Effectively Managing Crowd in Disaster Areas using Deep Learning Approach

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Abstract— Disaster management in densely populated areas poses significant challenges, often requiring swift and coordinated response efforts. In this study, we propose a novel approach to enhance disaster response through the integration of drone-based surveillance and advanced deep learning techniques. Our system leverages state-of-the-art object detection models, such as YOLO(You Only Look Once), to monitor crowds in disaster areas in real-time. By accurately detecting and tracking individuals, our system provides critical information on crowd count and density, facilitating resource allocation and decision-making processes during crisis situations. Additionally, we incorporate thermal imaging technology to classify injuries based on temperature variations, enabling prompt identification and prioritization of medical assistance for affected individuals. Through autonomous crowd monitoring and injury classification, our project aims to improve the effectiveness and efficiency of disaster response efforts, ultimately reducing casualties and mitigating the impact of disasters on affected communities.

I. INTRODUCTION

Searching and rescuing (SAR) has traditionally relied heavily on human efforts, but with recent technological advancements, it can become autonomous. Employing drone surveillance paired with cutting-edge computer vision technology has the potential to save more lives during disasters by increasing efficiency [16]. The counting method based on regression is generally used in the crowd-counting scene. By learning the characteristic information corresponding to the crowd in the image, the total number of people can be regressed directly, or we can regress to the crowd density map, and then calculate the total number of people from the crowd density map [3]. Detecting objects in videos or images could be accomplished using various methods and techniques, such as deep learning-based approaches like SSD (Single Shot Detector), YOLO (YouOnly LookOnce), Faster R-CNN[5].FIR also known as thermal imaging or infrared thermography. It detects the temperature fluctuations around the nostril area as the temperature during inhalation and exhalation is similar to that of the external environment and the human body[4].

So far, numerous individuals have suffered due to the absence of effective disaster and pandemic management systems. Predicting disasters accurately has been a challenge, resulting in delayed evacuations from affected areas. Moreover, adequate mitigation measures have not been implemented following disasters. Similarly, during the pandemic, efficient measures to contain the outbreak and prevent its spread were not effectively followed[2]. To fill this gap our project utilizes computer vision technologies such as YOLO (You Only Look Once) particularly used for object detection and crowd counting. Additionally, our system integrates FIR (thermal imaging) technology to accurately classify injuries based on temperature fluctuations, enabling prompt medical intervention for those in need. Through these advancements, we address the shortcomings of traditional SAR methods and contribute to more efficient disaster and pandemic management systems.

II. RELATED WORK

During natural disasters such as earthquakes or floods, access to affected areas can be restricted due to debris or hazardous conditions. This hampers the ability of first responders to analyze the situation accurately and manage crowds effectively. By deploying drones equipped with YOLO v8, we can overcome this limitation by providing aerial surveillance and real-time monitoring of disaster zones. Drones can navigate through inaccessible areas, providing comprehensive coverage and visibility of crowd movements and conditions on the ground.

Traditional methods of crowd management often rely on manual counting and tracking by human responders, which is time-consuming and prone to errors, especially in chaotic disaster scenarios. With YOLO v8's advanced object detection capabilities, drones can automate the method of crowd counting and tracking. By accurately identifying and tracking individuals in real-time, drones equipped with YOLO v8 enable rapid and precise assessment of crowd size, density, and movement patterns, facilitating more informed decision-making by disaster response teams.

In the aftermath of a natural disaster, efficient resource allocation is crucial for delivering timely aid and support to affected populations. However, without accurate and up-to-date information on crowd distribution and needs, resource allocation efforts may be inefficient or misdirected. Drones equipped with YOLO v8 can provide valuable situational awareness by continuously monitoring crowd dynamics and identifying areas of high activity or concentration. This enables response teams to prioritize resource allocation based on real-time data, ensuring that aid and assistance reach those who need it most in a timely manner.

Assessing injuries and prioritizing medical assistance in disaster scenarios could be challenging, particularly when working with large crowds or remote locations. Traditional methods of injury assessment may be slow or inaccurate, leading to delays in providing critical medical care to those in need. By integrating thermal imaging technology with YOLO v8 on drones, we can overcome this challenge by enabling rapid and automated injury classification based on temperature variations. Drones that are equipped with thermal imaging cameras can quickly identify individuals with potential injuries and prioritize their evacuation and medical treatment, ultimately saving lives and minimizing the effect of disasters on affected communities.

III. PROPOSED METHODOLOGY

3.1. Victim Detection and Resource Allocation

3.1.1 Dataset

The training process of our model involved utilizing a wide variety of thermal images sourced from different datasets. This dataset encompasses a diverse range of environments and scenarios, including indoor and outdoor settings, industrial facilities, and urban landscapes. Dataset is meticulously annotated with object labels and bounding boxes coordinates, facilitating research in detection of objects, classification, and tracking tasks. For the testing phase, we focused on the FLIR , AAU PDT and OSU thermal dataset. By utilizing these datasets for testing, we aim to see that our model could effectively detect, and classify across various environments and conditions encountered in disaster scenarios.

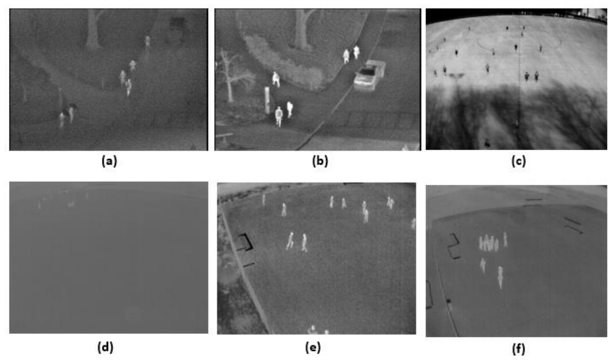


Figure 1. Sample thermal images from (a,b) OSU thermal dataset and (c–f) AAU PD T dataset.

3.1.2 The YOLO Model

YOLO (You Only Look Once) stands out as a widely recognized object detection model, prized for its rapidity and precision. It introduces a novel concept of utilizing an end-to-end neural network, enabling simultaneous predictions of bounding boxes and class probabilities. This distinctive approach to object detection has propelled YOLO to the forefront, surpassing other real-time detection algorithms by a significant margin. Since its inception in 2015, several enhanced versions of YOLO have emerged, each refining and advancing upon its predecessor.

YOLOv8 (You Only Look Once version 8) serves as a pivotal component in our object detection pipeline, enabling precise and efficient detection of persons within thermal images. The main architecture of YOLOv8 builds upon the prior versions of the YOLO algorithms.

YOLOv8 utilizes a CNN that can be divided into mainly two parts: the backbone and the head. A modified form of the CSPDarknet53 architecture plays as backbone of YOLOv8. This architecture consists of 53 layers of convolution and employs cross-stage partial connections to improve information flow between the different layers. The head of YOLOv8 consists of multiple convolutional layers followed by a series of fully connected layers. These layers are mainly used for predicting bounding boxes, objectness scores, and class probabilities for the objects detected in an image.

One of the key features of YOLOv8 is to provide self-attention mechanism in the head of the network. This mechanism allows the model to focus on different parts of the image and adjust the impact of different features based on their relevance to the task. Another important feature of YOLOv8 is its capability to do multi-scaled object detection. In detecting objects across various sizes and scales within an image, the model employs a feature pyramid network. This network comprises multiple layers designed to identify objects at varying scales, enabling the model to detect both large and small objects present in the image.

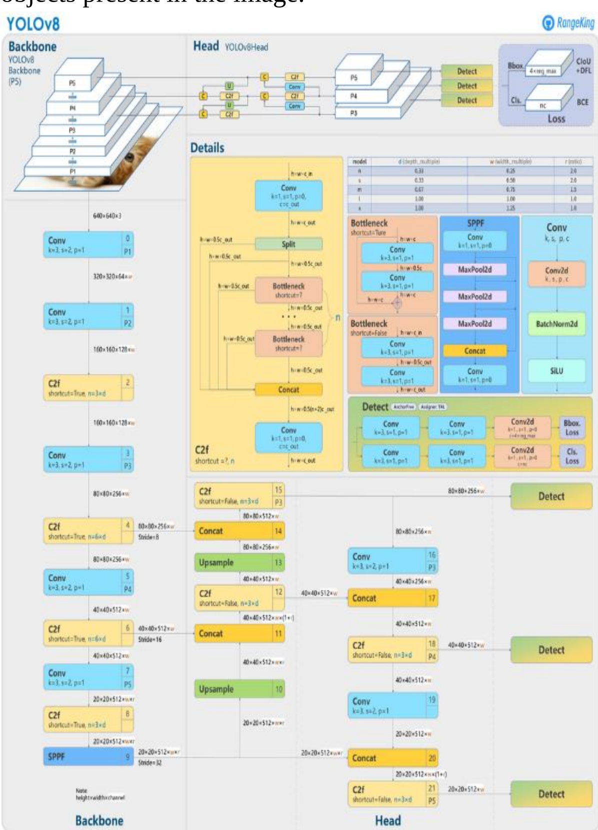


Figure 2. YOLOv8 Architecture

3.1.3 Object Detection and Counting

The algorithm works on the following four approaches:

1. Residual blocks
2. Bounding box regression
3. Intersection Over Unions or IOU for short
4. Non-Maximum Suppression.

1. Residual blocks: This first step starts by dividing the original image (A) into NxN grid cells of equal shape, where N in our case is 4 shown on the image on the right. Each cell in the grid is the reason for localizing and predicting the class of object that it covers, along with the probability/confidence value.

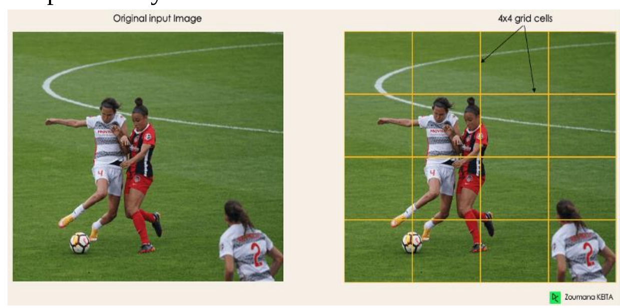


Figure 3. Dividing image into 4x4 grid cells

2. Bounding box regression: The next step is to determine the bounding boxes which correspond to rectangles highlighting all the objects that are in the image. We can have as many bounding boxes as there are objects within a given image.

YOLO determines the attributes of these bounding boxes applying a single regression module in the following format, where Y is the final representation of vector for each bounding box.

Y = [pc, bx, by, bh, bw, c1, c2]

This is important during the phase of raining tthe model.

- pc corresponds to the probability of grid containing an object. For instance, all the grids in red will have a probability score higher than zero.

-bx, by are the x-y coordinates of the center of the bounding box with respect to the enveloping grid cell.

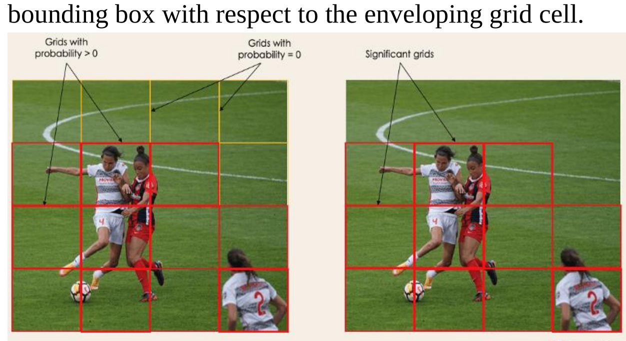


Figure 4. Probability scores of grid containing objects

- bh, bw correspond to the height and the width of the bounding box concerning the enveloping grid cell.
- c1 and c2 correspond to the two classes Player and Ball. We can have as many classes as your use case requires.

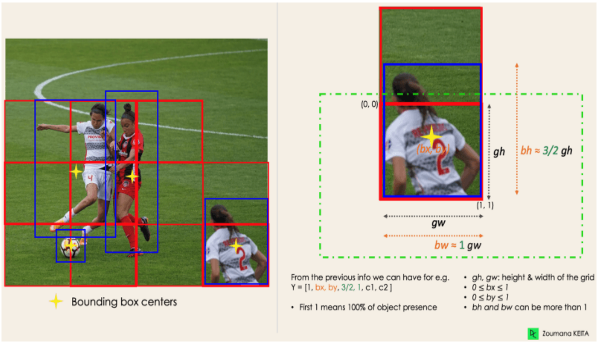


Figure 5. Identifying Bounding box dimensions

3. Intersection Over Unions or IOU: A single object that is in an image can have multiple grid box candidates for prediction, even though not all are relevant. The goal of IOU (a value between 0 and 1) is to discard such grid boxes to keep the ones that are relevant. The user defines its IOU selection threshold, which might be, for example, 0.5.

Then YOLO computes the IOU of each grid cell which is the Intersection area divided by the Union Area.

Finally, it ignores the prediction of the grid cells having an IOU ≤ threshold and considers those with an IOU > threshold.

Below is an illustration of applying the grid selection process to the bottom left object. We can observe that the object originally had two grid candidates, then only "Grid 2" was selected at the end.

Figure 6. Selecting grids that are relevant using IOU

4. Non-Max Suppression or NMS: Setting a threshold for the IOU is not always enough because the object could have multiple boxes with IOU beyond the threshold, and leaving all those boxes might include noise. Here is where we can use NMS to keep only the boxes with the highest probability score of detection.

By utilizing YOLOv8, the project is able to accurately identify and count individuals, providing important information for crisis response efforts.

3.1.4 Resource Allocation

Upon detecting and counting individuals in the thermal images, the project proceeds to allocate resources on the detected count. A predetermined set of resources is allocated for each individual identified in the images, considering certain factors such as medical supplies, personnel, and equipment required for assisting. This resource allocation process is guided by established guidelines and protocols for disaster response, ensuring efficient utilization of available resources to address the needs of individuals identified in the thermal imagery.

3.2 Temperature detection and Classification

3.2.1 Image Processing for Temperature Detection

The methodology employed in this study aims to detect temperature variances in thermal images through a chain of image pre-processing techniques. The process involves several steps including thresholding, morphological operations, contour identification, and temperature calculation.

3.2.2 Thresholding and Preprocessing

Initially, the thermal image undergoes binary thresholding to segment regions of interest. In this step, a predefined threshold value is applied to classify pixels as either foreground or background based on their intensity levels. Pixels with values exceeding the threshold are set to maximum intensity, indicating potential regions of interest for temperature detection.

3.2.3 Morphological Operations

Following thresholding, morphological operations such as erosion and dilation are utilized for the binary image. Erosion is utilized for reducing the size of foreground objects and eliminate small noise regions, whereas dilation is employed to restore the eroded regions and smooth out the boundaries of objects of interest. These operations collectively aid in cleaning the image and enhancing the structural information necessary for subsequent analysis.

3.2.4 Contour Identification

Contours are then collected from the processed binary image using contour detection algorithms. Contours represent the boundaries of connected components within the given image and it serves as a fundamental tool for identifying closed structures or regions of interest.

3.2.5 Temperature Calculation and Analysis

For each identified contour, bounding boxes (recatangular) are generated to encapsulate the corresponding regions. The area of each rectangle is evaluated to ensure its size meets a predefined threshold, beyond which temperature calculations are performed. Pixel intensities (Mean) within those rectangles are computed, reflecting the average temperature of the enclosed regions.

A conversion factor is applied to map pixel intensities to temperature values, accounting for hardware-specific characteristics and sensor calibrations. The resulting temperatures obtained are then compared with a predefined threshold to determine potential anomalies or critical temperatures indicative of thermal events.

3.2.6 Injury Classification

Considering the calculated temperatures, a classification scheme is employed to categorize regions as either "Severely Injured" or "Not Severely Injured". This classification is done on a temperature threshold, below which regions are classified as " Severely Injured", indicating potential abnormal temperature conditions.

The threshold temperature is considered by looking at a study:

Table I: BODY TEMPERATURES IN CONTROL SUBJECTS AND INJURED PATIENTS

	Body temperature (°C) (Mean ± s.e.m.)†				T_a (°C) (Mean ± s.e.m.)‡		Time from accident (h)
	T_c	$T_{\overline{sk}}$	$(T_C - T_{\overline{sk}})$	T_B	Wet bulb	Dry bulb	
Control	37·3 ± 0·1 (18)*	32·8 ± 0·2 (18)	4·5 ± 0·2 (18)	35·8 ± 0·1 (18)	16·5 ± 0·3 (14·0–19·4) median 16·8	24·2 ± 0·5 (19·5–27·4) median 24·2	—
Minor (ISS 1–5)	37·1 ± 0·1 (19)	32·0 ± 0·3 (10)	5·1 ± 0·2 (10)	35·4 ± 0·2 (10)	16·1 ± 0·5 (12·5–18·4) median 15·9	23·4 ± 0·5 (20·0–27·5) median 23·8	1·25–4·5 median 2·0
Moderate (ISS 6–12)	37·3 ± 0·1 (38)	32·3 ± 0·2 (32)	4·9 ± 0·2 (32)	35·6 ± 0·1 (32)	16·0 ± 0·3 (12·2–20·0) median 15·9	23·3 ± 0·3 (19·0–26·5) median 23·3	0·5–8·5 median 2·5
Severe (ISS >12)	36·5 ± 0·2† (25)	31·7 ± 0·2† (21)	5·0 ± 0·2 (18)	34·9 ± 0·2† (21)	16·2 ± 0·3 (13·5–18·5) median 16·3	24·0 ± 0·4 (21·5–28·0) median 23·6	0·5–4·5 median 2·0

Formulae for calculation of $T_{\overline{sk}}$ and T_B given in text.
* No. of patients shown in parentheses.
† Significantly different from controls at $P < 0·001$ (t test).
‡ Range shown in parentheses.

Table II: CLINICAL FEATURES OF PATIENTS AND CONTROL SUBJECTS

	No. of patients*	Age (yr) Median	Age (yr) Range	Season†
Control	18 (9)	44	19–58	—
Minor (ISS 1–5)	19 (16)	35	19–78	2 : 9 : 2 : 6
Moderate (ISS 6–12)	38 (30)	33	14–74	9 : 7 : 6 : 16
Severe (ISS > 12)	25 (17)	30	17–80	3 : 8 : 7 : 7

* No. of males in parentheses.
† Distribution of patients according to the four quarters of the year.

Figure 7. Body temperatures in control subjects and injured patients.

3.2.7 Visualization and Output

Finally, visualizations are generated to illustrate the detected regions and associated temperatures overlaid on the original thermal image. Bounding boxes that are drawn near the identified regions, with corresponding temperature values displayed for visual interpretation and analysis. Accordingly, based on threshold the person is classified as severely injured or not injured.

IV. RESULTS AND DISCUSSIONS

This section includes the evaluation results of proposed system. The evaluation focuses on three key aspects: person detection performance, resource allocation based on detected population, and preliminary injury classification using image processing techniques. The YOLOv8 object detection model was used for person detection, and a separate model was implemented for injury classification based on temperature readings.

4.1 Person Detection:

The overall performance of three popular object detection models - YOLOv8x, YOLOv7x, and YOLOv5x - for person detection in disaster scenarios are compared. The dataset used to train the model of disaster-specific images containing people in various poses and environmental conditions. The metrics of evaluation employed were mean Average Precision (mAP), precision, and recall.

- mAP: YOLOv8x got the highest mAP of 88.8%, indicating its superior capability of accurately localizing and classifying people in the images.

- **Precision:** YOLOv8x also demonstrated the highest precision (92.0%), signifying less false positive rate, that is the model rarely mistakes objects for people.
- **Recall:** While YOLOv7x exhibited a slightly higher recall (80.7%) compared to YOLOv8x (78.9%), the difference is minimal. This shows that both of the models effectively detect most people in the images.

Table. 1: Comparison of Person Detection Performance Metrics

Model	mAP	Precision	Recall
YOLOv8x	88.8%	92.0%	78.9%
YOLOv7x	88.2%	86.9%	80.7%
YOLOv5x	83.4%	47.7%	87.2%

YOLOv5x, despite a high recall, suffers from a significantly lower precision. This implies the model detects many objects as people, leading to a high number of false positives. Considering the critical nature of resource allocation in disaster relief, YOLOv8x emerged as the optimal choice for its balanced performance in both precision and recall.

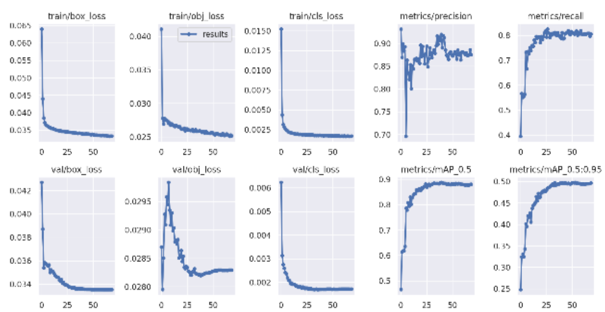


Figure. 8: Training graphs for the person detection model.

The training graphs depict the performance of the person detection model during training. The graphs present the loss functions and evaluation metrics over training epochs, providing insights into the model's convergence behavior.

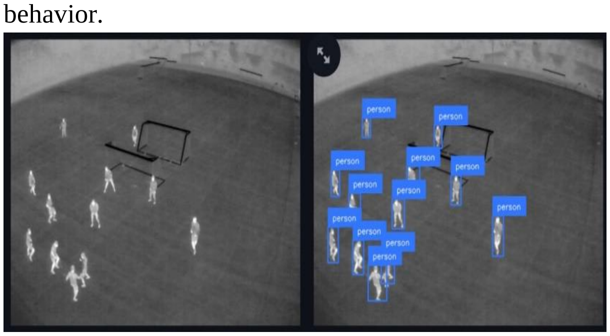


Figure. 9: Predicted class label ("person")

After passing the input image through the model, it accurately identifies and labels individuals as "person." Fig. 9 illustrates this process, with the left side showing the input image and the right side displaying the detected class labels.

After the detection of individuals from the input image, a heatmap representing both the spatial distribution of detected persons and temperature variations is generated. The heatmap gives significant insights on the thermal characteristics of the scene, highlighting areas of interest for further analysis and response prioritization.

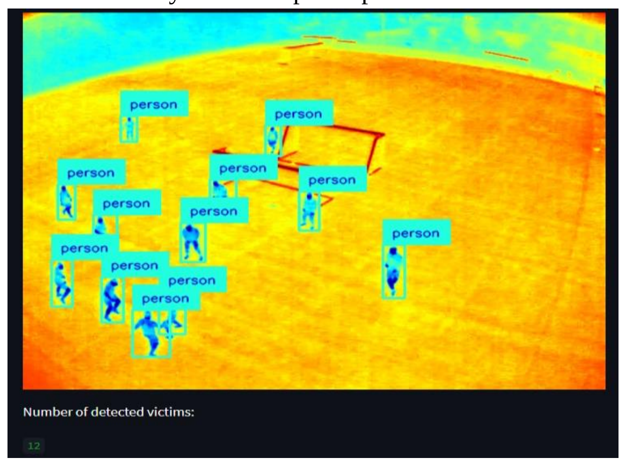


Figure. 10: Heatmap of the Detected Persons

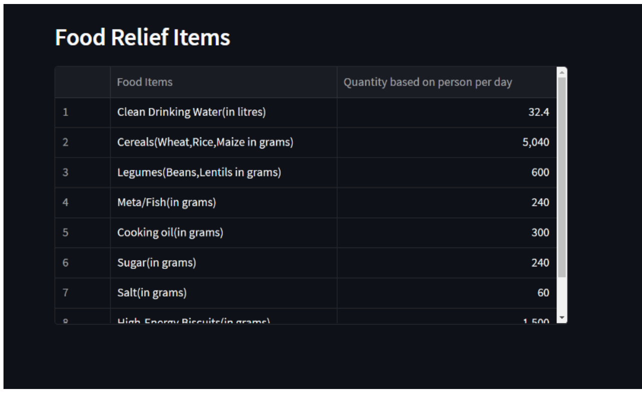
By visualizing the temperature distribution alongside the detected bounding boxes, emergency responders can better understand the thermal dynamics of the disaster area, facilitating more informed decision-making and resource allocation strategies.

4.2 Resource Allocation:

The resource allocation table outlines the allocation strategy on the total number of detected people. This information is crucial as the total number of individuals directly influences the required amount of resources (e.g., food, medical supplies) for effective disaster relief efforts.

Non-Food Relief Items

	Non Food Items	Total Quantity based on per person
1	Clothing/Bedding	12
2	Mattresses/Mats	12
3	Bathing Soap	12
4	Laundry Soap	12
5	Toothbrush	12
6	Toothpaste	12
7	Shampoo	12



Food Relief Items

	Food Items	Quantity based on person per day
1	Clean Drinking Water(in litres)	32.4
2	Cereals(Wheat,Rice,Maize in grams)	5,040
3	Legumes(Beans,Lentils in grams)	600
4	Meta/Fish(in grams)	240
5	Cooking oil(in grams)	300
6	Sugar(in grams)	240
7	Salt(in grams)	60
8	High Energy Biscuits(in grams)	1,500

Figure. 11: Resource Allocation Table for Disaster Relief.

Resource Allocation Table outlines the distribution of both food and non-food relief items on the total count of detected individuals in the disaster-affected area. Non-food items such as clothing, bedding, and other hygiene products that are important for maintaining personal well-being and dignity.

Food items including water, cereals, legumes, and high-energy biscuits provide essential nutrition and sustenance. The allocation method ensure that both immediate survival needs and long-term well-being are addressed effectively.

4.3 Injury Classification:

A preliminary screening approach using temperature readings was employed. A threshold of 89.06°F (31.7°C) was established to identify individuals with potentially high body temperature, that can be an indicator of injury.

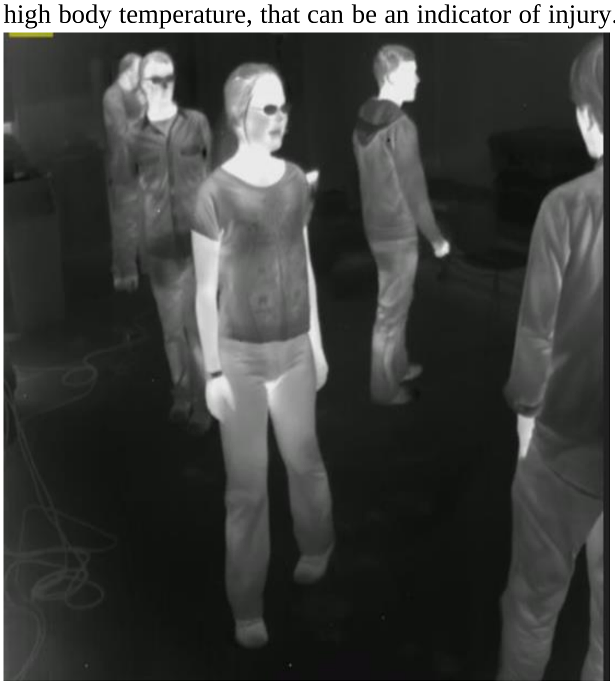
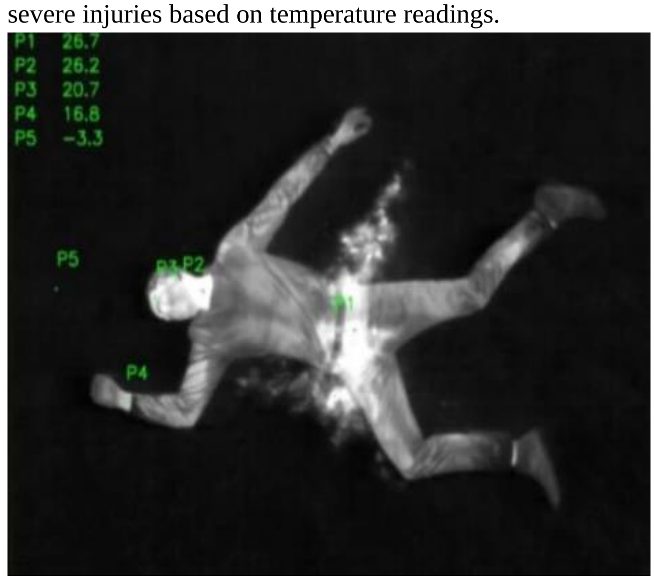


Figure. 12: Temperature Analysis and Injury Classification Result (No Severely Injured Individuals Detected)

The given input image on the left side in Fig.12 is given as a input. Fig. 12 illustrates the process of temparture analysis. On basis of the contour of the body part, the temperature for each is detected.

Four individuals were screened. While six temperature readings were collected (potentially including face and hand measurements for some individuals), none of the recorded temperatures (91.78°F, 90.38°F, 92.1°F, 92.59°F, 91.46°F, 93.2°F) exceeded the designated threshold(89.06°F). This suggests that there are no severe injuries based on temperature readings.



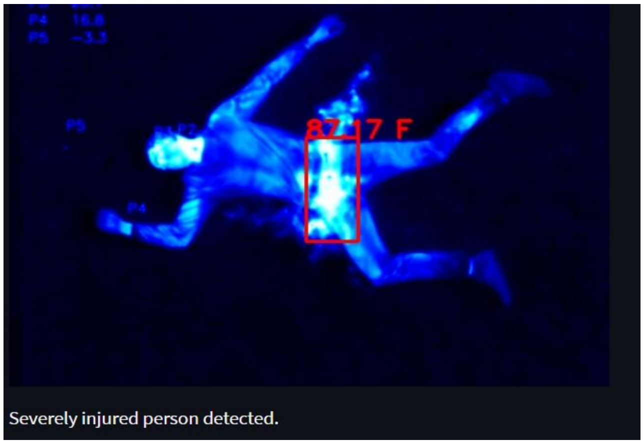


Figure. 13: Temperature Analysis and Injury Classification Result (Severely Injured Individuals Detected).

In cases where individuals exhibit temperatures below the threshold, further evaluation may be warranted. Fig.13 exemplifies this scenario, with the detected temperature of an injured person falling below the threshold, indicating the severely injury person.

In Figure 13, a thermal image of an individual is analyzed for temperature readings. Temperature of 87.17°F is detected, indicative of severe injury. This temperature deviation from the expected range prompts further medical evaluation and intervention. The identification of such cases assists emergency responders in prioritizing medical assistance and allocating resources to individuals requiring urgent care.

The results presented demonstrate the efficacy of the suggested method in detecting individuals, allocating resources, and identifying potential injuries in disaster-affected areas.

V. CONCLUSION

The study presents a comprehensive framework for crowd monitoring and management in disaster areas using thermal imaging technology. By integrating advanced object detection algorithms, resource allocation strategies, and injury classification techniques, the proposed system offers a holistic approach to disaster response and management.

The results of the study underscore the importance of leveraging thermal imaging technology for real-time situational awareness and decision-making in disaster scenarios. By deploying drones equipped with this technology, response teams can quickly understand crowd movements and deploy resources efficiently. Additionally, thermal imaging automates injury assessment, ensuring timely medical assistance for those in need.

The work signifies a significant step toward autonomous disaster management systems, leveraging technological advancements to minimize the impact of disasters and save lives. Ultimately, these innovations has the capability to revolutionize response efforts in disasters and enhance resilience in the face of natural or man-made disasters.

Further research is warranted to refine and optimize the proposed framework for broader implementation and scalability in real-world disaster scenarios. Collaboration between academia, industry, and government agencies is essential to drive innovation and address the evolving challenges of disaster management.

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