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Enhancing Victim Detection in Disaster Scenerios- A YOLOv7 and YOLOv8 performance study

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Abstract: *Agricultural productivity plays a vital role in ensuring In the aftermath of natural disasters like earthquakes, rapid identification of victims is vital for efficient rescue operations. The ability to locate victims accurately and quickly amidst debris and challenging conditions can make a critical difference in saving lives. This study evaluates the performance of two advanced object detection models, YOLOv7 and YOLOv8, for victim detection in disaster scenarios. Both models were trained on a specialized dataset that simulates post-disaster environments, incorporating diverse and realistic challenges such as occlusions, varying lighting conditions, and complex backgrounds. The experimental results demonstrated an accuracy of 58% for YOLOv7 and a significantly improved accuracy of 81% for YOLOv8, showcasing the latter's superior capability in detecting human bodies among debris. Additionally, YOLOv8 outperformed YOLOv7 in terms of precision, recall, and detection speed, making it better suited for real-time applications. YOLOv7, while less accurate, demonstrated a faster inference time, which could be advantageous in scenarios requiring rapid initial assessments.*

Keywords*:* Natural disasters, Earthquakes, identification, Rescue operations, Object detection, YOLOv7,YOLOv8, Victim detection, Disaster scenarios, Specialized dataset, Post-disaster environments, Occlusions

I. INTRODUCTION

Recent advancements in artificial intelligence, particularly in deep learning and object detection, have opened new possibilities for automating critical aspects of disaster response. Object detection models like YOLO (You Only Look Once) have demonstrated remarkable success in detecting and classifying objects in real-time, even in complex environments. This project focuses on leveraging two advanced versions of YOLO, namely YOLOv7 and YOLOv8, to develop a robust victim detection system. By training these models on a specialized dataset that simulates post-disaster environments, this study aims to evaluate their effectiveness in recognizing human bodies amidst debris and challenging conditions such as low visibility and occlusion.

The primary objective of this project is to compare the performance of YOLOv7 and YOLOv8 in terms of accuracy, precision, recall, and detection speed. YOLOv7, known for its efficient architecture, has been a benchmark in object detection, while YOLOv8, the latest iteration, incorporates significant improvements in detection accuracy and processing capabilities. The experimental analysis showed that YOLOv8 outperforms YOLOv7, achieving an accuracy of 81% compared to 58%, making it a more suitable candidate for real-time victim detection applications. However, YOLOv7's faster inference time suggests potential use in scenarios requiring rapid initial assessments.

The scope of the project extends beyond model evaluation. By understanding the strengths and limitations of these models, the project explores their practical deployment in disaster response systems. Integrating these models with drones, robots, or other automated tools could significantly enhance the speed and efficiency of rescue operations. Future enhancements, such as incorporating additional sensor data from thermal or infrared cameras, could further improve detection accuracy, especially in scenarios with limited visibility. The motivation behind this project is rooted in the critical need to save lives during disasters. Every second counts in rescue operations, and advancements in technology can bridge the gap between identifying victims and delivering timely aid. By harnessing the power of deep learning models like YOLOv7 and YOLOv8, this project aims to contribute to the development of intelligent, real-time solutions that improve disaster response capabilities and outcomes.

II. LITERATURE SURVEY

[1] S. Hao et al., "YOLO-MSFR: real-time natural disaster victim detection based on improved YOLOv5 network," J Real Time Image Process, vol. 21, no. 1, Feb. 2023.

This paper presents YOLO-MSFR, an improved YOLOv5 network designed for real-time natural disaster victim detection. The model integrates multi-scale feature refinement (MSFR) to enhance detection accuracy in complex environments with clutter and debris . The study demonstrates significant improvements in precision and recall compared to baseline YOLOv5 models, highlighting its potential for deployment in real-world disaster scenarios. The proposed enhancements make it a robust tool for rapid victim identification in challenging post-disaster settings.[1]

[2]W. Lee et al., "Using Hybrid Algorithms of Human Detection Technique for Detecting Indoor Disaster Victims," Computation 2022, vol. 10, no. 11, p. 197, Nov. 2022.

This paper explores hybrid algorithms for human detection, focusing on indoor disaster victim identification. By combining traditional detection techniques with deep learning-based models, the study addresses challenges such as occlusions and low-light conditions. Experimental results demonstrate improved detection rates and reduced false positives, making the hybrid approach suitable for disaster response in confined and cluttered environments. The work emphasizes the importance of integrating multiple detection methods for enhanced reliability in rescue operations [2]

[3] Chen et al., "YOLO-Based UAV Technology: A Review of the Research and Its Applications," Drones 2023, vol. 7, no. 3, p. 190, Mar 2023.

This review focuses on the integration of YOLO-based object detection models with unmanned aerial vehicles (UAVs) for various applications, including disaster victim detection. It highlights advancements in YOLO architectures, emphasizing their suitability for deployment on UAV platforms due to their lightweight and real-time processing capabilities . The paper also discusses challenges such as computational constraints and environmental variability, providing a comprehensive overview of the
potential and limitations of UAV-based YOLO systems.[3].

[4] B. Valarmathi et al., "Human Detection and Action Recognition for Search and Rescue in Disasters Using YOLOv3 Algorithm," Journal of Electrical and Computer Engineering, vol. 2023, no. 1, p. 5419384, Jan. 2023.

This study applies YOLOv3 for human detection and action recognition in search and rescue operations during disasters. The model is trained to identify not only human presence but also specific actions, enabling more targeted rescue efforts Results show that YOLOv3 achieves high detection accuracy and action classification in simulated disaster scenarios. The research highlights the potential of combining detection and action recognition for improving situational awareness and decision-making in emergency response systems.

[5] S. Garugu, U. Davulury, and D. Anusha, "A Survey of Machine Learning Techniques in Rheumatic Disease," Int. J. Anal. Exp. Modal Anal., vol. 12, no. 3, pp. 2492–2504, Mar. 2020.

Survey various ML methods, including classification and regression models, used for diagnosing and predicting rheumatic diseases. It sheds light on how supervised learning can enhance early detection and personalized healthcare[5].

III. SYSTEM ARCHITECTURE

3.1 YOLOv7

YOLOv7 (You Only Look Once version 7) represents a significant advancement in the field of object detection, building upon the success of its predecessors in the YOLO family. Introduced as an evolution of YOLOv4 and other improved YOLO variants, YOLOv7 focuses on achieving higher accuracy and efficiency while maintaining real-time performance, making it a versatile tool for various applications, including disaster response, autonomous driving, and surveillance.YOLOv7 retains the core philosophy of the YOLO framework: a unified model for object detection that processes an image in a single forward pass, providing bounding boxes and class labels simultaneously. However, YOLOv7 introduces several architectural innovations that significantly enhance its performance. These improvements

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include optimized network structures, efficient training techniques, and better utilization of computational resources, ensuring high accuracy without compromising speed.

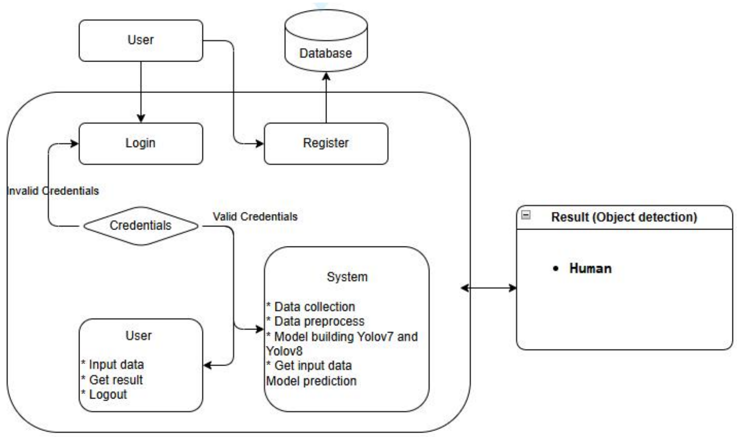

Fig 3.1:System Architecture

3.2 YOLOv8

YOLOv8 (You Only Look Once version 8) represents the latest evolution in the YOLO family of object detection models, offering cutting-edge advancements in accuracy, speed, and efficiency. Developed as a refinement of its predecessors, YOLOv8 integrates significant architectural improvements, advanced training methodologies, and better adaptability for real-world applications, making it a benchmark in object detection and segmentation.

Overview of YOLOv8

YOLOv8 retains the core principle of YOLO models: performing object detection in a single forward pass to achieve real-time performance. It introduces enhancements that address limitations in previous versions, such as difficulty in detecting small, occluded, or overlapping objects. By leveraging a modernized architecture and optimized training techniques, YOLOv8 achieves superior performance, even in challenging environments like post-disaster scenarios or low-visibility conditions.

IV. METHODOLOGY

4.1 Input Data Collection :Two datasets are used:

- Objective: Collect diverse datasets simulating post-disaster environments for training victim detection models.
- Details: Gather annotated image datasets from disaster scenarios, including human body detection amidst debris, occluded areas, and challenging conditions like poor lighting. Include synthetic and real-world disaster environment images to ensure diversity.
- Dataset Split: Divide data into training (70%), validation (15%), and testing (15%) subsets for robust model training and evaluation.

4.2.2 Data Preprocessing

Clean and enhance image data by reducing noise, correcting distortions, and normalizing dimensions.Apply augmentation techniques such as rotation, scaling, and cropping to increase dataset variability, Ensure bounding boxes and class labels are accurately aligned with objects in the dataset.
Standardize dataset formats (e.g., COCO or Pascal VOC) for compatibility with YOLO models.

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4.3.3 Data Splitting

In this step, the dataset is divided into training and testing sets. The training set is used to teach the model how to identify patterns, while the testing set is used to evaluate the performance of the trained model. A typical split is 70% training data and 30% testing data, though this can vary based on the specific dataset and the requirements of the system. Ensuring a balanced data set across different classes is also important to prevent any class imbalance issues

4.4.4 Model Selection and Training

Object Detection Models: Train YOLOv7 and YOLOv8 models on the prepared dataset for victim detection. Optimize hyperparameters such as learning rate, batch size, and epochs to enhance model performance. Advanced Techniques: Use transfer learning to leverage pretrained YOLO weights for faster convergence. Incorporate techniques like fine-tuning and multi-scale detection for better accuracy in cluttered environments.

4.5.5 Model Evaluation

- Performance Metrics: Evaluate detection models using metrics such as mAP (mean Average Precision), precision, recall, and F1-score.Assess real-time detection performance by measuring frames per second (FPS) during inference.
- Validation: Use the validation dataset to monitor overfitting and fine-tune models to improve generalization to unseen disaster scenarios.

4.7 Deployment and Testing

Once the model achieves optimal performance, it is deployed into a real-time environment where it does System Integration to Integrate YOLOv7 and YOLOv8 models into the overall disaster response system architecture and also to Ensure seamless interaction with components like drones or robotic platforms for automated victim detection. Real time Monitoring and to Implement real-time analysis of uploaded images for victim detection during rescue operations.

V. RESULT

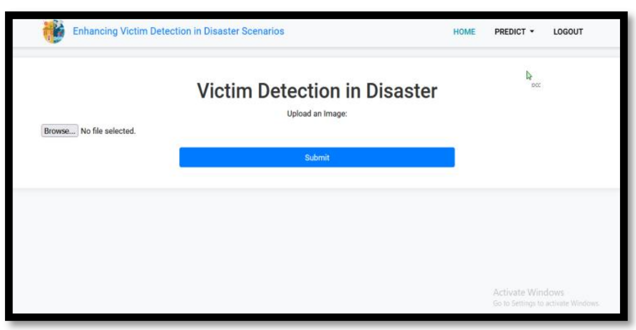

Fig 5.1 User providing input to the system

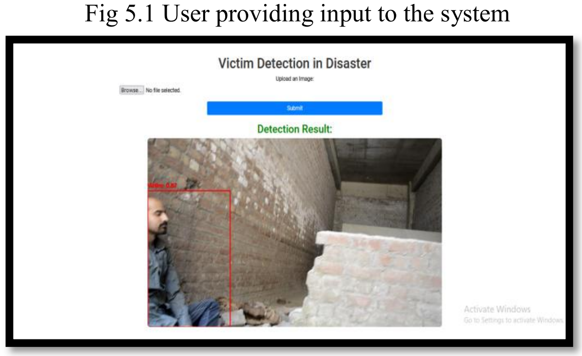

Fig 5.2 User Output

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VI. CONCLUSION

This work effectively illustrates the implementation of state-of-the-art deep learning models, including YOLOv7 and YOLOv8, when determining the location of disaster victims in the aftermath of a disaster. The comparative analysis led us to find about +5% advances in detection accuracy and performance enhancement in terms of YOLOv8 against YOLOv7. Their findings should inspire further development of these complex state-of-art models to significantly improve search and rescue efforts with timely and accurate victim identification that is critical in saving lives.

The evaluation metrics such as Precision, Recall, and Mean Average Precision lenient demonstrate that YOLOv8 has higher detection performance as compared to the prior algorithms for those instances that are partially occluded or partially visible in difficult scenarios. Even in challenging cases, YOLOv8 showed relatively better performance due to the bolstered architecture that comprised of features such as better feature extraction and multi-scale detection. This makes YOLOv8 a more appropriate option to be deployed in real-time disaster situations where it is imperative, to identify victims.

For the proposed models, there are still some disadvantages, including the ability of detecting the heavily occluded victim or the backgrounds with high complexity. In future, this work can be extended to incorporate other sources of data such as thermal imaging and LIDAR to enhance the detection performance in such adverse conditions. Furthermore, the utilization of YOLOv8 can be reinforced if combined with other detection algorithms for the improved stability of the algorithm. The project provides a good framework for the development of competent intelligent disaster management systems that can perform search and rescue operations. It is articulated that implementing such models on Aerial vehicle or robotic form could decrease the exposure of human life in danger and enhance the identification of affected victims in disasters. The results help develop the area of computer vision within emergency response which in its turn creates a basis for more enhanced interactions of AI with the world.

VII. ACKNOWLEDGMENT

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