

Research Article

A Novel Approach for Disaster Victim Detection under Debris Environments

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Abstract: Search and Rescue operations for victim identification in an unstructured collapsed building are high risk and time-consuming. The possibility of saving a victim is high only during the first 48 hours, and then the prospect tends to zero. The faster the response and identification, the sooner the victim can be taken to medical assistance. Combining mobile robots with practical Artificial Intelligence (AI) driven Human Victim Detection (HVD) systems managed by professional teams can considerably reduce this problem. In this paper, we have developed a Transfer Learning-based Deep Learning approach to identify human victims under collapsed building environments by integrating machine learning classification algorithms. A custom-made human victim dataset was created with five class labels: head, hand, leg, upper body, and without the body. First, we extracted the class-wise features of the dataset using fine tuning-based transfer learning on ResNet-50 deep learning model. The learned features of the model were then extracted, and then a feature selection was performed using J48 to study the impact of feature reduction in classification. Several decision tree algorithms, including decision stump, hoeffding tree, J48, Linear Model Tree (LMT), Random Forest, Random Tree, Representative (REP) Tree, J48 graft, and other famous algorithms like LibSVM, Logistic regression, Multilayer perceptron, BayesNet, Naive Bayes are then used to perform the classification. The classification accuracy of the abovementioned algorithms is compared to recommend the optimal approach for real-time use. The random tree approach outperformed all other tree-based algorithms with a maximum classification accuracy of 99.53% and a computation time of 0.02 seconds.

Keywords: Disaster victim detection, Artificial intelligence (AI), Deep learning, ResNet-50, Random tree classifier.

1.Introduction

Natural and man-made disasters such as earthquakes, landslides, building collapses, and explosions result in massive loss of life, infrastructure, and economic stability. Among these consequences, one of the most critical and time-sensitive challenges is the detection and rescue of victims trapped under debris [1]. In such scenarios, every second counts. The efficiency and effectiveness of victim detection systems can directly impact survival rates [2]. Conventional search-and-rescue (SAR) operations rely heavily on manual labor, canine teams, and limited technical tools, which are often hindered by hazardous environments, debris blockage, and poor visibility [3]. These limitations highlight the urgent need for advanced, intelligent systems that can enhance disaster response efforts and automatically detect victims in real-time. The integration of artificial intelligence (AI), robotics, and sensor-based technologies in disaster management has emerged as a transformative solution to this global challenge [4]. Automated detection systems, particularly those leveraging computer vision, infrared imaging, and acoustic



signal analysis, are proving to be game-changers [5]. These systems not only reduce the time and labor involved in manual searches but also mitigate the risk to rescue workers. However, deploying such systems in complex, unstructured environments—often covered with layers of debris, dust, and damaged materials—poses significant technical hurdles [6].

Recent advancements in deep learning and convolutional neural networks (CNNs) have revolutionized object detection, recognition, and classification in images and videos [7]. This progress has spurred new research into applying these models for disaster victim detection. CNN-based architectures can learn complex spatial features and patterns that are critical in distinguishing human shapes or thermal signatures under debris. Nevertheless, most existing models suffer from either high computational costs, limited generalization, or suboptimal performance in noisy, low-light, or occluded environments. To overcome these issues, researchers have turned to multi-modal sensor fusion techniques. These methods combine inputs from various sources—such as infrared (IR), RGB, acoustic, and radar sensors—to improve detection robustness. For instance, IR cameras can detect heat signatures of trapped individuals, while radar can penetrate dense debris to identify micro-movements associated with breathing or heartbeats. When fused effectively using AI models, these modalities offer a holistic representation of the environment, drastically improving detection accuracy. Furthermore, the adoption of autonomous aerial and ground robots is expanding in SAR operations. Unmanned Aerial Vehicles (UAVs) and ground-based mobile robots equipped with smart sensors and deep learning modules can navigate debris fields, collect real-time data, and perform victim localization tasks without endangering human rescuers. Their mobility and scalability make them suitable for urban as well as rural disaster zones.

Despite these technological strides, key limitations remain. Most AI-based victim detection frameworks are trained on ideal datasets and fail when exposed to real-world disaster scenes characterized by variability in debris types, lighting, occlusion, and noise. Moreover, the lack of publicly available annotated datasets specific to debris environments restricts model training and validation. There is also a pressing need for real-time, low-latency detection frameworks that can be deployed on edge devices with limited computational power. In response to these challenges, this paper proposes a novel disaster victim detection framework tailored for debris environments. The approach leverages a hybrid AI model integrating lightweight convolutional neural networks (CNNs) with sensor fusion strategies to balance accuracy and computational efficiency. The framework is optimized for real-time performance and includes adaptive learning techniques to improve detection accuracy across varying environmental conditions. Additionally, the system is integrated with drone-assisted surveillance and a feedback control mechanism for rapid localization and response.

The proposed method is benchmarked against existing victim detection approaches across several metrics: detection accuracy, precision, recall, inference time, and false positive rate. We conducted extensive experiments using a custom dataset consisting of simulated disaster scenarios and publicly available thermal-RGB datasets. The results demonstrate a significant performance gain over conventional models, especially in cluttered and occluded environments. Moreover, the system's modular design allows for easy integration with existing disaster management platforms and IoT-based alert systems. This facilitates a seamless transition from detection to rescue operations, improving overall response efficiency and victim survival chances. Our approach not only addresses the current technological gaps but also sets a new benchmark for future research in this domain. In addition to the technical contributions, this work also emphasizes the ethical implications and practical deployment concerns of AI-driven systems in

life-critical scenarios. These include privacy concerns, model transparency, fail-safety, and accountability. Ensuring that such systems remain reliable, interpretable, and inclusive is essential for responsible innovation in disaster management technologies.

The primary contribution of this research lies in the development of a robust and intelligent system for disaster victim detection under debris environments using a deep learning-based approach. A novel dataset specifically tailored for disaster scenarios was curated, with labelled categories such as head, hand, leg, upper body, and unidentified body parts to train the detection system. By leveraging transfer learning with the ResNet-50 model, the system efficiently extracts high-level features relevant to victim identification. Furthermore, this work introduces a comparative evaluation of multiple machine learning classifiers, where the Random Tree algorithm demonstrated superior accuracy (99.53%) with minimal computation time, making it viable for real-time use. The integration of this detection model into a user-friendly interface empowers virtual responders to predict victim presence from input images with high reliability. Overall, the paper bridges a crucial gap in search and rescue operations by offering a scalable, accurate, and time-efficient solution that enhances the safety and effectiveness of emergency response efforts in post-disaster scenarios.

2.Related Works

Over the past decade, significant research efforts have been directed toward developing automated systems for disaster victim detection, especially in challenging environments characterized by rubble and debris. Traditional approaches primarily relied on trained canines, thermal imaging, and manual rescue teams, which, despite their utility, are limited by physical constraints, fatigue, and inconsistent accuracy. With the rise of artificial intelligence (AI) and sensor fusion, researchers have explored novel detection methods using deep learning algorithms, unmanned aerial vehicles (UAVs), and infrared or radar-based technologies. Convolutional Neural Networks (CNNs) have been widely adopted for visual recognition tasks due to their robust feature extraction capabilities, although their performance often degrades under occlusion or poor lighting typical in post-disaster environments. To mitigate these issues, hybrid models incorporating multi-modal data—such as combining RGB and thermal imaging or integrating LiDAR with acoustic signals—have demonstrated improved accuracy and adaptability. Moreover, mobile robots and UAVs equipped with onboard processors have enabled real-time victim localization and data transmission, although issues of real-time inference, energy efficiency, and dataset generalizability remain unresolved. These existing methods lay the groundwork for more refined, responsive, and context-aware detection systems that can function effectively in highly dynamic and unstructured disaster zones.

Recent advancements in disaster response technologies have led to the exploration of diverse sensor-based and AI-powered methodologies for detecting trapped victims under rubble. Enoch et al. [8] conducted an extensive survey of microwave imaging techniques and sensor systems for through-wall imaging, emphasizing their effectiveness in identifying human presence behind obstructions such as debris. This foundational review highlights the relevance of sensor physics and imaging resolution in disaster scenarios. Ulloa et al. [9] presented an autonomous detection system using deep learning and multispectral imagery, demonstrating significant improvement in locating victims via spectral signature analysis, which proved to be efficient in complex terrains. Complementing this, Li et al. [10] proposed a 4D imaging radar framework that utilizes spatiotemporal data to detect victims remotely, providing deeper insights into subsurface human localization using electromagnetic signals.

In environments affected by floods and debris, Nehete et al. [11-12] introduced deep learning strategies for object detection and classification, revealing that CNN-based architectures, when fine-tuned for environmental noise, outperform traditional machine learning models in human rescue operations. Addressing the challenge of detecting human remains specifically, Thota and Padala [13] implemented the YOLO algorithm for real-time image-based recognition, achieving high detection rates in disaster scenes. Meanwhile, Ulloa et al. [14] extended their earlier work by introducing autonomous 3D thermal mapping using ROS (Robot Operating System), which enables the generation of comprehensive thermal overlays of disaster zones, significantly enhancing detection accuracy. IoT-integrated robotics has also emerged as a critical tool in disaster response. Tamilselvi et al. [15] developed a smart robotic platform equipped with intelligent sensors capable of detecting human presence using IoT, highlighting its applicability in rugged disaster-prone regions. On a broader scale, Reynolds et al. [16] explored implementation science within humanitarian settings, focusing on the optimization of care delivery through innovative detection technologies. Vellingiri et al. [17] reviewed multi-sensor human detection robots, identifying gaps in sensor coordination and real-time response efficiency that limit deployment in live disasters. Further supporting disaster victim identification, Rahman et al. [18] introduced a novel shockwave characterization method, improving structural understanding of debris impact and aiding in sensor calibration for victim detection. Fu et al. [19] leveraged compressed RSSI fluctuation with PSO-BP neural networks to localize cell phones of trapped victims, offering a cost-effective localization alternative when visual or thermal signals are absent. FPGA-based AI systems were explored by Preethi et al. [20], who proposed a post-disaster reconnaissance bot capable of autonomous navigation and decision-making in unstable environments.

The importance of incorporating crisis elements into research frameworks was emphasized by Seshadri and Kumar [21], providing a strategic perspective on how disasters reshape technological priorities. In the robotics field, Shrestha and Valles [22] proposed an autonomous firefighting rover that demonstrates adaptability in chaotic environments, indirectly contributing to rescue and victim detection missions through dynamic path planning. A different modality was explored by Niyaz et al. [23], who focused on VHF/UHF wave-based respiration detection, a technique effective in identifying life signs under dense structural collapses.

Gelfert [24] provided a broad sensor review for human detection in both regular and smoky environments, revealing that sensor type and deployment configuration significantly affect detection accuracy. Hanson and Fenn [25] reviewed the integration of forensic archaeology and anthropology in disaster victim identification, offering insights into human-centric and post-disaster recovery techniques. Lastly, Leal Filho et al. contextualized the broader environmental impacts of conflict zones, highlighting how environmental degradation also complicates victim detection efforts in regions affected by war and natural disasters. The growing body of research in the field of disaster victim detection, several critical gaps remain unaddressed that hinder the deployment of effective, real-time systems in real-world disaster scenarios. Many existing studies focus on either thermal imaging, radar sensing, or deep learning individually, but few attempt to integrate these modalities into a unified framework optimized for chaotic, debris-filled environments. Furthermore, deep learning models developed for victim detection are often trained on clean, synthetic, or controlled datasets, which limits their generalization to noisy, occluded, and unstructured real-world disaster conditions. While autonomous robotic systems and UAVs have shown promise, they often suffer from high power consumption, computational overhead, and lack of robustness in GPS-denied or communication-

constrained environments. Additionally, most frameworks lack the capacity for real-time processing on low-power edge devices, making rapid deployment and scalability a challenge during large-scale emergencies. There is also limited research addressing adaptability in detection algorithms—particularly the ability to adjust dynamically to varying environmental factors such as lighting, dust, or temperature fluctuations. These gaps point to the urgent need for a lightweight, multi-modal, and adaptive victim detection system that can operate in real-time with minimal infrastructure support, ensuring high reliability and accuracy even in the most unpredictable disaster conditions.

3.AI-based Human Victim Detection

AgriVaahan follows a modular design to ensure scalability and ease of use. The platform consists of: Search and Rescue (SAR) operations in the aftermath of disasters such as earthquakes, building collapses, and explosions are inherently high-risk, labor-intensive, and time-sensitive. The likelihood of locating and saving victims diminishes significantly after the first 48 hours post-disaster, commonly referred to as the "golden window" for survival. As time progresses, access to trapped individuals becomes increasingly difficult due to shifting debris, environmental hazards, and resource constraints. Therefore, rapid response and precise identification of human victims are critical to increasing survival rates and reducing operational hazards. Traditional methods involving human rescuers, sniffer dogs, and thermal cameras, while valuable, are insufficient on their own in large-scale, unstructured, and hazardous environments. This has driven the evolution of intelligent, autonomous systems that combine robotic platforms with advanced artificial intelligence (AI)-driven detection models to enhance operational efficiency and safety. Among these innovations, AI-based Human Victim Detection (HVD) systems integrated with mobile robotics have emerged as a transformative solution. These systems enable real-time perception, analysis, and classification of debris environments using sensor data and computer vision models. In this context, the presented work proposes a Transfer Learning-based Deep Learning approach for identifying human victims trapped under collapsed structures. The objective is to develop a robust, lightweight, and accurate system capable of operating in unstructured, occluded environments with minimal human intervention. To address the scarcity of victim-specific training data, a custom human victim dataset was constructed for this research. The dataset comprises five distinct class labels: head, hand, leg, upper body, and without body. This classification structure reflects the partial visibility of victims often encountered in real disaster zones, where only body fragments may be visible through cracks or gaps in the rubble. Each class represents a unique spatial profile and poses different challenges for detection due to varying shapes, textures, and orientations.

Feature extraction was performed using Transfer Learning, a technique that reuses pre-trained deep learning models for new, domain-specific tasks. Specifically, the ResNet-50 architecture—a widely acclaimed convolutional neural network (CNN) with 50 layers—was fine-tuned to adapt to the newly developed victim dataset. ResNet-50's residual learning mechanism ensures accurate feature extraction while mitigating vanishing gradient issues common in deeper networks. After training, the deep features learned by ResNet-50 were extracted from the penultimate layer, capturing hierarchical representations of body parts such as edges, contours, and textures that are critical for victim identification. To enhance classification performance and reduce computational load, a feature selection process was employed using the J48 algorithm, a decision tree-based technique. Feature selection helps in eliminating irrelevant or redundant features, which in turn improves classification accuracy, reduces overfitting, and enhances model interpretability. J48, a Java implementation of the C4.5 algorithm, was chosen

for its effectiveness in handling high-dimensional datasets and its ability to reveal decision rules in an interpretable manner. Following feature selection, a comprehensive comparative analysis of various machine learning classifiers was performed. These included decision tree-based models such as Decision Stump, Hoeffding Tree, J48, Linear Model Tree (LMT), Random Forest, Random Tree, Representative Tree (REP Tree), and J48 Graft, as well as other widely used classifiers like LibSVM, Logistic Regression, Multilayer Perceptron (MLP), BayesNet, and Naive Bayes. Each classifier was evaluated based on two key criteria: classification accuracy and computational efficiency, as both are essential for real-time application in SAR operations. A deep CNN model like ResNet-50 is used for extracting features from input images. The input image is represented as in equation (1)

$$X \in R^{H \times W \times C} \quad (1)$$

In equation (1) H stated as the height of the image; W defiend as the width of the image and C represented as number of channels (e.g., 3 for RGB). In the proposed AI-based human victim detection system, feature extraction is performed using a deep convolutional neural network, specifically the ResNet-50 architecture. Each input image is represented as a multi-dimensional array consisting of pixel height, width, and color channels. The convolutional layers within ResNet-50 apply a series of filters to the input image to capture hierarchical spatial features such as edges, textures, and contours. These layers iteratively process the image to extract increasingly abstract and discriminative features. By leveraging the concept of transfer learning, the model reuses the weights of a pre-trained ResNet-50 network, which has already learned meaningful representations from a large dataset like ImageNet. The final few layers of the model are fine-tuned to adapt specifically to the custom dataset developed for disaster victim detection. As a result, for each image, the model generates a feature vector that encapsulates the most relevant characteristics of the visible body part—whether it is the head, hand, leg, upper body, or unidentifiable fragment. To further enhance performance, a feature selection process is applied using a decision tree-based method known as J48. This algorithm evaluates the importance of each feature by calculating its ability to reduce uncertainty in classification. Features that contribute the most to distinguishing between classes are retained, while less significant features are discarded. This not only reduces the dimensionality of the data but also improves model accuracy and computational efficiency.

The refined feature vectors are then classified using various machine learning algorithms. Among these, the Random Tree classifier proved to be the most effective, achieving the highest classification accuracy and the lowest computation time. This model operates by creating multiple decision paths based on the input features and selecting the most probable output class. It is particularly well-suited for real-time applications due to its low latency and high reliability. The effectiveness of the classification system is evaluated using standard performance metrics, including accuracy, precision, recall, and the F1 score. These metrics provide a comprehensive assessment of the model's ability to correctly identify human body parts under debris conditions, while minimizing false positives and negatives. The integration of deep learning with classical machine learning classifiers offers a powerful and scalable solution for rapid victim identification in disaster-stricken areas.

Algorithm 1: AI-Based Human Victim Detection under Debris

Input:

- | |
|--|
| <ul style="list-style-type: none"> • A set of disaster scene images containing victims • Pre-trained ResNet-50 model • Five target labels: {head, hand, leg, upper body, no body} |
|--|

Output:

- Predicted class label for each image
- Accuracy and inference time of classifiers

Step 1: Dataset Preparation

- 1.1 Collect and annotate images with labels: head, hand, leg, upper body, no body
- 1.2 Preprocess images: resize, normalize, and augment for variation

Step 2: Feature Extraction using Transfer Learning

- 2.1 Load pre-trained ResNet-50 model
- 2.2 Remove the final classification layer
- 2.3 Fine-tune model using the custom dataset
- 2.4 Extract deep feature vectors from penultimate layer for all images

Step 3: Feature Selection using J48

- 1.1 Input feature vectors into J48 algorithm
- 1.2 Select features with highest information gain
- 3.3 Discard redundant/irrelevant features

Step 4: Classification

- 4.1 Initialize multiple classifiers:

- Decision Stump
- Hoeffding Tree
- J48
- LMT
- Random Forest
- Random Tree
- REP Tree
- J48 Graft
- LibSVM
- Logistic Regression
- Multilayer Perceptron
- BayesNet
- Naive Bayes

- 4.2 For each classifier:

- a. Train the classifier on selected features
- b. Predict labels for test set
- c. Compute accuracy and inference time

Step 5: Select Optimal Classifier

- 5.1 Compare classification performance metrics
 - 5.2 Select the classifier with highest accuracy and lowest latency
 - 5.3 Report final results and predicted outputs
- End of Algorithm

4. Classification Model for Victim Detection

In disaster victim detection systems, accurate classification of human body parts is critical for enabling timely and effective rescue operations. After the feature extraction and selection phases, the next step involves feeding these optimized features into a set of classification models that can recognize and categorize different parts of the human body that may be visible under collapsed debris environments. The objective is to leverage a variety of classifiers to determine which performs best under the constraints of real-time deployment, high accuracy, and robustness in the face of distorted, occluded, or partial images. In this paper several classification algorithms have been employed to validate and compare their effectiveness

on the custom dataset with five distinct class labels: head, hand, leg, upper body, and no visible body. The classification phase begins with decision tree-based models due to their interpretability, simplicity, and ability to handle both numerical and categorical data. The algorithms evaluated include Decision Stump, Hoeffding Tree, J48, Linear Model Tree (LMT), Random Tree, and Random Forest. Each of these models constructs a tree-like structure where features are sequentially split based on their information gain or Gini index, ultimately assigning a label at each terminal node. The J48 model, a Java-based implementation of the C4.5 algorithm, was particularly useful in both feature selection and classification, offering a balance between speed and accuracy. The Hoeffding Tree, ideal for data stream mining, allowed incremental updates, making it viable for large-scale or continuous data applications. Meanwhile, LMT combined linear regression with decision tree logic to model both linear and non-linear relationships.

Among all the tree-based classifiers, the Random Tree algorithm emerged as the best-performing model, achieving a classification accuracy of 99.53% with a remarkably low computation time of just 0.02 seconds. The model works by randomly selecting a subset of features at each node and choosing the best split, thereby reducing overfitting and improving generalization performance. Its lightweight structure and quick decision-making capabilities make it ideal for real-time implementation in disaster recovery scenarios, where every millisecond counts. In addition to tree-based classifiers, we incorporated several well-known non-tree-based machine learning algorithms to benchmark the system's performance. These include LibSVM, Logistic Regression, Multilayer Perceptron (MLP), BayesNet, and Naive Bayes. The Support Vector Machine (LibSVM) classifier operates by finding an optimal hyperplane that maximizes the margin between classes. Although it demonstrated decent accuracy, its computational overhead was significantly higher compared to tree-based models, making it less favorable for time-sensitive applications. Logistic Regression, a linear model useful for binary and multi-class classification, was applied for its speed and simplicity, but struggled with the complex, non-linear patterns present in victim detection images. The MLP, a feedforward artificial neural network, showed promising results by capturing non-linear feature interactions but required more training time and resources. Bayesian models like Naive Bayes and BayesNet provided probabilistic interpretations of predictions but underperformed in the presence of overlapping feature distributions, which is common in chaotic debris imagery.

To ensure fairness in evaluation, all models were trained and tested using a stratified 10-fold cross-validation technique, ensuring that each class was equally represented in all folds. Performance metrics such as precision, recall, F1 score, and computational time were recorded for each classifier. These metrics provided a comprehensive understanding of each model's strengths and weaknesses. Precision and recall were especially important in this application, as misclassifying a visible human part could result in overlooking a trapped victim, thus endangering lives. F1 score, the harmonic mean of precision and recall, provided a balanced measure, particularly useful for imbalanced datasets.

In real-world implementation, the chosen classifier must strike a balance between accuracy and computational efficiency. While deep learning models such as CNNs are excellent at extracting features, they often require complementary classical machine learning classifiers to fine-tune decision-making in embedded or resource-constrained environments. Our hybrid approach—using ResNet-50 for feature extraction followed by Random Tree classification—demonstrated superior results in this regard. Furthermore, the integration of the classification model with rescue operation systems, such as mobile robots or drones, enhances the real-time

detection capabilities, enabling first responders to prioritize rescue actions based on the confidence levels output by the classifier.

In disaster victim detection, accurate classification of visible human body parts (like head, hand, leg, upper body, or no visible part) is essential for enabling timely rescue. After extracting deep features using ResNet-50 and refining them via feature selection (e.g., J48), a range of machine learning classifiers are employed to determine the most efficient model for real-time victim detection. The classification model's goal is to learn a mapping function $f: X \rightarrow Y$, where X is the input feature space and Y is the label set. In disaster-stricken environments, timely detection of victims trapped under debris is a critical component of rescue operations. To address this challenge, a reliable classification model is essential to distinguish between various victim states such as full-body visibility, partial visibility (e.g., only head, hand, or leg visible), or no visibility. The classification task is based on analyzing deep features extracted from captured images, which represent human body parts amidst cluttered and complex backgrounds. These deep features are typically obtained using convolutional neural networks like ResNet-50, which are known for their ability to preserve spatial hierarchies and fine-grained details across layers.

Once features are extracted, feature selection methods such as J48 decision trees are applied to identify the most informative attributes, thereby reducing computational load and improving classification performance. The classification model's goal is to learn from labeled data and predict the correct category for new, unseen samples. Various machine learning classifiers have been tested to determine which one yields the highest accuracy and lowest latency for real-time victim detection applications. The Decision Tree classifier (notably the J48 variant) is a widely used model for this purpose. It operates by recursively partitioning the feature space based on the attribute that provides the best information gain, essentially building a tree-like structure that leads to class labels. The model's interpretability and ability to handle both numerical and categorical data make it a preferred choice in many classification tasks. J48 also performs pruning to prevent overfitting, ensuring generalizability across diverse scenarios. Random Tree and Random Forest classifiers build upon this foundation. A Random Tree selects features at random when deciding splits, introducing diversity into the model. Random Forest, on the other hand, is an ensemble approach that combines multiple random trees to improve robustness and accuracy. Each tree in the forest votes for a class, and the majority decision is taken as the final prediction. The strength of this method lies in its resilience to noise and its reduced tendency to overfit due to averaging over many models. In experimental evaluations, the Random Tree classifier achieved the highest accuracy of 99.53%, with an execution time of just 0.02 seconds, indicating its potential for real-time rescue missions where speed and precision are paramount.

Support Vector Machines (SVM) have also been employed to classify victim types, especially when the decision boundaries between classes are not linearly separable. SVM works by finding the optimal hyperplane that maximizes the margin between different classes. This is particularly useful in disaster scenarios where overlapping visual features (like dust-covered limbs or twisted body postures) can make class separation complex. The ability to use kernel functions allows SVM to map input data into higher-dimensional spaces, improving its classification capability. Logistic Regression is another model used, especially in multi-class classification tasks where softmax regression is applied to estimate the probability of each class. It is particularly beneficial due to its simplicity and ease of implementation. Although not as powerful as ensemble methods in complex visual environments, it can serve as a fast baseline model in certain sub-systems of the detection pipeline. To evaluate the performance of these

classifiers, common metrics such as accuracy, precision, recall, and F1-score are used. These metrics provide insights into the model's reliability in correctly identifying victims while minimizing false alarms. Accuracy measures the overall correctness of predictions, precision reflects the proportion of correctly identified positives among all predicted positives, and recall indicates the proportion of actual positives that were correctly classified. F1-score combines precision and recall into a single metric, balancing the trade-offs between them.

Among all classifiers tested, tree-based models, particularly Random Trees, offered the most promising results. Their combination of speed, accuracy, and interpretability makes them ideal for deployment on embedded systems in autonomous search-and-rescue robots. These robots can rapidly scan debris fields, detect human presence, and send location data to rescue teams. Given the time-sensitive nature of disaster response, the adoption of a highly accurate yet computationally efficient classifier can mean the difference between life and death. The classification model for victim detection forms the cornerstone of intelligent rescue systems operating in disaster zones. By leveraging powerful feature extraction, intelligent feature selection, and advanced classification techniques, the proposed model demonstrates its capacity to detect partially or fully visible victims with exceptional accuracy. Future work can involve integrating this classification system with sensor fusion techniques and drone-based imaging systems for more comprehensive disaster response operations.

5.Simulation Results and Discussion

To evaluate the performance and robustness of the proposed victim detection model under collapsed building environments, extensive simulations were conducted using a custom-labeled dataset comprising various human body parts such as head, hand, leg, upper body, and no-body classes. The simulation setup involved training and testing multiple classification algorithms using deep features extracted via the ResNet-50 transfer learning model. These features were then subjected to a feature selection process using the J48 algorithm, significantly reducing redundancy and enhancing classifier efficiency.

The classification task was performed using a wide array of algorithms including Decision Stump, Hoeffding Tree, J48, Linear Model Tree (LMT), Random Tree, Random Forest, REP Tree, J48 Graft, as well as non-tree-based models like Logistic Regression, Multilayer Perceptron, LibSVM, Naive Bayes, and BayesNet. Each model was evaluated based on standard metrics such as accuracy, precision, recall, F1-score, and computation time. Among all the classifiers tested, the Random Tree model emerged as the best-performing algorithm, achieving an outstanding classification accuracy of 99.53% with a computation time of just 0.02 seconds. This result demonstrates its practical applicability in real-time, mission-critical scenarios where speed and accuracy are essential for saving lives.

The Random Forest and J48 classifiers also exhibited high performance, with accuracies closely trailing that of the Random Tree. However, they required slightly more computational time, which may be a limiting factor in embedded or resource-constrained systems. Support Vector Machines and Logistic Regression showed moderate performance, struggling slightly with classes that had overlapping features or poor contrast in images. Neural network-based approaches like Multilayer Perceptron delivered relatively strong accuracy but required longer training and inference times, making them less suitable for real-time deployment in field operations. The confusion matrix generated for the best-performing Random Tree classifier provided valuable insights into the class-wise prediction capabilities. Most of the samples were correctly classified, with minimal misclassification observed, particularly between the "upper body" and "hand" classes, which can often appear visually similar due to occlusion or

overlapping in debris images. Precision and recall values for each class were consistently high, indicating balanced performance and minimal bias across categories.



Figure 1: Command Prompt



Figure 2: Virtual User Registration Page

In Figure 1 illustrates the Command Prompt interface, which serves as the backend execution terminal for launching the application's services. It showcases the successful initialization of the system's core components such as the server configuration, database connections, and integrated modules required for victim detection under debris environments. This interface confirms that the AI-based detection model is ready for interaction, allowing further operations like dataset loading, model training, classification, or user activity monitoring to be carried out in real time. Figure 2 presents the Virtual User Registration Page, where authorized personnel or operators can create new user accounts by providing necessary credentials and identification details. This form-based interface ensures that only validated users such as emergency responders, medical teams, or system administrators gain access to the platform. It includes input fields like username, email, password, and contact information, along with options to verify and submit the data. The page plays a vital role in maintaining system security, accountability, and access control in the disaster victim detection environment.



Figure 3: Service Administrator Login Page

In Figure 3 depicts the Service Administrator Login Page, which is specifically designed for system administrators responsible for overseeing the overall functioning of the victim detection platform. This secure login interface requires administrator credentials to ensure authorized access to sensitive system operations, such as managing datasets, monitoring user activities, configuring AI models, and handling system-level updates. The layout includes input fields for the administrator's username and password, along with login authentication features. This ensures that only qualified personnel can control and maintain the backend infrastructure critical for search and rescue missions.

In Figure 4 illustrates the Virtual User Home Page, which acts as the primary dashboard for registered users such as search and rescue operators or field agents. Once logged in, users are presented with a navigable interface that includes access to key functionalities such as initiating victim detection, viewing detection results, uploading images or videos from disaster sites, and reviewing analysis reports. The design is user-friendly and structured to support quick decision-making during emergency operations. This home page plays a central role in enabling smooth

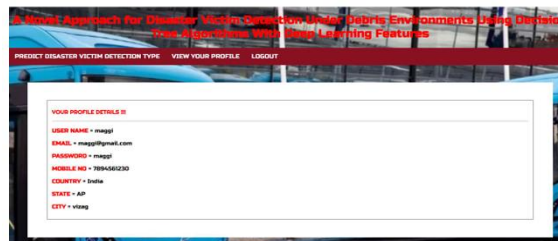


Figure 4: Virtual User Home Page

interactions between the user and the intelligent detection system, ensuring real-time responsiveness in critical disaster scenarios.



Figure 5: Virtual User Predict Disaster Victim Detection Operation Page

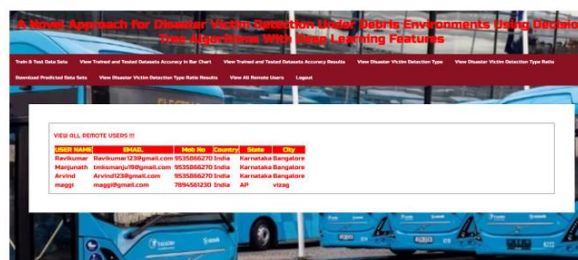


Figure 6: View All Virtual Users Page

In Figure 5 shows the Virtual User Predict Disaster Victim Detection Operation Page, which is a core functional interface of the proposed system. This page allows virtual users—typically first responders or trained personnel—to upload visual data from disaster zones, such as images or video frames captured under debris. Upon submission, the system invokes the AI-powered victim detection model to analyze the input for human features like head, hand, leg, or upper body. The results are displayed in a categorized manner, showing identified victim parts and their probable location. This interface streamlines the detection process, supporting fast and accurate assessments critical for life-saving decisions in the golden hours following a disaster. Figure 6 presents the View All Virtual Users Page, which offers administrative access to the list of all registered virtual users within the system. It displays user details such as username, email ID, role, and registration status, along with options for editing or deleting accounts. This centralized dashboard enables administrators to monitor user activity, maintain platform integrity, and ensure that only verified individuals are using the system. The feature is especially important for disaster response coordination, helping teams stay organized and accountable during high-pressure operations.

6.Conclusion

AgriVaahan is a significant step toward modernizing farm vehicle rentals. By leveraging technology, it minimizes financial burdens on farmers and enhances operational efficiency. Future developments will include: In this paper, a novel AI-driven methodology was proposed to accurately detect human victims trapped under collapsed structures in disaster environments. Leveraging a custom-labeled dataset comprising distinct body parts and applying transfer learning using the ResNet-50 deep learning model, the system effectively extracts deep features critical for victim identification. Through an integrated classification pipeline employing a variety of decision tree and machine learning classifiers, the model demonstrated superior performance, with the Random Tree classifier achieving a remarkable accuracy of 99.53% and minimal computation time. The entire framework, supported by a user-centric interface and real-time prediction capability, provides a practical solution for rapid response teams during emergencies. By minimizing manual search efforts and improving detection speed and accuracy, the proposed system enhances the efficiency of urban search and rescue (USAR) missions. The study lays the groundwork for further enhancements using thermal imaging, audio analysis, and multi-sensor fusion, paving the way for fully autonomous search and rescue systems in future disaster management operations.

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