Design of an Infrared Camera Module for Human Detection in Search-and-Rescue Operations

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Abstract: *This paper reports on the design of an infrared camera module for human detection in search-and-rescue missions, specifically after earthquakes. The camera module employs advanced computer vision techniques, combining YOLOv8 with CNNs for pre- processing. The pre-processing stage involves the enhancement of thermal images through noise reduction and contrast improvement to ensure the reliable detection of humans under adverse conditions, such as low visibility and occlusion. The system was tested in simulated debris environments using a Hexapod robot and exhibited high accuracy and robust performance. The results are a testament to the camera module's potential in assisting with fast and efficient rescue operations..*

Keywords: Infrared Camera, YOLOv8, Hexapod Robot, Post-Disaster Operations, SAR.

I. INTRODUCTION

Disastrous conditions leading to collapsing of building, falling debris, and damage of infrastructure raise a significant challenge for conventional search-and-rescue activities, which are usually slow, hazardous, and likely to expose the rescuers. The urgency of effective rescue operations in such a hostile environment demands innovative solutions capable of independent operation in harmful environments. Robotic systems will possibly be the future in assisting these operations due to their ability to negotiate debris and provide real-time information to rescuers. But the detection of the presence of humans by the robot, especially under debris, is limited by poor visibility, occlusion, and environmental interference.

In recent years, vision-based detection systems have come to represent one of the most efficient tools in robotics, particularly in search and rescue missions. The traditional systems use visible light cameras but less effective when used in low-light or obstructed environments, where the presence of human being is difficult to detect. Infrared cameras are particularly useful in such scenarios, as they capture thermal signatures, which are visible even in complete darkness. Infrared cameras can detect living beings, especially humans, whose body temperature is notably different from the surrounding environment by 33sensing temperature differences.

This paper develops an infrared camera module for integration on a robotic platform, applied in human detection in the post- earthquake search and rescue. The camera module will be designed to robustly operate under harsh environments of dust, smoke, or high temperature—common under such post-earthquake settings. State-of-the-art computer vision algorithm are available onboard the module to postprocess the raw infrared image acquired from the camera toward effective human presence detection.

The camera module makes use of YOLOv8, the state-of-the-art deep learning-based object recognition model known for its high accuracy and speed, which makes it appropriate for real-time detection in dynamic environments. The object detection capability of YOLOv8 involves detecting a variety of objects including human bodies by processing every frame of the video and returning bounding boxes around the detected objects. This paper shows how the YOLOv8 model can be optimized to detect humans under debris in post-disaster environments, using infrared imagery.

Even with models like YOLOv8, human detection in infrared images remains difficult due to noise, occlusion, and low contrast. For this purpose, we create a pre-processing stage with Convolutional Neural Networks (CNNs). CNNs are used in order to pre-process infrared images, and hence improves contrast, removes noise, improves resolution, and assisting in highlighting human shapes better separate it from their background.

Accuracy of the YOLOv8 model is enhanced through this pre-processing stage. Human detection is accurate. Unlike the conventional systems, which is based on an object detection models alone, this method, which integrates YOLOv8 with CNN-based pre-processing, makes the camera module accurate and robust. The modules' real-time ability is to process which is essential to the time critical nature of search and rescue operations, so that the system can give some instant feedback to the robotic platform and navigate it through wreckage. The suggested camera module is intended to be deployed on a Hexapod robot, a six-legged platform capable of moving across uneven and blocked terrain.

The Hexapod robot with the camera module is able to autonomously sense human presence, which enhances search operations while reducing human exposure to risk in dangerous environments. This paper explores the design, implementation, and testing of the infrared camera module, highlighting its potential impact on improving search-and-rescue efforts in disaster-stricken areas.

II. HARDWARES SPECIFICATIONS

The hardware of the camera module consists of the various key components. These components work together to carry out the intended task. The key components used in this module are listed below.

1. **Infrared Camera:**

    An IR camera is selected to capture thermal images that detect heat signatures, enabling the identification of humans in low visibility conditions such as darkness, smoke, or dust. The camera's resolution and frame rate are optimized to ensure that sufficient thermal data is captured while maintaining a balance with real-time processing capabilities.

Figure 1: Infrared Camera

2. Processing Unit:

The processing unit chosen is the Raspberry Pi 5, which has a good balance of computational power and energy efficiency. The Raspberry Pi 5 has enough processing power to handle real-time data capture, image preprocessing, and deep learning model inference. It allows the system to be operated in a mobile setting without bulky, high-power systems.

Figure 2: Raspberry pi

3. Camera Module:

The camera module is tested on a Hexapod robot, a six-legged robot platform. The Hexapod's ability to navigate through complex and rough terrain makes it ideal for search-and-rescue operations, where debris often obstructs traditional wheeled robots. The robot can move over any uneven surfaces and use the infrared camera module to scan large areas for potential human survivors under debris.

III. SOFTWARE PIPELINE

The software pipeline aims to process infrared video data efficiently for human detection and output the detection results in real time to the robot's navigation system. The pipeline can be divided into several steps. Here are the key steps divided into the following subpoints:

1. Data Acquisition:

In this step, thermal images are captured by the infrared camera and streamed in real time to the Raspberry Pi. The camera runs continuously; frames are fed into a processing unit for further processing. Frames are captured rapidly, with a high temporal resolution to ensure no critical data is missed in fast-moving or dynamic scenarios. Varying levels of heat emitted by objects in the environment are captured by an infrared camera, and by their distinct thermal signature, humans stand out.

2. Preprocessing with CNN:

Once the raw infrared images are captured, they are preprocessed for quality enhancement to improve the detection. Preprocessing in thermal imaging is very essential because the images are normally noisy, low contrasted, and distorted, and these conditions can degrade the performance of the detection algorithms.

A custom-designed CNN is used to process the thermal frames. The CNN performs several tasks which improve the quality of the images. Thermal images are usually noisy due to environmental conditions or inadequacies of the sensor technology. The CNN filters remove random noise allowing enhanced clarity in the images. Thermal images normally show poor contrast, in that human heat may be too weak relative to the surroundings.

The CNN makes use of histogram equalization techniques to make hot spots visible and thereby separate the humans from the surrounding scene. The CNN also performs edge enhancement on the thermal image, making it sharper at the edges and boundaries between different regions, which enhances the ability of the detection model to separate humans from other objects in the environment. Super-resolution is used to enhance the resolution of images, and therefore, finer details are picked up. The raw infrared data is transformed by the CNN into enhanced frames for clearer and more detailed images for human detection.

3. Human Detection with YOLOv8:

The preprocessed frames are forwarded to YOLOv8, an advanced deep learning-based object detection model. YOLOv8 can process images in real time, which is important for the deployment in search-and-rescue robots. The model is fine-tuned on a dedicated dataset of thermal images containing labeled human bodies, which enables the model to detect human thermal signatures. Once processed, YOLOv8 generates boxes bounding around detected humans, along with confidence scores that indicate the likelihood that the detected object is a human. These bounding boxes and scores are used to identify human survivors under debris or in hard-to-reach areas.

4. Optimization:

For improving the performance of YOLOv8, several optimization techniques are applied. Technique like Non-Maximum Suppression (NMS) technique is used in order to remove redundant bounding boxes that may occur through multiple overlapping detections of one human. NMS refines the detection results by ensuring that only the bounding box with the highest confidence is kept, thus reducing the false positives.

YOLOv8 uses TensorRT, a high-performance library for deep learning inference, to optimize it. TensorRT accelerates the YOLOv8 model on the Raspberry Pi, such that human detection occurs in real-time with minimal latency. TensorRT optimizes both the model architecture and the inference process to speed up frame rates and efficiency in computation.
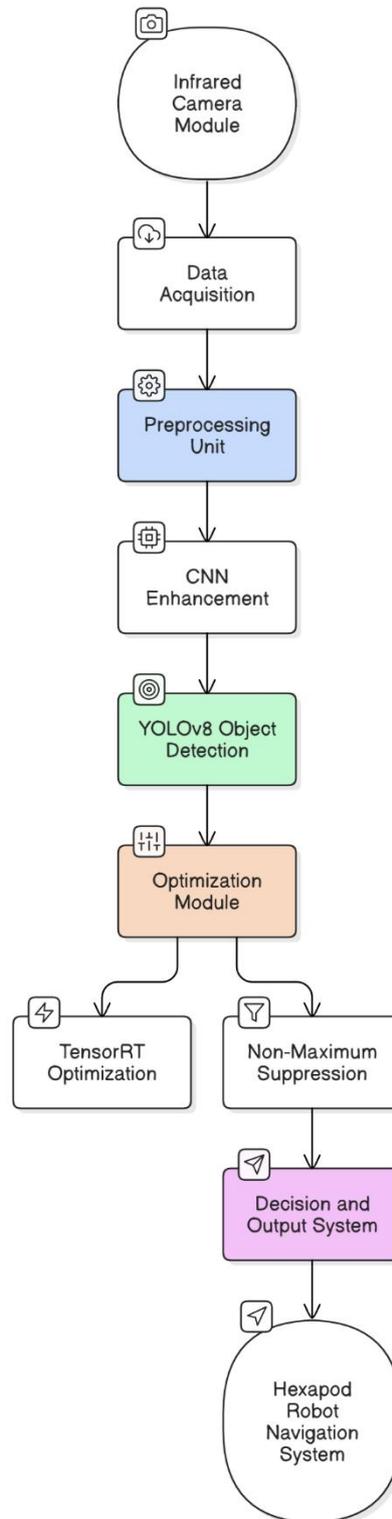
Figure 3: Block Diagram

5. **Data Output:**

The final detection outputs, i.e., bounding boxes and confidence scores, are passed on to the navigation system of the robot. The robot then utilizes this information to determine its next course of action, whether change direction or concentrate on certain areas where human survivors has been detected. This feedback system then allows the robot to move around within wreckage, scanning for human survivors and reacting to dynamic environment changes. In short, the infrared camera module combines hardware elements with advanced image preprocessing and detection methods to offer real-time and accurate human detection for search and rescue missions. With object detection via YOLOv8 and CNN based preprocessing, the system can operate robustly in harsh post disaster scenarios.

IV. LIMITATIONS

Although the suggested infrared camera module exhibits encouraging performance in the detection of human survivors in earthquake search-and-rescue operations, there are some limitations noted:

1. *Occlusion and Partial Visibility:* The technology is based on the detection of thermal signatures, which can be occluded by heavy debris, insulating objects, or corpses buried under heavy layers of debris. When heat is fully occluded, the accuracy of detection can be dramatically reduced.

2. *Environmental Interference:* Infrared camera performance can be impacted by environmental conditions like extreme temperatures, high humidity, and smoke. Ambient temperature fluctuations can lead to false alarms or prevent proper human detection.

3. *Small Training Dataset:* While the YOLOv8 model is fine-tuned using thermal image datasets, real large and multi-varied datasets related to post-disaster contexts are scant. This limitation might affect the model's generalizability to actual disaster environments.

4. *Computational Constraints:* Utilization of a Raspberry Pi 5 is an energy-saving option; still, it compromises on processing power. Real-time detection can be compromised under heavy computational loads, which could impact response time.

V. VALIDATION

We have presented details on the experimental testing and performance standardization below to ensure the accuracy and reliability of the proposed infrared camera module.

1. **Testing Configuration:**

Post-disaster scenarios are simulated with environments looking like debris. Ambient disturbances (dust, smoke), ambient temperature ranges, and degrees of partial and full opacities are all examples thereof. In controlled test environments, the Hexapod robot equipped with the infrared camera module is positioned between humans who are giving off heat signatures that very closely approximate true body temperatures.

2. Performance Metrics:

The infrared camera module is validated in various essential performance areas to ensure reliability when used in search and rescue operations. Identification accuracy uses recall and precision values for reducing incorrect classifying of non-human heat signatures and ensuring maximum detection rates. (Target: 85% Recall, 90% Precision).
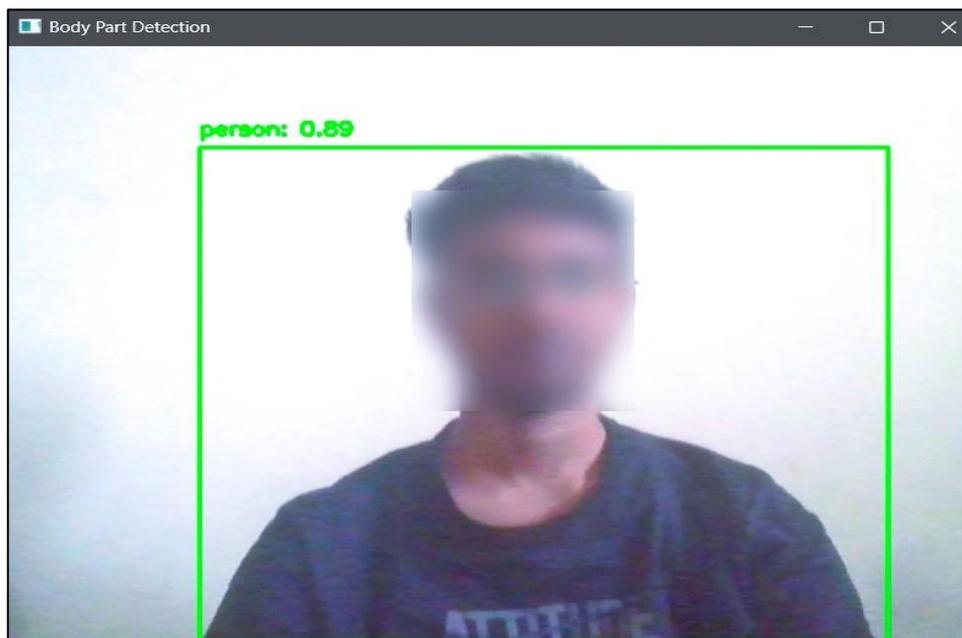

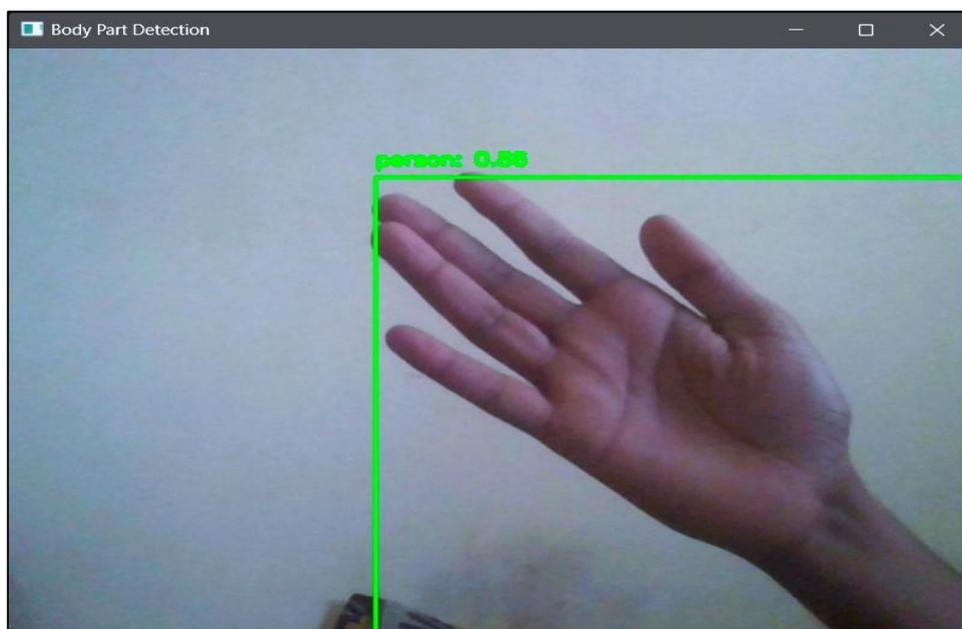Figure 4: Body Part Detection (Face)

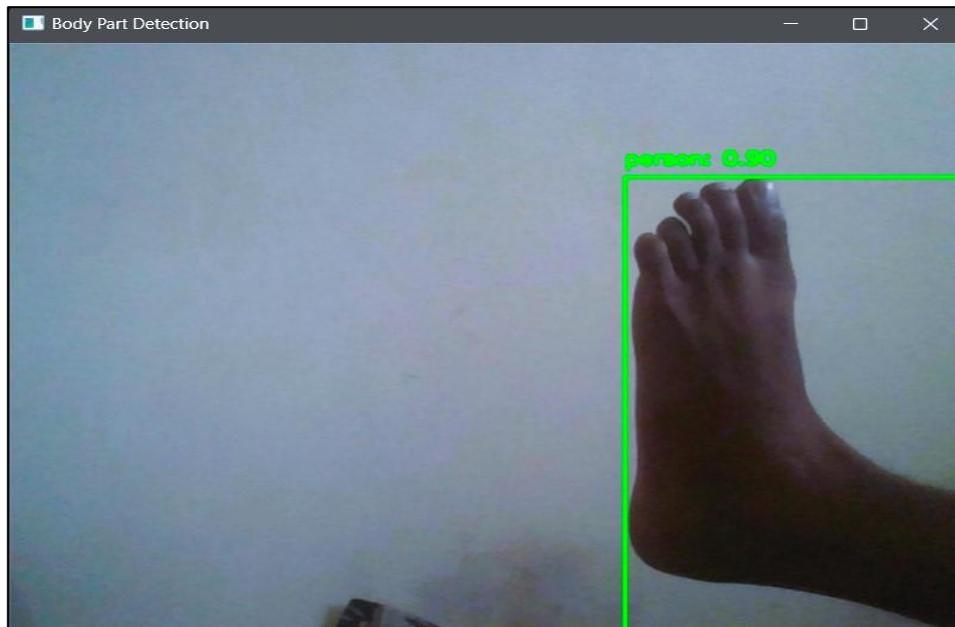
Figure 5: Body Part Detection (Hand)

Figure 6: Body Part Detection (Foot)

Figure 4, 5, 6: To reduce unnecessary alarms and ensure that survivor is not overlooked, False Positives & False Negatives measure invalid detections. (Target: 5% of false negatives and 10% of false positives). For robotic platforms, processing speed is quantified in frames per second (FPS) and inference time to ensure real-time detection. (FPS > 10–15 and inference time ≤ 100 MS per frame are the targets). We can enhance the performance of robotic search and rescue activities by tuning these parameters to ensure the system can deliver fast, accurate, and consistent human detection.

3. Model Performance Evaluation:

While evaluating the effectiveness of the infrared camera module in detecting humans for post-earthquake search and rescue missions, model performance of the YOLOv8 object detection model plays a significant role. As a measurement of detection accuracy gains, the images are initially enhanced by a tailored CNN.

4. Experiments and Real-world Verification:

The software will be tested in real search-and-rescue operations with emergency response teams. Ensuring detection outcomes effectively guide the Hexapod robot's motion in dynamic search-and-rescue scenarios is the objective of integration with autonomous navigation.

VI. CONCLUSION

This paper explains the development of an infrared camera module to be used in search and rescue operations after an earthquake to locate human beings. In challenging environments, the approach significantly enhances detection precision by employing CNN- based preprocessing for noise reduction

and contrast enhancement, and YOLOv8 for real-time object detection. While software optimizations accelerate inference and enable real-time operation, hardware optimized for deployment on a Hexapod robot ensures mobility in terrain filled with debris. With different occlusion levels and environmental conditions, experimental results under disaster simulation scenarios indicated reliable performance, minimal false positives, and satisfactory detection accuracy. Successfully integrating the system with autonomous navigation enables post-disaster search operations to be more effective and less hazardous for humans. This leaves the way open for practical use in actual rescue operations.

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