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Utilizing Robotic System for Disaster Scene Classification - A Deep Learning Approach

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Abstract: Disaster scene classification plays a vital role in emergency management by facilitating rapid assessment and response to scenarios such as floods, earthquakes, and wildfires. Traditional image classification methods face challenges due to the complexity and variability of disaster scenes, which often include irregular patterns and diverse environmental factors. In recent years, deep learning, particularly convolutional neural networks (CNNs), has demonstrated significant potential in improving the accuracy of disaster scene classification. This project integrates a CNN-based approach with a remote-controlled robot equipped with real-time image-capturing capabilities. The robot navigates disaster zones, capturing images that are processed using CNN architecture like VGG16 and VGG19 to classify disaster scenes efficiently. The robotic system enhances situational awareness by autonomously collecting vital information in hazardous environments, transmitting real-time data for classification, and providing timely insights for emergency response. This integration of robotics with deep learning not only automates disaster scene classification but also reduces reliance on large, labeled datasets, improving performance and response effectiveness.

I. INTRODUCTION

Natural disasters such as floods, cyclones, earthquakes, and wildfires cause significant loss of life and property. Effective disaster response requires real-time situational awareness to assess damage, allocate resources, and coordinate rescue operations. Traditional methods often expose responders to hazardous conditions and suffer from delays in data collection. Advancements in artificial intelligence (AI) and robotics offer an efficient solution to enhance disaster management.

This project proposes a robotic system integrated with deep learning models, specifically Convolutional Neural Networks (CNNs) such as VGG16 and VGG19, for disaster scene classification. The robot, equipped with cameras, sensors, and wireless communication, autonomously navigates disaster zones, capturing real-time images and transmitting them for classification. The CNN model processes these images to accurately categorize disaster scenes, enabling authorities to make informed decisions quickly. The system operates autonomously, reducing human risk while improving response efficiency. It can detect and classify different disaster scenarios, such as flooded regions, fire-stricken areas, or collapsed buildings, helping emergency teams prioritize critical locations. The use of wireless communication ensures seamless data transmission, allowing real-time monitoring and decision-making. The hardware implementation consists of a chassis, gear DC motors, cameras, and communication modules, while the software framework employs TensorFlow or PyTorch for deep learning. Future enhancements include integrating additional sensors, improving classification accuracy, and extending operational range. By combining robotics, AI, and wireless technology, this project presents a scalable and effective tool for modern disaster management.

II. LITREATURE SURVEY

A. Deep Learning ways for Disaster Scene Classification: The application of deep learning (DL) techniques in disaster scene classification has garnered significant attention in recent years due to the increasing improved image quality but also provided better data for deep learning models to work with. Tang and Chen [4] extended the application of DL by highlighting the importance of mobile image analysis in disaster management, focusing on how mobile devices can assist in capturing and analyzing disaster scenes in real-time. The proliferation of mobile technology allows for broader data collection and contributes to faster disaster response. Moreover, Arnold and Yamazaki [5] emphasized the use of CNNs for scene parsing in mobile robots during emergency situations. Their work demonstrated how CNNs could be integrated into robotic systems for real-time disaster scene classification, enabling robots to act as first responders. This real-time processing capability allows for immediate assessment of disaster situations and more informed decision-making. Bird et al. [7] further underscored the effectiveness of CNN transfer learning for disaster scene classification, bridging the gap between simulation and real-world scenarios, thus improving the overall performance of disaster response systems.

B. Domain-Specific Applications: The domain-specific applications of deep learning in disaster management highlight how tailored approaches can yield better results for disaster scenarios. Khan et al. [10] presented the Deep Fire dataset and deep transfer learning benchmarks, which were specifically designed for forest fire detection. Their study illustrates the flexibility of DL techniques to adapt to different types of disasters. Lu et al. [11] employed deep learning and transfer learning for landslide detection through object-oriented image analysis, showing the capability of these availability of high-resolution imagery and the computational power needed for deep learning models.

Various studies have demonstrated the potential of Convolutional Neural Networks (CNNs) and other deep learning frameworks in enhancing disaster response efforts. The primary goal of these studies is to develop efficient algorithms for identifying and assessing disaster-affected areas in real-time, which can aid decision-makers in deploying resources more effectively. Xu et al. [1] explored the use of deep learning for rainfall data prediction through remote sensing images, illustrating the ability of DL models to capture intricate details from satellite imagery. Their novel approach to scene classification offers promising avenues for disaster management. Similarly, Dotel et al. [2] utilized CNNs to perform catastrophe assessments by analyzing topographical features in satellite imagery, further cementing the role of DL in disaster assessment. This method of analyzing large datasets of remote sensing images allowed for faster and methods to address specific disaster-related challenges. In the context of urban search and rescue, Zhang et al. [12] and Arnold et al. [5] explored the use of deep learning for 3D mapping of disaster-stricken areas, particularly in urban environments.

By using robot-assisted systems, they demonstrated how DL could assist in the localization and rescue of victims. This line of research underscores the potential of combining DL with robotic systems to improve the speed and accuracy of disaster response operations. Zhang et al. [13] also proposed a sensory system for 3D mapping in search and rescue missions, providing a foundation for future advancements in robotic disaster relief.

The study by Hanif et al. [14] introduced VRBaggedNet, an ensemble-based deep learning model designed for the classification of catastrophic events. This model demonstrated competitive performance in identifying and categorizing disaster scenes, offering insights into how ensemble methods could improve disaster classification accuracy. Gopika et al. [15] developed a human-detecting robot for disaster relief, further showcasing how DL models can be integrated into robotic platforms for victim search and rescue. Their system was able to navigate through disaster-affected areas and locate victims, enhancing the overall efficiency of the relief efforts.

III. PROBLEM STATEMENT

To develop a robotic system that captures real-time images of disaster scenes and uses deep learning models (VGG16, VGG19) to classify various disaster scenarios such as cyclones, earthquakes, floods, and wildfires, improving disaster response and management.

IV. PROPOSED SYSTEM

This study presents the development of a remote-controlled robotic platform designed to enhance disaster response through real-time scene classification [8]. The system integrates high-resolution camera sensors and deep learning algorithms to assess disaster-affected areas efficiently [15]. The robot is engineered to traverse hazardous environments, capturing detailed images to identify and evaluate natural disasters such as floods, earthquakes, wildfires, and cyclones [10].

To achieve accurate classification, the system employs Convolutional Neural Networks (CNNs), particularly VGG16 and VGG19 architectures, ensuring robust image processing and feature extraction [6]. Wireless communication is utilized for seamless image transmission to a cloud server, enabling rapid analysis and decision-making [9]. This framework enhances situational awareness by providing emergency responders with critical insights, reducing dependency on extensive labelled datasets, and improving overall disaster management efficiency [12].

Key hardware components include high torque geared DC motors for mobility [16], an ESP32 or Raspberry Pi for control and data processing [17], and advanced imaging sensors for real-time data acquisition [18]. Software frameworks such as TensorFlow and OpenCV are leveraged to process and analyse the collected data effectively [3]. By integrating these technologies, the proposed system aims to support first responders in making informed decisions, ultimately improving response times and mitigating disaster impacts [14].

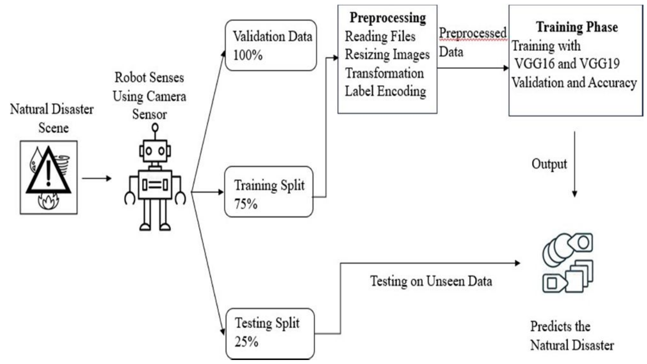

Fig. System Architecture

The proposed system architecture aims to classify natural disaster scenes using a camera-equipped robot and deep learning models. The robot captures images of disaster scenarios through its camera sensor, which are then split into training (75%), testing (25%), and validation (100%) datasets. The collected images undergo preprocessing steps such as file reading, image resizing, transformation, and label encoding to prepare them for model training. Preprocessed data is used to train deep learning models—specifically VGG16 and VGG19—while performance is monitored using the validation set. Once trained, the model is tested on unseen data to evaluate its accuracy and generalization. The final output predicts the type of natural disaster, enabling automated scene classification for disaster response systems.

V. EXISTING SYSTEM

Modern disaster management strategies increasingly integrate artificial intelligence (AI) and robotic technologies to enhance emergency response and situational awareness[8] One of the widely studied approaches involves the use of Convolutional Neural Networks (CNNs), particularly deep architectures such as VGG16 and VGG19, for disaster scene classification[6]. These models are typically trained on publicly available datasets, such as those sourced from Kaggle, which include categorized images of natural disasters like cyclones, earthquakes, floods, and wildfires[10]. The data is pre-processed and systematically divided into training, validation, and testing subsets to ensure accurate classification [18]. Existing systems have demonstrated high accuracy, with VGG16 achieving up to 93% and VGG19 reaching 97% after extensive training cycles [3]. Additionally, robotic platforms equipped with high-resolution cameras and environmental sensors have been deployed to autonomously navigate disaster-affected areas, collect visual data, and relay real-time information to cloud-based processing units [15]. Wireless communication enables seamless data transmission, allowing for rapid image analysis and decision-making, which can significantly enhance disaster response efforts [9].

Despite these advancements, existing solutions still face several challenges. Many rely on extensive labelled datasets, which may not always be available or comprehensive enough for real-world scenarios [12]. Moreover, limitations in wireless communication, high computational demands on embedded systems, and the need for real-time inference in harsh environments affect operational reliability [17]. These constraints highlight the need for more adaptive, efficient, and scalable disaster response frameworks that integrate optimized deep learning models with robust robotic technologies [16].

VI. MATERIALS AND METHODS

A. Software Requirements

The proposed disaster management system utilizes a robust software stack for training, deployment, and real-time inference of deep learning models. The selected tools ensure efficient data preprocessing, model optimization, and seamless integration with hardware components.

1. Programming Languages

Python 3.x – Used for machine learning, image processing, and system integration.

C/C++ – Utilized for low-level hardware control, specifically for ESP32 firmware development.

2. Machine Learning & Deep Learning Frameworks

TensorFlow / Keras – Implements and trains CNN architectures (VGG16, VGG19) for disaster classification.

PyTorch (Optional) – Alternative deep learning framework for experimentation.

3. Image Processing & Computer Vision
OpenCV – Performs image preprocessing, feature extraction, and real-time video processing.
Pillow (PIL) – Handles image dataset manipulation.
4. Data Processing & Analysis
NumPy & Pandas – Facilitates dataset management and numerical computations.
Scikit-Learn – Provides data preprocessing, feature scaling, and evaluation metrics.
Matplotlib & Seaborn – Used for data visualization and performance analysis.
5. Model Training & Deployment
Google Colab / Jupyter Notebook – Cloud-based environments for training and testing models.
TensorFlow Lite / ONNX – Optimizes deep learning models for deployment on edge devices.
6. Hardware Communication & Control
RPi.GPIO / pigpio – Manages Raspberry Pi-based motor and sensor interfacing.
PySerial – Enables serial communication between Raspberry Pi and ESP32.
7. Networking & Remote Monitoring
MQTT / WebSockets – Facilitates real-time data exchange between the robot and cloud services.
Flask / Fast API – Implements a lightweight API for remote monitoring and control.
8. Cloud & Data Storage
Firebase / AWS IoT (Optional) – Provides cloud-based storage and real-time access to disaster data.
SQLite / PostgreSQL (Optional) – Manages structured data for logging and analysis.

B. Hardware Requirements

Hardware Requirements for Disaster Management Robot

The proposed disaster management robotic system integrates advanced hardware components for autonomous navigation, real-time image processing, and disaster scene classification. Designed for efficiency in disaster-affected areas, it ensures durability, computational power, and reliable communication.

1. Processing Unit
Raspberry Pi 4 (4GB/8GB RAM): Handles AI model inference and image processing.
ESP32 (Optional): Manages lightweight tasks and wireless communication.
2. Mobility & Actuation
Geared DC Motors (12V, 300-600 RPM): Enables smooth navigation on rough terrain.
Motor Driver (L298N / BTS7960): Controls motor speed and direction.
Servo Motors (SG90 / MG995): Adjusts camera angles and sensor positioning.
Wheels/Tracks: Chosen based on terrain requirements.
3. Camera & Vision System
Raspberry Pi Camera Module v2 / HQ Camera: Captures high-resolution images for scene classification.
4. Sensors
Ultrasonic Sensors (HC-SR04 / TF-Luna LiDAR): Detects obstacles for autonomous movement.
IMU (MPU6050 / MPU9250): Provides stability and orientation tracking.
Gas & Smoke Sensors (MQ-2 / MQ-135):Detects hazardous gases.
Temperature & Humidity Sensor (DHT22 / BME280): Monitors environmental conditions.
5. Power Supply
Li-Po Battery (11.1V, 2200mAh or higher):Primary power source.
Voltage Regulator (LM2596 / XL4015):Provides stable power output.
6. Communication & Networking
- *Wi-Fi Module (ESP32 / Raspberry Pi Wi-Fi/ELRS):* Enables wireless data transmission.
7. Chassis & Structural Components
Aluminum / 3D-Printed Chassis: Lightweight yet durable.

This system optimizes real-time scene classification, navigation, and environmental monitoring, supporting first responders in disaster response and recovery.

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VII. EXPERIMENTAL RESULT

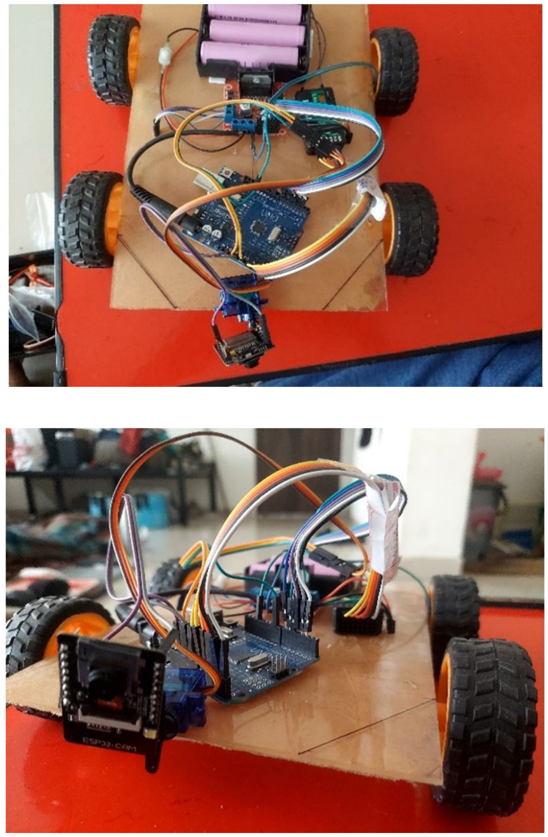

Fig. Robot

Prototype of a disaster management robot featuring an Arduino Uno, L298N motor driver, ultrasonic sensor, camera module, and a lithium-ion battery pack. Designed for real-time scene classification and navigation in disaster zones, the robot supports environmental monitoring and wireless data transmission.

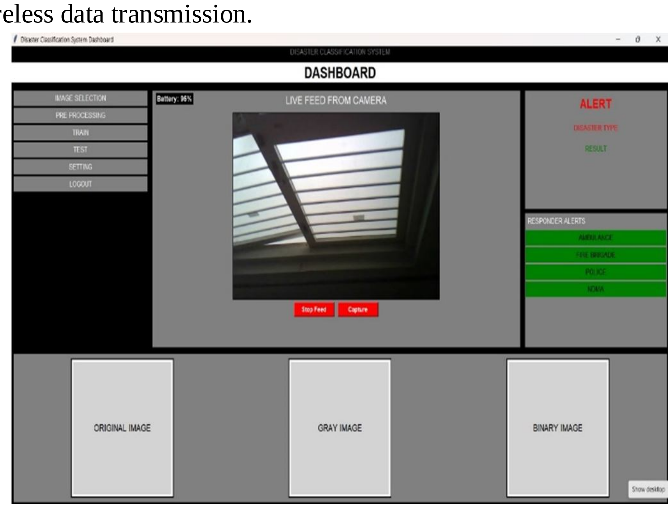

Fig. GUI of Disaster Scene Classification

Graphical User Interface (GUI) of the Disaster Classification System. The dashboard displays a live camera feed, battery status, classification controls, and responder alerts for emergency services such as ambulance, fire brigade, and police.

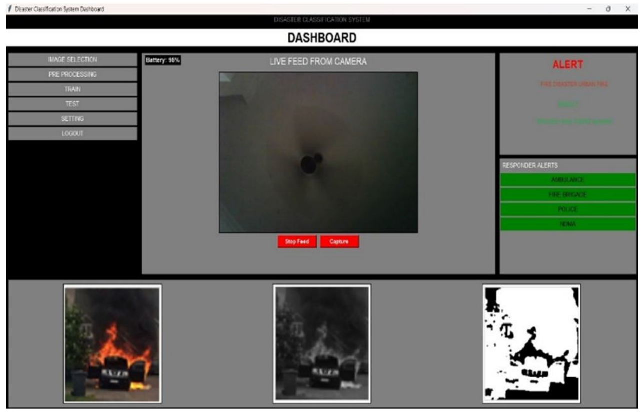

Fig. Image Processing

Disaster classification interface using deep learning. The GUI displays the original, grayscale, and binary versions of the input image. A convolutional neural network (CNN) is used to classify the disaster type, with the result and execution time shown on screen.

VIII. MATHEMATICAL MODEL

A. *Mathematical Model for Disaster Management Robot*

The mathematical model provides a structured representation of the system, defining its input, process, and output relationships. The project involves robotic navigation, deep learning-based disaster scene classification, real-time data transmission, and decision-making.

1. System Definition

Let S be the overall system:

$$S = \{I, P, O\}$$

where:

- I is the set of inputs
- P is the set of processes applied to inputs
- O is the set of outputs

2. Input Parameters (I)

$$I = \{X, V, S, T\}$$

where:

- $X \rightarrow$ Image dataset captured by the robot's camera
- $V \rightarrow$ Velocity and position of the robot
- $S \rightarrow$ Sensor data (ultrasonic, gas, IMU, etc.)
- $T \rightarrow$ Environmental conditions

3. Process (P)

Deep Learning-Based Scene Classification

The system uses Convolutional Neural Networks (CNNs) for disaster classification. The input image X is passed through convolutional layers:

$$Z = W.\ X + B$$

where:

- Z is the feature map
- W represents the filter weights
- X is the input image matrix
- B is the bias term

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The ReLU activation function introduces non-linearity:

$$f(Z) = \max(0, Z)$$

The final classification probability for disaster type $\mathcal{Y}i$ is computed using Softmax Function:

$$P(\mathcal{Y}i) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

The Loss Function (Categorical Cross-Entropy):

$$L = -\sum_{i=1}^{N} \mathcal{Y}i \, log(\hat{\mathcal{Y}}i)$$

where:

- $\mathcal{Y}i$ is the true label
- $\hat{\mathcal{Y}}i$ is the predicted probability

The network updates weights using Gradient Descent

$$w = w - \eta \frac{\partial L}{\partial W}$$

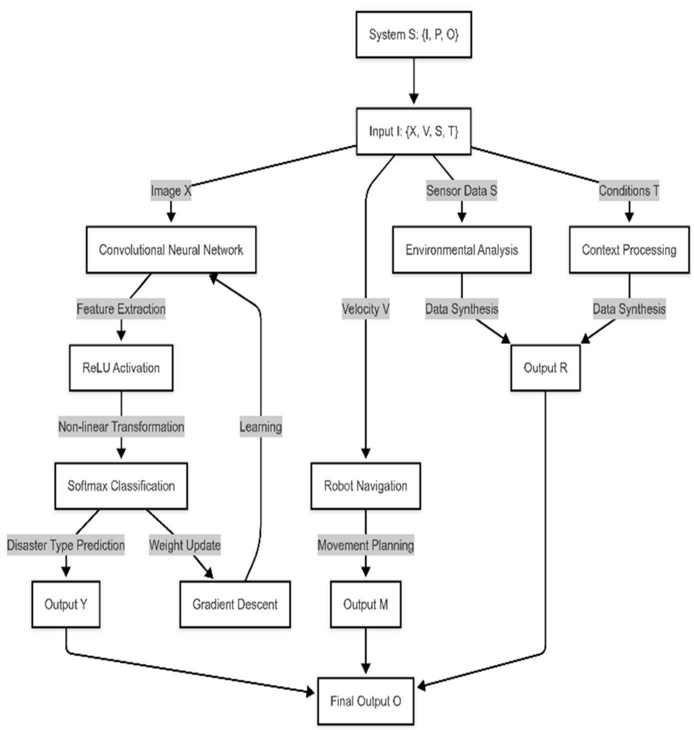
Where is the learning rate

4. Output (O)

$$O = \{Y, M, R\}$$

where:

- Y = Predicted disaster classification output
- M = Robot's movement direction
- R = Data sent to emergency response team



Flow chart of Disaster Scene Classification

Flowchart of the disaster classification and response system. The process integrates image input, sensor data, and contextual information for CNN-based disaster type prediction, robot navigation, and final decision synthesis.

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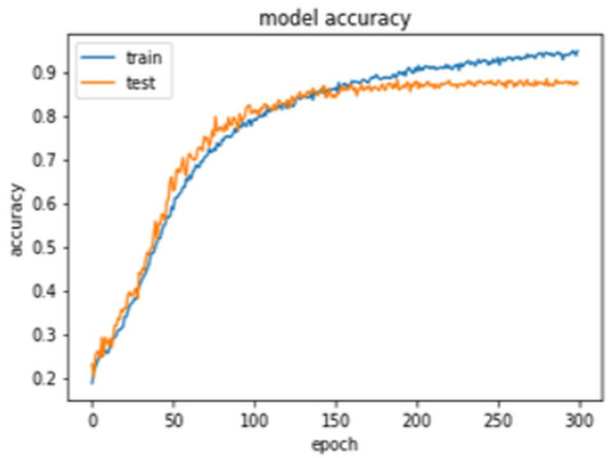
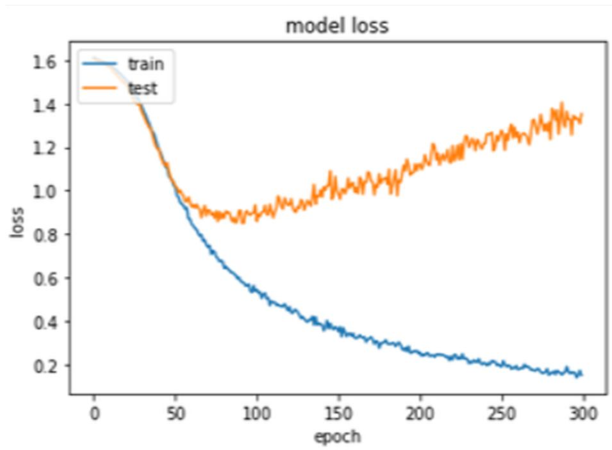
IX. SIMULATION RESULT



The graph illustrates the training and testing accuracy of the model over 300 epochs. As shown, both the training and testing accuracy steadily improve during the early epochs, indicating effective learning. The training accuracy continues to increase, reaching above 0.95, while the testing accuracy plateaus around 0.88 after approximately 200 epochs. This slight divergence between training and testing accuracy suggests minor overfitting, which is typical in deep learning models trained for extended periods. Overall, the graph demonstrates that the model achieves high accuracy and generalizes well to unseen data.



The graph shows the training and testing loss over 300 epochs. Initially, both training and testing losses decrease, indicating that the model is learning effectively. However, after around 50 epochs, the testing loss begins to increase while the training loss continues to decrease, suggesting the onset of overfitting. By the end of training, the training loss falls below 0.2, while the testing loss rises above 1.0. This growing gap between training and testing loss indicates that although the model performs well on training data, its performance on unseen data is negatively affected due to overfitting.

X. CONCLUSION

The use of deep learning techniques in disaster management has been investigated in this research study, with particular attention paid to robot integration, domain- specific applications, and scene categorization. After a thorough analysis of pertinent research, deep learning - more specifically, CNNs has become an effective method for categorizing catastrophe scenes, enabling accurate and rapid identification of various natural disasters such as cyclones, earthquakes, floods, and wildfires. Additionally, domain- specific applications have demonstrated the versatility of deep learning in addressing specific challenges within disaster management, including remote sensing imagery analysis, social media sensing, and forest fire detection. Furthermore, the integration of robots equipped with advanced sensors and cameras offers a promising approach to enhance situational awareness and streamline response efforts in disaster scenarios. By leveraging deep learning algorithms for real-time data analysis and decision-making, these robotic platforms can autonomously navigate through affected areas, collect vital information, and communicate with emergency responders, thereby mitigating risks and improving overall response effectiveness.

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