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Water Sustainability Enhancement with UAV and AIoT: An Integrated Technology for Water Quality and Flood Hazard Monitoring using the Internet of Drones

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Abstract: Globally, there are challenges in minimizing the effects of water pollution and global warming everywhere. We want to apply a sensor network connected to an Esp32 and Tensorflow lite integrated system to map the flood conditions for drone-based water surface waste collection. Finally, a GSM sim 800L Module is incorporated to notify the user about the monitored conditions, such as trash level and other data. An ultrasonic sensor is utilized to detect the water level. The outcome shows a high chance of tracking water levels and monitoring floods. This innovative technology allows users to receive warnings and be warned remotely. The Inception-v3 model on clean and unclean water images obtained 97% accuracy on testing USING Inception-v3, and using the proposed circuit diagram, a prototype is developed for possible deployment in such water resource region for possible operation and application is presented in the paper.

Keywords: Water Sustainability, AIoT, Ultrasonic Sensor, Sim 800L, Esp32-Cam

Introduction

Sampling and monitoring water quality are essential to protecting the ecosystem around water. There are now severe environmental and societal issues due to water pollution and global warming (López-Serrano et al., 2023). Reducing these problems requires efficient water resource management and monitoring. Water management and its use have become increasingly important as cities experience substantial urban development and population rise (Mvongo et al., 2021). Studies using remote sensing ocean color have already been conducted to assess the nutrient availability, biodiversity, and water quality along the coast. Water-quality investigations of coastal waters have been made possible in recent years by Unmanned Aerial Vehicles (UAVs) outfitted with multispectral sensors. These UAVs were initially intended for agricultural uses. However, when applied to UAV photos taken over water areas, generally utilized photogrammetric algorithms are ineffective because the sea surface constantly changes.

Drones are changing how we observe the earth system and are increasingly used for high-resolution water quality monitoring (Greenland et al., 2019). The global water crisis can be eradicated by utilizing this kind of technology, and sustainability in the water resources field can be assured, too. Pollution prevention and environmental protection are important issues for all nations worldwide. Water quality monitoring plays a crucial part in maintaining a healthy water environment in the hydrological climate by helping to identify abnormal situations promptly and providing feedback on the efficacy of the actions performed. In situ measurements are used in conventional water quality monitoring (Crispim et al., 2021).

Traditional flood and water quality monitoring techniques' manual nature and absence of real-time data frequently pose limitations. Technological developments in Artificial Intelligence of Things (AIoT) offer novel prospects for improving these surveillance systems. To create an all-encompassing water quality and flood danger monitoring system, this article investigates the integration of drone technology with ESP32, TensorFlow Lite, and many sensors. The technology seeks to improve response times and decision-making processes by giving users accurate, up-to-date data and warnings (Zarei et al., 2021).

Methods

The multi-parameter detection system included a microprocessor, turbidity, total dissolved solids (TDS), and hydrogen potential (pH) sensors. Using the rapidly exploring random trees (RRT) obstacle avoidance path planning technique and the proposed layered hybrid improved particle swarm optimization (LHIPSO), the UAV's flight route was adjusted to increase sampling efficiency (Bermejo-Martín & Rodríguez-Monroy, 2020). The LHIPSO algorithm was compared to the dynamic adjustment (DAPSO), particle swarm optimization (PSO), and other algorithms in simulation trials. The simulation results validated the suggested algorithm's efficiency, demonstrating that the LHIPSO method had better global optimization capability and stability when compared to the other algorithms.

In particular, for degraded waterways (such as rivers, lakes, and reservoirs), the suggested UAS-based hardware platform for water quality investigations (UASWQP) seems to be a viable instrument for improving environmental research operations. According to the initial findings, the suggested UASWQP efficiently provides real-time visualization of water quality components to the ThingSpeak Cloud web services (Bonetti et al., 2022). Additionally, gathering a sufficient water sample for in-depth examination at lab facilities was simple as necessary. This study aimed to investigate the predictive power of drone-based multispectral images for crucial water quality metrics in an intermittently closed and opened lake or lagoon, or ICOLL. Temperature, salinity, pH, dissolved oxygen (DO), chlorophyll (CHL), turbidity, total suspended sediments (TSS), coloured dissolved organic matter (CDOM), green algae, cryptophytes, diatoms, blue-green algae, and total algal concentrations were measured during three water quality sampling campaigns (Mamba, 2023).

After doing DistilM statistical studies to identify the bands that accounted for the most significant variation in the water quality data, linear correlations between particular band/band ratios and water quality measures were carried out (Berger et al., 2023). The authors present centimetre-scale water quality information at two distinct locations along the Maltese coastline, enhancing the current approximations obtained for the area from Sentinel-3 OLCI images at a significantly lower spatial resolution of 300 m. The Chl-a and TSS values determined for the regions under study fell between 0 and 3 mg/m3 and 10 and 20 mg/m3, respectively, and were within the predicted limits. Spectral comparisons were also performed in addition to certain statistical computations like RMSE, MAE, or bias to validate the results. To address the issues above, we provide an enhanced MPP method (dubbed IMP-MPP) that chooses models with more filtering conditions and sample pixels based on clustering outcomes.

This study used Qingshan Lake in Hangzhou City, Zhejiang Province, China, as its study location to assess the turbidity and suspended solids indicators (Abadi & Kelboro, 2021). The suggested IMP-MPP algorithm analyzes and processes 45 in situ samples and UAV images surrounding the sampling spots in conjunction with the average value technique and MPP for comparison. According to the experimental findings, the optimal inversion model for SS that the IMP-MPP algorithm produced had a determination coefficient, average relative error, and comprehensive error of 0.8255, 15.08%, and 0.1981, respectively (Kwon & Bailey, 2019).

Our suggested idea is to create a drone system driven by AIoT specifically designed to use UAV drone technology to locate flood hazards and check water quality remotely. With the help of this cutting-edge system, flood-related hazards may be remotely monitored, allowing for the early forecast of possible flood events. It also allows us to evaluate water quality in isolated areas, improving our comprehension of the surrounding environment. This system uses uncrewed aerial vehicle (UAV) technology to collect vital data flexibly and effectively. This helps improve flood control plans and environmental monitoring programs (Zhang et al., 2023).

A. Proposed Work

The system setup begins with a drone design and development to monitor floods and clean and dirty water. DIY drone technology is a step toward utilizing an AIoT-comprised system for remote monitoring and alerts to conserve water-related hazards and early alerts in flood-related situations to local people residing in a community (Nishad & Kumar, 2022).

The sensor network inside the drone allows users to monitor live flood-related issues and get notified. Computer vision using the Inception-v3 model allows for remote live monitoring of flood hazard conditions (Aguiar et al., 2022).

B. Drone design and development

Table 1. Drone design and development components

Component	Function
Frame	Provides structural support and housing for all other components.
Motors (Brushless)	Generate thrust to lift and maneuver the drone.
Propellers	Convert motor torque into thrust.
Electronic Speed Controllers (ESCs)	Regulate the speed of the motors based on control signals.
ESP32 Microcontroller	The central processing unit for controlling the drone's flight dynamics, stability, and navigation.
GPS Module	Provides geolocation data for navigation and positioning.
IMU (Inertial Measurement Unit)	Measures the drone's orientation and movement (including accelerometers and gyroscopes).
Battery (Li-Po)	Supplies power to all the drone's components.
Power Distribution Board (PDB)	Distributes power from the battery to various components.
Telemetry System	Enables remote communication to monitor flight data and drone status.
Ultrasonic Sensor	Measures water levels for flood monitoring.
TensorFlow Lite Model	Runs on the ESP32 for real-time image processing and waste detection.
GSM SIM 800L Module	Sends notifications to users about water quality and flood conditions.
Communication Module (e.g., 2.4 GHz Radio, Wi-Fi)	Facilitates communication between the drone and the ground control station.

Component	Function
Landing Gear	It provides a stable base for takeoff and landing, protecting the drone's components.

C. The following are the main parts of the suggested system:

Drone Technology: To identify waste and keep an eye on the condition of the water, drones fitted with cameras take pictures of the water's surface. To recognize and categorize waste products, the acquired photos are analyzed using a TensorFlow Lite model that has been trained beforehand. ESP32-CAM: Based on the Espressif Systems ESP32 processor, the ESP32-CAM is an inexpensive microcontroller development board with built-in camera capabilities. Owing to its powerful capabilities, small size, and versatility (Guo et al., 2020).

D. System circuit diagram:

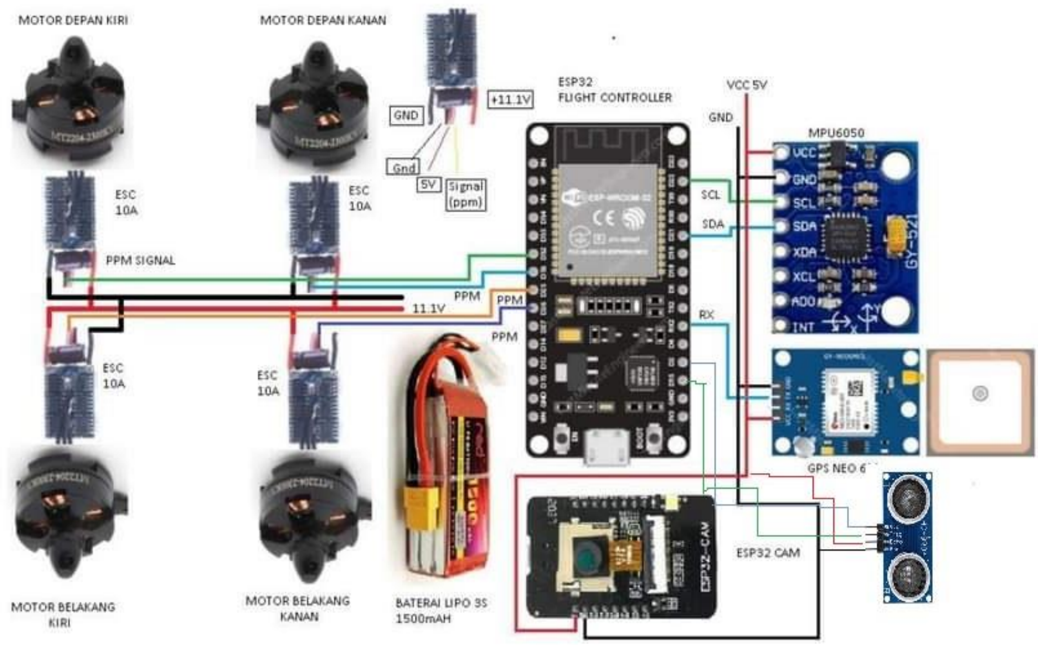

Figure 1. Water sample images

1. ESP32 Microcontroller: The ESP32 microcontroller acts as the GSM module's central processing unit and manages data gathering and communication among various sensors.
2. Ultrasonic Sensor: Ultrasonic sensors measure water levels and provide vital information for flood monitoring. Processing of the sensor data reveals variations in water levels, suggesting possible flood dangers.

3. GSM SIM 800L Module: This integrated module allows users to receive notifications. It sends information about flood conditions, water waste levels, and water quality to a distant server, which notifies consumers by SMS or other means.
4. TensorFlow Lite Model: An ESP32-based machine learning model is trained with transfer learning on the Inception-v3 algorithm and found to detect waste in water photographs with 92% accuracy.

The ultrasonic sensor can give the affected flooded area a range or level. The equation can provide the ultrasonic sensor-based distance:

$\text{Distance} = (\text{Speed of Sound} \times \text{Time})/2$ ………………………………………………Equation.1.

About Dataset:

The dataset consisted of 2 classes of images, 40 & 21 in number, in a directory and trained with a CNN model.

Training set image counts:
Clean-samples: 31
Dirty-samples: 16

Testing set image counts:
Clean-samples: 9
Dirty-samples: 5

Figure 2. Water sample images

E. Hyperparameters used:

The key hyperparameters used in the script are listed here, along with their values and a brief explanation (Garcia et al., 2019):

Table 2. Model hyperparameters

Hyperparameter	Value	Description
target_size	(150, 150)	The size to which all images will be resized.
batch_size (train)	128	The number of images to be processed together during training.
batch_size (test)	12	The number of images to be processed together during testing/validation.
class_mode	'categorical'	The type of label arrays that are returned are one-hot encoded arrays.
rescale (train/test)	1.0/255	Rescaling factor. Applied to all images.
shear_range	0.2	Shear Intensity (Shear angle in counter-clockwise direction in degrees).
zoom_range	0.2	The range for random zoom.
horizontal_flip	True	Randomly flip inputs horizontally.
weights	'Imagine'	Pre-trained weights were used to initialize the model.
include_top	False	Whether to include the fully-connected layer at the top of the network.
input_shape	(150, 150, 3)	The shape of the input image is 150x150 pixels with three color channels (RGB).
units (Dense layer 1)	128	Number of neurons in the first dense layer after the global average pooling layer.
activation (Dense layer 1)	'rel'	The activation function is used in the first dense layer.
units (Dense layer 2)	2	The number of neurons in the final dense layer should match the number of classes.
activation (Dense layer 2)	'softmax'	The activation function is used in the final dense layer for multi-class classification.
optimizer	Adam()	The optimizer is used to compile the model.
loss	'categorical_crossentropy'	The loss function is used to train the model.

Hyperparameter	Value	Description
metrics	['accuracy']	List of metrics to be evaluated by the model during training and testing.
epochs	20	Number of epochs (iterations over the entire dataset) for model training.
shuffle (test generator)	False	Whether to shuffle the data in the test generator.

These hyperparameters are essential to setting up and training the model. Modifying them can significantly affect how well the model performs and behaves throughout training.

Result and Discussion

The deployed system was tested in various settings to see how well it monitored flood hazards and water quality in real-time—the drone's capacity to acquire and transfer high-definition photographs made detecting and classifying waste possible. The Inception v33-trained TensorFlow Lite model handled these photos effectively while retaining high accuracy levels, with an approximate accuracy of 92%.

The ultrasonic sensor made reliable water level readings possible by mapping them to specific risk zone water levels. Water levels can be calculated and sent via SIM800L to dedicated users to notify them, which is essential for prompt flood monitoring and detection. Thanks to the integration of the GSM module, users could respond promptly to possible threats by receiving real-time alerts on flood conditions and water quality (L. C. C. da Silva et al., 2019).

The inception V3 deep learning model could obtain 92% accuracy on the Inception-v3 algorithm and effectively predicted both water classes.

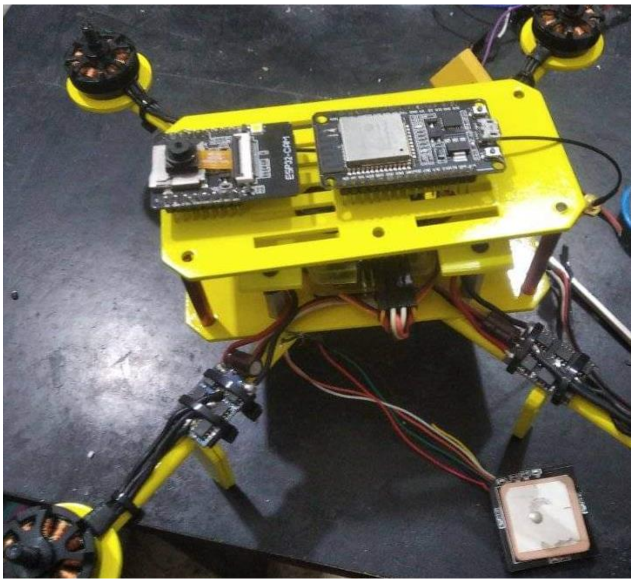

Figure 3. Proposed drone system

The drone system can be utilized, as shown in Figure .3, to capture floods, and the tensorflow lite model deployed in the esp-32 module allows users to deal with computer vision-based prediction for clean or dirty water. Also, sim 800L is utilized to get SMS notification alerts. This will enable people from remote localities to get messages through an AIoT-based system (Ahmed et al., 2021).

A. Ultrasonic sensor-based water level detection

The ultrasonic sensor yielded a good result in predicting the water level. This helps with the early monitoring of floods using SMS technology. Early warnings can be made, though high-quality drones have already been built to monitor any specific geo-locations through live video feeds. Still, this self-built drone system can utilize sensors-based technology to monitor water levels precisely. The figure below shows the ultrasonic sensor monitored values, which gives the range of water levels above a fixed threshold level (J. da Silva et al., 2020).

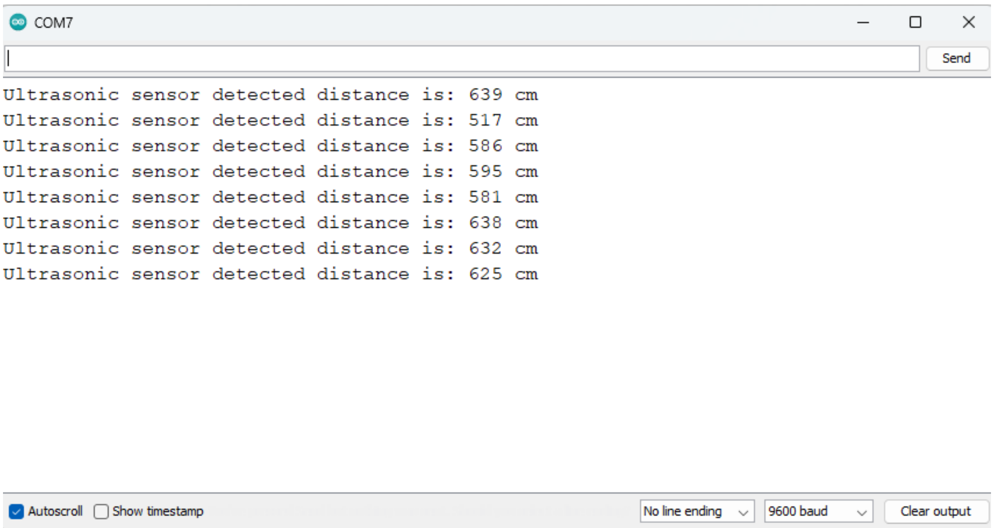

Figure 4. Ultrasonic sensor values from serial monitoring

B. Future Work

Future work will extend the system's functionalities and versatility to contribute to more proficient natural checking and administration arrangements. Improving the system's capabilities might include joining extra sensors and information sources, progressing the strength of the machine learning models, and creating more modern information analytics instruments. Versatility endeavors will guarantee that the framework can be conveyed in different geographic areas and adjusted to distinctive natural settings. Moreover, joining prescient analytics and mechanized reaction instruments makes the framework more proactive in overseeing natural risks. These headways will create a more comprehensive and versatile checking framework, eventually contributing to superior natural stewardship and more flexible communities (Faúndez et al., 2023).

Conclusion

Using AIoT technology in flood hazard and water quality monitoring over more conventional approaches has several benefits. The suggested system gives consumers precise, real-time data and notifications using drone technology, ESP32, TensorFlow Lite, and several sensors. The model's high accuracy and successful implementation highlight this approach's promise in tackling the problems of water pollution and global warming. Future work will expand the system's functionalities and scalability to contribute to more efficient environmental monitoring and management solutions.

The model was trained using the Inception-v3 Deep learning model, and an excellent accuracy of about 97% was obtained on the testing set. This model can be used to manage water quality and increase sustainability practices worldwide, creating a healthier world for all.

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