COLLEGE OF ENGINEERING AND TECHNOLOGY
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A Novel Approach for Disaster Victim Detection Under Debris Environments Using Decision Tree Algorithms With Deep Learning Features

SEMINAR REPORT

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BONAFIDE CERTIFICATE

This is to certify that the Seminar report entitled '**A NOVEL APPROACH FOR DISASTER VICTIM DETECTION UNDER DEBRIS ENVIRONMENTS USING DECISION TREE ALGORITHMS WITH DEEP LEARNING FEATURES'** is a bonafide record of the seminar report presented by **JAMESY JOSEPH** during the academic year 2024-2025 towards the partial fulfillment of the requirement of the award of B. Tech Degree in Computer Science and Engineering of APJ Abdul Kalam Technological University, Thiruvananthapuram.

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ABSTRACT

Search and rescue (SAR) operations following building collapses face significant challenges. These missions are inherently dangerous and require immediate action, especially since the likelihood of rescuing a victim decreases dramatically after the first 48 hours post-incident. Therefore, the swift identification and assistance of victims are crucial for their survival. To address this challenge, we propose an innovative solution that combines mobile robotics with advanced Artificial Intelligence (AI) systems focused on Human Victim Detection (HVD), which can significantly improve the effectiveness of rescue efforts. In this study, we introduce a deep learning approach that utilizes transfer learning to identify human victims in the chaotic environments of collapsed structures. Our method incorporates various machine learning algorithms specifically designed for search and rescue operations. We created a specialized dataset consisting of images of human body parts, categorized into five classes: head, hand, leg, upper body, and without body. This classification system helps rescuers quickly identify where to search for survivors trapped under debris.

To develop our model, we employed the ResNet-50 deep learning architecture, refining it to extract relevant features from our dataset. We then improved the model's performance by selecting the most important features using the J48 algorithm, which enabled us to assess the effect of feature reduction on classification accuracy. After identifying the optimal features, we tested a range of classification algorithms, including various decision tree methods (such as decision stump, Hoeffding tree, J48, Random Forest, and Random Tree), as well as other well-established algorithms like LibSVM, logistic regression, multilayer perceptron, BayesNet, and Naive Bayes. Our results demonstrated that the Random Tree algorithm achieved the highest accuracy, successfully identifying victims with an impressive accuracy rate of 99.53%.

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ABBREVIATIONS

ABBREVIATIONS	DESCRIPTION
CNN	CONVOLUTIONAL NEURAL NETWORK
DL	DEEP LEARNING
HVD	HUMAN VICTIM DETECTION
J48	A DECISION TREE CLASSIFICATION ALGORITHM
ML	MACHINE LEARNING
SAR	SEARCH AND RESCUE
TL	TRANSFER LEARNING

CHAPTER 1
INTRODUCTION

Disasters, whether natural (earthquakes, floods) or human-made (building collapses), cause significant devastation, often trapping individuals under rubble. A swift response is essential to increase survival rates, as the likelihood of saving lives decreases dramatically after the first 48 hours. However, identifying victims in debris-filled, unstructured environments is a formidable challenge. This report explores a novel method combining DL and ML to improve disaster victim detection under these challenging conditions. Specifically, a Convolutional Neural Network (CNN) is used for feature extraction, followed by classification using decision tree algorithms. This approach aims to enhance the speed and accuracy of SAR operations. The motto is to develop a snake-like robot for rescue assistance for human victim detection in these environments.

Victim identification in collapsed buildings presents major challenges for responders, mainly due to uncertainties in victims' bodies and the surrounding environment. This work addresses these challenges by using human anatomical information to aid identification. RGB and thermal image-based datasets are particularly useful in search and rescue scenarios for detecting human victims. Here, an RGB image-based custom dataset is used for human victim identification (HVI) in collapsed, unstructured building environments. Convolutional neural networks (CNNs), a type of deep learning (DL) model, are commonly used in computer vision tasks due to their ability to automatically learn and classify image features without manual engineering.

However, DL models require significant data and computational power. To address this, machine learning (ML) models such as decision trees, logistic regression, and support vector machines are used to enhance classification results with fewer hardware requirements. These ML models are more interpretable and resource-efficient than DL models. After extracting features from a pre-trained CNN, the study applies feature selection to eliminate irrelevant data, allowing ML classifiers to perform efficient and accurate victim identification. This combined approach leverages the strengths of both DL and ML for enhanced identification accuracy in resource-constrained environments.

This report provides an overview of the types and roles of sensors and components in an approach for detecting disaster victims, emphasizing recent advances and the challenges they present. The goal is to offer insights that may guide future innovations and improvements, ultimately aiming for safer, more accessible healthcare solutions.

CHAPTER 2

LITERATURE REVIEW

In disaster scenarios, rapid and accurate human victim detection (HVD) is critical for effective search and rescue (SAR) operations. Traditional HVD methods, which are commonly used in these situations, rely on physical signals such as body heat, carbon dioxide (CO_2) emissions, and sound. Techniques like thermal imaging can detect infrared radiation emitted by human bodies, allowing rescuers to locate victims by their body heat, especially in dark or night conditions. However, thermal imaging is limited by environmental conditions like insulation from debris and adverse weather, which can obscure heat signatures. Similarly, CO_2 detection senses carbon dioxide exhaled by victims, but its effectiveness can be affected by air circulation and high CO_2 levels in the environment. Sound-based methods, which use sensitive microphones to detect noise from trapped individuals, can help locate conscious victims who can make sounds, though they struggle in noisy environments and with unconscious victims.

Despite their usefulness, traditional techniques often face reliability challenges in complex disaster environments. Variations in temperature, air quality, and background noise can interfere with these detection methods, making them less consistent across diverse scenarios. These limitations have driven the need for more robust, adaptable technologies for HVD that can handle the unpredictability of disaster scenes more effectively and reliably.

Deep learning (DL) has emerged as a powerful tool in the field of HVD, especially with Convolutional Neural Networks (CNNs), which excel at recognizing and classifying visual patterns. CNNs are particularly useful for HVD as they can analyze complex images and identify distinct body parts, helping locate victims amidst debris. However, training CNNs requires extensive labeled data, which can be difficult to obtain in disaster scenarios. Transfer Learning (TL) addresses this challenge by leveraging models pre-trained on large, general-purpose datasets. By fine-tuning these models for HVD, TL allows CNNs to effectively detect victims in disaster environments with relatively small datasets.

One common approach in TL is to use CNN models like ResNet-50, known for its accuracy and effectiveness in handling complex image tasks. In HVD, ResNet-50 can be fine-tuned to recognize specific victim features, such as body parts, allowing it to differentiate victims from surrounding debris. This fine-tuning leverages the pre-trained model's general visual features, which significantly reduces training time and improves the model's performance on disaster-specific tasks.

Machine learning (ML) classifiers, when combined with CNNs, further enhance HVD capabilities by efficiently classifying the visual features extracted by CNNs. Decision tree algorithms, such as J48 and Random Tree, are commonly used in these hybrid approaches due to their simplicity and computational efficiency. These classifiers create rules to differentiate between classes, making them suitable for real-time applications where rapid decision-making is essential. Other algorithms, like Support Vector Machines (SVM), can also be used for classification but require more computational resources, which can be a limitation in SAR operations that demand quick responses.

The hybrid approach that combines CNNs with ML classifiers, particularly in a transfer learning framework, offers a promising solution for HVD in disaster settings. This combination leverages CNNs’ strength in feature extraction with the classification power of ML algorithms, creating an adaptable, high-accuracy detection system. Together, these methods provide a flexible, efficient approach that overcomes the limitations of traditional HVD methods, supporting faster and more reliable victim detection in SAR missions.

CHAPTER 3

EXISTING SYSTEM

The existing systems for human victim detection (HVD) in disaster scenarios rely primarily on traditional sensor-based approaches, which have limitations in real-world application due to their dependency on environmental factors. These techniques generally include thermal imaging, CO_2 detection, and sound-based systems to locate victims trapped in rubble.

1. **Thermal imaging**: It uses infrared sensors to detect the heat emitted by human bodies, allowing SAR teams to identify victims even in low-light or nighttime conditions. However, its effectiveness can be significantly reduced when victims are covered by heavy debris, which insulates body heat and makes thermal signals harder to detect. Additionally, adverse weather conditions like rain and fog can interfere with infrared imaging, further impacting its reliability.

2. **CO_2 detection**: Another traditional method which senses carbon dioxide levels in the vicinity to locate breathing humans. This method leverages the fact that living humans exhale CO_2, creating a distinct concentration in the air near victims. However, the accuracy of CO_2 detection is highly susceptible to the surrounding environment. High levels of background CO_2 or poor air circulation within debris can cause false readings or completely mask the presence of victims. This is particularly problematic in open or windy environments, where CO_2 disperses more quickly, reducing the chances of accurate detection. Consequently, while useful in controlled conditions, CO_2 detection has limitations that make it unreliable in the unpredictable environments typical of disaster sites.

3. **Sound-based detection**: This system represent another existing approach to HVD, wherein sensitive microphones or geophones detect sounds like tapping, cries for help, or other noises made by trapped individuals. Sound-based detection is valuable because it can identify victims who are conscious and able to make noise, even if they are not visible. However, this method has several limitations as well. It is heavily influenced by environmental noise, such as machinery or wind, which can interfere with the detection process. Furthermore, the method is ineffective for detecting unconscious or immobilized victims who cannot generate any sounds, thus limiting its applicability to a subset of potential victims.

While traditional methods provide essential tools for SAR, they have critical limitations in complex and unstructured disaster environments. These techniques often depend on specific conditions to function effectively, which can limit their performance in varied real-world settings. The effectiveness of thermal and CO_2 sensors, for instance, diminishes with environmental changes such as insulation from rubble or air quality issues, while sound-based systems are hindered by ambient noise. As a result, these traditional systems are not always adaptable to the complex and varied conditions encountered in disaster zones, where rapid victim identification can be a matter of life and death.

The inherent limitations of traditional HVD techniques underscore the need for more advanced, adaptable systems that can overcome environmental constraints. Recent developments in deep learning (DL) and machine learning (ML) offer promising solutions. Deep learning models, particularly Convolutional Neural Networks (CNNs), can effectively classify visual information and are robust against many of the limitations of traditional sensors. By applying CNNs to image-based victim detection tasks, these new methods can identify complex visual cues from scenes filled with debris, providing a higher accuracy rate and adapting better to environmental changes than traditional methods.

CHAPTER 4
PROPOSED SYSTEM

The proposed disaster victim detection system presents a novel and robust approach by combining deep learning (DL) and machine learning (ML) techniques, specifically designed to address the limitations of traditional human victim detection (HVD) methods in complex disaster scenarios. Traditional techniques, like thermal imaging and CO_2 detection, often face challenges in SAR operations due to environmental obstructions or signal interference. In contrast, this new approach utilizes advanced DL and ML methods to identify victims more effectively, even when only partial body parts are visible through debris. This improvement significantly enhances the system's capability to perform in challenging, unstructured environments, making it a valuable asset in time-sensitive SAR missions where traditional detection tools may fall short.

At the core of this system is a Convolutional Neural Network (CNN) model, specifically ResNet-50, known for its ability to accurately analyze visual data. ResNet-50, pre-trained on a large dataset, is repurposed through transfer learning (TL) to work with a custom-made dataset created to represent realistic disaster environments. This dataset contains RGB images of five specific classes: head, hand, leg, upper body, and images without visible body parts. By training on these classes, the CNN learns to identify partial body parts, which is crucial in SAR missions where victims may be partially obscured by rubble. The ability to distinguish between body parts provides a critical advantage over traditional methods, allowing the model to locate victims in a way that thermal imaging or CO_2 sensors alone cannot.

Transfer learning is an essential component of this system, allowing ResNet-50 to transfer its learned general visual features to the task of disaster victim detection. Instead of training the network from scratch, TL enables the use of a pre-trained model that already recognizes fundamental image features, thereby minimizing the need for extensive new training data. This not only reduces the time required for model preparation but also improves its accuracy by utilizing high-level features learned from a broader dataset. For disaster applications, where collecting a vast amount of labeled data is often impractical, TL offers a practical solution. Consequently, the system becomes more adaptable and resource-efficient, allowing it to be deployed across different SAR operations with minimal adjustments.

Beyond feature extraction, the proposed system includes a feature selection and classification phase where ML classifiers refine the CNN’s outputs. Specifically, the J48 decision tree algorithm is used to select only the most relevant features from those extracted by ResNet-50, enhancing computational efficiency by reducing unnecessary data without sacrificing accuracy. Once the optimal features are identified, multiple ML classifiers are tested to determine the best performer for classifying body parts under debris. Among these classifiers, the Random Tree algorithm achieves exceptional results, with an accuracy of 99.53% and a processing time of only 0.02 seconds, making it ideal for real-time SAR applications where every second counts.

This hybrid approach effectively combines DL’s capability to handle complex, unstructured data with the speed and interpretability of ML classifiers. The CNN extracts detailed visual features while the decision tree classifiers perform rapid and accurate classification, achieving a balance of high accuracy and low latency. Additionally, the reliance on RGB images and TL makes the system more flexible and scalable, reducing the need for large, custom datasets. The proposed system offers a significant advancement over traditional methods, capable of overcoming environmental challenges such as low visibility and signal blockages. Ultimately, it provides SAR teams with a scalable, powerful solution that can adapt to various disaster environments, helping locate victims quickly and accurately.

CHAPTER 5

MATERIALS IN SYSTEM

The processes involve in creating a robust dataset, extracting meaningful features using deep learning, and classifying these features using machine learning. This section highlights each stage, from data acquisition to feature selection and classification, which together form a comprehensive framework for effective human victim detection (HVD) in disaster scenarios. Together from the below given methods create a robust, hybrid system that leverages the strengths of deep learning and machine learning for efficient and accurate human victim detection in disaster scenarios. Each stage of the pipeline is designed to optimize the model's performance in unstructured, real-world SAR environments.

5.1 CUSTOM DATASET

A custom dataset was created specifically for this study to simulate real disaster conditions. Images of various human body parts (head, hand, leg, upper body) were captured in debris-filled environments, mimicking real-world disaster scenarios. The dataset was divided into five classes: head, hand, leg, upper body, and images without visible body parts. Data augmentation techniques, including rotation, scaling, and lighting variations, were applied to diversify the dataset, resulting in 10,000 images across the five classes. Each image was resized to 224x224 pixels to be compatible with ResNet-50's input layer. Fig 5.1, Table 5.1, Table 5.2 shows the data acquisition and pre-processing.

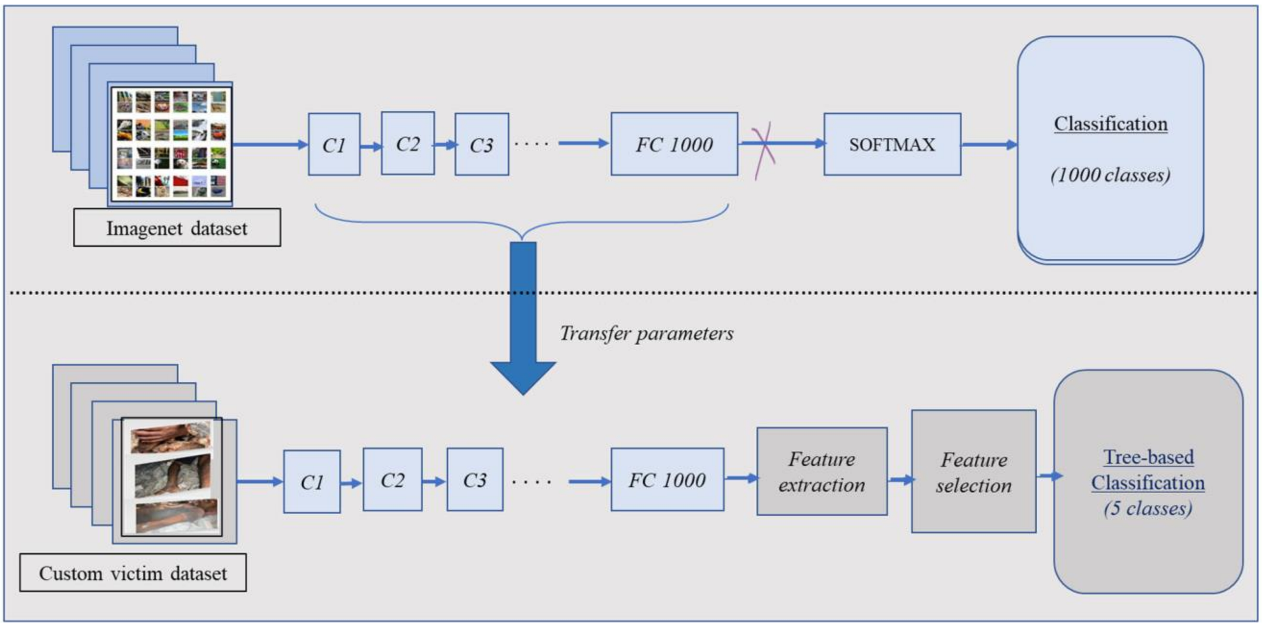

Fig 5.1. Data Acquisition and Augmentation Workflow

Parameter	Data Acquisition Device
Voice	Microphone
Aroma	CO_2 Sensor
Body Warmth	Thermal Camera
Motion	Accelerometer
Facial Form	Camera
Skin Color	RGB Camera
Body Shape	Depth Sensor

Table 5.1. Parameter and Data Acquisition Devices

Camera specification	
Camera resolution	10120x6328 pixels
Video recording	4K UHD (3840x2160) 30 fps
Pixel size	0.8µm pixel

Table 5.2. Camera Specification

5.2 RESNET-50 MODEL

ResNet-50, a pre-trained Convolutional Neural Network (CNN) architecture, was selected for feature extraction. Known for its robustness in image classification tasks, ResNet-50 contains 49 convolutional layers and a fully connected layer. This architecture's residual learning framework helps prevent vanishing gradients, enabling the model to learn and retain complex visual features effectively. A detailed overview of ResNet-50's architecture is shown in Fig 5.2.

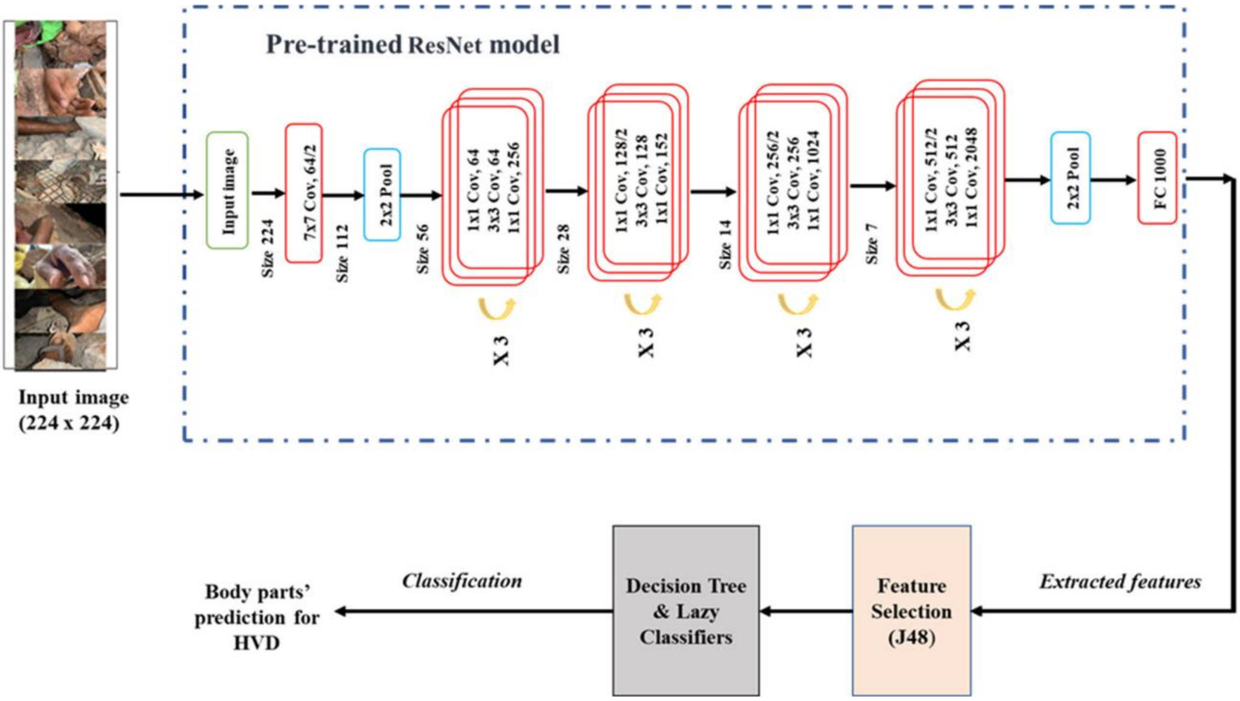

Fig 5.2. The Architectural Feature Learning of ResNet-50

5.3 MACHINE LEARNING CLASSIFIERS

Various machine learning classifiers were evaluated for the classification task, including Random Tree, J48, and Naive Bayes. These classifiers were chosen for their effectiveness in handling structured data and their suitability for classification tasks. The performance of each classifier was assessed based on its accuracy and computation time to identify the most efficient algorithm for real-time SAR applications.

Classifier used	Approach	Application	Dataset Type	Inferences
Naive Bayes, SVM, Neural Networks	Supervised Learning	Analyzing social media sentiment for marketing	Labelled Text Data	Accurately predict the sentiment of a given text with high accuracy
Random Forest, Naive Bayes, SVM	Supervised Learning	Identifying spam emails	Labelled Email Data	Achieving high precision and recall scores on spam detection
Random Forest, SVM, Neural Networks	Supervised Learning	Identifying fraudulent financial transactions	Labelled Transaction Data	Accurately detecting fraudulent transactions with high accuracy
SVM	Feature Selection	Prediction of liver cancer Recurrence	Gene expression data	Feature selection with the SVM model improved prediction performance compared to using all gene expression features.
LSTM	Time Series Analysis	Stock price prediction	Stock market data	LSTM model outperformed traditional time series models in predicting stock prices.
Decision Tree	Feature Selection	Predicting customer churn in the telecom industry	Customer behaviour data	The decision tree model with feature selection accurately predicted customer churn.
SVM	Feature Selection	Classification of Alzheimer's Disease	Brain imaging data	SVM model with feature selection achieved high accuracy in the classification of Alzheimer's Disease.

Table 5.3. Machine Learning-based classification approaches in various applications.

CHAPTER 6
METHODS IN SYSTEM

By following these methods, the study developed a robust, high-performance system for HVD in disaster environments, integrating CNN-based feature extraction with ML classification to achieve real-time applicability.

6.1 DATA ACQUISITION AND PRE-PROCESSING

The custom dataset was created by capturing images of team members' body parts positioned within debris, under varied lighting and spatial configurations. Data augmentation techniques such as rotation, scaling, and lighting adjustments were applied to the dataset to enhance its variability, ensuring the model's adaptability to various SAR conditions. The final dataset contained 10,000 images, with each class comprising 2000 images. Fig 6.1 demonstrates the steps in data acquisition and augmentation, from initial image capture to pre-processing.

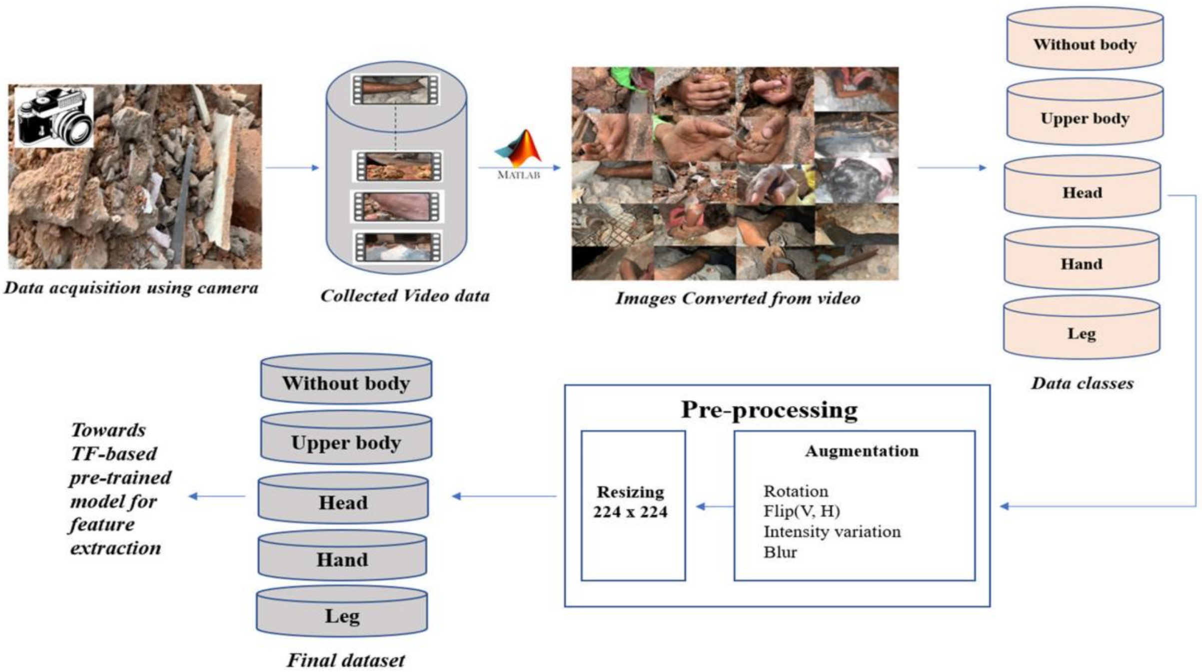

Fig 6.1. Stages in Dataset Creation.

The confusion matrix provides a detailed assessment of the model's classification performance across five body-part classes: head, hand, leg, upper body, and images without visible body parts. With each row representing the true class and each column the predicted class, the diagonal elements of the matrix indicate correct classifications, while off-diagonal values show misclassifications. The matrix demonstrates a high level of accuracy, as most predictions align along the diagonal, confirming the model's strong ability to distinguish body parts even in complex, debris-filled settings. Minimal misclassifications underscore the effectiveness of feature selection and the Random Tree classifier. Additionally, the matrix provides insights into areas for potential improvement, such as reducing confusion between similar classes if necessary. Overall, the confusion matrix confirms the model's high accuracy (99.53%) and its reliability for real-time SAR applications as shown in Fig 6.2 and Table 6.1.

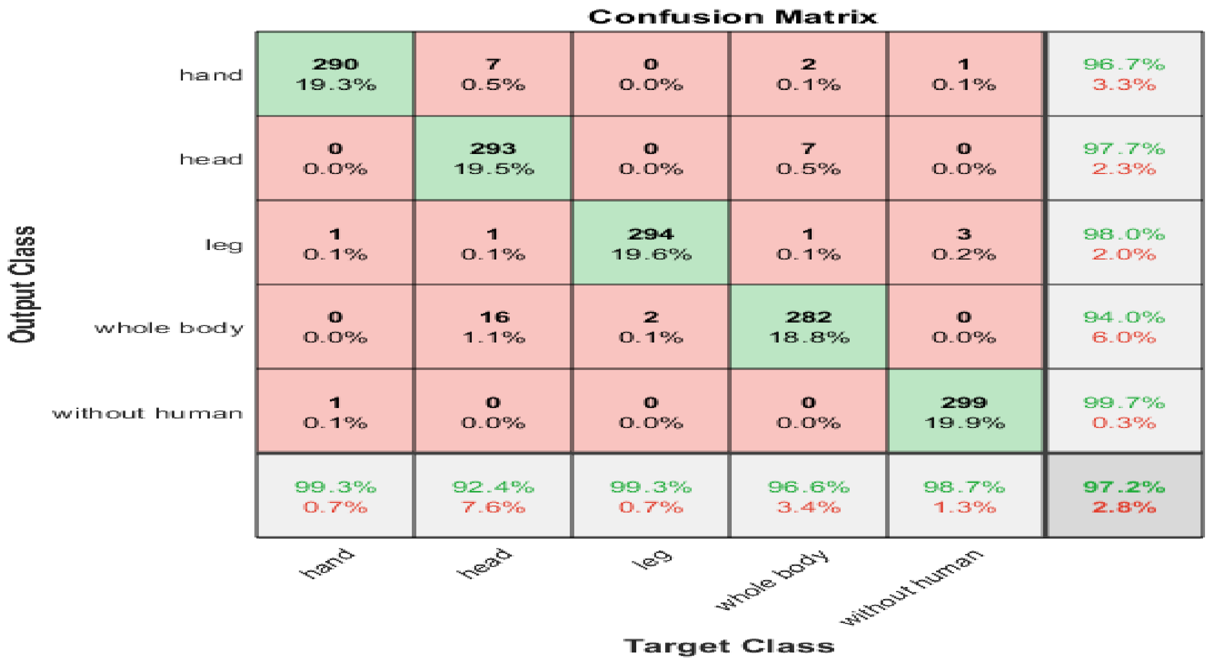

Fig 6.2. Confusion Matrix

=== Confusion Matrix ===

a	b	c	d	e	<-- classified as
1974	7	11	1	7	a = hand
1	1963	3	29	4	b = head
12	5	1976	1	6	c = leg
0	59	4	1937	0	d = whole body
2	2	1	4	1991	e = without human

Table 6.1. Classification of Confusion Matrix

6.2 FEATURE EXTRACTION WITH CNN-BASED TRANSFER LEARNING

Transfer learning was applied to the ResNet-50 model to perform feature extraction on the custom dataset. Transfer learning allows a pre-trained model to apply its knowledge to a new, smaller dataset with minimal retraining, enhancing its feature-detection capability. The top layers of ResNet-50 were fine-tuned to adapt to the custom HVD dataset, producing a 1000-dimensional feature vector for each image. These feature vectors, saved as a CSV file, were used as inputs for the classification stage. Fig 6.3 illustrates the transfer learning framework with ResNet-50, showing the steps taken to adapt the model to the new dataset. Table 6.2 and Table 6.3 shows CNN and learning models.

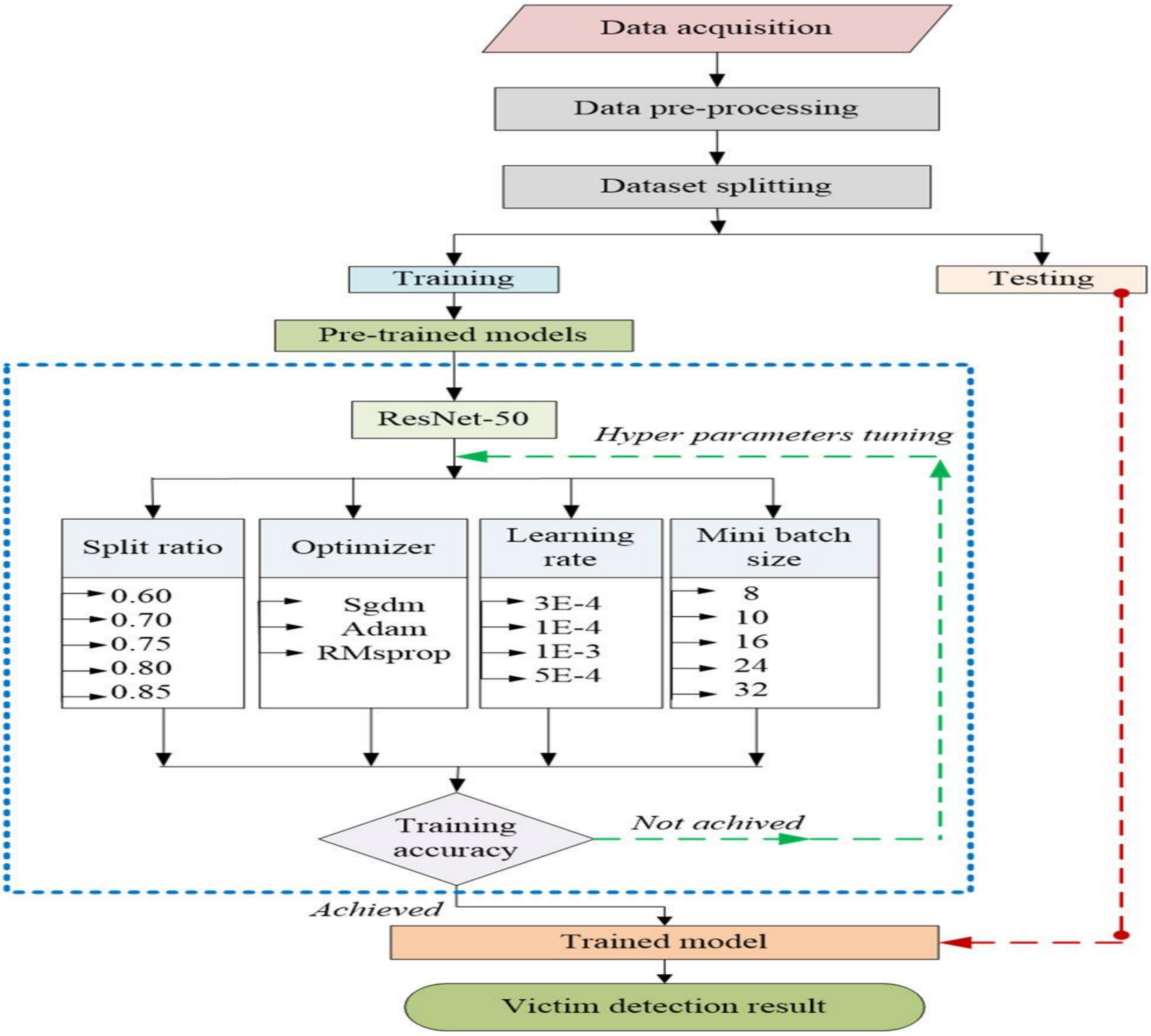

Fig 6.3. Transfer learning based on hyperparameter tuning on ResNet-50 pre-trained network.

Application	CNN Model Type
Object Detection	YOLO, SSD
Image Classification	ResNet, VGG
Human Pose Estimation	OpenPose, DensePose
Semantic Segmentation	U-Net, Mask R-CNN
Image Generation	GAN, Variational Autoencoders
Medical Image Analysis	AlexNet, GoogLeNet
Fault Detection	Custom CNN, ResNet-based

Table 6.2. CNN model types and its application.

Learning model	Purpose/ features	Network/ model	Image type	Dataset source
Deep learning [14]	Disaster victim detection	MobileNet, SSD	RGB	INRIA
Basic deep learning [15]	For identifying objects in real-time video feeds using CNN models	Alex Net, GoogLeNet ResNet-50	RGB	ImageNet, CIFAR10,and CIFAR 100
Deep learning (2012) [16]	Classification using deep CNN. • The neural network) comprises 60 million parameters, 650,000 neurons [5-convolutional layers+ max-pooling layers+ three full y connected layers+1000-way softmax] • They attained top-1 and top-5 error rates (37.5% and 17.0%, res pectively) on the test data.	Alexnet	RGB	ImageNet
Transfer learning (2018) [17]	The valuable feature presentation of pre-trained networks can be transferred to target tasks using a novel two-phase strategy developed by integrating CNN transfer learning and online data augmentation.	AlexNet, VGG, ResNet	RGB	ImageNet
Transfer learning (2018) [18]	With Transfer Learning, the Inception-v3 CNN architecture model was retrained to see if it would perform accurately and effectively with new picture datasets.	Inception-V3	RGB	CIFAR-10, MNIST
Transfer learning [2017] [19]	Malware family classification approach using a deep neural network	ResNet-50	RGB	Custom-dataset
Transfer learning (2021) [20]	Improved image classification with VGG19 and several custom feature extraction techniques (ORB, SIFT, Shi-Tomasi corner detector, and SURF algorithms)	VGG-19	RGB	Caltech-101
Deep learning (2020) [2]	Regardless of the type of image input, a reliable detector was found in low-lighting and body part occlusion situations.	YOLO RetinaNet		Custom-dataset
Deep learning (2021) [21]	Proposed Improved Visual Geometry Group-13 (IVGG13), a modified VGG16 model for pneumonia X-rays image classification	IVGG13	X-ray	Kaggle
Transfer learning (2019) [22]	For cat-dog classification	VGG-16	RGB	ImageNet
Transfer learning (2022) [23]	For misfire classification in spark ignition engines	AlexNet, VGG-16, GoogleNet, Resnet	Vibration signal	Custom made
Transfer learning [24]	For image-based dietary assessment	GoogLeNet	RGB	Custom-made
Transfer learning [25]	For automated brain image classification	VGG-16	MR	From the Harvard M edical School reposit ory
Basic Deep learning [26]	For pose estimation	Faster R-CNN	RGB	COCO public dataset
Basic Deep learning [27]	To distinguish between body parts in a position estimate	Single Shot Multi-box Detector (SSD)	RGB	MPII Human Pose and Leeds Sports Poses datasets
Basic Deep learning [28]	To identify hands for a hand-pose estimator	You Only Look Once (YOLOv2)	RGB	Custom- made
Basic Deep learning [29]	For body part instance segmentation	Feature Pyramid Net work (FPN)	RGB	DensePose-COCO dataset.
Basic Deep learning [30]	Used in operating rooms to locate upper body parts. The network produced a score map for upper body components using RGB-D data as input. Then the classification was done with a random forest classifier.	ResNet	RGB-D	Custom dataset

Table 6.3. CNN-based classification approaches in various applications.

6.3 FEATURE SELECTION USING J48 DECISION TREE ALGORITHM

To optimize classification efficiency, the J48 decision tree algorithm was used for feature selection, reducing the initial set of 1000 features to 98 essential features. This reduction minimizes computation time and enhances model efficiency, which is crucial for SAR operations requiring rapid decision-making. Fig 6.4 demonstrates the J48 feature selection process, where the most relevant features were identified and retained based on their contribution to classification accuracy.

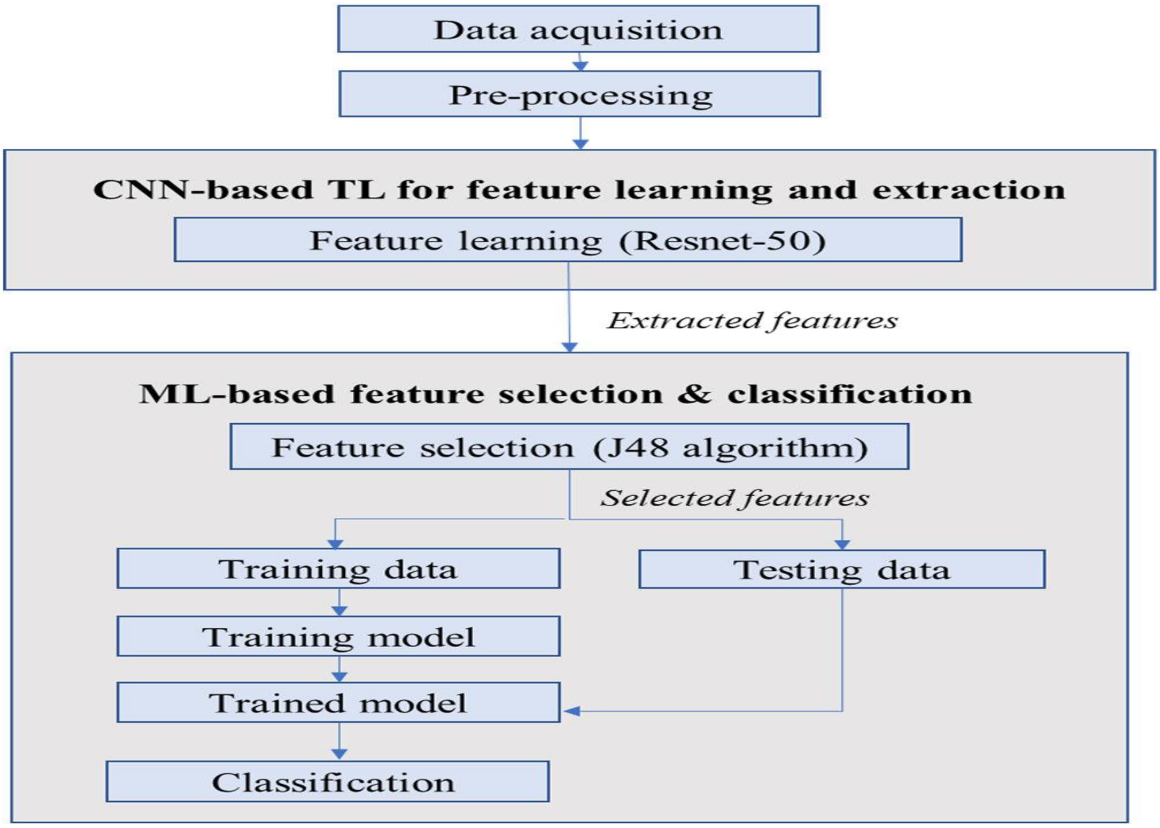

Fig 6.4. Human victim detection approach by combining DL features and ML classifiers

6.4 CLASSIFICATION USING TREE-BASED ALGORITHMS

After feature selection, various classifiers (Random Tree, J48, and Naive Bayes) were used to classify the images into one of the five body-part classes. The Random Tree classifier achieved the highest accuracy at 99.53%, with a computation time of 0.02 seconds, making it the most effective for real-time applications. Fig 6.5 compares the performance of each classifier in terms of accuracy and speed. Table 6.4 provides a detailed comparison of classifier results, highlighting Random Tree as the preferred choice.

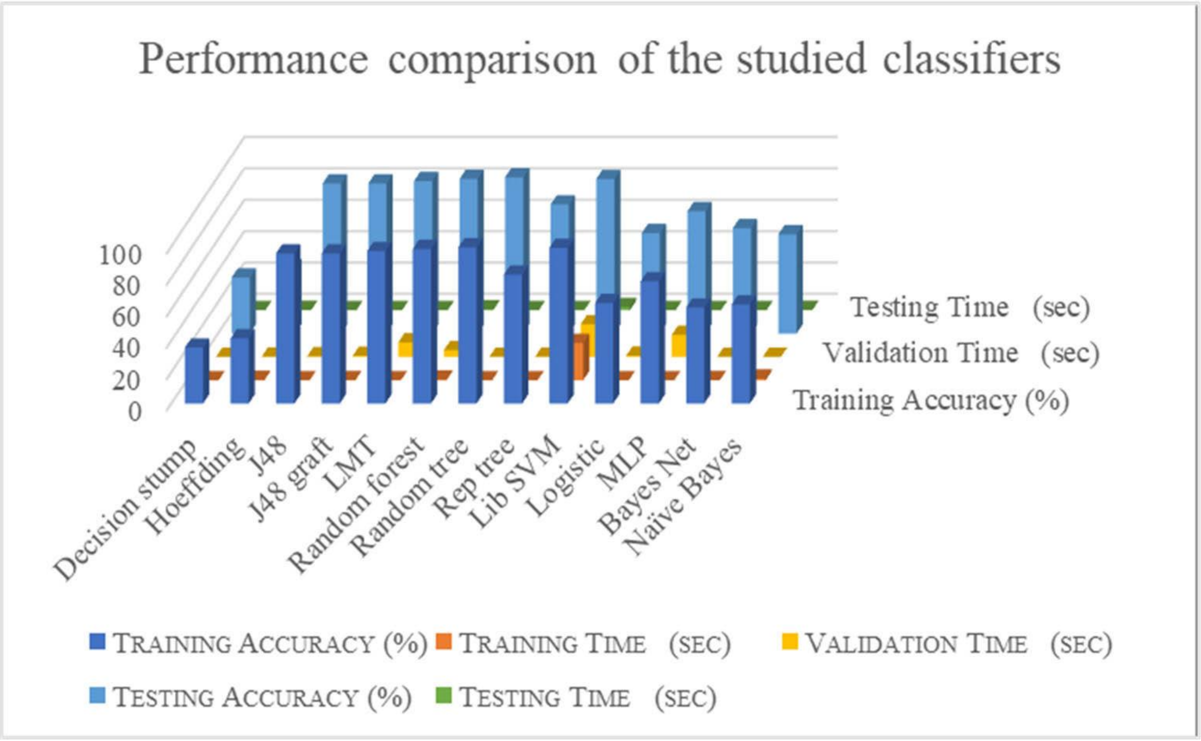

Fig 6.5. Performance comparison of classifiers

	Classifier	Training		Validation		Testing	
		Accuracy (%)	Time (s)	Accuracy (%)	Time (s)	Accuracy (%)	Time (s)
Tree based classifiers	Decision stump	35.69	0	35.58	0.03	35.69	0.03
	Hoeffding	41.58	0.19	63	0.11	41.58	0.16
	J48	95.66	0.01	73.02	0.38	95.66	0.04
	J48 graft	95.66	0.08	74.02	0.73	95.66	0.03
	LMT	97.17	0.01	79.19	9.2	97.17	0.03
	Random forest	98.53	0.53	88.68	4.26	98.53	0.49
	Random tree	**99.53**	**0.01**	**72.35**	**0.07**	**99.53**	**0.02**
	Rep tree	82.19	0.01	69.96	0.11	82.19	0.03
Other classifiers	Lib SVM	99.24	23.71	97.29	20.75	98.41	1.99
	Logistic	64.07	0.01	63.68	0.79	64.07	0.02
	MLP	77.91	0.03	75.2	14.05	77.91	0.06
	Bayes Net	61.17	0.04	65.6	0.08	67.11	0.05
	Naïve Bayes	63.24	1.12	62.99	0.03	63.24	0.11

Table 6.4. Comparison of classification accuracy and time required to build a model for various classifiers.

CHAPTER 7
ADVANTAGES

The proposed system offers several distinct advantages, making it an effective and reliable tool for disaster victim detection in search and rescue (SAR) operations, offering high accuracy, real-time processing, and adaptability to improve rescue outcomes in disaster environments:

1. **High Detection Accuracy:** One of the major strengths of the system is its exceptional classification accuracy of 99.53%. This high accuracy is critical in SAR scenarios, as it allows rescuers to reliably detect and distinguish between various body parts within complex, debris-filled environments. Accurate detection increases the likelihood of identifying and locating victims, which is crucial during emergency response efforts.

2. **Real-Time Processing Capability:** With a classification speed of only 0.02 seconds per image, the system is designed to function in real-time. This rapid processing speed is invaluable in SAR missions, where time is a critical factor, especially during the initial 48 hours after a disaster, when the chances of survival are highest. The system's efficiency allows for faster detection and response, which can ultimately save lives.

3. **Robust Feature Extraction Through Transfer Learning:** The integration of transfer learning (TL) using the ResNet-50 model enhances the system's robustness by leveraging pre-trained knowledge to handle complex images of disaster sites. TL enables the model to perform well with the relatively small custom dataset used in this study, as ResNet-50 can extract detailed and meaningful features that improve the system's performance in challenging environments.

4. **Optimized Feature Selection for Efficiency:** By applying the J48 decision tree algorithm for feature selection, the system reduces the number of features from 1000 to 98 without compromising accuracy. This optimized feature set minimizes computational requirements, enabling the model to operate efficiently even on limited hardware. This efficiency is beneficial for SAR applications where the system may need to run on portable devices like drones and rescue robots with constrained resources.

5. **Greater Adaptability Compared to Traditional Methods**: Unlike conventional methods such as thermal imaging or CO_2 detection, which can be unreliable in changing environmental conditions, this system leverages deep learning and machine learning to detect human victims using visual data alone. This adaptability makes it less vulnerable to environmental factors and more versatile across diverse disaster scenarios, increasing its applicability and reliability in SAR operations.

CHAPTER 8
DISADVANTAGES

While the proposed system shows promise for disaster victim detection, several limitations could affect its performance in real-world SAR applications. The below given disadvantages highlight areas where future improvements could make the system more versatile, reliable, and effective for SAR applications in diverse and challenging environments.

1. **Limited Dataset Diversity:** The custom dataset used in this study, although designed to simulate disaster conditions, may lack the diversity needed to fully represent all possible scenarios in real disaster environments. With only five body-part classes, the model’s ability to generalize to unfamiliar environments, different types of debris, and varying lighting conditions could be limited. Expanding the dataset to include more diverse examples would improve the model’s robustness and adaptability.

2. **Dependence on Visual Data:** Since this system relies solely on RGB visual data, it may face challenges in low-visibility conditions such as heavy dust, smoke, or darkness common occurrences in disaster zones. Victims who are obscured or not clearly visible could go undetected, reducing the system’s effectiveness. Integrating additional data sources, like thermal or infrared imaging and sound detection, could enhance the system’s reliability under such conditions.

3. **Sensitivity to Model Fine-Tuning:** The model's performance depends significantly on the fine-tuning of the ResNet-50 layers for effective transfer learning. Improper fine-tuning may lead to suboptimal results, potentially causing misclassifications. This requirement for precise tuning demands technical expertise, which may not always be feasible in emergency SAR deployments that need quick and efficient setup.

4. **Hardware and Power Constraints:** Although the feature selection process optimizes computational efficiency, the system still requires relatively high-performance hardware for real-time processing. This requirement could be a drawback in SAR scenarios where the model needs to run on portable, battery-powered devices like drones or rescue robots. Hardware limitations and power constraints could hinder the system's performance, especially during extended missions.

5. **Lack of Real-World Validation:** The model has primarily been tested in controlled, simulated environments, so its performance in real disaster scenarios remains unverified. The unpredictable nature of SAR environments could present unforeseen challenges, and without real-world testing, the model’s reliability and robustness in field operations are uncertain. Further validation in live SAR conditions is necessary to confirm the model’s practical effectiveness.

CHAPTER 9
CONCLUSION

This paper presents a novel and effective approach to disaster victim detection, offering significant improvements in speed and accuracy for search and rescue (SAR) operations within challenging, debris-laden environments. By integrating deep learning (DL) through transfer learning with the ResNet-50 model for feature extraction, and machine learning (ML) classifiers particularly the Random Tree algorithm for classification, the system achieves an impressive accuracy of 99.53% with real-time processing capabilities. This high accuracy and efficiency make it a valuable tool for SAR teams, addressing many limitations of traditional methods like thermal imaging and CO_2 detection by providing robust image-based classification that adapts better to variable conditions.

However, the system does have certain limitations. Its reliance on RGB visual data may reduce effectiveness in low-visibility conditions typical of disaster zones, and its performance would benefit from a more diverse dataset to enhance generalization across different scenarios. Additionally, while the model has demonstrated excellent results in controlled settings, real-world testing remains necessary to verify its reliability and resilience in actual SAR operations.

In conclusion, this research makes a valuable contribution to advancing AI-driven solutions in disaster response. The system’s demonstrated ability to accurately detect human victims within complex environments could significantly enhance SAR effectiveness. Future work could focus on expanding the dataset, incorporating additional sensor types (e.g., thermal or audio), and conducting field tests to optimize the system's practical application in real-life disaster scenarios.

CHAPTER 10
FUTURE SCOPE

The proposed system has demonstrated promising results in improving search and rescue (SAR) operations, but there are several areas where future research and enhancements could further optimize its effectiveness and adaptability for real-world disaster scenarios.

1. **Expanding Dataset Diversity:** Future work could focus on expanding the dataset to include a broader range of disaster scenarios, victim positions, and environmental conditions. A more diverse dataset would enable the model to generalize better to different real-world settings, including varied debris types, lighting conditions, and orientations of trapped victims, increasing its robustness and adaptability.

2. **Incorporating Multi-Sensor Data:** Currently reliant on RGB visual data, the system could benefit significantly from integrating additional sensor types, such as thermal, infrared, and audio. Multi-sensor fusion would enhance its performance in low-visibility conditions like smoke, dust, and darkness, making the model more versatile and effective in detecting victims when visual information is limited.

3. **Conducting Real-World Field Testing:** Although the model has shown high accuracy in controlled settings, testing it in actual SAR environments would be essential to validate its reliability and adaptability under real disaster conditions. Field tests would reveal practical challenges and allow for refinements that ensure consistent performance across unpredictable and varied SAR scenarios.

4. **Optimizing for Portable SAR Devices**: To facilitate deployment on resource-limited devices such as drones and mobile robots, future development could focus on optimizing the model for lower power consumption and reduced processing requirements. A lightweight version of the model would be suitable for portable SAR applications, allowing for extended use in remote or resource-constrained environments.

5. **Implementing Real-Time Feedback Mechanisms:** Future iterations of the system could include real-time feedback features to assist SAR teams actively. For example, the system could send alerts when a potential victim is detected and provide additional information on the location and detected body parts, improving situational awareness and decision-making for SAR personnel.

These future directions would make the system more versatile, efficient, and robust, further enhancing its potential as a valuable tool in diverse and demanding SAR operations.

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