021) — This study compares anomaly-detection approaches, including Local Outlier Factor and Random Forest, using real turbidity and pH data from a water-treatment environment. The work provides a deployment-oriented example of unsupervised anomaly detection and also illustrates the importance of model-parameter selection.

Meleshko et al. (2020) — Meleshko and co-authors study machine-learning methods for identifying incorrect and unusual sensor readings in cyber-physical water-supply systems. The experiments include simulated operating conditions and show that learned patterns can be used to distinguish normal measurements from abnormal sensor behaviour.

Muharemi et al. (2019) — This work evaluates several machine-learning algorithms for water-quality anomaly detection using a real-world dataset. The authors discuss class imbalance, with normal observations greatly outnumbering problematic observations, and examine how different algorithms respond to this imbalance.

Rathore et al. (2017/2018 in the project source) — Rathore and co-authors propose a method for detecting and correcting smooth and abrupt sensor drift in low-cost IoT sensors. The work supports the inclusion of a dedicated sensor-health stage before higher-level anomaly detection and prediction.

- *Research Gap*

The reviewed studies show that IoT sensing has become a practical approach for collecting water-quality measurements, while machine learning can support anomaly detection, forecasting, classification, and sensor-health analysis. Existing systems commonly monitor parameters such as pH, turbidity, temperature, TDS, conductivity, dissolved oxygen, or related variables and may transmit the measurements through Wi-Fi, LoRa, or cloud platforms.

A recurring limitation is that sensing, calibration, anomaly detection, forecasting, and alert generation are often treated as separate functions. Practical deployments also face sensor drift, fouling, noise, missing data, intermittent connectivity, and the difficulty of distinguishing a genuine water-quality change from a faulty measurement.

The proposed project addresses this gap by bringing the main stages together in a single layered architecture. The system combines low-cost sensing, edge-side validation, wireless communication, backend processing, machine-learning integration, and a user-facing dashboard. The architecture also explicitly separates sensor faults from water-quality warnings where the available data allows such a distinction.

The project is deliberately designed as an expandable platform rather than a claim of complete water-safety assessment. The current prototype measures temperature, TDS, and turbidity. A future pH-estimation model may use these measurements, but it must be trained and validated using synchronized measurements from an actual calibrated pH sensor before the estimate can be treated as reliable.

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➢ *System Architecture*

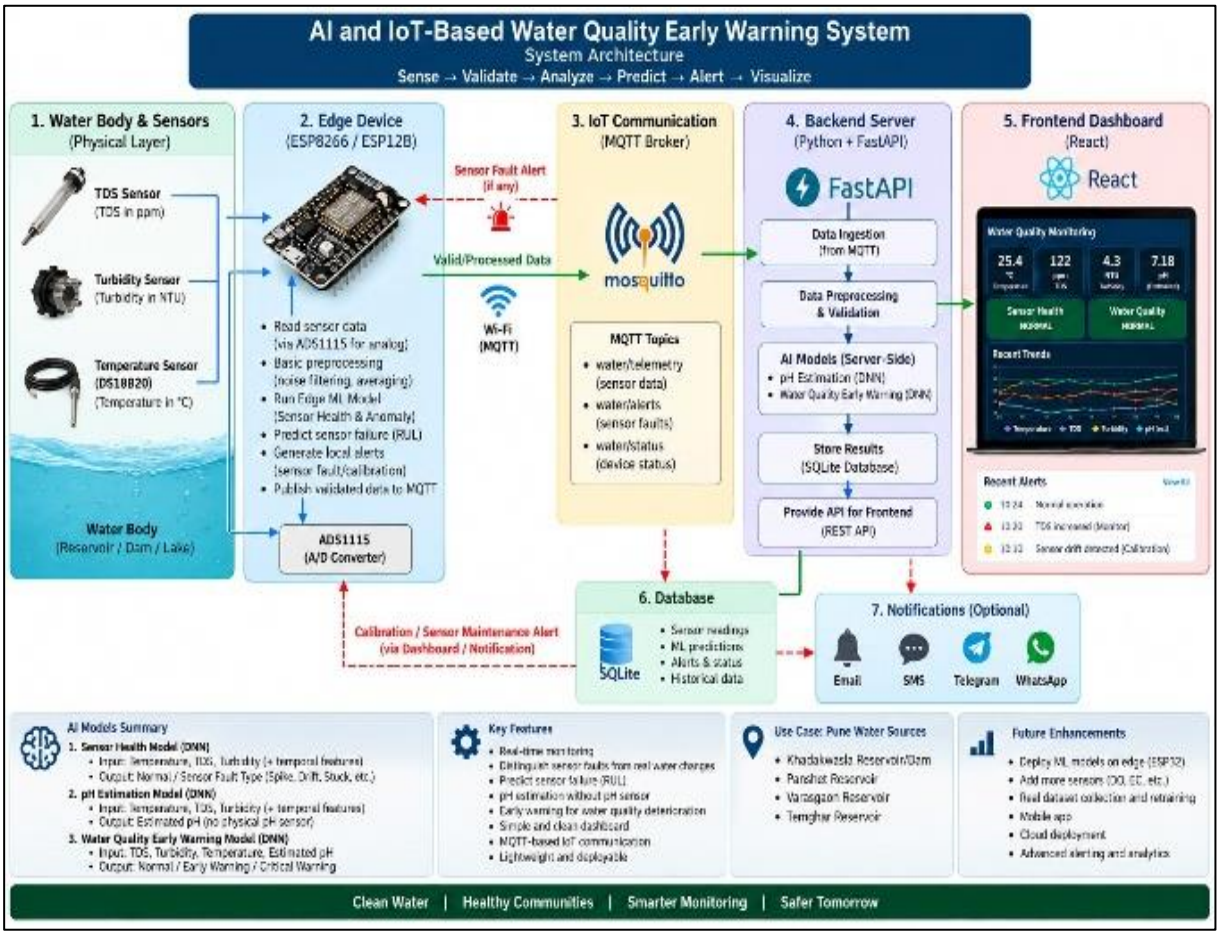


Fig 1 System Architecture

The proposed system uses a layered architecture that separates sensing, edge processing, communication, backend analysis, and user interaction. The overall workflow can be represented as:

Sense → Validate → Analyze → Predict → Alert → Visualize

This structure makes it possible to test the hardware independently, replace the communication method when required, and add machine-learning models without changing the basic sensing layer.

➢ *AI/ML Layer*

The AI/ML layer provides the analytical functions of the proposed system. Sensor readings can first be cleaned through validation, filtering, averaging, normalization, and feature extraction. A lightweight model may then be used for sensor-health analysis, including detection of spikes, drift, stuck readings, or other unusual behaviour.

A separate server-side model can estimate pH from temperature, TDS, turbidity, and temporal features. The purpose of this feature is to provide an estimated value when a physical pH sensor is unavailable. The estimate is not equivalent to a direct pH measurement and must be experimentally validated before being used for dependable water-quality decisions.

Another server-side model can analyze corrected measurements and classify the monitored condition into categories such as Normal, Early Warning, or Critical Warning. The architecture therefore allows sensor-health analysis and water-quality analysis to be treated as related but different tasks.

➢ *Hardware Layer*

The hardware layer contains the physical sensors and the microcontroller used to acquire their readings. The practical setup contains a temperature sensor, a TDS sensor, and a turbidity sensor. During initial testing, the sensors are connected to an Arduino Uno R3. The final version can use an ESP8266 NodeMCU V3 (ESP-12E/ESP8266MOD) to provide Wi-Fi connectivity.

The temperature sensor measures water temperature in degrees Celsius. The TDS sensor provides information related to dissolved substances in the water, while the turbidity sensor responds to cloudiness and suspended particles. For analog measurements, an ADS1115 ADC can be connected through I2C to provide higher-resolution readings than the Arduino Uno's built-in 10-bit ADC.

The architecture does not require a physical pH sensor for its proposed estimation stage. Instead, pH can be estimated by a server-side model using the available parameters. This

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approach reduces the hardware requirement, but it also makes model validation especially important.

➢ *Connectivity Layer*

The connectivity layer transfers validated sensor information from the edge device to the backend. During Arduino-based testing, the readings can be transmitted over the serial connection to a computer. In the final ESP8266 configuration, Wi-Fi can be used to transmit measurements without a direct USB serial connection.

ESP8266 → Wi-Fi → MQTT Broker → FastAPI Backend

MQTT is proposed as the lightweight telemetry protocol. Separate topics can be used for sensor telemetry, alerts, and device status. The backend subscribes to the required topics and processes the incoming measurements.

➢ *Backend and Data Layer*

The backend layer is implemented conceptually using Python and FastAPI. It receives measurements from the communication layer, validates and preprocesses the data, performs server-side analysis, and exposes processed information to the frontend.

A lightweight database such as SQLite can be used to store sensor readings, predictions, alerts, device status, and historical measurements. The REST API can then provide current readings, historical data, predictions, and alert information to the dashboard.

The backend also provides a suitable location for computationally heavier machine-learning models. For example, a pH-estimation model can use temperature, TDS, turbidity, and temporal features, while a separate model can analyze changes across multiple parameters for early-warning classification.

➢ *Application Layer*

The application layer is the main interface used by the operator. The dashboard presents current sensor measurements, graphical trends, connection status, range information, and system messages in a form that is easier to interpret than raw serial output.

The dashboard can also display sensor-health information, predicted pH when a validated model is available, and warnings when abnormal readings or communication problems are detected. Optional notification channels may be added in future versions.

➢ *Working of the System*

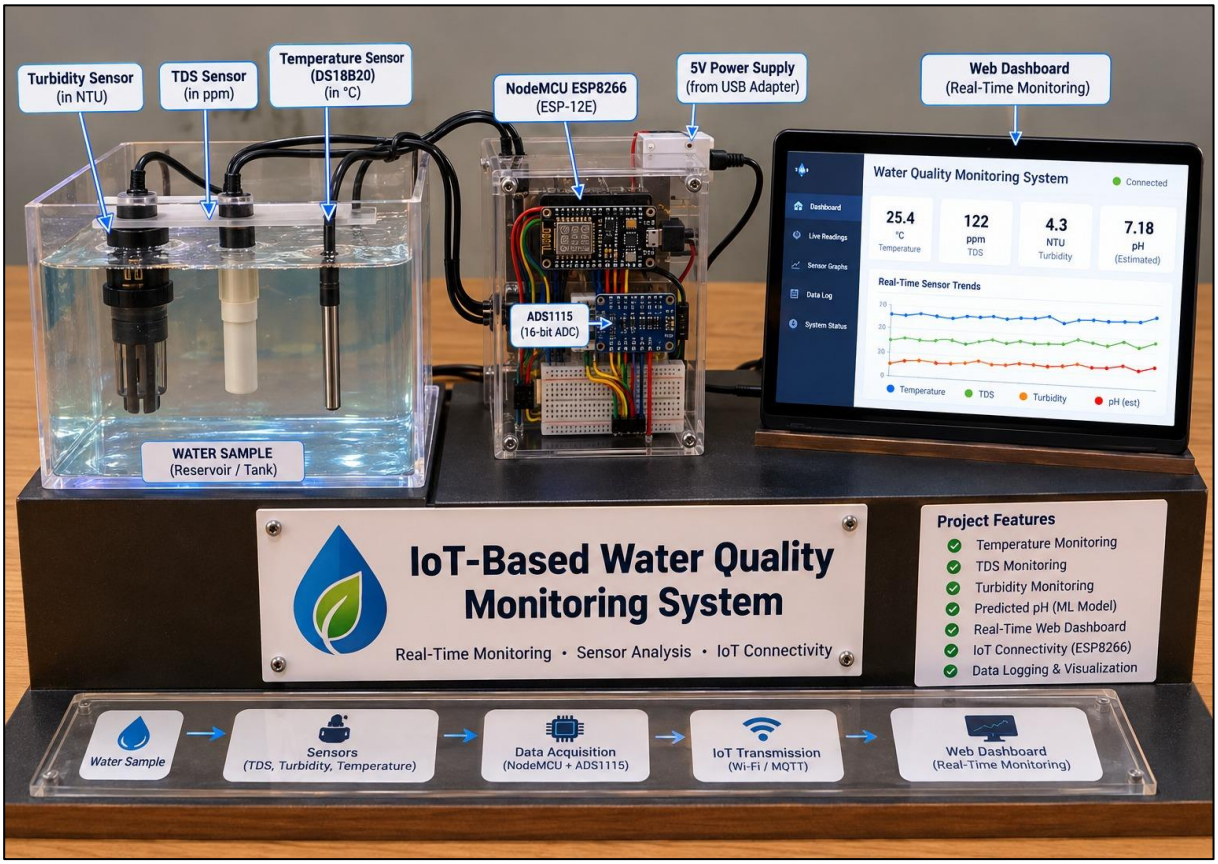


Fig 2 Working of the System

The Water Quality Monitoring System is designed to observe important physical and electrical characteristics of water in near real time. The present prototype focuses on temperature, TDS, and turbidity. Each sensor produces a measurement that is read by the microcontroller and passed to the processing and communication stages.

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The temperature sensor provides the water-temperature reading. The TDS sensor measures the electrical response associated with dissolved substances, while the turbidity sensor provides an indication of water cloudiness caused by suspended particles. The readings are not treated as absolute laboratory measurements until the sensors have been calibrated for the intended use.

For initial testing, the sensors are connected to an Arduino Uno R3. The microcontroller reads the sensors and sends formatted data through the serial interface. The computer-side application receives the serial data and updates the monitoring dashboard.

After the Arduino-based stage is verified, the same sensing concept can be migrated to the ESP8266 NodeMCU V3. The ESP8266 provides Wi-Fi connectivity, allowing the device to transmit sensor data to the backend without depending on a direct serial connection to the monitoring computer.

An ADS1115 module can be used for the analog sensor inputs. The ADC communicates with the ESP8266 through I2C, allowing the TDS and turbidity channels to be sampled at higher resolution. The measured values can then be filtered, validated, formatted, and transmitted.

The basic system flow is:

Water Sample → Sensors → ADC/Signal Processing → Microcontroller → Data Transmission → Backend → Dashboard → Real-Time Monitoring

During a monitoring session, the frontend should retain the readings collected from the moment the device becomes connected until the device is disconnected. This avoids losing historical points because of periodic frontend updates and allows the graphs to represent the complete active session.

A predicted pH value can be added after a suitable machine-learning model has been trained. The training process requires synchronized temperature, TDS, turbidity, and actual pH measurements collected using a calibrated pH sensor. The model should be evaluated on data that was not used for training before the predicted pH is presented as a meaningful result.

III. SYSTEM SCREENS

The monitoring application is organized as a dashboard so that the operator can view current values and trends without reading raw serial messages.

➢ *Live Sensor Readings*

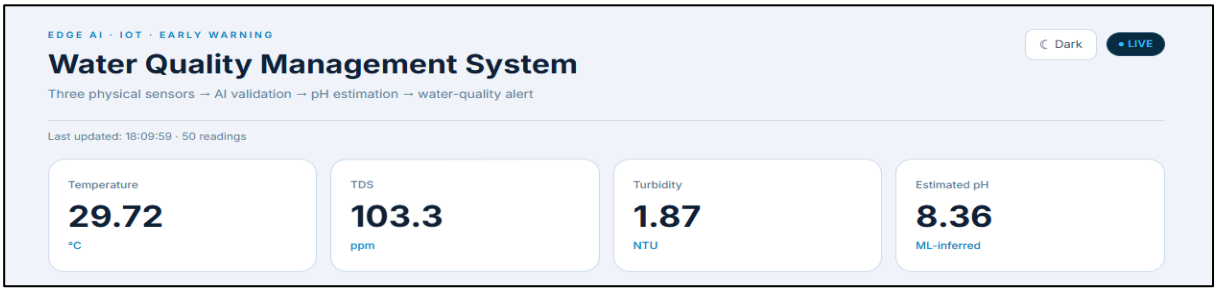


Fig 3 Live Sensor Readings

The main dashboard displays the current temperature, TDS, and turbidity values. A predicted pH value is displayed only when a validated prediction model is available. Each measurement can also have a status indicator showing whether the value is being received normally or requires attention.

➢ *Real-Time Graphs*

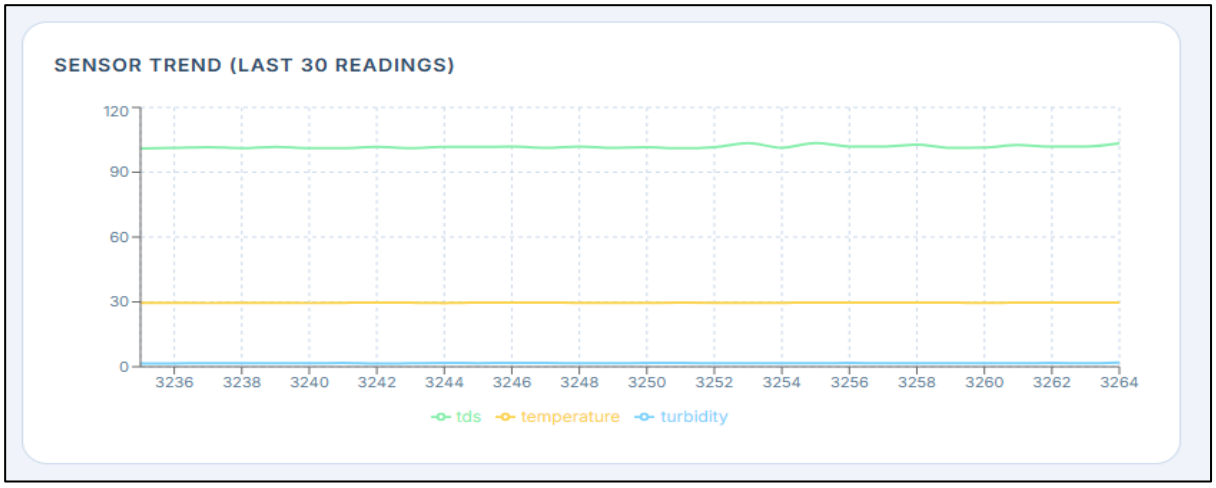


Fig 4 Real-Time Graphs

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Separate graphs are provided for temperature, TDS, turbidity, and predicted pH when the prediction feature is active. The graph data belongs to the current monitoring session and is retained in the browser while the device remains connected. The page should update the values without reloading the entire document, so previously collected points are not erased.

➢ *Connection Status*

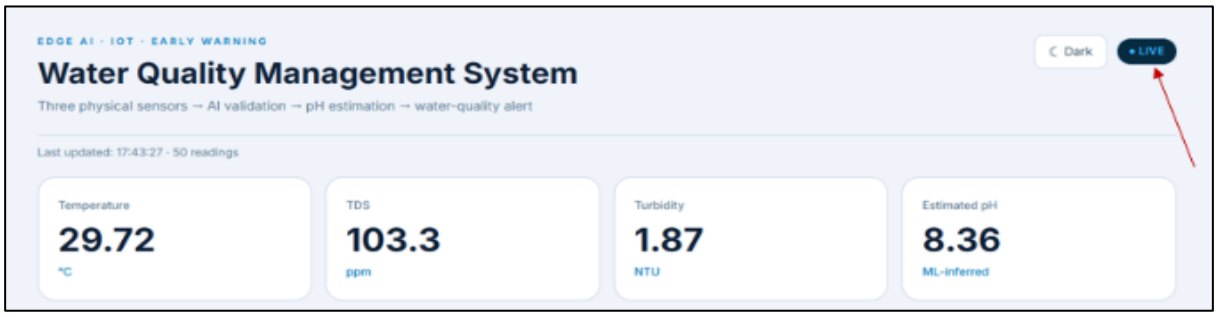


Fig 5 Connection Status

The dashboard indicates whether communication with the monitoring device is active. An online state means that recent sensor data has been received. An offline state indicates that communication has stopped or that the device is no longer detected.

➢ *Range Analysis*

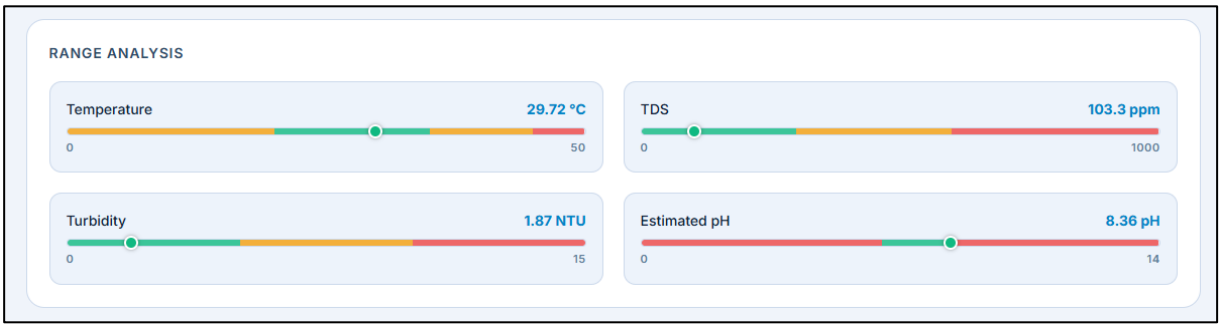


Fig 6 Range Analysis

The interface can show the current sensor value relative to a selected monitoring range. This gives the operator a quick visual reference for the position of a reading within the configured range. The ranges should be treated as monitoring references and should be adjusted for the specific sensor and application.

➢ *System Status*

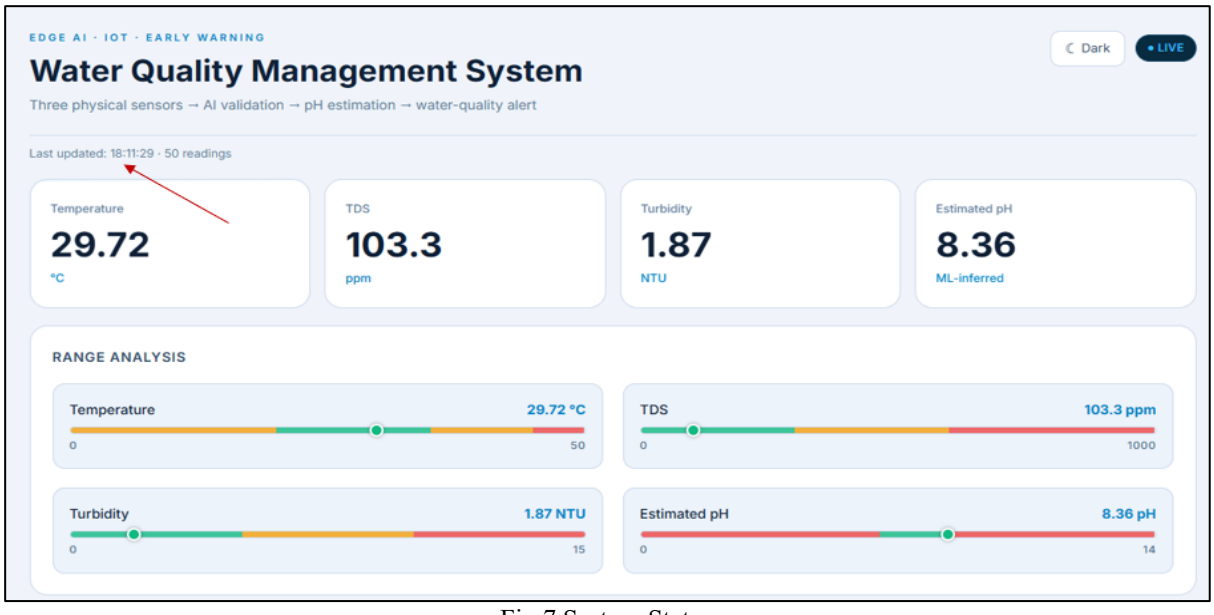
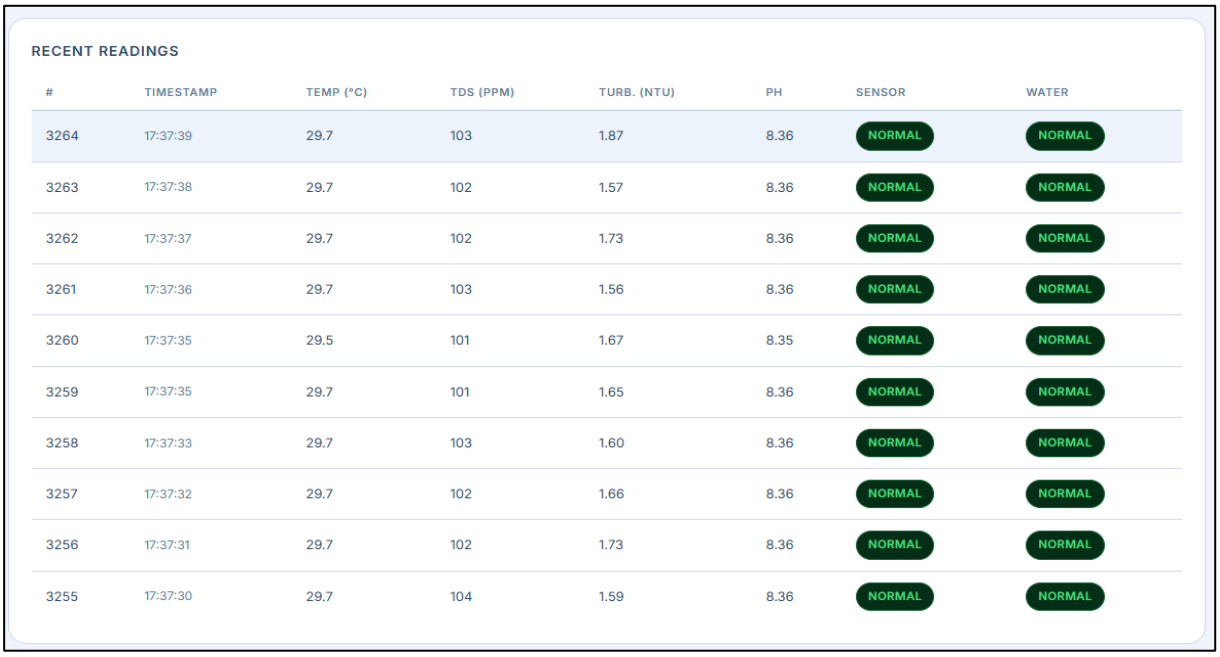


Fig 7 System Status

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The system-status area displays the latest update time, connection state, and a short description of the current system condition. This section provides a quick summary without requiring the operator to inspect each sensor card individually.

➢ *Recent Readings*



RECENT READINGS

#	TIMESTAMP	TEMP (°C)	TDS (PPM)	TURB. (NTU)	PH	SENSOR	WATER
3264	17:37:39	29.7	103	1.87	8.36	NORMAL	NORMAL
3263	17:37:38	29.7	102	1.57	8.36	NORMAL	NORMAL
3262	17:37:37	29.7	102	1.73	8.36	NORMAL	NORMAL
3261	17:37:36	29.7	103	1.56	8.36	NORMAL	NORMAL
3260	17:37:35	29.5	101	1.67	8.35	NORMAL	NORMAL
3259	17:37:35	29.7	101	1.65	8.36	NORMAL	NORMAL
3258	17:37:33	29.7	103	1.60	8.36	NORMAL	NORMAL
3257	17:37:32	29.7	102	1.66	8.36	NORMAL	NORMAL
3256	17:37:31	29.7	102	1.73	8.36	NORMAL	NORMAL
3255	17:37:30	29.7	104	1.59	8.36	NORMAL	NORMAL

Fig 8 Recent Readings

The system has recent readings area in order to visualise the readings for accurate study.

➢ *Applications*

- Domestic Water Monitoring — The system can be used to observe changes in household water and provide an early indication of unusual sensor readings.
- Water Treatment Systems — The sensors can be used to observe water conditions at different stages of a small-scale treatment process.
- Aquaculture — Temperature, turbidity, and dissolved-solids measurements can provide useful information for monitoring fish tanks and aquaculture systems.
- Educational and Research Projects — The platform can demonstrate sensor interfacing, ADC acquisition, embedded programming, IoT communication, data visualization, and machine-learning integration.
- Environmental Monitoring — The system can be adapted to monitor water samples from different sources and compare changes in measured physical properties.
- IoT-Based Remote Monitoring — After migration to the ESP8266, sensor measurements can be transmitted through Wi-Fi and viewed through a web dashboard without maintaining a direct serial connection to a computer.

➢ *Advantages*

- Real-time monitoring — Enables continuous observation of water-quality parameters.
- Multiple parameters — Monitors temperature, TDS, and turbidity in a single system.
- Low-cost implementation — Uses affordable and commonly available sensors and microcontrollers.
- Graphical visualization — Displays sensor readings through real-time graphs and trends.
- IoT connectivity — ESP8266 enables wireless transmission of sensor data.
- Expandable architecture — Additional sensors, models, and communication methods can be integrated.
- User-friendly dashboard — Presents readings, status, alerts, and trends in an organized interface.
- Data analysis capability — Collected data can be used for calibration, anomaly detection, and machine-learning analysis.
- Portable design — The hardware can be assembled into a compact monitoring unit.
- Future automation — The system can be extended with alerts, cloud storage, mobile applications, and automated monitoring.

IV. LIMITATIONS

- Sensor calibration requirement — Sensor readings require proper calibration and may be affected by temperature, environmental conditions, and sensor placement.
- Limited parameters — The current system measures temperature, TDS, and turbidity; these parameters alone cannot provide a complete assessment of water quality.
- Predicted pH limitation — pH is not directly measured by the current hardware. Any AI-based pH estimation

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depends on the quality and diversity of the training data and must be experimentally validated before reliable use.

V. FUTURE SCOPE

- Additional Sensors — pH, dissolved oxygen, conductivity, and other water-quality sensors can be integrated for more comprehensive monitoring.
- Cloud Integration — Sensor data can be stored on cloud platforms for long-term monitoring and remote access.
- Advanced Hardware — The system can be converted into a compact, battery-powered IoT device for portable and field-based monitoring.

VI. CONCLUSION

The Water Quality Monitoring System demonstrates how embedded sensing, IoT communication, data processing, and web-based visualization can be combined to monitor selected water-quality parameters. The practical prototype measures water temperature, TDS, and turbidity and presents the collected measurements through a monitoring dashboard.

The project uses the Arduino Uno R3 as the initial development and testing platform. This stage allows sensor connections, ADC readings, serial communication, and calibration procedures to be verified before the system is migrated to the ESP8266 NodeMCU V3. The ESP8266 adds Wi-Fi connectivity and therefore provides a practical path toward remote monitoring.

The proposed architecture separates the sensing, communication, backend, and application responsibilities. It also provides a place for machine-learning models to analyze sensor behaviour, estimate pH, and identify possible water-quality changes. The predicted pH feature is intentionally treated as a future analytical capability rather than as a direct measurement.

A complete pH-estimation model would require a sufficiently large dataset containing synchronized temperature, TDS, turbidity, and actual pH measurements obtained using a calibrated pH sensor. The model would then need independent validation before its predictions could be considered dependable.

Overall, the project provides a low-cost and expandable foundation for water-quality monitoring. Future development can include longer-term data logging, improved calibration, sensor-health models, validated pH estimation, cloud connectivity, notification services, additional sensors, and more comprehensive water-quality analysis.

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