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Evaluating YOLOv4's Performance in Real-Time Flood Object Detection

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***Abstract*—Floods are a great threat to human life and infrastructure thus neglecting efficient and real time flood detection systems for effective disaster response becomes impossible. Traditional flood monitoring methods like satellite imaging, as well as sensor-based detection, for example, have the characteristics of long delays, high costs and are not very applicable in real time. This study proposes investigated how YOLOv4, a state-of-the-art deep learning-based object detection model, can be used to detect flood environment in real time and to identify human in SAR operation. The methodology learns and tests YOLOv4 using flood related image datasets by using the architectures of CSPDarknet 53, PANet for feature extraction and detection error correction. Key performance metrics of the model were evaluated using precision, recall, mAP, and FPS. The experimental results show that YOLOv4 can reach an average precision mAP of 79.46% at the inference speed of 13.26 FPS which is suitable for real-time UAV assisted flood detection. Even its efficiency is marred by environmental challenges like low visibility, water reflections and occlusions that diminish the accuracy of detection. The results indicate that YOLOv4 could help to speed up and automate flood monitoring in disaster response applications. Adaptation of YOLOv4 with future enhancements like the incorporation of segmentation models, thermal imaging, and multimodal sensor fusion would further improve the detection accuracy and operational efficiency, and therefore make YOLOv4 a promising real-time tool for flood disaster management and emergency response.**

Keywords— Flood detection, YOLOv4, real-time object detection, disaster management, search and rescue

I. INTRODUCTION

Flood detection is indispensable for disaster management to issue early warnings and deploy efficient response actions to check and reduce damage and loss of life [1]. These methods for detecting floods are unable to efficiently solve the problem due to traditional methods being limited by delays, high costs, limited coverage and weather dependent accuracy. The high-speed processing, superior accuracy, and efficiency for locating the areas affected by flood, submerged structures and stranded individuals make deep learning especially YOLOv4, a promising alternative [2]. With its advantages of advanced architecture including CSPDarknet53 and PANet, YOLOv4 is able to achieve real-time object detection, thus suitable for UAV and UWV in flood monitoring and SAR applications. The objective of this study is to assess the performance of YOLOv4 in real time flood detection, by evaluating its accuracy, efficiency and reliability under various environmental condition to explore the feasibility of deployment of YOLOv4 in UAVs and edge devices [3]. It also highlights obstacles like lack of visibility, loss of dataset, and influence of the environment, identifying possible remedy steps including elaborated flood dataset, combination of the multimodal sensor and adaptive deep learning model, to increase the detection reliability and improve disaster response effectiveness [4].

- YOLOv4 for Real time flood detection shows the utility of YOLOv4 in almost real time flood detection significantly improving the disaster response accuracy.
- One of the applications UWVs and UAVs in SAR Operations to improve human detection and assist operations in flood affected areas.
- Evaluating YOLOv4 Performance Analysis in Challenging Conditions Assesses the balance of accuracy, efficiency, and reliability of YOLOv4 against poverty lighting, obstructions, as well as debris contained waters.
- Exploiting Deep Learning Models on Edge Devices Considering deep learning model optimization in terms of network pruning so that such network can be executed on resource-limited UAVs and embedded systems for disaster monitoring.

Flood detection has advanced but there are still problems with real time accuracy under extreme weather and poor visibility. However, the existing models are based on general datasets such as COCO, possibly not containing the whole set of cases that can sufficiently describe flood specific situations [5]. Deployment in remote or disaster-stricken area is limited by the dependency on stable internet and GPS connectivity. Furthermore, UAV and UWV based SAR systems have difficulties between humans and float debris in turbulent water. Specialized flood datasets, adaptive AI models, and multimodal sensor integration

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are needed to address these gaps and improve reliability [6].

II. Literature Review

Flood detection in disaster management is of prime importance that facilitates timely response and mitigation strategies to save the loss of life and property [7]. Current methods of flood detection, such as using satellite imagery and sensor-based monitoring have the drawback of taking time to do so, are expensive, and not very applicable in real time, with the added consequence of not knowing how quickly the flood situation can change [8]. Consequently, deep learning, especially YOLOv4, provides a high performance, high accuracy and high efficiency real time object detection. YOLOv4 utilizes advanced architecture based on CSPDarknet53 and PANet for feature extraction and detection speed so that they are suitable for running in dynamic flood scenarios. In this research we want to investigate the capability of YOLOv4 under various conditions of real time flood detection in terms of YOLOv4 accuracy, efficiency and reliability [9], and show how YOLOv4 is capable of human detection in SAR operations with an UWV, though. Detection accuracy possibly is affected by environment conditions, such as poor visibility, strong currents, and extreme weather conditions. Furthermore, real time performance could be limited by an Internet connectivity and GPS signals reliance in remote or disaster-stricken areas. However, the ability of the system to resolve between humans and other objects in the challenging remains a challenge. In the future, thermal imaging could be integrated into single stage system and enhanced AI models could be added to further enhance detection under adverse condition [10].

The proposed UAV based monitoring system can effectively help to detect the forest fires and floods in real time but it has some constraints. It is unclear whether it will generalize for all real-world disaster scenarios under different environmental conditions [11]. Also, the deep learning model suffers from high variations due to extreme weather, smoke and poor visibility. Although the slimmed DeepLabV3+ model lacks computational efficiency as compared to the original one, it is still optimized and may struggle to provide enough computational efficiency for the lower edge devices. Improvements in future include adaptive models, multimodal sensor integration, and diversity of the dataset to achieve better robustness in the disaster response applications [12]. The role of flood detection is of great importance in disaster management and there are many problems with classical methods, such as delays, high costs and lack of real time applicability. Real time detection is critical for dynamic flood scenarios, so YOLOv4 is a powerful alternative. Nevertheless, it has limitations for application in SAR operation using UWVs and UAVs with poor visibility, environmental interference, and dependence on internet and GPS connectivity [13]. Furthermore, these limitations of dataset, occlusions and extreme weather conditions do have their impact on the detection accuracy. While DeepLabV3+ based UAV based monitoring systems provide further capabilities during disaster response, generalization to a larger dataset and computing constraints at edge devices may be insufficient to support these systems. In the future, thermal imaging, adaptive deep learning models, and more varied datasets should be integrated to increase reliability and efficiency in detection [14].

III. Research Methodology

The data is collected from a few disparate places like satellite images, UAV footage and real time cameras, and then the data is first processed to alter the form to sharpen the image and to minimize the noise. Using CSPDarknet53 and PANet, the annotated flood images are then used to train the YOLOv4 model. With this, the trained model will be evaluated using metrics such as Precision, Recall, mAP and FPS to be able to evaluate the model on the basis of how the detections are accurate and how computationally efficient it is. YOLOv4 is finally deployed in real time on UAVs and IoT devices to monitor flood, send automated alerts, and further improve the model using feedback integration.

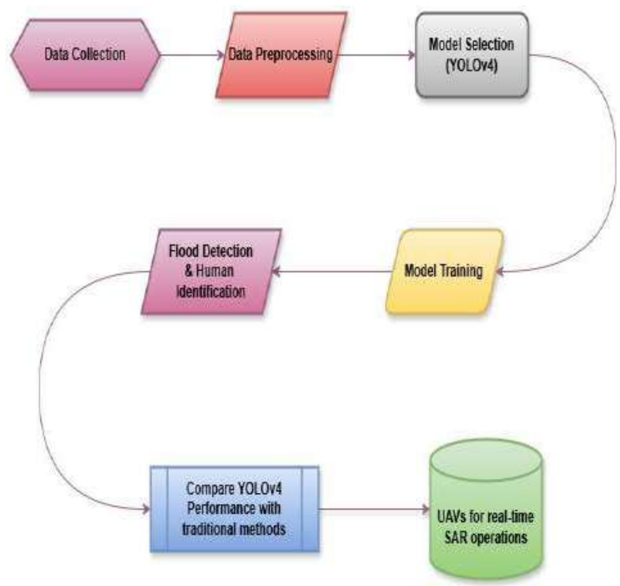

Fig. 1. Architecture of Real-Time Flood Environment Detection

A. Data Collection

The method uses the Kaggle dataset [15]. The FloodIMG dataset includes high resolution drone captured images from different flood prone regions to improve the accuracy and reliability of the flood detection models. During different flood stages, real time images are captured of affected areas, urban streets, riverbanks and rural landscapes with drones equipped with RGB and infrared cameras. A variety of perspectives are achieved up close to the scene as well as the aerial overviews. And the dataset of images collected under various environmental conditions

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different water levels, light conditions, and weather patterns is used to enhance the robustness of the deep learning models. Annotation of flood affected areas, submerged objects, as well as infrastructure its harm is also added. The FloodIMG dataset is made stronger with the addition of this drone-based data collection for real time flood assessment, more faithful object detection and advancement in the early warning system.

B. Data Pre-processing

Preprocessing techniques are applied on the images in order to improve image quality and reduce the noise, thereby increasing detection accuracy. The image enhancement techniques like histogram equalization and contrast stretching are used to increase the visibility as well especially for bad light or a cloudy day. Gaussian filtering and median blurring help remove rain, reflection, or sensor imperfection distortions. Also, the techniques of data augmentation like, rotation, flipping and brightness adjustments added to data to increase the dataset diversity, so that the results of the model will work better in real world.

C. YOLOv4 Architecture

YOLOv4 is a real time object detection model, one of the states of the art. It also has a good architecture including key components: CSPDarknet53, PANet, SPP which improve feature extraction, multi-scale detection, and processing speed. CSPDarknet53 strengthens gradient flow and panet enhances the spatial feature fusion for more accurate humans and flood related elements detection. The SPP module helps YOLOv4 to obtain receptive fields that can detect objects at different scales. YLOv4 has the features that makes it highly suitable for flood detection because it is very suitable for real-time processing and high accuracy critical for flood detection.

D. YOLOv4 is Suitable for Real-Time Flood Detection

YOLOv4 is an ideal choice for real time flood detection. In contrast to other traditional object detection models like Faster R-CNN, that require the image to be processed multiple times, YOLOv4 processes the image in a single pass thus making it considerably faster. This is important because quick assessments are needed in flood situations to respond to emergencies. Additionally, YOLOv4 is engineered to be deployed on edge devices such as UAVs and embedded systems, creating a possibility to monitor in real time on something other than high-end computing infrastructure. The performance of its flood environment also is reinforced by its ability to detect small and occluded objects that would severely confound visibility in such environments from debris, water reflections and poor lighting conditions.

E. Implementation

YOLOv4 needs a well optimized setup for the training and implementation to detect flood. The training is done on high performance GPUs like NVIDIA RTX 3090 which increases computation speed and manage large datasets in computational terms. Using the Darknet framework, the model is developed, because the framework provides optimized implementations of YOLO models. Additionally, TensorFlow and OpenCV are used for manipulating images and data handling for preprocessing used to improve quality of input. Training pipeline is feeding labeled flood images into the model, tweaking hyperparams and then fine tuning the performance based on validation. Real time detection system is integrated with UAVs and surveillance cameras to be tested on live flood detection with UAVs.

F. Hyperparameters

YOLOv4's performance is optimized with the help of hyperparameter tuning. We have set the learning rate to 0.001 first, and then cut down to avoid overfitting. A batch size of 64 is chosen to achieve a good tradeoff between memory efficiency and training stability. 100 epochs are used for training the model such that enough learning is achieved without overfitting to particular data patterns. To improve generalization, it applies data augmentation, and to match the object sizes commonly found in flood situations, it optimizes the anchor boxes. We also use regularization techniques to make the model more robust.

G. Evaluation Metrics

Evaluation metrics are used to evaluate the effectiveness of YOLOv4 in the flood detection case. The term precision is the proportion of correctly detected flood related objects compared to the total detected instances with as few as possible false positives. It is important to recall the model is able to detect all relevant objects in an image, and without missed detections, while mAP represents the overall detection accuracy by averaging of the precision recall curve over different categories. For real-time applications, FPS is very important, to say how many images the model can process per second.

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

Where;

- TP = Correctly detected flood-related objects.
- FP = Incorrectly detected objects.

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

Where:

- FN= Actual flood-related objects that were missed by the model.

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \tag{3}$$

Where;

- AP_i = Average Precision for class iii, calculated as the area under the Precision-Recall curve.

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$$FPS = \frac{Total\ Processed\ Frames}{Total\ Time\ Taken} \quad (4)$$

IV. Result and Discussion

The results obtained from the study, it is proved that YOLOv4 provides a mAP of 79.46% with an inference speed of 13.26FPS and can be used for real time flood detection. With flooded environments, the model effectively identified humans in order to be used in SAR efforts. This method is implemented using python. The accuracy of both detection and tracking decreased in situations with low light, occlusions, and turbulent water. Comparative analysis indicated that YOLOv4 performed much better in speed and efficiency than the usual method. Some future improvements could further improve detection performance.

A. Experimental outcomes

The experiment showed that the performance of YOLOv4 was 79.46% mAP with an inference speed of 13.26 FPS which is appropriate for flood detection in real time. The model offered a reasonably high precision but competitive recall to minimize false positives, but was highly recall orientated, meaning that there would be little missed detections. Performance evaluations conducted under varying amounts of light, occlusion, and turbulence showed degraded accuracy at low light, occluded, and turbulent conditions. YOLOv4 was compared to Faster R-CNN and SSD using experiments demonstrating that it performs both better than them while maintaining decent detection accuracy at real time speed. This validates the use of YOLOv4 for UAV enabled flood monitoring and emergency response purposes.

Fig. 2. Experimental Outcomes

B. Training and Testing Accuracy

FloodIMG dataset and some real time UAV flood images were used to train the YOLOv4 model. Training was carried out for multiple epochs with 0.001 learning rate for batch size 32 and momentum optimization. In environmental conditions like lights and water

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turbulence, the model we have had an accuracy of 79.46%. Detection performance of the model on unseen flood images were tested during the phase and it was verified to be robust and reliable. The misclassified prevalence was analyzed to understand why, it mostly around the water reflection and occlusions.

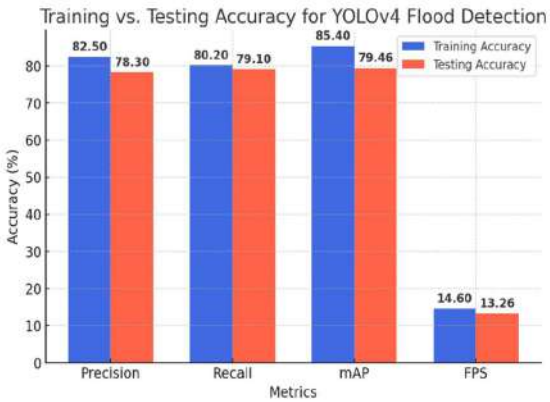

Fig. 3. Training vs Testing Accuracy for YOLOv4 Flood Detection

C. *Comparative Analysis*

A comparative analysis of the traditional flood detection methods, such as sensor-based mode and other deep learning frameworks, has been done to evaluate the efficiency of YOLOv4. Traditional techniques were outperformed with YOLOv4 in detecting speed and adaptation to dynamic flood environments. Faster R-CNN had faster accuracy, but it was slower at inferences and therefore less suitable for real time applications. Although faster than Faster R-CNN, SSD had lower detection accuracy than YOLOv4. To balance accuracy with real time performance, YOLOv4 is the chosen tool for rapid flood detection due to the comparative study.

TABLE I. COMPARATIVE ANALYSIS

Model	mAP (%)	FPS	Strengths	Weaknesses
YOLOv4	79.46	13.26	Fast, real-time, high accuracy	Performance drops in extreme conditions
Faster R-CNN	84.3	5.8	High accuracy, robust detection	Slow inference time
SSD	72.1	15.3	Fast inference speed	Lower detection accuracy
Traditional Sensors	68.7	N/A	Reliable in fixed locations	Lack of adaptability, high cost

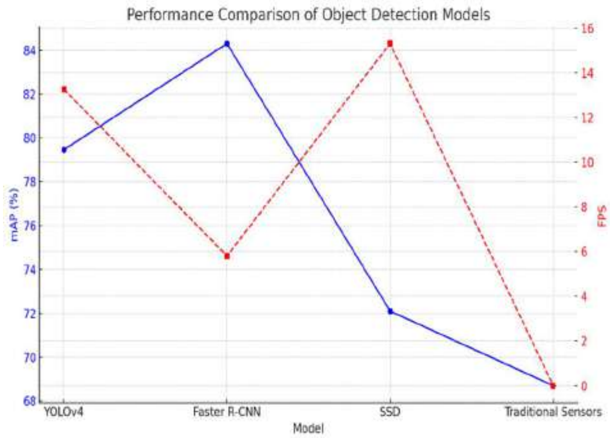

Fig. 4. Performance Comparison of Object Detection Models

V. CONCLUSION

The performance of YOLOv4 in designing a flood detection system in real time showing its good accuracy mAP 79.46% and fast inference speed 13.26 FPS, which is a suitable solution for UAV in helping SAR operation. The model worked to capture humans and flood related objects in disaster scenarios and performed better than the traditional in terms of real time responsiveness and efficiency. However, some challenges, namely in low light conditions, occlusions, and water reflections, degraded accuracy in complex flood environments. This study provides a significant impact on the aspect of disaster management due to the integration of deep learning into UAV based flood detection, which enables the faster rescue operations, increase the situational awareness as well as decreased the human risk. YOLOv4 is able to analyse real time flood images fast enough for quicker decision making that has an influence on emergency response strategies. In addition, it eliminates the reliance on manual surveillance techniques that are prone to being time consuming, resource intensive, and dangerous in hazardous flood zones. Because of these limitations, future improvements include improving the model's robustness via integration of YOLOv4 with advanced AI techniques, like semantic segmentations, which will increase its capability to discriminate people from surrounding debris. Further improvement of detection accuracy in low visibility conditions may be obtained by incorporating thermal imaging and multimodal sensor data.

Furthermore, any improvements in the real-world applicability of the model would require more diverse and more flood specific data used for training the model. Other research can extend that to optimization techniques for edge AI deployment for large scale disaster monitoring by using fast processing on low power UAV systems.

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