Human Remains Detection in Natural Disasters using YOLO: A Deep Learning Approach

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ABSTRACT

Natural catastrophes are defined as events whose precise location and timing are unexpected. Natural disasters can cause property damage and death. The NDRF has to coordinate rapid evacuation to help victims of natural disasters minimize their losses. In reality, the evacuation process is rather challenging. The journey begins with tackling challenging terrain and ends with equipment limitations. Most studies focus on classifying various types of disasters, estimating the amount of damage incurred during a disaster, and identifying victims in post-disaster situations. Many studies use image processing to locate victims in vulnerable locations. This study aims to establish a system for identifying human bodies after natural disasters to assist NDRF teams and volunteers find bodies in hard-to-reach areas. The You Only Look Once (YOLO) method is used in conjunction with artificial intelligence's computer vision algorithms and the Python programming language to effectively detect human bodies with an accuracy of 96%.

Keywords-convolution neural networks; YOLO; object detection; disaster management; natural disasters; National Disaster Response Force (NDRF); National Disaster Management Authority (NDMA)

I. INTRODUCTION

Natural disasters frequently strike India, with disastrous results for the populace. According to the National Disaster Management Authority (NDMA), India experiences significant losses in terms of both life and property as a result of natural disasters every year. 279 documented disasters in India in 2019 affected more than 40 million people and claimed 9,921 lives. Cyclones, landslides, and floods are the three most frequent natural disaster-related causes of death in India. The northeastern states, particularly Assam and Bihar, are particularly susceptible to these kinds of disasters. According to the National Disaster Management Authority (NDMA) and other sources, since 2013, India has experienced a series of devastating natural disasters that have claimed lives. This study seeks to fill gaps in disaster management and response by examining the efficacy of current strategies and suggesting new enhancements. The goals include identifying the key elements that contribute to disaster vulnerability in these locations and evaluating the effectiveness of disaster response measures to limit losses.

Web-based data indicate that 18 disasters have been documented. During a tragedy, one of the most crucial things to do is evacuate the victims. However, there are many issues when evacuation is put into practice. In many cases, rescue teams cannot accomplish their task due to inadequate technology in the victim evacuation process. The scope of research in the field of computer vision is growing as a result of novel real-time observation systems, which enable academics to conduct original research on a range of subjects. Object detection is one area of computer vision that is used to find particular items, which can also be associated with the recognition of real-world objects, animals, and people. Object detection extracts the desired area of the item using a variety of image processing technologies.

YOLO (You Only Look Once) is a collection of cutting-edge deep learning algorithms designed for real-time object detection. Unlike traditional object detection methods that apply classifiers to various sections of an image, YOLO detects both bounding boxes and predicts class probabilities in the same assessment. YOLO is ideal for applications that require fast and reliable object recognition. In terms of recognizing human bodies, YOLO's efficiency in processing and analyzing visual data allows for quick identification and localization, which is crucial for prompt disaster response. This study aims to improve detection accuracy and operating efficiency in difficult situations by leveraging YOLO's advanced capabilities. According to [1], YOLO is a fast, precise, and effective object identification method with good performance.

TABLE I. IMMEDIATE AND DIRECT DEATHS FROM DISASTERS

Year	Disaster Details	#Deaths
2013	Kedarnath floods/Uttarakhand floods (June 2013)	Over 5,700 (including those missing and presumed dead)
2014	Cyclone Hudhud (Oct 2014)	Approximately 124
2015	Chennai floods (Nov-Dec 2015)	Approximately 500
2016	Cyclone Vardah (Dec 2016)	Approximately 38
2017	Gujarat floods (July-Aug 2017)	Approximately 224
	Cyclone Ockhi (Nov-Dec 2017)	Over 200
2018	Kerala floods (Aug 2018)	Approximately 483
	Cyclone Titli (Oct 2018)	Over 85
2019	Cyclone Fani (May 2019)	Approximately 89
	Bihar floods (July 2019)	Approximately 130
	Maharashtra floods (Aug 2019)	Over 60
2020	Cyclone Amphan (May 2020)	Approximately 98 in India
	Assam floods (July 2020)	Approximately 149
2021	Uttarakhand floods and landslide (Feb 2021)	Approximately 80
	Cyclone Tauktae (May 2021)	Approximately 169
	Cyclone Yaas (May 2021)	Approximately 20
2022	Assam floods (June-July 2022)	Over 190
2023	Cyclone Biparjoy (June 2023)	Approximately 7
	Sikkim floods (Oct 2023)	Approximately 40

Numbers may vary due to different sources and updates over time.

To aid in the identification of victims in challenging or susceptible areas, where humans or rescue teams cannot directly contact them, a drone can be used to capture images. The goal of this project is to use a computer vision system that combines aerial images using the YOLO neural network approach to detect human bodies during rescue operations in hazardous or difficult-to-reach places. This research effort aims to design a system to detect human bodies in natural disaster situations.

II. RELATED WORKS

Although there are numerous approaches to computer vision research for the management of natural disasters, the first challenge in this field is the lack of tagged imagery data, as described in [2]. However, a large multimodal dataset of natural disasters, collected from the Internet, was released. In [3], the objective was to collect and categorize visual data shared on social networks to provide situational awareness for the start of relief efforts. In [4], a novel dataset was proposed to categorize disaster types and assess damage severity. The MEDIC dataset was proposed for multitasking learning [5]. According to [6], the ImageB4Act dataset contains 3662 images that can be used as a source to identify bodies through computer vision techniques and support humanitarian organizations in their relief efforts by enabling object detection, particularly for human bodies during natural disasters.

According to [1, 7] YOLO can be used to find victims in natural disasters. In [8], it was observed that the severity level of damage from social media images can be evaluated using deep-CNN features during disasters. In [9], damage identification and determination of its extent in the affected area were examined. In [10], deep learning algorithms were utilized to identify the type of disaster and then automate the emergency response to manage crises. Identifying victims during disasters is a difficult process [11, 12]. This study focused on preventing deaths during natural disasters, employing human sounds and sensor systems to locate people buried in rubble. Some studies also used convolution neural network techniques to identify objects, focusing on post-disaster images of earthquakes and floods. Many studies have used artificial intelligence methods, such as machine learning, computer vision, and convolution neural network techniques, in the field of disaster management to identify objects during disasters [13], trash on the water surface [14], preventive measures [15], damage severity [16], victims [1], and disaster type [10]. In [17], a YOLO-based computer vision system was proposed, achieving 89% mean average precision in recognizing diverse forms of floating debris under difficult situations. In [18], a deep learning model was proposed, using YOLO to detect abandoned rubbish, providing a useful dataset for developing smart waste management. According to [19], fire and smoke detection using YOLO outperforms existing methods in terms of accuracy and efficiency. In [20, 21], YOLO-based models were used for automated tomato disease diagnosis, highlighting the need for additional research to improve performance and support sustainable agriculture.

III. PROPOSED APPROACH

This study proposes an approach to identify human bodies from an imagery dataset during natural disasters, as the identification of human bodies in natural disaster scenarios is one of the major challenges for search and rescue teams. This study used the COCO dataset [10] for training and the ImageB4Act dataset [6] for testing the system developed through the Darknet-53 convolutional neural network architecture using YOLOv3.

Fig. 1. The proposed method for detecting human bodies.

A. *Step-by-step Procedure of the Proposed Method*

1. Load YOLOv3 model
2. Get output layer names
3. Define add_noise function
4. Load and process test image
5. Prepare the image for YOLOv3
6. Forward pass through YOLOv3
7. Process bounding boxes
8. Apply non-maximum suppression
9. Draw bounding boxes
10. Display image

B. Algorithm for the Proposed Method: YOLO Object Detection with Noisy Images

```
Algorithm 1: The proposed model
Input:
  Pre-trained YOLO weights W
  YOLO configuration file C
  Class labels file L
  Input image I
  Noise addition function fnoise
Output:
  Image with detected bounding boxes

1: Load the pre-trained YOLO model using
   the weights W and configuration file C.
   yolo_net = cv2.dnn.readNet(W,C)
2: Load class labels from file.
   classes=[c1,c2,…cn],
   where n is the number of classes.
3: Retrieve output_layer_names =
   yolo_net.getUnconnectedOutLayersNames()
4: Apply the noise addition function
   fnoise to the input image I
   In=fnoise(I)
5: Obtain the dimensions of the noisy
   image
   In:(H,W)=shape(In)
   Create a blob from the noisy image
   using scaling factor s=0.00392 and
   target size 416×416
6: Set the blob B as the input to the YOLO
   network
   yolo_net.setInput(B)
7: Perform a forward pass to get the
   output detections O from the network
   O =
     yolo_net.forward(output_layer_names)
8: Process Bounding Boxes
   Create empty lists for class IDs,
   confidences, and bounding boxes
   For each detection Di in O:
     Extract scores,
     Determine maximum score class,
     Get the confidence for the detected
     class
9: Eliminate redundant overlapping by
   non-maximum suppression bounding boxes
10: Draw bounding boxes
    For index i in indexes:
      Extract coordinates for the bounding
      box
11: Show the noisy image with the
    recognized bounding boxes
    cv2_imshow(In)
```

IV. EXPERIMENTATION

To enable effective and precise object detection, especially for humans in noisy images, the proposed YOLO-based object detection system combines hardware and software components. Python, OpenCV, NumPy, Matplotlib, and the YOLO model make up the software stack, while a powerful processor, GPU, lots of RAM, and SSD storage make up the hardware configuration. Data collection and potential noise addition are the first steps of the procedure. Next comes preprocessing, which involves converting the input image into a blob.

After loading the YOLO model, the blob is configured as the network's forward pass input, resulting in detections. Bounding boxes are treated in the post-processing stage to eliminate redundant boxes and filter out low-confidence detections using non-maximum suppression. This architecture offers a scalable framework for more computer vision research and development because of its meticulously designed components and workflow, which ensure reliable object detection even under difficult circumstances.

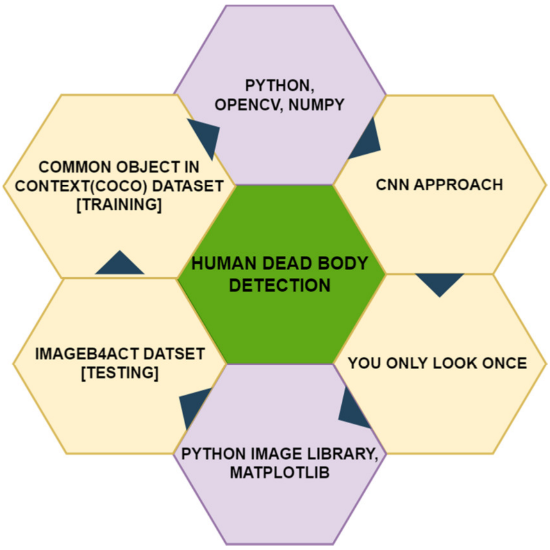

Fig. 2. The architecture of the proposed human body detection system for disasters.

V. RESULTS AND DISCUSSION

The proposed system was developed using Google Collaborator, OpenCV, and the Darknet-53 framework architecture. The COCO dataset [10] was used for training and the ImageB4Act dataset [6] was used for testing.

Fig. 3. Human bodies (alive and dead) detected in the image.

Fig. 4. Detection of a human body without any other noisy human objects.

Fig. 5. Detection of human bodies under disaster conditions even with other noisy human objects.

Fig. 6. Detection of human bodies. However, some bodies still need to be detected by the YOLO model.

Fig. 7. Different natural disaster locations - human body detection in flood zones and snowy regions.

It can be observed YOLO can effectively detect human bodies. The system can detect live victims in noisy images which is also an effective way to detect bodies in an image. Various YOLO models have been employed to detect objects. The proposed model achieved an accuracy of 96% (proportion of correctly predicted cases including true positives and true negatives), and precision of 100% (ratio of successfully predicted positive cases to total expected positives). The proposed model did not detect any false positives. Recall was 96% (ratio of successfully predicted positive instances to total actual positives). The high levels of accuracy (96%), precision (100%), and recall (96%) can significantly improve rescue operations. The high precision of the system ensures minimal false positives, which reduces resource waste and directs efforts where they are most needed. Its strong memory ensures that most human remains are accurately recognized, lowering the danger of missing important cases. These great performance results not only allow for effective and timely rescue efforts but can also boost the morale of rescue workers by providing reliable information. Furthermore, the system's accuracy helps to alleviate family concerns by delivering consistent and timely information. Continuous improvement and monitoring can build on these positive results, ensuring that the system remains a critical tool in disaster response.

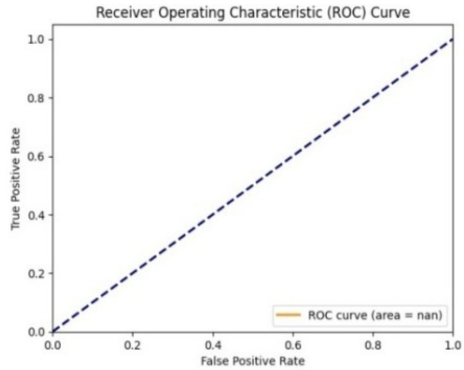

Fig. 8. Relationship between true and false positive rates at different levels. An area under the curve of approximately 0.98 indicates excellent performance.

TABLE II. COMPARATIVE STUDIES OF YOLO IN NATURAL ENVIRONMENT MANAGEMENT PROCESSES

Studies with YOLO in various environental aspects	Year of publish
Object detection in aerial imagery [22]	2019
Fire detection [23]	2021
Detection of victims [1]	2021
Disaster type detection [10]	2021
Trash detection on water surface[14]	2022
Automated solid waste detection [17]	2022
Abandoned garbage detection [18]	2023
Fire and smoke detection [19]	2024
Plant leaf disease detection [20]	2024
Tomato disease detection comparing different versions of YOLO [21]	2024

All these investigations show that identifying human bodies or remains is a difficult task that can carried out effectively using YOLO. In [24], it was stated that YOLO is an object detector rather than a conventional classifier. The testing evaluations indicate that NDRF teams can benefit from having an automated human body detection process to aid in relief activities more successfully.

VI. CONCLUSION

In [1], natural disaster victims were detected using YOLO with an accuracy of 89%, using a dataset of 200 images (100 for training and 100 for testing). In [7], victims were detected using YOLO with an accuracy of 95.49%, on a dataset of 279 images (244 for training and 35 for testing). In comparison, this study presents an object detection approach for human bodies in natural disaster scenarios using YOLO. The COCO dataset [10] was used for training, which contains approximately 330 K images, and approximately 500 images from the ImageB4Act dataset [6] were used for testing. Most research focuses on categorizing disaster types, estimating damage, and finding victims in post-disaster situations, with a particular emphasis on using image processing to locate people in vulnerable areas. Based on this context, the proposed method can identify human bodies after natural disasters. The experimental evaluation showed that a decent accuracy of 96% can be achieved. However, other elements can influence the results, such as the identification of many corpses dispersed throughout an image and the detection of bodies in noisy images. To support the search and rescue team in carrying out relief operations during natural disasters, additional research is needed to achieve greater accuracy in detecting human bodies using convolutional neural network approaches in the field of computer vision. Implementing AI to recognize human bodies creates significant ethical opportunities to improve responsible conduct. This study prioritized privacy, ensuring that sensitive data is handled with extreme caution, using the COCO dataset [10] and the ImageB4Act dataset [6]. The dedication to fairness and the prevention of bias in utilizing the available AI models encourages equitable outcomes across a wide range of contexts, ensuring that the technology works well for everyone.

This study also recognizes the emotional and psychological impact on rescue workers and their families and strives to provide clear and helpful information to reduce pain. Following legal and regulatory guidelines keeps the proposed approach ethical and compliant, demonstrating its commitment to responsible and purposeful use of technology.

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