Vision System for Recognition of Water Level, Rain Water, and Flood Detection

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***Abstract* – Several flood detection techniques have been designed to accurately measure water levels around the environment as a means to mitigate accidents or be prepared for such scenarios. This paper presents a system that detects water levels and floods within the 2 surveillance cameras. Gathered images were trained into the YOLOv5 algorithm, enabling the system to recognize floods. By operating at a few seconds of intervals, the system can notify users if the water levels are rising around the area. This study concludes that the most optimal position and camera to be used for this study is the outdoor camera, showing better results as seen from the gathered data.**

Keywords - flood, rainwater, YOLOv5, solar energy, image detection

I. INTRODUCTION

Floods have been known to be a destructive form of natural disaster, where several deaths have already been recorded throughout history. According to an article by CDC [1], standing floods also spread illnesses, infectious diseases, and chemical hazards. This also states that floods have provided more deaths than any other disasters related to typhoons. With this, local government units have been providing citizens with several mitigations to prevent the rise of floods and protect people around the area. General cleaning of sewage for clogging, elevating roads, and even evacuation areas is done to keep people safe from these events. News stations are also very active during typhoons to alert people beforehand if a flood may soon occur. In that case, evacuation would be done sooner. This paper will provide a system to measure if floods can rise within the area. Moreover, the study is part of the objectives of the ASEAN IVO project in helping generate studies to protect the environment and prevent disasters[2].

Several studies have tackled different variants and designs for general flood detection or mitigation. [3] A study was conducted in 2007, and a similar study was done in Spain. Using ENVISATs or Environmental Satellites, a group of researchers created a system to monitor floods on a larger scale where it was used in plains to assess and monitor vegetation. [4] In 2015, A similar study was also conducted where it used video surveillance in real-time to monitor flooding within the area. Stationary video cameras were placed in certain areas designed to be adapted to rural and urban areas. Background subtraction was used in this study with the help of the CUDA (Compute Unified Device Architecture) algorithm. This compared input footage with one another, processing these changes in parallel.

The study of Filonenko et al. [4] introduced real-time flood detection utilizing surveillance cameras that can be applied for rural and urban areas that can function only during the day. [4] Detection depends on the video quality and stability, where heavy weather conditions could affect its performance. The study provides a vision system to detect water and flood levels, providing information essential for flood casualty prevention and flood awareness. Previous studies used satellites to detect and monitor water levels or floods. The water level in the satellite image is hard to determine, but it can distinguish if the flood is occurring in an area. Although the water level can still be detected using the height of the human body, this becomes inconsistent. This study will use surveillance cameras as a cheaper option and prove their accuracy in monitoring these data.

The study's main objective is to create a solar-powered vision system for flood and rainwater level detection and recognition. The following are the secondary objectives. 1. develop a remote sensing vision system using CCTV and solar power, 2. build datasets for rainwater and flood to train using YOLOv5, 3. Build datasets for water level detection and recognition, train using YOLOv5 4. Recognize water level visually using a controlled environment set-up and determine the optimum sensor/camera position.

The significance of the study includes the following: (1) The output will support monitoring the flood-prone areas. (2) This system will detect the presence of flood rising. (3) A good-quality camera can expand the system to multiple locations. This paper will provide another design in aiding flood detection. This design will use cameras attached to specific areas.

The study will focus on flood detection using YOLOv5. The different characterization of the flood includes the water level and the distance of the flood from the camera. Several trials will be done on a pool for simulation. The system's maximum distance will depend on the specification of the camera. This research is limited to one algorithm for flood detection and will not prevent the flood in the area.

II. LITERATURE REVIEW

A. *Flood Detection Method*

The study [5] utilizes color-based categorization to separate the flood water with the color brown. Each recognized face is highlighted by a rectangle that is painted over it. Bounding boxes are then drawn in relation to the rectangle used for face detection, beginning with each face that has been detected. The torso, hips, knees, and legs are roughly the four parts that divide the human body. Figure 2.12 shows the segmentation of the human.

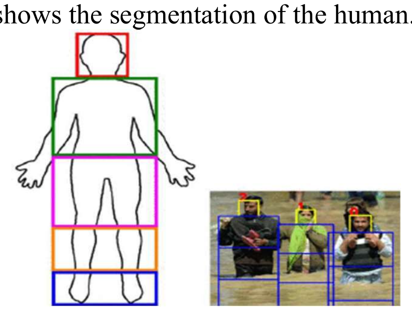

Fig 2.1. Human bodies segmented.

The study [6] utilizes YOLOv5. It uses an original custom dataset with augmented color and saturation adjustments to train and apply a custom model to recognize particular pantry objects in various lighting conditions and orientations. The dataset was divided into three categories where it was utilized to verify and deduce the accuracy of the training, including its precision, recall, and mean average precision (mAP) for each epoch.

Another similar study in flood mitigation was conducted by [7], where forecasting and monitoring system was developed. A standalone sensor station was developed with ultrasonic sensor, microcontroller, GSM module, and solar panel.

B. *Solar Energy*

In the study of Javagar et al. [8], solar energy was obtained through the solar panel to utilize charging power stations for electric vehicles. Implementing the suggested system will lower electricity costs and reduce charge and discharge losses.

According to the study [9] by Shivaleelavathi et al., the study's primary goal is to create solar lighting that utilizes a timer-based sun tracking system to capture the maximum amount of solar irradiation and keep the photovoltaic panels perpendicular to the sun's rays. It also provided a formula for how much power the system needs to select a photovoltaic panel.

III. METHODOLOGY

A. *YOLOv5 Algorithm*

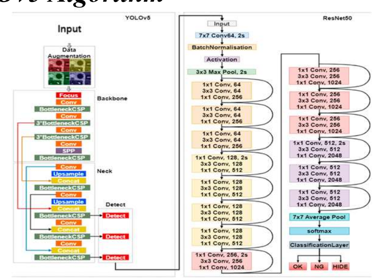

Fig 3.3. Image Processing Algorithm [9]

Figure 3.3 above shows the image processing YOLOv5 algorithm used in this system.

The YOLO network consists of 3 parts: Backbone, Neck, and Head. The backbone component takes the input images and produces feature representations of different levels. The neck component combines the features from the backbone and outputs three scales of feature maps. The head component performs object detection on the feature maps obtained from the neck. [10]

Using cluster centroids as reference points, it is estimated that the box's dimensions as offsets. It also applies a sigmoid function to predict the box's center coordinates relative to the filter's location. [11]

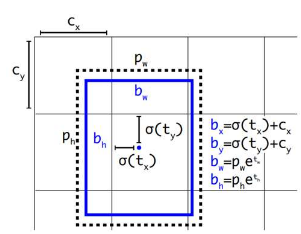

Fig 3.4. Bounding boxes with Dimension and Location Prediction

A ResNet-50 was used in this study, which is a convolutional network with about 50 layers deep. The idea of shortcut connections allowed

CNN to have more convolutional layers without suffering from the vanishing gradient problem.

B. Reference Point

The reference for the classification of the water level and how one can determine if it already exhibits flood, the MMDA flood gauge was used.

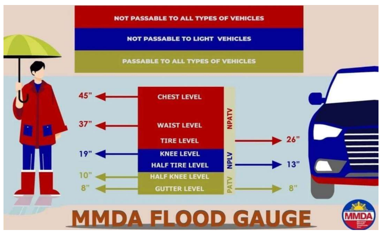

Fig 3.2. MMDA Flood Gauge

C. Collection of Datasets

The datasets were captured using Samsung J1+ and Samsung S22 smartphone devices. The resolution of images that were captured is at a resolution of 1280x720 pixels.

Datasets consist of (1) Reference Point Set and (2) Rainwater Set, and (3) Null Set. The Reference Point Set consists of pictures with the Reference Point with annotated classes of each color. The Rainwater set consists of puddles while the Null set contains the absence of the reference point and the rainwater. The total dataset contains 1000 images.

Fig 3.3 Example of the Reference Point Color Yellow

Figure 3.5 shows what the water level looks like in the reference point with the yellow marker. As seen here, the water level is at its lowest level, showing that the rainwater accumulated was not that much.

D. System Setup

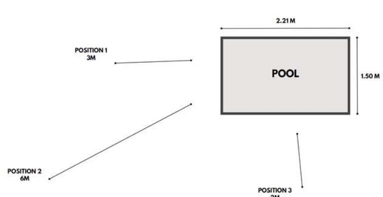

Fig 3.4. Testing Area

Figure 3.4 shows the system setup for this study. These cameras in the system will be placed at different positions in the area for data observation. The height of the camera for all positions is at 5 ft high. Position 1 would be placed 3 meters from the pool, position 2 would be placed 6 meters from the pool, and position 3 would be placed 2 meters from the pool. All are intended for better observation.

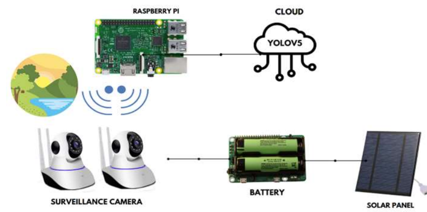

Fig 3.5 System Setup & Schematic Diagram.

Figure 3.5 above shows the system setup for this study. A solar panel is placed above the surveillance camera, providing direct alternative solar energy for the system. The YOLOv5 library will be integrated into the cloud, which would be the processing unit for the system.

IV. RESULTS

A. *YOLOv5 Training*

The YOLOv5 was trained for 100 epochs using a custom dataset. The results for precision, recall, mAP, training loss and validation were calculated for each epoch of training.

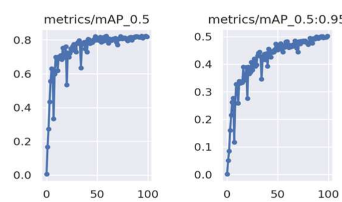

Fig 4.1 mAP 0.5 and mAP 0.5:0.95

Fig 4.2 Training Loss for Box

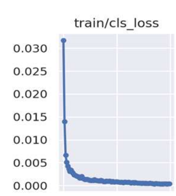

Fig 4.3 Training Loss for CLS

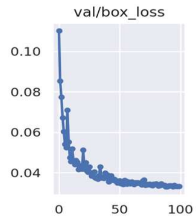

Fig 4.4 Validation Loss for Box

A metric called mean average precision (mAP) is used to assess how well object detection algorithm is doing. As observed in Fig 4.1, the highest mAP 0.5 value throughout the 100 epoch has a result of highest value of 0.83 and average of 0.73 on 100 epochs. While the mAP of 0.5:0.95 as a result of 0.51 highest value and 0.42 average for 100 epochs.

For figures 4.2, 4.3, and 4.4, shows as the training progressed, the loss curves approached each other. This suggests that the algorithm performed well and predicted during the training.

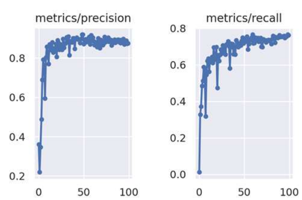

Fig 4.5 Precision and Recall Graph

Figure 4.5 show the graph for the precision and recall curve. As the precision increases, the recall also increases. This indicates that the performance of the system is good on the datasets since it maintains to be at a high value.

B. ***Testing Results***

The test was done using two cameras in a controlled environment. The test consists of different positions of the camera from the reference point and different levels of the water. Each table consists of 20 trials for both cameras.

Table I
Comparison Results for Camera 1 & 2 on Flood - Position 1 (3 Meters), Position 2 (6

No. of trials	Position 1 Accuracy (3 Meters)		Position 2 Accuracy (6 Meters)		Position 3 Accuracy (2 Meters)	
	Cam 1	Cam 2	Cam 1	Cam 2	Cam 1	Cam 2
1	94	84	82	76	96	82
2	96	92	92	76	92	92
3	92	82	89	62	94	82
4	94	92	92	73	95	92
5	95	89	89	75	96	89
6	94	83	83	73	92	83
7	94	86	82	73	94	82
8	97	84	92	75	95	92
9	94	84	89	72	94	89
10	94	83	82	73	94	83
11	93	88	83	75	97	86
12	95	92	82	73	96	82
13	92	89	92	73	92	92
14	93	83	89	75	94	89
15	92	92	82	73	95	82
16	95	89	92	73	94	92
17	93	83	82	75	94	89
18	92	82	92	73	97	83
19	93	92	89	73	96	86
20	93	89	83	75	92	84
Avg Accuracy	93.75%	86.9%	86.9%	73.3%	94.5%	86.55%

Meters), Position 3 (2 Meters)

Comparing the results from Position 1, 2, and 3. Position 3 has the highest results for accuracy since it is also the closest and has a distance of 2 meters to the reference point but the position of the camera is too close to the reference point making the field of view of the camera narrow.

The optimal distance for the camera to be from the reference point is position 1 with a distance of 3 meters. This way, the camera can capture the reference point clearly without being too far or too close. If the camera is too far, the reference point will be hard to see. If the camera is too close, the reference point will be too zoomed in.

The camera from position 2 with a distance of 6 meters from the pool still has good accuracy. However, the distance between the camera and the reference point is 6 meters making the reference point far away and barely seen by the camera.

Table II
Comparison Results for Camera 1 & 2 on Flood with Rain - Position 1 (3 Meters) and Position 2 (6 Meters)

No. of trials	Position 1 Accuracy (3 Meters)		Position 2 Accuracy (6 Meters)	
	Cam 1	Cam 2	Cam 1	Cam 2
1	89	62	92	73
2	92	73	89	73
3	89	62	82	75
4	83	73	83	72
5	82	75	82	73
6	92	73	92	75
7	89	73	89	73
8	89	75	82	73
9	83	72	83	75
10	82	73	82	72
11	89	73	92	73
12	95	73	89	75
13	89	75	82	73
14	92	72	83	73
15	89	62	92	73
16	92	73	89	73
17	89	75	82	75
18	92	73	83	73
19	89	73	82	73
20	83	75	92	75
Avg Accuracy	88.45%	71.75%	86.1%	73.5%

For position 1 and 2, both cameras are used to compare the results with a simulated rain. The data shows the accuracy decreases as the presence of rain exist on the vision of the camera. Position 1 has an average accuracy of 86.1% and 73.5% for both cameras with a distance of 3 meters. For position 2, similar to the previous results when the distance increases the accuracy also lowers and the presence of rain also contributes on lowering the accuracy.

Table III

Comparison Results for Camera 1 & 2 on Puddle - Position 2 (6 Meters)

No. of Trials	Camera 1 (Accuracy in Percentage)	Camera 2 (Accuracy in Percentage)
1	74	72
2	75	73
3	78	68
4	72	72
5	73	65
6	73	64
7	74	65
8	79	67
9	72	63
10	73	66
11	73	69
12	74	71
13	78	72
14	76	72
15	78	68
16	79	67
17	78	67
18	75	69
19	78	62
20	78	71
Avg Accuracy	75.5%	68.15%

Table IV shows the results of accuracy in detecting puddles for both cameras. The results show that the average accuracy for camera 1 is 75.5% while camera 2 is at 68.15%. The test is done at a distance of 6 meters away from the camera to the reference point and different amounts of puddles were used.

C. ***Solar Panel and Battery***

The solar panel that was used have 100 Watts, 12 V, and 3 A. The battery is a Li-Ion battery that has a capacity of 10000mAh. One CCTV camera that has a 2 A and 5 V.

Equation (1) shows the computation on charging time. The capacity of the battery has 10000 mAh and 3 A for the solar panel. The result shows 3.333 hours of charging time to fully charge the 10000mAh battery. Equation (2), shows the theoretical discharge rate of a battery with a capacity of 10000 mAh with a load of 1 A of a CCTV. The battery was able to provide power for up to 10 hours for 1 CCTV. For 2 cameras, 10 hours will be distributed for each camera since it has the same current. Therefore, if both cameras are running, they can last up to 5 hours.

(1) Theoretical Computation Charging Time

Battery Capacity: 10000 mAh
Charging Current of Solar Panel: 3 A

$$\frac{10Ah}{3\,A} \approx 3.3333\ Hours$$

(2) Theoretical Computation Discharge Rate

Battery Capacity: 10000 mAh
Current of CCTV: 1 A

$$\frac{10Ah}{1\,A} \approx 10\ Hours$$

A test has been made where a battery was charged using the solar from 8:00 AM to 12:00 PM, 4 hours of charging time. The battery was discharged with a load of two cameras at the same time around 12:20 PM to 4:16 PM and lasted 3 hours and 56 minutes.

V. CONCLUSION

In this paper, the YOLOv5 algorithm is trained for detecting floods and their height. Camera 1 has durable materials that can withstand environmental conditions while camera 2 has a sensitive IR sensor that can alter the color of the video which will result in incorrect detection. The most optimal location for the camera is 3 Meters away from the reference point. The presence of rain also affects the accuracy of detection. The detection of the flood is dependent on whether the reference point of the flood is visible. It is recommended to put a light source in the area to highlight the markings on the reference more. In addition, adding more training images of the same location will improve the accuracy of the detection.

VI. ACKNOWLEDGEMENT

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