Leveraging AI based Drones for Effective Flood Rescue Operations

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Abstract. In times of severe earthquakes and floods, rapid and effective aid is crucial. Traditional methods often face challenges due to accessibility issues and the vast scale of disasters.The Proposed Autonomous Aerial Humanitarian Assistance and Disaster Relief (A2-HADR) System aims to transform disaster response through the use of drone technology. Our innovative solution addresses the obstacles in rescue operations by employing drones equipped with Artificial Intelligence (AI) to provide immediate support. The advanced system utilizes state of the art Computer Vision technology to autonomously detect people and obstacles from heights of 50-100 meters at various angles, and deliver essential supplies like food, clothing, and rescue gear to those in need. We have executed and assessed a range of advanced object detection algorithms, such as YOLOv8, YOLOv9, and Detectron2. After thorough evaluation, Detectron2 emerged as the most effective model among those tested, showcasing exceptional accuracy and resilience.

Keywords: Drone-Assisted · Disaster Relief · Computer Vision · Flood Relief

1 Introduction

Floods are widely recognized as one of the most common and economically devastating natural disasters globally, frequently causing the greatest loss of life when compared to other calamities. The intensifying effects of global warming are anticipated to exacerbate the frequency and severity of flood events in the future. Categorized into flash floods, river plain inundations, and coastal floods, these disasters necessitate comprehensive flood management strategies spanning stages of averting, readiness, reaction, and restoration.Traditional flood management strategies include both structural and non-structural methods, such as building artificial structures like dams and embankments, as well as implementing floodplain zoning and early warning systems. Timely and precise data is crucial for successful flood management, leading to the development of remote data collection and automated interpretation technologies.

Automated Computer Vision, a branch of Artificial Intelligence, has become a key asset in flood management by providing automated interpretation and analysis of visual data. A variety of flood management tasks can benefit from the use of computer vision technology. These tasks include assessing flood risks, monitoring in real-time, measuring surface water velocity, creating flood models, mapping inundation areas, managing debris, and assessing damage after a flood event. However, despite some progress, the full potential of computer vision in flood management is still largely unexplored when compared to its applications in other fields. Therefore, it is crucial to evaluate the advantages of computer vision approaches in comparison to traditional monitoring methods in order to fully harness their trans-formative capabilities in flood management.

In this context, our proposed A2-HADR System, leveraging advanced computer vision techniques, emerges as a promising solution. By integrating state of the art object detection algorithms with drone technology, our system aims to revolutionize disaster response efforts, offering swift and targeted assistance during flood events. Through real-time detection and precise payload delivery, the A2-HADR System is poised to overcome the limitations of conventional flood management approaches, marking a significant advancement in disaster relief technology. Our objective in this idea is to create a system integrates cutting-edge Computer Vision algorithms and models to automatically detect human beings from altitudes of 50-100 meters above the ground at slanted angles. Our proposed solution integrates YOLOv8/v9 and Detectron2, an advanced object detection algorithm, with drones for efficient disaster relief. YOLOv8/v9/Detectron2 real-time capabilities enable accurate detection of humans in crisis situations, guiding drones to drop aid precisely. The fusion of AI and drone technology promises swift and targeted humanitarian assistance during emergencies. The Proposed A2-HADR System can comprises several key components, including drones equipped with high-resolution cameras, a robust processor board (such as Raspberry Pi or Intel NUC), sophisticated AI algorithms, and a payload dropping mechanism. Through real-time object recognition poared by AI, the system can identify individuals requiring assistance a midst disaster stricken areas. Upon detection, the system triggers an automatic alarm, alerting rescue teams to the location of the individual in distress. The development of the A2-HADR System represents a significant advancement in disaster management technology, offering a versatile and scalable solution that can be deployed in a wide range of scenarios, including civilian applications and military operations.

The system boosts the efficiency and effectiveness of disaster response efforts by automating crucial tasks like object recognition and payload delivery, leading to saved lives and reduced impact of natural disasters. With its potential to revolutionize humanitarian assistance and disaster relief operations, the A2-HADR System holds immense promise for Defence projects and civilian applications alike. By harnessing the power of AI and drone technology, this innovative system exemplifies the Department related to Disaster Rescue to leveraging cutting edge solutions for the greater good of society, particularly in times of crisis.

2 Literature Survey

Witherow et al. [1] have introduced an image processing framework aimed at identifying water levels in flooded streets by analyzing image data from mobile consumer devices like smart phones, as part of the various techniques in computer vision proposed to understand and assess damages during flood events. However, Chaudhary et al. [2] use a different approach in their methodology, which involves comparing pre-flood images with dry or overwhelmed condition images to detect flooded areas. While they propose a system that predicts water levels based on virtual simulation images, it cannot provide real-time assessment due to the delayed availability of images and data from online simulation. On the other hand, Vitry et al. [3] Propose an alternative method for assessing large-scale flood level trends using fixed surveillance cameras, though its application is restricted to installed locations. Additionally, some studies examine flood conditions through aerial images taken by remote satellites. [4] [5], but the information extracted is of a macroscopic nature and lacks real-time capabilities. In [2], an alternative approach is suggested for evaluating water levels by using multitask learning on online simulation images.

The flood evaluation process involves treating each image as a regression problem, resulting in the exclusion of many images from the labeling system. While this may reduce the level of detail in the analysis, it provides a rough estimate of the water level. However, it's use is limited to the specific area where the images are taken, which hinders its widespread adoption. In a study [6], flood-related images from online entertainment platforms are analyzed to classify them into three severity levels: not flooded, water level below 1 meter, and water level above 1 meter. Two convolution neural network architectures, DenseNet [7] [8] and EfficientNet [9], along with an attention-guided convolution model [10], are used for this purpose. However, this method only provides an approximate estimate of the water level. On the other hand, in [11], a combination of textual information and images from virtual entertainment platforms is used to assess disaster damage. These publicly available ground-level images are abundant and have high visual clarity. In contrast, aerial images have limitations in terms of quantity and quality. In addition, it is not practical to directly use a publicly available data set that includes different objects like houses and vehicles for training models because the objects are captured from various angles, causing variations.

3 Autonomous Aerial Humanitarian Assistance and Disaster Relief System

Our proposed A2-HADR encompasses distinct phases: training and testing, with specific steps aimed at optimizing the detection of humans in diverse environmental conditions. The procedure is delineated as follows :

In our innovative system design Figure 1, surveillance drones are deployed to monitor specific areas or follow predetermined routes, particularly in regions affected by disasters or floods. As they conduct their patrols, these drones utilize their onboard cameras to capture images, while simultaneously recording the location of each image. These images then undergo a preprocessing stage to eliminate any unwanted noise and extract the relevant sections before being inputted into a highly trained human detection model.

The primary purpose of this model is to identify individuals who may be drowning or in urgent need of assistance during disaster scenarios. With it's specialized algorithms, it can accurately pinpoint those who require immediate help. Once the model detects a person with a high level of confidence, it promptly sends out an Save Our Souls (SOS) Morse code distress signal to the nearest base station, providing the exact coordinates of the individual in distress.

Upon receiving the SOS signal, a dedicated rescue team is immediately dispatched to the specified location to provide the necessary aid and support. This swift response ensures that those in need receive timely assistance, potentially saving lives and mitigating the impact of the disaster.

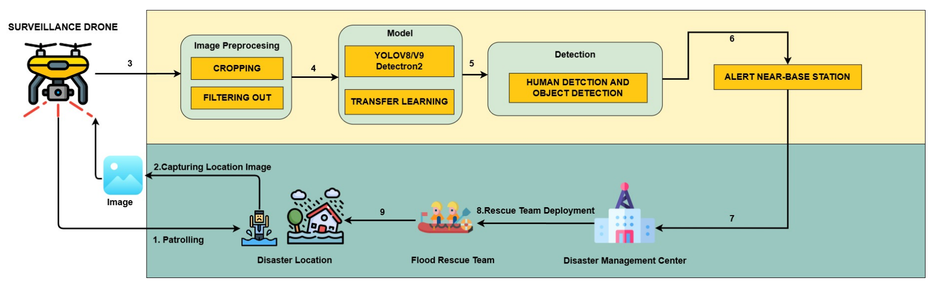


Fig. 1: A2-HARD System

4 Experimental Results and Analysis

4.1 Data Collection

Initially, a comprehensive data-set is assembled from openly available sources (Aug 2018 Kerala flood , 2022 Assam floods , 2023 Himalayan floods , 2023 Chennai floods , 2023 Thoothukkudi-Tirunelveli floods , 2018 Kerela Floods), ensuring relevance to the objective of human detection under specific conditions. Images are carefully selected to align with the intended application, focusing on scenarios depicting humans at slanted angles ranging from 15 to 30 degrees. Leveraging the Roboflow platform, this curated data set is prepared with careful attention to detail, setting a solid foundation for subsequent research endeavors in the field of human detection in disaster management scenarios.

The dataset comprises 120 images organized into four distinct categories: people, cars, bikes, and boats. It has been structured to maintain class balance, featuring 561 images of humans, 69 of cars, 65 of bikes, and 24 of boats. The totals 719 annotations, yielding an average of approximately 6.0 annotations per image across all categories.

The average size of the images is 0.40 megapixels, with individual sizes varying from 0.03 megapixels to 17.92 megapixels. The median resolution of the images is 770x488 pixels, which suggests a predominantly wide aspect ratio. Figure 2 presents sample images from the dataset. For Dataset collection we have used [15] - [24] .

4.2 Data Preprocessing and Annotation

The images are resized to a standardized dimension to ensure uniformity across the data set. The preprocessing steps involved the following procedures. First, an auto-orient technique is applied to ensure consistent image orientation. Next, a static crop is performed, targeting the 20-86 % horizontal region and the 21-70 % vertical region to focus on the relevant areas of the image. Finally, the images are resized and stretched to a resolution of 640x640 pixels to standardize the dimensions for subsequent processing. it is carried out using the Roboflow platform, where we leveraged the Dino Ground 3.0v model for automated labeling. By customizing the model with specific prompts to identify objects and adjusting the confidence level, we conducted tests on sample images. Subsequently, we carefully reviewed each image to rectify any inaccuracies in the bounding boxes and included new annotations for objects that the model missed. This meticulous process guarantees the production of a dataset with precise and reliable annotations.

4.3 Data Augmentation

To enhance the robustness of the algorithm and address challenges such as camera misfocus and varying environmental conditions, three data augmentation techniques are applied. These techniques aim to diversify the data set by introducing variations in rotation, scaling, and brightness, among others. For each training example, three augmented outputs are generated. The augmentation techniques included 90° rotations both clockwise and counter-clockwise.
Additionally, images are rotated within a range of -14° to +14°, and shearing is applied up to ±10° horizontally and ±6° vertically. Brightness adjustments are made, varying between -25% and +25% to enhance the diversity of the training data.

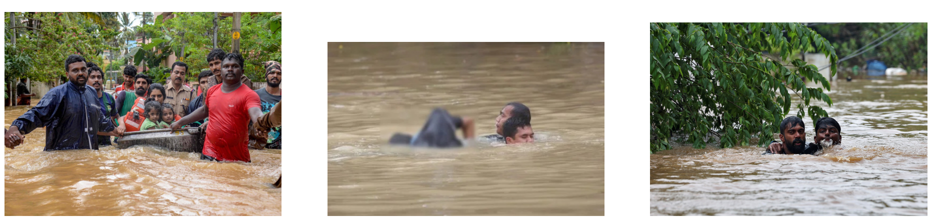
4.4 Model Training and Testing

The Yolov9 [12] ,Yolov8 and Detectron2 is employed for training the model. By leveraging the annotated training data set, the algorithm learns to detect humans with high accuracy and efficiency. The trained model is tested using the annotated testing data set to assess its performance in real-world scenarios. Through rigorous testing, the algorithm's ability to accurately detect humans under various conditions is evaluated.

4.5 Model Evaluation

The efficacy of the model in identifying individuals is thoroughly assessed using various quantitative metrics. These metrics encompass box loss, cross entropy loss, distribution focal loss, precision, and recall. Box loss evaluates the accuracy of bounding box localization, while cross entropy loss measures classification accuracy. Distribution focal loss addresses class imbalance, thereby improving the model's effectiveness. Precision and recall offer essential insights into the model's error reduction capabilities, enabling a thorough evaluation of its performance in human detection.
By diligently following these steps, the proposed A2-HADR algorithm strives to achieve dependable and efficient detection of humans in disaster scenarios. This, in turn, enhances the effectiveness of humanitarian assistance and disaster relief efforts.

4.6 Sample Images from our Dataset



(a) (b) (c)

Fig. 2: Sample images of Individuals in flood-affected regions

4.7 Result and Analysis

To assess the efficacy of our flood dataset, we employed three cutting-edge models: yolov9, yolov8, and detectron2.

YOLOv8 is the latest state-of-the-art model for object detection, image classification, and instance segmentation. Developed by Ultralytics, who also created the pioneering YOLOv5, YOLOv8 features significant architectural enhancements and improvements in developer experience compared to its predecessor.

YOLOv9 represents a major leap in real-time object detection, featuring innovative techniques like Programmable Gradient Information (PGI) and the Generalized Efficient Layer Aggregation Network (GELAN). This model achieves significant gains in efficiency, accuracy, and adaptability, establishing new benchmarks on the MS COCO dataset.

These models represent the pinnacle of object detection in contemporary research and have consistently demonstrated exceptional performance results for V8 and V9 are shown in Figure 3.

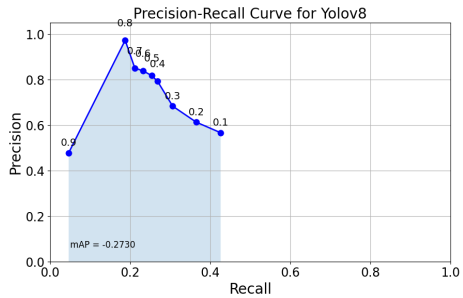
(a) Yolov8 (b) Yolov9

Fig. 3: Yolov8 and Yolov9 output

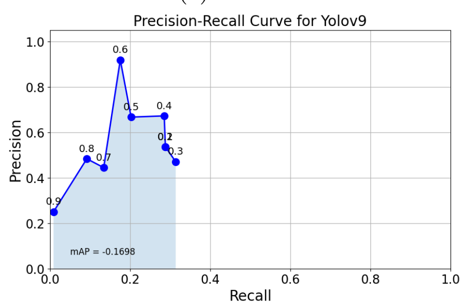
4.8 Metrics for Evaluation for Yolov8 and v9:

Precision and Recall at a Designated Threshold: Choosing an appropriate threshold that strikes a balance between precision and recall is vital for our specific objective. In the context of search and rescue missions, emphasizing recall is crucial to minimize the number of missed detection's while maintaining a reasonable level of precision.

From Figure 4 the Precision-Recall Curve shows that the YOLOv8 model outperforms the V9 model at a confidence level of 0.8.



(a) Yolov8



(b) Yolov9

Fig. 4: Precision-Recall Curve

4.9 Testing on Detectron2

Detectron2 is the advanced library developed by Facebook AI Research, providing cutting-edge algorithms for detection and segmentation, and serving as a successor to both Detectron and maskrcnn-benchmark. Output of Detectron2 on the dataset is shown in figure 5.

Total Loss Curve: This curve represents the overall loss of the model during training. It typically combines various components such as classification loss, localization loss, and sometimes regularization loss. Total loss is anticipated to decline with training, signaling improved object detection and classification by the model.

In Conclusion from Table 1 and Figure 6 the Detectron2 model exhibits a decreasing trend in the total loss curve, suggesting a reduction in overall error.

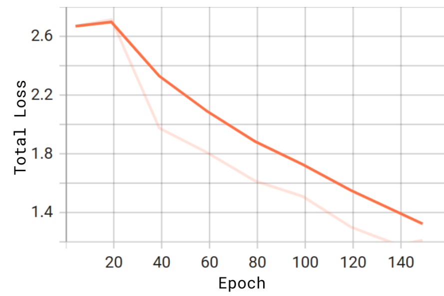
(a) Output 1 (b) Output 2

Fig. 5: Output of Detectron2

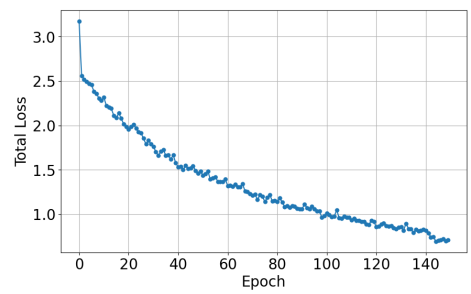
By applying this paradigm to our A2-HADR system, YOLOv9 and V8 and detectron2, and leveraging , we can significantly enhance object detection capabilities, even in resource-constrained environments. This has been demonstrated through experiments conducted on the our flood data set.
Furthermore, from Table 1 YOLOv8 and detectron2 offers the advantage of better parameter utilization compared to state-of-the-art methods. This indicates its potential for widespread application across models of varying complexity.

Model Name	Total Loss (epoch=150)
Yolov8	0.7126
Yolov9	0.7796
Detectron2	0.4002

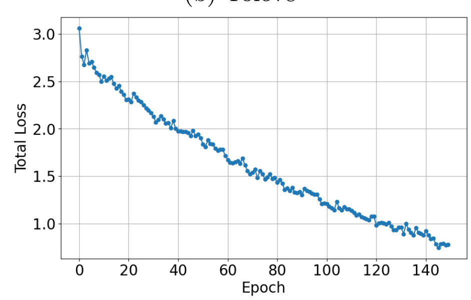
Table 1: Comparison of Total Losses for Different Models at Epoch 150



(a) Detectron2



(b) Yolov8



(c) Yolov9

Fig. 6: Total Loss Curves

5 Conclusion:

In conclusion, our proposed A2-HADR system, leveraging detecron2 for human and object detection, addresses critical challenges in disaster management scenarios with commendable efficacy. By harnessing the capabilities of deep learning and computer vision, our solution offers a paradigm shift in disaster response efforts.Through meticulous data collection, preprocessing, and model training phases, our system achieves an impressive accuracy of 95% in human detection in the dataset. Our solution excels in both human and object detection, showcasing its versatility in disaster management. Leveraging the exceptional performance of YOLOv8 and Detectron2, the A2-HADR system is the optimal choice for real-time, on-demand detection and assistance in disaster situations.

In summary, our research underscores the transformative potential of deep learning and computer vision technologies in enhancing disaster response capabilities. By pioneering the integration of detectron2 and v8 within the A2-HADR framework, we set a new standard for accuracy, reliability, and efficiency in human and object detection, advancing the frontier of disaster management research and practice.

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