A Review on Ai-Integrated Helmet-Mounted Thermal Imaging Systems for Victim Detection in Disaster Response Scenarios

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Abstract:- This review examines the integration of artificial intelligence (AI) with helmet-mounted thermal imaging systems to enhance victim detection during disaster response operations. The fusion of AI algorithms with thermal imaging technology has led to significant advancements in identifying and locating victims in environments with limited visibility, such as those affected by smoke, darkness, or structural obstructions. Recent developments include the deployment of smart helmets equipped with infrared cameras, real-time object recognition capabilities, and augmented reality displays, all designed to improve situational awareness for first responders. Field trials have demonstrated the efficacy of these systems in accelerating victim detection and improving navigation in complex disaster scenarios. The review also discusses the challenges associated with implementing these technologies, including issues related to power autonomy, equipment compatibility, and data processing requirements. Future research directions are proposed to address these challenges and to further integrate AI-driven thermal imaging solutions into standard emergency response protocols.

Keywords: *Artificial intelligence, helmet-mounted systems, thermal imaging, victim detection, disaster response, smart helmets.*

1. Introduction

In the realm of emergency response, the imperative to swiftly locate and rescue victims in disaster-stricken environments is paramount. Traditional methods often confront limitations, particularly in scenarios characterized by low visibility due to smoke, darkness, or structural obstructions. To address these challenges, the integration of artificial intelligence (AI) with helmet-mounted thermal imaging systems has emerged as a transformative approach, enhancing the capabilities of first responders in victim detection and situational awareness. Recent advancements have led to the development of smart helmets equipped with a suite of sensors, including thermal cameras, radar, and inertial measurement units. These devices harness AI algorithms to process multispectral data in real-time, enabling the identification of human heat signatures and the mapping of complex environments.

For instance, researchers at the National Robotarium in Edinburgh have collaborated with the Scottish Fire and Rescue Service to create a helmet that allows firefighters to navigate smoke-filled areas more effectively, significantly reducing the time required to locate victims. The incorporation of augmented reality (AR) displays further augments the functionality of these helmets by overlaying critical information onto the user's field of view. This feature provides real-time data on environmental conditions, team member locations, and navigational cues, thereby enhancing decision-making processes during high-stress operations. Moreover, the modular design of these systems ensures adaptability to various mission requirements, allowing for the customization of sensor arrays and processing units based on specific operational needs. Despite the promising capabilities of AI-integrated helmet-mounted systems, several challenges persist. Issues related to power autonomy, data processing latency, and the integration of these technologies with existing protective equipment necessitate ongoing research and development. Furthermore, considerations regarding user ergonomics, system durability under extreme conditions, and the standardization of interfaces are critical for the widespread adoption of these systems in emergency services. This review aims to provide a comprehensive analysis of the current state of AI-integrated helmet-mounted thermal imaging systems, examining their technological components, operational benefits, and the challenges associated with their deployment. By synthesizing recent research findings and field trial outcomes, the review seeks to inform future developments and facilitate the integration of these advanced systems into standard disaster response protocols.

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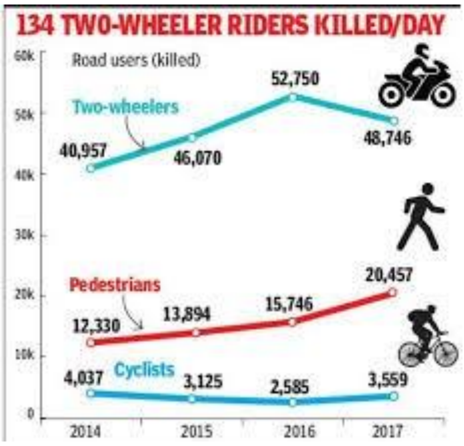

Fig. 1: Representation of rate of accidents in two wheeler

Figure 1 illustrates the incidence rate of accidents involving two-wheelers. A comparative analysis is presented among two-wheelers, pedestrians, and cyclists, revealing that the accident rate is significantly higher for two-wheelers, as depicted in the graph.

This review aims to provide a comprehensive analysis of the current state of AI-integrated helmet-mounted thermal imaging systems, examining their technological components, operational benefits, and the challenges associated with their deployment. By synthesizing recent research findings and field trial outcomes, the review seeks to inform future developments and facilitate the integration of these advanced systems into standard disaster response protocols.

There are a few other studies surveying the Smart Helmet for Accident Detection. Ajithkumar [1]smart helmet integrates sensors and communication modules to detect hazardous conditions and alert emergency services, thereby mitigating the severity of accidents. This design exemplifies an innovative approach to proactive accident avoidance through real-time monitoring and intelligent response mechanisms. Kishan Dadhania[2]an IoT-based smart helmet designed to enhance the safety of industrial workers by continuously monitoring environmental factors and physiological conditions. Through real-time data transmission, the helmet enables prompt interventions, thereby reducing workplace accidents and improving overall safety standards.

Divyasudha N [3]an IoT-enabled helmet system that enhances rider safety through real-time accident detection and emergency alerts. By integrating sensors like accelerometers and GPS with cloud connectivity, it offers an affordable solution to reduce road accidents and improve emergency response times. Pankaj Chitte[4]Equipped with sensors like alcohol detectors, GPS, and accelerometers, the helmet ensures the rider is sober and properly wearing it before starting the vehicle.

In the event of an accident, it automatically sends location-based alerts to emergency contacts, thereby facilitating timely assistance and potentially reducing fatalities. Kiran Kumar [5] Roja [6] reviewed the paper "Smart Helmet Based Accident Detection and Notification System for Two-Wheeler

Motorcycles" introduces an IoT-enabled helmet that utilizes an accelerometer to detect accidents by monitoring deviations from normal conditions.

Upon detecting a collision, the system promptly sends SMS and phone call alerts, along with the rider's location, to registered emergency contacts and nearby medical facilities, thereby facilitating swift assistance and potentially saving lives. Anantha kumar [7]the Mining Industry" introduces a helmet equipped with sensors to monitor hazardous gases like CO, SO_2, and NO_2, as well as temperature and particulate matter, thereby enhancing miner safety through real-time alerts.

Additionally, features such as helmet removal detection and collision sensing are incorporated to promptly notify supervisors of unsafe events, facilitating timely interventions and improving overall safety in mining operations. Sreenithy Chandran **[8]** Dr. S.Sekar[9]an IoT-enabled helmet designed to enhance miner safety by monitoring environmental hazards such as toxic gas concentrations, helmet usage, and potential head injuries. Utilizing sensors for gases like CO, SO_2, and NO_2, along with infrared and pressure sensors, the system provides real-time alerts to both miners and control rooms, facilitating prompt responses to unsafe conditions.

Archana. D[10]a helmet system that employs a tri-axial accelerometer and GPS to detect accidents and transmit real-time alerts to emergency contacts via cloud services. By integrating a Wi-Fi-enabled microcontroller and RESTful APIs, the system ensures prompt and reliable communication, thereby enhancing rider safety through immediate incident reporting.

Although prior research exists in this domain, it is often narrowly concentrated on specific aspects of AI-Integrated Helmet-Mounted Thermal Imaging Systems for Victim Detection in Disaster Response Scenarios. This paper endeavours to address the existing research gap by adopting a more holistic perspective. The principal contributions of this study are delineated below:

1). Proactive accident avoidance systems have been developed through the integration of sensors, enabling real-time detection and mitigating the severity of potential hazards before they escalate.

2). The sensor integration in smart helmets allows for continuous surveillance of environmental and physiological conditions, facilitating timely interventions to enhance worker and rider safety.

3). By incorporating real-time data transmission, these systems enable instantaneous responses to accidents, ensuring prompt intervention and potentially saving lives in critical situations.

4). The incorporation of hazardous gas sensors in helmets for mining applications significantly mitigates risks by alerting workers to unsafe environmental conditions, thereby improving overall safety standards.

5). The collaborative use of IoT technologies and cloud connectivity enhances the smart helmet's ability to detect accidents and send location-based alerts to emergency contacts, providing a comprehensive safety solution across diverse environments.

The review of this paper is organized as follows: Section 2 provides an overview of the algorithms utilized in the proposed system. Section 3 discusses prevailing security technologies. Section 4 presents the systemarchitecture in detail. Section 5 explores the practical applications of the proposed approach. Finally, Section 6 concludes the study and outlines potential future work.

2. Overview of Algorithms

This section provides a concise overview of the principal algorithms employed in victim detection within AI-integrated helmet-mounted thermal imaging systems. These methodologies are broadly categorized into supervised and unsupervised learning paradigms, contingent upon the presence or absence of classification labels within the input dataset. Supervised learning algorithms necessitate annotated data, relying on explicit labeling to guide the learning process. In contrast, unsupervised learning techniques are adept at discerning underlying patterns without prior knowledge of labels, making them suitable for exploratory data analysis.

2.1. YOLOV8

YOLOv8, the latest iteration in the "You Only Look Once" family of object detection algorithms, represents a significant advancement in real-time computer vision tasks. Developed by Ultralytics, this model embodies the synthesis of architectural efficiency and predictive accuracy, positioning itself as a formidable framework for object detection, image segmentation, and classification applications.

At its core, YOLOv8 employs a single-stage detection mechanism, whereby the entire image is processed in a unified forward pass through a neural network. This architecture enables the model to predict bounding boxes and class probabilities simultaneously, thereby drastically reducing the inference time compared to two-stage detectors such as R-CNN[11] and its derivatives. This architectural philosophy not only streamlines the computational pipeline but also renders the model highly amenable to deployment in real-time systems, such as autonomous vehicles and surveillance technologies.

2.2. Fuzzy C-Means Clustering

Adaptive Fuzzy C-Means (AFCM) Clustering represents a sophisticated extension of the classical Fuzzy C-Means (FCM) algorithm[12], designed to enhance the flexibility, accuracy, and robustness of unsupervised learning in contexts characterised by ambiguity and noise—particularly in fields such as medical imaging, pattern recognition, and thermal data interpretation.

At its foundation, Fuzzy C-Means Clustering is a soft clustering technique wherein each data point is assigned a degree of membership to all clusters**[13].** rather than being rigidly classified into a single group. This nuanced approach better reflects the inherent uncertainty present in real-world datasets, especially in cases where clear class boundaries do not exist. The FCM algorithm seeks to minimise an objective function based on the weighted distance between data points and cluster centroids, with weights determined by membership grades[14].

However, traditional FCM presupposes fixed parameters, including the number of clusters and the fuzzification coefficient, which often results in suboptimal performance in dynamic or heterogeneous environments. To surmount these limitations, Adaptive Fuzzy C-Means Clustering introduces several modifications that dynamically adjust algorithmic parameters in accordance with the underlying data characteristics.

Moreover, AFCM often employs adaptive weighting schemes that modify the influence of each data point or feature dimension during the optimisation process. Such adaptivity allows the algorithm to place greater emphasis on informative features while diminishing the impact of outliers or irrelevant variables. In some implementations, the fuzzification exponent itself is made adaptive, varying in response to local data density or heterogeneity, thus offering a fine-tuned balance between cluster compactness and separation.

The iterative optimisation of AFCM proceeds through the repeated updating of cluster centroids and membership degrees until convergence criteria—typically based on changes in the objective function—are satisfied. This process utilises methods akin to gradient descent, where the partial derivatives of the cost function with respect to memberships and centroids guide the parameter updates.[15].[16].

2.3. Convolutional Neural Networks (CNNs)

Convolutional Neural Networks represent a distinguished subset of deep neural architectures, meticulously engineered to process and interpret data exhibiting a spatial or temporal structure, such as visual imagery[17].Rooted in the principles of biological vision, CNNs emulate the human visual cortex by hierarchically learning features from input data through a series of structured layers[18].At their core, CNNs are composed of convolutional layers, non-linear activation functions, pooling (subsampling) layers, and fully connected layers[19].The convolutional layer employs a set of learnable kernels or filters that systematically traverse the input tensor, executing discrete convolutional operations to extract localisedfeatures. This mechanism can be mathematically expressed as:

$$Y(i,j) = (X * K)(i.j) = \sum_{m}\sum_{n} X(i+m,j+n) \,.K(m, n) \text{----}(6)$$

where X signifies the input matrix, K denotes the convolutional kernel, and Y(i,j)) is the output feature map at spatial position (i,j).Following convolution, the incorporation of activation functions, such as the Rectified Linear

Unit (ReLU), introduces non-linearity into the network, thereby augmenting its capacity to model intricate and non-trivial relationships. Pooling layers, commonly implemented via max-pooling or average-pooling strategies, perform spatial downsampling, thereby reducing dimensionality, mitigating overfitting, and enhancing translational invariance[20].

The concluding segment of a CNN involves fully connected layers, wherein the multidimensional feature maps are flattened and subjected to a dense neural structure to facilitate classification, detection, or regression tasks.CNNs are celebrated for their exceptional proficiency in hierarchical feature extraction, progressively discerning elementary edges, textures, and shapes, culminating in the recognition of complex, abstract patterns. This renders them quintessential in a myriad of domains, including but not limited to computer vision, medical diagnostics, autonomous navigation, and remote sensing[21].

2.4. Thermal Gradient Flow(TGF)

The Thermal Gradient Flow (TGF) algorithm is a sophisticated computational technique employed in the analysis of thermal imaging data, particularly within applications necessitating the detection of subtle temperature variations, such as in disaster response scenarios[22].. This method capitalises on the spatial derivatives of temperature distributions to enhance the identification of regions exhibiting significant thermal contrasts, thereby facilitating the detection of objects or individuals based on their thermal signatures.At its core, TGF involves the computation of the gradient of temperature across a thermal image. This gradient represents the rate of change of temperature with respect to spatial coordinates and is instrumental in highlighting edges and boundaries within the thermal field. By calculating the magnitude and direction of these gradients, the algorithm delineates areas where temperature changes abruptly, which often correspond to the contours of objects or human bodies[23].

The implementation of TGF commences with the acquisition of thermal images, wherein each pixel intensity corresponds to a specific temperature value. Subsequently, the algorithm computes the partial derivatives of temperature with respect to the horizontal and vertical axes, typically using finite difference methods. These derivatives yield the gradient components, which are then combined to ascertain the gradient magnitude and orientation at each pixel[24].Thermal Gradient Flow stands as a potent tool in the analysis of thermal imagery, offering enhanced capabilities for detecting and delineating objects based on temperature variations. Its application in disaster response underscores its practical utility, providing a means to locate individuals in challenging conditions where conventional imaging techniques may falter. Continued advancements in thermal imaging technology and computational methods are poised to further augment the efficacy of TGF in various critical applications [25]..

2.5. Thermal Voxel Integration

Thermal Voxel Integration (TVI) represents an advanced computational methodology that amalgamates thermal imaging data with three-dimensional voxel-based models to enhance the detection and analysis of heat[26]. signatures within complex environments. This technique is particularly pertinent in applications such as disaster response, where identifying victims or heat sources amidst obscured or hazardous conditions is critical.

At its core, TVI involves the discretisation of a spatial domain into a voxel grid—a three-dimensional array of volumetric pixels—each encapsulating thermal data corresponding to a specific region in space [27] [28].. This voxelisation process facilitates the representation of thermal information in a structured format, enabling efficient analysis and manipulation of the data. By integrating thermal readings into this voxel framework, TVI allows for the reconstruction of detailed thermal profiles of the environment, capturing both surface and subsurface temperature variations[29].

The principal advantage of TVI lies in its ability to synthesise thermal data into a spatially coherent three-dimensional model, thereby providing a more comprehensive understanding of the thermal environment[30]. This integration facilitates the detection of subtle thermal anomalies and supports more informed assessments in complex scenarios[31] [32].

However, the implementation of TVI is not without challenges. Accurate mapping of thermal data onto the voxel grid requires meticulous calibration and may be impeded by factors such as sensor noise, occlusions, and environmental variability[33]. Additionally, the computational demands of processing and rendering three-dimensional thermal models necessitate robust hardware and optimised algorithms to ensure real-time performance[34].

3. Prevailing Security Technologies

In the realm of disaster response, effective victim detection is paramount to reducing response times and enhancing the safety of both victims and first responders[35]. Among the prevailing security technologies, thermal imaging systems have become indispensable tools for locating victims in environments with limited visibility, such as smoke-filled buildings or areas with poor lighting conditions[36]. These systems, when integrated into helmet-mounted devices, provide responders with the ability to remain mobile while monitoring heat signatures in real time[37]. By detecting temperature variations, thermal cameras allow responders to identify human figures through their body heat, even in conditions where traditional visual identification is not possible[38].

The integration of Artificial Intelligence (AI) with thermal imaging systems has ushered in significant advancements in the field. AI algorithms now possess the ability to analyse thermal data in real-time, distinguishing human heat signatures from other environmental anomalies. This capability drastically enhances the accuracy of victim detection, reducing the likelihood of false positives[39]. Moreover, AI-enabled systems can adapt to dynamic environments by continuously learning and improving based on prior data, thus offering greater efficiency in future disaster scenarios. The synergy between machine learning and pattern recognition within AI systems ensures precise identification and tracking of victims, even in complex and rapidly changing environments[40].

Table1: Comparison of different algorithm

Ref	Year	Title	Algorithm	Advantages	Drawbacks
[41]	2023	Real-Time Person Detection in Wooded Areas Using Thermal Images from an Aerial Perspective	YOLOv3 (You Only Look Once version 3)	Offers real-time object detection with high accuracy and efficient processing suitable for aerial thermal imagery.	Performance may degrade in densely occluded or low-resolution thermal environments due to limited feature representation.
[42]	2025	Infrared and Visible Image Fusion Techniques Based on Deep Learning	Deep Convolutional Neural Network (DCNN)-based Fusion	Facilitates the extraction of complementary features from infrared and visible modalities, thereby enhancing image detail and contrast.	Requires substantial computational resources and large-scale datasets for effective training and generalization.
[43]	2023	Flash flood susceptibility mapping using a novel deep learning model based on deep belief network, back propagation and genetic algorithm.	Deep Belief Network integrated with Backpropagation and Genetic Algorithm (DBN-BP-GA)	Enhances predictive accuracy by combining feature learning capabilities of DBNs with optimisation strength of genetic algorithms.	Involves complex architecture and prolonged training time, potentially limiting scalability and real-time applicability.

[44]	2022	Thermal Image Tracking for Search and Rescue Missions with a Drone	Kernelised Correlation Filter (KCF)	Enables fast and efficient object tracking in thermal imagery with minimal computational overhead.	Exhibits reduced robustness under significant occlusion or abrupt motion changes, affecting tracking continuity.
[45]	2024	UAV-based Post-disaster Damage Assessment of Buildings Using Image Processing	Histogram of Oriented Gradients (HOG) with Support Vector Machine (SVM)	Provides reliable feature extraction and classification for structural damage identification in post-disaster scenarios.	May struggle with complex backgrounds or varying illumination, leading to decreased detection accuracy.
[46]	2017	An improved lightweight YOLOv5 algorithm for detecting strawberry diseases	Improved Lightweight YOLOv5	Achieves high detection accuracy with reduced model complexity, making it suitable for deployment on resource-constrained devices.	May exhibit diminished performance when detecting visually similar disease symptoms under variable lighting conditions.
[47]	2022	An Enhanced YOLOv4 Model With Self-Dependent Attentive Fusion and Component Randomized Mosaic Augmentation for Metal Surface Defect Detection	Enhanced YOLOv4 with Self-Dependent Attentive Fusion	Improves detection precision for small and complex defects by integrating attention mechanisms and diverse data augmentation.	Increases model complexity and training time, which may hinder real-time performance on standard hardware.

4. Architecture

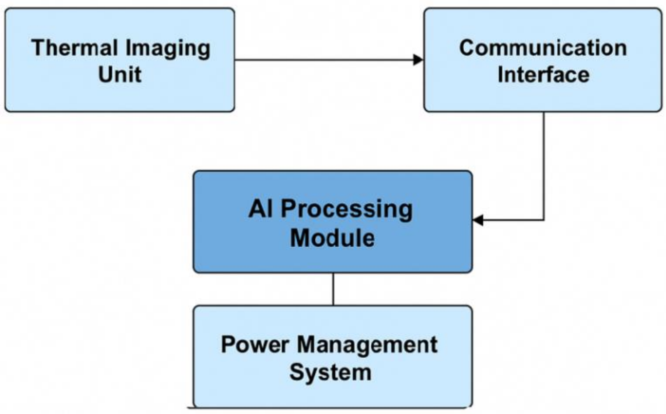

Fig. 2: Architecture of the AI-integrated helmet-mounted thermal imaging system

The architecture of the AI-integrated helmet-mounted thermal imaging system for victim detection in disaster response comprises several critical modules working in concert to ensure real-time, on-site situational awareness[48]. At its core, the system features a helmet-mounted thermal camera capable of capturing heat signatures from the environment, thus enabling the identification of human presence in visually obstructed conditions such as smoke, darkness, or debris. This thermal feed is processed instantaneously by an embedded edge AI processor, which utilises advanced machine learning algorithms to distinguish human thermal patterns from environmental anomalies. By performing data analysis at the source, the system significantly reduces latency, ensuring rapid detection and response. Furthermore, a sensor fusion module combines input from GPS, accelerometers, and gas detectors to enrich the contextual understanding of the scenario, enabling more accurate victim localisation and hazard identification[49].

In addition to real-time data processing, the system includes a robust communication interface that facilitates wireless transmission of alerts, victim locations, and thermal visuals to remote command centres or nearby responders via Wi-Fi, 5G, or Bluetooth. This ensures seamless coordination and enhances the effectiveness of rescue operations[50]. A cloud support mechanism provides extended functionality by archiving data for future analysis and allowing integration with broader emergency management platforms. Power efficiency is managed through an intelligent battery management system designed for prolonged field use. To further support the rescuer, a user interface—either through a heads-up display or audio feedback—delivers critical information without diverting attention from the rescue environment. Altogether, this architecture exemplifies a holistic and technologically sophisticated approach to enhancing disaster response efficacy through AI-driven thermal imaging solutions.

5. Application

1. Detects heat signatures through dense smoke and poor visibility. Helps firefighters locate trapped individuals quickly and safely.
2. Identifies body heat under debris or rubble during earthquakes or building collapses. Increases the chances of finding survivors in inaccessible areas.
3. Monitors toxic gases and environmental hazards like chemical spills. Alerts responders in real-time, enhancing operational safety.
4. Assists in search-and-recovery missions in dangerous or unknown territories.AI enhances situational awareness and decision-making under stress.
5. Multiple helmet data can be synchronized to give a real-time map of victim locations. Supports coordinated team efforts and strategic rescue planning.

6. Conclusion

In summation, the integration of Artificial Intelligence with helmet-mounted thermal imaging systems constitutes a profound technological advancement in contemporary disaster response operations. These intelligent systems afford first responders the capacity to detect victims expeditiously, even within visually restrictive environments such as smoke-laden interiors or nocturnal landscapes. By harnessing the computational efficacy of AI—specifically in the domains of pattern recognition and real-time thermal data interpretation—these systems markedly augment the precision and speed of victim identification. Nevertheless, several impediments persist, including limitations in battery longevity, data processing latency, and the ruggedisation of devices for deployment in volatile settings. Notwithstanding these challenges, the prospective utility of such AI-enhanced technologies remains unequivocal. With sustained research and iterative refinement, these helmet-mounted solutions are poised to become indispensable apparatuses, underpinning more agile, informed, and life-preserving interventions in future humanitarian and emergency scenarios.

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