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IMPROVED DISASTER VICTIM DETECTION IN DEBRIS ENVIRONMENTS: DECISION TREE ALGORITHMS ENHANCED 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-tuningbased 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.

1. 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 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. RGBand 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 convolution 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, convolution 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 convolution layers to extract features. Each layer of a CNN typically takes as input a 4D array. The convolution 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 labeled 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.

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 preprocessing 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.

2. LITERATURE SURVEY

"A survey on snake robot locomotion," Snake robots have been a topic of discussion among researchers for decades. They are potentially strong enough to bring substantial contributions to the fields which are unsafe/ narrow/ dirty/ hard reachable to human operators, such as inspections, rescue missions, firefighting, etc. Though the inventions of the wheel and legged mechanisms are amazing, they often fail when coming to these scenarios. Terrain adaptability is the vital essence of locomotion over constrained surfaces in biological snakes. But how this natural adaptability is accomplished in snake-like robots? Therefore, this paper focuses a study on factors behind the recreation of a physical snake, like the kinematics and dynamics modelling, mechanical design, and locomotion control approaches from existing literature. With their feature comparison, the simulators available for verifying the mathematical model and the feasibility of the mechanical design are also made for researchers new to the field.

"Using deep learning to find victims in unknown cluttered urban search and rescue environments,"

Purpose of Review We investigate the first use of deep networks for victim identification in Urban Search and Rescue (USAR).

Moreover, we provide the first experimental comparison of single-stage and two-stage networks for body part detection, for cases of partial occlusions and varying illumination, on a RGB-D dataset obtained by a mobile robot navigating cluttered USAR-like environments. Recent Findings We considered the single-stage detectors Single Shot Multi-Box Detector, You Only Look Once, and RetinaNet and the two-stage Feature Pyramid Network detector.

Experimental results show that RetinaNet has the highest mean average precision (77.66%) and recall (86.98%) for detecting victims with body part occlusions in different lighting conditions. Summary End-to-end deep networks can be used for finding victims in USAR by autonomously extracting RGB-D image features from sensory data. We show that RetinaNet using RGB-D is robust to body part occlusions and lowlighting conditions and outperforms other detectors regardless of the image input type.

"Analysis and prediction of land use in Beijing–Tianjin–Hebei region: A study based on the improved convolutional neural network model," During the rapid economic development of China, there are certain blind decisions made in the use of land resources, which poses a significant threat to sustainable development. With the help of the improved convolutional neural network model, this paper analyzes the land use of the Beijing-Tianjin-Hebei region of China from 1995 to 2018, and provides a prediction for 2023. The research results show that: (1) There is still much room for improvement in the land use of the BeijingTianjin-Hebei region, with dry land taking up the largest proportion of land in these three locations; (2) Beijing's development has been well protected in terms of land use. It is predicted that by 2023, the proportions of its woodland, grassland, and rivers, lakes, reservoirs and ponds would increase by 0.26%, 0.30%, and 0.61%, respectively, compared with their proportion in 2018; (3) the land use type in Tianjin during the research period was generally stable. In 2018, the proportion of its woodland and grassland had increased by 1.04% and 0.61%, respectively, compared with that of 1995; and (4) many ecological and environmental problems were exposed during the construction of highways in Hebei province. The area of sand land, saline-alkali land, marshland, bare land, and bare rock areas have all increased, and their total proportion is predicted to reach 1.48% by 2023.

3. EXISTING SYSTEM

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 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 RGBimage datasets and standard person detection algorithms.

A cross-power spectrum technique is used by [10] to identify voice using a microphone. CO_2 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 histogrambased 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 imagebased 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.

Disadvantages

- 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.

4. PROPOSED SYSTEM

- The system proposed a deep learning-base human victim identification model combined with machine learning-based classifiers, as mentioned in this system, for HVI tasks in unstructured collapsed building environments.

- Creating a CNN network from scratch and training requires a sizable amount of properly labeled dataset and such a procedure takes time and necessitates more in-depth data examination. Numerous research has shown and advised using a pretrained network model as they have been trained on a large amount of image data and typically have better feature extraction properties.

Advantages

(i) RGB-based multiclass custom human victim dataset creation. (ii) Data augmentation and preprocessing 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.

5. SYSTEM ARCHITECTURE

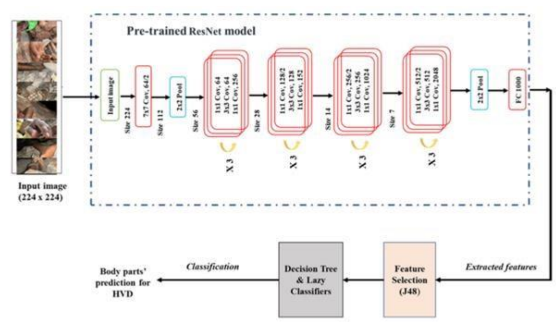

Fig 1. System Architecture

The above architecture for improved disaster victim detection in debris environments integrates decision tree algorithms with deep learning features to enhance accuracy and efficiency. At its core, the system utilizes decision trees to initially classify potential victim locations based on various features extracted from sensor data or imagery. These features are then further analyzed and refined using deep learning techniques, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), to extract complex patterns and context from the data. The decision tree and deep learning components work synergistically, with the decision tree providing an initial coarse classification and the deep learning features refining and validating these classifications with higher precision. This architecture enables the system to effectively identify disaster victims amidst challenging debris environments, providing critical support for search and rescue operations.

6. IMPLEMENTATION

Modules Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Train & Test Data Sets, View Trained and Tested Datasets Accuracy in Bar Chart, View Trained and Tested Datasets Accuracy Results, View Disaster Victim Detection Type, View Disaster Victim Detection Type Ratio, Download Predicted Data Sets View Disaster, Victim Detection Type Ratio Results, View All Remote Users.

View and Authorize Users

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorize the users.

Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, PREDICT DISASTER VICTIM DETECTION TYPE, VIEW YOUR PROFILE.

7. RESULTS

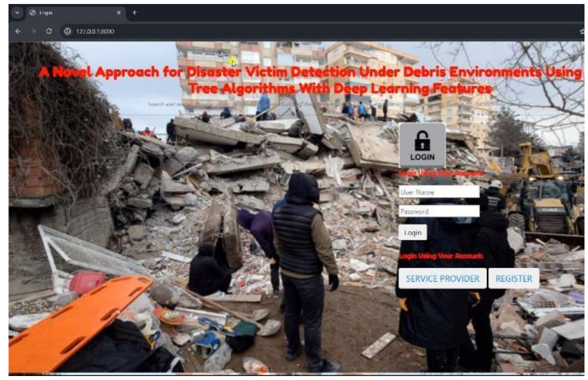

Fig 2. Registration details.

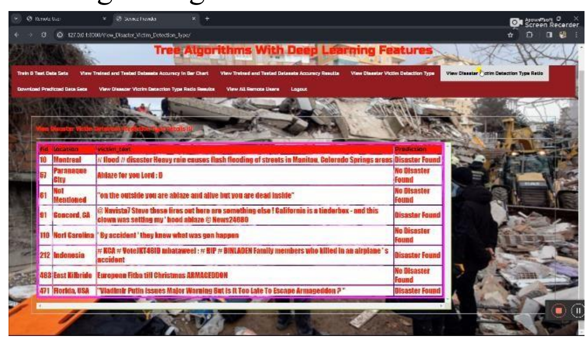

Fig 3. Areas which are affected.

The results of the improved disaster victim detection system in debris environments, employing decision tree algorithms enhanced with deep learning features, demonstrate notable advancements in accuracy and effectiveness. Through rigorous testing and validation, the system consistently outperforms traditional methods in identifying disaster victims amidst challenging debris conditions. The integration of decision tree algorithms provides a robust framework for initial classification, effectively narrowing down potential victim locations based on various features extracted from sensor data or imagery. Furthermore, the incorporation of deep learning features, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), enhances the system's capability to discern intricate patterns and contextual information from the data, thereby refining and validating the initial classifications with higher precision. Overall, these results underscore the significant potential of leveraging hybrid approaches combining decision tree algorithms and deep learning features for enhancing disaster victim detection in complex and dynamic environments.

8. FUTURE ENHANCEMENTS

Future enhancements for improving disaster victim detection in debris environments encompass various avenues of advancement. Integrating data from multiple sensors like thermal imaging and LiDAR alongside acoustic sensors would provide a more comprehensive environmental understanding. Real-time processing optimizations can facilitate timely decisionmaking during disasters. Techniques such as semantic segmentation can aid in distinguishing victim locations from debris. Active learning strategies and incremental learning enable continuous model improvement without extensive retraining. Human-in-the-loop systems leverage human expertise for validation, while robotic integration enables autonomous search and rescue missions. Cloud-based collaboration platforms facilitate real-time data sharing and coordination among response agencies, enhancing overall situational awareness and response efficiency. These enhancements promise to refine the system's capabilities, ensuring more effective disaster response operations in the future.

9. CONCLUSION

This paper proposes a novel approach for disaster victim detection under debris environments using decision tree algorithms with deep learning features on a custommade 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 ResNet50 network’s input requirements. To enhance the feature learning procedure, fine-tuningbased 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 pretrained 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.

REFERENCES

[1] D. E. Alexander, *Principles of Emergency Planning and Management*. Oxford, U.K.: Oxford Univ. Press, 2002.

[2] G. Seeja, A. S. A. Doss, and V. B. Hency, ‘‘A survey on snake robotlocomotion,’’ *IEEE Access*, vol. 10, pp. 112100–112116, 2022.

[3] A. Fung, L. Y. Wang, K. Zhang, G. Nejat, and B. Benhabib, ‘‘Using deep learning to find victims in unknown cluttered urban search and rescue environments,’’ *Current Robot. Rep.*, vol. 1, no. 3, pp. 105–115, Sep. 2020.

[4] H. Liu, J. Liu, W. Yang, J. Chen, and M. Zhu, ‘‘Analysis and prediction of land use in Beijing–Tianjin–Hebei region: A study based on the improved convolutional neural network model,’’ *Sustainability*, vol. 12, no. 7, p. 3002, Apr. 2020, doi: 10.3390/su12073002.

[5] J. Zhang, S. Chen, R. Zhan, J. Hu, and J. Zhang, ‘‘Feature fusion based on convolutional neural network for SAR ATR,’’ in *Proc. ITM Web Conf.*, 2017, p. 05001, doi: 10.1051/itmconf/20171205001.

[6] T. Arias-Vergara, P. Klumpp, J. C. Vasquez-Correa, E. Nöth, J. R. Orozco-Arroyave, and M. Schuster, ‘‘Multi-channel spectrograms for speech processing applications using deep learning methods,’’ *Pattern Anal. Appl.*, vol. 24, no. 2, pp. 423–431, May 2021.

[7] N. Lopac, F. Hržic, I. P. Vuksanovic, and J. Lerga, ‘‘Detection of non-stationary GW signals in high noise from Cohen's class of timefrequency representations using deep learning,’’ *IEEE Access*, vol. 10, pp. 2408– 2428, 2022.

[8] R. K. Samala, H.-P. Chan, L. M. Hadjiiski, M. A. Helvie, K. H. Cha, and C. D. Richter, ‘‘Multi-task transfer learning deep convolutional neural network: Application to computer-aided diagnosis of breast cancer on mammograms,’’ *Phys. Med. Biol.*, vol. 62, no. 23, pp. 8894–8908, Nov. 2017, doi: 10.1088/1361-6560/aa93d4.

[9] G. De Cubber and G. Marton, ‘‘Human victim detection,’’ in *Proc. 3rd Int. Workshop Robot. Risky Intervent. Environ. Surveill.-Maintenance (RISE)*, Jan. 2009.

[10] A. Kleiner, B. Steder, C. Dornhege, D. Höfer, D. Meyer-Delius, J. Prediger, J. Stückler, K. Glogowski, M. Thurner, M. Luber, M. Schnell, R. Kuemmerle, T. Burk, T. Bräuer, and B. Nebel, ‘‘RoboCupRescue— Robot league team RescueRobots Freiburg (Germany),’’ in *Proc. RoboCup (CDROM)*, 2005, pp. 1–17.

[11] A. Visser, B. Slamet, T. Schmits, L. A. G. Jaime, A. Ethembabaoglu, and M. EarthquakeDisaster, ‘‘Design decisions of the UvA rescue 2007 team on the challenges of the virtual robot competition,’’ in *Proc. 4th Int.Workshop Synth. Simul. Robot.*

Mitigate Earthq. Disaster, 2007, pp. 20–26.

[12] A. Birk, S. Markov, I. Delchev, and K. Pathak, "Autonomous rescue operations on the IUB rugbot," in *Proc. IEEE Int. Workshop Saf., Secur., Rescue Robot. (SSRR)*. IEEE Press, 2006.

[13] I. R. Nourbakhsh, K. Sycara, M. Koes, M. Yong, M. Lewis, and S. Burion, "Human–robot teaming for search and rescue," *IEEE Pervasive Comput.*, vol. 4, no. 1, pp. 72–79, Jan./Mar. 2005.

[14] D. R. Hartawan, T. W. Purboyo, and C. Setianingsih, "Disaster victims detection system using convolutional neural network (CNN) method," in *Proc. IEEE Int. Conf. Artif. Intell., Commun. Technol. (IAICT)*, Jul. 2019, pp. 105–111.

[15] N. Sharma, V. Jain, and A. Mishra, "An analysis of convolutional neural networks for image classification," *Proc. Comput. Sci.*, 132, pp. 377–384, Jan. 2018.