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RESEARCH ARTICLE

A Novel Approach for Disaster Victim Detection Under Debris Environments Using Decision Tree Algorithms With Deep Learning Features

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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, hoeffiding 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.

INDEX TERMS Search and rescue, disaster victim detection, collapsed building, deep learning, decision tree algorithms, machine learning, ResNet-50, decision tree classifiers.

I. INTRODUCTION

Massive earthquakes, floods, plane crashes, tsunamis, and building collapses are only a few examples of the many catastrophic natural and human-caused disasters that plague the world. Disaster management is essential for reducing and avoiding the losses these catastrophes cause. Fig.1 depicts the mortality statistics in building collapses caused by earthquakes and other factors worldwide over the last few years. According to the emergency relief cycle [1], the four stages of disaster management include prevention, preparedness, reaction, and recovery. This work comes under the preparedness and reaction phases of the disaster management cycle to aid fast rescue assistance for identifying victims. This work is a continuation of our previous work [2] as part of our motto to develop a snake-like robot for rescue assistance for human

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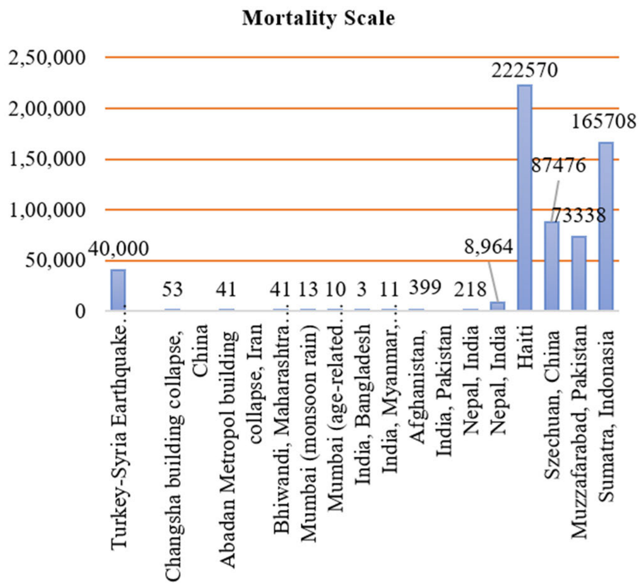

FIGURE 1. **Recent data on building collapses worldwide caused by earthquakes and other causes (2005-2023). [NGDC Statistics, BBC, & Times of India].**

victim detection in earthquake environments. According to Urban Search And Rescue (USAR), the chances of saving a victim are only good for the first 48 hours of the rescue operation, after which the probability is almost zero. Hence, the faster the rescue mission higher the probability of saving a life.

Victim identification in the collapsed building environment is one of the chief challenges for responders. One of the main concerns is the accuracy of identification. Accurately identifying victims in this situation is often difficult because of the uncertainties in the victims' bodies and the surrounding environment. Despite these potential limitations, this work tries to identify victims using the information available to responders based on human physical anatomy. A detailed study of human identification methods is discussed in the next section. RGB and thermal image-based datasets are more useful in search and rescue scenarios involving the detection of human victims [3]. An RGB image-based custom dataset is employed in this work for HVI in collapsed, unstructured building scenarios. Once we have a dataset, its features must be learned to identify the victim accurately. Deep learning (DL) has emerged as a powerful tool for computer vision applications, including image classification and object detection. The most common deep learning models are convolutional neural networks (CNNs), which can be applied to many data types [4]. CNNs have become increasingly popular due to their ability to learn and extract relevant features from raw image data and classify them into different categories based on those features without manual feature engineering.

CNN architecture is constituted of different layers: the input layer, convolutional layer, pooling layer, and fully connected layers are the main types of layers used in CNN. The input layer takes in a set of images and runs them through a series of convolutional layers to extract features. Each layer of a CNN typically takes as input a 4D array. The convolutional layer, the first layer in a CNN, uses filters to scan over the input data to detect features or patterns such as edges, corners, and other relevant information. The pooling layer, which follows the convolutional layer, down-samples the output from the convolutional layers by [5] taking the maximum or average value within a specific window size, reducing the spatial dimensions of the data while preserving important information. Finally, the output of the convolutional and pooling layers is flattened into a 1D array that serves as the input to the fully connected layers. The fully connected layers are the last set of layers in a CNN and are typically used for classification or regression tasks. They take in the flattened output from the previous layers and use weights to perform matrix operations that transform the input data into predictions or outputs. Other layers, such as activation, batch normalization, and dropout, can be used to improve the performance and stability of CNN. Furthermore, the arrangement and number of each type of layer can be customized to suit specific tasks and datasets, allowing for a high degree of flexibility and adaptability in designing CNN architectures. Combining these layers allows CNNs to extract features and learn patterns from large sets of images, making them powerful tools for object detection, image recognition, and more [4], [6], [7].

The success of CNN in image-related tasks has led to their application in other fields, such as natural language processing, speech recognition, and even drug discovery. This highlights the versatility and potential of CNNs as a powerful tool for various applications beyond image-related tasks. However, CNN requires a large amount of labelled data to perform well. Such a large amount of data is lacking in victim identification which is necessary for a CNN training assignment. This issue can be resolved by employing Transfer Learning (TL) techniques. TL is another technique to help deep learning systems improve their accuracy. They use pre-trained models from other tasks to help improve the learning speed and the accuracy of the new model being trained. Transfer learning helps to use the knowledge gained from a model trained on a larger dataset in a task-oriented small dataset with minimal fine-tuning, as shown in Fig. 2. That is, first, the network parameters are pre-trained using the source data, followed by their application in the target domain, and finally, the network parameters are tuned for improved performance [8]. The main benefits of TL are increased classification accuracy and accelerated training. More literature on CNN and TL is discussed in detail in the next section.

When DL models learn features from complex problems at the cost of massive data and high computation time, ML models, such as decision trees, logistic regression, and support vector machines, are easier to interpret and require fewer data and computational resources to train. Therefore this paper has tried to improve the results using ML's benefits.

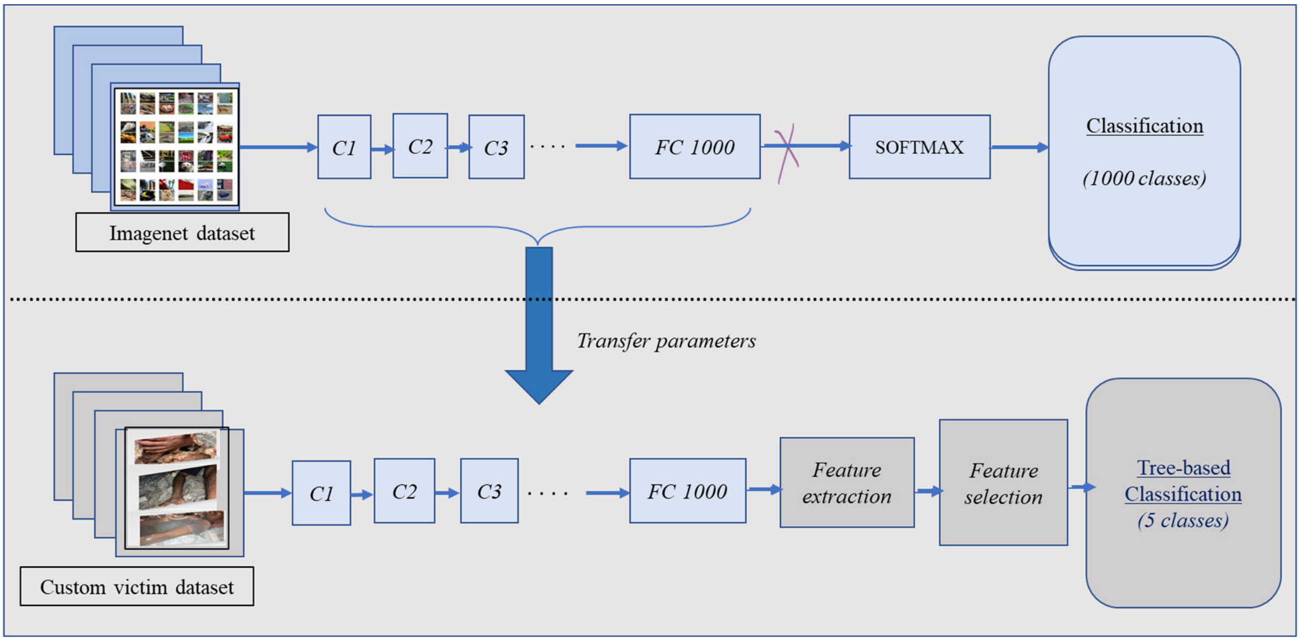

FIGURE 2. Concept of integration of transfer learning and ML-based classification for human victim detection (HVD).

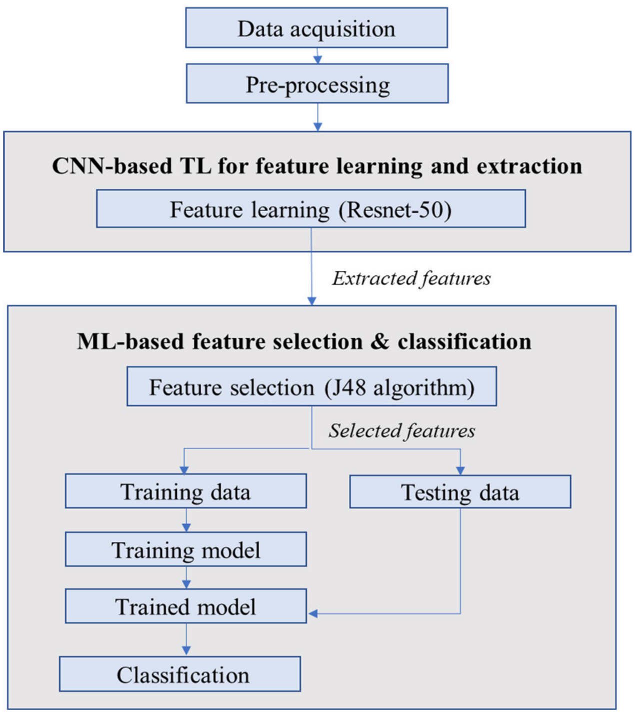

FIGURE 3. Proposed human victim detection approach (HVDA) by combining DL features and ML classifiers.

ML algorithms deliver extremely accurate classification results quickly and with few hardware requirements. Features extracted from the pre-trained model are used for classification with ML-based classifiers after feature selection (i.e., discarding insignificant features). Detailed literature on ML-based classifiers is provided in the next section.

Therefore, this paper proposed a deep learning-based human victim identification model combined with machine learning-based classifiers, as shown in Fig.3, for HVI tasks in unstructured collapsed building environments. The significant features of the work are listed below.

(*i*) *RGB-based multiclass custom human victim dataset creation.*
(*ii*) *Data augmentation and pre-processing for enlarging the size and quality of the dataset.*
(*iii*) *Transfer Learning-based feature learning.*
(iv) *Integration of DL-based feature extraction with ML-based feature selection and classification for victim detection.*

Human detection using ML classifiers is a less explored area. Our proposed integration approach for human victim detection is not found anywhere in the literature. The paper is organized as follows. Section II discusses the literature related to human detection, deep learning, and ML concepts. The materials and methods used, like data acquisition, dataset creation, and work methodology, are detailed in section III, followed by the results and discussions in section IV.

II. LITERATURE REVIEW

Many questions must be addressed for an application-oriented task like HVI in a collapsed building environment. Hence, the literature is based on three major questions before the authors.

(i) What can all parameters/dataset types be used for human identification?
(ii) What approach can address the identification of the victim?
(iii) How better can the approach be made?

The previous section discussed that victim identification in unknown and unstructured environments is highly uncertain. Using a machine to distinguish a human body or portion from a debris environment is challenging. To detect human

TABLE 1. Human detection parameters and their data acquisition devices.

Physical parameter	Data acquisition device	Features found in articles and their effectiveness
Voice	Microphone	• Crosspower Spectrum Phase technique [10]: This method uses the Fourier transform to calculate the phase shift of both signals. • If there is not too much background noise, this method can correctly pinpoint the direction of the sound source.
Temperature	IR cameras Pyroelectric sensors	• IR cameras accurately represent the heat in the environment, which is particularly helpful for human detection [12,13]. • Pyroelectric sensors comprise two infrared sensors; therefore, they can only detect the sensor's or the person's movement [13].
Scent	CO2 sensor	• CO2 sensors are capable of monitoring carbon dioxide emissions as well as a victim's breathing pattern. It is highly directional and dependent on air conditions like temperature, humidity, dust, and dust wind. However, the drawback is that a CO2 sensor's response time is prolonged; therefore, the sensor must be closer to the victim to acquire helpful information.
Motion	Sonar, laser, visual & IR camera	• These sensors can indicate that someone is alive in the area [13].
Skin colour	3D Colour histogram	• One is given histograms for the skin and non-skin classes based on training sets after learning the probability that a specific colour value belongs to the skin and non-skin classes. [11] • These methods have a flaw in that they: 1) In unstructured outside settings, there is no prior knowledge of the colors in the environment (this could result in many false positives). 2) The field of view of most outdoor robot cameras is relatively big, which lowers the number of pixels on a person's face (which would reduce the detection rate).
Face	RGB cameras	• It works by identifying and measuring facial features in an image
Body Shape	RGB, RGB-D and IR cameras	• Using RGB or IR image datasets, standard person detection algorithms can quickly identify human body parts. Nevertheless, actual life victim positions are usually unpredictable and may not tend to stand up or look straight into the camera [3]. • RGB-D is more robust against illumination and texture variations.
Combined approaches	Combination of multiple acquisition devices.	• Using a variety of cues together can improve outcomes. Multiple teams have therefore researched hybrid techniques, combining, for instance, motion, sound, and heat in [13] or motion, sound, and faces in [10].

presence, physical characteristics such as voice, aroma, body warmth, motion, facial form, skin colour, and body shape are used [9]. Several research teams have developed algorithms for human victim detection based on detecting these physical features in recent years. Table 1 lists the most widely used human identification parameters with their features. Quick human body identification can be made with RGB-image datasets and standard person detection algorithms. A cross-power spectrum technique is used by [10] to identify voice using a microphone. CO2 sensors sense the gas emission, so the breathing pattern is identified to detect humans. However, the prolonged response time and atmospheric air quality in terms of dust, humidity, and temperature bring this option to a downside. 3D colour histogram-based skin identification is another way [11], but there can be drastic pixel reduction when mobile robots use them in outdoor environments as they have a relatively wide field of view.

Nevertheless, actual life victim positions are usually unpredictable and may not tend to stand up or look straight into the camera. RGB-D is more robust against illumination and texture variations.RGB and thermal image-based datasets are more useful in search and rescue scenarios involving the detection of human victims. An RGB image-based custom dataset is employed in this work to identify human victims in collapsed, unstructured building scenarios. Once we have a dataset, its features must be learned to identify the victim accurately. Deep Learning algorithms primarily used for image and video analysis can automatically detect patterns in images and classify them into different categories based on those patterns. Different deep-learning techniques for different applications are listed in Table 2, in which learning models are classified into three categories, namely Basic deep learning models (standard pre-trained networks), deep learning models (application-based models trained from scratch), and Transfer learning-based models (task-based models derived from pre-trained models). It was found that most of the deep learning-based human detection studies used bounding box-based detection methods like YOLO. However, for rescue assistance, fast determination of the presence of a victim is more important when the location of the acquisition device is obvious. Therefore, the usual classification (without the bounding box) is enough for victim detection applications.

TABLE 2. CNN-based classification approaches in various applications.

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

Once CNN performed well with the approached TL technique, authors tried to improve the accuracy further with traditional ML techniques. In the context of machine learning-based classification, the term "classification" refers to the process of identifying which of several categories a given input belongs to. There are two primary types of classification: binary classification, which involves classifying input data into one of two categories, and multiclass classification,

TABLE 3. Machine Learning-based classification approaches in various applications.

Classifier used	Approach	Application	Dataset Type	Inferences	Article Reference
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	[31]
Random Forest, Naive Bayes, SVM	Supervised Learning	Identifying spam emails	Labelled Email Data	Achieving high precision and recall scores on spam detection	[32]
Random Forest, SVM, Neural Networks	Supervised Learning	Identifying fraudulent financial transactions	Labelled Transaction Data	Accurately detecting fraudulent transactions with high accuracy	[33]
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.	[34]
LSTM	Time Series Analysis	Stock price prediction	Stock market data	LSTM model outperformed traditional time series models in predicting stock prices.	[35]
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.	[36]
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.	[37]

which involves classifying input data into one of several categories [38]. Several machine learning algorithms can be used for classification tasks, including decision trees, support vector machines, and logistic regression. These algorithms work by learning from training data and then using this knowledge to classify new data. Table 3 depicts different machine learning classifiers applied for different applications. Out of the different ML classifiers available, Decision Trees, Logistic Regression, Naïve Bayes, Randon trees, and Support Vector Machines (SVM) are found to be predominantly used. The following conclusions were drawn from the literature mentioned above:

(*i*) *Many studies have been conducted employing thermal and RGB images for victim detection.*

(*ii*) *Multiple convolutional layers comprised of pre-trained CNN architectures were often employed. (In fact, most human detection approaches dealt with SSD, YOLO, RCNN, etc, which are basically bounding box based concept which is not our interest)*

(*iii*) *Machine learning techniques like kNN, SVM, Naive Bayes, and Decision trees yielded precise findings in a condensed amount of time.*

(*iv*) *CNN architectures have received appreciation for their superior feature extractor capabilities.*

(*v*) *The use of ML algorithms for classification and feature extraction from CNN is a less-examined combination.*

Additional difficulties encountered during experimentation include a) Limited availability of HVD datasets in public repositories, b) Requirements for high-end hardware, and c) Performance improvement of the proposed model.

TABLE 4. Specifications of the camera used for data acquisition.

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

III. MATERIALS AND METHODS

The current research aims to distinguish between distinct body parts to detect human victims in a disaster-affected building environment. Any human body part can be found, verifying the victim's existence. The investigation is described in the following sections based on the suggested Human Victim Detection Approach (HVDA) in Fig. 3:

A. DATA ACQUISITION AND PRE-PROCESSING

The first and most challenging stage in this work was the data acquisition as the dataset is expected to be diverse with unpredictable and uncertain positions and body parts of human victims after a natural calamity like an earthquake hits a building. A huge demolished building was selected as the simulation environment where our team members acted lying in different positions below and over the debris with dust and artificial bloodstains over the body to create a real-like scenario. This work is finally intended to be applied to a snake-like robot for rescue assistance, so the robot's height, speed, motion pattern, unexpected flip-overs, and different lighting conditions were considered in collecting the data. The obtained video sequences were then converted to image frames for further processing. The camera specifications and a detailed flow of dataset creation are provided in Table 4 and Fig.4, respectively. From the converted images, we created five data classes (leg, hand, head, upper body, without body) with 1000 selected images in each class. Then each class underwent pre-processing, including augmentation based on the expected lighting conditions, flip-overs of the robot, and rotations based on uncertain angles of body positions to form 2000 images per class, including 1000 original and 1000 augmented images. So, the final dataset is a multiclass (5 classes) with 10,000 images with 2000 images per class. Finally, the data was resized to 224 × 224 to meet the input requirement of the selected pre-trained ResNet50 model.

B. CNN-BASED TRANSFER LEARNING FOR FEATURE EXTRACTION

An overview of CNN has already been discussed in section II. Creating a CNN network from scratch and training requires a sizable amount of properly labelled datasets. Such a procedure takes time and necessitates more in-depth data examination. Numerous research has shown and advised using a pre-trained network model as they have been trained on a large amount of image data and typically have better feature extraction properties [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30]. Many CNN designs, including AlexNet, GoogLeNet, ResNet, and VGGNet, have been made accessible to the general public along with their pre-trained versions. ResNet50 is chosen for our study based on our previous comparative study on different pre-trained models with the same dataset using the concept of Transfer Learning. The automatic learning of distinct features for each class from the labels given in the dataset is the crucial characteristic of CNN.

1) ResNet PRE-TRAINED NETWORK

The most successful and valuable network of the ILSVRC-2015 is the residual network (ResNet) [39]. There are many advantages to using the ResNet architecture, but precise classification and high convergence rates stand out. The ResNet architecture was trained with the common objects in context (COCO) data collection. By stacking residual units, the ResNet design was created. Depending on the number of residual units and layers present, ResNet designs can assume many different shapes. The ResNet design partially succeeded due to identity shortcuts, in which the output identity value matches the input identity. Like other networks, ResNet uses convolution pooling with fully connected layers. The ResNet-50 architecture used in the research has one fully connected layer and 49 convolutional layers. The proposed approach with different distinguishing attributes of the used pre-trained network is shown in Fig 5.

TABLE 5. Architectural features of ResNet50.

Model: ResNet50
No. of layers: 50
Learnable parameters: 25.7 million
Input image size: 224 x 224

TABLE 6. Optimal hyperparameters obtained after fine-tuning.

Model	Classification accuracy for different hyperparameters (%)					Overall accuracy (%)
	Split ratio	*Solver*	*Batch size*	*Learning rate*	*Epoch*	
ResNet-50	*0.85*	*SGDM*	*8*	*0.0001*	*10*	97.2

With only a few minor modifications (hyperparameter tuning) in the topmost layers, transfer learning has developed into a powerful method for extracting and classifying unique image datasets. The activated neurons found in the final fully connected layer of ResNet50 are used in the current research to extract the features. Therefore, we extracted the features from FC-1000, the last fully connected layer and saved it in a CSV file. For each image that passed, a CSV file having 1000 features was used to store the image features. Then, the best classifier to identify human body parts can be found by using machine learning classifiers on the extracted image features. The methodology used for optimal feature learning is depicted in Fig. 6. Tables 5, 6, and Fig 7 provide information on ResNet50's architectural features, the optimal hyperparameters obtained by fine-tuning the pre-trained ResNet-50 model and the final confusion matrix were obtained with the optimal hyperparameters.

C. FEATURE SELECTION BASED ON J48 AND CLASSIFICATION USING TREE-BASED ALGORITHMS

Feature selection is finding and selecting the most important characteristics that could help achieve the intended class forecast. The classifier's efficiency may suffer as a result of the existence of irrelevant information that can significantly raise the estimation complexity. Consequently, the feature selection procedure discards characteristics that are less important to increase the classification accuracy of the classifier. Decision tree methods are frequently employed in feature selection because they reflect information effectively. A decision tree resembles a graph model that appears like a tree to create criteria for classification. A typical tree includes stems, roots, leaves, and nodes. The attributes used for classification are shown as nodes that are linked from root to leaf by branches. The labels of different groups are shown on the decision tree's leaves, and the nodes have classes attached to them that need to be categorized [40]. In a decision tree, the classification of features begins at the base and descends deeply through the nodes until a pure leaf is found. The

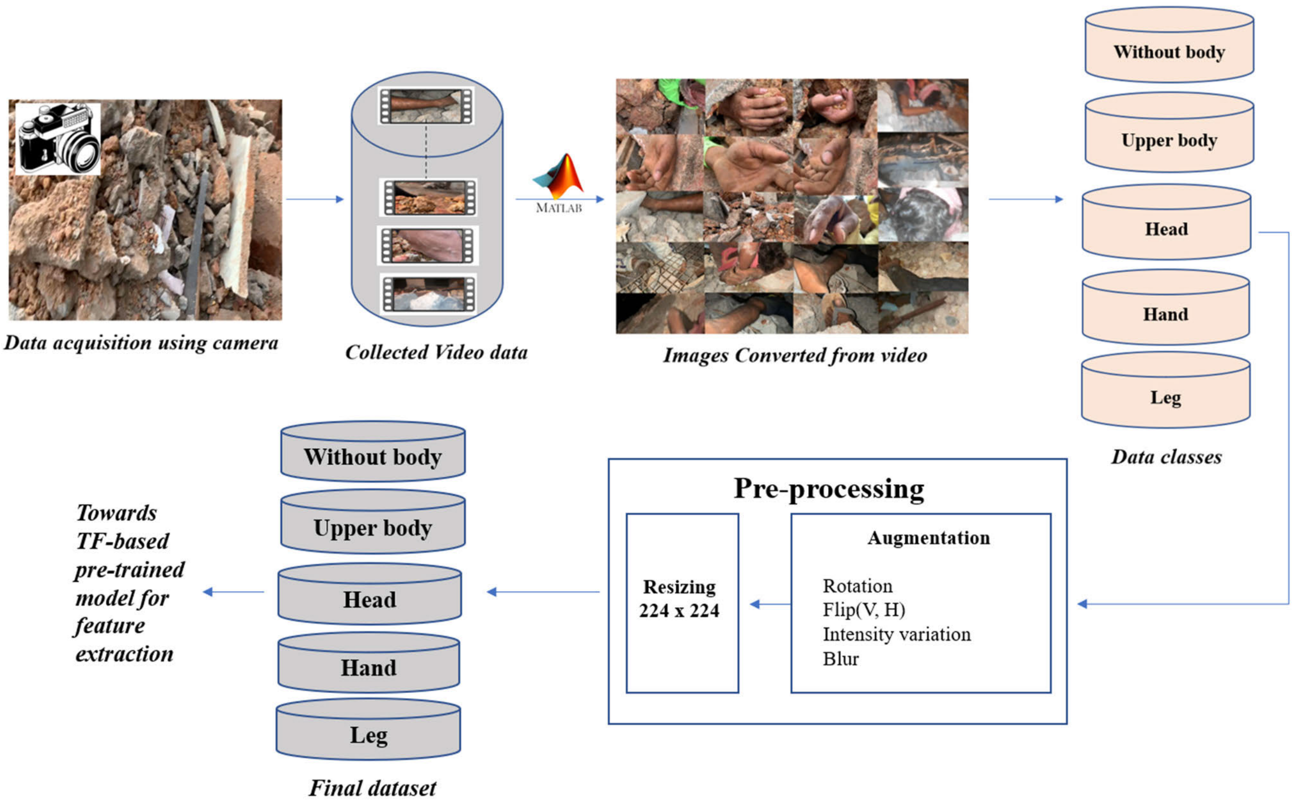

FIGURE 4. Stages in dataset creation.

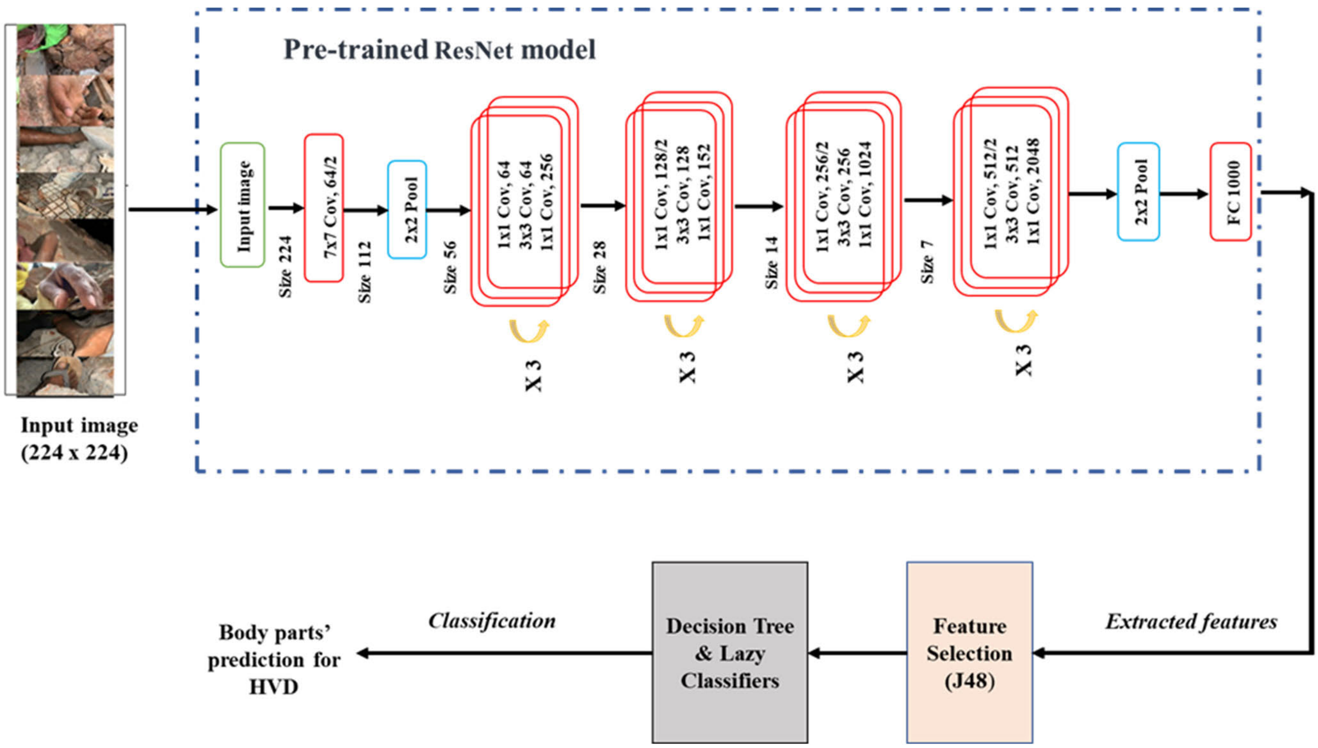

FIGURE 5. The architectural feature learning of ResNet-50 followed by the classification workflow of the proposed HVDA.

decision node determines the most important and practical features for classification based on the appropriate estimation parameters.

A depth-first technique is used to describe the decision tree, where the importance of the features decreases from top to bottom. The top node represents the most important feature,

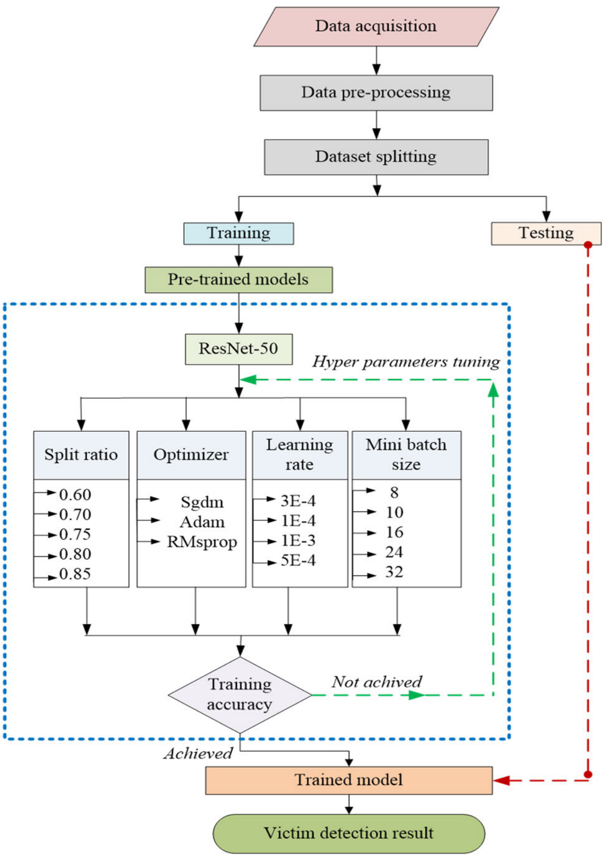

FIGURE 6. Transfer learning based on hyperparameter tuning on ResNet-50 pre-trained network.

FIGURE 7. Confusion matrix of ResNet 50 network for human victim dataset.

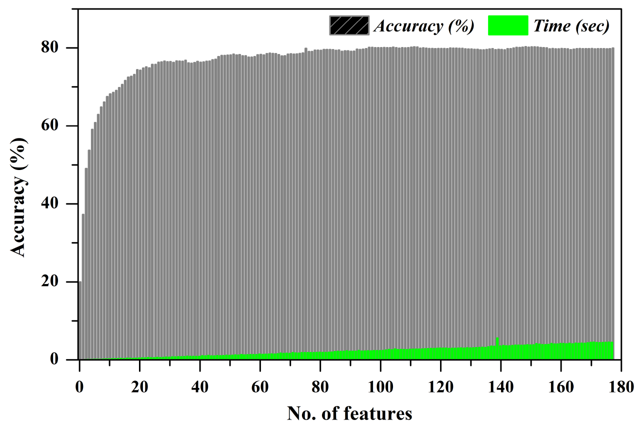

FIGURE 8. Plot showing the influence of feature combinations on classification accuracy.

whereas the bottom node represents the least important feature. In order to locate the essential features that are sufficient to classify the test condition, it is helpful to reduce the features starting at the bottom (taking into account duplication). One hundred seventy-eight features were ultimately chosen as the relevant traits in this manner.

After selecting features, a feature classification technique categorizes instances into the appropriate classes. Lazy classifiers are used in the current work to perform the classification problem. The phrase "decision tree" (DT) designates that choices are made for a categorization issue that has a tree-like structure. A DT's structure comprises leaf, internal, and terminal nodes. DT applies the divide and conquers strategy, which divides the input data into several more manageable parts (nodes and leaves) and then combines them to make a decision. The if-then rule serves as the foundation for the fundamental workings of the DT. A decision tree with an incremental pattern is created for classification by making every DT leaf and node adhere to the working principle. The procedure continues until the training data's final component is present by sequentially learning new rules. At regular intervals, the tuples that satisfy the fundamental requirements of the rules are deleted. Training continues until a goal has been attained. The tree is built hierarchically, with the top node acting as the root node. Decision nodes, which include numerous decision leaves and branches, are the nodes that correlate to the root nodes. DTs have modest data needs, are simple to learn and visualize, and can handle categorical data.

As the name implies, lazy classifiers accumulate the instances throughout training but do not perform actual work until classification. Based on a smaller Euclidean distance between the training sample and the provided test sample, lazy classifiers identify the training sample and forecast that the training sample will belong to the related class. The K-star method [41], locally weighted learning (LWL), and (Instance-based learner) IBk are the classifiers used in this work. The lazy classifiers taken into account for the investigation are described in Table 7.

IV. RESULTS AND DISCUSSIONS

A. EXPERIMENTAL ANALYSIS

The current study aims to integrate deep learning features and machine learning classifiers to identify and categorize various human victim body parts in collapsed building situations. Before being loaded into the ResNet50, (the selected pre-trained deep learning network for feature learning), the dataset, including various body component images, is pre-processed. By fine-tuning the model's hyperparameters (TL), the optimal accuracy of 97.2% was obtained (Table 6). CNN model extracts essential features for each image class, which

TABLE 7. The adopted classifiers and their description.

Classifier	Description
Decision stump	Using a one-level decision tree, instances are categorized by sorting them according to the values of their features. The one-level prediction with a single input feature and attribute drive the decision stump's output.
Hoeffiding	The hoeffiding tree is a DT for massive data streams that incrementally learns and assumes that the data distribution does not vary over time. As a result, the model created by a non-incremental learner and that learned by the hoeffiding tree are essentially similar.
J48	J48 is essentially a modified version of the C4.5 algorithm. The approach uses recursive data partitioning to get a classification DT for a particular dataset.
LMT	LMT has a structure similar to a typical DT and executes logistic regression operations at the leaves. LMTs are created by combining induction trees and logistic regression.
Random tree	An efficient decision tree called a random tree (RT) builds a tree containing N random features at each node. The program effectively combines numerous massive sets of RT to build accurate models.
Random forest	With the creation of several decision trees, random forest categorizes any issue. An ensemble of DT is first built to build an RF decision tree. The object is then classified by being placed into a specific class using the votes gathered from different trees.
Reduced Error Pruning (REP) tree	The most thorough and straightforward method for pruning a DT is the reduced error pruning (REP) tree. In order to create a DT quickly, the REP tree uses information gain as the split criterion and adopts a reduced error pruning strategy.
J48 graft	J48 graft DT seeks to increase the likelihood of accurately classifying cases outside the training data. This technique avoids prediction mistakes and only produces a single tree. A J48 DT is used to create grafted DT utilizing the J48 graft method.
Lib SVM	For kernelized support vector machines (SVMs), LIBSVM supports the sequential minimal optimization (SMO) technique, covering both regression and classification.
Logistic regression	To characterize the relationship between the dependent and independent variables, logistic regression determines the best model that fits the data.
MLP	This model uses stochastic gradient descent or LBFGS to optimize the log-loss function.
BayesNet	Bayesian Network Classifiers are a type of classifier that utilizes Bayes' Theorem and strong (Naive) independence assumptions.
Naïve Bayes	Naive Bayes classifier assumes that a certain class feature's presence (or absence) has nothing to do with the presence (or absence) of any other feature.

TABLE 8. Comparison of classification accuracy and time required to build a model for various 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

are then saved in a CSV file. To do this, decision trees and lazy classifiers are used. They include decision stumps, hoeffding, J48, J48 grafted, LMT, random forests, random trees, REP trees, locally weighted learning (LWL), K-star method (KS), and IBK. Using the J48 decision tree technique, relevant extracted features are nominated as the most important and helpful for victim classification. The classification accuracy of all the classifiers is compared to identify the predominant classifier. This section compares the effectiveness of lazy and tree-based classifiers and the effect of features on classification accuracy. For each image fed into the pre-trained ResNet, 10,000 image features were collected from its final fully connected layer. However, the complete set of extracted features might not contribute to the accurate victim classification. Therefore, irrelevant features in classification tasks may require longer training times and more sophisticated computations. Hence, deleting pointless features from classification jobs will improve classifier performance.

J48 is frequently utilized for feature selection of the different decision tree algorithms available. The J48 decision tree technique is used in the current work to choose the most critical features from the retrieved 1000 features of 10,000 images. The J48 decision tree technique was used in an experimental test on the extracted features to determine the time needed to build the model and classification accuracy. For this, the number of objects used ranged from 2 to 400.

```
=== 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
```

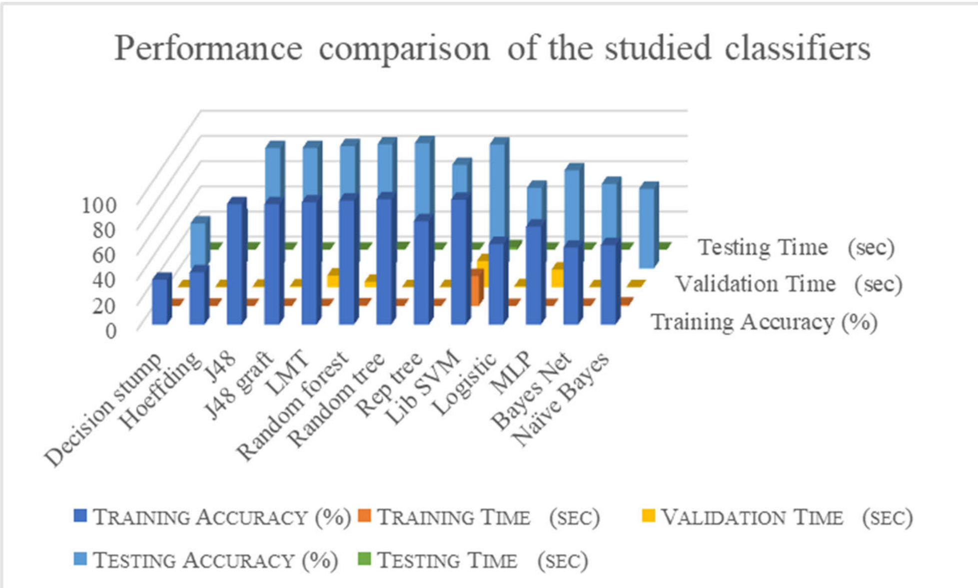

FIGURE 9. Performance comparison of classifiers used in the study.

TABLE 9. Comparison of state-of-the-art algorithms.

Algorithm	Application	Accuracy/ References
Naïve Bayes	PVM fault classification with multiclass thermal image	94.1% [42]
SVM	Fault classification	[43], [44]
kNN	String-level fault detection	98.7% [45]
Random forest	PV cell defect using electroluminescence images	[46]
Random forest	Visual fault detection in photovoltaic modules	98.25% [47]
kNN	Visual fault classification in photovoltaic modules	98.95% [48]
Proposed HVDA	Human victim detection	99.53%

The values were recorded and plotted on a 2D graph with the classification accuracy and time taken on the Y-axis against the number of objects on the X-axis. The response revealed that the categorization accuracy drops as the number of objects increases. At M=12, from 480 features, the significant instances were reduced to 177 with 79.03% accuracy. Almost 300 data points were discarded with just a 3% sacrifice in accuracy. Therefore, M=12 can be chosen as an optimum number of objects for the feature selection process. The J48 decision tree method handles removing redundant features and choosing important ones. Hence the figure depicts the J48 decision tree used to choose the image features for the current investigation. The decision tree ranks the features from the most significant to the least significant in descending order of relevance.

The following section discusses the dimensionality reduction procedure used in the current investigation. When visualizing the tree, the less significant attributes are ignored and will be absent. Initially, just the tree's root node is considered for evaluating the classification accuracy. Also, the combination of the root node and the following prominent node's classification accuracy is examined. The procedure mentioned above is continuously carried out for all feature combinations found in the decision tree, and the classifier's performance for each combination is recorded. Fig.8 shows the effect of feature combinations on classification accuracy. The classification accuracy is almost constant, from 177 to 92 features (79.7% accuracy). When keep on reducing the features beyond 92, the accuracy was found to be reduced significantly. This indicates that 92 features are sufficient for the particular classification task so that the remaining features can be eliminated. Therefore, a random choice between

90-100 and 98 features that gave 80.04 % accuracy in 2.35 sec are considered for further investigations.

1) PERFORMANCE COMPARISON

The performance comparison of classifiers on the selected features obtained from the J48 algorithm is explained in this section. The data augmentation technique creates the five classes of victim body part image datasets of 10000 images. Each class in the dataset contains an equal number of images, accounting for 2000 images per class. Pre-trained ResNet-50 network extracts feature from the image and are stored in CSV files. The selected victim image features acquired using the J48 algorithm are classified using a decision tree and lazy set of classifiers, namely, decision stump, hoeffding, J48, J48 graft, Random forest, random tree, LMT, REP tree, locally weighted learning (LWL), K-star algorithm (KS), IBK. The selected ninety-eight features were adequate for classifying the victim information. The performance of the classifiers was evaluated with the help of a tenfold cross-validation technique. During a tenfold cross-validation, the complete dataset is split into ten equal parts, in which nine parts are used for training while one part is kept for testing.

Table 8 compares classification accuracy for training testing and validation and the time required to build a model for tree-based and lazy classifiers. Further, the procedure runs for ten cycles until every part is used as a test set. A plot displaying the performance comparison of the classifiers used is presented in Fig 9. In addition, a state-of-the-art comparison is made in Table 9 with pre-existing classifiers.

V. CONCLUSION AND FUTURE SCOPE

This paper proposes a novel approach for disaster victim detection under debris environments using decision tree algorithms with deep learning features on a custom-made Human Victim Detection (HVD) dataset. This model aims to assist Urban Search and Rescue (USAR) teams in quickly finding human casualties in areas with collapsed buildings. The five categories of HVD images were head, hand, leg, whole body, and without the body. The HVD dataset was pre-processed with several data augmentation functions to increase the dataset's size based on the application conditions, and it was subsequently downsized to fit with the pre-trained ResNet-50 network's input requirements. To enhance the feature learning procedure, fine-tuning-based transfer learning was applied. The learned features were removed, and only the significant characteristics were selected for additional classifications based on machine learning. Random trees outperformed all other classifiers. Finally, it can be concluded that integrating the TL-based CNN features with ML classifiers can significantly improve classification performance. More accuracy in a shorter amount of time is ensured by the feature extraction method employing pre-trained ResNet-50. A maximum classification accuracy of 99.53% for all five test classes is provided using random tree methods in 0.02s. The results show that the proposed approach is feasible and reliable regarding accuracy and computation time.

Though transfer learning is a promising expansion in the field of DL, helping learn features even from small datasets from the knowledge obtained from huge datasets, the proposed Human Victim Detection Approach (HVDA) dataset could be expanded further to include the maximum possible images.

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