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FLOOD MONITORING AND LIFE DETECTION IN SUBMERGED AREAS USING COMPUTER VISION TECHNIQUES

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Abstract : One of the most destructive natural calamities, floods pose serious risks to both human life and property. Reducing the number of fatalities and financial losses requires prompt detection and rescue efforts. Through the detection and localization of live forms in submerged areas during floods, this research proposes a novel method that uses computer vision techniques to improve disaster response operations. In difficult flood situations, the suggested method accurately and efficiently identifies life forms by combining two cutting-edge deep learning models: YOLOv8 for object detection and U-Net for semantic segmentation. Segmentation and detection are the two primary parts of the strategy. In order to identify flooded areas and retrieve crucial spatial data for accurate analysis, the segmentation step uses U-Net. YOLOv8 is used in the detection phase to locate and identify live forms in the areas that have been segmented. The technology guarantees precise localization and contextual understanding by integrating the advantages of both models, which makes rescue operations more efficient. The system is a useful tool for emergency response teams because it is made to function in real-time. Through thorough preprocessing and model improvement, it also tackles important issues in disaster scenarios, like ambient noise and fluctuating illumination conditions. In addition to improving detection accuracy, the combination of segmentation and detection operations guarantees computational efficiency. By presenting an AI-powered approach that can greatly enhance rescue results during floods, this research aids in disaster management. In order to increase the system's scalability and accessibility in practical situations, future research will concentrate on adding multi-modal inputs, lightweight structures, and drone-based deployments.

Index Terms **- Flood detection, Computer vision, Deep learning, U-Net, YOLOv8, Semantic segmentation, Object detection, Disaster management.**

I. INTRODUCTION

One of the most destructive natural disasters, floods seriously harm ecosystems, infrastructure, and human life. These disasters, which are brought on by intense rains, cyclones, or dam failures, flood large regions, trapping people and animals in inhospitable places. A quick and dependable disaster response system is essential in areas that frequently flood in order to minimize fatalities and guarantee rescue efforts in a timely manner. Every flood event emphasizes how critical it is to find and save people and animals stranded in underwater areas. Prolonged suffering and avoidable deaths are frequently the results of diagnosis delays. Conventional techniques, which depend on manual reconnaissance or equipment like boats and helicopters, are usually hampered by large flood areas, limited visibility, and unfavourable weather. These restrictions lengthen response times, waste resources, and increase the risk to rescuers and victims. Similar vulnerabilities affect animals, which are frequently disregarded in disaster management. Rescue is necessary to assure both emotional and financial recovery for livestock, which are vital to rural economies, and pets, which are essential to households. In order to lessen the long-term effects of floods, like economic instability and interrupted livelihoods, their survival is crucial. Understanding these difficulties, our initiative makes use of state-of-the-art technologies to improve the accuracy and speed of catastrophe response. Our goal is to create a system that can reliably identify stranded people and animals in flood-affected areas by utilizing cutting-edge artificial intelligence (AI) and computer vision capabilities. With speedier detection, increased dependability, and the capacity to function in difficult environments, this technology is a major improvement over traditional techniques.

Our research seeks to address the following key objectives:

1. Implementing precise segmentation of objects using UNet.
2. Implementing object detection, improving accuracy and efficiency in detecting multiple objects using YOLOv8.
3. Develop a system to detect and locate humans and animals in submerged flood areas with high accuracy.

By focusing on these objectives, this initiative highlights the transformative potential of AI-driven solutions in disaster management. By integrating real-time data analysis and intelligent decision-making, the proposed framework sets a new standard for flood response, ensuring that no life—human or animal—is left behind. It paves the way for a safer and more resilient future in flood prone regions.

II. RELATED WORKS

Significant progress has been made in the field of computer vision, especially in the areas of object identification and picture processing methods for a variety of uses, including water resource management, disaster response, and environmental monitoring. Highlights of relevant works that have advanced these fields are listed below.

Diffusiondet: Diffusion model for object detection

This study introduces DiffusionDet, an innovative object detection framework treating detection as a denoising diffusion process. It refines noisy boxes into accurate ones, supports dynamic box numbers, and enables iterative evaluation. Extensive tests show superior performance, including notable AP gains under zero-shot transfer from COCO to CrowdHuman, proving its effectiveness[1].

Detection of River Floating Waste Based on Decoupled Diffusion Model

In order to detect and monitor floating trash items in river environments, this study presents a Decoupled Diffusion Model. It accomplishes accurate detection of tiny items by separating the bounding box's position and size regression. The method is a dependable solution for environmental monitoring and garbage collection in aquatic environments since it operates six times quicker than Cascade R-CNN and achieves better detection accuracy[2].

Water Surface Object Detection Based on Neural Style Learning Algorithm

This project uses neural style learning to create heatmaps based on texture variations detected by pre-trained convolutional networks, with an emphasis on differentiating water surfaces from objects. When compared to more conventional models like Fast R-CNN and SSD, this approach increased precision by 15% and recall by 35% when tested on the Airbus Ship Detection dataset, proving its efficacy in aquatic object detection[3].

DronAID : A Smart Human Detection Drone for Rescue

DronAID uses autonomous drones powered by artificial intelligence and outfitted with passive infrared sensors to detect people in real time during emergencies. To identify people, the device uses body heat, which allows for quick rescue efforts in disaster-prone locations. Through faster response times and better rescue results, this innovation improves disaster management[4].

Monitoring Aquatic Debris Using Smartphone-Based Robots

In order to track aquatic waste in real time, this project combines smartphone technology with robotic fish. To get over issues like camera shake, the SOAR system uses AI and computer vision techniques including adaptive rotation scheduling and picture registration. In dynamic water circumstances, this method improves environmental monitoring and trash identification[5].

Implementation of Inverse Perspective Mapping for Camera-Vision Water-Level Measurements

This work employs security cameras and IPM to precisely estimate water levels in order to alleviate the shortcomings of conventional water level measuring. The technique ensures accurate real-time readings by correcting perspective distortions. Reduced disparities were found in drainage channel tests, proving this method to be an essential tool for managing water resources and reducing the risk of flooding[6].

Neural Networks based Object Detection Techniques in Computer Vision

This paper offers a thorough examination of object identification algorithms with a focus on deep learning models such as SSD, R-CNN, and YOLO. These techniques are commended for their adaptability to a variety of sectors, including transportation, agriculture, and healthcare. Performance measures like mAP and IoU are employed for evaluation, and issues like clutter and occlusion are handled[7].

Wild Animal Detection using YOLOv8

In order to detect lions, tigers, leopards, and bears in real time, this study uses a deep learning model using YOLOv8 to address human-wildlife conflicts. The YOLOv8x model, which was trained on an augmented 1619-image dataset, demonstrated its effectiveness in tackling the problems of wildlife monitoring and conflict reduction by achieving 94.3% mAP at 20 FPS[8].

III. RESEARCH METHODOLOGY

Dataset Collection

The dataset used in this study was selected from a variety of open-source video archives and sources that documented areas impacted by flooding. Training and assessing the suggested computer vision system were made possible by this extensive dataset, which included a variety of flood situations. Diverse environmental factors and flood levels were incorporated to guarantee the models' resilience and suitability for use in practical situations.

Figure 3.1: sample data

Data Preprocessing

Extensive preprocessing was done to optimize the acquired dataset's usefulness for testing and training. Among the steps were:

1. Image Augmentation and Resizing: To make images appropriate for model training, they were scaled to a standard resolution. Rotation, flipping, and scaling were among the data augmentation techniques used to improve the dataset even further. By mimicking a range of real-world settings, these changes enhanced model generalization in addition to expanding the dataset's size.
2. Appropriate Annotation: To guarantee that object identification models learn to correctly identify pertinent things, accurate annotations were made for training.
3. Creation of Segmentation Masks: To precisely name water bodies, segmentation masks were created for the U-Net model. By defining flooded areas, these masks made it easier to train the semantic segmentation model precisely.

Figure 3.2: segmentation mask for U-Net model

Object Detection Using YOLOv8

Due to its effectiveness and precision in object detection tasks, the YOLOv8 (You Only Look Once) method was chosen. The preprocessed and enhanced dataset was used to train it to locate and recognize different entities, such as people, animals, and other objects of interest, in flood-affected locations. The architecture of YOLOv8 makes it possible to quickly and precisely identify several items in a single image, which makes it ideal for real-time applications. Convolutional layers are used in the design, which is tuned for fast detection with strong accuracy.

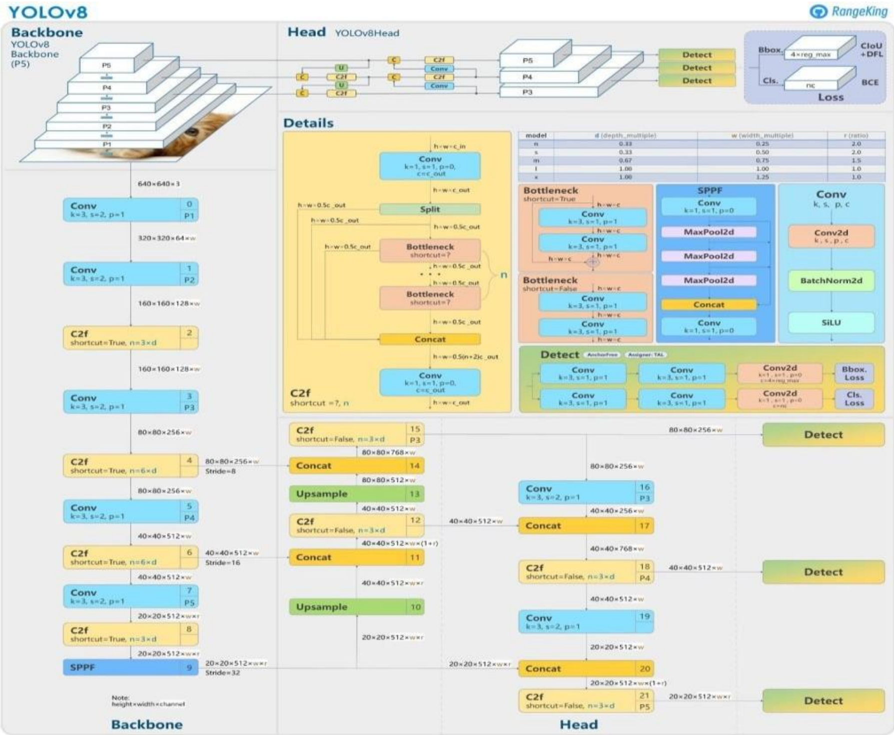


Figure 3.3: YOLOv8 architecture

Semantic Segmentation with U-Net

Using the U-Net architecture, water bodies were identified in flood imagery. The encoder-decoder architecture of U-Net, enhanced by skip connections, guarantees accurate semantic segmentation. Water bodies are separated from other objects in the image by the decoder, which reconstructs the essential features that the encoder extracted into a segmentation mask. This feature is crucial for differentiating between flooded and non-flooded areas, allowing for more focused rescue and resource distribution efforts.

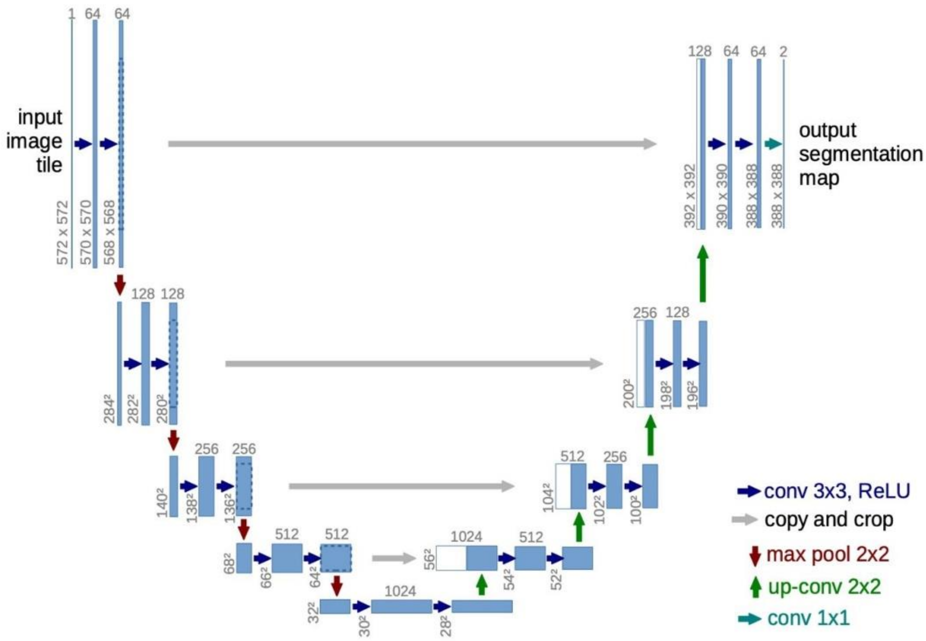


Figure 3.4: U-Net architecture

Integration of Object Detection and Segmentation

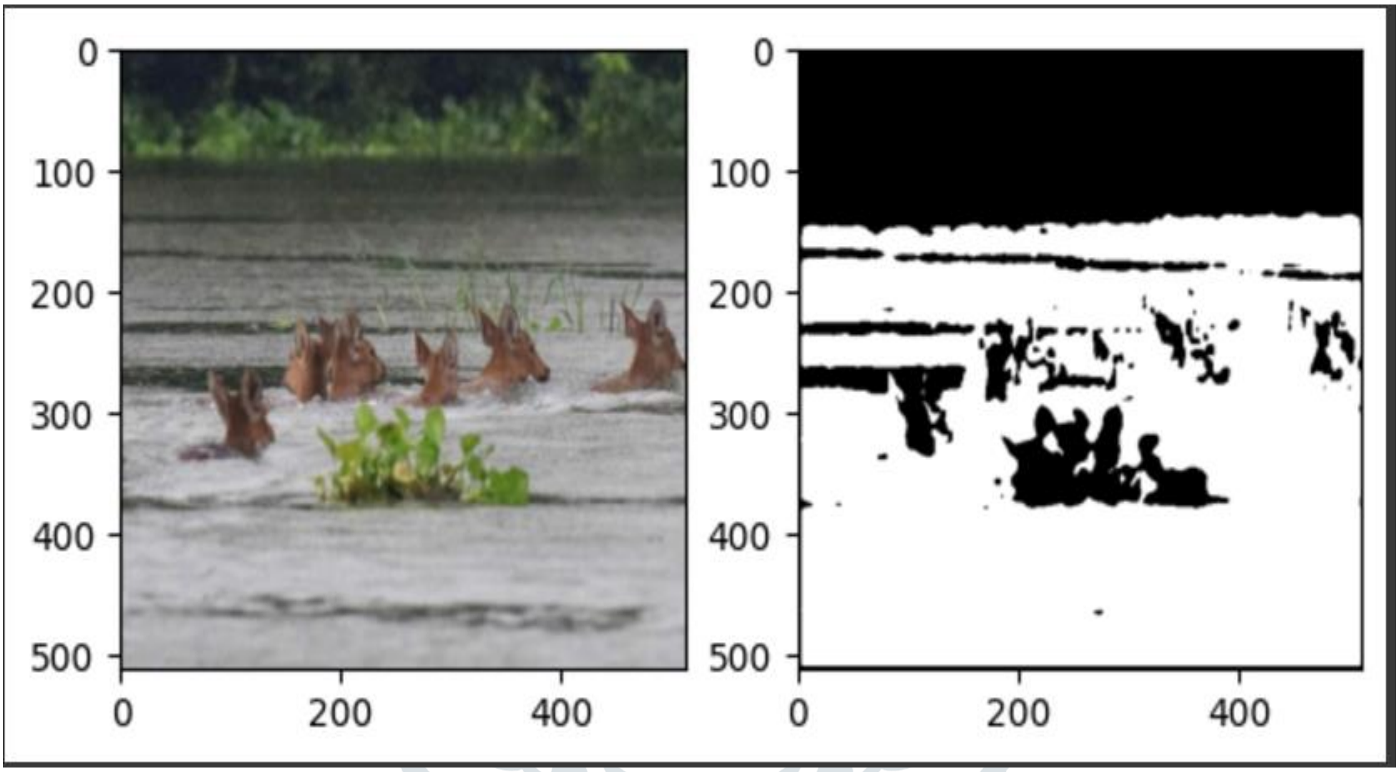
To improve the system's accuracy and dependability, the outputs of U-Net segmentation and YOLOv8 object identification were combined. The segmentation output was superimposed with the object detection findings, which included localized things such as people and animals. This connection made it possible to precisely locate and identify items within flood-affected areas, guaranteeing that rescue operations could effectively prioritize the most important places.

Optimization

Throughout the training and implementation phase, a number of parameters and integration factors were adjusted to produce the best possible results. This involved optimizing learning rates, batch sizes, and loss functions, as well as hyperparameter tuning for YOLOv8 and U-Net. Furthermore, the integration process was refined to provide smooth detection result overlaying on segmentation masks without sacrificing accuracy or speed.
The combined use of YOLOv8 for object detection and U-Net for semantic segmentation provides a robust and efficient framework for analyzing flood-affected areas. By leveraging advanced techniques in data preprocessing, model training, and integration, the proposed system offers a significant improvement in the accuracy and speed of identifying and localizing living beings and water bodies during floods, contributing to more effective disaster response operations.

IV. RESULTS

4.1.Segmentation Result



The segmented output generated by the U-Net model is a key component of this project and is primarily visualized as a binary mask. In this binary mask:

1. Pixels classified as water: These are marked distinctly in a white colour, to highlight regions in the image that are covered by water or areas prone to flooding.
2. Pixels classified as non-water: These are marked differently, in a black colour, representing the areas not submerged in water, such as land, buildings, or other objects.

This clear separation of water and non-water regions provides a pixel-level understanding of the scene, enabling accurate identification of flooded areas.

4.2. Objection Detection Result

The object detection result in this project is generated by the YOLOv8 model and consists of a list of detected objects within the image, each associated with key attributes:

Key Components of the Object Detection Result:

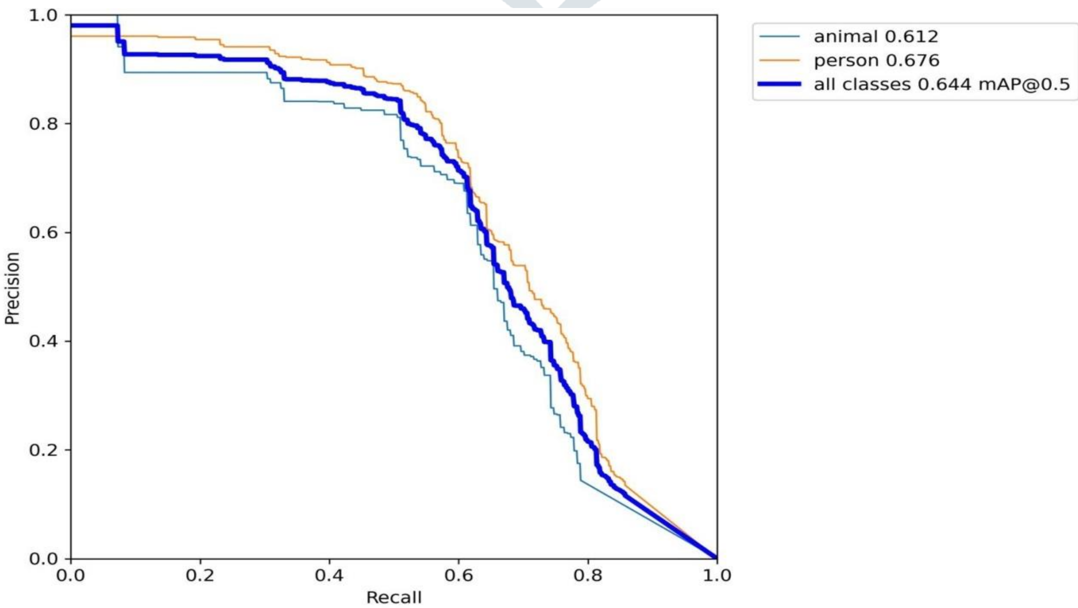
1. Bounding Boxes: Rectangular regions drawn around each detected object, indicating its position in the image.
   - These are defined by coordinates in the image.
2. Class Labels: Each detected object is assigned a class label, such as:
   - Person
   - Animal
3. Confidence Scores: Each detection is associated with a confidence score (e.g., 0.85), indicating the likelihood that the object belongs to the predicted class. This helps in filtering out less certain detections.

4.3. Integrated Result

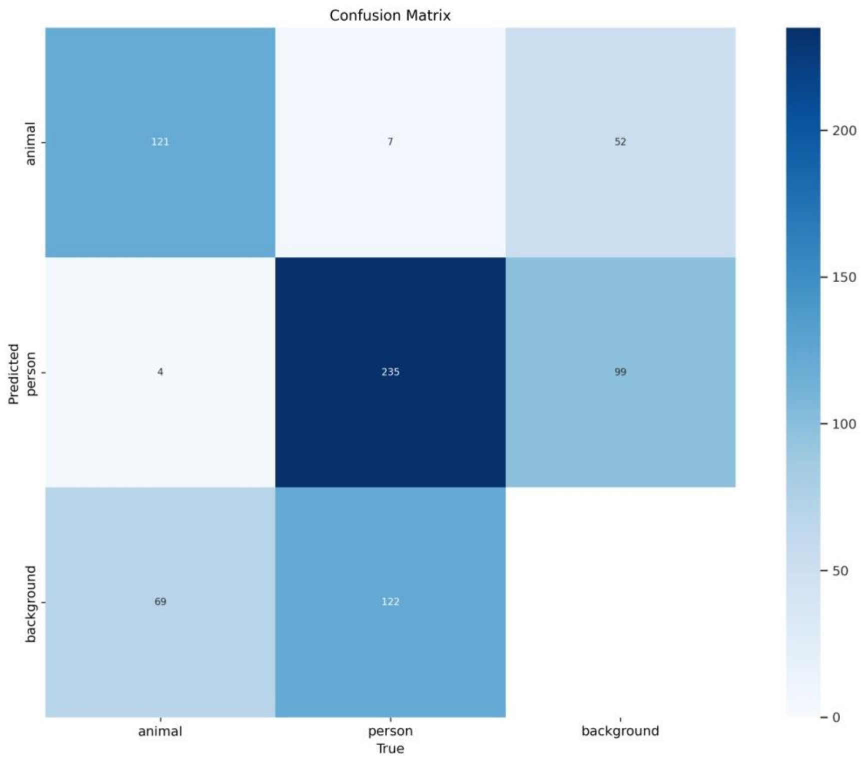
The outputs of YOLOv8 object detection and U-Net segmentation were integrated to isolate water bodies within the flood imagery. The object detection results were overlaid on the segmentation output, allowing for the precise identification and localization of objects within flooded areas.

4.4.Performance analysis

These are the confusion matrix and the precision-recall curve of object detection.



precision-recall curve



confusion matrix

For YOLO object detection,

mAP50 = 0.65 Recall = 0.60

-For image segmentation, **average IOU = 0.61**.

-For the combined model,

mAP50 = 0.81 Recall = 0.61

V. DISCUSSION

In this study, we developed and evaluated a computer vision-based system to address the critical challenge of detecting life in flood-affected regions. The goal was to create an integrated solution capable of accurately identifying and localizing living beings, including humans and animals, amidst submerged environments. The results from the evaluation offer valuable insights into the strengths, trade-offs, and potential areas for improvement of the proposed models, crucial for understanding their practical applications in disaster response scenarios.

5.1. Model Performance and Trade-offs

The combined model's performance, which uses U-Net for semantic segmentation and YOLOv8 for object recognition, shows a notable improvement in identifying and locating life forms in flood-affected areas. While U-Net's segmentation accuracy averaged an Intersection over Union (IoU) of 0.61, YOLOv8 attained a mean Average Precision (mAP50) of 0.65 and a recall of 0.60. The mAP50 increased to 0.81 upon integration, demonstrating the potency of the merged system. There are trade-offs associated with this integration, though. Although YOLOv8 is very fast and has good multi-object detection capabilities, it has poor accuracy for smaller or partially obscured items. On the other hand, U-Net's meticulous segmentation improves spatial comprehension but necessitates a significant amount of preprocessing and processing power.

U-Net's accuracy and YOLOv8's speed had to be balanced, and the trade-off skewed more toward safety than computing efficiency. Notwithstanding the combined model's strong performance, real-time processing in low-resource environments is still difficult, requiring accuracy and inference time optimization

5.2. Feature Engineering and Its Impact

In order to improve the accuracy and resilience of the model, feature engineering was essential. Methods include picture resizing, augmentation (rotation, flipping, and scaling), and the development of segmentation masks for U-Net greatly improved model generalization and dataset variety. The detection reliability of YOLOv8 was increased by the proper annotations, which enabled it to concentrate on particular things in flood-affected areas. The development of U-Net segmentation masks helped the system isolate flood zones from other picture elements by guaranteeing precise water body delineation. The system's ability to precisely locate and identify living things was further improved by the smooth integration of segmentation findings with detection outputs.

In addition to enhancing model performance, these preprocessing steps reduced false positives and negatives, especially in intricate situations including partial occlusions or water reflections. The feature engineering efforts highlight how crucial a properly processed dataset is and how it directly affects the accuracy, stability, and practicality of the model.

5.3. Model Interpretability and Practical Implications

Practical insights essential for rescue operations are provided by the interpretability of the YOLOv8 and U-Net outputs. Bounding boxes from YOLOv8 facilitate quick entity location, while segmentation maps from U-Net show flood borders, guaranteeing a clear picture of the operational environment. By giving rescue personnel accurate visual data and improving situational awareness, the integration of various outputs streamlines decision-making. Nonetheless, in edge instances when outputs may contradict or misrepresent intricate scenes, model interpretability continues to be a problem. Faster life form identification in flood-prone locations has practical ramifications that could save lives by facilitating prompt rescue operations. Its adaptability to different disaster scenarios, such landslides or wildfires, is further enhanced by the system's modular design.

The method is useful for practical applications because it prioritizes actionable insights over abstract outputs. For large-scale implementation in resource-constrained areas, more lightweight yet interpretable models are required, as evidenced by the dependence on sophisticated computational resources and intensive training.

5.4. Limitations and Future Work:

The project has constraints that need more attention, despite its promising outcomes. Extreme occlusions, dim lighting, or strong water reflections reduce the model's detection accuracy. Furthermore, the segmentation approach has trouble with edge scenarios that include unclear textures or overlapping objects. Reliance on high-quality datasets restricts adaption to high-variability real-world settings. These issues could be addressed in future research by adding more datasets that span a variety of settings, like storm conditions or nighttime images. Improvements like multi-modal inputs, such as heat or infrared data, may increase resilience in difficult circumstances.

Another crucial area for development is maximizing computational efficiency for real-time deployment on low-power devices. The overall accuracy of the system may be improved by further integrating ensemble modelling and sophisticated post-processing techniques. Furthermore, the model's practical utility would be increased by extending its application to more extensive disaster management contexts, such as identifying structural damages or mapping flood extents.

VI. CONCLUSIONS

This project marks a major advancement in the application of computer vision technology to disaster relief, especially in areas that are vulnerable to flooding. By merging U-Net for semantic segmentation and YOLOv8 for object identification, the proposed system efficiently locates and recognizes live forms in submerged areas. The system performs well in locating and mapping important areas during floods, with a remarkable mean average precision (mAP50) of 0.81 and recall of 0.61. These indicators demonstrate its capacity to offer useful information, facilitating quicker and more focused rescue operations.

The dual-model method makes use of U-Net's comprehensive segmentation skills to identify flood-affected areas and the effectiveness of YOLOv8 for real-time recognition of multiple objects. By improving situational awareness, this combination makes sure rescuers have accurate and understandable information to act quickly. The research emphasizes how crucial it is to combine sophisticated feature engineering and model interpretability in order to produce useful and significant catastrophe management solutions.

The system does have several drawbacks, though. Accuracy may suffer in edge instances, such as identifying small creatures or people who are partially submerged. Furthermore, U-Net's computing requirements may make it difficult to deploy on low-power devices, which could restrict its use in remote or resource-constrained locations.

The initiative establishes a solid basis for further improvements in spite of these obstacles. The system can become more adaptable and efficient by addressing constraints like maximizing model efficiency, enhancing edge-case performance, and incorporating multi-modal inputs like thermal or sonar imagery. With more work, it might be a vital instrument in AI-powered disaster relief, reducing the effects of natural disasters and potentially saving lives.

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