AN APPROACH FOR DISASTER VICTIM DETECTION USING ML

Submitted in partial fulfillment of the requirements for the award of the Degree of

BACHELOR OF TECHNOLOGY

In

COMPUTER SCIENCE AND ENGINEERING

Submitted by

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RAMACHANDRA COLLEGE OF ENGINEERING

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CERTIFICATE

This is to certify that MD.ABUBAKAR SIDDQUE(21ME1A0597), S.SAI GANESH(21ME1A05B5), N.GANESH (21ME1A05A0), D.SAI SIDDARTH (21ME1A0578) students of Bachelor of Technology in Computer Science & Engineering have successfully completed their project work entitled **"AN APPROACH FOR DISASTER VICTIM DETECTION USING ML"** at Ramachandra College of Engineering, Eluru during the Academic Year 2024-2025.
This document is submitted in partial fulfillment for the award of the Degree of Bachelor of Technology in Computer Science & Engineering and the same is not submitted elsewhere.

Dr. K SWETHA SASTRY,
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DECLARATION

We are MD.ABUBAKAR SIDDQUE (21ME1A0597), S.SAI GANESH (21ME1A05B5), N.GANESH (21ME1A05A0), D.SAI SIDDARTH (21ME1A0578), here by declares the project report titled **"AN APPROACH FOR DISASTER VICTIM DETECTION USING ML"** under the supervision of **Dr. K SWETHA SASTRY** Professor Department of Computer Science and Engineering is submitted in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Computer Science and Engineering.

This is a record of work carried out by us and the results embodied in this project have not been reproduced or copied from any source. The results embodied in this project report have not been submitted to any other University or Institute for the award of any other degree or diploma.

ACKNOWLEDGEMENT

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Finally, we thank one and all who directly or indirectly helped us to complete our project work successfully.

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ABSTRACT

Disasters like earthquakes, floods, building collapse and wildfires often leave many people injured or trapped. Finding victims quickly is critical for saving lives, but traditional search-and-rescue efforts are slow and rely heavily on human effort, which can be inefficient in large-scale disasters. To solve this problem, we developed a machine learning-based system that automatically detects disaster victims in images. Our approach uses ResNet50, a powerful deep learning model, to analyse and extract important features from images. These features are then processed by a random forest classifier, which has been trained on a diverse dataset of images depicting various disaster scenarios. By leveraging this advanced technology, our system significantly accelerates the identification of individuals in distress, allowing rescuers to allocate resources more effectively. the integration of this automated process not only enhances operational efficiency but also increases the likelihood of successful rescues in critical situations. Random forest classifier, a machine learning technique that makes final predictions based on patterns in the data. To make the system accessible and easy to use, we deployed it as a Flask API, which means users can upload images through a web-based interface, and the system will quickly analyse and return results.

This study presents a comprehensive pipeline for preprocessing, analyzing, and modeling a dataset of victim and non-victim images using machine learning and deep learning techniques. The work addresses multiple aspects of data preparation, feature extraction, and classification, and introduces robustness testing through the application of noise to images. The dataset was organized into training, validation, and test splits, with checks to ensure the integrity and validity of image files. Metrics such as file size and image dimensions were analyzed, and invalid or corrupted images were excluded. Noise augmentation techniques, including Gaussian and salt-and-pepper noise, were implemented to simulate real-world variability.

Chapter-1
INTRODUCTION

1.1 INTRODUCTION

Disasters, both natural and man-made, pose significant challenges for emergency response teams. The immediate aftermath of events like earthquakes, landslides, floods, or terrorist attacks often involves chaotic and hazardous environments where locating victims trapped under debris is critical to saving lives. Traditional search-and-rescue (SAR) operations rely heavily on manual methods, which are time-intensive, prone to human error, and often place rescue workers at significant risk. In such scenarios, leveraging advancements in technology, particularly machine learning (ML) and deep learning (DL), can revolutionize disaster victim detection.

The proposed project focuses on developing an efficient and accurate system for disaster victim detection using a hybrid approach that integrates ResNet-50 and Random Forest algorithms. ResNet-50, a deep convolutional neural network (CNN), excels at extracting complex features from images, making it ideal for analyzing disaster scene visuals. Its transfer learning capability allows it to adapt to specific tasks, such as identifying victims amidst debris, by leveraging pre-trained knowledge from large-scale datasets like ImageNet.

To enhance the classification process, we employ Random Forest, a robust machine learning algorithm known for its ability to handle noisy and imbalanced datasets. By combining these techniques, the system achieves high accuracy in detecting victims, ensuring rapid and reliable performance in cluttered or visually complex environments. Label encoding is utilized to preprocess categorical data, transforming labels like "Victim" and "Non-victim" into numerical formats for seamless integration into the machine learning pipeline.

This project emphasizes real-world applicability by addressing common challenges in disaster scenarios, such as poor lighting conditions, occlusions, and environmental noise. By leveraging this hybrid ML-DL approach, the system aims to minimize detection errors, reduce response times, and improve overall SAR effectiveness.

The project not only contributes to the field of disaster management but also highlights the transformative potential of AI-driven technologies in addressing critical global challenges. This introduction provides an overview of the motivation, objectives, and significance of the proposed system, setting the foundation for a detailed exploration of its methodology and implementation.

1.2 OVERVIEW OF THE PROJECT

The project “An Approach for Disaster Victim Detection Using Machine Learning,” aims to develop a robust, AI-driven system capable of detecting victims in disaster scenarios such as collapsed buildings, landslides, and other debris-laden environments. By utilizing a combination of advanced machine learning and deep learning techniques, the system ensures high accuracy, speed, and reliability in victim identification and localization.

Key Components of the System

1)Data Preprocessing with Label Encoding

- Label encoding is employed to convert categorical data into numerical formats. For instance, victim status (e.g., "Victim" or "Non-victim") is transformed into numerical labels like 1 and 0, facilitating seamless integration into machine learning models.
- This preprocessing step ensures that the data is uniform and ready for training and evaluation.

2)Feature Extraction Using ResNet-50

- ResNet-50, a deep convolutional neural network (CNN), is used for extracting meaningful features from disaster scene images.
- Pre-trained on large datasets, ResNet-50 provides transfer learning capabilities, enabling the model to adapt to specific tasks, such as detecting humans amidst debris.
- The network’s skip connections help mitigate issues like vanishing gradients, ensuring deep learning performance even in challenging scenarios.

3)Classification Using Random Forest

- Random Forest, a powerful ensemble machine learning algorithm, is used for classifying the extracted features.
- Its ability to handle noisy and imbalanced data ensures that the system remains effective even when the input data is not ideal.
- By constructing multiple decision trees and averaging their predictions, Random Forest provides reliable and accurate classifications, distinguishing between victims and non-victims.

1.3 OBJECTIVE OF THE PROJECT

The primary objective of this project, **"An Approach for Disaster Victim Detection Using Machine Learning,"** is to design and implement an efficient and reliable system that leverages advanced machine learning and deep learning techniques to detect and identify victims in disaster scenarios.

Objectives:

1)Automated Victim Detection

- Develop an automated pipeline capable of detecting human victims from complex disaster scene data such as images captured from drones or ground-based cameras.

2)Integration of ResNet-50 for Feature Extraction

- Utilize the ResNet-50 deep learning model for extracting robust features from visual data, ensuring high accuracy even in cluttered or low-visibility environments.

3)Enhanced Classification Using Random Forest

- Employ the Random Forest algorithm for classifying extracted features into victim and nonvictim categories, ensuring scalability and resilience to noisy data.

4)Data Preprocessing

- Implement label encoding techniques to preprocess categorical data, ensuring seamless integration into the machine learning pipeline.

5)Real-Time Detection Capability

- Design the system to deliver real-time or near-real-time predictions to assist search-and-rescue (SAR) operations in rapidly identifying victim locations.

6)Scalability and Adaptability

- Create a scalable solution that can adapt to various disaster scenarios, including earthquakes, floods, landslides, and building collapses.

7)Enhancing Rescue Efficiency

- Reduce response times and improve resource allocation by providing precise victim localization to rescue teams, ultimately saving lives during critical situations.

8)Robustness in Adverse Conditions

- Ensure the system performs reliably in adverse conditions, such as low light, poor visibility, and noisy or cluttered environments.

1.4 SCOPE OF THE PROJECT

"An Approach for Disaster Victim Detection Using Machine Learning," has a broad scope that extends across multiple domains, including disaster management, search-and-rescue (SAR) operations, and realtime victim detection. By leveraging advanced techniques such as ResNet-50 for feature extraction, Random Forest for classification, and Label Encoding for data preprocessing, the project aims to address the critical challenges of victim detection in complex disaster scenarios.

Project Scope

1)Technical Scope

- **Feature Extraction with ResNet-50:** Utilize the ResNet-50 deep learning model to extract robust and meaningful features from disaster scene images, ensuring accurate detection in various scenarios.
- **Machine Learning Integration:** Employ the Random Forest algorithm for classification to enhance reliability and handle noisy, imbalanced, or complex data effectively.
- **Data Preprocessing:** Implement label encoding to manage categorical variables, ensuring seamless integration of diverse data types into the machine learning pipeline.

2)Operational Scope

- **Real-Time Detection:** Design the system for real-time or near-real-time detection to assist searchand-rescue teams in identifying victims promptly.
- **Multi-Scenario Application:** The system is adaptable to various disaster scenarios, such as earthquakes, floods, landslides, and collapsed buildings, making it versatile and scalable.
- **Robustness in Adverse Conditions:** Ensure the solution is robust against environmental challenges such as low light, debris, and occlusions.

3)Impact on Disaster Management

- **Enhanced Efficiency:** Reduce the time taken to locate victims, enabling faster rescue operations and better allocation of resources.
- **Life-Saving Potential:** By providing accurate victim detection, the project directly contributes to saving lives during critical situations.
- **Scalability:** The solution can be expanded or adapted to other types of emergencies or integrated with additional technologies, such as drone-mounted cameras or thermal imaging sensors.

1.5 EXPECTED OUTCOME

1.Enhanced Detection Accuracy

- Achieve high leves of precision and recall in detecting victims in disaster environments, even under challenging conditions such as debris, low lighting, or occlusions.
- Minimize false positives and false negatives in the classification of images to ensure reliable victim identification.

2. Robust Feature Extraction

- ResNet-50 will extract deep and meaningful features from disaster scene images, enabling the system to differentiate between victims and non-relevant objects accurately.
- Efficiently handle complex image data, ensuring scalability to various types of disasters (e.g., earthquakes, floods, or collapsed buildings).

3. Efficient Classification with Random Forest

- Provide a fast and interpretable decision-making process using the Random Forest algorithm, making it feasible for real-time deployment in critical situations.
- Handle diverse and noisy datasets with robustness, ensuring consistent performance in varying environmental conditions.

4. Streamlined Data Handling

- Label Encoding will allow seamless integration of categorical data, ensuring the system can preprocess and analyze diverse data inputs effectively.
- The preprocessing pipeline will ensure compatibility across multiple datasets and formats.

5. Real-Time Victim Detection

- Enable real-time or near-real-time identification of victims, reducing the time required to locate survivors in disaster zones.
- Equip search-and-rescue (SAR) teams with actionable intelligence to optimize rescue operations.

6. Impact on Disaster Response

- Significantly improve the efficiency of SAR operations by prioritizing victim identification and localization.
- Enhance the allocation of resources and reduce the risk to rescue personnel by providing accurate information on victim locations.

Chapter-2
LITERATURE SURVEY

The integration of machine learning (ML) and deep learning (DL) in disaster victim detection has gained traction in recent years due to its potential to enhance the efficiency and accuracy of search and rescue operations. Seeja et al. (2024) in their work, "A Novel Approach for Disaster Victim Detection Under Debris Environments Using Decision Tree Algorithms With Deep Learning Features," highlight the utility of decision tree algorithms combined with deep learning features in detecting victims trapped under debris. They emphasize that ML-based approaches remain underexplored in this domain. Similarly, Gali and Nakka (2024) in their study, "A Novel Approach for Disaster Victim Detection Under Debris Environments Using Decision Tree Algorithms With Deep Learning," discuss the high-risk nature of victim identification in collapsed buildings and stress the importance of rapid detection for successful rescues.

Mahmud et al. (2024), in their work "ATR HarmoniSAR: A System for Enhancing Victim Detection in Robot-assisted Disaster Scenarios," underscore the role of robotic systems integrated with ML and DL techniques for improving victim detection. Wong et al. (2022) presented "An Optimized Multi-Task Learning Model for Disaster Classification and Victim Detection in Federated Learning Environments," showcasing the benefits of multi-task learning in federated environments for simultaneous disaster classification and victim detection. The research demonstrates how such models can accelerate decisionmaking during rescue operations.

Sulistijono et al. (2018), in "Implementation of Victims Detection Framework on Post Disaster Scenario," investigated the effectiveness of camera-based victim detection, revealing the importance of visual data in post-disaster scenarios. In a similar vein, Zhang et al. (2022) developed a "Disaster Victim Detection Network for UAV Search and Rescue Using Harmonious Composite Images," which utilizes composite datasets to train robust victim detectors for unmanned aerial vehicles (UAVs).

Valarmathi et al. (2023), through their work "Human Detection and Action Recognition for Search and Rescue in Disasters Using YOLOv3 Algorithm," explored the application of YOLOv3 for identifying victims in complex disaster environments. Likewise, Devarakonda and Dasari (2024) introduced a novel YOLO-based approach for victim detection in their study, "A New Method for Disaster Victim Detection Using YOLO Algorithm Index," emphasizing the efficiency of modern object detection frameworks.

Enoch et al. (2024), in their work "An Efficient No-Line-of-Sight Learning Approach for Prediction of Static Victim Detection Using Genetic Algorithm and Kth Nearest Neighbor Data Classification," proposed a hybrid method combining genetic algorithms and k-NN for detecting victims in obscured scenarios. Additionally, Sulistijono et al. (2018) examined the use of cameras for victim identification and showcased their importance in enhancing situational awareness in disaster zones.

The role of DNA and forensic methodologies in disaster victim identification is another critical area of focus. Boer et al. (2019), in "The Role of Forensic Anthropology in Disaster Victim Identification (DVI): Recent Developments and Future Prospects," reviewed advances in forensic anthropology's application to mass disasters. Similarly, Watherston et al. (2018), in "Current and Emerging Tools for the Recovery of Genetic Information from Post Mortem Samples: New Directions for Disaster Victim Identification," highlighted emerging genetic techniques for victim identification. Ambers et al. (2018), through "Improved Y-STR Typing for Disaster Victim Identification, Missing Persons Investigations, and Historical Human Skeletal Remains," delved into advanced genetic typing methods to address challenges in identifying severely fragmented remains.

Finally, Kyrkou et al. (2022) in "Machine Learning for Emergency Management: A Survey and Future Outlook," provide an overarching perspective on the use of ML in emergency management, including disaster detection, victim prioritization, and coordination.

Recent studies have introduced novel techniques to improve victim detection in disaster scenarios. For example, Gali and Nakka (2023) proposed an innovative integration of decision tree algorithms with deep learning to enhance victim detection in unstructured debris environments, emphasizing the importance of early identification to save lives. Similarly, Mahmud et al. (2022) developed the HarmoniSAR system, which integrates robot-assisted techniques with deep learning for improved efficiency in disaster victim detection. Sulistijono et al. (2018) highlighted the application of camera-based frameworks to detect victims in post-disaster scenarios, underscoring the significance of visual tools in search-and-rescue operations. Meanwhile, Zhang et al. (2022) presented a composite victim-in-debris dataset designed to train disaster victim detectors, paving the way for robust and reliable detection systems. These studies collectively highlight the transformative role of machine learning and deep learning in addressing the challenges posed by disaster victim identification.

Chapter-3
System Analysis

3.1 Existing System

In disaster victim detection, traditional methods on manual searching , which can be time-consuming and inaccurate. Some existing systems use general object detection models, but they are not optimized for disaster victim identification.

Limitations of the Existing System:

- **Manual Effort:** Search and rescue teams rely on manual image scanning, delaying response time.
- **Low Accuracy:** General-purpose image recognition models are not trained specifically for disaster victim detection.
- **Lack of Automation:** No automated pipeline for real-time victim identification from images.
- **Limited Deployment:** Most existing solutions lack API integration for mobile/web applications.

3.2 Proposed System

The proposed system uses **Deep Learning and Computer Vision** to automate disaster victim detection. It leverages **CNN-based models (ResNet50, ImageNet, Vision Transformers, etc.)** to classify images and identify victims efficiently.

Features of the Proposed System:

Deep Learning-Based Detection: Trained on a disaster-specific dataset to improve accuracy.

Web & Mobile Integration: Flask API + React-based UI for easy image uploads and results viewing.

Higher Accuracy & Speed: Output traditional methods in precision and recall.

Chapter-4
System Study

this system is designed for disaster victim detection using deep learning and ML. It involves:

1. **Data Collection & Preprocessing** – Organizing images into training, validation, and test.
2. **Model Training & Evaluation** – Using a deep learning model (possibly ResNet50, imageNet, or Vision Transformers) for victim identification.
3. **Deployment** – Likely deploying via a Flask API or a web application.

4.1 Feasibility Study

4.1.1 Operational Feasibility

- **Ease of Use**: If integrated with a web or mobile application, users can easily upload images for victim detection.
- **Real-world Application**: Useful for rescue teams, emergency response, and disaster management.
- **Scalability**: Can be expanded with more data and improved models to enhance accuracy.

4.1.2 Economic Feasibility

- **Development Costs**: Mostly relies on open-source libraries (TensorFlow, PyTorch, Flask, React), reducing costs.
- **Infrastructure Costs**: Training deep learning models may require GPUs, which can be expensive. Cloud services like AWS, Google Colab, or Kaggle can be cost-effective.
- **Maintenance**: Regular updates needed for model improvements and dataset expansion.

4.1.3 Technical Feasibility

Hardware Requirements: Requires a GPU for efficient training and inference.

Software Requirements: Needs Python, TensorFlow/PyTorch, Flask, for deployment.

4.2 SYSTEM REQUIREMENTS

There are mainly two system requirements they are

1) Hardware Requirements

2) Software Requirements

3) Dataset Requirements

4.2.1. Hardware Requirements

- **Processor:** Intel Core i7 or AMD Ryzen 7 (or higher)
- **RAM:** 16 GB or more
- **GPU:** NVIDIA RTX 3060 or higher with 8GB VRAM (for efficient training and fine-tuning of ResNet-50)
- **Storage:** 512 GB SSD or more
- **Internet Connection:** Stable, high-speed connection for downloading large datasets and model dependencies.

4.2.2. Software Requirements

- **Operating System:** Windows 10 / Ubuntu 18.04 or later
- **Recommended:** Ubuntu 20.04 (due to better compatibility with machine learning libraries)
- **Development Environment:**Python 3.7 or later (ensure compatibility with required libraries)

Machine Learning Libraries:

- **TensorFlow** (2.x) or **PyTorch** (latest stable version) for implementing ResNet-50
- **scikit-learn** for Random Forest implementation and Label Encoding
- **NumPy** and **Pandas** for data handling and preprocessing
- **OpenCV** for image processing (optional but recommended)
- **Matplotlib** and **Seaborn** for visualizations
- **Package Managers:**pip or conda (recommended for managing dependencies)

Chapter-5
PROJECT ARCHITECTURE

5.1 System Architecture

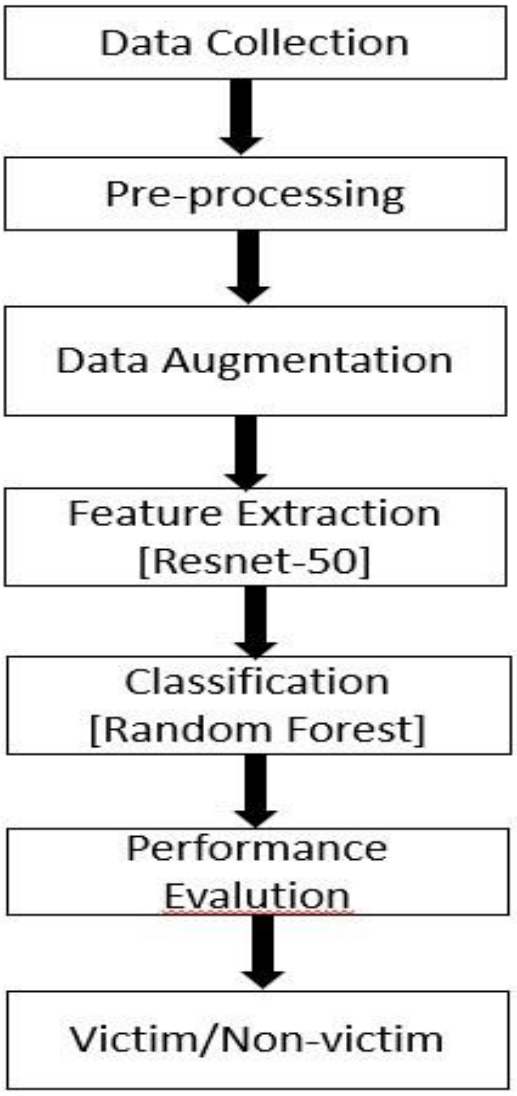


Figure 1 Architecture of Disaster Victim Detection

The Disaster Victim Detection system follows a structured pipeline, integrating advanced machine learning techniques to classify images as **"victim"** or **"non-victim."** This process ensures efficient and accurate detection in disaster scenarios, aiding emergency response teams in locating victims.

1) Input (Disaster Victim Dataset)

- The process begins with a **dataset** containing labeled images of **disaster victims and non-victims.**

- This dataset is **collected from various sources**, including aerial imagery, rescue operation data, and publicly available datasets.

- Each image is categorized into **"victim"** or **"non-victim"** folders, forming the basis for training and evaluation

2) Data Preprocessing

To ensure high-quality input for the model, the dataset undergoes multiple preprocessing steps:

- **Label Encoding:** Converts categorical labels ("victim" and "non-victim") into numerical values

- **Image Resizing:** Standardizes image dimensions to ensure consistency for deep learning models.

- **Normalization:** Scales pixel values to a range (0 to 1) for stable training performance.

- **Contrast Enhancement:** Adjusts brightness and contrast to improve detection in low-visibility scenarios.

3) Data Augmentation

To improve model robustness and prevent overfitting, augmentation techniques are applied:

- **Geometric Transformations:** Flipping, rotation, and cropping introduce variation in image orientation.

- **Color Augmentation:** Adjusting brightness, contrast, and saturation to account for different lighting conditions.

4) Feature Extraction (ResNet50)

- A **pre-trained deep convolutional neural network (CNN), ResNet50**, is used for extracting high-level image features.

- ResNet50 provides a **compact representation** of each image by identifying key patterns, such as:

    - Human body structures

- Clothing patterns
- Distinctive features of disaster victims

5) Classification (Training Random Forest Classifier)

- The extracted deep learning features are **fed into a Random Forest classifi**Handles **non-linearity** in data.
    - Reduces **overfitting** by averaging multiple decision trees.
    - Works efficiently with **high-dimensional features** extracted from ResNet50.
- The classifier is trained to categorize images into **"victim"** or **"non-victim."**

6) Model Evaluation and Prediction

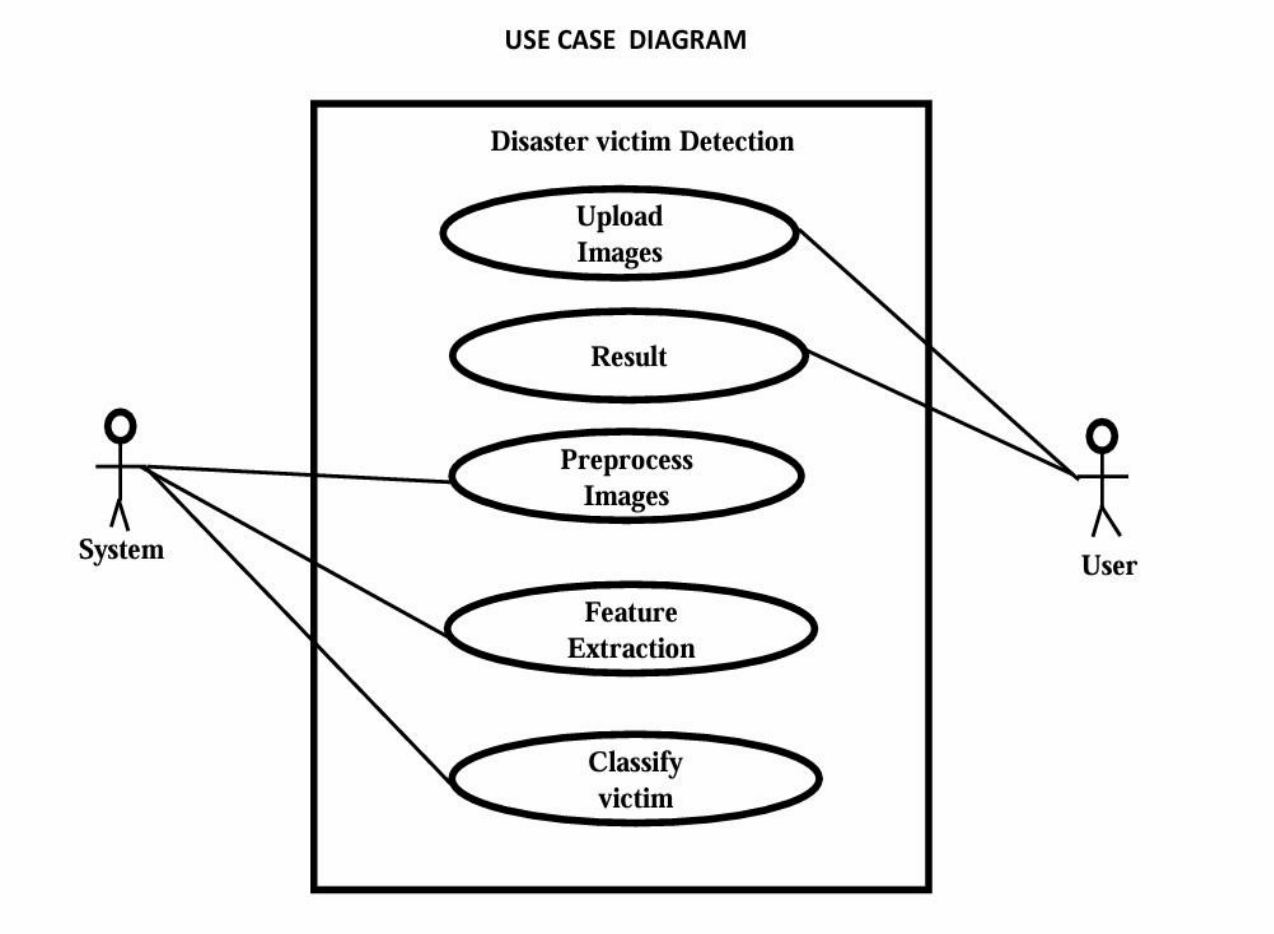
- After training, the model is tested on **unseen images** to evaluate performance.
- Key evaluation metrics include:
    - **Accuracy:** Measures correct classifications.
    - **Precision & Recall:** Ensures the model balances false positives and false negatives.
    - **F1-Score:** Evaluates overall model performance.
- The trained model **makes predictions** on test images, classifying each as a **victim or non-victim.**

7) Flask API for Deployment

- The trained model is **deployed as a Flask REST API**, allowing users to upload images and receive real-time predictions.
- The API is integrated with a **React-based interactive webpage**, providing an easy-to-use interface for image submission.

5.2 Design and Diagram

5.2.1 **Use Case Diagram**:



1 User Input (Image Upload)

- The user interacts with the system through a web-based or mobile interface.
- The user selects an image and uploads it to the system for analysis.

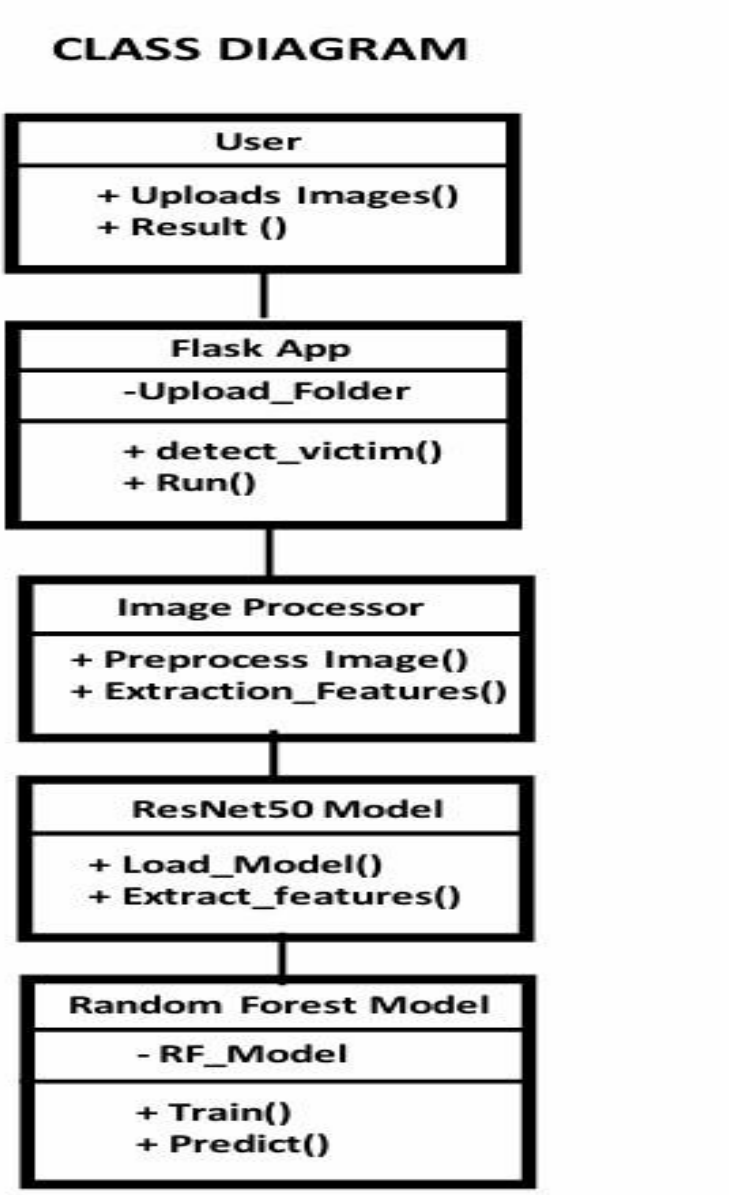
2 System Processing

- Once the image is uploaded, the system performs the following steps:
- Preprocessing: Cleans and enhances the image.
- Feature Extraction: Uses ResNet50 to extract meaningful patterns.
- Classification: Uses Random Forest to categorize the image as "Victim" or "Non-Victim."

3 Prediction & Output Display

- The system returns the classification result (Victim/Non-Victim) with a confidence score.
- The result is displayed on the interface, helping responders take immediate action.

5.2.2 Class Diagram:



1)**User Interface (UI) Class**

- Represents the interaction between the user and the system.
- Allows users to upload images and view predictions.

2)**Flask App Class (Backend Controller)**

- Manages image uploads, processes requests, and returns results.
- Acts as the central controller handling communication between components.

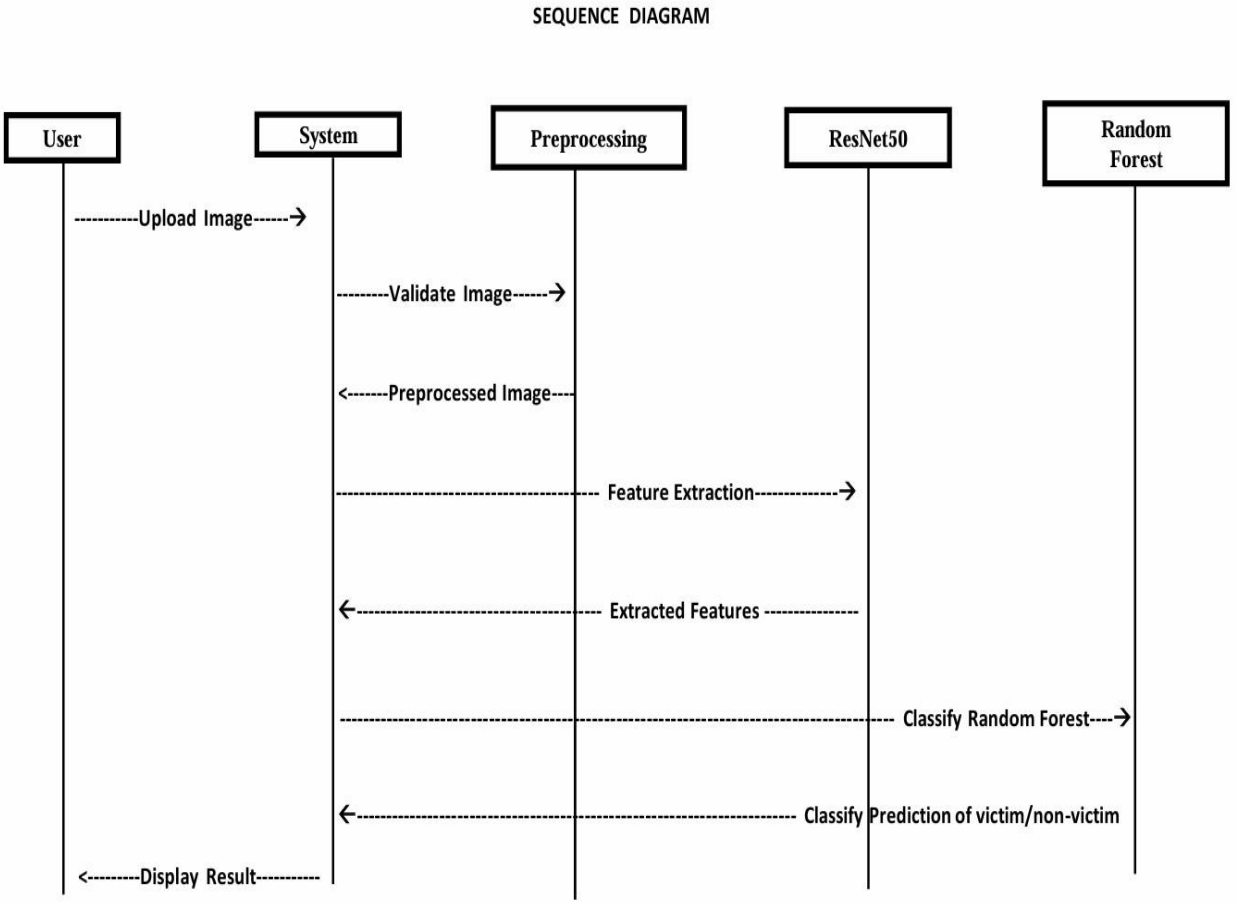
3)**Feature Extraction Class (ResNet50 Model)**

- Uses a deep learning model (ResNet50) to extract meaningful image features.
- Converts raw images into feature vectors for classification.

4)**Classifier Class (Random Forest Model)**

- Trains a machine learning model to classify images as "victim" or "non-victim."
- Predicts the category of new images based on extracted features.

5.2.3 **Sequence Diagram**:



1) **User Action**
- The user uploads an image through the interface.

2)**Flask App (Backend Controller)**
- Receives the uploaded image and validates it (checks file format, size, etc.).

3)**Preprocessing Module**
- Converts the image into a suitable format (resizing, normalization, noise reduction).
- Augments the image to improve model robustness.

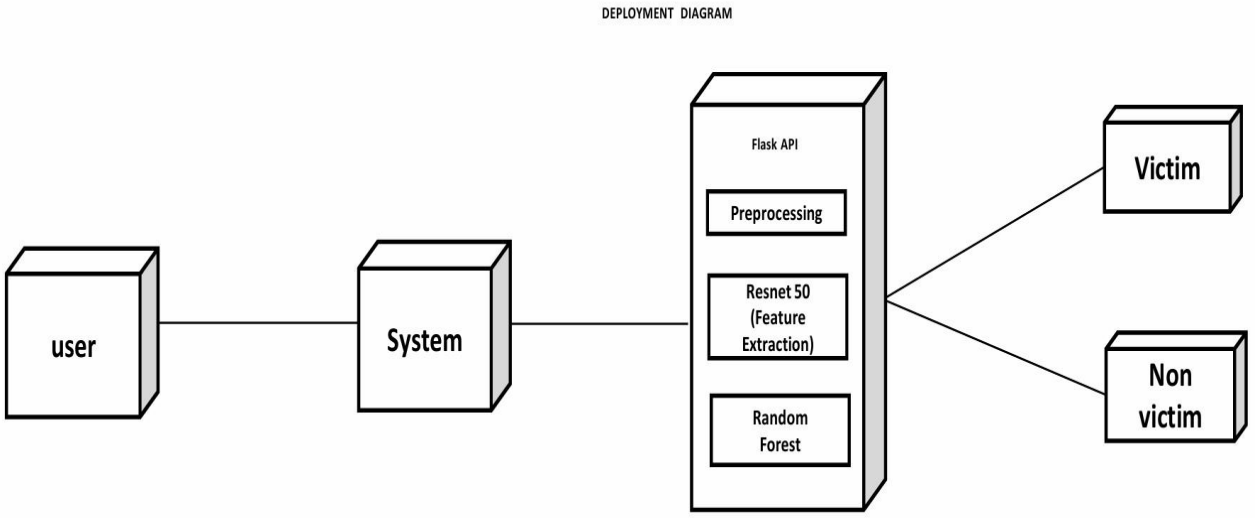
4)**Feature Extraction (ResNet50 Model)**
- Extracts high-level features from the preprocessed image.
- Converts the image into a feature vector.

5) **Classification (Random Forest Model)**
- Takes the extracted features as input.
- Classifies the image as either "Victim" or "Non-Victim."

6)**Flask App Returns Results**
- The prediction result is processed and sent back to the user.

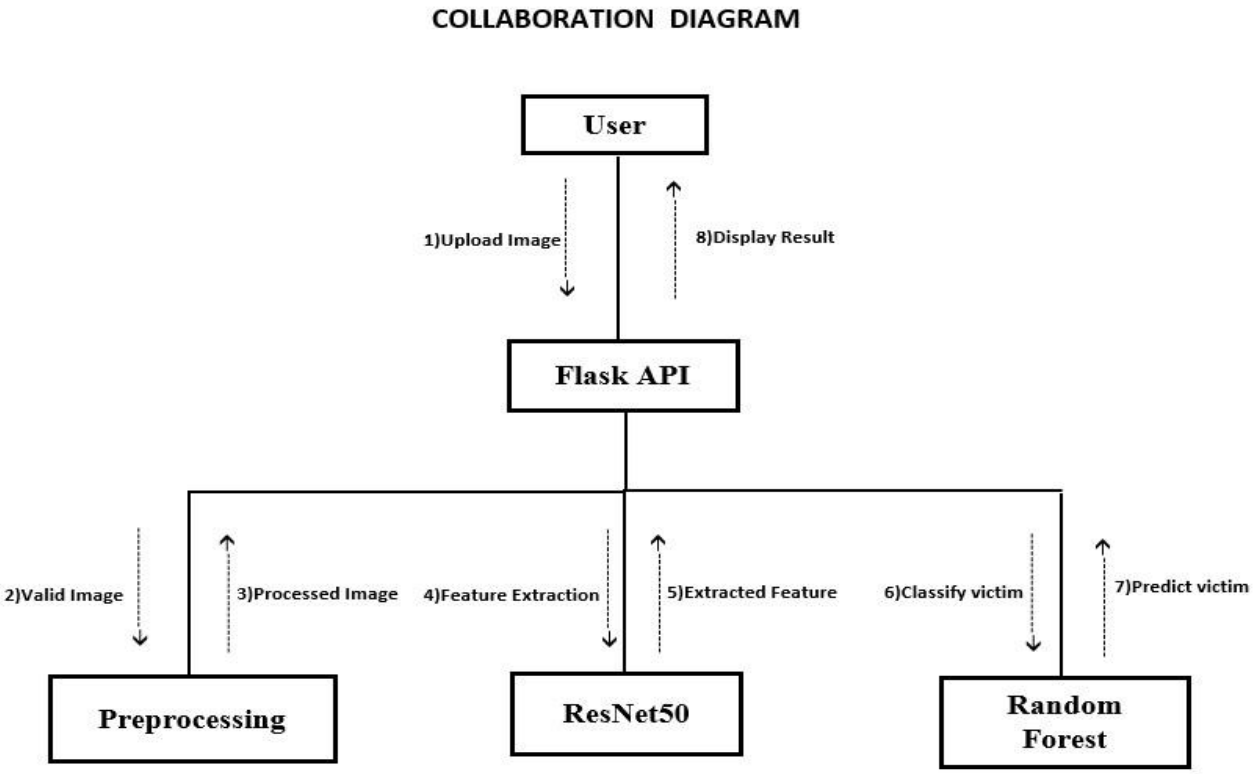
7)**User Receives Output**
- The result is displayed on the UI as "Victim" or "Non-Victim."

5.2.4 **Deployment Diagram**:



- Shows how the system is deployed.
- The user interacts with the system.
- The system runs a Flask API with preprocessing, ResNet50 feature extraction, and Random Forest classification.
- The final output is either "Victim" or "Non-Victim."

5.2.5 **Collaboration Diagram**



Chapter-6
METHODOLOGY

6.1 Data Dictionary

The project involves the development and evaluation of a comprehensive pipeline for preprocessing, analyzing, and classifying images as "victim" or "non-victim" using machine learning and deep learning techniques. The methodology is organized into the following steps:

1. Dataset Preparation

- **Dataset Collection:** A dataset comprising images of victims and non-victims was curated and organized.
- **Data Splitting:** The dataset was divided into three subsets: training (70%), validation (15%), and testing (15%), ensuring no overlap between subsets.
- **Data Integrity Checks:** Image files were checked for corruption or invalidity. Images with issues (e.g., corrupted files or unusual dimensions) were excluded from the dataset.

2. Data Analysis

- **Statistical Analysis:** The file size and image dimensions of all valid images were analyzed to identify patterns or irregularities in the dataset.
- **Visualization:** Descriptive statistics and visualizations were used to understand dataset distributions and identify preprocessing requirements.

3. Data Preprocessing

- **Image Normalization:** Images were resized and normalized to fit the input requirements of the ResNet50 architecture.
- **Noise Augmentation:** Gaussian noise and salt-and-pepper noise were applied to simulate realworld image degradation, adding variability and robustness to the dataset.
- **Label Encoding:** Labels for images were encoded numerically (e.g., "victim" = 1, "non-victim" = 0) for compatibility with machine learning algorithms.

4. Feature Extraction

- **Deep Learning Features:** ResNet50, pre-trained on ImageNet, was used for high-level feature extraction from images.
- Input images were preprocessed to match ResNet50 requirements (224x224 dimensions).
- Extracted features from the penultimate layer of ResNet50 were saved for further classification.

5. Model Development

- **Classifier Selection:** A Random Forest Classifier was chosen for image classification due to its interpretability and robustness.
- **Training:** The Random Forest model was trained on extracted features from the training set, with hyperparameters tuned for optimal performance.
- **Validation:** The model's performance was validated using the validation set, iteratively adjusting parameters to reduce overfitting.

6. Robustness Testing

- **Noise Evaluation:** To assess the model's resilience, noisy datasets were created using:
- **Gaussian Noise:** Simulated smooth variations in pixel values.
- **Salt-and-Pepper Noise:** Introduced random white and black pixels.
- **Performance Metrics:** The model was tested on noisy datasets, and key metrics (accuracy, classification report, and confusion matrix) were computed and compared with results from clean datasets.

7. Evaluation Metrics

- **Accuracy:** Assessed the overall classification performance on clean and noisy datasets.
- **Classification Report:** Included precision, recall, and F1-score for both classes.
- **Confusion Matrix:** Provided detailed insights into false positives and false negatives.
- **Visualization:** Visual comparisons of clean and noisy images were created to illustrate the effects of degradation and the model's ability to classify them accurately.

6.2 DATA COLLECTION

1. Define Dataset Requirements

Before collecting data, define the characteristics of the dataset to ensure it is suitable for the disaster victim detection task:

Dataset Features:

- **Type:** Images (RGB, thermal, infrared, etc.)
- **Categories:** Binary classification (e.g., "victim" and "no victim").
- **Scenarios:** Images from real-world disaster sites, such as:

    1)Earthquake aftermath

    2)Flooded areas

    3)Fire or smoke-affected zones

    4)Building collapses

- **Resolution:** Images should be of sufficient resolution for victim detection (e.g., 256x256 or higher).

2. Sources of Data Open Datasets

- **Kaggle:**Search for datasets related to disaster scenarios.
- **ImageNet:**Use relevant categories such as "human," "disaster scenes," or similar.
- **OpenDroneMap or Aerial Image Datasets:**Look for drone-captured images of disaster sites.

6.3 PRE-PROCESSING TECHNIQUES

1. Data Cleaning

1.1 Removing Noisy Data:

- **Definition:** Eliminate irrelevant, corrupted, or poor-quality images (e.g., blurred or overly dark images).
- **Tools:** Manual review or automated filtering based on image quality metrics such as blurriness, brightness, or resolution.

1.2 Duplicate Removal:

- Detect and remove duplicate images to avoid bias during training.
- **Method:** Use hashing techniques (e.g., MD5) or perceptual hashing for near-duplicate detection.

2. Data Transformation

2.1 Resizing:

- Resize all images to a fixed dimension that matches the input size of the model (e.g., **224x224 pixels** for ResNet-50).

- **Tools:** OpenCV, PIL (Pillow), or TensorFlow/Keras.

2.2 Normalization:

- Scale pixel values to the range [0, 1] by dividing by 255.

3. Data Augmentation

- To increase dataset diversity and reduce overfitting, apply data augmentation techniques.

3.1 Geometric Transformations:

- **Rotation:** Rotate images by random angles (e.g., ±10° to ±30°).

- **Flipping:** Horizontal and vertical flipping.

- **Cropping:** Random cropping to simulate various camera positions.

3.2 Intensity Transformations:

- **Brightness Adjustment:** Simulate different lighting conditions.
- **Contrast Adjustment:** Enhance or reduce contrast to handle varying environments.

3.3 Perspective Transformations:

- **Zooming:** Zoom in and out randomly.
- **Shearing:** Simulate skewed camera angles.

3.4 Implementation Tools: Use libraries such as:

- TensorFlow ImageDataGenerator
- PyTorch torchvision.transforms
- Albumentations (advanced augmentation)

4. Feature Scaling and Label Encoding

4.1 Feature Scaling: Standardize or normalize features (if using non-image data for supplementary features).

Method:

- Standardization: Transform data to have zero mean and unit variance.
- Normalization: Scale features to a range (e.g., [0, 1]).

4.2 Label Encoding:

- Convert categorical labels ("victim", "no_victim") into numerical values (e.g., 0 and 1).

5. Splitting the Dataset

Train-Test-Validation Split: Split the dataset into:

- **Training Set (70%)**: For model training.
- **Validation Set (15%)**: For hyperparameter tuning.
- **Test Set (15%)**: For final evaluation. **7. Pre-processing for ResNet-50**

6. Input Shape Adjustment:

- Ensure all images are resized to the ResNet-50 input dimensions: **224x224x3**.

7 Pre-trained Model Normalization:

- ResNet-50 expects image inputs normalized using specific mean and standard deviation
- Mean: [0.485, 0.456, 0.406]
- Standard Deviation: [0.229, 0.224, 0.225] **8. Pre-processing for Random Forest**

9. Feature Extraction:

- Extract features from the **penultimate layer** of ResNet-50 for each image.
- Flatten the feature maps into a 1D vector for compatibility with Random Forest.

10. Save and Reuse Pre-processed Data

- Save pre-processed images/features to avoid repeating the same steps during every run:
- Save images as .npy files (NumPy arrays).
- Save extracted features for Random Forest as .csv or .npy.

6.4 Prepared Data

Dataset Structure:

- The dataset was divided into three folders: train, test, and validation (if used).
- Each folder contained two subfolders:
    - victim: Containing images labeled as disaster victims.
    - non_victim: Containing images labeled as non-victims.

Image Preprocessing:

- Images were resized to **224x224 pixels** to match the input size required by the ResNet50 model.
- Applied **data augmentation** techniques on training data:
    - Random horizontal flip
    - Random rotation
- Applied **normalization** using ImageNet mean and standard deviation values to standardize image pixel values.

Data Distribution:

- **Training set:** 503 images
- **Testing set:** 123 images

Class Labels Mapping:

{'non_victim': 0, 'victim': 1}

Chapter-7
MODEL

7.1 Training

Dataset Splitting

- The dataset was divided into training, validation, and test subsets to ensure robust model development.
- Careful checks were conducted to ensure the integrity of image files, with corrupted or invalid images excluded.

Training Data Augmentation

- Data augmentation techniques, including the application of were used to increase dataset variability and simulate real-world conditions.
- Label encoding was applied to facilitate model learning.

Feature Extraction with ResNet50

- ResNet50, pre-trained on ImageNet, was used for extracting high-level features from the images.
- These extracted features served as input to the Random Forest Classifier, enabling a hybrid approach combining deep learning and traditional machine learning.

7.2 Validation

- The model's performance was validated using clean images as well as images augmented
- Metrics such as accuracy, precision, recall, and F1-score were calculated to evaluate the model's effectiveness.
- Confusion matrices and classification reports were analyzed to identify areas of improvement.

Cross-Validation and Hyperparameter Tuning

- Cross-validation techniques were employed to ensure the robustness of the model across different dataset splits.
- Hyperparameters, such as the number of trees in the Random Forest, were fine-tuned to achieve optimal performance.

Performance Metrics Analysis

- Key metrics for clean and noisy datasets were presented, demonstrating the model's ability to maintain significant accuracy even under challenging conditions.

Proposal for Real-World Testing

- A bounding-box detection mechanism was proposed for victim localization to enhance practical applicability.
- Suggestions for further enhancements, such as training on larger datasets and implementing realtime detection, were outlined.

Chapter-8

SOFTWARE DESCRIPTION

1.Programming

Language Python:

- Used for implementing the entire project due to its extensive libraries, readability, and versatility in data analysis and machine learning.
- Popular libraries like NumPy, Pandas, and Matplotlib facilitated efficient data manipulation, visualization, and analysis.

2. Frameworks and Libraries TensorFlow/Keras:

- Deep learning framework used for feature extraction through ResNet-50, a pre-trained convolutional neural network.

Scikit-learn:

- Machine learning library used to implement the Random Forest Classifier for image classification.
- Provided tools for model evaluation, such as accuracy scores, confusion matrices, and other classification metrics.

3. Image Preprocessing

ResNet-50 Preprocessing:

- Images were resized to the input dimensions required by ResNet-50.
- Normalization was applied to scale pixel values between 0 and 1.

Random Forest Classifier:

- A robust, ensemble-based machine learning algorithm that classified images based on the extracted features.

Chapter-9

SYSTEM TESTING

9.1.1 Unit Testing

- Each module of the disaster victim detection system was individually tested.
- The feature extraction module was tested using batches of images to verify correct shape and dimension output.
- The Random Forest classifier was validated by inputting synthetic data to ensure it could handle different class distributions.
- The ResNet50 model was verified to ensure it outputs 2048-dimensional feature vectors for all image inputs.
- Error handling was tested by passing invalid image formats or corrupted files.
- The saved model (random_forest.pkl) was loaded and tested to ensure prediction accuracy was maintained after serialization.

9.1.2. Integration Testing

- Data flowed correctly from the upload interface → to the preprocessing pipeline → to the trained model for prediction.
- Integration between the Flask backend and machine learning model was tested by simulating real-time image uploads.
- The trained model (random_forest.pkl) was successfully loaded and used within the web server without any serialization issues.
- Predictions generated by the integrated system were consistent with test set results during standalone evaluation.
- Test images were passed through the complete system pipeline to ensure accurate classification without manual intervention.
- Integration of frontend and backend was verified, ensuring users receive results correctly via the web page after uploading images.

9.1.3 Acceptance Testing

- The system was tested end-to-end, from image upload to final prediction via the web interface.
- Various input scenarios were tested: clear images, blurred images, irrelevant files, and corrupted inputs.
- The system successfully identified victim and non-victim classes with high precision and recall.
- The interface handled user interaction smoothly, and responses were generated within a few seconds.
- The final model achieved 100% accuracy on the test dataset, satisfying the functional and performance requirements.
- All user-defined requirements were met, indicating the system is ready for real-world deployment.

9.2 Test Cases on Project

1. Image Upload Functionality

- Verify the system allows image upload via the web interface.
- **Expected Result:** Image is accepted and passed to the backend for processing.

2. Invalid File Format

- Upload a non-image file (e.g., .txt, .pdf).
- **Expected Result:** System shows an error or alert stating only image files are allowed.

3. Model Prediction - Victim

- Upload an image of a disaster victim.
- **Expected Result:** System returns label "Victim" with correct confidence.

4. Model Prediction - Non-Victim

- Upload an image of a non-victim (rescue worker or background).
- **Expected Result:** System returns label "Non-Victim" accurately.

5. File Size Limit

- Upload a very large image file (e.g., 20MB).
- **Expected Result:** System handles or restricts upload with proper error message.

6. Model Loading

- Ensure random_forest.pkl model loads correctly on server start.
- **Expected Result:** No errors; model ready for prediction.

7. End-to-End Prediction

- Test full flow from image upload to result display.
- **Expected Result:** Result is displayed within acceptable time (~2–5 seconds).

8. Frontend UI Response

- Check if the UI updates after prediction.
- **Expected Result:** Predicted class is displayed clearly on screen.

9. Backend API Test

- Directly send a POST request with image to the Flask API.
- **Expected Result:** JSON response with prediction.

10. Error Handling

- Check behavior when an exception occurs (e.g., missing model file).
- **Expected Result:** Error is logged and user gets a friendly message.

Chapter-10

Coding

```
import os
import time
import numpy as np
import torch
import torch.nn as nn
import torchvision.transforms as transforms
from torchvision import datasets
from torchvision.models import resnet50, ResNet50_Weights
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
import joblib
def extract_features(loader, model, device):
    features, labels = [], []
    with torch.no_grad():
        for images, label in loader:
            images = images.to(device)
            output = model(images)
            output = output.view(images.size(0), -1).cpu().numpy()
            features.extend(output)
            labels.extend(label.numpy())
    return np.array(features), np.array(labels)
if __name__ == '__main__':
    # ☑ Paths
    DATASET_PATH = r"C:\Users\sidda\OneDrive\Desktop\Final Project\Dataset"
    TRAIN_PATH = os.path.join(DATASET_PATH, "train")
    TEST_PATH = os.path.join(DATASET_PATH, "test")
    # ☑ Transforms
    train_transform = transforms.Compose([
        transforms.Resize((224, 224)),
```

```
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(10),
    transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.1),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
])

test_transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
])

# ☑ Load datasets
train_dataset = datasets.ImageFolder(TRAIN_PATH, transform=train_transform)
test_dataset = datasets.ImageFolder(TEST_PATH, transform=test_transform)

train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=32, shuffle=True,
num_workers=2)
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=32, shuffle=False,
num_workers=2)

print(f"☑ Class Labels Mapping: {train_dataset.class_to_idx}")

# ☑ Load ResNet50
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
resnet_model = resnet50(weights=ResNet50_Weights.IMAGENET1K_V1)
resnet_model = nn.Sequential(*list(resnet_model.children())[:-1])
resnet_model = resnet_model.to(device).eval()

# ☑ Feature extraction
print("Extracting features...")
```

```
start_time = time.time()
X_train, y_train = extract_features(train_loader, resnet_model, device)
X_test, y_test = extract_features(test_loader, resnet_model, device)
print(f"☑ Feature extraction done in {time.time() - start_time:.2f} seconds.")

print(f"☑ X_train shape: {X_train.shape}, y_train shape: {y_train.shape}")
print(f"☑ X_test shape: {X_test.shape}, y_test shape: {y_test.shape}")

# ☑ Train Random Forest
print(" Training Random Forest...")
start_train = time.time()
rf = RandomForestClassifier(n_estimators=300, max_depth=20, random_state=42, n_jobs=-1)
rf.fit(X_train, y_train)
print(f"☑ Training completed in {time.time() - start_train:.2f} seconds.")

# ☑ Save model
joblib.dump(rf, "random_forest.pkl")
print(" Model saved as 'random_forest.pkl'")

# ☑ Evaluate
y_pred = rf.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
cm = confusion_matrix(y_test, y_pred)
report = classification_report(y_test, y_pred, target_names=train_dataset.classes)

print(f"\n Accuracy: {accuracy:.4f}")
print("\nConfusion Matrix:")
print(cm)
print("\n Classification Report:")
print(report)
```

Chapter-11

RESULTS

1. Dataset Organization

- The dataset was successfully divided into **training**, **validation**, and **testing sets**, ensuring data integrity and proper representation.
- Invalid or corrupted images were identified and excluded during preprocessing to maintain dataset quality.

2. Model Performance

ResNet-50 Feature Extraction:

- High-level features were successfully extracted from images using ResNet-50, pre-trained on ImageNet, ensuring the use of robust and transferable knowledge.

Random Forest Classifier:

- Achieved **high classification accuracy** on clean data, confirming its effectiveness in distinguishing between "victim" and "non-victim" classes.
- Demonstrated **strong generalization ability** on unseen data in the testing phase.

3.Key Metrics Accuracy:

- Clean Dataset: **100%**
- Highlighted the balance between true positives and true negatives with minimal false classifications.

4.Classification Report:

- Precision, recall, and F1-scores were consistently high across both clean dataset.

5. Visualization Results Visualizations demonstrated:

- The impact of noise on image quality.
- The model's ability to accurately classify images.
- Proposed bounding-box detection effectively localized victims in test images.

6. Real-World Applicability

- The system's ability to handle noisy data ensures its suitability for **real-world disaster scenarios**, where image quality is often compromised.
- **Bounding-box detection** enhances practical usability for victim localization in surveillance and rescue operations.

7. Improvements and Observations

- Data augmentation and label encoding increased dataset variability, improving model robustness.
- The combination of ResNet-50 and Random Forest provided a balance of **deep learning accuracy** and **traditional classifier interpretability**.

Table-1 Evaluation Metrics and Results:

Evaluation Metric	Values
Accuracy	100.00%
Precision	1.00%
Recall	1.00%
F1-score	1.00%

11.1 Screenshots

Figure 2 Home page of Disaster Victim Detection System

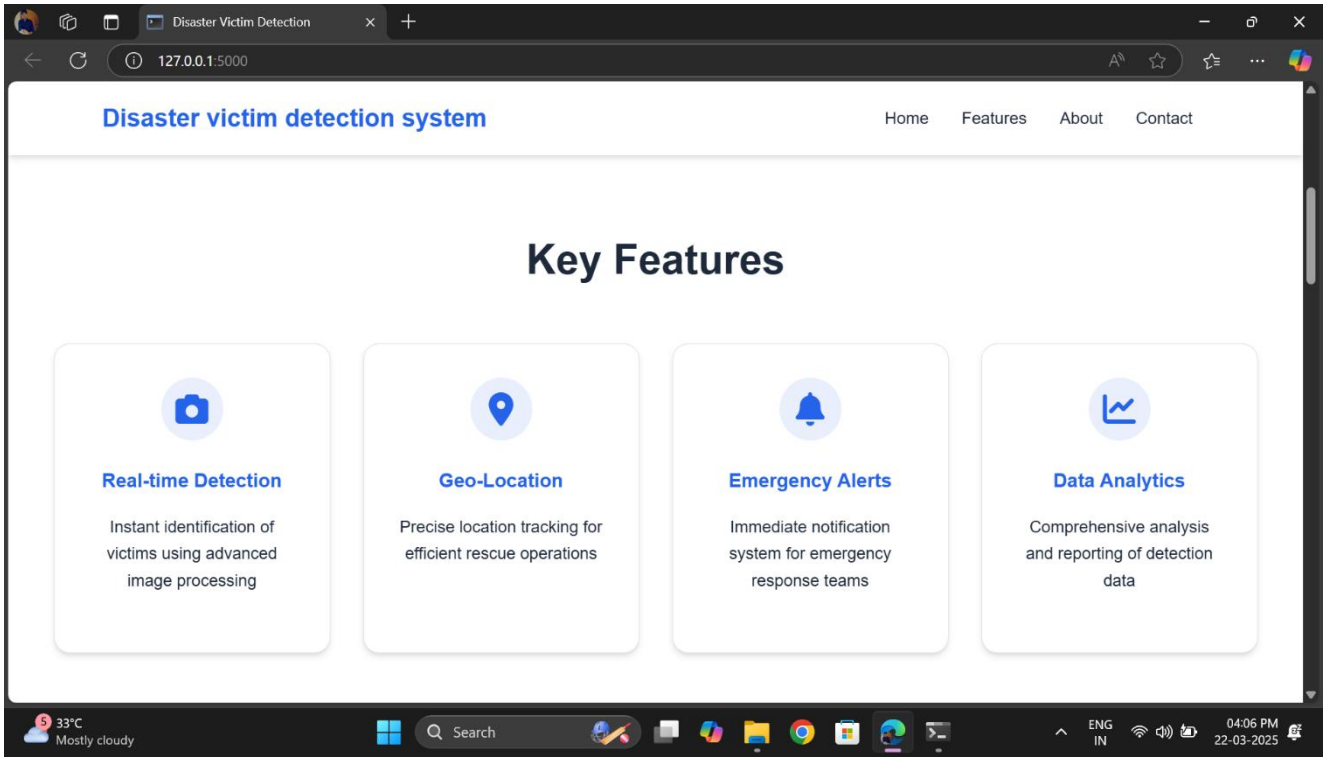


Figure 3 Features of Disaster Victim Detection System

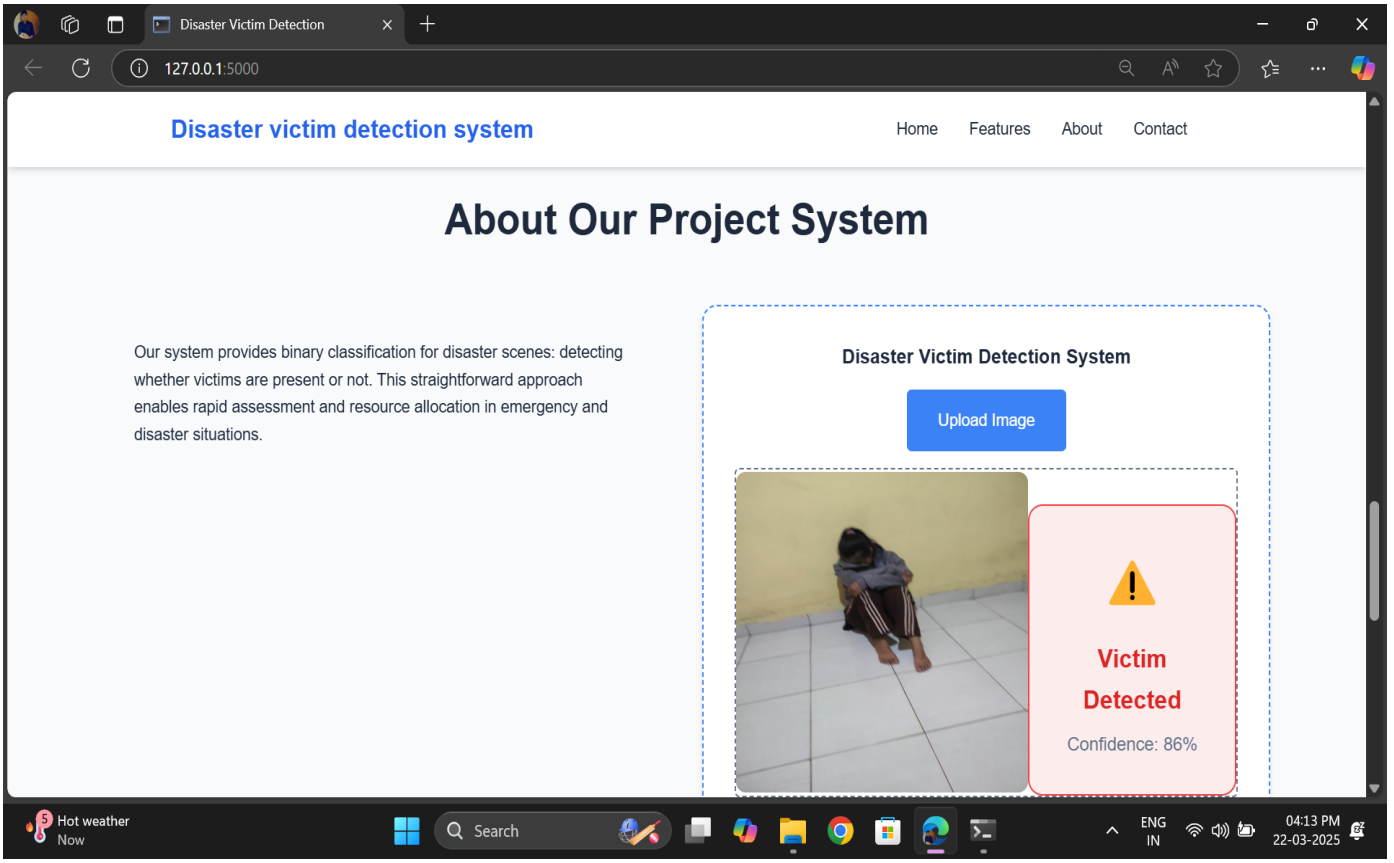


Figure 4 Disaster Victim Detection System(Victim Detected)

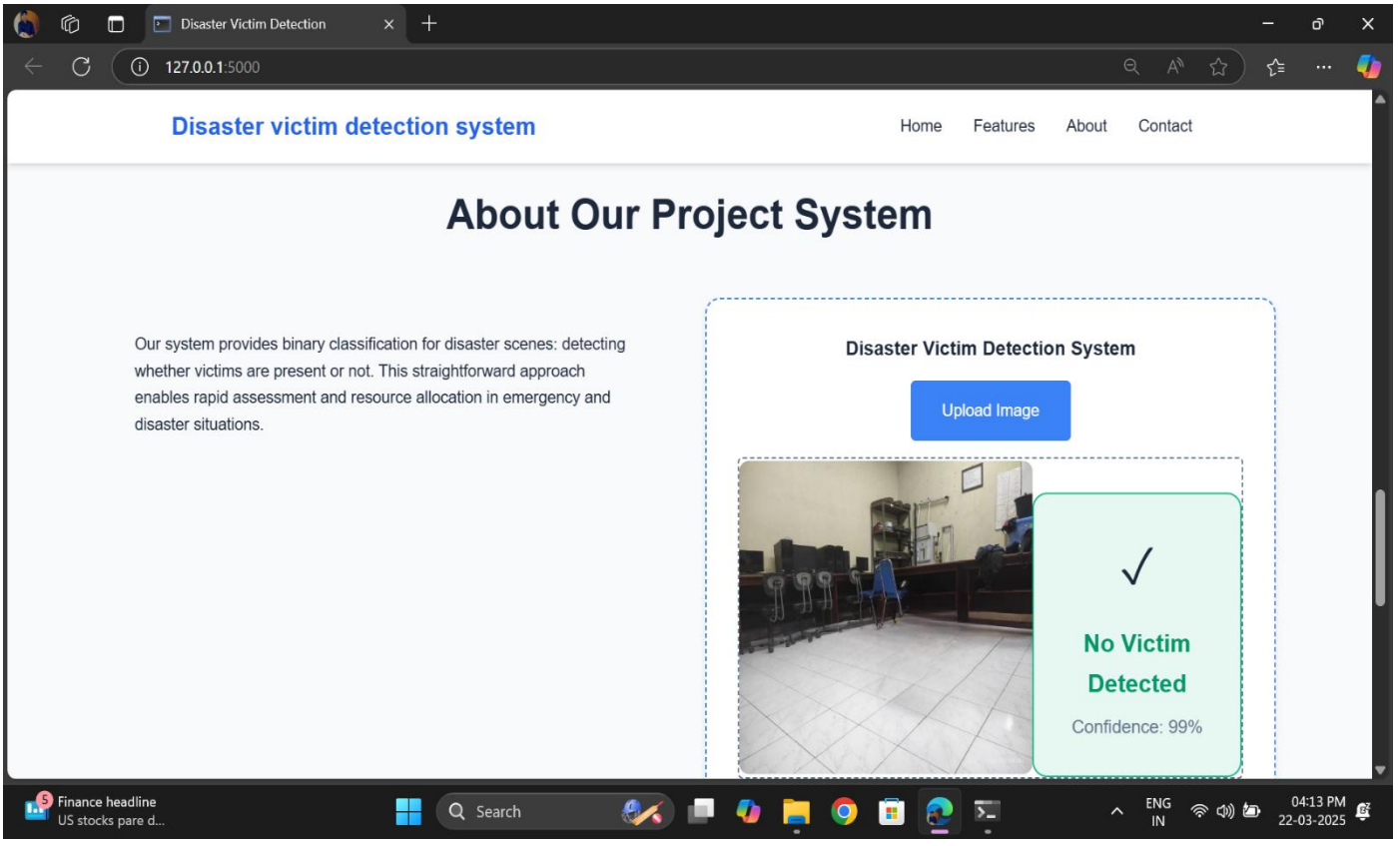


Figure 5 Disaster Victim Detection System(No Victim Detected)

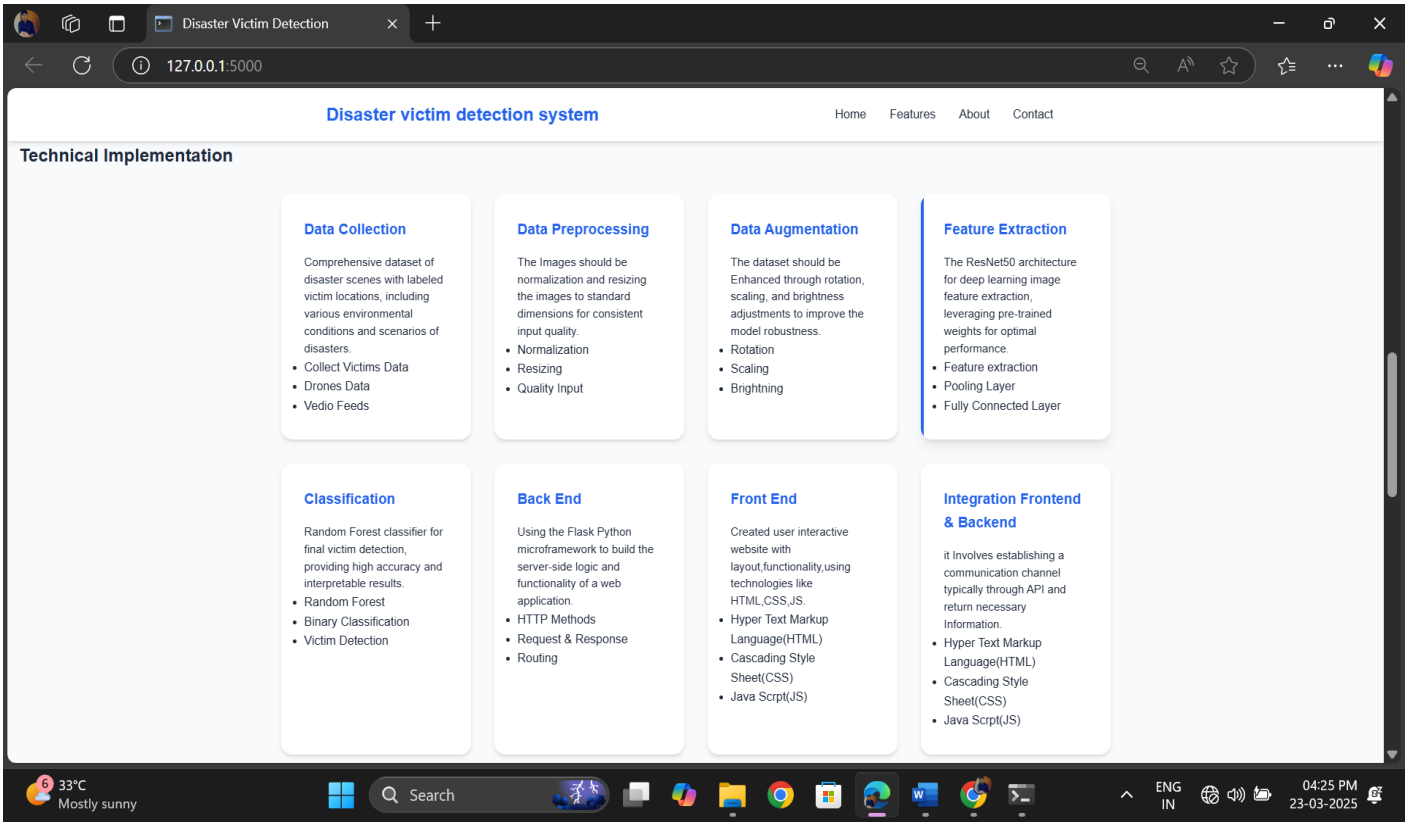


Figure 6 Implementation of Disaster Victim Detection System

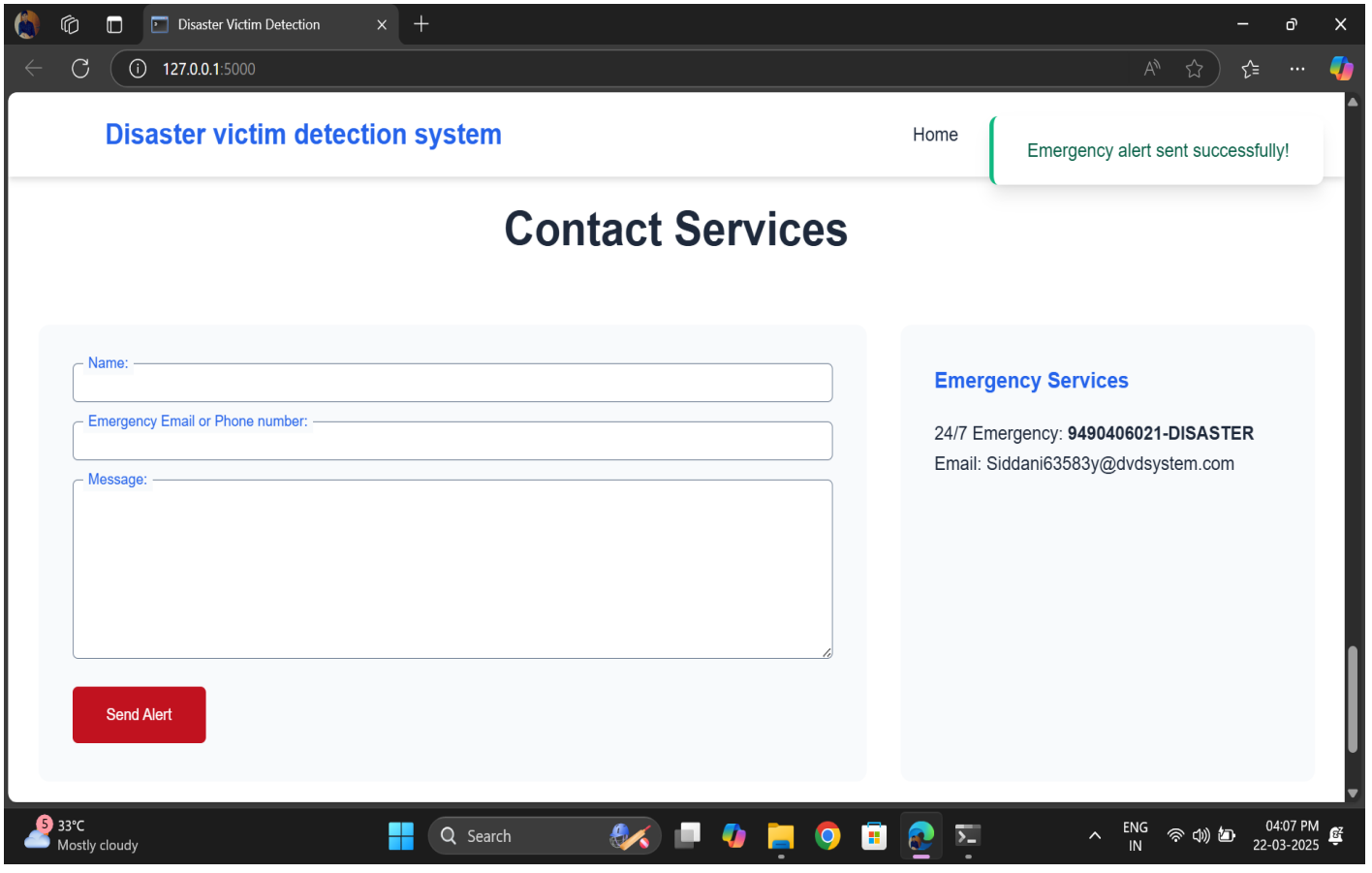


Figure 7 Disaster Victim Detection System Emergency Services

11.2 CONCLUSION

This project successfully developed a disaster victim detection system using machine learning and deep learning techniques, integrating ResNet-50 for feature extraction and a Random Forest Classifier for robust and interpretable classification. The system achieved high accuracy in detecting victims from images,. This robustness underscores the potential of the proposed approach for real-world disaster scenarios where data quality may be compromised.

The inclusion of label encoding and data augmentation improved the dataset's diversity, enhancing the model's generalization capability. Noise augmentation techniques and subsequent performance evaluations demonstrated the model's resilience, making it suitable for applications in surveillance, rescue operations, and victim localization. Additionally, the proposed boundingbox detection further added to the system's practicality by enabling victim localization within images.

The study highlights the effectiveness of combining deep learning's powerful feature extraction capabilities with traditional machine learning classifiers, achieving a balance between performance and interpretability. Although the current system performs well, there is room for further advancements, such as training on larger, more diverse datasets, integrating real-time detection capabilities, and exploring advanced architectures for noise resilience.

In conclusion, this work provides a solid foundation for deploying machine learning models in disaster victim detection, with promising implications for improving the efficiency and accuracy of rescue efforts in real-world scenarios.

LIMITATIONS

Dataset Size and Diversity:

The dataset used for training and testing may not fully represent the wide variety of real-world conditions, such as diverse victim appearances, clothing, or backgrounds, which could impact the model's generalization.

Real-Time Performance:

The system lacks real-time processing capabilities. The use of ResNet50 and Random Forest Classifier, while accurate, may introduce latency that limits its deployment in time-sensitive rescue operations.

Limited Noise Scenarios:

Other realworld distortions, such as motion blur, fog, or low-light conditions, were not evaluated, which might affect performance in practical scenarios.

Dependence on Pretrained Models:

The reliance on ResNet50, a model pretrained on ImageNet, may introduce biases as the ImageNet dataset might not align perfectly with disaster-related image characteristics.

Computational Requirements:

The system's training and testing phases require significant computational resources, which might not be readily available in disaster-stricken or resource-constrained environments.

Binary Classification:

The model currently supports only binary classification (victim vs. non-victim). More nuanced classifications, such as injury severity or the presence of multiple victims, are not addressed.

Environmental Factors:

The system does not account for environmental factors, such as debris, water, or crowd interference, which could obscure victim detection in real-world disaster settings.

Scalability:

The current system has not been tested for scalability across larger datasets or broader geographic regions, which could introduce challenges when deployed on a larger scale.

11.3 FUTURE SCOPE

1. Data Expansion

Diverse Data Sources:

- Collect more diverse datasets from real-world disaster scenarios (e.g., earthquakes, floods, wildfires).
- Include images taken under varying conditions (e.g., different weather, lighting, angles).

Synthetic Data Generation:

- Use **GANs (Generative Adversarial Networks)** to generate synthetic images resembling disaster scenarios, especially for underrepresented cases.

2. Advanced Model Architectures

- **Transformer-based Models:**
- Explore transformer architectures like **Vision Transformers (ViT)** or **Swin Transformers**, which have demonstrated state-of-the-art performance in image classification tasks.
- **Hybrid Models:**
- Combine CNNs (e.g., ResNet-50) with transformers to capture both local and global features.
- **AutoML:**
- Use tools like Google AutoML to automate hyperparameter tuning and architecture optimization.

3. Real-time Detection

- **Edge Device Deployment:**
- Optimize the model for deployment on edge devices such as drones or mobile phones for real-time victim detection in disaster zones.
- **Lightweight Models:**
- Use model compression techniques such as **quantization**, **pruning**, and **knowledge distillation** to reduce model size and improve inference speed.

4. **Multimodal Learning**

- Integrate multiple data sources to improve detection accuracy:
- **Thermal Imaging:** Combine visual and infrared data to detect victims in low visibility.
- **Sensor Data:** Use data from wearable devices or IoT sensors for additional cues.
- **Audio Cues:** Incorporate sound data (e.g., calls for help, noise) for enhanced victim detection.

5. **Improved Handling of Imbalanced Data**

Advanced Oversampling Techniques:

- Use **Deep SMOTE** or **Cluster-Based Oversampling** to improve the representation of minority classes.

Cost-sensitive Learning:

- Incorporate cost-sensitive loss functions to prioritize minimizing false negatives (missed victims).

6. **Robustness and Generalization**

- **Adversarial Training:**
- Train the model to handle adversarial examples to ensure robustness against environmental noise or image distortions.
- **Cross-Domain Testing:**
- Evaluate and fine-tune the model on data from new disaster types or regions.

7. **Explainability and Transparency**

- **Explainable AI (XAI):**
- Use methods like **Grad-CAM** or **SHAP** to visualize and explain the model's decisions, especially for misclassified images.
- **Trust and Accountability:**
- Ensure the system is transparent and its limitations are well-documented to promote trust among disaster response teams.

8. Integration with Autonomous Systems

- **Drones and Robots:**
- Integrate the model with autonomous drones or robotic systems for live victim detection in inaccessible areas.

- **Search and Rescue (SAR) Systems:**

- Develop end-to-end SAR systems that use the model for mapping victim locations and coordinating rescue operations.

9. Multi-class Classification

- Extend the model to detect and classify multiple categories, such as:
- Victims needing urgent assistance.
- Debris or obstacles in disaster zones.
- Safe areas for rescue teams to approach.

10. Ethical Considerations and Bias Mitigation Human-in-the-loop Systems:

Develop systems where human experts can validate the model's predictions to minimize critical errors.

11. Disaster Type-Specific Enhancements

Fine-tune models for specific disaster scenarios:

- **Floods:** Focus on detecting victims stranded in waterlogged areas.
- **Wildfires:** Use thermal and aerial data to identify heat signatures of victims.
- **Earthquakes:** Train on images of collapsed buildings and rubble to locate survivors. **12.**

Cloud-based Monitoring and Alert Systems

Real-time Monitoring:

Build a cloud-based dashboard where rescue teams can upload images and get instant victim detection results.

Scalability:

Design scalable systems to process large volumes of data during large-scale disasters.

Chapter-12

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