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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 in the world. In order to map the flood conditions, we want to apply a sensor network connected to a Esp32 and Tensorflow lite integrated system for drone-based water surface waste collection. Finally, a GSM sim 800L Module incorporated is used to send notifications to 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 that there is a high chance of tracking water levels and monitoring floods. By using this innovative technology, users can 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 of water quality are essential to protecting the ecosystem around water. There are now serious environmental and societal issues as a result of 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 is always changing. Drones are changing the way we observe the earth system and are being utilized more and more for high-resolution water quality monitoring (Greenland et al., 2019). The global water crisis can be eradicated by utilizing this kind of technology and for sure sustainability in water resources field can be assured too. Pollution prevention and environmental protection are important issues for all nations in the world. Water quality monitoring plays a crucial part in maintaining a healthy water environment in the hydrological environment by helping to identify abnormal situations in a timely manner and providing feedback on the efficacy of the actions performed. In situ measurements are used in the conventional approach of monitoring water quality(Crispim et al., 2021). The manual nature of traditional flood and water quality monitoring techniques, as well as their absence of real-time data, frequently pose limitations. Technological developments in the field of Artificial Intelligence of Things (AIoT) offer novel prospects for improving these surveillance systems. In order 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).

Materials and 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). In simulation trials, the LHIPSO algorithm was compared to the dynamic adjustment (DAPSO), particle swarm optimization (PSO), and other algorithms. The efficiency of the suggested algorithm was validated by the simulation results, which demonstrated 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 to improve 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, it was simple to gather a sufficient water sample for in-depth examination at lab facilities as necessary. The aim of this study was to investigate the predictive power of drone-based multispectral images for key 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), colored dissolved organic matter (CDOM), green algae, crytophyta, diatoms, bluegreen 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 greatest variation in all of 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 centimeter-scale information of water quality 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 that were determined for the areas under study fell between 0 and 3 mg/m3 and 10 and 20 mg/m3, respectively, and were within the predicted limits. To validate the results, spectral comparisons were also performed in addition to certain statistical computations like RMSE, MAE, or bias. To address the aforementioned issues, we provide an enhanced MPP method (dubbed IMP-MPP) that chooses models with more filtering conditions and samples pixels based on clustering outcomes. This study used Qingshan Lake in Hangzhou City, Zhejiang Province, China, as its study location in order to assess the turbidity and suspended solids indicators(Abadi & Kelboro, 2021). The suggested IMP-MPP algorithm, in conjunction with the average value technique and MPP for comparison, analyzes and processes 45 in situ samples as well as UAV images surrounding the sampling spots. 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 on creating a drone system driven by AIoT that is specifically designed to use UAV drone technology to remotely locate flood hazards and check water quality. 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 provides the capacity to evaluate the quality of water in isolated areas, which improves our comprehension of the surrounding environment. This system uses unmanned aerial vehicle (UAV) technology to collect vital data in a flexible and effective way. This helps improve flood control plans and environmental monitoring programs(Zhang et al., 2023).

Proposed Work

The system setup begins with drone system design and development for the purpose of monitoring flood as well as clean and dirty water figuring out. The DIY drone technology is a step to utilize a AIoT comprised system for remote monitoring and alert to conserve water related hazards and early alerting in flood related situations to local people residing in a community(Nishad & Kumar, 2022).

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

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	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 (includes 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.

Component	Function
Telemetry System	Enables remote communication for monitoring 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.
Landing Gear	Provides a stable base for takeoff and landing, protecting the drone's components.

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 versatile(Guo et al., 2020) .

System circuit diagram:

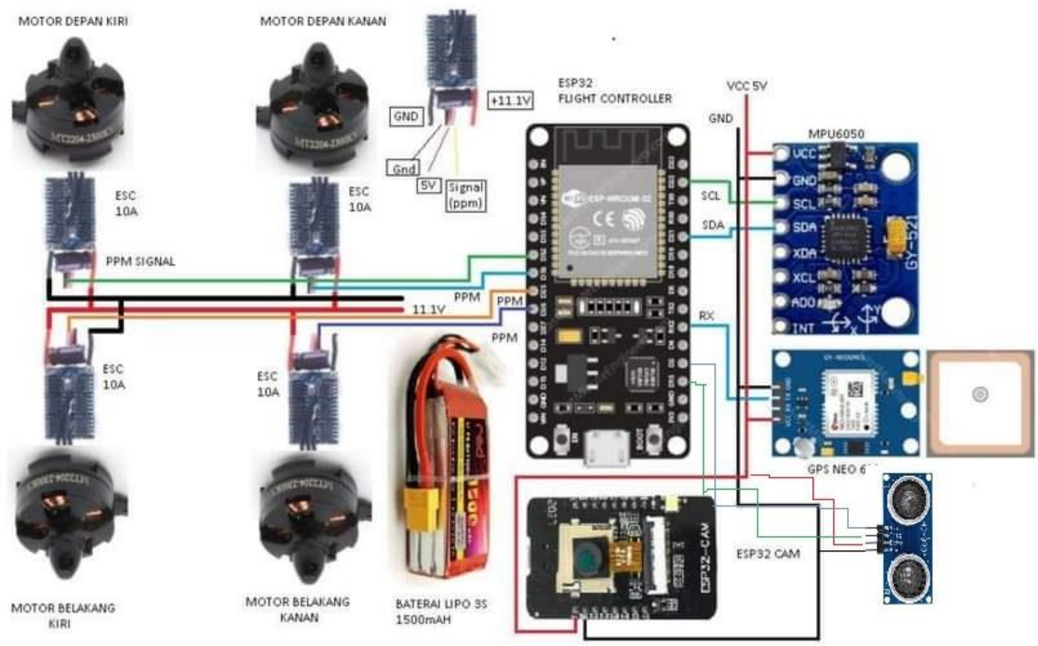

Figure 1. Water sample images

1. *ESP32 Microcontroller: Acting as the GSM module's central processing unit, the ESP32 microcontroller manages data gathering and communication amongst a variety of sensors.*

2. *Ultrasonic Sensor: To measure water levels and provide vital information for flood monitoring, ultrasonic sensors are used. Processing of the sensor data reveals variations in water levels, suggesting possible flood dangers.*

3. *GSM SIM 800L Module: This module is integrated and allows users to get notifications. It sends information to a distant server about flood conditions, water waste levels, and water quality. The server then notifies consumers by SMS or other means.*

4. *TensorFlow Lite Model: An ESP32-based machine learning model is trained with transfer learning on Inception-v3 algorithm and found to detect waste in water photographs with 92% accuracy.*

The ultrasonic sensor can give the range or the level of the affected flooded area. The ultrasonic sensor based distance can be given by the equation:

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

About Dataset :

Dataset consisted of 2 classes of images 40 & 21 in numbers 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

Dirty water sample Image

Clean Water sample image

Figure 1. Water sample images

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: 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	Range for random zoom.
horizontal_flip	True	Randomly flip inputs horizontally.
weights	'imagenet'	Pre-trained weights used for initializing 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, which is 150x150 pixels with 3 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)	'relu'	Activation function used in the first dense layer.

Hyperparameter	Value	Description
units (Dense layer 2)	2	Number of neurons in the final dense layer, which should match the number of classes.
activation (Dense layer 2)	'softmax'	Activation function used in the final dense layer for multi-class classification.
optimizer	Adam()	The optimizer used for compiling the model.
loss	'categorical_crossentropy'	Loss function used for training the model.
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 training the model.
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 have a big effect on how well the model performs and behaves throughout training.

Results and Discussions

The deployed system was put to the test in a variety of settings to see how well it performed in monitoring flood hazards and water quality in real time. The precise detection and classification of waste was made possible by the drone's capacity to acquire and transfer high-definition photographs. The Inception v33-trained TensorFlow Lite model handled these photos effectively while retaining high accuracy levels, with an approximate accuracy of 92%.

Reliable water level readings were made possible by the ultrasonic sensor by mapping it to specific risk zone water level can be calculated and sent via SIM800L to dedicated users for notifying them, which was essential for prompt flood monitoring and detection. Users were able to respond promptly to possible threats by receiving real-time alerts on flood conditions and water quality thanks to the integration of the GSM module(L. C. C. da Silva et al., 2019).

The inception V3 deep learning model could obtained 92% accuracy on Inception-v3 algorithm and was seemed to be very effective in predicting both water classes.

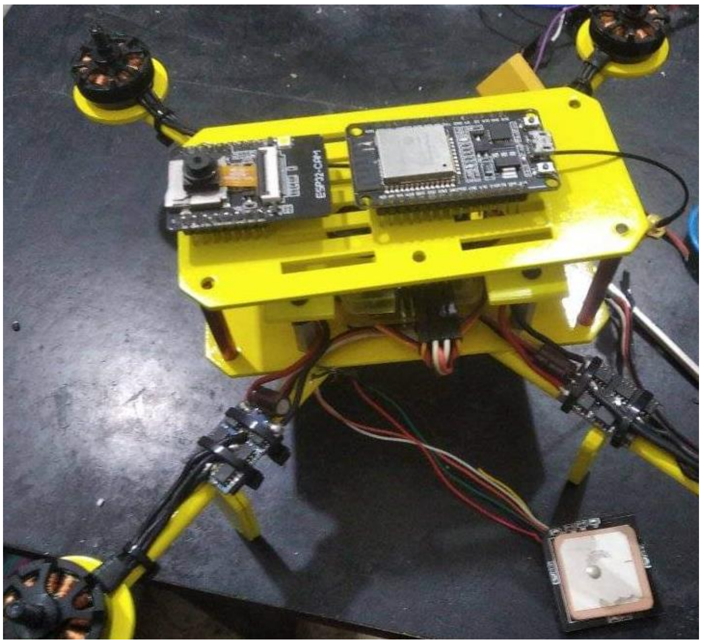

Figure 3. Proposed drone system

The drone system can be utilized as shown in figure .3 to capture flood 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 and also sim 800L is utilized for getting SMS notification alerts. This allows remote locality people to get messages through AIoT based system(Ahmed et al., 2021).

Ultrasonic sensor based water level detection

The ultrasonic sensor yielded a good result on predicting the water level. This helps to early monitoring of flood using sms technology early warnings can be made, though high quality dornes have been built already to monitor through live video feed for any specific geo locations but this self built drone system can be effective to utlilize sensors based technology for more precise monitoring of water level. The figure below shows the ultrasonic sensor monitored values which gives the range of water level above a fixed threshold level(J. da Silva et al., 2020).

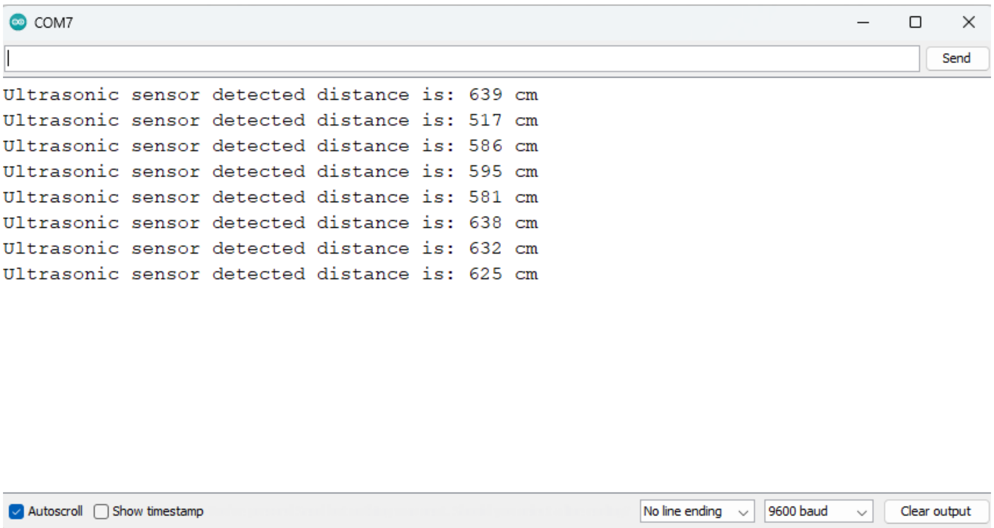

Figure 4. Ultrasonic sensor values from serial monitoring

Future Work

Future work will center on extending 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 point to 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 seem make the framework more proactive in overseeing natural risks. These headways will point to make a more comprehensive and versatile checking framework, eventually contributing to superior natural stewardship and more flexible communities(Faúndez et al., 2023).

Conclusion

There are several benefits to using AIoT technology in flood hazard and water quality monitoring over more conventional approaches. The suggested system gives consumers precise, real-time data and notifications by utilizing drone technology, ESP32, TensorFlow Lite, and a number of sensors. The model's high accuracy and successful implementation highlight this approach's promise in tackling the problems of water pollution and global warming. In order to contribute to more efficient environmental monitoring and management solutions, future work will concentrate on expanding the system's functionalities and scalability.

The model was trained using Inception-v3 Deep learning model and excellent accuracy of about 97% was obtained on the testing set. This model can be used for other purposes in managing water quality and increasing sustainability practices throughout the world creating a healthier world for all.

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