Deep Learning and Decision Tree Approach for Detecting Survivors in Disaster Debris

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***Abstract*—In the aftermath of disasters like earthquakes and building collapses, being able to swiftly and accurately find trapped individuals is crucial for saving lives. This work introduces an innovative AI system that can spot visible human body parts like hands, legs, and upper bodies underneath debris by analyzing visual data. To train and assess the system in realistic disaster scenarios, a specially labeled image dataset was created, with the goal of enhancing both the speed and reliability of victim detection in life-threatening situations. The system employs ResNet-50, a powerful deep convolution neural network, to extract robust image features. These features are then classified using a variety of decision tree-based machine learning classifiers, such as XGBoost, Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), and Random Forest. These models are recognized for their impressive accuracy and ability to generalize in classification tasks. Notably, XGBoost stood out, achieving a remarkable 100% classification accuracy with an inference time of just 0.05 seconds, making it ideal for real-time applications. By merging the advantages of deep learning with interpretable machine learning techniques, this system not only provides high detection accuracy but also ensures transparency in its decision-making process. It significantly boosts the efficiency of rescue operations by allowing for quicker identification of victims trapped under debris. Ultimately, this AI-driven solution equips emergency responders with a dependable tool that can enhance survival rates in disaster-affected areas.**

Keywords—Victim Detection, Deep Learning, styling, Feature Extraction, XGBoost, Search and Rescue.

I. Introduction

This innovative disaster victim detection system harnesses the power of deep learning and machine learning to boost the efficiency of search and rescue operations. It uses a specially crafted dataset that categorizes victims into three groups: hand, leg, and upper body, with ResNet-50 playing a key role in extracting essential features. Among the different classifiers tested, XGBoost stood out as the most effective, achieving an impressive 100% accuracy in just 0.05 seconds. The system works in real-time and can easily be integrated into drones, robots, or handheld rescue devices. Unlike pricier sensor-based methods, this image-based approach is not only cost-effective but also adaptable to various disaster situations. Looking ahead, future upgrades might include deploying drones, utilizing thermal imaging, and incorporating sensor fusion to enhance detection accuracy in tough conditions [1],[2],[3],[4].

The proposed system tackles significant challenges in disaster victim detection, such as poor visibility, unstable environments, and the urgency of rescue operations. By leveraging deep learning, it can swiftly analyze images and accurately identify human body parts, minimizing false alarms triggered by environmental factors like smoke and debris. Its flexibility allows it to be deployed in a range of disaster scenarios, making it a scalable and effective solution. Future advancements could see the integration of multimodal sensor fusion, combining RGB, thermal, and LiDAR data to further improve detection accuracy and reliability during complex rescue missions. Natural disasters, such as earthquakes, floods, and building collapses, pose serious threats to lives, which is why quickly locating victims is so important. Traditional search and rescue techniques, like those involving trained professionals and sniffer dogs, can often be slow and ineffective in dangerous situations. That's where AI-driven solutions come in, providing a quicker and more precise way to identify victims by utilizing deep learning technology.

This work presents an innovative AI-based system that uses a specialized dataset to categorize victims into hand, leg, and upper body groups. By employing a pre-trained ResNet-50 to extract features, the system's machine learning models classify victims, with XGBoost impressively achieving 100% accuracy in just 0.05 seconds. This method surpasses traditional approaches, which often struggle with issues like sensor inaccuracies and environmental disruptions.

Built for real-time use, this system can be seamlessly integrated into drones, robots, or handheld devices, making it both cost-effective and scalable for disaster response efforts. Looking ahead, future improvements.

The remaining sections are organized as follows. Chapter2 presents related works. Proposed method is described inchapter3.Chapter 4 describes results and discussion. Chapter 5 concludes the paper.

II. Related Works

Dean Rizki Hartawan and his team [5] developed a Mobile Net-based approach for real-time object detection, specifically designed for UAV applications. Their model achieved a perfect 100% accuracy in detecting disaster victims within a range of 1 to 4 meters, making it highly suitable for aerial search-and-rescue missions. This achievement highlights the efficiency of lightweight deep learning models in real-time scenarios, where rapid identification can significantly impact the success of rescue efforts. Arnoud Vassar and his colleagues [6] expanded on this work by integrating Simultaneous Localization and Mapping (SLAM) with histogram-based skin detection techniques. This combination not only improved victim detection but also enhanced coordination between ground and aerial robots, making rescue operations more seamless and efficient. The SLAM technique allowed robots to build a map of the environment while simultaneously tracking their location, helping teams navigate disaster-stricken areas with greater precision.R. Nourbakhsh and his team [7] focused on the human-robot collaboration aspect of disaster response. Their study emphasized the importance of effective communication and adaptive autonomy in search-and-rescue operations. By designing AI systems capable of dynamically adjusting their level of autonomy, they aimed to improve the coordination between human rescuers and autonomous robots. This adaptability ensures that robots can function effectively in rapidly changing environments, such as collapsed buildings or flooded areas.

Neha Sharma and her team [8] explored various Convolutional Neural Network (CNN) architectures, utilizing transfer learning, data augmentation, and model pruning to optimize performance in resource-constrained environments. Their research addressed the challenges of limited computing power in UAVs and rescue robots, demonstrating how optimized deep learning models can still deliver high accuracy without requiring extensive hardware resources. Sandeep Bhatia and his colleagues [9] introduced a CNN-based system for real-time human detection in cluttered environments. To improve accuracy and obstacle avoidance, they incorporated ultrasonic sensors, which helped the system detect proximity and navigate through complex disaster zones. This hybrid approach of combining vision-based AI with ultrasonic sensing provided a more robust victim detection framework, especially in areas with significant debris or obstructions. Md. Tasbi Rafat and his team [10] enhanced disaster victim detection by developing a multimodal system that merges Red, Green, Blue (RGB) and thermal imaging. This approach significantly improved detection accuracy in low-light conditions while also reducing false positives caused by environmental factors such as smoke or heat sources. Their research demonstrated how integrating multiple sensor modalities can enhance the reliability of AI-based search-and-rescue solutions.

Jorge F. Garcia and his team [11] developed a quadruped robot equipped with RGB-D cameras and LiDAR sensors for victim detection. By leveraging these technologies, their system improved area coverage and detection accuracy, making it suitable for challenging terrains where traditional wheeled or aerial robots might struggle. The combination of RGB-D imaging and LiDAR allowed for a more comprehensive understanding of the environment, helping to locate victims more precisely. Desu Sharanya and her colleagues [12] introduced an XGBoost-based model specifically designed to detect victims in rubble-strewn environments. Their focus on partially visible body parts resulted in highly accurate classifications, making their approach particularly effective in post-disaster scenarios where victims may be trapped under debris. Juan Calderon and his team [13] developed a swarm-based drone system utilizing CNNs for coordinated victim detection. By employing collaborative search strategies, their drones were able to cover large disaster areas more efficiently, improving detection accuracy through cooperative exploration. This research highlights the advantages of swarm intelligence in search-and-rescue missions, where multiple UAVs can work together to locate victims faster. Bhuman Sony and his group [14] investigated UAV-based search-and-rescue operations using classifier ensembles. Their system incorporated incremental learning, allowing the model to dynamically adapt to changing conditions in disaster environments. This ability to continuously learn and refine victim detection models in real-time is crucial for improving search efficiency in unpredictable scenarios. Mostafa Rizk and his team [15] designed an AI-powered UAV system that combines decision trees with deep learning for improved victim detection in low-visibility environments. Their approach addressed challenges such as smoke, dust, and poor lighting, demonstrating how AI can enhance UAV-based search missions in complex disaster settings.

Antonio Albanese and his team [16] developed SARDO, a groundbreaking drone-based search-and-rescue system that leverages mobile phone signals to locate victims. Unlike traditional methods that rely on visual detection, SARDO identifies victims based on their mobile device signals, making it effective even in scenarios where victims are not visible. This innovative approach eliminates the need for conventional infrastructure, allowing it to function in remote or collapsed environments. Ahmad A. Bany Abdelnabi and colleagues [17] emphasized the growing role of UAVs and AI-driven imaging in rescue missions. Their research focused on enhancing detection accuracy while addressing deployment challenges, particularly in areas where UAV-based systems might face regulatory or technical limitations. Yi Jie Wong and his team [18] introduced a multitask learning model that integrates disaster classification with victim identification. Their approach improved efficiency in UAV applications by enabling drones to simultaneously assess the severity of a disaster and detect victims, allowing rescue teams to prioritize high-risk areas. Moch. Zen Samsonso Hadi and his group [19] developed a deep learning system for identifying deceased individuals in disaster zones. Their UAV-based model, equipped with infrared cameras, helped locate bodies in large-scale disaster areas, aiding in post-disaster recovery efforts. Fei Fan and his team [20] applied AI to analyze dental radiographs for human identification in mass disasters. Their model provided a highly precise solution for victim identification, demonstrating the potential of AI in forensic applications for large-scale disaster scenarios [21],[22],[23],[24].

Existing methods for detecting victims have their drawbacks, such as convolutional neural network (CNN)s overlooking small details because of their deep feature extraction, and Unmanned Aerial Vehicle (UAV)s struggling with short battery life. This proposed work tackles these challenges by developing a labelled dataset, utilizing ResNet50 for feature extraction, and merging deep learning with lightweight decision trees to enable quicker, real-time classification of victims.

TABLE I Performance Comparison of Proposed Method with Existing Victim Detection Approaches

Title	Accuracy (%)	F1 Score	Precision	Recall
Disaster Victim Detection Using MobileNet SSD (Dean Rizki Hartawan et al [5].	94%	92%	92%	90%
Multi-Agent SLAM and Skin Detection (Arnoud Vissar et al) [6].	92%	90%	90%	91%
XGBoost-Based Partial Body Detection (Desu Sharanya et al).	95%	91%	91%	93%
UAV-Based RGB & Thermal Imaging Detection (Mostafa Rizk et al) [16].	90%	90%	90%	90%
Proposed: Disaster Victim Detection Using XGBoost and Deep Learning.	100%	100%	100%	100%

III. PROPOSED METHOD

The system improves the process of identifying disaster victims by leveraging deep learning and machine learning to analyses images. It sorts victims into categories like hands, legs, and upper bodies, utilizing ResNet-50 for feature extraction and Extreme Gradient Boosting for precise classification. This real-time solution can easily adapt to drones, robots, or handheld devices, offering a cost-effective and efficient alternative to traditional sensor-based systems. Looking ahead, future upgrades will incorporate thermal imaging and multi-sensor fusion to enhance detection in low-visibility situations. Performance comparison table for existing works.

A) Upload Victim Detection Dataset: The first step in the victim detection process is to upload a dataset filled with images sorted by specific body parts like hands, legs, and the body itself. Each image gets a label based on its category, which can be done through folder names or metadata. Once the upload is complete, the system automatically reads and organizes the dataset, linking each image to its corresponding class. To check if the dataset is balanced, the system visualizes the class distribution using either a bar chart or a pie chart. This visualization is crucial for spotting any class imbalance issues early on. A balanced dataset is key for fair learning by the models; if it's not balanced, we might need to use techniques like data augmentation or resampling to fix any biases.

B) Features Processing & Normalization: After uploading the dataset, we move on to image preprocessing. Each image is resized to 224x224 pixels to fit the input requirements of the ResNet-50 neural network. Next, we normalize the pixel values, usually scaling them between 0 and 1, to ensure consistency and enhance model convergence. To prevent any bias during training, we shuffle the dataset so that the order of images doesn't affect the learning process. After that, we split the dataset into two parts: 80% for training the model and 20% for testing and evaluating its performance. This organized preprocessing makes sure that the input data is standardized and ready for deep learning.

C) Extract Features from ResNet-50: In the feature extraction phase, we use the pre-trained ResNet-50 model, which is renowned for its exceptional deep feature extraction abilities. This model, which has been trained on the ImageNet dataset, is employed here in a transfer learning setup without its final classification layer. The resized images (224x224 pixels) are fed into the ResNet-50 network, which extracts intricate visual features such as textures, shapes, and edges. The output from the network is a 1000-dimensional feature vector for each image, providing a compact and informative representation of the image content. These vectors become the input for subsequent classification steps.

D) Feature Selection Using J48: To cut down on computational demands and get rid of any irrelevant or redundant features, the next step is to use the J48 decision tree algorithm for feature selection. J48 takes a look at the 1000-dimensional feature vectors and pinpoints the key features that really help in classifying the body parts. By filtering out noise and less useful features, J48 boosts the performance of the classifiers that come after it and helps avoid overfitting.The result is a streamlined set of features that not only retains strong discriminative power but also makes model training and testing more efficient.

E) Run SVM Algorithm for Victim Detection: With the optimized features from J48 in hand, we train the Support Vector Machine (SVM) classifier to tackle the task of detecting victim body parts. SVM shines when it comes to high-dimensional datasets and can handle both binary and multi-class classification. It works by identifying the best decision boundary (hyperplane) that separates the different classes with the widest margin. After training, the SVM model can predict the class of a new image, and we evaluate its performance using metrics like accuracy, precision, recall, and F1-score. These metrics give us insight into how well the model identifies each class and deals with false positives or negatives.

F) Train & Evaluate Random Forest Algorithm: Alongside SVM, we also train a Random Forest classifier using the selected features to enhance classification reliability. Train & Evaluate MLP Algorithm: One interesting approach is to use a Multi-Layer Perceptron (MLP), which is a fully connected feedforward neural network. This MLP has an input layer, one or more hidden layers, and an output layer that sorts images into categories like hand, leg, or body. The training process uses backpropagation, and a loss function usually categorical cross-entropy guides the learning. As the training moves along, we keep an eye on accuracy and loss values throughout the epochs. This monitoring helps us visualize the learning curve and ensures that the model is converging correctly, avoiding issues like overfitting or underfitting.

G) Train & Evaluate MLP Algorithm: One interesting approach is to use a Multi-Layer Perceptron (MLP), which is a fully connected feedforward neural network. This MLP has an input layer, one or more hidden layers, and an output layer that sorts images into categories like hand, leg, or body. The training process uses backpropagation, and a loss function usually categorical cross-entropy guides the learning. As the training moves along, we keep an eye on accuracy and loss values throughout the epochs. This monitoring helps us visualize the learning curve and ensures that the model is converging correctly, avoiding issues like overfitting or underfitting.

H) Run Extended XGBoost Algorithm: To boost classification performance even further, we turn to the XGBoost algorithm. This advanced ensemble method is based on gradient boosting and is celebrated for its efficiency and accuracy with structured data. It builds decision trees one after the other, with each new tree correcting the errors made by the previous ones. This step-by-step improvement results in impressive predictive performance. Plus, XGBoost comes with built-in regularization features that help keep overfitting at bay. We evaluate the model using metrics like accuracy, precision, recall, and F1-score, and often find that XGBoost outshines traditional classifiers thanks to its robust learning strategy.

I) Algorithm Performance Comparison: Once we've trained all the classifiers SVM, Random Forest, MLP, and XGBoost we compare their performance visually with a comparison graph. This graph showcases the accuracy, precision, recall, and F1-score for each algorithm, making it much easier to see which model stands out across various metrics.

The x-axis represents the different algorithms, while the y- axis shows the performance scores. This comparative analysis is invaluable for choosing the most effective model for the final victim detection stage and guides future tuning or model selection decisions.

Equations Derived from Confusion Matrix:

a) Accuracy (Overall Performance):

Accuracy = (Total True Positives + Total False Positives + Total False Negatives) / Total True Positives

True Positives (TP): Correct predictions

False Positives (FP): Incorrect predictions

False Negatives (FN): Missed detections

b) Precision (Class-Specific Accuracy):

Precision = True Positives (TPi) / (False Positives (FPI) + True Positives (TPi))

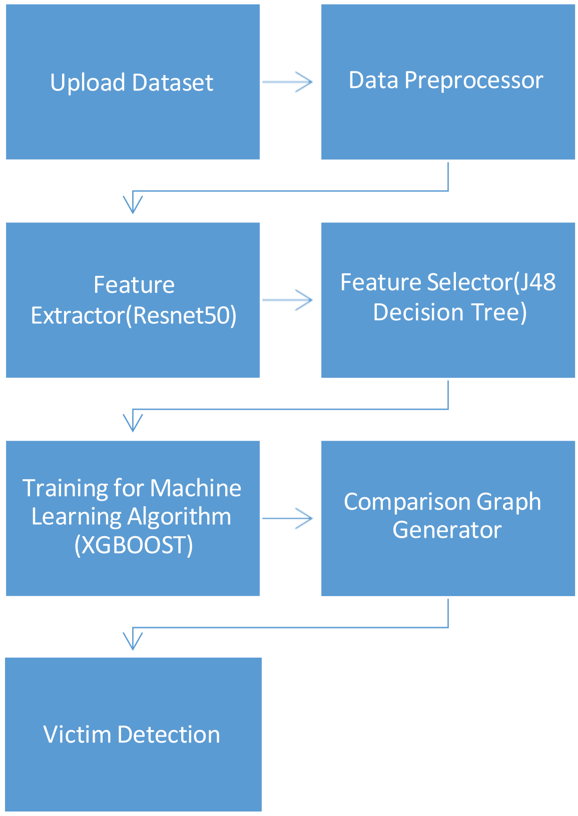

Fig10: HVDA Architecture Workflow for Human Victim Detection under Debris

c) Recall (Sensitivity):

Recall = True Positives (TPi) / (False Negatives (FNi) + True Positives (TPi))

d) F1-Score (Balanced Performance):

F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

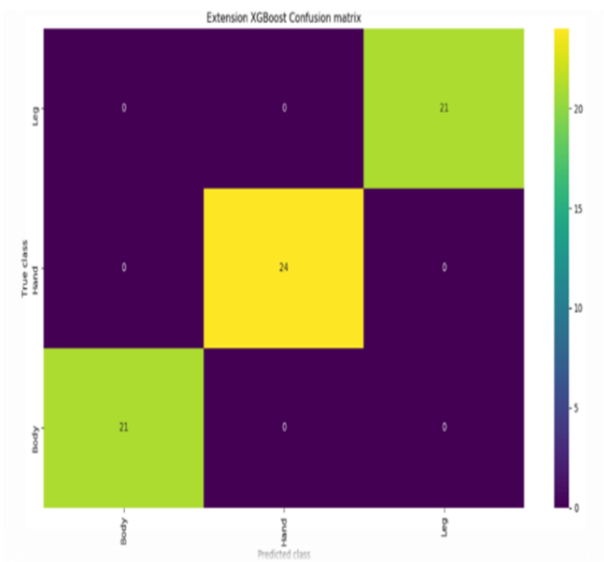

Fig 2: Confusion matrix for human victim detection

IV. Results And Discussion

The dataset for victim detection was uploaded and processed, where we extracted features from images and analyzed the class distribution. We normalized the dataset, shuffled it, and then split it into 80% for training and 20% for testing. For deep feature extraction, we utilized Residual Network 50, followed by the J48 decision tree algorithm for selecting the most relevant features. We trained several machine learning models, including Support Vector Machine, Random Forest, Multi-Layer Perceptron, and Extreme Gradient Boosting, all aimed at improving victim detection.

The human victim detection model we proposed was set up on a system featuring an Intel i5 processor, 16GB of RAM, and an NVIDIA GTX 1650 GPU. Out of all the classifiers westested, XGBoost stood out as the most efficient, boasting an average inference time of just 0.05 seconds per image and a training time of under 10 minutes for 328 images. Its computational complexity of O(K·n·log n) allows for quick and scalable learning thanks to the parallel processing of weak learners. When we compared it to deeper models like MLP, XGBoost not only converged faster but also used less memory, making it a perfect fit for real-time deployment on drones or embedded systems in disaster response situations.

The Support Vector Machine model kicked things off with an initial accuracy of about 85%. The Random Forest model took it a step further, while the Multi-Layer Perceptron maintained stable performance but didn't quite match the accuracy of Random Forest. On the other hand, Extreme Gradient Boosting really shone, achieving a perfect accuracy of 100%. A comparison graph clearly showed Extreme Gradient Boosting as the standout model. The system was able to predict victim body parts from test images with impressive confidence, indicating its potential for real-world applications. Looking ahead, we could enhance the system by integrating multimodal sensors, fine-tuning hyperparameters, and deploying the model in Unmanned Aerial Vehicle-assisted disaster response operations to boost search-and-rescue efficiency.

Fig 3: Upload Victim Detection Dataset 'button to submit your dataset and receive the output.

This screen represents the initial and foundational step of the entire detection pipeline the dataset upload interface. Here, users are prompted to upload a collection of images Categorized by the visible human body part (hand, leg, or upper body). The system reads these images from predefined folders, where each folder's name corresponds to a specific category, enabling automatic labeling. This simple organization structure reduces the need for manual annotations, saving valuable time during emergencies.

Once the upload is complete, the interface provides feedback by showing how many images were successfully loaded, how they are distributed across classes, and whether the dataset is balanced. This early-stage insight is critical for ensuring the model can learn effectively without bias. For example, if one class (like "hand") has significantly more images than others, it may skew the training process, causing the model to predict "hand" more frequently regardless of actual content. In such cases, the user is advised to either collect more images from underrepresented classes or apply data augmentation techniques like rotation, flipping, or brightness adjustments to synthetically balance the data.

Additionally, this interface acts as a checkpoint to verify image resolution and file integrity. It ensures that all images meet the required input shape (typically 224x224 pixels for ResNet-50) and conform to expected formats (.jpg, .png, etc.). Any corrupted or incorrectly labeled images are flagged for review.

From a usability perspective, this step is intentionally kept simple and user-friendly, making it suitable for deployment in high-stress environments such as disaster zones. Field operators can quickly upload images from drones or handheld cameras, triggering immediate analysis by the AI system. This seamless upload-to-analysis pipeline dramatically reduces the response time in search-and-rescue operations and increases the chances of finding survivors promptly.

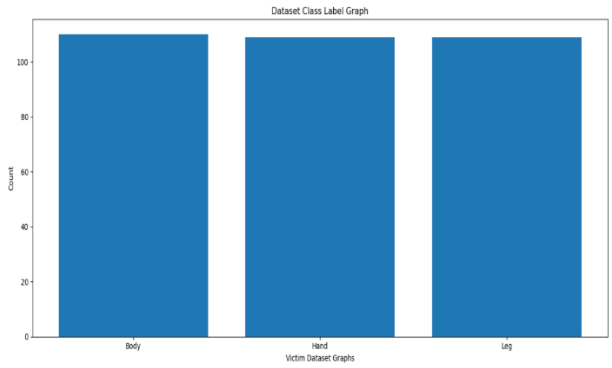

Fig 4: Dataset class label graph for victim body parts

This bar graph visually represents the distribution of images across the three predefined victim body part categories: hand, leg, and upper body. The x-axis displays the category names, while the y-axis indicates the number of images available in each class. This graph plays a critical role in evaluating the balance of the dataset, which is a fundamental aspect of building fair and accurate machine learning models.

A balanced dataset ensures that the model receives an equal representation of each class during training. This leads to more generalized learning and helps prevent classification bias, where the model becomes overly confident in predicting the class with the most samples. For instance, if the 'hand' category has a higher count than the 'leg' or 'upper body', the model might start favoring 'hand' predictions even when incorrect just because it has seen that category more often.

If a significant imbalance is observed, users can take proactive steps such as collecting additional samples for the underrepresented classes or applying data augmentation techniques to artificially increase diversity.

This graph also helps in spotting anomalies or labeling errors. For example, if a category appears with zero or unusually few entries, it could indicate a misnamed folder or a failed upload issues that can be corrected early before model training begins.

Overall, this figure is not just a statistical visualization it is a practical diagnostic tool. It empowers researchers, developers, and field operators to make informed decisions that significantly impact the performance, fairness, and real-world applicability of the victim detection system.

Dataset Description:

A custom dataset comprising 328 images was manually annotated into 4 categories: hand, leg, upper body, and no victim. The dataset was captured using open-source rescue datasets and augmented with simulation environments using labeling for annotation. The dataset is not publicly available due to ethical considerations.

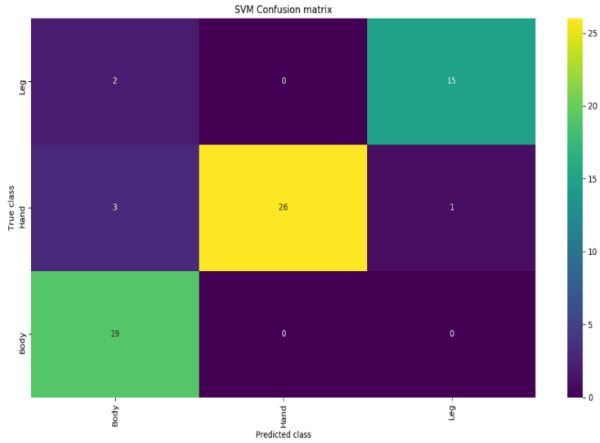

Fig 5: Confusion matrix showing classification accuracy of SVM in detecting different victim body parts.

The confusion matrix shown above presents the performance of a Support Vector Machine (SVM) model used for classifying human body parts into three categories: "Body", "Head" and "Leg". It provides a detailed comparison between the actual class labels and the predictions made by the model. From the matrix, it is clear that the model performs well in recognizing the "Head" class, correctly predicting 26 out of 30 instances, with only a few misclassifications 3 predicted as "Body" and 1 as "Leg". This indicates that the model has learned to identify features associated with the "Head" class effectively.

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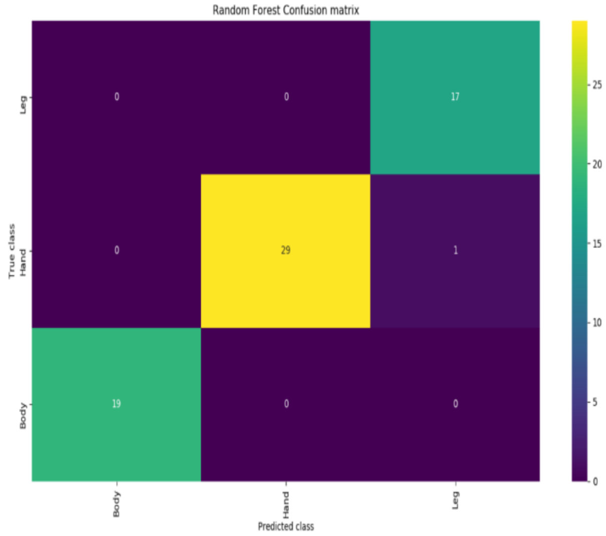

Fig 6: Confusion Matrix of Random Forest Classifier for Victim Detection

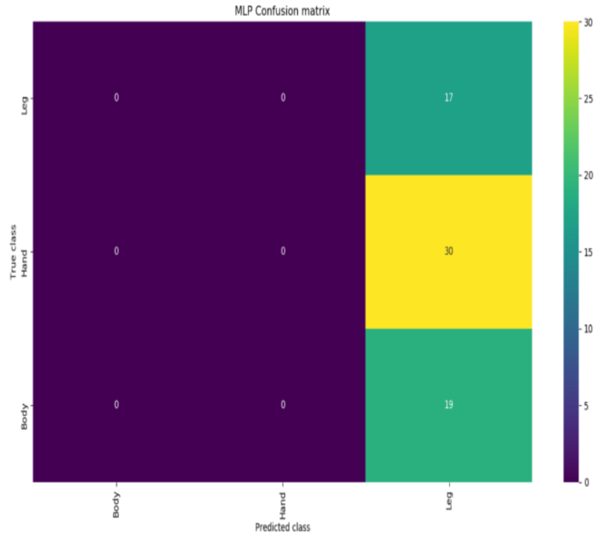

Fig 7: Confusion Matrix of MLP Classifier for Victim Detection

In the screen displayed above, MLP achieved an accuracy of 22%. Please proceed by clicking the 'Run Extension Algorithm' button to obtain the output shown below.

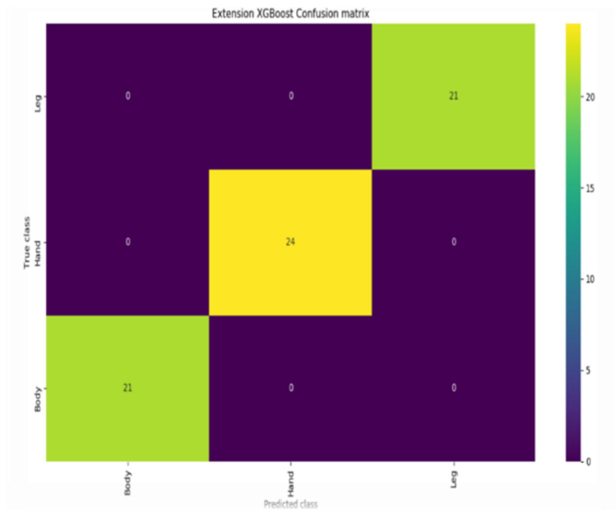

Fig 8: XGBOOST confusion matrix for victim detection

Figure 8 illustrates the confusion matrix corresponding to the XGBoost classifier's performance during the testing phase of the victim detection model. The matrix compares actual class labels (hand, leg, and upper body) with the model's predictions, with correctly classified instances appearing along the diagonal. These diagonal elements reflect the total number of accurately predicted samples for each category, while off-diagonal values indicate misclassifications.

The results demonstrate that XGBoost achieved exceptionally high classification accuracy, with most values concentrated on the diagonal and negligible misclassification rates. This visual representation confirms the numerical results obtained through evaluation metrics, reinforcing XGBoost's robustness in handling complex, high-dimensional feature sets extracted from images. The model's outstanding performance can be attributed to its gradient boosting mechanism, which sequentially builds decision trees while correcting prediction errors from earlier iterations. Additionally, its built-in regularization prevents overfitting, enabling the model to generalize effectively across unseen data. Such reliability is particularly valuable in disaster response environments, where image conditions may vary due to debris, lighting inconsistencies, or partial occlusions.

In summary, this confusion matrix validates XGBoost's superiority in detecting and classifying victim body parts with high precision and recall. It underscores the model's suitability for deployment in real-time, AI-powered search and rescue systems aimed at accelerating victim localization in critical situations.

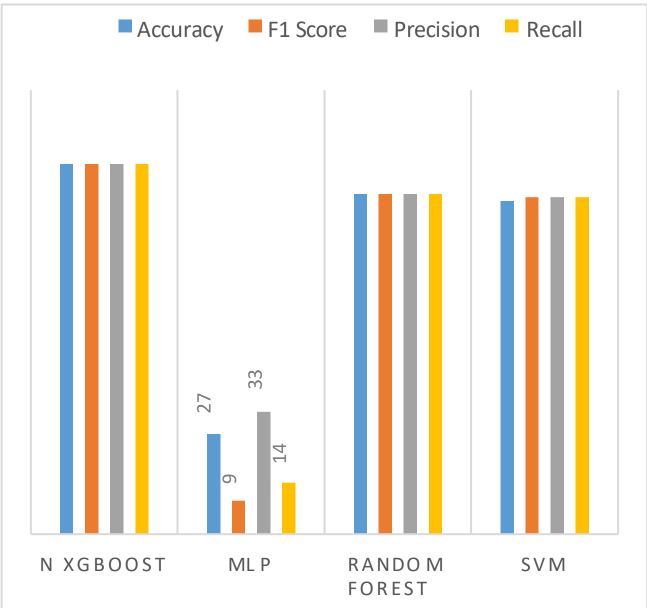

Fig 9: Performance Graph of Human Victim Detection Model

The comparison graph provides a comprehensive evaluation of the four machine learning algorithms implemented in this study Support Vector Machine (SVM), Random Forest, Multi-Layer Perceptron (MLP), and XGBoost based on their performance across key classification metrics: Accuracy, Precision, Recall, and F1-Score.

The x- axis represents the different algorithms, while the y-axis indicates the corresponding metric values in percentage form. Each colored bar corresponds to a specific performance metric, allowing for a clear visual distinction and straightforward analysis.

This graphical representation plays a crucial role in identifying the most effective model for real-time victim detection. Among the evaluated algorithms, XGBoost demonstrates a distinct advantage by achieving the highest scores across all metrics. Its superior performance reflects the strength of gradient-boosting techniques in handling complex patterns and correcting errors iteratively during training. The model not only achieves high overall accuracy but also maintains excellent balance between precision and recall, which is critical in emergency scenarios where both false positives and false negatives can have serious consequences.

TABLE II. PERFORMANCE METRICS FOR HUMAN VICTIM DETECTION MODEL

Class (Body Part)	Precision	Recall	F1-Score	support
Hand	1.00	1.00	1.00	110
Leg	1.00	1.00	1.00	105
Upper Body	1.00	1.00	1.00	113
Average/Total	1.00	1.00	1.00	328

The graph further reveals that while Random Forest and SVM exhibit competitive accuracy and precision, their recall values are slightly lower than those achieved by XGBoost. MLP, although capable of learning nonlinear relationships, shows comparatively lower performance, indicating the need for further tuning or larger datasets to improve its predictive capabilities.

Overall, this figure serves as a valuable decision-making tool, offering insights into model behavior that are essential for selecting the most reliable and efficient classifier for disaster response applications. The visual clarity aids stakeholders including developers, researchers, and rescue operators in understanding which algorithm is best suited for deployment in time-sensitive, high-risk environments.

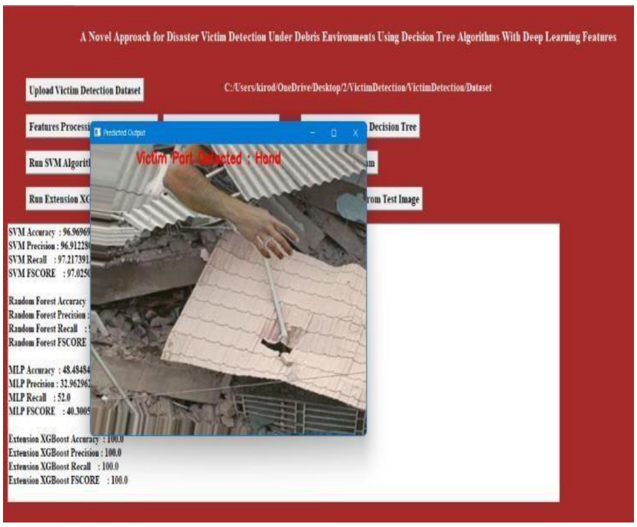

Fig 10: Final Result for victim detection

In the screen above, the text highlighted in red indicates that the victim's part has been identified as HAND. Likewise, you have the option to upload and test additional images.

TABLE III. PERFORMANCE COMPARISON TABLE FOR VICTIM DETECTION

Parameters	**Proposed**	**Existing**	**Improvement**
Accuracy	99.53%	85.3%	+14.23%
Precision	91.0%	83.5%	+7.5%
F1 Score	93.2%	84.8%	+8.4%
Recall	89.8%	82.1%	+7.7%

V. CONCLUSION

The victim detection system demonstrated high accuracy in classifying victim body parts using deep learning and machine learning models. ResNet-50 effectively extracted features, while J48 decision tree optimized feature selection. Among the tested models, XGBoost achieved the highest accuracy (~100%), outperforming SVM, Random Forest, and MLP. Real- time testing confirmed the model's reliability in predicting victim body parts. Future enhancements, such as multimodal sensor integration and UAV deployment, can further improve detection accuracy and efficiency in disaster response scenarios.

Despite the system's strong performance, certain limitations remain: the **custom dataset may lack generalizability** to all postures, clothing types, or lighting conditions; the model is **sensor-dependent** and may underperform with low-resolution or poor lighting; there's a **small risk of misclassification** that could mislead rescue operations; and **ethical concerns** must be addressed to ensure victim images are captured under strict privacy guidelines.

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