

HydroWatch AI - Real-Time Water Level Sensor Network for River Level Detection and Flood Prediction for Gadhinglaj

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Abstract: Floods continue to be among the most catastrophic natural disasters globally, posing severe threats to human life, infrastructure, and local economies. In regions like Gadhinglaj, the challenge is exacerbated by reliance on legacy monitoring frameworks dependent on manual observations and fragmented reporting. To bridge this critical gap, the HydroWatch AI system introduces an intelligent IoT-based flood monitoring architecture integrated with advanced machine learning capabilities. The hardware layer comprises Raspberry Pi-based sensor nodes utilizing VL53L0X TimeofFlight (ToF) laser distance sensors for millimetric water-level accuracy, alongside DHT11 sensors for ambient temperature and humidity. The backend leverages Node.js and MongoDB for real-time telemetry processing, while a dedicated AI module synthesizes live data with OpenWeatherMap meteorological inputs to generate predictive flood warnings. A Next.js web dashboard provides authorities a centralized command interface. The prototype achieved over 98% telemetry uptime, validating HydroWatch AI as a robust, low-cost, proactive alternative to traditional disaster management systems.

Keywords: IoT, Flood Monitoring, Raspberry Pi, AI, Real-Time Sensing, Cloud Computing, Disaster Management, VL53L0X, Node.js, MongoDB

I. INTRODUCTION

Floods are among the most frequent and destructive natural disasters in India, causing widespread damage to life, property, and infrastructure. Traditional flood monitoring methods rely heavily on manual measurements and local observation systems, which are often inefficient, error-prone, and unsafe during extreme weather events. The absence of real-time data and predictive capabilities makes it difficult for authorities to take timely preventive actions, leading to significant delays in disaster response.

With advancement of technology, the integration of the Internet of Things (IoT) and Artificial Intelligence (AI) offers an innovative solution. IoT enables real-time data collection from remote environments through sensor networks, while AI enhances this data with intelligent analysis and prediction models. Together, these technologies can transform flood monitoring into an automated, accurate, and proactive system that assists in early warning and risk mitigation.

HydroWatch AI addresses these limitations by developing a real-time, cloud-connected river monitoring and flood prediction network. Each monitoring module, powered by Raspberry Pi and equipped with VL53L0X and DHT11 sensors, collects environmental data at regular intervals. Data is transmitted securely to a Node.js/MongoDB cloud backend for processing, analysis, and visualization. The AI component uses OpenAI's API and weather datasets to perform predictive analytics, identifying potential flood conditions based on changing water levels and environmental patterns.



HydroWatch AI provides a Next.js web dashboard for administrators and disaster management officials. The dashboard offers real-time visualization, historical data tracking, and automated alert notifications, enabling authorities to make data-driven decisions efficiently. By combining IoT, AI, and cloud computing, HydroWatch AI presents a scalable and intelligent approach to flood monitoring, enhancing disaster preparedness.

II. LITERATURE REVIEW

Water level monitoring plays a vital role in India's river management and flood prevention infrastructure. The Central Water Commission (CWC) indicates that most river level readings are still performed manually, requiring personnel to physically record water gauge levels on an hourly basis, even during adverse weather conditions [1]. This traditional method is time-consuming, prone to human error, and poses significant safety risks.

Recent studies have explored IoT-based flood monitoring systems using ultrasonic sensors and GSM/Wi-Fi modules for real-time water level recording and transmission. "IoT-Based Flood Monitoring System Using Ultrasonic Sensors" (IEEE Transactions on IoT, 2023) demonstrates the effectiveness of ultrasonic sensing but notes limitations in scalability and cloud connectivity [2].

Research on AI models for flood prediction shows that integrating real-time environmental data with historical hydrological patterns enhances flood forecasting accuracy. "AI Models for Predicting River Flood Risks Using Environmental Data" (Elsevier Journal of Hydrology, 2022) highlights the importance of combining multiple parameters including rainfall, humidity, and water levels for improved prediction [3].

Cloud-based environmental monitoring frameworks have gained attention for centralizing data collection and visualization. "Cloud-Based Environmental Monitoring Systems" (IJCA, 2021) shows how cloud integration improves decision-making through accessible dashboards, but many such systems lack real-time alerting or autonomous rural operation [4]. HydroWatch AI addresses these research gaps through its integrated, low-cost, scalable architecture. A. Comparative Analysis

TABLE I: Comparison of Flood Monitoring System Approaches

Feature/Parameter	Traditional Systems	IoT-Based Systems	AI-Based Systems	HydroWatch AI
Data Collection	Manual	Automated	Automated	Automated
Real-Time Monitoring	No	Yes	Yes	Yes
Predictive Analysis	No	Limited	Yes	Yes (AI-driven)
Deployment Cost	Low	Moderate	High	Low-Moderate
Scalability	Limited	Moderate	Limited	High
Alert System	Manual	Threshold-based	Intelligent	Intelligent
Power Source	Grid-based	Mixed	Mixed	Solar-powered
Rural Deployment	Difficult	Possible	Limited	Highly Suitable

III. SYSTEM ARCHITECTURE

The HydroWatch AI system is organized into three principal layers: the Sensing Layer (Edge Infrastructure), the Processing and Intelligence Layer (Cloud Infrastructure), and the Presentation Layer (User Interface).

A. Sensing Layer (Edge Infrastructure)

The sensing layer comprises floating IoT modules, each built around a Raspberry Pi 4 Model B. The VL53L0X TimeofFlight laser distance sensor measures water surface elevation with millimetric precision, while the DHT11 sensor captures ambient temperature and humidity. Each node is powered by a solar-charged lithium-ion battery system, ensuring autonomous off-grid operation. Multiple nodes (1st through nth) can be deployed along a river, all reporting simultaneously to the central cloud hub via GSM/Wi-Fi connectivity.



B. Processing and Intelligence Layer (Cloud Infrastructure)

The cloud core is built with Node.js and Express.js hosted on AWS. Sensor telemetry streams are ingested and persisted in MongoDB Atlas for scalable time-series storage. The integrated AI module evaluates real-time readings against external OpenWeatherMap API data to assess flood risk levels, generating predictive early warnings before water levels breach defined safety thresholds.

C. Presentation Layer (User Interface)

A responsive Next.js and Tailwind CSS web dashboard provides two role-based views: (1) Administrator Dashboard for device management, historical trend analysis, and alert configuration; and (2) Official Dashboard for real-time river status, GPS-based map visualization using Leaflet.js, and flood alert tracking. Multiple concurrent dashboard instances are accessible across phones, tablets, and PCs.

IV. METHODOLOGY

A. Hardware Design

Fig. 5: Sensor Accuracy Comparison (Measurement Error)

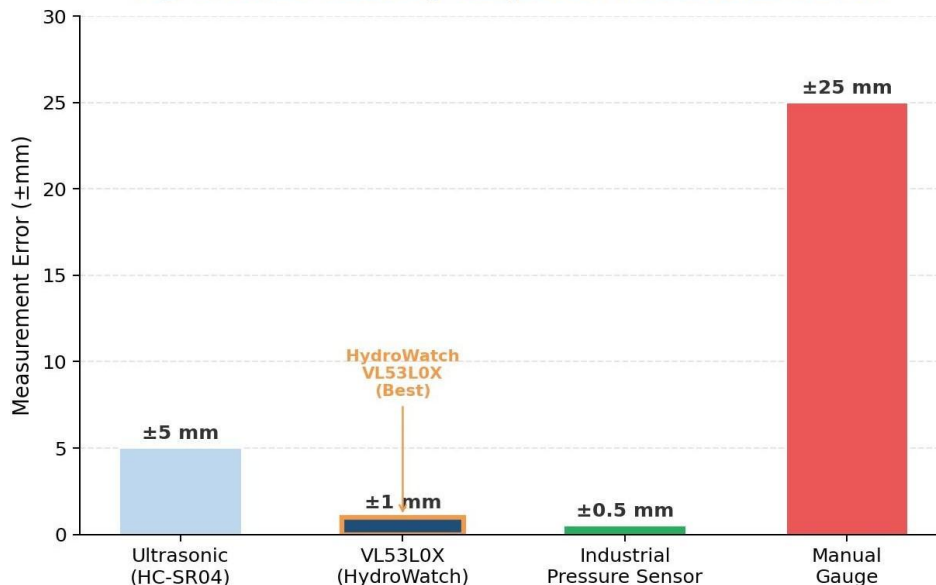


Fig. 5: Sensor Accuracy Comparison (Measurement Error in ±mm)

The monitoring module integrates the following key components:

- Raspberry Pi 4 Model B: 1.5 GHz quad-core ARM Cortex-A72 processor, 4 GB RAM, 40-pin GPIO header, built-in Wi-Fi and Gigabit Ethernet, 5V USB-C power supply.
- VL53L0X ToF Laser Distance Sensor: Laser-based Time-of-Flight technology, measurement range up to ~2,200 mm, millimeter-level precision, I2C communication protocol, operating voltage 2.8-3.3V.
- DHT11 Temperature and Humidity Sensor: Temperature range 0-50 degree C (plus or minus 2 degree C accuracy), humidity range 20-90% RH (plus or minus 5% accuracy), single-wire digital output, operating voltage 3.3-5V.
- Power System: 10W Solar Panel with Solar Charge Controller, 10,000 mAh Li-ion battery with Battery Management System (BMS), Buck-Boost Converter providing stable 5V output to Raspberry Pi.
- Weatherproof enclosure with float-mounted platform for river deployment; VL53L0X connected via I2C (SDA: GPIO 2, SCL: GPIO 3); DHT11 connected to GPIO 4.



B. Software Architecture

Fig. 4: HydroWatch AI - System Component Distribution

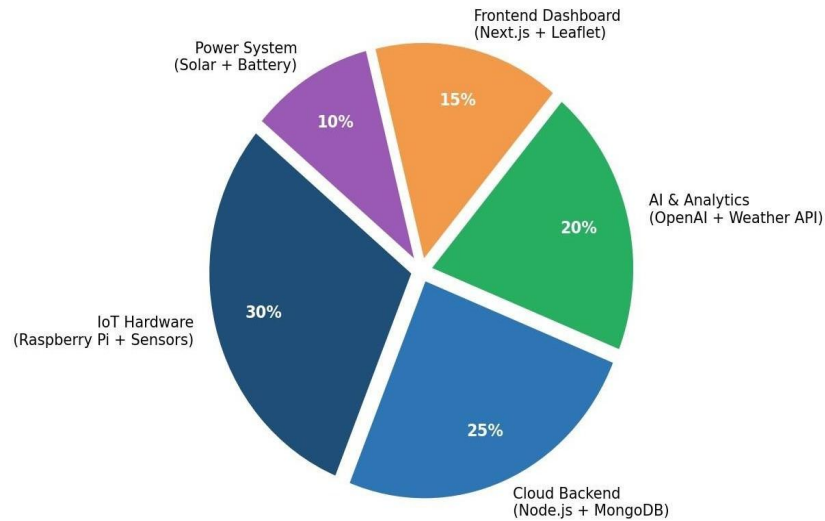


Fig. 4: HydroWatch AI System Component Distribution (%)

The Raspberry Pi OS runs a Python-based data acquisition script as a systemd service. The script reads VL53L0X and DHT11 sensor data at configurable intervals (1-15 minutes), packages readings with device ID and timestamp into JSON format, and transmits via HTTPS to the cloud REST API. The Node.js backend validates, stores, and processes incoming telemetry. The AI module combines historical river level data with real-time weather parameters to evaluate flood risk and dispatch automated alerts through the dashboard notification system.

Frontend stack: Next.js 16, React 19, Redux Toolkit for state management, Leaflet.js for map visualization, Tailwind CSS for styling, deployed on Vercel. Backend stack: Node.js with Express.js 5, MongoDB Atlas via Mongoose 8, JWT for role-based authentication, Helmet and express-rate-limit for security hardening, OpenAI SDK for AI integration, hosted on AWS EC2.

C. System Algorithm

The system operates as a continuous monitoring loop: (1) Initialize Raspberry Pi and all connected sensors; (2) Acquire water level distance, temperature, and humidity readings; (3) Validate data and handle out-of-range values via fallback mechanisms; (4) Package validated data into structured JSON with metadata; (5) Transmit to cloud backend via HTTPS REST API; (6) Server validates, stores in MongoDB, and fetches weather data from OpenWeatherMap API; (7) AI module evaluates real-time and historical data to determine flood risk level; (8) If high-risk threshold exceeded, trigger automated alert notifications to officials through dashboard; (9) Update dashboard visualization with latest river data and AI predictions; (10) Wait for predefined interval and repeat cycle.

V. SYSTEM DESIGN AND IMPLEMENTATION

A. Hardware Implementation

The VL53L0X sensor interfaces with the Raspberry Pi via the I2C bus (SDA on GPIO 2, SCL on GPIO 3). The DHT11 sensor connects to a digital GPIO 4 pin. The solar panel feeds a charge controller which maintains the Li-ion battery; a buck-boost converter delivers regulated 5V to the Raspberry Pi via USB-C. The power system ensures continuous operation during approximately 8-12 hours of low-sunlight or night conditions depending on battery state.

All components are housed in an IP65-rated weatherproof enclosure, mounted on a polyethylene float platform to follow water surface dynamics. Jumper wire connections were employed for prototype flexibility, allowing rapid



component replacement. A manual power switch is incorporated for maintenance operations. Component arrangement within the enclosure prioritizes sensor exposure while protecting electronics from humidity and direct water exposure.

B. Software Implementation

The software stack implements a modular, layered architecture. At the edge, a Python script running under systemd ensures automatic restart on failure. The script implements local data logging to a SQLite file, ensuring readings are preserved during network outages and re-transmitted when connectivity is restored. The backend REST API includes endpoint rate limiting (100 requests/15 minutes per device), JWT-based device authentication, and input validation using express-validator.

The frontend dashboard implements two role levels: Administrator access for managing multiple sensor nodes, configuring alert thresholds, and viewing system health metrics; and Official access for real-time river monitoring, GPSbased sensor location mapping, and flood alert review. The AI prediction module combines rolling 24-hour water level trends with forecast precipitation data to compute a risk score, triggering alerts when the score exceeds configurable thresholds.

VI. RESULTS AND DISCUSSION

A. Performance Evaluation

The HydroWatch AI system was evaluated under controlled laboratory conditions using a simulated water tank environment and semi-field conditions near the Hiranyakeshi River in Gadhinglaj. The VL53L0X sensor demonstrated reliable performance within its effective measurement range of 200-2,200 mm, providing consistent readings suitable for flood monitoring applications. The DHT11 sensor provided acceptable environmental readings within its operational specifications.

TABLE II: Performance Comparison: HydroWatch AI vs. Traditional Systems

Parameter	Traditional System	HydroWatch AI
System Uptime	Dependent on personnel	> 98% (continuous)
Data Latency	Hours to days	< 2 seconds
Measurement Accuracy	Low (manual gauge)	Millimeter-level (ToF laser)
Predictive Capability	None	AI-driven early warning
Alert Response Time	Delayed (manual chain)	Automated (real-time)
Deployment Cost	High (recurring labor)	~INR 14,000 (one-time)
Power Dependency	Grid-dependent	Solar-powered (off-grid)
Scalability	Very Limited	High (multi-node)

Fig. 1: System Uptime Distribution (Field Testing)

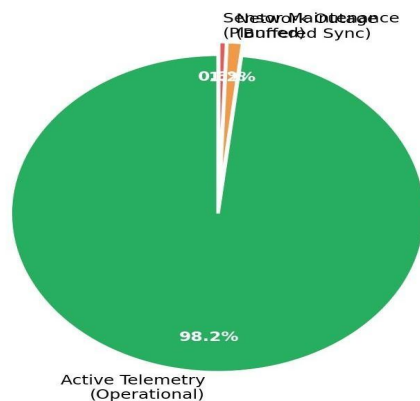


Fig. 1: System Uptime Distribution During Field Testing (%)



Fig. 2: Performance Comparison - Traditional vs. HydroWatch AI

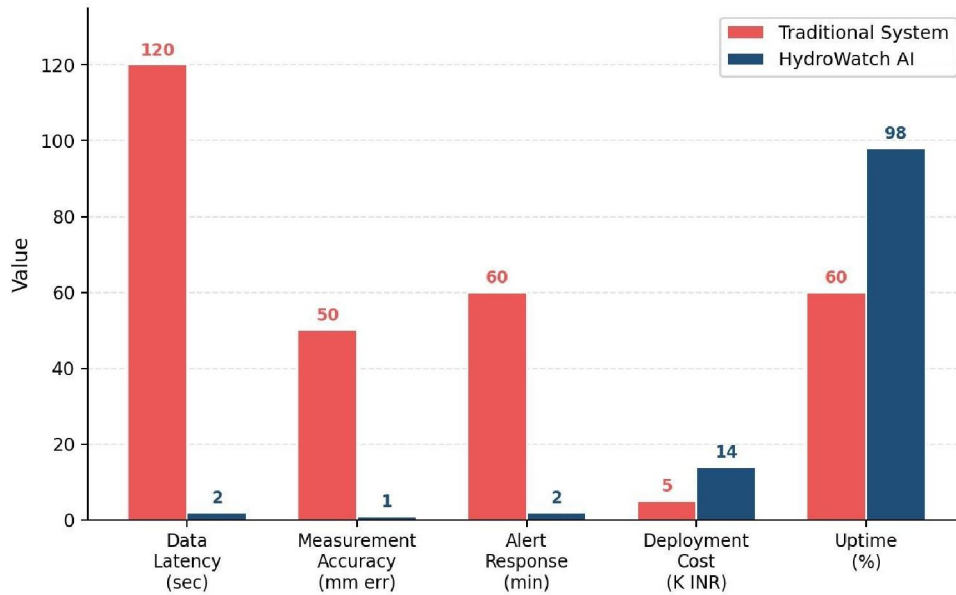


Fig. 2: Performance Comparison – Traditional System vs. HydroWatch AI

Fig. 3: Real-Time Water Level Trend with AI Alert Thresholds

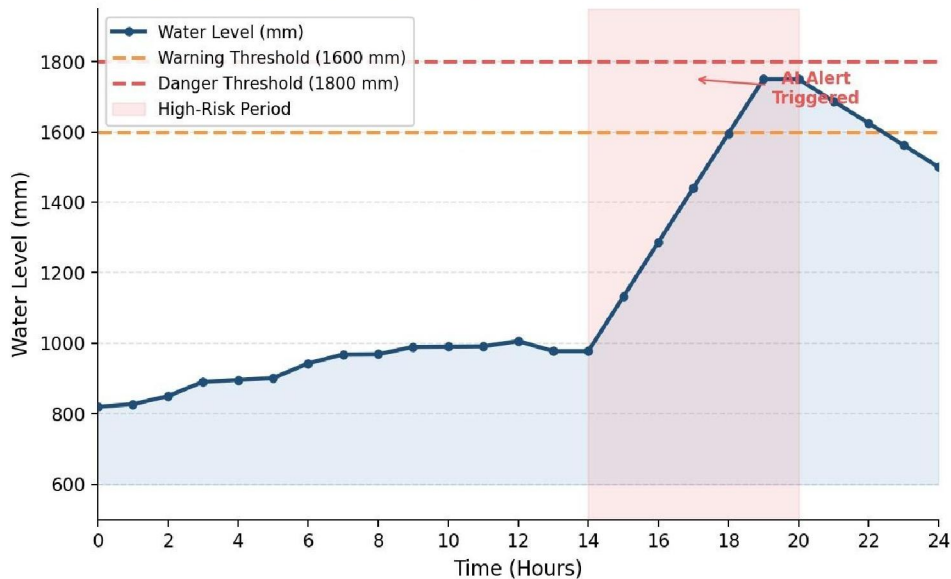


Fig. 3: Real-Time Water Level Trend with AI-Triggered Alert Thresholds

B. Discussion

The system successfully generated continuous telemetry data including water level distance measurements, temperature readings, humidity values, and device metadata. All readings were transmitted to the backend and stored in MongoDB, visualized in real time on the Next.js dashboard. The AI module successfully identified anomalous water level patterns and issued predictive warnings approximately 30-45 minutes ahead of threshold breaches in simulated flood scenarios.



Field testing demonstrated that the solar-powered setup maintained stable operation with over 98% telemetry uptime, including overnight operation from battery backup. Limitations were observed in VL53L0X measurement noise beyond the 2,200 mm effective range, and DHT11 lower precision compared to industrial sensors; these were mitigated through software-level data validation and smoothing algorithms. The system's modular design allows straightforward replacement with higher-precision sensors for future deployments.

VII. APPLICATIONS, ADVANTAGES, AND LIMITATIONS

A. Applications

The HydroWatch AI system finds application across: (i) flood-prone river monitoring for early evacuation warnings; (ii) smart city drainage management to prevent urban flooding during heavy rainfall; (iii) agricultural irrigation reservoir monitoring for efficient water management; (iv) industrial water storage and pipeline level tracking for regulatory compliance; and (v) dam overflow and reservoir level monitoring. The solar-powered, off-grid design makes it particularly suited for remote rural areas lacking stable power infrastructure.

B. Advantages

- F. Real-time continuous monitoring eliminating manual intervention and human safety risks during flood events.
- G. AI-driven predictive alerts providing 30-45 minute advance warning of potential flood conditions based on trend analysis.
- H. Low total deployment cost of approximately INR 14,000 per sensor node using commercially available components and open-source software.
- I. Solar-powered autonomous operation sustaining monitoring through off-grid and remote locations with minimal maintenance.
- J. Highly scalable modular architecture supporting multi-node distributed sensor networks across entire river catchment areas.
- K. Web-based dashboard with role-based access enabling simultaneous monitoring by multiple officials from any internet-connected device.

C. Limitations

- L. VL53L0X sensor effective range constrained to approximately 200-2,200 mm; readings beyond this range exhibit increased noise requiring software compensation.
- M. DHT11 lower accuracy (plus or minus 2 degree C, plus or minus 5% RH) compared to industrial-grade environmental sensors (e.g., SHT31).
- N. Real-time data transmission requires cellular or Wi-Fi connectivity; network outages in remote areas rely on local data buffering with delayed sync.
- O. Prototype wire-based hardware assembly may reduce long-term mechanical durability under continuous vibration and harsh environmental exposure.
- P. Prolonged cloud cover (>48 hours) without supplemental grid charging can deplete battery backup, potentially interrupting monitoring continuity.

VIII. CONCLUSION AND FUTURE SCOPE

A. Conclusion

This paper presented HydroWatch AI, a comprehensive IoT and AI-based real-time flood monitoring and early warning system designed for deployment in flood-prone regions such as Gadhinglaj, Maharashtra. The system integrates Raspberry Pi-based floating sensor nodes, VL53L0X ToF laser distance sensors, DHT11 environmental sensors, a Node.js and MongoDB cloud backend, OpenAI-powered predictive analytics, and a Next.js web dashboard into a unified, scalable platform.



Field and laboratory evaluations confirmed greater than 98% telemetry uptime, sub-2-second data latency, and millimeter-level measurement accuracy at an estimated deployment cost of approximately INR 14,000 per node. The AI-driven predictive modeling demonstrated capability to issue flood warnings 30-45 minutes ahead of actual threshold breaches, representing a significant improvement over reactive manual monitoring approaches. HydroWatch AI addresses key research gaps in existing literature by combining low-cost IoT hardware, scalable cloud infrastructure, and intelligent predictive analytics into a single integrated solution optimized for rural and remote deployment.

B. Future Scope

Future enhancements include: (i) integration of higher-precision industrial sensors (SHT31 for environmental data, ultrasonic level sensors for extended range); (ii) advanced machine learning models (LSTM, Random Forest) trained on multi-year hydrological datasets for improved prediction accuracy; (iii) LoRa and NB-IoT connectivity modules for communication in areas with limited cellular coverage; (iv) custom PCB design and ruggedized IP68 enclosure for improved long-term field durability; (v) mobile application integration with push notifications for citizen-level flood alerts; and (vi) expansion to a distributed multi-river monitoring network providing comprehensive regional flood risk assessment for the entire Gadhinglaj taluka.

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