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Research Article

An Efficient Smart Flood Detection and Alert System based on Automatic Water Level Recorder Approach using IoT

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Abstract:

An innovative flood detection system may track an increase in water levels. Deployed in cities or other areas of interest, the system consists of sensors. Both mains energy and solar power are viable options for the sensors. To detect impending flooding promptly, a flood warning system uses reliable and up-to-date sensing equipment such as rain gauges, water level sensors, and flow rate sensors for the smart alert system. The challenging characteristics of smart flood detection and alert systems are that some people may not be able to access the warnings, and flash floods may happen too quickly for a warning to be adequate. Hence, in the proposed method, the Automatic Water Level Recorder enabled the Internet of Things (AWLR-IoT), which integrates a low-cost cloud to overcome the challenges of the smart flood detection and alert system and increase optimization modelling and efficiency. Among the most destructive natural catastrophes that may happen on Earth is flooding. After that, a Wireless Sensor Network (WSN) is used to accomplish the flood prediction utilizing data from sensors enabled by the Internet of Things. Heavy rainfall and the following water outflow cause flooding in nations with certain climate conditions. The system monitors humidity, temperature, water level, water rise rate, and rainfall to identify when a flood is imminent. The function of the AWLR-IoT sensor is for monitoring and recording in a database with real-time sensing. This research shows that the low-cost AWLR-IoT sensor has reduced processing time compared to conventional data processing.

1. Introduction

Despite offering a novel approach to a critical environmental issue, a cloud-based smart flood monitoring and alert system that is low-cost encounters numerous obstacles. Concerns regarding the accuracy and reliability of flood detection devices are high [1]. The system aims to utilize inexpensive sensors and analyse data in the cloud; however, a major challenge is a need to guarantee accurate flood detection in many scenarios with complicated topography [2]. Other worries from the system's dependence on cloud infrastructure include data latency and connectivity challenges [3]. This becomes even more problematic in areas that are geographically remote or vulnerable to natural disasters, where internet connectivity is limited [4]. Moreover, scalability could become a problem as the system grows to include more people or regions [5]. Finding a balance between efficiency, scalability, and the system's utility and reliability is a continuous effort because sacrificing one could destroy the other [6]. Consideration of possible socio-economic consequences is additionally crucial; these include, are not limited to, how vulnerable groups can obtain access to the system and how it could replace traditional monitoring systems and ways of life [7]. Develop a comprehensive strategy to tackle these issues head-on to manage flood risks effectively [8]. Incorporating reliable cloud infrastructure, community engagement, strong sensor technologies, and regulatory considerations into this plan's execution is essential [9].

An affordable smart flood detection and alarm system that operates in the cloud uses various existing techniques to detect and notify of impending floods [10]. Installing inexpensive sensors in flood-prone places allows for continuous monitoring of

water levels, which is one popular strategy [11]. Ultrasonic, pressure, and conductivity sensors are a few technologies that these sensors can use to detect changes in water levels reliably [12]. A cloud platform accepts data collected from various sensors and processes and analyses it in real-time [13]. Using machine learning algorithms to scour sensor data for trends that might suggest a flood is about to happen [14] is common practice. To get a better look at the flood conditions happening across a larger area, the system may additionally use remote sensing techniques like radar data or satellite images [15].
Even if these strategies might work, there are still a lot of obstacles to get beyond. An enormous challenge is the reliability and accuracy of the sensor readings, especially in outlying or harsh areas without adequate infrastructure [16]. In more remote areas, it may be very labour- and resource-intensive to calibrate and maintain the sensors such that they constantly work. Integrating several data sources and ensuring compatibility and interoperability across various sensor kinds and platforms are additional technological hurdles [17]. Additional worries about data security, privacy, and connectivity come from depending on cloud infrastructure, especially in areas with bad internet service [18]. Another major obstacle must be solved to increase the system's coverage area without decreasing its operational efficiency or cost-effectiveness. Overcoming these obstacles and creating a trustworthy flood detection and alert system requires a comprehensive plan considering technical, logistical, and socio-economic aspects.

Problem statement

An early warning system and accurate, quick flood detection are heavily emphasized in the problem statement for the Low-Cost Cloud-based Smart Flood Detection and Alert System. Challenges that need fixing include the lightning-fast arrival of flash floods, the difficulty of getting alerts to everyone, and the need to enhance the system's performance in light of changing weather patterns. The suggested solution combines AWLR-IoT technology which specifies water level recorders enabled by the Internet of Things with a very inexpensive cloud architecture to overcome these problems and improve flood detection and warning capabilities.

Objectives

- Developing a reliable system for detecting floods can be accomplished using low-cost sensors and cloud computing.
- Facilitate the dissemination of flood warnings to all individuals, particularly those who reside in underserved or remote areas.
- By improving the alarm system's efficiency and responsiveness, it will be possible to provide better warning of flash floods and other flood situations that are evolving rapidly.

The remainder of the research follows Section II's literature review. A Smart Flood Detection and Alert System Hosted in the Cloud at an Affordable Price. The outcomes of the AWLR-IoT are covered in Section III. Section IV contains the results and discussion, while Section V contains the summary and recommendations.

2. Literature Survey

This review focuses on several approaches put forth by various scholars, all of which bring something special to the surface regarding ways to improve flood control and response capacities.

Smart IoT Flood Monitoring System (S-IoT-FM)

Zahir developed the S-IoT-FM, S. B. et al. [19] and uses a web server to provide real-time water level monitoring. It notifies people promptly, allowing them to take proactive actions for evacuation. Its low-cost construction and ease of maintenance improve flood prediction and response, reducing property and life loss in rural and urban locations.

Internet of Things (IoT)

The suggested approach by Chaduvula, K. et al. [20] uses IoT technology in conjunction with GSM modules and sensors to identify increasing river water levels (IoT-GSM). Using a GSM modem, an 8051 microcontroller processes data and sends out SMS warnings. Float switches, light-emitting diodes, LCDs, and other components make flood monitoring possible. The paper aims to minimize loss of life and property by providing timely warnings.

Decision Tree Algorithm (DTA)

To warn of potential danger, Vinothini, K. et al. [21] use the Internet of Things to track flood levels. Sensors track variables, including humidity, water level, and temperature. Connected devices receive data processing from the PIC microcontroller using Wi-Fi. The system uses the cloud and the DTA to categorize data. The results confirm that the flood monitoring and warning capabilities are successful, with an accuracy rate of 99.6 %.

Real-Time Flood Monitoring (R-TFM)

Using NodeMCU-based wireless sensor nodes connected with the Blynk application, Sabre et al. [22] provide a R-TFMand early warning system. Ultrasonic and rain sensors detect water levels and the intensity of rainfall, which then trigger alerts through buzzer and LED. Victims receive email data for forecasts and real-time updates using the Blynk app. The efficacy of early flood detection and warning has been validated through testing.

ES-LSTM

Hourly precipitation forecasting using an ES-LSTM and RNN-based model with ANN and DT for classification is proposed by Hayder, I. M. et al. [23].With meteorological data from Australia, ES-LSTM managed a MAPE of 3.17, an RNN of 6.42, an ANN prediction accuracy of 96.65%, and DT of 84.0%. The accuracy of flood forecasts was improved using ES-LSTM and ANN, which outperformed other models.

Internet of Things -based solution (IoT-S)

To better anticipate and control catastrophic events like floods in India's Bihar state, Khan et al. [24] present an IoT-S. A disaster-alert smartphone app notifies the proper authorities in the event of an imminent disaster. The model improves the precision and velocity of responses, which could reduce casualties and property damage caused by floods.

Out of all these options, the AWLR-IoT is the most effective one when it comes to flood management.

3. Proposed Method

A novel technique is presented in this paper: an inexpensive online smart flood monitoring and alert system. This is in response to the increasing threat of floods, particularly in places that are susceptible to unexpected inundations. The system is designed to quickly identify and notify authorities and residents about potential flood hazards by using sensors, energy from renewable sources of information, and Internet of Things, or IoT, technologies. It solves the problems of accessibility and quick reaction by combining the AWLR-IoT along with a cheap cloud infrastructure. It highlights the methodology's potential to improve flood forecast accuracy and optimize response efforts in this introduction, which covers its major components. Table 1 is analysis of related works with advantages and limitations. Figure 1 shows smart flood detection. A hierarchical architecture is included into the Smart Flooding Detection system to carefully watch, analyse, and distribute important data linked to floods. In locations prone to flooding, sensors are placed at strategic intervals to detect changes in the amount of water quickly, rainfall, and other relevant characteristics; these sensors act as the primary data collectors. These sensors provide the system with crucial insights. The microcontroller/embedded system co-operates with the flood sensors to coordinate and oversee their functions. This part prepares the data collected by the sensors to be sent to the Gateway Device, which is the system's nerve centre. This critical component collects information from various flood sensors and sends it to the cloud system for processing. The system's scalable computation and storage capabilities provided by the cloud infrastructure are vital for managing massive amounts of sensor data. At this stage, data is processed and analysed using

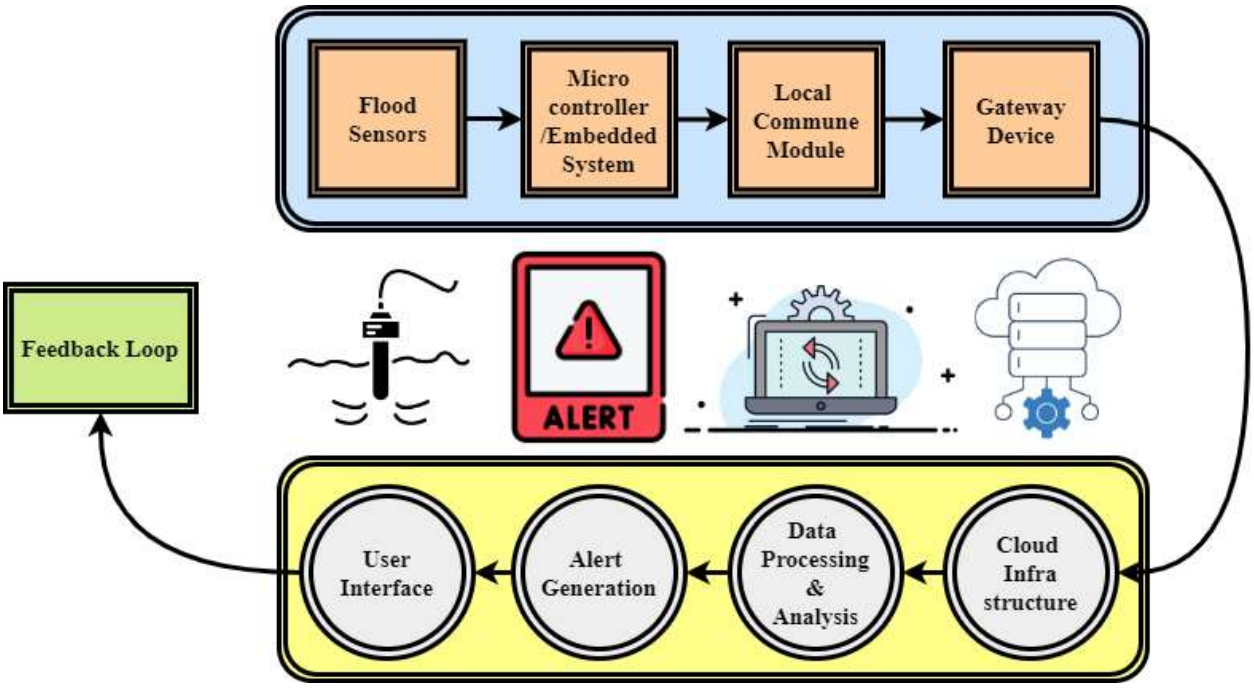

Figure 1. *Smart Flood Detection*.

Table 1. *Analysis of related works with advantages and limitations*

Method	Advantages	Limitations
S-IoT-FM	Real-time water level monitoring.Timely notifications for proactive actions	Reliance on web server connectivity May require internet access for notifications
IoT-GSM	Utilizes IoT technology for flood monitoring Sends SMS warnings through GSM modem	Limited coverage area based on GSM network availability May require additional cost for SMS alerts
DTA	Uses IoT for flood monitoring Cloud-based data processing for categorization	Complexity in implementation due to cloud integration Potential latency in data processing
R-TFM	Real-time monitoring and early warning system Utilizes wireless sensor nodes and Blynk app	Reliability dependent on stable internet connection Limited scalability in case of extensive deployment
ES-LSTM	Hourly precipitation forecasting Improved accuracy in flood forecasts	Requires historical meteorological data for training Computational complexity may hinder real-time operation
IoT-S	Disaster-alert smartphone app for authorities Precision and velocity in responses	Dependent on smartphone adoption Requires active participation from authorities for effective response

algorithms and artificial intelligence to find trends, patterns, and anomalies that might suggest a flood is about to happen in the raw data collected by the sensors. Data analysis leads to Alert Generation, where stakeholders are swiftly notified of possible flood threats through the system's warnings and alerts. These warnings are delivered across several means to guarantee prompt communication and response, including public warning systems, mobile apps, email, and short message service (SMS). The User Interface is a platform that presents data visualizations in real-time, flood notifications, and other relevant information in an easy-to-understand way. It helps users engage and make decisions. The system is not complete without the Feedback Loop, which allows for ongoing optimization and modification. The system strengthens resilience in flood-prone places by continuously improving algorithms, increasing forecasting accuracy, and adapting to changing flood dynamics. It analyses user input, performance indicators, and environmental data. A key component in bolstering resilience and protecting communities from floods, the Smart Flood Monitoring system integrates these elements to provide a complete solution for early flooding detection, quick reaction, and successful risk reduction.

$$\mathrm{T_j} + \mathrm{Y_M} = \arg\mathrm{T_j} \max - \sum_{k} q\left(i_k^l|\mathrm{T_j}\right) \log q\left(i_k^l|\mathrm{T_j}\right) + \mathrm{I_M}([\mathrm{Y_0}, \mathrm{Y_1}, \dots, \mathrm{Y_{M-1}}]) \quad (1)$$

In the equation 1, where finding the ideal choice variable T_j and supplementary variable Y_M is the goal of the maximization problem that the equation depicts. With a collection of M variables $Y_0, Y_1, \dots, Y_{M-1}$ and their respective logarithms weighted, the objective function aims to minimize the adverse sum of the conditional odds $q\left(i_k^l|T_j\right)$ and the information that share I_M. The conditional likelihood of seeing a certain event i_k^l in relation to the choice variable T_j is probably represented by the term $q\left(i_k^l|T_j\right)$.

$$\min_H m(H) = \sum_{l=1}^{L} \frac{p_l}{p} . M_l(H), \text{where } M_l(H) = \frac{1}{p_l} \sum_{j \ni Q_l} m_j H \quad (2)$$

The average loss $m(H)$ can be minimized by identifying the optimal assumption H using the minimization problem represented by the equation 2. The average loss is calculated by adding together all the class-specific losses, which are calculated as the product of the prior probability p_l and the conditional likelihood $M_l(H)$, then multiplying by the class-specific loss. In this case, the average loss within class Q_l is denoted by $M_l(H)$, which is calculated as the product of the individual losses inside $Q_l$and the inverse of the initial likelihood p_l. To get the greatest possible classification performance, the equation seeks to minimize the average loss and identify the hypothesis H that fits the data the most. This essentially strikes a balance

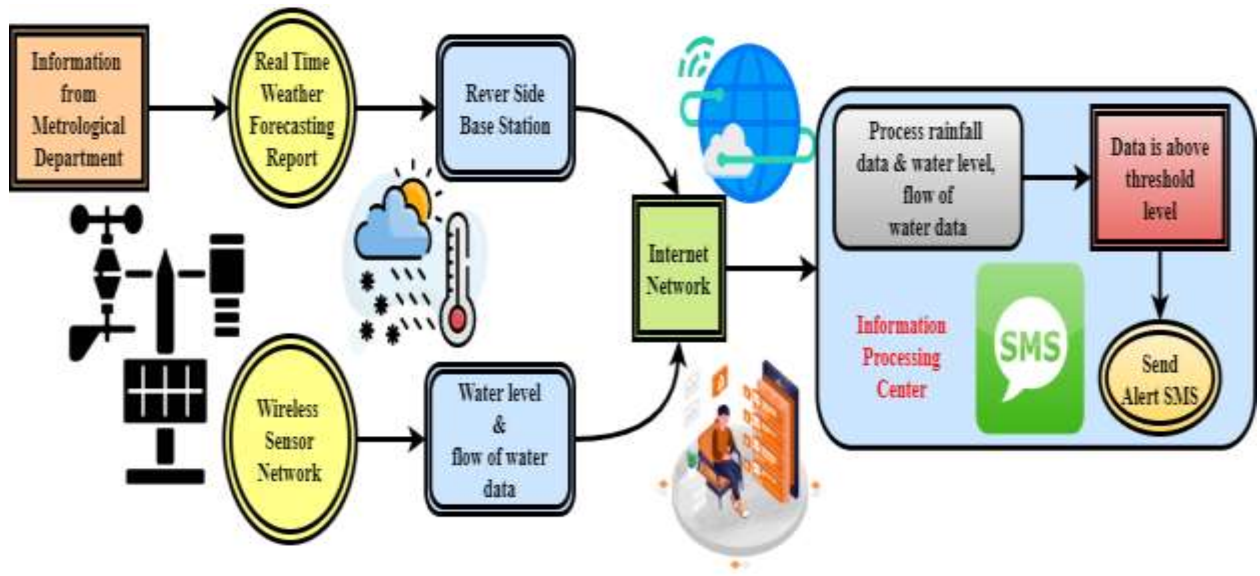

***Figure 2.** Flood Alert System using WSN*

between prior experience and conditioned probabilities.The Flooding Alert System integrates environmental data with current technologies to identify floods early and disseminate warnings. Predicting when and how much rain will fall is essential in the lead-up to floods, and this method is based on data collected by the hydro meteorological department. Smart placement of node sensors in flood-prone regions allows for the continuous, real-time monitoring of critical variables including water level, rainfall quantity, and relative humidity.

In a multi-hop sensor network, the sensor nodes act as the primary data collectors and relay the collected data to a command-and-control hub. In this case, the present flood state is determined by analysing the data that comes in streams using sophisticated processing techniques. The detected water level is used to classify this state, providing a detailed insight of the flood severity from low to extreme.

The solution makes use of SMS (short message service) notifications to guarantee direct and quick connection with impacted persons. Residents in flood-prone zones may receive immediate flood status updates through the system, which allows for rapid decision-making and proactive risk mitigation. Along with SMS warnings, the design incorporates a disaster and alarm system that makes use of Zigbee modules inside a network of sensors (WSN). This part allows for the dissemination of severe weather warnings and detailed weather reports to those who need them. The system can detect crucial thresholds and send out notifications based on them by using decision tree analysis.

Multiple tiers make up the Flood Alert System's implementation, and all work together to provide flood warnings. The hydro logical department provides the initial real-time rainfall data that is used as a basis for flood prediction. Then, the WSN gathers information on the river's flow and present water level, giving a picture of the flood's dynamics as it happens in real time (figure 2). In the third implementation stage, threshold values are determined by processing the acquired data, which indicate the likelihood of upcoming floods. Lastly, the system rapidly notifies riverfront communities and ground stations of the imminent threat by activating SMS warnings when certain criteria are surpassed. Communities can better react to flood dangers and increase overall resilience due to the Flood Alert System's multi-level strategy guarantees the prompt and targeted distribution of vital information.

$$\mathrm{E_{qs}}\left(\mathrm{F_{ql}}(\mathrm{n_1}).\mathrm{F_{ql}}(\mathrm{n_2})\right) + (\mathrm{X})_{\mathrm{aggregate\_G(1)}} = \mathrm{n_1} + \mathrm{or} \times \mathrm{n_2} + \mathrm{Efd_{q2}}\left(\mathrm{X_{global}}\right) \qquad (3)$$

The expected value of the sum of two functions, expressed as $\mathrm{E_{qs}}\left(\mathrm{F_{ql}}(\mathrm{n_1}).\mathrm{F_{ql}}(\mathrm{n_2})\right)$, is involved in the connection represented by the equation 3. An aggregate operation applied to the variable X, denoted as $\mathrm{aggregate\_G(1)}$. The anticipated value of the function $\mathrm{X_{global}}$ under a particular condition q2, denoted as $\mathrm{Efd_{q2}}(\mathrm{X_{global}})$, and the product of $\mathrm{n_1}$ and $\mathrm{n_2}$, representing the sum of these two variables, are identical to this.

$$\text{Bwfs}\left(\text{Fp}_{\text{dq1}}(\text{X}_{\text{loca.l}})\right) = \frac{1}{\text{L}} \times \left(\text{Fp}_{\text{dq1}}(\text{X}_{\text{loca.l1}})\right) \times \left(\text{Fp}_{\text{dq1}}(\text{X}_{\text{loca.l2}}) \ldots \text{Fp}_{\text{dq1}}(\text{X}_{\text{loca.ln}})\right) \quad (4)$$

The function $\text{Fp}_{\text{dq1}}(\text{X}_{\text{loca.l}})$, represented as Bwfs $\left(\text{Fp}_{\text{dq1}}(\text{X}_{\text{loca.l}})\right)$, is subject to a weighted average operation in equation 4. Where the weight of each term is inversely proportionate to the total number of terms, indicated as L. With each instance represented by $\text{X}_{\text{loca.l}}$, $\text{X}_{\text{loca.l1}}$,$\text{X}_{\text{loca.l2}}$..., $\text{X}_{\text{loca.ln}}$, representing a unique location l1, l2,..., ln, this process determines the mean value of the function. In Figure 3, the Water Detection System based on a combined structure which is AWLR-IoT enabled. The heart of the system is a collection of sensors placed in flood-prone locations to measure things like water level, flow rate, and rain gauges. The main data gathering devices are these sensors, which continually monitor important characteristics that might indicate a flood. The sensors provide their data to the AWLR-IoT framework, which processes and communicates all the acquired data. This part combines the ability to automatically record water levels with internet of things technology, making data processing and transfer easier. When it comes to collecting data from sensors and processing it further, the AWLR-IoT system is an essential go-between.

After receiving the data, the AWLR-IoT system connects to a WSN to forecast when a flood would occur. The WSN improves readiness by predicting possible flood occurrences and evaluating hazards utilizing real-time data and predictive algorithms. After processing, the data is sent to a database in the cloud where it may be stored and analysed further. Quick, real-time processing and data evaluation are made possible by the cloud architecture's scalable computing and storage capabilities. Here, a high-tech warning system is in place to assess incoming data streams, identify potential flood hazards, and promptly issue alerts and warnings. The flood alert system has an alarm mechanism that goes off when it detects a flood. Users are then notified through several channels, such mobile applications, email, or text message. This way, communities and individuals are alerted quickly enough to take the required measures to protect lives and property. Improved flood detection as well as response capabilities will lead to safer and more resilient flood-prone areas, which is the goal of the

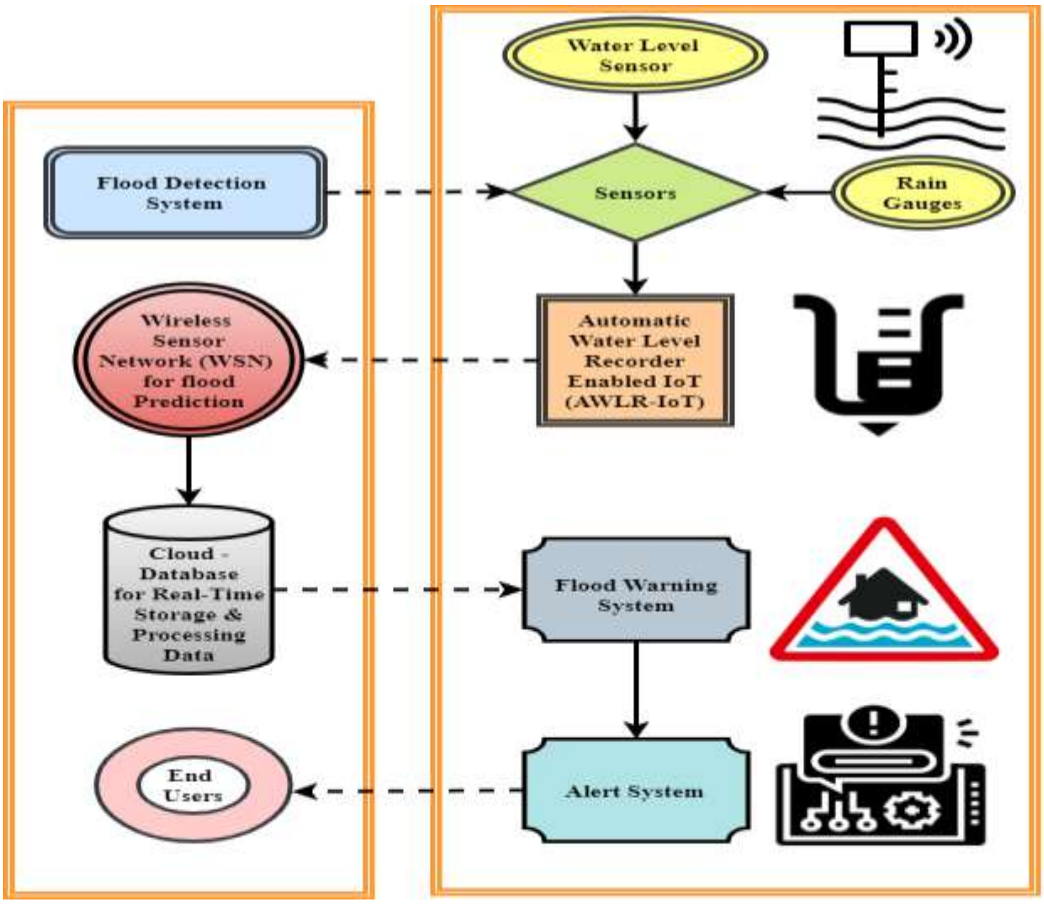

Figure 3. *Automatic Water Level Recorder enabled the Internet of Things*

Flood Detection System. The solution allows preventive steps to be taken by seamlessly combining sensor technologies, IoT capabilities, and the infrastructure of the cloud. This reduces the effect of floods and improves overall disaster preparation.

$$X_{loca.l} + X_{bhh\_g(j)} = Bwfs\left(Fp_{dq1}(X_{loca.l})\right) + Efd_{q2}(X_{global}) \quad (5)$$

In the equation 5, two variables are shown by the equation: one, $X_{loca.l}$, which represents a local variable at position l, and another, $X_{bhh\_g(j)}$, which represents a variable linked to a particular function bhh_g(j). The equation includes two terms: one that represents the weighted average operation performed on a function $Fp_{dq1}(X_{loca.l})$ over many times at location l, and the other that represents the anticipated outcome of a global variable X_{global} under a circumstance q2.

$$(X)_{bhh_{g(j)}} + X_{local_J} = Efd_{q2}(X_{global}) + X_{local_J} - \exists\, \Delta 2_L(X_{local_L}, c) \quad (6)$$

The context-dependent connection between the variables is shown by the equation 6 for the detection accuracy analysis. The combined value of a function-associated variable $bhh_{g(j)}$ and a local variable X_{local_J} is shown on the sum of two terms, $(X)_{bhh_{g(j)}}$ and X_{local_J}. By moving equation, two new terms are added: the anticipated outcome of a global variable X_{global} under a particular circumstance q2, and another instance of the local variable denoted by X_{local_J}. A term $\Delta 2_L(X_{local_L}, c)$ is included in the equation, indicating that there is a change or variation in the local variable X_{local_L}, c with relation to another variable c. For the purpose to provide communities and authorities with up-to-the-minute predictions of impending floods, the Flooding Warning System is vital. The project information is kept in a data centre in the cloud centre, which always makes it accessible. An essential part of the system is the real-time automatic alerts that warn stakeholders by email or text message as soon as certain parameters go beyond certain boundaries. In the case of floods, this allows for the prompt implementation of safety measures.

The Cloud-based Data Lake is the backbone of the Flood Warning System; it allows for the creation of a web dashboard that displays real-time flood predictions. This dashboard is designed to work in tandem with cloud notification systems, so warnings may be sent to relevant authorities through several channels, such as smartphone notifications, email, and text message. Stakeholders may get alerts and messages across many platforms, and the Cloud-based Flood Prediction Dashboard can be linked to other websites using REST API calls. This allows for the interchange of information. The system is more effective because all essential stakeholders are constantly informed about creating flood scenarios through this interoperability. Figure 4 (Web-based information-lake-based flood warning system) summarises a full-scale Flood Warning System that uses a Data Lake setup. Authorities and communities may stay informed and take proactive actions to limit the effect of flooding disasters through real-time monitoring, automatic notifications, and interaction with cloud-based services.

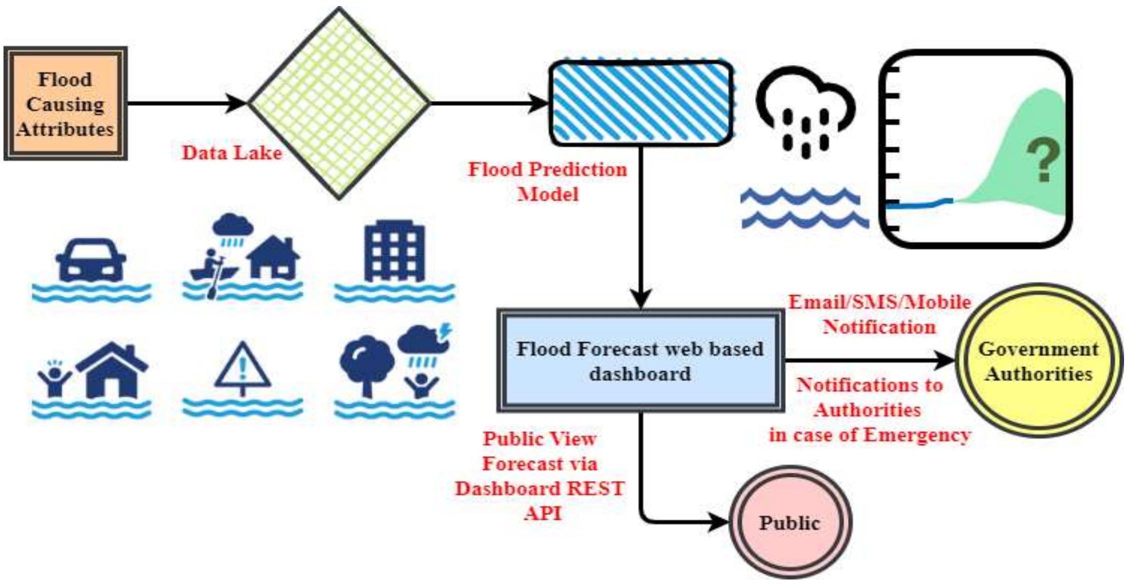

Figure 4. *Web-based data-lake-based flood warning system*

$$Q_U + L = Q_{buf} + LT + \frac{\sqrt{6}}{\nabla}\left[0.5572 + Mp\left[Mp\left[\frac{U}{U-1}\right]\right]\right] \tag{7}$$

A link between quantities connected to a system's dynamics is described by the equation 7 for the response time analysis. The amount of $U-1$ representing specific variables or parameters is shown by $Q_U + L$. Where it includes many terms, this is equal to $Q_{buf} + LT + \frac{\sqrt{6}}{\nabla}\left[0.5572 + Mp\left[Mp\left[\frac{U}{U-1}\right]\right]\right]$. The variable Q_{buf} is probably a buffer quantity, LT is a term involving L and T, and the expression inside the square root implies a complicated calculation with $\sqrt{6}$, U, and Mp, was the functions of operations.

$$Q_{buf} + T \times J_U = \frac{1}{p}\sum_{j=1}^{p} QJ \times \left[\frac{1}{p}\sum_{j=1}^{p}\left(Q_j - Q_{buf}\right)^2\right] \times \frac{Qu}{Ue} \tag{8}$$

Several variables and factors are involved in the cost-effective analysis depicted by the equation 8. The equation$Q_{buf} + T \times J_U$ implies that there is a buffer amount Q_{buf}plus the product of two parameters or variables, which are probably represented by U and J_U. On the right side, which features several terms, this is equal to $\frac{1}{p}\sum_{j=1}^{p}$ QJtimes $\left[\frac{1}{p}\sum_{j=1}^{p}\left(Q_j - Q_{buf}\right)^2\right]$. The quantity QJ is probably a combination of Q and J, the square root of the disparity between QJ and the buffer amount is $\left(Q_j - Q_{buf}\right)^2$, and the ratio of Qu to Ue is probably$\frac{Qu}{Ue}$. Showcasing a complex strategy to guarantee smooth communication between end-users and an established machine learning model, Figure 5 demonstrates the full process of handling warnings through model deployment. The use of serialization techniques like pickle to store the trained model while keeping its precision and function intact is crucial to this procedure. The user interface, which is a user-friendly interface for interaction, is a Flask-based responsive online dashboard. Clients may use this dashboard to test or validate the model by sending new information to the Flask the application programming interface (Next, the Flask API gets the model that was stored, puts it into memories, and uses it to evaluate the client's input. It then uses the model's categorization capabilities to provide predictions. Once the categorization is complete, the Flask API returns the findings to the user, who may then obtain up-to-the-minute, accurate forecasts.

Enclosing the whole system inside a Docker image guarantees that the model can be used across many platforms and environments. This includes the

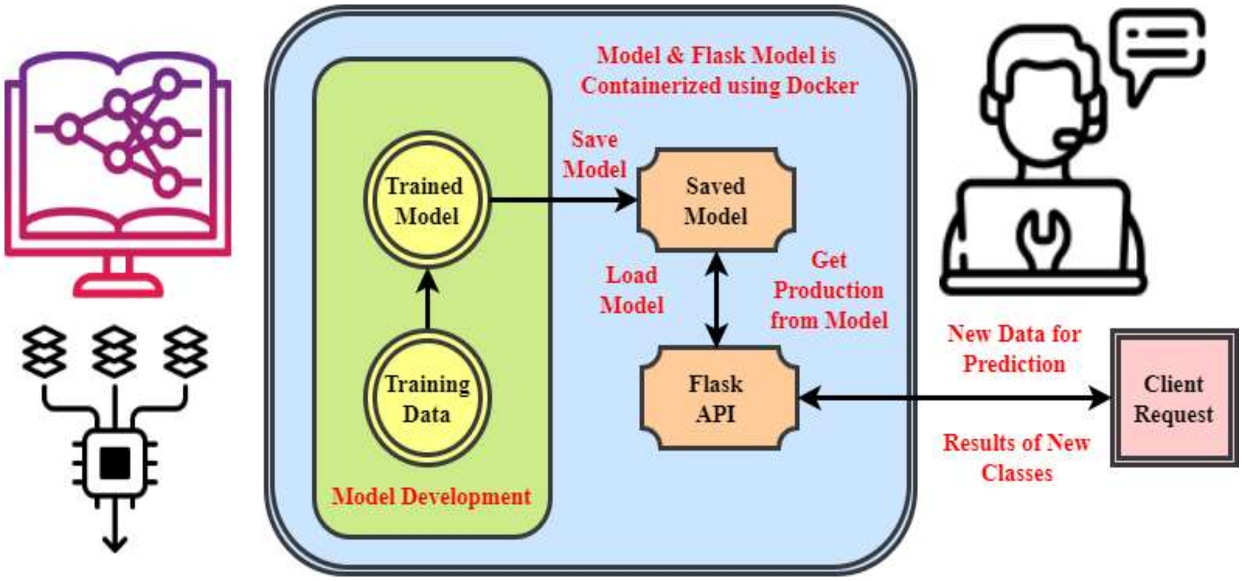

Figure 5. *Management of alerts enabled by model deployment.*

trained model, the Flask API, and any related software packages or runtime libraries. The Docker Hub registry then serves as a central repository for this image, making it easy to access and distribute. Due to the Docker image's exceptional flexibility, the model and its related components may be easily deployed and executed on any Docker support, irrespective of the underlying OS or hardware setup. Because of its mobility, compatibility problems are eliminated, and the deployment procedure is simplified, allowing it to be used in more contexts and by more people. Figure 5 shows a sturdy method for handling notifications brought about by model deployment, which involves enclosing the model itself and its deployment technology in a Docker image. Users will have no trouble interacting with the deployed artificial intelligence model owing to this simplified approach, which improves productivity, scalability, and accessibility.

$$u_q + u_d = DB^{0.22}\, sf^{-0.35} \times \left(\frac{4 \times J \times M}{j^{2/3}}\right)\left(\frac{ds + 0.0007j}{t^{1/3}}\right) \tag{9}$$

A system's reliability parameters and their relationships are shown by the equation 9. On the left side, the total of u_q and u_d, which probably indicate velocities or flow rates, is denoted by $u_q + u_d$. The right side of the equation, which includes many terms, is equal to $DB^{0.22}\, sf^{-0.35}$times $\times \left(\frac{4 \times J \times M}{j^{2/3}}\right)\left(\frac{ds+0.0007j}{t^{1/3}}\right)$. In this context, it is probable that $DB^{0.22}$ and $sf^{-0.35}$ stand for particular parameters, whereas J, M, j, ds, and t denote additional variables or coefficients.

$$T_{angle} \times T_{grade} = \tan^{-1}\left({}^{z}/_{y}\right) + (100\,\%)\, {}^{z}/_{y} \tag{10}$$

Two variables, T_{angle} and T_{grade}, are related in the equation 10 to grade the user satisfaction and usability analysis by using the of trigonometric functions and measures of ratios. The arctangent function, this is equal to $\tan^{-1}\left({}^{z}/_{y}\right) + (100\,\%)\, {}^{z}/_{(100\%)}$. In this case, z and y probably stand for user satisfaction.

Finally, a potential option to lessen the destructive effects of floods is the Low-Cost Cloud-based Intelligent Flooding Detection and Alert System. The system uses cutting-edge sensor technology and Internet of Things connection to deliver precise alerts in a timely manner, allowing for pre-emptive steps to be taken to protect lives and property. A major step forward in flood detection and reaction capabilities has been achieved with the incorporation of a cost-effective cloud infrastructure, which increases accessibility and processing efficiency. The findings show that as compared to more conventional approaches, the AWLR-IoT sensor's continuous observation and data recording greatly decrease processing time. This fresh strategy can significantly increase resistance against one of the most devastating natural catastrophes the planet has ever seen.

4. Results and Discussion

The research aims to improve disaster preparedness and response skills by assessing the system thoroughly to lower flood risks.

Dataset description: The offered dataset is a great tool for detecting flood events since it combines optical and Synthetic Aperture Radar (SAR) image time series, which are not always easy to find. Since clouds may make it difficult to see floods, SAR data is a vital option for reliable detection [25]. Unfortunately, there is often a lack of labelled datasets necessary to do machine learning on SAR data. This dataset provides a wealth of labelled optical and SAR image time series, thereby bridging the gap. To better identify flood events, researchers may use this dataset to train machine learning models; this will increase disaster response and mitigation capabilities.

In the figure 6, an affordable cloud-based smart flood detection and alarm system is tested for detection accuracy within the framework of the detection accuracy analysis. To study the fluctuations in water level, this investigation will evaluate the accuracy and reliability of the sensors placed in flood-prone locations. Factors such as sensor calibration, ambient variables, and the possibility of false positives and negatives are considered during the examination. Another facet that is examined in this research is how well the system reacts to flood alerts. When floods strike quickly, like in flash floods, this becomes even more crucial. People test the cloud architecture to see how well it processes and analyses sensor data in real time. This aims to test the system's flood detection and notification capabilities. The accuracy study examined several obstacles, including data latency, network problems, and the incorporation of numerous data sources produces 97.9%. The

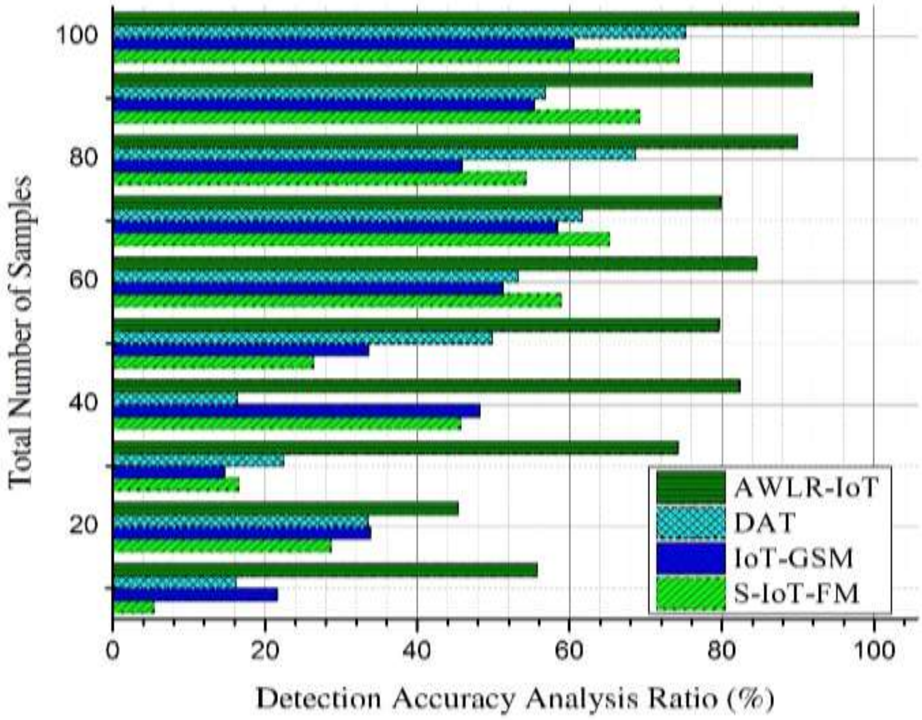

Figure 6. *Detection Accuracy Analysis*

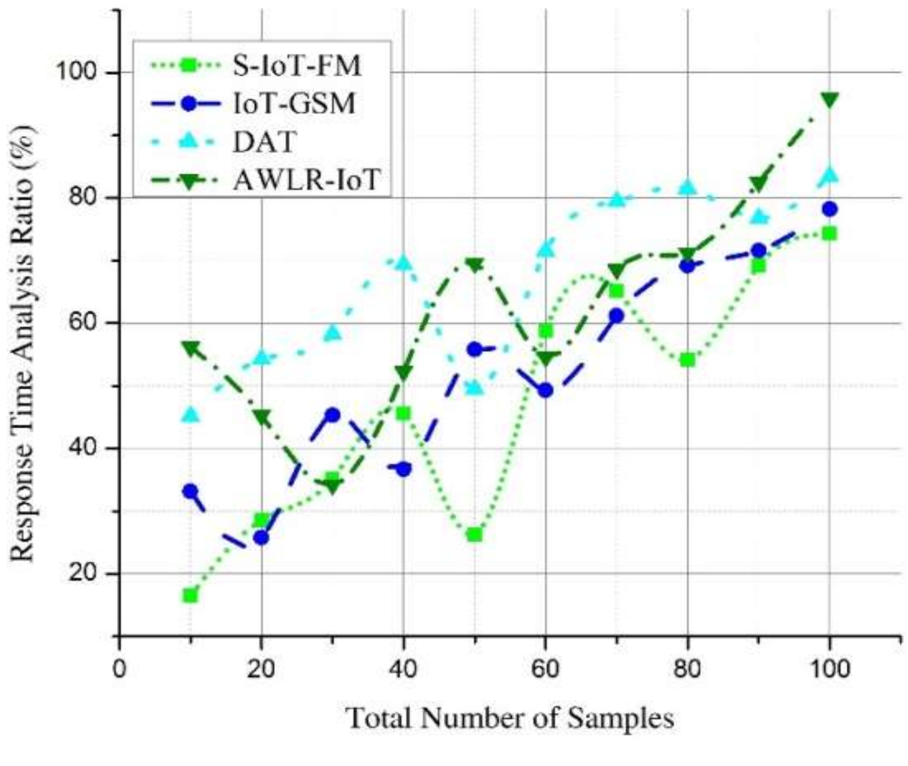

Figure 7. *Response Time Analysis*

Detection Accuracy Analysis seeks to enhance a cost-effective cloud-based smart flood detection and alert system's capacity to reduce flood risks and enhance disaster preparedness and response by identifying potential improvement areas and optimizing the system's algorithms and functions.

In the above figure 7, the primary goal of the Response Time Analysis for an Affordable Cloud-Based Smart Flood Detection and Alert System is to assess how quickly the system notifies users when floods are about to occur. This research aims to find out how long it takes to go from seeing a flood indicator such as a rise in water level or the severity of rainfall to getting an alarm and sending it to the right people. To determine the system's reaction time and its ability to alert populations to danger, the investigation will look at response times in different situations and under different environmental circumstances. To determine bottlenecks and improve system performance, people conduct an exhaustive examination into the factors that impact response times, including sensor placement, data transfer latency, and the speed of cloud processing. The paper considers possible remedies that can mitigate the effect of interruptions to system or network connectivity on reaction times produces 95.9%. The reaction Time Analysis seeks to improve a cheap, cloud-based smart flood detection and alert system's efficiency and reliability by analysing reaction times. This aims to lessen the likelihood of floods and the damage that floods can inflict to vulnerable communities.

In the above figure 8, the capability of the system to save costs while increasing the probability of flooding is examined in the Cost-effectiveness Analysis of a Low-Cost Cloud-based Smart Flood Detection and Alert System. Investment and operational costs related to the flood detection and alert system's installation and upkeep are both factored into this study. There are many moving parts for the total cost, including data transmission and processing, cloud infrastructure setup and maintenance, sensor acquisition and installation, software integration, and employee training. By comparing these costs to the system's efficacy in lowering flood damages and losses associated with floods, the analysis aims to ascertain if the system is cost-effective. Several factors are considered during the evaluation process, such as the system's capacity to accurately detect flood scenarios, the timeliness of its warnings, and the availability of preventive measures to mitigate floods. To optimize efficiency without sacrificing performance, the study may investigate other deployment tactics or technological solutions. The Cost-effectiveness Analysis aids decision-makers in allocating resources and prioritizing investments in flood management infrastructure by measuring the cost-benefit ratio and identifying potential for cost reductions or efficiency improvements produces 98.9%. While there may be societal benefits to a low-cost cloud-based smart flood detection and alert system, the

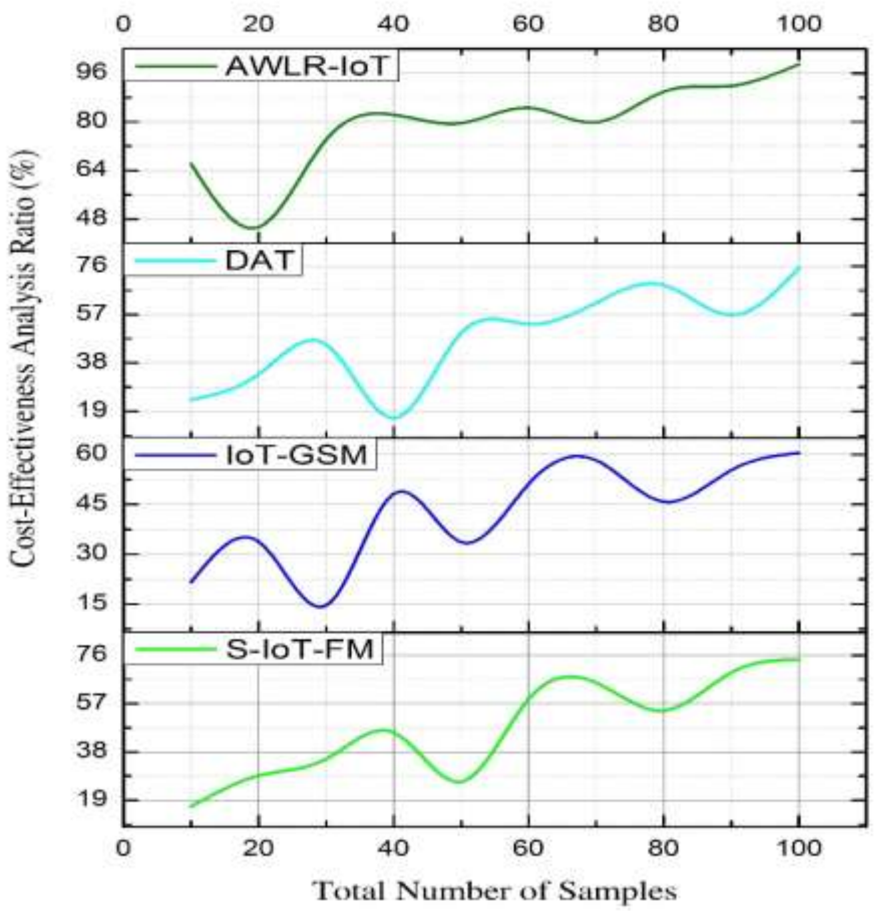

Figure 8. *Cost-effectiveness Analysis*

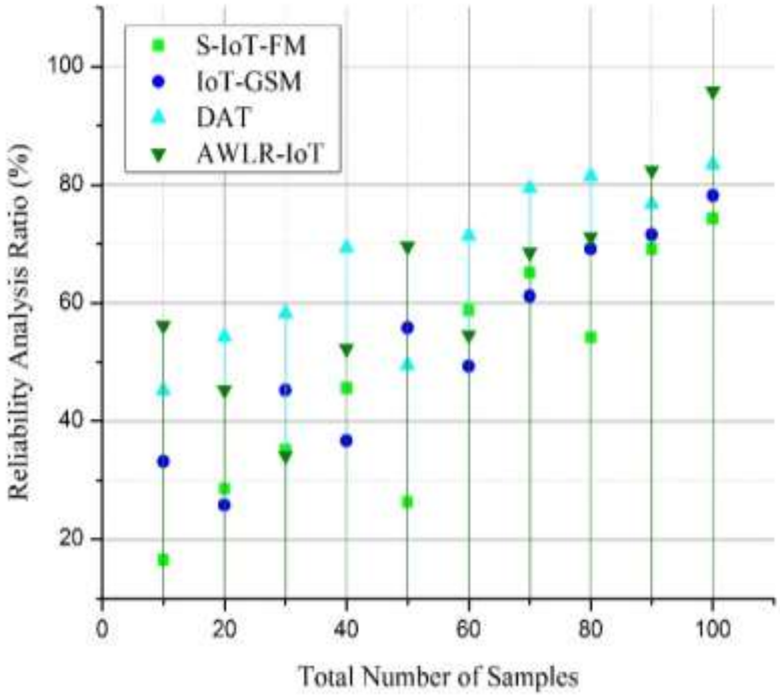

Figure 9. *Reliability Analysis*

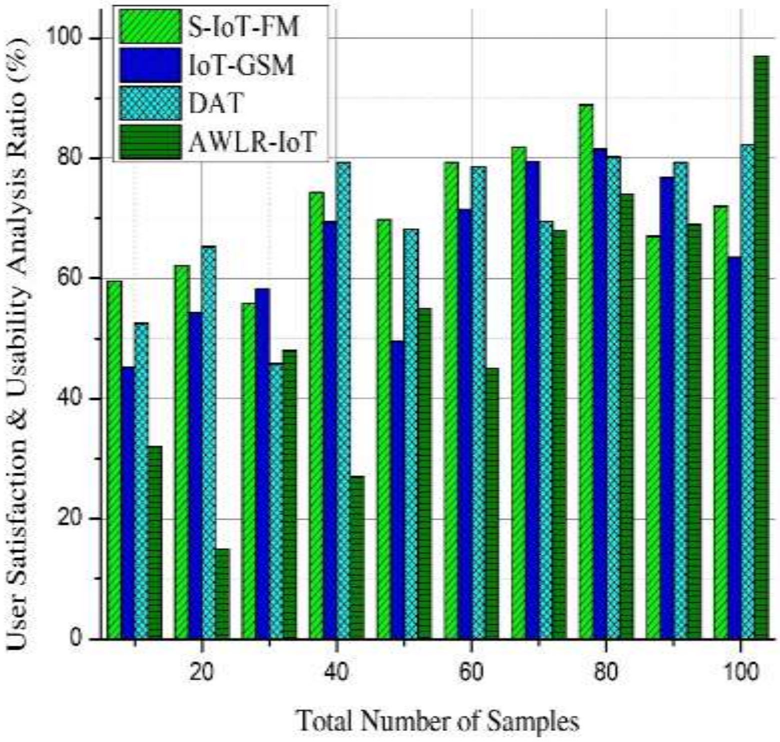

Figure 10. *User Satisfaction and Usability Analysis*

main objective is to minimize costs without sacrificing any of these benefits.

In the above figure 9, an affordable smart flood detection and alarm system that operates in the cloud is examined in the Reliability Analysis for That System to determine its consistency and dependability. The purpose of the system is to detect and notify people when floods occur. A system's dependability is assessed by considering many elements, such as the accuracy of data transmission, the availability of cloud infrastructure, the strategies for alert dissemination, and the performance of sensors. The analysis's goal is to find the system's reliability measures, like its mean time between failures and mean time to repair, by looking at past data and doing simulations. The paper considers how well the system responds in difficult conditions, like when the network is down or bad weather is on the horizon. People are investigating potential sources of false positives and false negatives as part of our endeavours to increase the system's overall reliability and lower the frequency of incorrect warnings. The paper can include stakeholder and end-user feedback to help uncover reliability concerns or user experience challenges. Doing so would be done with an eye towards practical implementation needs. One way to make a Low-Cost Cloud-based Smart Flood Detection and Alert System more reliable and trustworthy is to use the insights from the Reliability Analysis.

This analysis finds areas of weakness and potential improvement. Because the analysis finds places where things may be better, this is within the realm of possibility produces 95.8%. Ensuring a high level of reliability is crucial for improving the system's effectiveness in reducing flooding risk and avoiding potential effects on affected areas. This change will boost the stakeholders' faith in the system's capabilities.

In the figure 10, the present research aims to assess the effectiveness and ease of use of an inexpensive, cloud-based smart flood detection and alert system from the perspective of the end-users. Community people, municipal officials, and first responders are all stakeholders whose opinions must be gathered with the purpose of complete this study. Doing so allows one to gauge the degree of contentment with the system's efficiency and utility. Important factors that are included in the analysis include how quickly and clearly flood notifications are sent, how easy it is to understand and act upon the information provided, and how the system is used overall. The study additionally looks at how easy the system is to use for different types of users, such as those with physical impairments or low-tech knowledge, so flood alerts can be available to everyone. Listening to customer feedback can improve the quality of our user interface, alerting systems, and user support services. Including end-user feedback into the review process is an attempt to detect usability issues and potential solutions. Through this action, people can enhance the system's capacity to lessen flood risks and strengthen communities' resilience produces 96.5%. To ensure the effective adoption and effectiveness of a low-cost cloud-based smart flood detection and alert system in protecting lives and property from floods, it is vital to prioritize user enjoyment and usability. Viewed by stakeholders, this will foster a climate of more trust and acceptance. Emphasizing the need of prioritizing user satisfaction and usability for effective adoption, these data demonstrate the system's efficacy in decreasing flood risks and improving community resilience.

5. Conclusion

Smart Flood Detection and Alert System in the Cloud at a Low Cost Might Reduce Devastation from Floods. Rapid flood event identification and alarms are made possible by innovative technology such as Wireless Sensor Networks (WSN) and the AWLR-IoT. Widespread deployment is now feasible, even in resource-constrained rural areas, because to the system's scalability and accessibility enabled by inexpensive sensors and cloud-based infrastructure. Predicting when floods may occur, the system keeps a constant eye on weather conditions like humidity, water level, water rise rate, and rainfall. Being proactive can help us cut emergency response times and improve flood forecasts. Installing flood detection systems is often hindered by a lack of funding, especially in less developed nations. Using inexpensive sensors that are fuelled by solar, or mains electricity can make the system more affordable and sustainable. However, not everyone has equitable access to flood warnings, and flash floods can still hit rapidly. To enhance the system's accuracy, precision, and ability to adjust to evolving flood conditions, further research and development are necessary. Communities may become more resilient and better prepared for floods with the help of a cloud-hosted smart flood detection and alert system which does not break the financial institution. Since floods are still an existential threat to people's lives and livelihoods all across the globe, humanity are in dire need of modern, affordable flood detection technology. Wireless Sensor Network is studied and reported in the literature [26-30].

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
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