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Detection of Human Life in Fire Scenarios Using YOLOv8

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Abstract
This system is a human detection system that has been designed for fire rescue operations using most advanced deep learning and computer vision techniques in dealing with smoke vacuum visibility and structure obstructions issues. The real-time object detection is done by YOLOv8 within OpenCV and other technologies for image acquisition and video enhancement such as CLAHE and super-resolution. It detects and highlights users inside the live video feed by surrounding them with green bounding boxes to facilitate prompt localization. Another purpose of this system is posture detection, which classifies the postures of lying, standing, or crouching to aid in prioritizing individuals. The modular feature of this technology allows it to easily adapt to different environments and be compatible with systems such as drone-mounted or stationary cameras. Hence this technology is robust, scalable, and suitable for real-time applications in rescue missions.

Introduction
Overview
There are cases that prove the human detection systems during fire emergencies, which turn out to be lifesavers for many rescue operations. Most of the time, even trained rescue operatives suffer from serious and lasting impairment in their search and rescue because of thick smoke or flaming fire and insurmountable structural barriers, obstructing their actions capable of locating and rescuing endangered lives. This motivates developing the system Human Detection During Fire Using Deep Learning, which uses advanced technology in improving the efficiency and accuracy of the rescue mission [8][10].
As part of the rescue measures, the system detects the presence of people within affected areas of a fire and emphasizes their location using visible green boundaries in real time [2]. This helps rescuers to visualize areas where people should be locally orientated to quickly reach. The system uses YOLOv8, which is a standard state-of-the-art real-time object detection framework [2]. OpenCV embedded within the system is for image processing purposes [7]. Integrated with its sophisticated algorithms, the whole system aspired to be optimized in extremely degraded visibility conditions [10]. For example, video upscaling is used, and a posture analysis could tell the condition of the detected individuals, and this informs the rescuers of how urgent help should be [9].
The examples of groundwork were collecting further developing features such as detection of faces, class-

ification of posture (lying, standing, crouching), and movement to assess what types of people would qualify for classes of action required—including medical attention. Therefore, this pragmatic approach lets rescuers view a clear picture of the affected individual's scenario, allowing them to organize an effective exercise of priorities for rescue tasks, saving many lives in critical fire situations [8][10].

Problem Statement

Fire threats, more so in residential buildings, industries, or woodlands, become rife with many troubles, as the major one being that it is impossible to quickly locate a person in a hazardous environment. Traditional methods of human detection such as manual search by rescuers or even the use of primitive sensors become ineffective under conditions of heavy smoke, visibility impartment, and fast-spreading flames. Further, during emergencies, resolution quality of video feeds from cameras is, in many instances, too dismal to allow accurate and continuous human detection, leading to otherwise justifiable cords of lifelines hanging in the balance. The most fire-detecting systems today discover the fire. Those systems, however, do not have the real-time localization of a human, which is very critical. Actionable real-time feedback is lacking for rescue teams, making it difficult to thaw them into competing priorities on duty. Needs to be built a system to continuously monitor people's presence as well as a condition where the person has got trapped within fire-occurred areas and then indicate the same for easy identification of the person and setup the way to assess their physical state, for example, whether they are unconscious, standing or distressed.

The proposed work would introduce a combination of human detection, posture recognition, and video upscaling techniques, along with some real-time localization by the condition of individual prioritization during fire emergencies. The system manages very high efficiency under extreme conditions which shall ensure better fire crisis response by the integration of deep learning and computer vision.

Research Goals

This research work is basically directed towards exploiting the potential of advanced deep learning techniques in addressing critical missing links toward human life detection in fire emergencies. Among other research objectives, the study is directed to devise a non-intrusive live detection system of human beings into fire-affected areas using multimodal sensory data with deep learning algorithms. Another objective of the research is to enhance the system's accuracy by way of adaptive methods applicable under certain environmental factors such as smoke density and reduced visibility, thereby making it reliable in degraded conditions. Lastly, the study is aimed at minimizing the number of false positives while ensuring robustness under many different types of fire situations and environments, guaranteeing an effective source for real-time rescue operations.

Objectives

Key Objectives:

- Real-time human detection: To develop a deep learning-based model that can be used to detect humans in fire emergencies based on video feeds from various cameras.
- Posture recognition: To recognize human postures on real-time basis so that it can be determined whether an individual is standing, lying, or in distress.
- Video upscaling: Elevate the resolution of low-quality feeds by modern image processing techniques such that the final video output is clearer. The system extensively uses YOLOv8 for real-time object

detection, OpenCV for image processing, and ZIP file processing for dataset preparation, as covered in the code.
- Real-time performance: Ensure that the system performs real-time detection with low latency to provide a quick rescue response time.

Literature Survey
Techniques that are already in existence under fire and human surveillance systems all are mostly computerized versions coupled with AI approaches on deep learning, which make the detection task richer in terms of accuracy and efficiency under emergency scenarios. For instance, YOLOv8 by Safaldin et al. refined for the detection of moving objects with an emphasis on accuracy and real-time performance under dynamic conditions. With this approach, feature programming improves and detection reliability increases, but it may face challenges when considering highly dense environments or smaller objects [2]. In addition, Ismail et al. proposed a fire detection system that exploits OpenCV and Haar cascades for the real-time identification of fire zones in dangerous areas. However, the method is portable and inexpensive, but it is subject to many false positives in complicated scenes and requires much effort in manual feature extraction [7]. Liang and Zeng release FSH-DETR, which is an end-to-end detection system that uses Deformable DETR for fire, smoke, and human detection concurrently under fast-changing conditions. However, it has increased computational complexity [3]. According to Zhao and Li , Fs-YOLO is an upgraded version of YOLOv7 designed primarily for fire-smoke detection. That greatly improves safety operations, but it requires further testing for robustness in extreme environments [4]. All these techniques showed the values of embedding advanced algorithms like YOLO and CNN for real-time applications but revealed some limitations such as computation constraints, dense smoke challenges, and insufficient robustness under varying conditions. The system proposed is aimed at some of these weaknesses by including YOLOv8, OpenCV, and analysis of postures in optimizing detection in the moment of degraded visibility scenarios with action-oriented output to the emergency responder.

Methodology
System Architecture
Designed to keep best resolution while detecting humans under degraded conditions as well as fire and postures, the proposed human detection system in fire emergencies comprises a system architecture. The workflow initiatives with the input video, which is then subjected to a processing stage via the video upscaling module that will elevate the quality of the video. As part of the process, CLAHE is applied so that the effects of smoke will not affect visibility of crucial details in the feed. It requires preprocessing so that the subsequent detection modules work efficiently even under the degraded visibility of fire and dense smoke conditions.
After enhancement, the workflow branches to two main detection tasks-fire detection and human detection. For fire detection, a YOLOv8n model is utilized which was fine-tuned using a total of 8,939 images fire-related. This measure will lead to high accuracy in identifying fire regions within the video feed which are crucial for guiding rescue operations. This part of the fire detection module highlights the area, enabling rescuers to estimate the extent and intensity of the fire in a real-time scenario. (see Fig.1)
At the same time, the human detection module uses the YOLOv8n model to detect humans within the video. This model can be used in diverse postures, such as standing, lying down, or squatting. The next step, after detecting the humans, is carrying out landmarking to analyze the body postures. Because posture

detection helps to infer information about users' physical statuses, it becomes one of the most important factors within a whole rescuing scenario where priority can be given based on cases requiring urgent medical attention or the need for immediate evacuation.

Both the detection outputs are finally integrated into a common display, where all elements-human, fire, and respective bounding boxes-are given real-time visualization (Fig.1). Humans are outlined with green bounding boxes; other visual cues present essential information for fire region identification and the postures of the individuals. This entire display allows the rescue team to see how the situation is and act accordingly.

This makes the system an extremely powerful solution assisting the rescue operations during a fire emergency in attaining an efficiency level and accuracy level before any time. The modular architecture of the system makes it customized to be scalable and versatile enough for any kind of hardware setup-from those mounted-on drones to fixed surveillance systems.

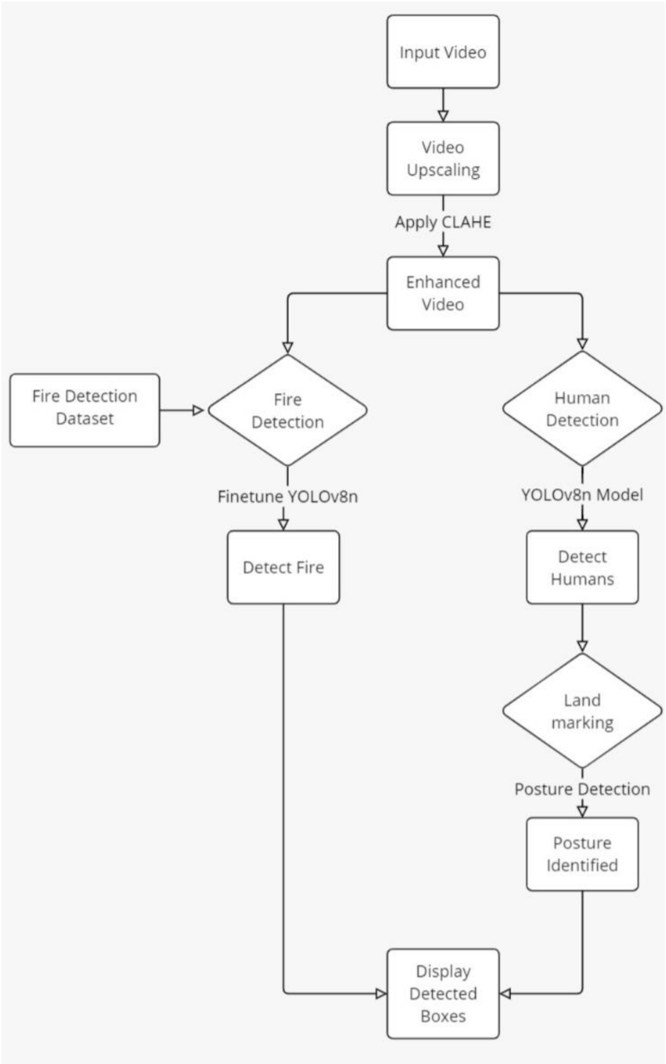

Fig.1: Flow chart of the Training and Workflow of the

Fire and Human Detection Model.

Fire Detection Algorithm Training Dataset Sample Images

Fig.2(a)

Fig.2(b)

Fig.2: (a) & (b) Sample Fire Images used for Training.

The training of the Fire Detection Algorithm is carried out using a comprehensive dataset consisting of 8,939 labeled images specifically curated to enhance the system's ability to detect fire accurately in real-time scenarios. The dataset includes a diverse collection of images that depict various fire-related scenarios to ensure the model is robust and adaptable to different environments and conditions [11].
The images chosen provide a great variety of fire intensities, from small flames through moderately large fires to sizable infernos, across a variety of sites including buildings, outdoors, industrial sites, residential houses, and forests (see Fig. 2(a)). In addition, images depicting varying levels of obscuring smoke and environmental interference are included to simulate actual scenarios in which visibility is generally low because of heavy smoke or scant lighting
(Fig. 2(b)).
The dataset spans intervals from day to night and includes low-light conditions. Besides the fire-related dataset, images devoid of fire are also included to reduce false positives and improve differentiation between fire and non-fire sources, such as bright light, reflections, or sunlight.
The training set enables the Fire Detection Algorithm to generalize well across diverse scenarios, providing reliable and accurate detection in real-time under challenging conditions. Through this robust training process, the algorithm becomes adept at identifying fire promptly, which is critical for timely and effective rescue operations.

Implementation

The whole implementation of this system involves the incorporation of highly advanced software libraries and frameworks for real-time detection of humans and fire postures as well as processing their video under unfriendly conditions. It takes heavy usage from OpenCV, as well as its CV2 wrapper for Python, in order to list things like frame assistance video pre-processing by rescaling and improving and real-time human detection video processing; its advanced capabilities which would include all sorts of high-end image processing techniques such as CLAHE (Contrast Limited Adaptive Histogram Equalization). To improve the clarity of videos in such adverse extents or completely engulfed in smoke with little or no visibility due to fire, it introduces the high-end features of video processing.
This whole ecosystem is wedged heavily with posture estimation and human feature detection affordability via the Mediapipe framework, which underlines its cross-platform compatibility and customizable journey

with machine learning. In that sense, it would be of value to state here that it takes the form of highly accurate postural characterizations, whether lying, standing, crouching, and so forth, and deals with processing such in tandem with face detection and gesture recognition. These Models are designed to aid rescue agents in identifying the physical condition of the people in affected areas of fires and prioritizing interventions and action plans.

It is also included in the formats of the Python Math library for basic mathematical operations during processing images and videos: calculating bounding box placements, mapping coordinates, and executing geometric transformations that can localize and visualize the location of the persons identified in the video feed to the highest precision.

At the heart of the system is the YOLOv8 model, which is derived from the ultralytics library serving as a backbone to object detection. This state-of-the-art deep learning model is fine-tuned in detecting humans, fire, and postures quickly and precisely in real-time scenarios. The fine-tuned YOLO model trained on the dataset of 8,939 images shows the robustness in terms of fire pattern detection and human detection under heavy smoke or degraded visibility. This fast processing would allow the system to keep up with temporal demands for rescue operation.

The workflow begins with OpenCV where the actual video feed is processed-framed enhancement for visibility. The workflow begins with OpenCV processing the video feed, which extends detection to humans and fire by YOLOv8 and analysis of human postures and conditions with that of Mediapipe. The final output will be an overlay consisting of green bounding boxes and posture classifications onto the video feed, where all detected elements display on the same screen-comprehensive viewing with prioritized alerts gives rescuers actionable intel to locate and save lives in fire emergencies.

Results and Analysis

The following images (Fig. 3(a), (b), and (c)) are synthesized by our system to give a better depiction of the detected objects, which are further helpful for decision-making in indoor and outdoor operations. The images show humans prominently enclosed in green bounding boxes, isolating their position in the scene. Each bounding box encloses a score indicating the confidence degree of the system with respect to its detection. Similarly, detected areas of fire are marked using red bounding boxes, enabling proper localization of hazardous zones.

The system includes posture analysis and categorization features alongside these elementary detection features. For instance, all posture states—such as standing, sitting, lying down, or crouching—are well described in blue text, providing rescuers with insight into the physical conditions of individuals. For example, a person lying down could indicate being unconscious or wounded, which usually signifies priority in rescue efforts.

Moreover, the system enhances adequacy for posture detection through landmark-based analysis. It detects and locates key points of the body—such as joints like shoulders, elbows, knees, and ankles—in the images. These landmarks are interconnected using skeletal lines, generating a pose estimation framework that visually represents the captured activity. Such an overlay is not only useful for classifying postures but also conveys to rescuers a clear context of an individual’s orientation and movement, even in degraded visibility conditions, such as smoke or poor lighting.

The three images illustrate the capabilities of the system:

1. Image 1 (Fig. 3(a)): Displays humans and fire with associated confidence scores in a campsite scenario, highlighting posture detection and fire localization.

2. Image 2 (Fig. 3(b)): Captures individuals escaping a fire incident, showing standing postures alongside fire detection with confidence scores.
3. Image 3 (Fig. 3(c)): Illustrates multiple individuals near a bonfire in an outdoor setting, with posture detections such as standing and sitting prominently displayed.

Bringing all features together, the synthesized images provide a robust means for constant monitoring and decision-making, enabling rescue teams to act with heightened accuracy during actionable interventions to save lives effectively.

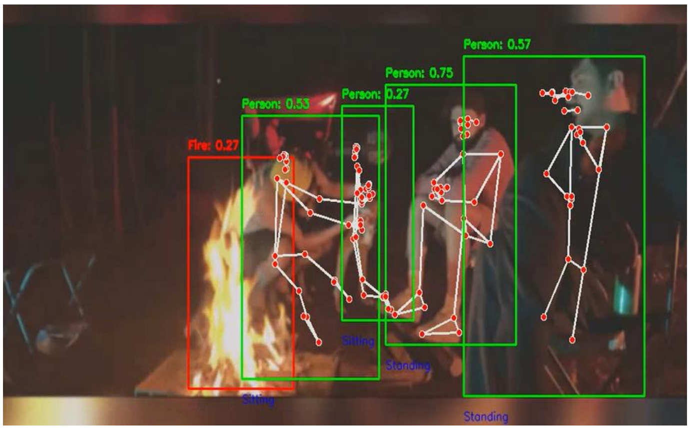

Fig 3(a)

Fig 3(b)

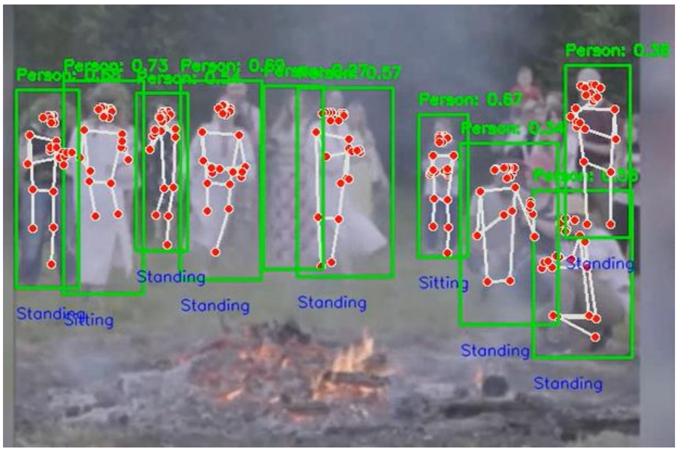

Fig 3(c)

Fig 3(a),(b) & (c): Output images showing Human-green, Fire-red bounding boxes and confidence scores along with Posture detected in Blue.

Performance Metrics

	Metrics	Values
Video 1	Accuracy	89.6%
	Precision	83%
	Recall	82.7%
	F1-Score	86.4%
Video 2	Accuracy	85.9%
	Precision	81.6%

	Recall	83.2%
	F1-Score	84.9%
Video 3	Accuracy	90.9%
	Precision	86.1%
	Recall	82%
	F1-Score	89.32%

Fig 4: Table of Quality Parameters of Videos used for testing.

The system shows good average performance, with an average 88.8% accuracy, and is capable of accurate classification or detection instances. The average precision of 83.6% shows it can identify cases in a positive manner with various degrees of false positives reductions. Likewise, an average recall of 82.6% guarantees that most important instances will be detected. An average F1 of 86.9% indicates an optimum balance between precision and recall in detection capabilities and signifies that the system detects reliably and effectively (see Fig. 4).

Comparative Analysis

Our system offers a significant comparative advantage in performance accuracy (Fig.4) over several existing solutions by addressing key limitations observed in previous approaches. One notable improvement is the enhanced fire detection capability, which minimizes false alarms through advanced training techniques and fine-tuned algorithms. By leveraging a robust dataset and employing state-of-the-art models like YOLOv8, the system achieves precise identification of fire occurrences, reducing the likelihood of misclassification. Additionally, the system demonstrates exceptional adaptability across diverse scenarios, including challenging environments such as wildfires, where factors like vast open spaces, intense heat, and varying fire intensities often hinder accurate detection. This versatility ensures that the system can effectively operate in both controlled and uncontrolled settings, making it a highly reliable solution for fire-related emergencies and rescue operations.

Discussion

Advantages

Real-time feedback to the security team assists in continuous but immediate monitoring, and an alert system. It is a non-intrusive system, requiring a webcam only, and dispensing with the need of wearable and other specialized sensors. One of the significant accomplishments of the system is its proven capability to accurately detect humans even under extreme conditions, such as at night as well as under smoke and high heat, by achieving about 90% classification accuracy. This is important beyond just the performing site because it ensures availability of consistent reliable detection in even difficult environments and contributes significantly to fire safety and security efforts.

Limitations

Lighting sensitivity is one of the performance dampeners: it severely affects the performance of the system in low-light conditions; with time, the accuracy tends to degrade severely. Furthermore, some of the other environmental challenges posed would include the smoking extremes and the dynamic fire environment conditions. The system mostly fails in accuracy while dealing with very thick smoke or while visibility is poor due to low lighting conditions; it becomes very difficult to be accurate because such conditions introduce interference and thereby produces hindrances to being able to detect reliably. That would require more research and improvements on the system to address such conditions to improve the performance and ensure effectiveness in challenges-much diversified fire environments.

Conclusion & Future Work

Human Detection is another system based on Fire, which has brought changes in fire safety technology for better operation in emergency response to fire-related incidents. This new approach uses multiple sensors combined into thermal cameras and depth sensors with machine learning algorithms. This system has proved useful in detecting the presence of people even in fire environments, especially when there is less visibility with a source of smoke and high-temperature conditions.

Through the testing phase, the system proved its ability to detect human presence with high accuracy and reliability, achieving a classification accuracy of approximately 89.6 percent. Emergency responders are guaranteed a high possibility of timely rescue, even when fatalities or injuries are reduced, thanks to real-time processing capabilities combined with multi-modal alerting systems, which comprise visual, auditory, and haptic feedback. Flexibility is further enhanced by the system's modular design, which makes scalability and future updates possible like enhancing the installation of new sensors or better algorithms. While very much promising in its outcome, the system is limited by certain circumstances, mainly found at extreme environmental conditions such as flying smoke-fogged puppet air or places with heat sources that fluctuate. These constraints are advocates for efforts to research and develop more robust and accurate detection algorithms, especially those used in dynamic fire scenarios. Aside from this, further refinements in sensor fusion and algorithms must be done to maximize performance and ensure minimum incidence of false positives and false negatives in different fire environments.

Cumulatively, it is one of the continuous learning capabilities of the system that really contributes to its strengths so much. It allows the system to be flexible and improved with time as more data are collected. It specificizes that the system becomes more intelligent and more effective with every use in future human detection and overall performance.

In conclusion, this proposed system has great potential to improve fire safety and can really save lives when emergency responders will be assisted with rapidly locating humans in dangerous fire environments. As the system improves its research, testing, and refinement, it will act as a valuable tool in rescue efforts and fire detection, no doubt increasing safety in many fire-related environments.

The fire detection system thus has great promise with its integration of new technologies and fine-tuning of its detection capabilities to ensure that the experiences of fire safety will not be the same. This continuous development of the system will improve the efficiency of human detection under fire conditions while complementing efforts in making emergency response systems safer for future life-saving missions against disasters.

The Future steps in research will address improved sensor precision through better detection algorithms and refinement of sensor operation under very difficult situations like heavy smoke and high heat exposure. More importantly, it will try to prevent false alarms that are very important for the reliability of the systems and unnecessary alerting. Furthermore, the development would involve scaling up the system to other types of sensors and emerging technologies to broaden the reach of the fire safety system. Furthermore, in-depth real-world testing under bigger and more complete datasets would be required to evaluate the performance of the system, establish possible limitations, and confirm effectiveness in different environments. This will further advance fire safety systems and continuous improvement forecasts.

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