BODHIVRUKSHA JOURNAL OF DIVERSE DISCIPLINE
E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

AIoT-Based Drainage Blockage Early Warning System

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Abstract— Urban drainage channels are often inspected only after water-logging has begun, and most low-cost IoT monitors raise a single alert when a water-level threshold is crossed. This paper reviews twenty studies on IoT blockage detection, level-based blockage analysis, ultrasonic sensing, machine learning for sewer systems and AIoT architectures, derives six research gaps from them, and proposes a conceptual AIoT-Based Drainage Blockage Early Warning System (AIoT stands for Artificial Intelligence of Things). The design places two HC-SR04 ultrasonic sensors upstream and downstream of a possible blockage together with a flow input, processes the readings on an ESP32 microcontroller every second, classifies the channel as Normal, Developing Blockage or Severe Blockage, and signals the result locally through green, yellow and red LEDs and a buzzer and remotely through a cloud dashboard. A transparent laboratory channel with a servo-controlled blockage is planned for repeatable testing. The circuit design and a Wokwi simulation are complete, and the estimated hardware cost is about ₹2,300. The contribution is a literature-grounded design and research agenda; the physical prototype and the machine learning classifier have not yet been built or validated.

Keywords— AIoT, drainage blockage detection, early warning system, ESP32, ultrasonic sensor, water-level monitoring, Random Forest, edge intelligence, smart cities.

I. INTRODUCTION

The urban drainage canals take away rain water and waste from the streets and the buildings.When a channel is blocked by solid waste, silt or debris, water builds up behind the obstruction and can overflow, causing water-logging, property damage, traffic disruption and public-health risks. Blockages are commonly found through periodic manual inspection or after residents complain, so the response comes late and the inspection effort is high.

The Internet of Things (IoT) makes continuous remote monitoring of drains affordable. Low-cost ultrasonic sensors, microcontrollers with Wi-Fi and cloud dashboards have been used to measure water level and send an alert when a limit is exceeded [1]–[3]. The Artificial Intelligence of Things (AIoT) goes one step further by adding learning and decision-making to the sensing nodes, so that the system

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can interpret the data instead of only reporting it [16], [17]. Moving part of the intelligence to the edge, close to the sensor, also reduces dependence on the network [18], [19].

A blockage changes the hydraulics of a channel in a measurable way. Water level rises upstream of the obstruction, drops or stays low downstream of it, and the flow reduces [4], [5]. A system that compares two measurement points and the flow, instead of watching one level against a fixed limit, can therefore notice a developing blockage earlier and can also tell how severe it is. This is the idea behind the system presented in this paper.

The principal contributions of this work are summarised as follows:

- A review of twenty studies on blockage detection, ultrasonic sensing, machine learning for sewer systems and AIoT, comparing their methods and findings.
- Six research gaps derived from that review, and a single main gap that no reviewed study closes.
- A conceptual, low-cost (about ₹2,300) AIoT early warning design that compares upstream and downstream levels with flow, classifies three blockage states on an ESP32 and alerts locally and remotely.
- A completed circuit design and Wokwi simulation, an implementation roadmap, a qualitative comparison with related work and an evaluation plan for the physical prototype.

The structure of the remaining paper is as follows. Section II offers literature review and discussion of previous works. Section III defines the problem, the aims and research questions. Section IV describes the architecture of the system, the test bench and cost. Section V discusses the methodology used for computation, classification and data collection. Section VI presents the ongoing progress of the project and simulation, comparative analysis and evaluation plan. Section VII presents the significance of sustainability. Section VIII describes limitations and practical issues. Section IX concludes the article and provides ideas for further development.

II. Related Work

In total, twenty research papers were examined and organized into five distinct themes, including blockage detection using IoT, blockage monitoring through equipment level monitoring, ultrasonic sensors for blockage identification and separation, machine learning for sewage systems, and the deployment of an AIoT architecture. The evolution of the field has advanced from the processes of manual inspection through threshold-based IoT notifications and level monitoring to AI-enhanced remote monitoring (Figure 1).Table I summarises the reviewed studies.

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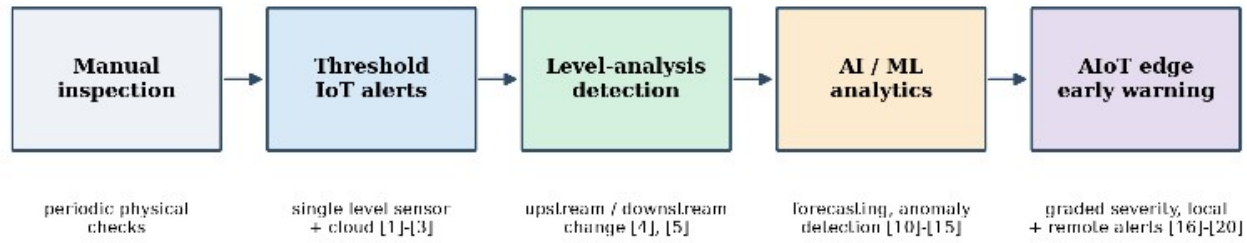


Fig. 1. Evolution of drainage monitoring, from manual inspection to AIoT early warning, with the reviewed studies that represent each step.

A. IoT-Based Blockage Detection

Navia et al. detect blockages in stormwater drains with an HC-SR04 ultrasonic sensor and a DHT22 sensor, send the data over LoRaWAN to a cloud platform and raise an alert when a blockage is possible [1]. Patil et al. use an ultrasonic sensor with an ESP8266 and Blynk, flag a blockage when the level passes a preset threshold, alert a control room and add a motorised cleaning unit [2]. Salehin et al. build an overload detection and alert system with an Arduino UNO, an Ethernet shield and a web server whose data can be viewed remotely by IP address [3]. All three rely on the level at a single point, and none reports graded severity.

B. Hydraulic Basis and Level-Based Analysis

Romanova et al. show with low-cost acoustic instrumentation that a blockage in a partially full pipe produces a measurable head loss that can be estimated and located [4]. Wang et al. identify and position sewer blockages from liquid-level analysis in pilot and full-scale tests, using the range and rate of level change upstream and downstream together with a threshold matrix [5]. They stress that the variability of the field imposes constraints on the final thresholds, which leads to the initiation of an algorithm of data preprocessing.

C. Ultrasonic Sensing, Filtering and Calibration

Pereira and colleagues tested HC-SR04 against reference scales in flowing water channels and observed that the measuring errors increased with increasing turbulence, although they remained lower than 0.020 m. In addition, Andayani et al. performed calibration of HC-SR04 sensors at a range between 14 cm and 250 cm, obtaining an error not exceeding 4.3%[9]. For noisy data, Bae and Ji combine a range cut-off, a modified Z-score and EWMA smoothing [6], and Al Tahtawi designs a Kalman filter for the HC-SR04, noting that a smaller covariance filters better but responds more slowly [7]. These studies support low-cost ultrasonic level sensing but are not tied to blockage classification.

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D. Machine Learning for Sewer Monitoring

Rosin et al. combine evolutionary artificial neural networks with statistical process control to detect blockages near combined sewer overflows with few false alarms [10]. Zhang et al. compare Elman, NARX, LSTM and GRU networks for flow and level forecasting, find LSTM and GRU strongest, and show that multi-task learning across several sensors generally beats single-task models [11]–[13]. Zhang et al. also apply unsupervised learning with dimensionality reduction to sewer data [14], and Russo et al. use a 1D-CNN autoencoder to flag anomalies from reconstruction error [15]. These methods are typically applied to city-scale sewer networks with rich data, not to a low-cost embedded early-warning node.

E. AIoT Architecture and Edge Intelligence

Zhang and Tao [16] and Siam et al. [17] survey AIoT and describe its sensing, computing and networking components. Zhou et al. [18] and Afachao and Abu-Mahfouz [19] argue that intelligence should move to the network edge where IoT data is produced. Singh et al. present the closest AIoT example in the sewer domain, a deep-learning forecasting demonstration across cloud and edge that predicts overflow-basin filling to enable early action [20].

Four patterns recur. Practical blockage-detection systems mostly use one sensor and a fixed level limit [1]–[3]. The studies that analyse upstream and downstream behaviour depend on thresholds and report field variability [5]. Machine learning is applied mainly to forecasting and anomaly detection at network scale [10]–[15], and the edge-AI literature is general rather than drainage-specific [16]–[19]. Finally, sensor-filtering work [6], [7] is rarely combined with blockage classification.

TABLE I. Comparative Summary of Reviewed Literature

Ref.	Study and method	Key finding
[1]	Navia et al. (2024): HC-SR04 + DHT22, LoRaWAN, cloud	Alert on possible blockage; single-point sensing.
[2]	Patil et al. (2025): ultrasonic, ESP8266, Blynk, motorised cleaner	Blockage flagged at a preset threshold; control room alerted.
[3]	Salehin et al. (year not confirmed): ultrasonic, Arduino UNO, web server	Detects overloaded drainage; remote view; no severity levels.
[4]	Romanova et al. (2012): acoustic sensing in laboratory pipes	Locates a blockage and estimates its head loss.
[5]	Wang et al. (2023): level sensors, threshold matrix	Upstream/downstream level range and rate identify a blockage; field variability noted.
[6]	Bae & Ji (2019): range cut-off, Z-score, EWMA	Removes out-of-range echoes and random dispersion.

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Ref.	Study and method	Key finding
[7]	Al Tahtawi (2018): Kalman filter, HC-SR04	Reduces noise; smaller covariance is better but slower.
[8]	Pereira et al. (2022): HC-SR04 vs reference rulers	Errors under 0.020 m; care needed beyond 0.4 m.
[9]	Andayani et al. (2016): HC-SR04 calibration	Works over 14–250 cm; maximum relative error 4.3%.
[10]	Rosin et al. (2022): evolutionary ANN + SPC	Detects blockages near overflows quickly, few false alarms.
[11]	Zhang et al. (2018): Elman, NARX, LSTM	LSTM best of the three for flow forecasts.
[12]	Zhang et al. (2018): LSTM and GRU, 5-min data	Strongest for longer multi-step forecasts.
[13]	Zhang et al. (2018): multi-task GRU/LSTM (DeepCSO)	Multi-task learning generally beats single-task.
[14]	Zhang et al. (2018): unsupervised learning	Label-free learning on sewer monitoring data.
[15]	Russo et al. (2019): 1D-CNN autoencoder	Flags anomalies in multivariate sewer series.
[16]	Zhang & Tao (2021): AIoT survey	Perceiving, learning, reasoning, behaving.
[17]	Siam et al. (2024): AIoT survey	Reviews core AIoT components and domain systems.
[18]	Zhou et al. (2019): edge deep-learning survey	AI should move to the edge.
[19]	Afachao & Abu-Mahfouz (2022): edge IoT review	Reviews intelligent IoT devices at the edge.
[20]	Singh et al. (2026): cloud and edge forecasting	Forecasts overflow-basin filling for early action.

III. Problem Statement

The system addresses the following problem statement: “Drainage Blockage Early Warning System – an AIoT-based system for early detection of urban drainage blockages by monitoring upstream and downstream water levels and flow patterns in real time.” Drainage blockages cause water-logging, flooding, property damage and public-health problems, yet most monitoring still relies on physical

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inspection or on a single level sensor that reacts only once water is already high. A warning is needed before the blockage leads to critical water build-up or overflow. Concretely, this decomposes into five objectives:

- To monitor the upstream and downstream water levels of a drainage channel using two ultrasonic sensors.
- To measure and simulate the water-flow condition using a flow input (a potentiometer in the simulation and a flow sensor in the hardware prototype).
- To analyse the sensor data with an AI-based decision and classification approach that identifies Normal, Developing Blockage and Severe Blockage conditions.
- The goal is to provide advanced warnings in real time via colored LED Lights and alarms while saving data in cloud for remote access.
- Conduct a thorough study of the recent literature on responses to problems of IoT and AIoT.

A. Research Gaps

In examining twenty relevant studies, one can observe six important gaps that warrant this project.

G1. Single-point, threshold-based detection. The use of the traditional system for monitoring one indicator leads to delayed action and inability to differentiate blockage from high flow [1, 2, 3].

G2. No graded severity. Most systems detect blockages as well as overloads but do not differentiate between developing and serious problems [1, 3].

G3. Limited intelligence at the node. Many studies focus on performance prediction and anomaly detection [10-15] and vice versa. It is difficult to find viable designs with AI capabilities in inexpensive microcontrollers.

G4. Handling noise generated by the sensor takes different path. Filtering and calibration of ultrasonic sensors are studied on their own [6]–[9] and rarely built into a blockage detection pipeline.

G5. Dependent on connection. As per the published findings, IoT devices send notifications via the Internet web server or control station. [1]–[3]; it is not mentioned in those articles if local alarms can be used in case of network breakdown.

G6. Limited controlled validation. Research shows variability with field trials, and prototypes have never been tested in controlled conditions with repeatable blockages.

Main gap: no reviewed study combines upstream–downstream level analysis, flow information, graded severity classification, edge processing with local alarms and a repeatable test bench in one low-cost system. This is the gap the proposed system targets.

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IV. System Architecture

A. Design Principles and Layers

The system eliminates the issues posed by four design concepts. It is comparative: it reads two points and the flow instead of one level (G1). It is graded: it reports Normal, Developing Blockage and Severe Blockage (G2). It is edge-first and dependable: the ESP32 classifies the state and sounds the local alarm even if the network is down (G3, G5). It is testable: a servo-controlled blockage on a transparent channel makes experiments repeatable (G6). Sensor validation and filtering are integrated into the pipeline (G4).

Fig. 2 shows the layers of the system. The sensing layer has two HC-SR04 ultrasonic sensors and a flow input. The edge layer is an ESP32 that acquires, validates and classifies the data. The IoT layer sends records over Wi-Fi to a cloud service, and the user interface presents a dashboard and notifications. ESP32 generates local alerts. Solar-powered battery and water quality and camera sensors are included in the block diagram for future implementation, but they are not part of the first version.

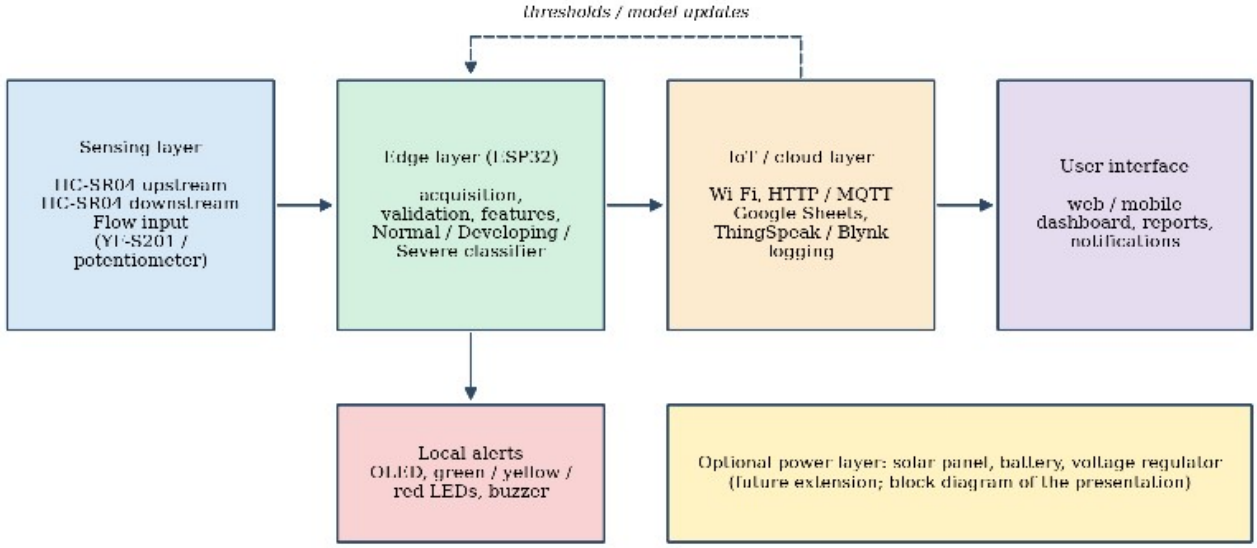


Fig. 2. Proposed stratified structure of the AIoT drainage blockage advanced notice program.

B. Hardware and Test Bench

The test implement (Fig. 3) is a clear drainage tube supplied from a pool of water using a tiny underwater pump operated by means of a relay system. The water flows through the ultrasonic detector situated before the waterflow detection device and through the mechanism for restricting waterflow (which is a barrier inserted or adjusted by the SG90 servo), after that the water reaches the ultrasonic detector located after the obstacle and flows away via the exit and to a collection bucket. Changing the

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position of the servo allows for creating an obstacle with the desired severity level.Table II lists the ESP32 connections used in the circuit design and the simulation.

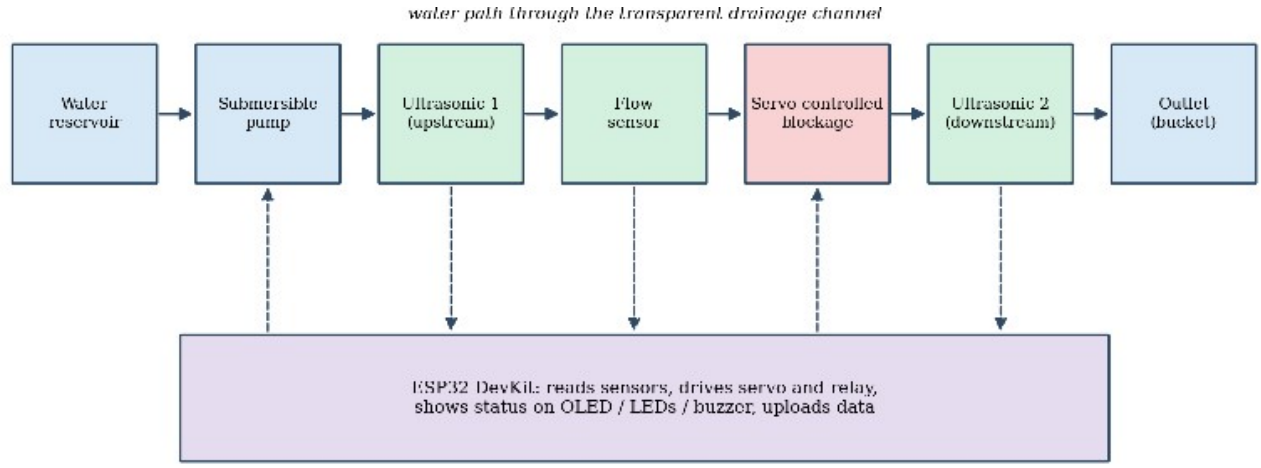


Fig. 3. The test platform of the laboratory will test water flow through the channel and the connection of the ESP32 board to the flow path.

TABLE II. ESP32 Connections and Component Roles

Component	ESP32 pin	Role / note
HC-SR04 #1 (upstream level)	GPIO 12 (TRIG), 13 (ECHO)	5 V supply; distance to water surface
HC-SR04 #2 (downstream level)	GPIO 14 (TRIG), 27 (ECHO)	5 V supply; distance to water surface
Flow input	GPIO 34	Potentiometer in simulation; YF-S201 in hardware
Green LED	GPIO 33	Normal; 220 Ω resistor
Yellow LED	GPIO 32	Developing blockage; 220 Ω resistor
Red LED	GPIO 26	Severe blockage; 220 Ω resistor
Buzzer	GPIO 25	Audible alert
OLED (SSD1306, I2C), servo (SG90), relay + pump	To be assigned	Hardware stage only; not in the simulation

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While constructing the hardware, we must reduce the 5 volts echo output from the HC-SR04 to match the ESP32's 3.3 volts logic level, using either a voltage divider or a level shifter. The YF-S201 pulse output has to undergo similar treatment. In the picture seen in Fig. 4, we can see that the completed circuit is displayed. Two ultrasonic sensors that operate on 5 volts, with their own trigger and echo pins, are connected to the circuit. Also, a potentiometer as a flow sensor is fitted at the analogue input GPIO 34. Each individual LED is protected by a 220 Ω resistor and the grounding point is the same as shown in the diagram. Finally, a buzzer is connected to GPIO

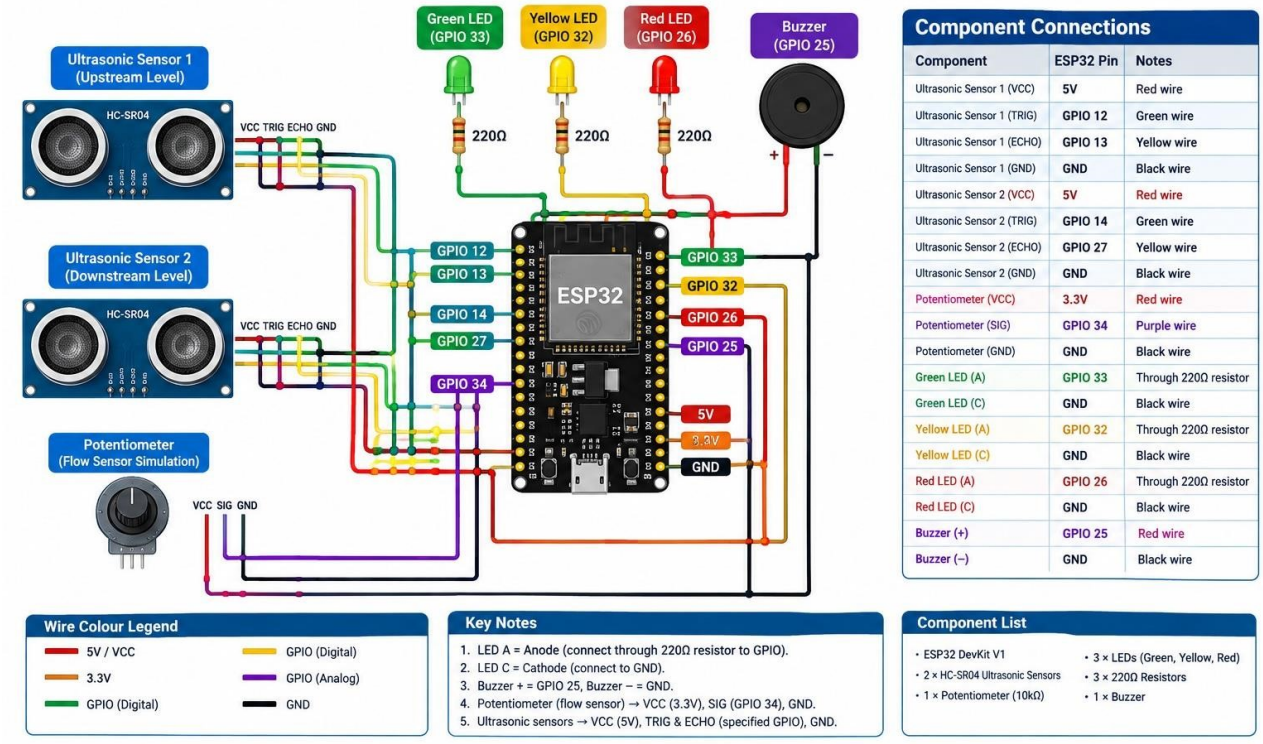


Fig. 4. Circuit diagram of the system: two HC-SR04 sensors, flow input (potentiometer), three LEDs, buzzer and ESP32, with the pin-wise connection table.

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C. Working Principle

The system works in six stages. (1) Water Supply: a submersible pump moves water from the reservoir into the transparent channel. (2) Sensing: the upstream ultrasonic sensor, the flow sensor and the downstream ultrasonic sensor measure the two water levels and the flow rate. (3) Controlled Obstruction: The servo device will create or modify an obstruction in such a way that users can create obstructions of known intensity. (4) Edge Analysis: Data from the ESP32 will be recorded, verified, and processed on-site. (5) Recognition and Alarm: Data from the classifier will classify the channel as Normal, Incipient Obstruction, or Major Obstruction and controlling the OLED, LEDs, and the buzzer. (6) Supervision and Action: All the data will be sent through the Wi-Fi via ThingSpeak or Blynk applications, which will display readings, flow, a real-time graph, and the action taken.

D. Estimated Cost

Table III shows the items and their estimated prices in Indian rupees. The total of the items amounts to ₹2,234; however, the total amount is rounded to about ₹2,300 during the presentation. Prices may differ in various places.

TABLE III. Components and Estimated Cost (INR)

Component	Qty	Unit price	Total
ESP32 DevKit V1	1	350	350
HC-SR04 ultrasonic sensor	2	150	300
YF-S201 water flow sensor	1	250	250
SG90 9 g servo motor	1	180	180
0.96-inch OLED SSD1306 I2C display	1	250	250
LEDs (green, yellow, red)	3	10	30
220 Ω resistors	6	2	12
Breadboard	1	120	120
Jumper wires (set)	1	150	150
5 V mini submersible water pump	1	200	200
5 V 1-channel relay module	1	100	100
Power supply for pump (5 V, 2 A+)	1	250	250
Active buzzer	1	30	30
Additional resistors	6	2	12
Total (itemised)			**2,234**

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V. METHODOLOGY

A. Sensing and Preprocessing

Every unit of HC-SR04 calculates the delay t for ultrasonic waves. The distance from the sensor to water surface is established based on the speed of sound and the known height of the sensor above the bottom level of the channel, as described by the formula:

$$d = t \times 0.0343 / 2 \quad (1)$$

$$h = H - d \quad (2)$$

In the simulation the channel height is set to H = 120 cm, and readings that fall outside the range $0 \le h \le H$ are rejected, in the manner of the range cut-off in [6]. The sensors are read once per second (a loop interval of 1000 ms). If the raw data prove noisy on the test bench, a moving average, EWMA [6] or Kalman filter [7] can be added. The comparison feature is the level difference between the two points:

$$\Delta h = h_{up} - h_{down} \quad (3)$$

together with the flow reading Q and the short-term rate of change of h_{up}, Δh and Q. When a blockage forms between the sensors, h_{up} and Δh tend to rise while Q falls [4], [5].

B. Classification and Alerts

The classifier maps the features to one of three states (Fig. 5). A rule-based baseline compares Δh, h_{up} and Q with thresholds calibrated on the test bench. The AI model proposed for the project is a Random Forest classifier trained on labelled test-bench runs in which the servo is held at open, partly closed and mostly closed positions. A Random Forest suits this problem because it handles a small number of numeric features, needs little tuning and can be exported to run on a microcontroller. Table IV gives the state-to-alert mapping.

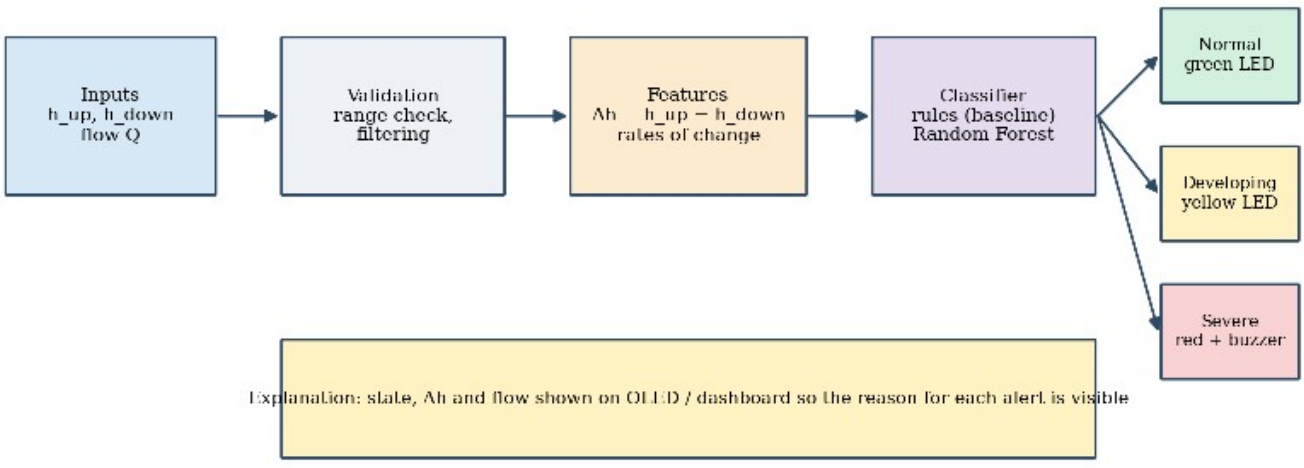


Fig. 5. Decision pipeline: inputs, validation, features, classification and alert states.

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Fig. 6 shows how the Random Forest is intended to work. The input features are the upstream level, the downstream level, their difference, the flow reading and the short-term rates of change; temperature is an optional extra. After cleaning the data (dealing with missing values, smoothing out noise, and scaling values), a labelled dataset was prepared from the servo runs. Different samples of data were used for training various decision trees, and finally, the majority vote of each tree determined the predicted action. The combination of decision trees allows for success against noise and overfitting, which is particularly beneficial in case of limited data. The required accuracy for classifying is above 90%, which has not been reached so far.

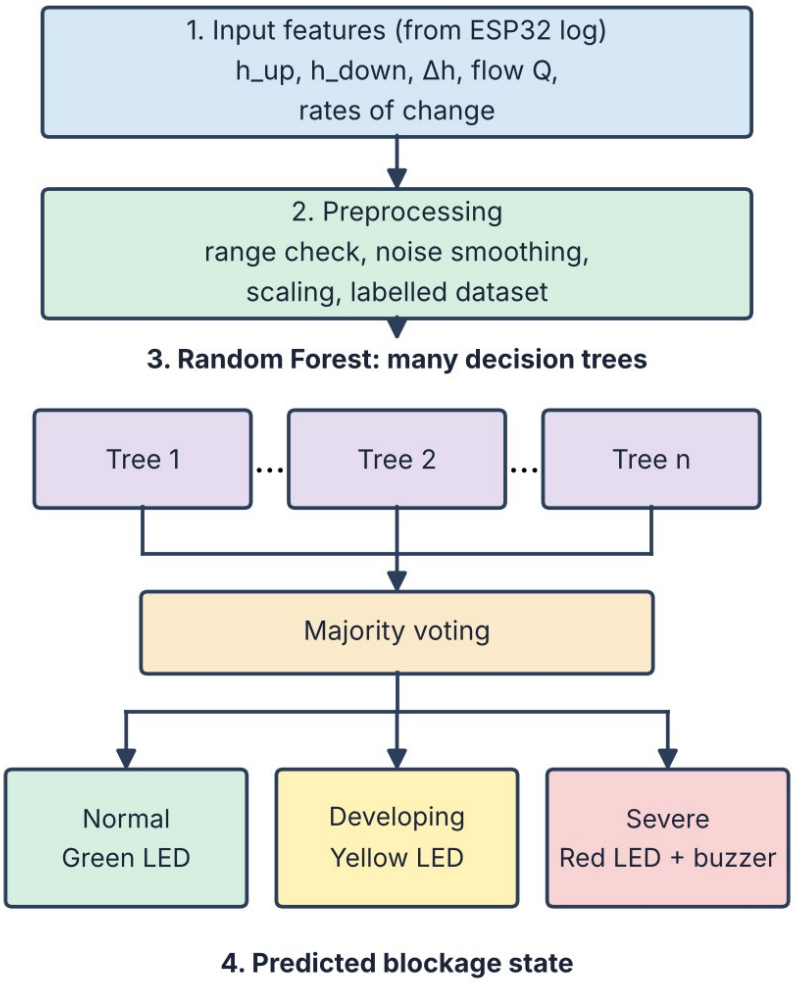


Fig. 6. Random Forest procedure involves the input data, preprocessing, voting of various trees, and predicted blockage status.

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TABLE IV. Classification States and Alerts

State	Indicator	Buzzer	Typical pattern (thresholds to be calibrated)
Normal	Green LED	Off	Levels similar at both points; flow steady
Developing blockage	Yellow LED	Short alert (configurable)	Upstream level rising relative to downstream; flow falling
Severe blockage	Red LED	On	Large level difference; flow strongly reduced

C. Data Logging and Reliability

ESP32 establishes Wi-Fi connection so that every data is sent to the cloud. Simulation sketch transfers data to Google Sheet through the internet. The hardware design supports the use of ThingSpeak or Blynk dashboard showing how to use MQTT as a third option. The firmware flowchart is presented in Figure 7 showing the reliability aspects. Outliers are removed and the last established value saved with the reading being qualified. No network connection is also vital in classification and local alerts. If there is no Wi-Fi access, the record is stored for later upload to manage connectivity (G5).

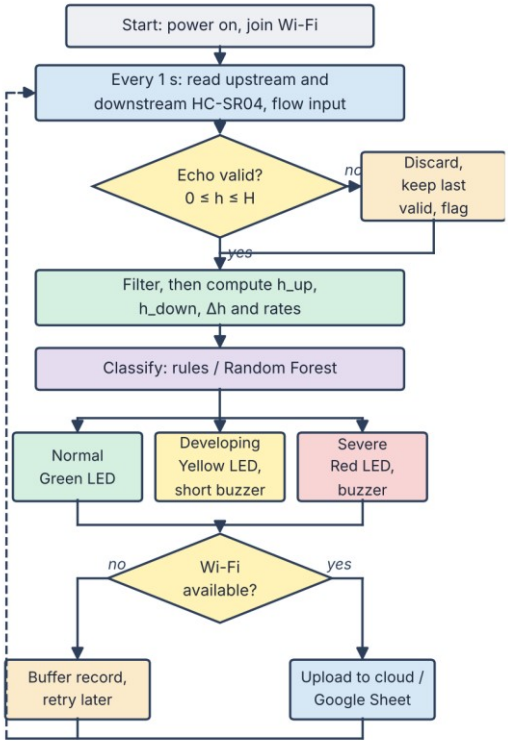


Fig. 7. The flowchart for firmware shows validation and classification as the key first steps, in addition to local alerts before uploading and buffering.

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VI. Project Status and Discussion

A. Implementation Roadmap

Fig. 8 outlines the phases involved in developing and testing the system. Phase 1 is the work described in this paper which consists of the literature review, gap analysis, problem statement, block and circuit diagrams, the Wokwi simulation of ESP32 with two ultrasonic sensors, a potentiometer flow data input, LEDs and a buzzer, and the cost calculation. Phase 2 would carry out the assembly and calibration of the test bench and the ultrasonic sensors in comparison to a reference ruler.would record labelled data at different servo blockage positions and flow rates and train the classifier. Phase 4 would run the model on the ESP32, connect the dashboard and add the alert logic. Phase 5 would evaluate the system with the measures in Table VI.



Fig. 8. Implementation roadmap. Phase one is complete and the upcoming phases are already outlined.

The simulation was constructed on the Wokwi online simulator (Fig. 9), which consists of the ESP32, two sensors of type HC-SR04, a potentiometer as the flow input, three LEDs with resistors, and a buzzer, connected to the pins listed in Table II.The sketch sets the channel height to 120 cm and the loop interval to 1000 ms, reads both sensors, rejects out-of-range echoes and posts the records to a Google Sheet over Wi-Fi. The simulation therefore confirms the wiring, the pin assignment and the logging path, but it does not test real hydraulics or a trained model.

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E-ISSN : 3139-1486
An Open Access, Peer-Reviewed, Multidisciplinary Scholarly Journal
Bi-monthly | Multilingual (English, Hindi, Marathi) | Academic Research
@ Volume 2, Issue 5 (September-October 2026) (Special Issue 1) ISSN: 3139-1486 (Online)

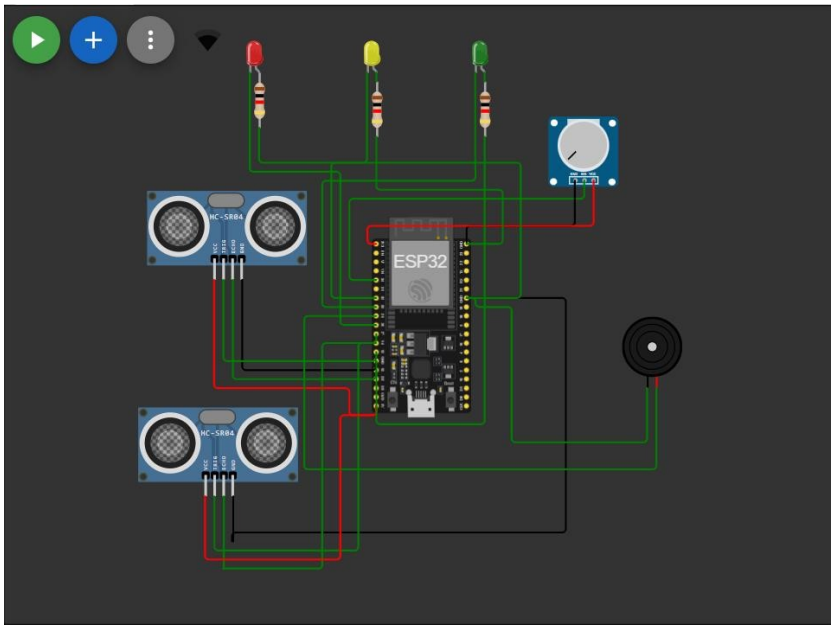


Fig. 9. Wokwi simulation of the ESP32 circuit used in Phase 1.

B. Comparative Analysis

Fig. 10 compares six representative reviewed studies with the proposed system on seven capabilities. A tick marks a capability the study covers, a tilde marks partial coverage and a blank means not reported. The marking is qualitative, is based only on the methods and findings summarised in Table I, and the proposed system is marked as intended by its design, not as demonstrated.

	Level sensing	Up/down stream	Flow sensing	Graded severity	AI / ML	Edge intelligence	Remote alert
[1] Navia 2024	✓						✓
[2] Patil 2025	✓						✓
[3] Salchin	✓						✓
[5] Wang 2023	✓	✓		~			
[10] Rosin 2022					✓		
[20] Singh 2026					✓	✓	
Proposed	✓	✓	✓	✓	✓	✓	✓

Fig. 10. Qualitative capability coverage of representative studies and the proposed system.

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The IoT blockage detectors cover level sensing and remote alerts [1]–[3], the level-analysis study adds the upstream–downstream comparison [5], and the AI studies cover learning and edge deployment but not a low-cost blockage node [10], [20]. The distinguishing feature of the proposal is therefore the combination, not any single component. Table V relates each research gap to the part of the system intended to address it.

TABLE V. Research Gaps and Proposed Response

Gap	Proposed response
G1 Single-point detection	Two-point level comparison plus flow input
G2 No graded severity	Three-state classification with matching LED and buzzer alerts
G3 Limited intelligence at the node	Random Forest classifier on the ESP32 (rule-based baseline first)
G4 Noise handled separately	Range check and filtering built into the pipeline
G5 Dependence on connectivity	Local alarm first; buffered upload when Wi-Fi returns
G6 Limited controlled validation	Servo-controlled test bench and evaluation plan (Table VI)

C. Evaluation Plan

Because the system has not been built, Table VI sets out the questions and measures that a future study needs. The rule-based baseline and the Random Forest should be compared with each other and with a single-sensor threshold detector like those in [1], [2]. Results should be reported for different flow rates and blockage positions rather than as one average.

TABLE VI. Proposed Evaluation Plan

Question	Measure
Does it classify correctly?	Confusion matrix, per-class precision and recall on held-out runs
Is the warning early?	Time from blockage onset to the Developing alert, versus a single-sensor threshold
Are false alarms low?	False alarms per hour at normal flow, including pump-speed changes
Are level readings accurate?	Error against a reference ruler, with and without filtering [8], [9]
Is it fast enough?	Delay from event to LED / buzzer and to dashboard update
Does it survive network loss?	Local alerts and buffered logging with Wi-Fi disabled

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Question	Measure
Is it stable and affordable?	Long continuous run, power use and total cost versus Table III

VII. Societal Relevance and Sustainability

A blockage found early is cheaper and safer to clear than one found after flooding. The proposed system is expected to contribute to five United Nations Sustainable Development Goals. SDG 6 (Clean Water and Sanitation) and SDG 11 (Sustainable Cities and Communities): earlier detection reduces water-logging and keeps drains working in cities. SDG 9 (Industry, Innovation and Infrastructure): the node is built from low-cost IoT parts and can be copied at many locations. SDG 12 (Responsible Consumption and Production): this SDG means fewer wasted resources and reduced manual inspection effort. SDG 13 (Climate Action): green alerts are provided to support flood resilience during heavy rains. These contributions are expected from the design and not measured.

VIII. Limitations and Practical Challenges

This paper has four major limitations. First, this is a design; meaning only the circuit and the Wokwi simulation exist which means that performance is expected but not measured. Second, the Random Forest classifier is proposed but it has not been trained, and the thresholds are not yet calibrated. Third, the flow input is a potentiometer in simulation, therefore the real flow sensor behavior is unknown. Fourth, the review features only twenty works, just enough to identify gaps but not enough to claim that anyone did not work on the gaps, and the capability comparison in Fig.10 is qualitative. Finally, the reviewed systems use various sensors, regions and backgrounds so it is impossible to treat their results as objectives, only as feasibility estimates.

The potential of ultrasonic level sensing has limitations. Many conditions like turbulence and foam, floating particles, temperature and mounting of the sensor impact the echo property and the error increases with the distance and turbulence [8], [9]. The in-field version will require waterproof box, stable power supply (solar battery layer on the block diagram), humidity protection and maintenance. Lab-conducted threshold values will not be valid in real drain, which is why calibration on site followed by retraining is included into the plan.

A drainage monitoring system does not collect any information about people's privacy, therefore, privacy risk is low, but cloud account, Wi-Fi credentials and dashboard still have to be safe and the transmitted data must be encrypted. The system should work as an assistant: missing the blockage or false alarm can create problems, therefore, warning should enhance rather than substitute inspection by responsible body.

IX. Conclusion and Future Work

In this paper, twenty researches regarding blockage detection, level-based analysis (LBA), ultrasonic (US) technology, use of machine learning (ML) in sewer system and artificial intelligence with internet of things (AIoT) have been analyzed. Most of the current low-cost systems work on one level of measurement only, have a fixed threshold, do not have level of severity, perform very little intelligence at the node and are

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hardly tested in a controlled manner.The proposed AIoT drainage blockage early warning system, which compares upstream and downstream levels with flow, classifies three blockage states on an ESP32, alerts locally and remotely and is tested on a servo-controlled channel, responds to these gaps. It is offered as a literature-grounded design, with a completed circuit and simulation, not as a validated system.

Future work will follow the roadmap in Fig. 8: build the test bench, calibrate the sensors, collect labelled data, train and compare the classifiers, and evaluate with the measures in Table VI. Later extensions include Kalman filtering [7], LSTM-based level forecasting to warn before a blockage builds [11], [12], autoencoder anomaly detection on the logged data [15], on-device inference [18], long-range communication such as LoRaWAN [1], and the optional water-quality sensor, camera and solar power layer from the project block diagram.

ACKNOWLEDGMENT

The authors thank Dr. Bhagyashree Dhakulkar, Head of the Department, and Dr. Vishal G. Puranik for their guidance during the literature survey and design stages of this project.

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