Human Detection in Disaster Scenarios for Enhanced Emergency Response Using YOLO11

Md Sadiq Z Pattankudi, Samarth Uppin, Abdul Rafay Attar, Kunal Bhoomaraddi, Rohan Kolhar and Sneha Varur

Department of SOCSE, KLE Technological University Hubballi, Karnataka, India

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Abstract: In disaster scenarios, the ability to rapidly and accurately detect key elements such as rescuers, victims, vehicles, and dangerous objects is crucial for effective and timely rescue operations. This research proposes applying You Only Look Once(YOLO11), a real time object detection model to detect aerial images captured by drone. To train the model, a custom dataset was created, containing four classes—rescuer, victim, vehicles, and dangerous objects—representing critical components in disaster environments. This dataset provided a comprehensive and controlled environment to evaluate the system's performance. The results demonstrated that the proposed system significantly enhances decision making processes, particularly in locating and rescuing human survivors during emergency situations. The model achieved an overall precision of 82.4%, recall of 30.5%, a mean Average Precision at IoU 50 (mAP50) of 36.1%, and a mean Average Precision (mAP) at IoU 50-95 (mAP50- 95) of 16.4%. These performance metrics highlight the reliability of the model in identifying critical objects in real time, with opportunities for further refinement to improve recall and precision balance, making it a valuable tool for disaster response teams.

1 INTRODUCTION

Natural disasters(Li et al., 2023) have a severe impact on human life(Baez et al., 2010), and with the rise in global warming, the frequency of events such as floods has significantly increased(Banholzer et al., 2014). Recent extreme weather events in Kerala have highlighted the ongoing challenges posed by climate change and vulnerabilities in infrastructure (Chaudhary and Piracha, 2021). Rapid response and efficient resource allocation are critical to minimizing casualties and reducing damage. However, the scale and unpredictability of such events make traditional methods of disaster management challenging. In recent years, Unmanned Aerial Vehicles (UAVs)(Das and Roy, 2023) have emerged as a significant technology in disaster management. Their ability to navigate through inaccessible terrains, capture high-resolution imagery, and deliver real-time data has revolutionized emergency response strategies(He et al., 2016; Sandino et al., 2021). UAVs have been successfully deployed to assess disaster-hit regions, monitor the extent of damage(Rahman et al., 2024b), and identify people in need of assistance. Research demonstrates that UAVs significantly reduce emergency response times and enhance situational awareness(van Tilburg and Kaizer, 2021), making them invaluable assets in the aftermath of natural disasters (Goodchild and Glennon, 2019). Parallel to advancements in UAV technology, object detection models have seen rapid evolution, with You Only Look Once (YOLO)(Terven et al., 2023) becoming a cornerstone in real-time image processing, It is a state-of-the-art object detection model that has shown remarkable performance in terms of both speed and accuracy(Sharma and Yadav, 2023). The recent development of these models has further enhanced its capabilities, making it highly suitable for real-time applications where both detection speed and precision are paramount. In drone-based disaster response and ability to detect objects accurately in aerial images becomes essential for identifying survivors, vehicles in complex and cluttered environments. Our work contributes to enhancing UAV-based disaster response by training a custom YOLO 11 model on a disaster-specific dataset containing classes such as rescuer, victim, vehicles, and dangerous objects(Patel and Sharma, 2023). The model is trained to identify critical elements in aerial

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images captured during emergencies, enabling rapid assessment and resource allocation in complex environments.

The primary objectives of our study are:

- To create a diverse dataset that captures common disaster scenarios, including flood zones and post-earthquake environments, with an emphasis on detecting humans, vehicles, and hazardous objects.
- Develop a YOLO 11-based object detection framework specifically optimized for drone imagery in disaster scenarios, building on this dataset.
- Evaluate the framework comprehensively based on critical metrics such as detection accuracy, inference speed, and real-time processing capabilities to ensure its reliability.

The paper contains the sections as follows:
Section II reviews literature survey, highlighting recent advancements in disaster response and object detection models. Section III of the paper provides a background study, offering an overview of key concepts used in UAV-based disaster management. Section IV outlines the proposed methodology, detailing data collection, model training, and deployment strategies. Section V represents the results and discussions, analyzing the performance of the system in various disaster scenarios. Finally, Section VI concludes with a summary of findings and explores potential directions for future research and implementation.

2 LITERATURE SURVEY

The integration of AI and drones for disaster management, particularly in search-rescue operations, has garnered attention in recent years. Drones equipped with AI algorithms are used for multiple tasks that include *damage assessment*, *victim localization*, and *resource allocation*. AI enables drones to autonomously detect critical objects, such as humans, vehicles, and infrastructure damage, which is crucial in situations where human intervention is limited or unsafe (Papyan et al., 2024). Object detection models, particularly those using *deep learning techniques*,(Deng and Yu, 2014; Alom et al., 2018) have shown promise in improving the efficiency of disaster response by enabling real-time identification and classification of objects in complex environments (Nehete et al., 2024).

Existing AI-based solutions for disaster management often rely on *signal-based detection*, such as mobile phone triangulation, which can be unreliable in areas where infrastructure is damaged or where survivors do not have access to mobile phones (Pan et al., 2023). This has led to an increasing interest in integrating *visual-based detection* systems, which can operate independently of infrastructure, providing a more robust and versatile approach to search and rescue missions (Lygouras et al., 2019).

While significant progress has been made in developing AI-driven drone systems for disaster management, several gaps remain in the current research. Many models still struggle with *accurate detection in obstructed environments* and often lack the *real-time processing* capabilities required for effective deployment in time-critical scenarios.

Our work involves building a *YOLO 11-based object detection model on a custom dataset*, which directly addresses the limitations found in existing systems. YOLO 11 is known for its *fast inference time* and *high accuracy in detecting objects*, even in cluttered and partially obstructed environments. By training the model on a custom dataset that simulates disaster scenarios, we can improve detection accuracy in environments typical of natural disasters. Additionally, YOLO 11's ability to process images in real-time ensures that the system can be deployed in search and rescue missions, where every second counts. In summary, our work builds on existing research by overcoming key limitations such as detection accuracy in complex environments and the need for real-time, visual-based object detection. By addressing these gaps, the YOLO 11-based model has the potential to significantly enhance the effectiveness of drone-assisted disaster response systems, ultimately improving the efficiency of search and rescue operations in natural disasters.

3 BACKGROUND STUDY

3.1 Unmanned Aerial Vehicles

UAV's(Kumar et al., 2023), usually known as drones, have proven to be invaluable tools for disaster management(Xie and Zhao, 2023), providing aerial perspectives that allow responders to assess and monitor large areas quickly and efficiently(Madnur et al., 2024). Drones can reach places that are inaccessible due to hazardous conditions(Wang and Lee, 2024; Rahman et al., 2024a), making them essential for locating survivors after natural disasters. These AI systems often rely on models such as CNNs(O'Shea and Nash, 2015) and more specialized architecture like YOLO, which can detect objects in real time.

Several notable studies have been pivotal in laying the foundation for human detection in disaster scenarios. These studies have focused on improving the accuracy and speed of AI-based detection models in dynamic and complex environments(Norvig, 2022; Chowdhury and Bose, 2024). Through these advances, our goal is to deploy an edge device capable of saving lives by helping to carry out effective search-and-rescue operations.

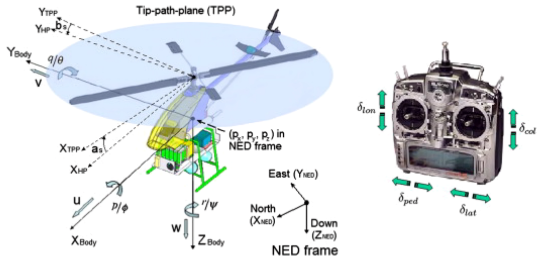

Figure 1: Schematic diagram of uav (Kontogiannis and Ekaterinaris, 2013).

3.2 You Only Look Once (YOLO 11)

YOLO 11, an advanced version of the You Only Look Once (YOLO) series, enhances aerial human detection in emergency response scenarios. By leveraging a single deep learning pass over an image, YOLO 11 can quickly detect and classify human figures in real-time from aerial footage, such as drones, even in environments like natural disasters. The network operates by applying convolutional layers to extract visual features such as shapes, movements, and patterns at varying levels of abstraction. This allows it to accurately recognize human figures, even in cluttered or obstructed areas. YOLO 11 has been trained in datasets with various aerial images, allowing it to generalize across hazardous conditions, providing first responders with immediate information on human location during emergencies. It's high speed and accuracy make it an invaluable tool in enhancing emergency response efforts by enabling faster, more effective rescue operations(Khanam and Hussain, 2024).

4 PROPOSED METHOD

4.1 Dataset Collection and Preparation

During the dataset creation process, we encountered a significant challenge: the lack of human presence in many publicly available disaster scenario image datasets. This absence of representation for victims

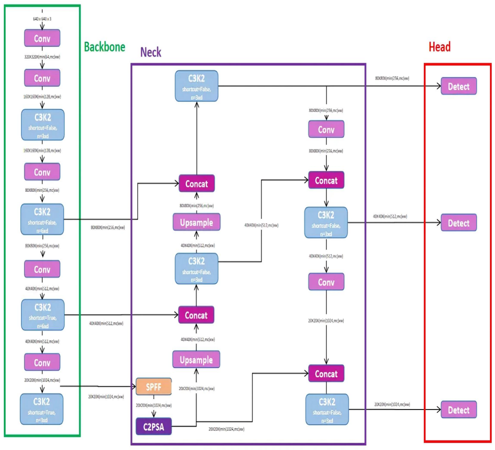

Figure 2: Architecture of YOLO 11 (Rao, 2024).

and rescuers created obstacles in effectively training the model for real-world applications. To overcome this, we developed a comprehensive dataset that simulates various disaster scenarios, such as floods, wildfires, and post-earthquake environments. Drone images of disaster-stricken areas were initially sourced from publicly available platforms like Google and disaster management resources.

Using Roboflow's advance annotation tool, bounding boxes were manually drawn around each object of interest within the images(Aqeel et al., 2024). This step was crucial for accurately identifying and localizing objects in disaster scenarios. Each object within the bounding boxes was classified into one of the predefined categories: victim, rescuer, vehicle, or obstacle. This classification ensured that the dataset was comprehensive and well-structured, reflecting the specific objects essential for search-and-rescue missions. By annotating each image in detail, the process maintained high consistency and precision, allowing the model to learn the necessary features for detecting these objects in real-world disaster situations.

4.2 Model Configuration and Training

Upon completing the annotation process, the dataset consisted of 150 images, carefully designed to represent a variety of disaster environments. This ensured that the model could generalize across different disaster conditions. The annotated dataset was then exported and prepared for training the YOLOv11 model. The model was trained on this dataset for 175 epochs, with a learning rate of 0.01, a value selected based on previous research, which strikes a balance between fast convergence and model stability for object detection tasks.

The model architecture utilizes a standard loss

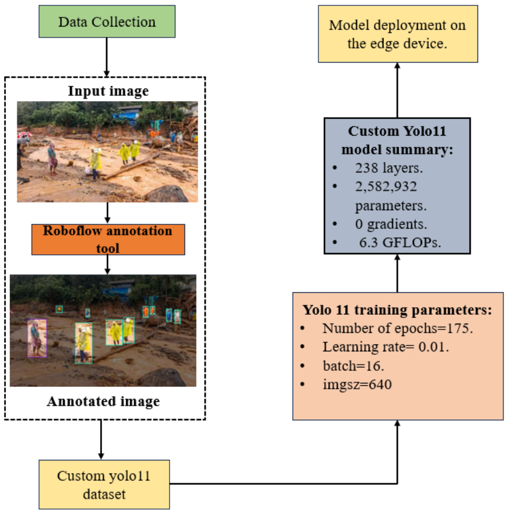

Figure 3: Methodology used to train the model.

function for object detection, which combines both classification and localization losses. The total loss (L) used in the YOLO model is the sum of the classification loss (L_{cls}), localization loss (L_{loc}), and confidence loss (L_{conf}):

$$L = L_{cls} + L_{loc} + L_{conf} \tag{1}$$

The classification loss is typically calculated using the cross-entropy loss:

$$L_{cls} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \tag{2}$$

where y_i represents the ground truth label, $\hat{y}_i$ is the predicted class probability, and N is the number of object classes.

The localization loss is calculated using the mean squared error between the predicted and true bounding box coordinates:

$$L_{loc} = \sum_{i=1}^{N} \left((x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 + (w_i - \hat{w}_i)^2 + (h_i - \hat{h}_i)^2 \right)$$

where x_i, y_i are the center coordinates, and w_i, h_i are the width and height of the bounding box for the i-th object.

The confidence loss quantifies how well the model predicts the presence of an object in a particular cell of the grid:

$$L_{conf} = \sum_{i=1}^{N} \left(C_i \left(1 - \hat{C}_i \right) \right)$$

where C_i is the confidence score (whether an object is present in the cell), and $\hat{C}_i$ is the predicted confidence score.

The learning rate was set at 0.01, following a learning rate decay scheme to gradually reduce the rate as training progresses to improve model stability and performance. The model architecture, comprising 238 layers and 2,582,932 parameters, was specifically designed to handle the complexities of aerial imagery in disaster scenarios, ensuring that it could effectively detect and classify objects, even in cluttered and obstructed environments typically found in disaster zones.

The model was trained with a validation set to monitor performance and prevent overfitting. In order to study the generalization capability and practical performance of the model, the testing was performed on the test set.

4.3 Area Calculation

Victim detection and positioning depend on the pose of the UAV camera and its projection of its environmental footprint. A victim is detected if their 2D local position $\mathbf{s}^0_{pv}(x,y)$ lies within the projected footprint of the camera, determined by summing the angles between $\mathbf{s}^0_{pv}$ and the corners of the boundaries of the footprint.

Geometrically, based on the design shown in Figure 6, the expected extent l of a vision-based sensor 2D projected footprint can then be computed using the following Equations (14) and (15):

$$l_{\text{top, bottom}} = s^0_{pu}(z) \cdot \tan\left(\alpha \pm \tan^{-1}\left(\frac{h}{2f} \right) \right) \tag{3}$$

$$l_{\text{left, right}} = s^0_{pu}(z) \cdot \tan\left(\pm \tan^{-1}\left(\frac{w}{2f} \right) \right) \tag{4}$$

where s^0_{pu} is the UAV altitude, α and β are the camera's pointing angles from the vertical z-axis and the horizontal x-axis of the world coordinate frame, w is the lens width, h is the lens height, and f is the focal length(Nandan Date, 2024).

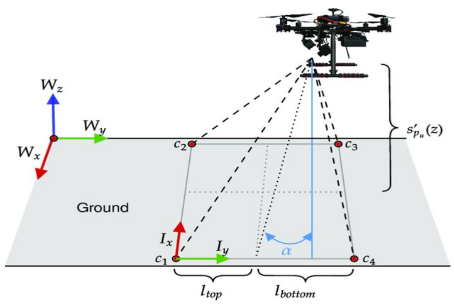

Figure 4: UAV camera coverage(Sandino, 2022).

As illustrated in 4, in Field Of View (FOV) Projection and Footprint Extent of a Vision-Based Sensor you have the setup of a camera mounted on the frame of a UAV defining the variable α as the angle going up/down from the vertical (or pitch), laying down the coordinates of the footprint corners c Using the following transformation, the footprint corners c in the camera center local coordinate frame I are translated to the world's coordinate frame W:

$$\begin{pmatrix} c_0(X) \\ c_0(Y) \end{pmatrix} = \begin{pmatrix} s^0_{pu}(X) \\ s^0_{pu}(Y) \end{pmatrix} + \begin{bmatrix} \cos(\varphi_u) & -\sin(\varphi_u) \\ \sin(\varphi_u) & \cos(\varphi_u) \end{bmatrix} \begin{pmatrix} c(X) \\ c(Y) \end{pmatrix}, \quad (5)$$

where s^0_{pu} represents the next position of the UAV, and φ_u is Euler yaw angle of the UAV, Since no actions change the heading of the UAV mid-flight, and yaw estimation errors are negligible, we can rewrite Equation(4) in the following form:

$$\begin{pmatrix} c_0(X) \\ c_0(Y) \end{pmatrix} = \begin{pmatrix} s^0_{pu}(X) + c(X) \\ s^0_{pu}(Y) + c(Y) \end{pmatrix}, \quad (6)$$

The detection confidence o_ζ that comes as part of the output data from the CNN object detector is modeled using the following equation:

$$o_\zeta = \frac{(1-\zeta_{\min})(d_{uv} - z_{\min} + \zeta_{\min})}{z_{\max} - z_{\min}}, \quad (7)$$

where $\zeta_{\min}$ is the minimally accepted confidence threshold, $z_{\max}$ and $z_{\min}$ are the maximum and minimum UAV flying altitudes, respectively, and d_{uv} is the Manhattan distance between the UAV and the victim.

5 RESULTS AND DISCUSSION

The model has been optimized during training to alleviate the output of the loss function, and its output was evaluated based on: **precision(P)**, where P is the proportion of accurately anticipated positive examples were among all positive predictions. **recall(R)**, where R is the proportion of the genuinely anticipated positive instances among all positive examples. mAP50 is a mean Average Precision at a threshold of 50% IoU, which reveals the model's precision in objects' prediction. mAP50-95 – a mean Average Precision on IoU thresholds.

Fig. 5 shows the F1-score versus confidence of 39% with confidence of 0.51. Basically, the confidence value gives an idea about how confident the model is with the defect detection; values close to 1 are completely confident in the positive detection of the correct defect.

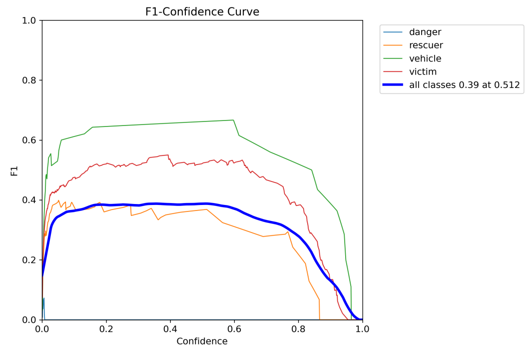

Figure 5: Plotting of F1-score vs. confidence

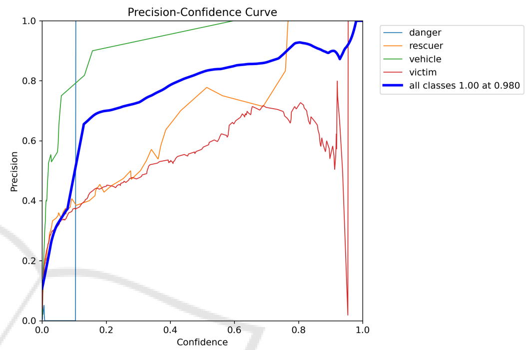

Figure 6: Plotting of precision vs. confidence

Fig. 6 illustrates the precision versus confidence for all classes. The model achieves a precision of 100% at a confidence threshold of 0.98. Higher confidence values indicate more reliable predictions, with vehicle performing consistently well, while rescuer and victim exhibit variability.

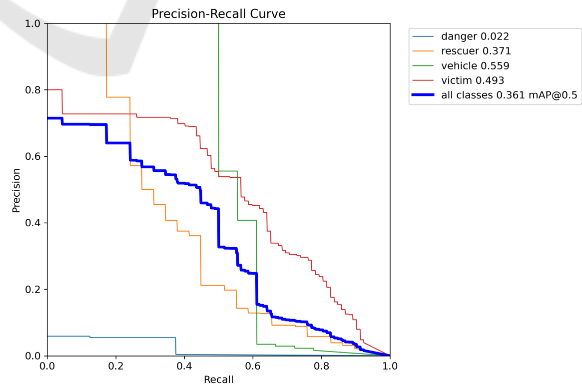

Figure 7: Plotting of precision vs. recall

Fig. 7 illustrates the precision-recall relationship of the proposed system, providing an overview of its detection performance across various classes.

Fig. 8 depicts the relationship between recall and confidence, illustrating how the model's ability to

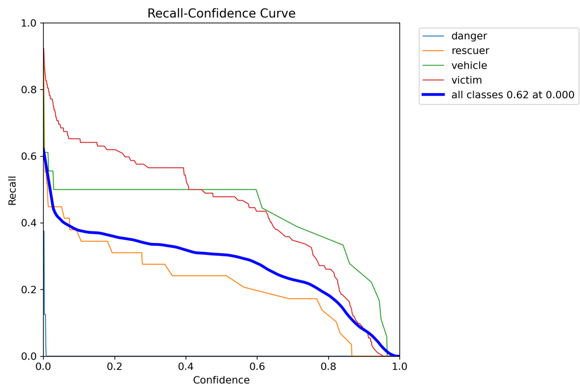

Figure 8: Plotting of recall vs. confidence.

identify relevant objects varies across different confidence thresholds.

Table 1: Detection performance for different classes.

Class	Box(P)	R	mAP50	mAP50-95
All	0.824	0.305	0.361	0.164
Danger	1.000	0.000	0.0222	0.00731
Rescuer	0.753	0.241	0.371	0.192
Vehicle	0.975	0.500	0.559	0.259
Victim	0.567	0.478	0.493	0.199

From table1, the class-wise performance of the model is as follows:

- **Danger Class**: Precision was 1.0, but recall was 0.0, indicating no detections. The mAP50 was 0.0222, and mAP50-95 was 0.00731, showing poor performance.
- **Rescuer Class**: Precision was 0.753, and recall was 0.241. The mAP50 was 0.371, and mAP50-95 was 0.192, highlighting the need to improve recall.
- **Victim Class**: Precision was 0.567, and recall was 0.478. The mAP50 was 0.493, and mAP50-95 was 0.199, indicating moderate performance with room for improvement.

In terms of inference speed, the model demonstrated significant efficiency, which is crucial for real-time applications in disaster response. The preprocessing time was 0.2 ms, meaning that the data was prepared quickly for analysis. The inference time, or the time taken by the model to process each image, was 2.2 ms, which is sufficiently fast for rapid decision-making. Overall, the model's efficiency in processing and analyzing images makes it suitable for deployment in emergency response situations, where every millisecond counts.

As shown in the figure9, we developed an application on the Roboflow platform, designed and tested on an edge device (a mobile phone) within a controlled experimental setting to assess its performance. Extending this approach, the edge device can be embedded in drones for real-time deployment, enabling implementation in critical scenarios, such as emergency rescue operations during natural disasters, such as floods. This deployment can facilitate rapid response by delivering automated insights, enhancing the efficiency and accuracy of search-and-rescue missions in challenging environments.

The findings demonstrate YOLO11's effectiveness in detecting crucial objects during disaster scenarios, significantly aiding rescue operations. The model's high speed allows it to perform well on drones with limited processing power, meeting the real-time constraints necessary for urgent decision-making. While YOLO11 provides substantial improvements over earlier models, challenges such as detection accuracy in low-light or highly obstructed conditions remain. Future work could focus on integrating additional sensors, such as infrared or Li DAR, to enhance detection capabilities in complex environments.

6 CONCLUSION

The training results highlight the strengths and areas for improvement of the model in detecting objects within disaster scenarios. The model demonstrates strong performance in detecting **victims**, as evidenced by the higher mAP scores (mAP50 = 0.56), suggesting that it is effective at identifying survivors in distress.However, performance in detecting other critical objects,such as **dangerous objects** and **rescuer**, showed relatively lower mAP scores, indicating areas that need further development. This performance gap can likely be attributed to the relatively small size of the dataset, especially the limited instances of certain categories, such as dangerous objects and rescuers. The model also exhibited strong detection capabilities for vehicles, suggesting that it performs reasonably well in identifying vehicles during disaster response operations. In disaster response scenarios, the model's precision and recall values reflect that it is relatively good at identifying objects of interest, but there is notable room for improvement, particularly in detecting distant objects, which are often encountered in real-world disaster scenarios.

The model's effectiveness could be enhanced through techniques such as data augmentation and expanding the dataset to include a broader range of disaster environments, helping to improve its generalization capabilities. These findings are consistent with similar studies in the field, where object detec-

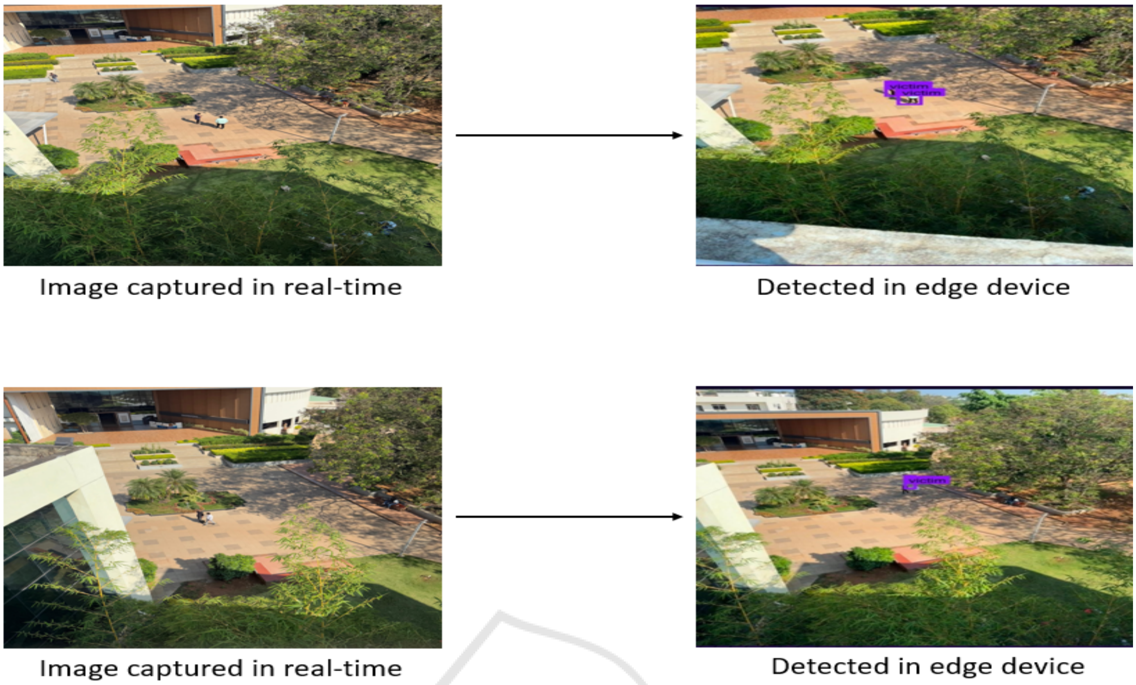

Figure 9: Testing in Real Time

tion models, particularly those based on the YOLO architecture, have been successfully deployed in real-time disaster monitoring systems, achieving effective results in terms of both speed and accuracy, to further optimize the model's performance, future work should include experimenting with different learning rates and exploring more diverse and comprehensive datasets. These advancements will be critical for improving the model's ability to detect various objects in dynamic and challenging disaster scenarios, ultimately enhancing its deployment in real-time search-and-rescue operations.

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