Real-Time Flood Monitoring and Alert Systems for Fluctuating Water Levels in Flood Prone Areas: A River-Based Approach Using Wireless Sensor Network and Computer Vision

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***Abstract* – Philippines' susceptibility to natural disasters, particularly in flood-prone areas like Bulacan, causes frequent disruptions to livelihoods, infrastructure damage, and significant economic setbacks. This study presents a real-time flood monitoring and alert system in Barangay Frances, Calumpit, Bulacan, to mitigate flood damage in the area. It utilizes a wireless sensor network to measure hydrological parameters. To be specific, water level (Ultrasonic Sensor), rainfall (tip bucket), and flow rate (Flow Meter) operate through the Wireless Sensor Networks (WSN) and the Internet of Things (IoT). In addition, the system uses the YOLOv5s model, integrated with a 1080p web digital camera to monitor the real-time water level of the area. The project also developed a mobile application, featuring notifications for alerts, flood monitoring, and data presentation. The project operates independently using solar panels and a battery, with internet connectivity provided by a portable Wi-Fi system. It comprises three nodes communicating via NodeMCU and an internet connection. Sensors collect data for monitoring, which is presented through a mobile application. Upon the results, the detection model achieved 99.6% precision, 99.1% recall, 99.3% mAP50, and 83% mAP50-95 in training and validation.**

Keywords – flood monitoring, wireless sensor network, computer vision, object detection, YOLOv5

I. INTRODUCTION

The Philippines, well-known for being vulnerable to natural disasters, has a topography and landscape primarily of rivers and dams, making it particularly difficult to live in areas that flood quickly. This susceptibility is best shown by the province of Bulacan in central Luzon, where its low-lying terrain serves as a natural reservoir for water from upstream regions and large bodies of water like the Angat and Bustos Dams. Flooding is a persistent hazard to Barangay Frances in Calumpit, Bulacan, jeopardizing infrastructure and lives. It is essential to find a proactive solution to these problems.

This study suggests a real-time flood monitoring, forecasting, and alerting system for Barangay Frances, Calumpit, Bulacan, responding to the urgent need for flood mitigation measures. Using the Internet of Things (IoT) and Wireless Sensor Network (WSN) technology and Multivariate Time-Series Models customized for river dynamics, this system seeks to deliver precise and timely water level forecasts during high tides and rainfall events. By providing early warning signals, the system aims to enhance residents' resilience and readiness against impending flood hazards by facilitating preventative steps and evacuation.

II. BACKGROUND OF THE STUDY

The Philippines has the recurring annual challenge of tropical cyclones on its over 7,000 islands. [1] With approximately 20 typhoons entering the Philippine Area of Responsibility (PAR) per year, more tropical cyclones (TCs) than anywhere else in the world; casualties were already fated. As the problem with typhoons is inevitable, the province of Bulacan is facing another problem, specifically Barangay Frances, Calumpit, Bulacan: being a low-lying area surrounded by various dams and rivers of Bulacan and its neighbouring regions, making it susceptible to floods during rainfall or even tides. In response to this issue, technologies have been developed to monitor and predict typhoon-related issues, particularly floods. One of these is the flood monitoring and forecasting system developed by the Pampanga River Basin Flood Forecasting & Warning Center (PRFFWC), which has been a primary system for flood level monitoring and forecasting for the Pampanga River Basin since 1973. Limited to Pampanga and only for flood levels, the flood level monitoring and forecasting system of PRFFWC is incapable of solving the problem faced by its neighbouring province, Bulacan.

Floodcast utilizes a Wireless Sensor Network (WSN) and the Internet of Things (IoT) to implement alarm systems and to monitor and predict floods, specifically in Barangay Frances, Calumpit, Bulacan - enhancing disaster preparedness and improving resource allocation. The system architecture is divided into four nodes, with the Wireless Sensor Network (Nodes 1, 2, and 3) located in a river in Barangay Sulipan, Apalit, Pampanga. The three nodes comprise an ultrasonic sensor, rain gauge, flow meter (inflow and outflow), and a digital web camera. These devices communicate with each other using pocket Wi-Fi located at Node 2, acting as its central hub. An ultrasonic sensor installed at Node 4 is responsible for the flood level in Barangay Frances, Calumpit, Bulacan. The Arduino Uno is solely responsible for gathering data from multiple sensors at Node 1, such as ultrasonic, rain gauge, and flow meter - data collected will be transmitted to the NodeMCU V3 microcontroller. NodeMCU V3 manages the transmission of the data flow gathered in Node 2. Another NodeMCU V3 is also connected to an ultrasonic sensor in Node 4. Lastly, the Raspberry Pi 4B microcomputer is connected to a web camera, allowing the real-time viewing of flood levels.

III. OBJECTIVES

This research journal aims to develop flood level monitoring and forecasting – including rising and receding water levels; specifically, it aims to:

- To design and fabricate a system using a Wireless Sensor Network (WSN) and the Internet of Things (IoT) that provides real-time monitoring of flood levels and alert warnings.
- To develop a water level staff gauge detection using YOLOv5s in a custom dataset.

This research journal aims to develop a system for flood level monitoring and forecasting (including rising and receding water levels) with an alert warning system. The system will collect data such as rainfall intensity, water level, and flow rate using its Wireless Sensor Network (WSN) and Internet of Things (IoT). The system also comprises a web camera connected to a Raspberry Pi 4B microcomputer used for flood-level monitoring.

This research journal aims to analyze the impact of variable changes, such as river water level, rainfall intensity, and river water flow, on the flood level in Barangay Frances, Calumpit, Bulacan, as observed in Barangay Sulipan, Apalit, Pampanga. The observed phenomena will be pivotal in developing flood monitoring, forecasting, and early warning systems, benefiting the residents during typhoons.

IV. RELATED LITERATURE

The study's proponent seeks to design and fabricate a flood monitoring system needed for flood mitigation measures in Barangay Frances, Calumpit, Bulacan. The goal is to provide a monitoring station situated in their upstream area to help local authorities and residents take preventive measures about the current and upcoming situation of floods, tides, and dam water releases. With advanced sensors and real-time data, the monitoring station will provide early warnings, allowing for timely evacuation and resource allocation. This initiative aims to protect lives and property in Barangay Frances, Calumpit, Bulacan, by strengthening community resilience and disaster preparedness.

A study by Patil et al. [2] proposed a flood warning system, requiring attention to these four primary factors: (1) data collection via gaging; (2) data processing; (3) the hardware and software; and (4) the dissemination of flood warning information. The system comprises an ultrasonic sensor for water level and rainfall measurement; a BMP180 barometric sensor for air pressure measurement; a DHT11 for temperature and humidity; and a Node MCU ESP 8266 as the microcontroller. The ESP will collect data from the various sensors to be computed and uploaded to the server. The front end of the web and mobile applications will receive this after being routed from the cloud database, where it will be stored. By making emergency evaluation more accessible, the proposed system enhances the effectiveness and efficiency of responding to catastrophic disasters. As a modification, the study's proponent seeks to design and develop a flood monitoring station that focuses on only three parameters for flood namely, water level, rainfall, and flow of water within the area.

The study by Natividad & Mendez [3] focuses exclusively on water level detection using an ultrasonic sensor and early warning system (via website and SMS) that warns citizens and concerned agencies about upcoming flood events. The two monitoring devices are supplied by a solar panel, regulator, and battery and include an ultrasonic sensor to measure the distance of the water level, an Arduino microcontroller to process the sensor's signal, a GSM module to send data or information from the microcontroller to the computer server. This study will serve as the basis for the hardware components that makes up the entire flood monitoring system. Similar to this study, the proponents will be utilizing a solar panel, charge controller, and battery to have a continuous power supply that operates 24/7.

A study by Dswilan et al. al [4] provided inspiration for this study. The research focuses on developing and testing the accuracy of river water level measurement for flood mitigation. The use of the ultrasonic sensor JSN-SR04T produced accurate results because it can detect distances ranging from 20 cm to 600 cm. The JSN-SR04T can also be placed higher and safer in the event of rain because the sensor and control board are in separate modules. Overall, the tests were successful in detecting water levels, water level conditions and sent information, making it advantageous for the community to monitor the flood and river flow. Similar to this study, the proponents will be utilizing an ultrasonic sensor JSN-SR04T calibrated from its specific reference point that ranges from 0 to 4.5 m situated on the side of the river.

The study by Quiao et al. [5] proposed a novel deep learning-based water level measurement method to address the limitations of current image-based water gauge reading approaches. These limitations include poor scene adaptability. The method proposed utilizes YOLOv5s for identifying the water gauge and all scale character areas in the original video image. It then applies image processing techniques to precisely locate the water surface line and calculate the actual water level. The validity of the method was confirmed through its application in a video monitoring station situated on a river in Beijing. The results demonstrate that the suggested approach can consistently and automatically read the water gauge in most instances, with an error margin of less than 1 cm. Experimental findings have evidenced the reliable identification of the water gauge in video images by YOLOv5s and the successful mitigation of complex background interference.

V. METHODOLOGY

A river-based approach to flood monitoring system offers precise and real-time data crucial for accurate forecasting. Monitoring three key parameters—water level, rainfall, and water flow—is essential for effective flood management. To achieve this, the system utilizes sensors such as the ultrasonic sensor JSN-SR04T for water level measurement, a tipping bucket for rainfall monitoring, a flow meter for tracking water flow, and a 1080p web camera for livestreaming of the water level staff gauge. These sensors use the Internet of Things (IoT) and Wireless Sensor Network (WSN) concepts to provide meteorological data, as well as predictive analysis to anticipate potential flooding events. Additionally, the device includes a mobile application with features for notifying local authorities and residents, improving user interaction, and ensuring timely response to flood hazards in the monitored area.

A. Design of the Device

The project's fabrication underwent some modifications from its initial plan until the device was placed in the deployment area, as shown in the figures below.

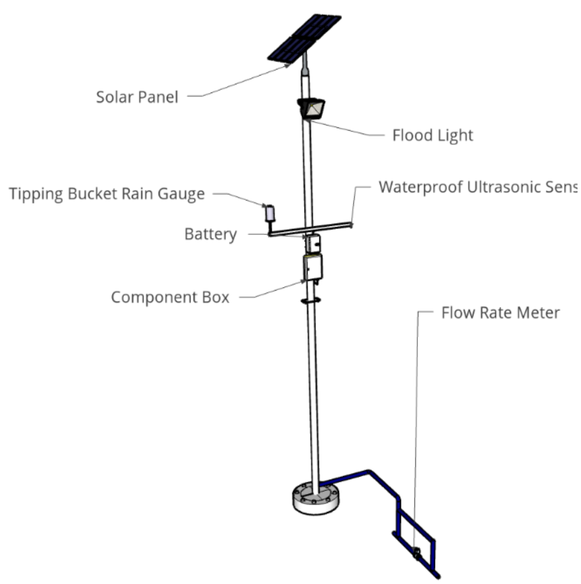


Fig. 1. *Node 1 Design*

Fig. 2. *Node 1 Actual Picture.*

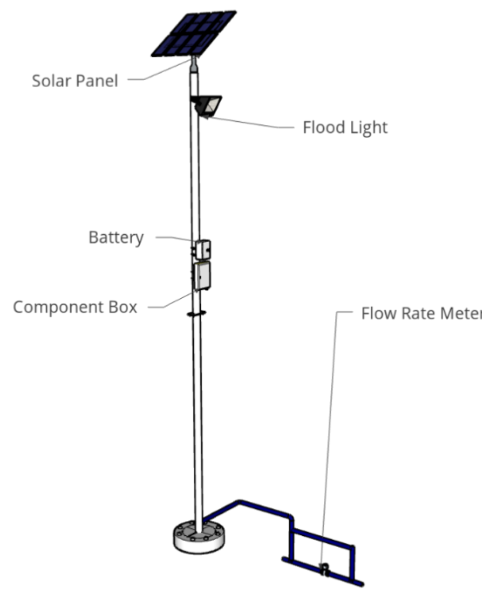


Fig. 3. *Node 2 Design*

Fig. 4. *Node 2 Actual Picture.*

Fig. 6. *Node 3 Actual Picture.*

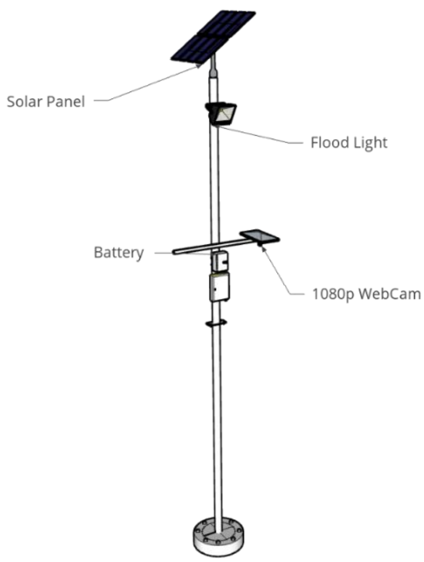


Fig. 5. *Node 3 Design*

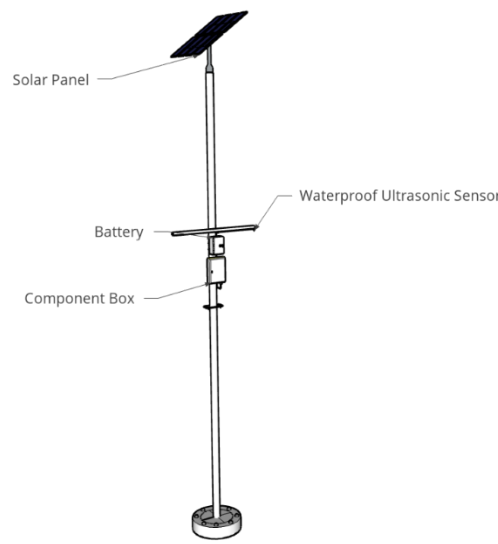


Fig. 7. *Node 4 Design*

Fig. 8. *Node 4 Actual Picture.*

B. *Functionality*

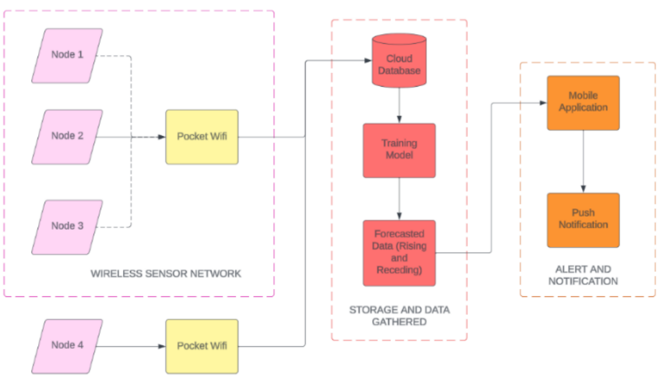


Fig. 9. *Block Diagram of the System.*

Figure 9 illustrates the system block diagram of the system. Nodes 1, 2, and 3 make up the wireless sensor network of the system connected to a pocket wifi, which serves as the central hub of the first monitoring station. Similar to this, node 4 is also connected to a pocket wifi. Transmission of data with these nodes are directly stored to the cloud database for real-time display, monitoring, analysis, and forecasting purposes.

Also, the entire system is integrated with a mobile application, which is necessary for live viewing of data, alert, and notification.

C. *Development of Custom Object Detection*

The researchers employed a data collection methodology involving a staff gauge for water level measurement. A boat was utilized to navigate a river, and a video recording was captured during the submersion of the staff gauge.

Fig. 10. Data Collection for Water Level Detection

Figure 10 shows a staff gauge submerged in water for the data collection process of water level measurements. This section provides the first step in performing custom object detection.

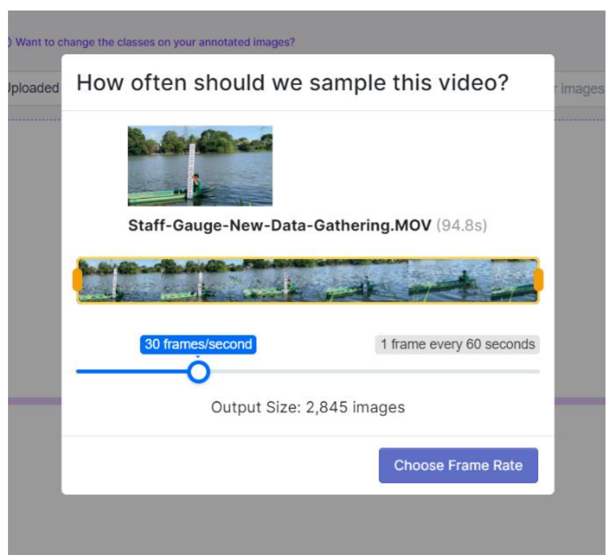


Fig. 11. Splitting the Video Data per Frame

Figure 11 shows how the video was split into frames. The total length of the video is 1 minute and 34 seconds, and it was divided into 30 frames per second, resulting in a total of 2,845 images.

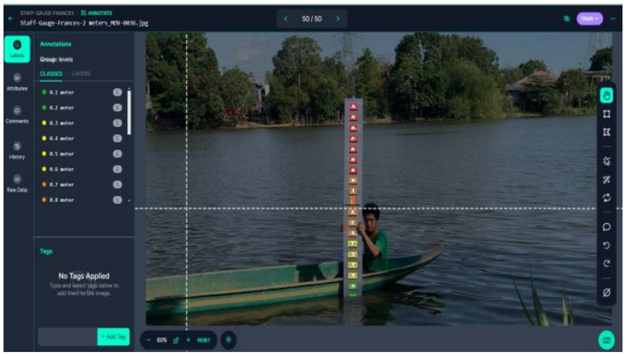


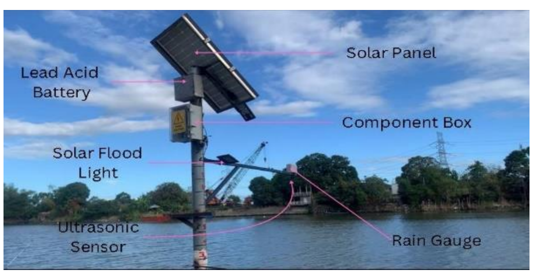
Fig. 12. Dataset Annotation

Figure 12 shows how the images were annotated and labeled with their assigned class using roboflow. Every level in the staff gauge has a label depending on the number itself.

VI. RESULTS AND DISCUSSION

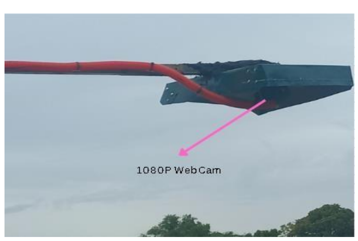
This section provides a thorough overview of the project's organizational structure, as well as the results of training, validation, testing, and actual video results of the YOLOv5s model.

A. Project Structural Organization

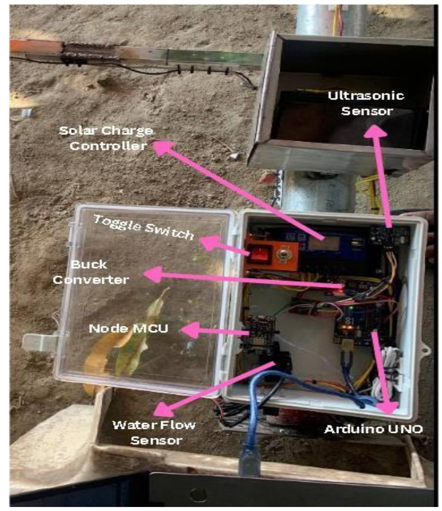


(a)

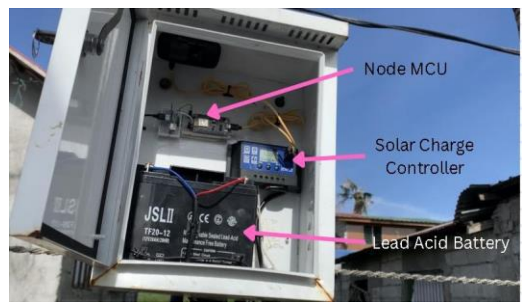
(b)



(c)



(d)



(e)

Fig. 13. Integration of Components

The integration of components between nodes 1 through 4 is shown in the figures above. Figure (b) depicts node 1's bottom view, while Figure (a) offers a side view. Nodes 1 through 3 are equipped with solar panels, a lead-acid battery, a solar floodlight, a component box, an ultrasonic sensor, and a rain gauge. They measure parameters like water level and rainfall. Node 3's side view is shown in Figure (c).

This device uses a Raspberry Pi microcomputer and a 1080p webcam for image processing. The interior of Node 1's component box is shown in Figure (d). It contains an Arduino Uno, a NodeMCU, a water flow sensor, a solar charge controller, a toggle switch, and a 5V DC/DC buck converter. All three of the nodes are located in Sulipan, Pampanga. Node 4, which is situated in Frances, Bulacan, is shown in Figure (e). This node monitors water levels and comprises a 1080p webcam, a Raspberry Pi, an ultrasonic sensor, a solar charge controller, a lead-acid battery, and a NodeMCU.

B. Mobile Application

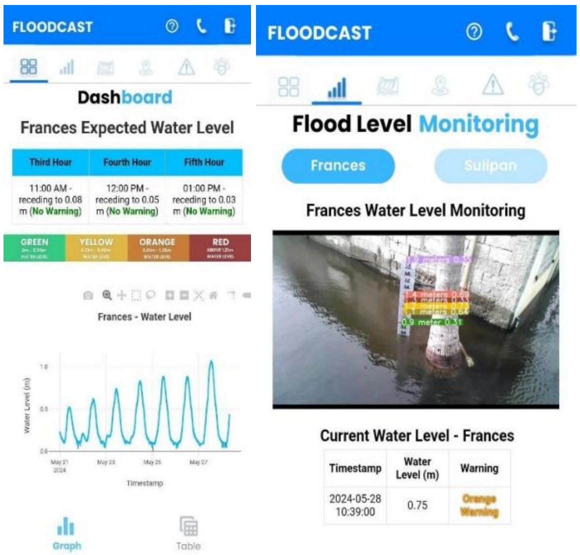


Fig. 14. Mobile App's Monitoring and Alert

The mobile application "Floodcast" provides a variety of functionalities to aid users in their preparedness for floods. The Floodcast mobile app, accessed on Android mobile phones, provides a prediction table that shows the expected water level conditions for the next three to five hours. It utilizes a classifier with four color categories (green, yellow, orange, and red) to indicate the severity of the water level. The app displays information on rainfall and water levels in France and Sulipan. The predictive model is executed on Google Colab. The mobile app conveniently incorporates real-time sensor data, encompassing numerical values and graphs. Implementing secure sign-up and login features guarantees user privacy and convenience. The mobile application offers extensive data to assist users in making well-informed choices and adequately preparing for potential flooding occurrences. Featuring a specialized interface that is easy for users to navigate, this resource promptly provides valuable and trustworthy information about floods.

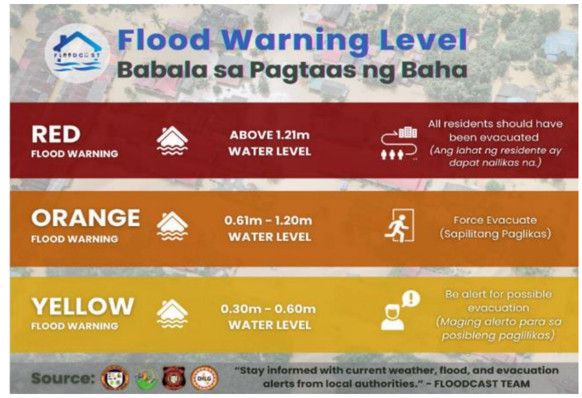


Fig. 15. Warning Standard used for Computer Vision

Figure 15 shows the flood warning standard utilized in the project study by the Philippine Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA).

Fig. 16. Flood Warning System in Mobile App

Figure 16 shows the flood warning level integrated into the project study to describe the predicted warning level status on the Dashboard Page and Frances's current water level on the Flood Level Monitoring Page.

C. Results of YOLOv5s Model

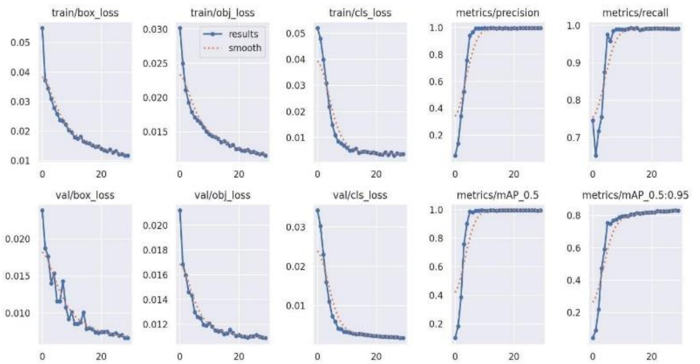


Fig. 17. Training and Validation Metrics

Figure 17 displays that the custom YOLOv5 model is learning and improving its performance on training and validation datasets. The smoothing lines help to visualize the overall trend and confirm that the model is improving its performance.

Model summary: 157 layers, 7061368 parameters, 0 gradients, 15.9 GFLOPs

Class	Images	Instances	P	R	mAP50	mAP50-95
all	754	9315	0.996	0.991	0.993	0.83
0.1 meter	754	228	1	0.984	0.985	0.766
0.2 meter	754	257	1	0.995	0.995	0.808
0.3 meter	754	288	0.998	0.99	0.995	0.799
0.4 meter	754	315	0.996	0.987	0.993	0.812
0.5 meter	754	387	1	0.984	0.994	0.779
0.6 meter	754	414	0.999	0.995	0.995	0.832
0.7 meter	754	450	1	0.99	0.995	0.831
0.8 meter	754	479	0.999	0.996	0.995	0.846
0.9 meter	754	488	0.992	0.99	0.984	0.844
1 meter	754	508	0.994	0.99	0.994	0.809
1.1 meters	754	531	0.994	0.991	0.995	0.828
1.2 meters	754	557	0.993	0.991	0.995	0.864
1.3 meters	754	585	0.993	0.987	0.984	0.827
1.4 meters	754	606	0.994	0.992	0.994	0.858
1.5 meters	754	629	0.994	0.99	0.993	0.836
1.6 meters	754	637	0.995	0.994	0.992	0.86
1.7 meters	754	644	0.995	0.992	0.994	0.846
1.8 meters	754	653	0.995	0.994	0.994	0.875
1.9 meters	754	659	0.995	0.993	0.995	0.857

Fig. 18. Model Summary of Results

Figure 18 summarizes performance metrics for a custom YOLOv5 model trained over 30 epochs. With high precision (0.996) and recall (0.991), the model captures almost all relevant instances and is accurate in its optimistic predictions.

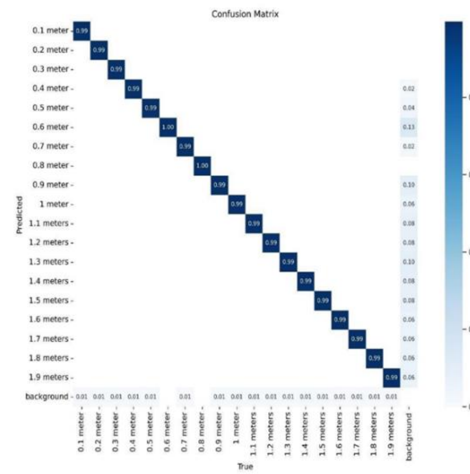


Fig. 19. Confusion Matrix

Figure 19 shows the confusion matrix of YOLOv5s. This graph represents the accuracy of each class in the trained dataset. The darker colors show that the model has high accuracy across all specified classes, with values close to 1.0.

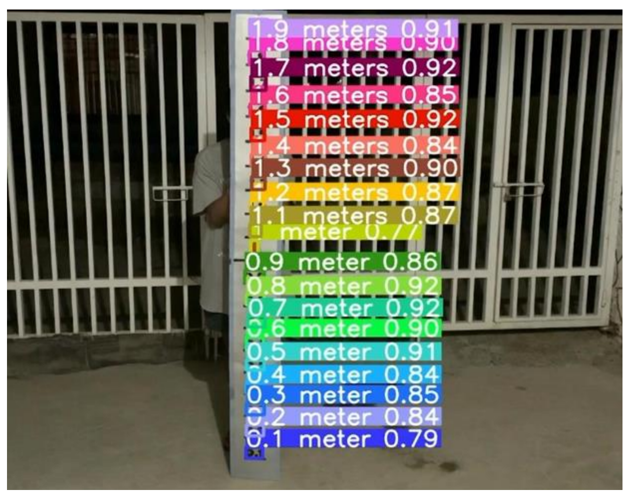


Fig. 20. Result of the Test Video of Standing Staff Gauge

Figure 20 above displays the result of the training video with a standing staff gauge. Each number equates a bounding box with a class of 0.1 to 0.9 meters. The footage demonstrated high accuracy for each class, as the trained dataset was gathered in that video.

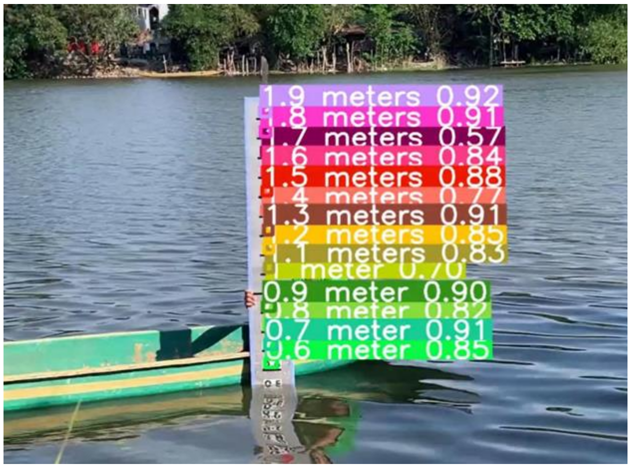


Fig. 21. Result of the Test Video with Increased Water Level

Figure 21 above displays the result of the training video with the actual increase of water level. The video showed that the bounding boxes from each number level are not visible as the water level increases.

Fig. 22. Actual Test Results of Object Detection from Staff Gauge in the Deployment Area

Figure 22 above executes the testing of the system in an actual setting. This test demonstrates the system's ability to accurately detect and label the number level. Each number equates to a bounding box with its respective class. However, some of the classes are not visible due to the camera angle.

VII. CONCLUSION

The project functions independently by utilizing power produced by solar panels and a battery. Additionally, it establishes its internet connectivity using a portable Wi-Fi connected to the system. The sensors employed in the project efficiently collect the necessary data, which is then used for the prediction component. The system consists of three distinct nodes communicating with one another via node MCU and an internet connection.

Moreover, the systems provide a mobile application as a central platform that presents all the essential data gathered from the sensors, including image processing results for flood monitoring and the system's predictions. Lastly, the system uses the YOLOv5s model, integrated with a 1080p web digital camera to monitor the real-time water level of the area. Upon the result of the study, the detection model has a training and validation accuracy of 99.6% precision and 99.1% recall, with a mAP50 value of 99.3% and mAP50-95 value of 83%, according to the study's findings.

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