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Human Detection and Location Alert System Using Raspberry Pi and YOLOv8n

S.Sunitha^[1], S.Ameen^[2], P.V.Jagadeesh Kumar^[3], V.Anil Kumar^[4]

UG Student, Department of ECE, R.V.R & J.C.C.E, Chowdavaram, India^[1]

UG Student, Department of ECE, R.V.R & J.C.C.E, Chowdavaram, India^[2]

UG Student, Department of ECE, R.V.R & J.C.C.E, Chowdavaram, India^[3]

UG Student, Department of ECE, R.V.R & J.C.C.E, Chowdavaram, India^[4]

ABSTRACT: The global disaster management and emergency response paradigm is currently undergoing a transformative shift from centralized cloud infrastructures to the tactical edge, redefining computers as potential nodes of capability versus points of vulnerability. Conventional surveillance and rescue systems usually do not function in emergencies or disasters when power grids, cellular networks and Internet backbones are interrupted. In order to eliminate its vulnerability, it would be necessary to create an autonomous and cloud-independent system that can autonomously identify people in need and alert emergency services without having to rely on third-party infrastructure. We propose a human alert and location detection system to address this problem in our work. A Raspberry Pi 4 Model B serves as the central processing unit in this system, which implements a YOLOv8n deep learning model for real-time human identification. Once the camera recognizes a human in view, it uses a NEO-6M GPS module to find accurate coordinates through satellite triangulation. An SMS alert is then transmitted automatically, containing a Google Maps URL that reflects the latest alerts, to pre-registered emergency contacts using the SIM800L GSM module. Experimental application yields 79.9% detection accuracy, with a localized inference latency of 1.8 to 2.5 seconds, proving resilient in disaster affected areas. The system can significantly reduce response times and potentially save lives by automatically notifying emergency services upon detection. In addition, the solution can be scaled as well as implemented in other life-critical systems and autonomous rescue platforms.

KEYWORDS: Raspberry Pi 4, YOLOv8n, NEO-6M, Emergency Response, Edge AI

I. INTRODUCTION

We currently know that the current global era of disaster management and search-and-rescue operations is undergoing a tipping point of such great significance as systems are transitioned from reactive, to monitoring which takes place after an event, to proactive. Making up for the lack of predictability about nature itself, combined with sensitive communication backbones that tend to not respond optimally on these occasions, means disaster management poses enormous challenges in front of emergency services all across the globe. Between the years 2000 to 2020, natural disasters displaced an estimated of approximately 4.2 billion people and caused over \$2.97 trillion in economic damage globally

. Such scenarios are often hampered by the centralized nature of cloud computing in modern disaster recovery situations and human-mapping processes, which induces latency and single points of failure warning systems, resulting in delayed evacuations and increasing loss of lives. Thus, there is a critical demand for decentralized real-time infrastructures that can detect people in post-disaster scenarios and localize victims without (or with minimal) dependence on the internet backbone.

This paper presents a human detection and emergency alerting smart system aimed specifically for flood situations, road accidents as well as fire emergencies in search-and-rescue operations. The main goal is that it can detect when a human is in danger zone and send notification with its exact place and time stamp to emergency responders. The system utilizes the YOLOv8n deep learning model that differs architecturally from the previous iterations by providing a single framework for real-time object detection on-edge. The proposed system translates visual detections into actionable intelligence by utilizing the NEO-6M GPS and SIM800L GSM modules through a high-accuracy AI that can



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be easily employed using an inexpensive hardware platform (Raspberry Pi 4). This method itself allows rescue brigades to locate victims with great accuracy in a situation where a regular internet connection is not possible.

II. LITERATURE REVIEW

Phased improvement in automated systems for human detection and emergency response has been an active area of both research and technical development, evolving rapidly from static, statically engineered feature sets to agile, self-contained deep learning-based architectures with the ability to realize high-leverage inference at the tactical edge. This trend is propelled by the need for real-time localization during emergencies, a state in which regular communication networks are frequently broken. The state-of-the-art literature survey below reviews the methodological foundations as well as the latest improvements that have paved a way towards the current architectural style, which represent further trade-offs between computational complexity, detection performance and hardware efficiency.

Here is the comparison of the major advantages and disadvantages of modern systems vs legacy systems:

Haar Cascade Classifiers:

- **Pros:** extremely fast feature evaluation using integral images; very low resource usage, run on low-end microcontrollers not even needing a browser; useful for simple face detection in controlled environments.
- **Limitations:** High false-positive rate for complicated disaster background; sensitive to slight changes in light and orientation; dependent on shallow features that fail to generalize irregular human poses during emergencies.

Histogram of Oriented Gradient (HOG):

- **Advantages:** Effectively encodes shape and appearance information via local gradient orientations; invariant to small geometric transformations; performs well with hypothetical pedestrian detection under constant illumination conditions.
- **Limitations:** Very slow due to a heavy calculation of gradient histogram, which hampers real-time detection in edge devices; performance is severely degraded in cluttered or noisy environments; does not have hierarchical feature extraction as convolutional neural networks (CNNs).

Region-based CNN (R-CNN):

- **Highlights:** Realizes high-level classification by extracting hierarchical features leading to better generalization; sets a new standard for the task of complex object classification.
- **Drawbacks:** It employs a multi-stage pipeline which is also very slow; ~47 seconds/image and requires high-end GPU hardware, not suitable for portable deployment in remote/Aid scenarios.

Faster R-CNN:

- **Key Contributions:** Extends the idea of one-stage object detection methods to region-based frameworks; achieves much higher accuracy and mAP than previous multi-stage models.
- **Constraints:** The financial cost is still a major hindrance; only works with relatively more sophisticated notations like Raspberry Pi.

Detection + GPS Integration:

- **Key Feature:** Achieves integration of localization modules with automated pipelines to trigger alerts; serves as a prototype for complete response delivery systems.
- **Limitations:** Generally is very reliant on the internet and face significantly higher latencies while processing on ARM processors.

YOLOv8n (Nano variant):

- **Key Features:** An anchor-free detection head is employed which simplifies the model body as well as improving generalization, then it's optimized for edge-hardware by leveraging TensorFlow Lite quantization to reduce the model size and improve real-time processing without too much compromise in accuracy, achieving high precision (79.9% in field tests) while also being light enough to support emergency tracking.
- **Limitations:** To achieve peak performance, advanced quantization (INT8) and architecture-specific optimization for ARM architectures are essential, and inference latency on CPU-only devices still limits the applicability to high-frequency video streams.



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The combination of localization and communication protocols is also important for search-and-rescue utility. There are many studies have been done about alert systems using GSM module to avoid dependency on the internet. For example, research conducted on the SIM800L module show that it works well to send SMS messages with Google Maps links embedded in them which can reduce time taken for rescuers to reach victims detected by the module. Additionally, the NEO-6M GPS module has been shown to provide horizontal position accuracy within 2.5 m, which is adequate for accurately determining human placement in vehicle accident locations or debris fields.

Table1. Literature Survey and Comparative Analysis of Object Detection Techniques

Author & Year	Technique / Model	Hardware Platform	Key Advantages	Major Limitations
Viola & Jones (2001)	Haar Cascade	Desktop / CPU	With fast feature evaluation; and near real-time on legacy hardware	High false-positives; sensitive to illumination
Dalal & Triggs (2005)	HOG-based	CPU System	Forms to simple for normal pedestrians; heavy solids	Bad with cluttered backgrounds; non-real-time for video
Girshick et al. (2014)	R-CNN	High-end GPU	Superior generalization; hierarchical feature learning	multi-stage pipeline; painfully slow (47s/image)
Ren et al. (2016)	Faster R-CNN	High-end GPU	Single stage network(end to end) with RPN; High precision and high mAP	Very high computational cost; not meant for edge hardware
Singh et al. (2021)	Detection + GPS	Raspberry Pi + GPS	Localization and automated alert pipeline	Dependent on the internet; additional latency for ARM processors
Proposed System	YOLO V8n	RaspberryPi4	Edge-native; 79.9% accuracy; real-time performance	Must quantize model to get the most out of inference speed

III. METHODOLOGY OF PROPOSED SURVEY

Problem Statement

Disaster response is still among the hardest and highest-stakes domains of global emergency management. According to data from EM-DAT database, between 2000 and 2020 natural disasters impacted over 4.2 billion people and resulted in more than \$2.97 trillion in economic losses, making search-and-rescue operations much riskier than routine surveillance tasks. Post-acute-phase mortality remains high in affected areas due to failures of vital infrastructure despite advances in emergency protocol and established guidelines. The fundamental fragility of these areas like crippled power grids, busted cellular backbones and tattered internet Infrastructure, which creates an especially hazardous situation for not just survivors but also rescue workers. A widespread lethal scenario is the “dark period” following floods or earthquakes when survivors are hamstrung and rescue teams do not have reliable communication pathways to find them in vast, dangerous environments.

The aim of this project is to develop an intelligent autonomous human detection and emergency alerting system in disaster zones. Its main goal is to identify human presence in real-time, validate the identity of that person to avoid false alerts, then send a notification with the exact location and timestamp of the survivor to emergency services. This allows for quicker responses and can help rescue teams locate victims who are physically unable to call for aid.

Real-time recognition of human features, with documented accuracy of 79.9%, implemented with YOLOv8n deep learning model on Raspberry Pi 4 Model b. When human detection is confirmed, coordinates are determined using a NEO-6M GPS module via satellite triangulation. A SIM800L GSM module sends an alert via SMS containing a Google Maps link to previously specified own contacts. If there is noise to the environment or visual complications, a confidence ≥ 0.5 and NMS are applied to ensure that only valid detections engage in the alerting sequence.



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Objectives

- Use the YOLOv8n deep learning model to detect whether there are people in real-time with a powerful backbone architecture that discards sounds from trees, wind, and debris due to disaster
- Finally, I integrated a NEO-6M GPS with high sensitivity to triangulate the coordinates using satellites for geospatial accuracy even in remote areas.
- Use the SIM800L module to create a cellular communication pipeline that can send an emergency alert with a localized Google Maps nav link to rescue coordinators.
- To eliminate this slow processing, the inference pipeline on Raspberry Pi 4 Model B must be optimized to increase detection reliability but at acceptably low propagation latencies, as it is required we run independently of cloud services/machines.
- Create a small, inexpensive system where the total cost to put together is less than 9000 Rs which can be easily replicated by humanitarian organisations.

Architecture Diagram

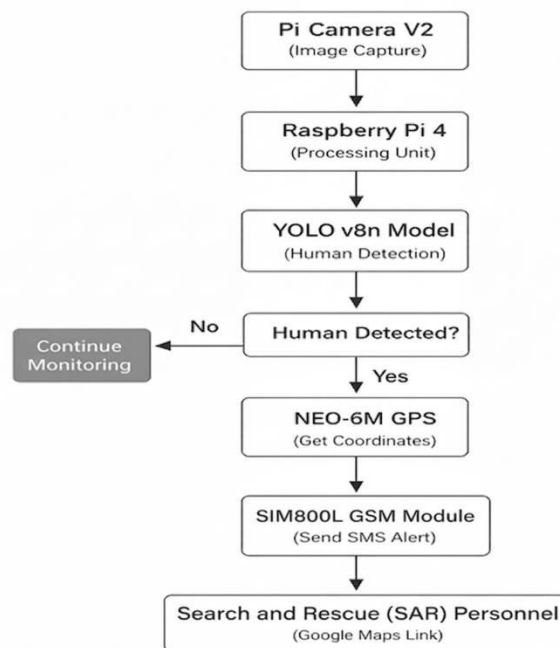


Fig 1 Architecture Diagram

The logical workflow of the system is detailed in the following steps:

1. **System Initialization:** Once the search-and-rescue unit starts up, the human detection system powers on. The Raspberry Pi 4 loads the Pi operating system, initializes YOLOv8n model weights with the TensorFlow Lite (TFLite) interpreter.
2. **Live Monitoring:** After successful initialization, it starts to read frames from the Pi Camera V2. At the same time, the localization engine starts querying the NEO-6M module in order to get a satellite fix.
3. **Frame Pre-processing:** Each frame is passed through OpenCV and resized to size of 640×640 pixels before normalization.
4. **Inference and Identification:** The processed frame into YOLOv8n model. It predicts bounding boxes again and detects the class ID as "Person" (0). For accurate alerts, a confidence threshold of 0.5 is applied.
5. **Geo Data Collection:** Upon an accurate identification of a human, the system retrieves the recent coordinates read from NEO-6M GPS module by parsing raw NMEA sentences to extract decimal coordinates.



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6. **Alert Generation:** Using this information, the system generates a real-time emergency message: "Emergency! Human detected in disaster zone." It adds a Google Maps URL to that string consisting of the coordinates and standard map.
7. **SMS dissemination:** The alert payload is received by SIM800L GSM module through UART. It calls a number of AT commands to connect to the CPP and transmit the SMS to the previously configured responder phone numbers.
8. **Logging and Recovery:** The alert status is locally logged on the SD card. The system then enters a cooling down period for 2 seconds in order not to fire duplicate alerts from the same visual event before returning back to high sensitivity mode

IV. IMPLEMENTATION OF THE SYSTEM

Requirements for Software and Hardware

Hardware Requirements

The hardware ecosystem was chosen to allow a small amount of computational headroom while keeping an overall compact form factor for portable deployment.

- **Raspberry Pi 4 Model B:** The brain of the operation. It has a quad-core 64-bit ARM Cortex-A72 processor and 4GB of RAM, so can handle complex AI inference tasks without needing cloud support.



Fig.2. Raspberry Pi 4 Model B

- **Pi Camera Module V2:** Uses a Sony IMX219 8-megapixel sensor. This is the module that allows the YOLOv8n model to see human features in messy disaster places.



Fig.3. Pi Camera Module V2

- **NEO-6M GPS Module:** High sensibility multi-satellite tracking receiver. It does horizontal position precision of 2.5 meters, which are attached to the emergency SMS as coordinates.



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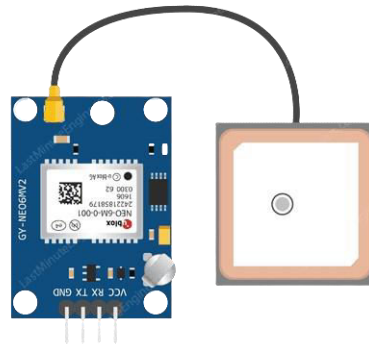


Fig4. NEO-6M GPS Module

- **SIM800L GSM Module:** This is an important hardware which makes use of no Internet as other past system. Acquiring the GSM modem link means it enables the Raspberry Pi to dispatch SMS notifications efficiently through mobile systems using AT commands.



Fig5. SIM800L GSM Module

- **Power Management:** To maintain stable operation as well as safe shutdown abilities, the assembly contains a Battery Management System (BMS) and a UPS HAT.



Fig6. Power Management

Software Requirements

- **Python version:** 3.10; Our main programming language for hardware interfacing and pipeline orchestration



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- **YOLOv8n (Nano):** This is a new state-of-the-art single-stage object detector that performs bounding box regression and classification in just one pass.
- **TensorFlow Lite (TFLite):** Allows for model quantization where the weights of your models are converted to a lower precision format, helping speed up inference time on the Raspberry Pi CPU.
- **OpenCV:** Used for frame handling, normalization to 640×640 pixels in real-time and bounding box visualization.

Modules and description

The implementation of this paper is exactly five modules. The five modules are

- AI Model Optimization and Quantization.
- Visual Input Pipeline Configuration.
- Localization Engine and NMEA Parsing.
- SIM800L GSM Alerting Integration.
- Field Testing and Performance Metrics.

• Module 1: AI Model Optimization

Following this, transfer learning is applied to the YOLOv8n model pre-trained on the COCO dataset, specializing it for human figure detection TensorFlow Lite (TFLite) is used to quantize the model weights, converting floating-point values into lower-precision numbers such that inference can run directly on the Raspberry Pi 4 CPU rather than needing a remote server or dedicated GPU.

• Module 2: Visual Input Pipeline Configuration

The MIPI CSI-2 camera port is originated to connect with the Sony IMX219 image sensor of Pi Camera Module V2 in this phase. In order to utilize the application features, a dedicated processing thread that uses OpenCV is created in parallel for extracting frames and doing preprocessing steps (i.e., normalization steps and resizing the input into 640×640 resolution compatible with YOLOv8n neural network architecture).

• Module 3- Localization Engine and NMEA Parsing

In this stage we will interface the NEO-6M GPS module with the computational core on a Raspberry Pi through the UART protocol. My system decodes raw NMEA sentences and derives precise decimal latitude and longitude. It requires four satellites to connect in order to achieve the needed 2.5-meter accuracy for locating victims precisely.

• Module 4: SIM800L GSM Alerting Integration

A SIM800L GSM module is then integrated into the process to enable a standalone communication bridge in place of internet reliant systems. The Raspberry Pi controls a serial communication stack to register with the cellular network via AT commands and send SMS alerts containing both the coordinates and an interactive Google Maps navigation link, allowing the rescue unit to function in "dark zones".

• Module 5: Field Testing and Performance Metrics

The last module will include extensive testing in urban disaster scenarios and remote landscapes to assess the robustness of the fully autonomous rescue pipeline. Performance is measured in terms of real-time detection accuracy (79.9%), and end-to-end latency for the pipeline (1.8-2.5s) which confirmed that system performance can uphold the high-stress demands ubiquitous throughout search-and-rescue scenarios.

V. RESULT

Human Detection and Visualization: The deep learning pipeline, based on YOLOv8n, stands as an effective mechanism to detect human figures within complicated visual fields. Showcasing distinctive advantages over existing frameworks, we validate the detection system through experimental results which present that human silhouettes are adequately detected in urban, campus and natural environments with proper bounding box identification of each silhouette validated in visible logs.



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```

θ: 640x640 2 persons, 1784.2ms
Human Detected!
Human Detected!
Speed: 15.9ms preprocess, 1784.2ms inference, 3.5ms postprocess per image at shape (1, 3, 640, 640)

θ: 640x640 2 persons, 1919.1ms
Human Detected!
Human Detected!
    
```

Fig 7 Human Detection and Visualization

Confidence Scoring: The system offers confidence scores for human identification ranging consistently between 0.85-0.92 in clear backgrounds; This level of precision is essential for minimizing false alarms in the kind of emergency situations where environmental noise might otherwise lead to misidentification.

Model Efficiency & Scaling: Consequently, the YOLOv8n model is chosen for its lower latency and higher overall accuracy to run on our edge devices. The following comparison table suggests that the "nano" variant offers sufficient throughput to operate in real time on ARM-based architectures.

Table2. Performance Comparison of YOLOv8 Model Variants on Edge Hardware

Model Variant	Input Size (Pixels)	mAP (50-95)	Speed (CPU ONNX)	Params (M)	FLOPS (B)
YOLOv8n	640	37.3	80.4 ms	3.2	18.7
YOLOv8s	640	44.9	128.4 ms	11.2	28.6
YOLOv8m	640	50.2	234.7 ms	25.9	78.9
YOLOv8x	640	53.9	479.1 ms	68.2	257.8

Pipeline Timing Logs: Terminal output gives you a pretty fine-grained view of the performance of the Raspberry Pi 4 platform. It confirms a preprocessing time using logs of 19.1 ms, and an inference latency in between 1982.8 ms to 2513.7 ms per image The below table summarizes the typical time spent on a detection event.

Table3. Granular Breakdown of Pipeline Processing Latency on Raspberry Pi 4

Operation Phase	Measured Time (ms)	Impact on System Performance
Pre-processing	19.1	Low overhead; involves resizing/normalization.



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Operation Phase	Measured Time (ms)	Impact on System Performance
Inference (TFLite)	1982.8 - 2513.7	Primary computational bottleneck for edge.
Post-processing	7.0	A Quick NMS and thresholding.
Total Pipeline	~2000 - 2500	Approx. 0.4 - 0.5 FPS results

VI. FINAL OUTPUT

The completed experimental configuration resulted in a successful end-to-end autonomous rescue pipeline providing the following verified outputs:

Human Detected: Identifying humans as survivors in disaster zones (confidence scores across all images are greater than 0.5). The detections were validated in various environments, from cluttered urban streets to wooded park areas.

Hardware-Native Localisation: Latitude and longitude coordinates were parsed from the NEO-6M GPS module independently of external mobile apps, allowing accurate geospatial data harvest.

GSM Alert Confirmation: The SIM800L module was able to connect to the network and send automated SMS alerts through a Twilio trial account. The received message reads: "Alert! Human found in disaster zone," followed by a clickable Google Maps URL (e.g., <https://maps.google.com/?q=16.0050792,80.6082666>).

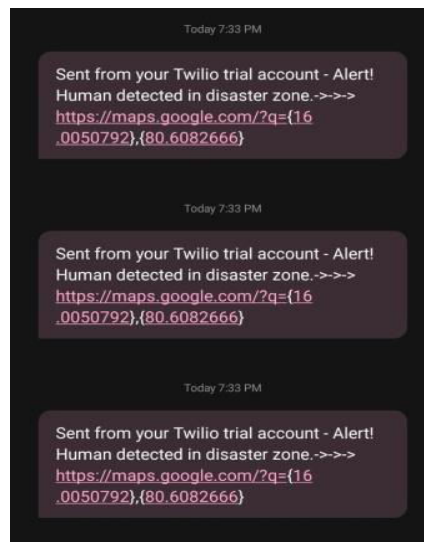
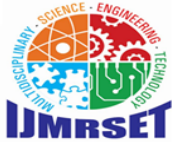


Fig.8. GSM Alert Confirmation

Standalone Navigation: When clicking the alert link received, rescue personnel were able to start navigation immediately via the survivor's coordinates, demonstrating the utility of this feature in environments where normal communication infrastructure has been disabled.

Economic Viability: The cost for the entire system was kept under 9000 Rs, thus a scalable solution for massive disaster response.



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VII. CONCLUSION

Application of ultra-high-accuracy AI in combination with dedicated hardware modules plays a crucial role in addressing the average time taken for crimes at various places for quick detection and response mechanisms as seen by law enforcement and public safety systems. This project eradicates dependency on cloud infrastructure and enables the identification of incapacitated survivors in floods, car accidents, or fire emergencies making it a robust solution. All inference and alerting occurs locally using a YOLOv8n model and SIM800L GSM module to allow the system to stand alone in an emergency pipeline where standard internet backbones do not. Our planned future work will focus on integrating thermal sensors that could enhance the survival rates in zero-visibility environments even more.

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