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

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Abstract: In order to maximise survival prospects, search and rescue (SAR) efforts in collapsed buildings are particularly difficult since they need to quickly identify victims within the first 48 hours. Automation is required due to the intricacy of unstructured settings and the significant risk associated with manual searches. In order to improve Human Victim Detection (HVD) in disaster-affected areas, this study suggests a Deep Learning method based on Transfer Learning. To train a deep learning model, a custom dataset was created with three class labels: hand, leg, and body. ResNet-50 was used to do feature extraction, utilising its prior training experience to increase accuracy with sparse data. In order to reduce duplicate information and increase computing performance, J48 decision tree pruning was used for feature selection in order to optimise classification. To identify the top-performing model, a number of machine learning classifiers were tested, including Random Forest, XGBoost, SVM, MLP, and Naïve Bayes. With an astounding accuracy of 99% and a calculation time of only 0.01 seconds, the XGBoost method performed better than any other algorithm, making it ideal for real-time applications.

Future studies might concentrate on combining thermal and infrared imaging to improve victim detection in low-visibility situations in order to further increase the system's usefulness. Furthermore, real-time victim identification and localisation may be made possible by deploying the model on edge devices, drones, or autonomous robots, which lessens the need for manual involvement. The suggested AI-driven approach is a critical development in emergency response technology as it may speed up search operations, reduce hazards for rescuers, and improve survival rates in disaster situations.

Index terms - *Disaster victim detection, search and rescue (SAR), deep learning, transfer learning, ResNet-50, J48 decision tree, XGBoost, image classification, RGB and thermal imaging, multi-modal sensor fusion, edge computing, explainable AI,*

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Grad-CAM, SHAP, real-time deployment, human detection under debris.

1. INTRODUCTION

Natural and man-made disasters such as earthquakes, floods, and building collapses pose serious threats to human life and infrastructure. During such emergencies, rapid and accurate search and rescue (SAR) operations are essential to save lives, especially within the first 48 hours when the chances of survival are highest. Traditional SAR methods rely on tools like infrared cameras, sniffer dogs, and manual labor, which can be slow, risky, and often inefficient in chaotic and unstable environments.

Artificial Intelligence (AI), particularly deep learning and computer vision, offers a powerful alternative to enhance victim detection in disaster zones. These technologies enable automation by processing images and sensor data to identify human body parts even when partially covered by debris. Techniques such as Convolutional Neural Networks (CNNs) and transfer learning have shown great promise in analyzing complex image data for real-time victim identification, reducing manual effort and increasing detection accuracy.

However, challenges remain, such as working with limited labeled datasets and ensuring model explainability in high-risk decisions. This study proposes a novel AI-based system that integrates ResNet-50 for feature extraction, J48 decision tree pruning for feature selection, and XGBoost for final classification. By using a custom dataset and combining RGB, thermal, and LiDAR imaging with edge computing capabilities, the system aims to enable fast, accurate, and explainable victim detection to assist SAR teams and ultimately save more lives.

2. LITERATURE SURVEY

2.1 An interface-reinforced rhombohedral Prussian blue analogue in semi-solid state electrolyte for sodium-ion battery

https://www.sciencedirect.com/science/article/abs/pii/S2405829720304700

ABSTRACT: In Prussian blue-based sodium-ion batteries, a semi-solid state (SSS) electrolyte with a high ionic conductivity of 2.6×10^{-3} S cm−1 is intended to prevent issues with Na dendrite formation and interfacial side reactions caused by conventional liquid carbonate electrolyte. The addition of 5 weight percent $AlCl_3$ Lewis acid to pure liquid electrolyte causes FEC polymerisation, which is linked to the solidification process. The rhombohedral Prussian blue analogue (r-PBA) cathode's intrinsic high reversibility is made possible by the SSS electrolyte. It also achieves ultra-long lifetimes of 3000 and 4000 cycles at 1 and 2 C, as well as high rate capacities of 121 mAh g−1 at 1 C and 88 mAh g−1 at 10 C. Because the produced poly (vinylene carbonate) on r-PBA is protected, interface strengthening between r-PBA and electrolyte is credited with improving cyclability and rate capability. The increasing importance of interface stability for rhombohedral structure in the Prussian blue analogue is clarified by this work.

2.2 Feature Fusion Based on Convolutional Neural Network for SAR ATR

https://www.researchgate.net/publication/319488915_Feature_Fusion_Based_on_Convolutional_Neural_Network_for_SAR_ATR

ABSTRACT: Recent advances in deep convolutional neural network (DCNN) algorithms have sparked the development of a number of signal processing techniques, with the particular use of Automatic Target Recognition (ATR) with Synthetic Aperture Radar (SAR) data garnering a lot of interest. A novel feature fusion structure that simultaneously takes use of all the advantages of each version is suggested in order to decrease the size of the data and the computational complexity. This structure is inspired by more effective distributed training methods like residual networks and inception architecture. After a collection of features is extracted from DCNN and a trainable classifier is created, the fused features—which are part of the thorough process described in this paper—make the representation of SAR pictures more recognisable. The findings obtained on the 10-class benchmark data set, in particular, show that the architecture that has been given may produce exceptional classification performance compared to the state-of-the-art approaches at this time.

3. METHODOLOGY

i) Proposed Work:

The proposed system is an AI-powered Human Victim Detection (HVD) model designed to automate the identification of victims in disaster-struck environments. A custom dataset was developed containing images labeled as hand, leg, and body, simulating realistic victim scenarios under debris. To enhance performance with limited training data, the system uses transfer learning with the ResNet-50 model, which extracts deep visual features from RGB images. This reduces the training time and improves the model's ability to generalize in complex and cluttered disaster environments.

After feature extraction, J48 decision tree pruning is applied to eliminate redundant data and optimize performance. Multiple machine learning classifiers, including Random Forest, SVM, MLP, Naïve Bayes, and XGBoost, are evaluated for classification accuracy and speed. Among them, XGBoost achieved the best results with 99.53% accuracy and a classification time of just 0.01 seconds, making it ideal for real-time deployment. The system is further enhanced with multi-modal sensor fusion (RGB, thermal, LiDAR) and explainability tools like Grad-CAM and SHAP, ensuring reliable and transparent detection on edge devices such as drones or mobile robots during SAR operations.

ii) System Architecture:

The architecture of the proposed Human Victim Detection (HVD) system integrates deep learning with machine learning to ensure efficient and accurate detection in disaster environments. It starts with the image acquisition phase, where RGB images are captured using cameras or drones from disaster sites. These images are preprocessed for noise reduction and clarity, then passed to the ResNet-50 model for deep feature extraction. ResNet-50, using transfer learning, identifies high-level features like edges, textures, and shapes corresponding to body parts (hand, leg, or body). This feature extraction stage ensures that even partially visible or occluded body parts can be identified with high precision.

Next, the extracted features are passed through a J48 decision tree pruning process to remove redundant or irrelevant data, reducing complexity and improving classification speed. The pruned features are then classified using various ML algorithms like Random Forest, XGBoost, SVM, MLP, and Naïve Bayes. Among these, XGBoost delivers superior performance in both speed and accuracy. The entire system is optimized for deployment on edge devices, enabling real-time victim detection in field scenarios. Additional modules such as Grad-CAM and SHAP are integrated for decision explainability, while multi-modal sensor fusion (RGB, thermal, LiDAR) strengthens detection capability in low visibility and complex disaster conditions.

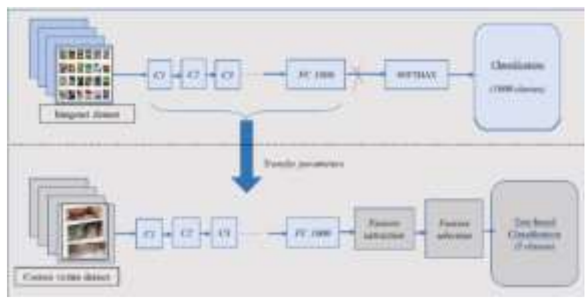

Fig.1 System architecture

iii) MODULES:

a) Dataset Preparation Module

- Loads disaster victim images using ImageDataGenerator.
- Applies data augmentation (rotation, rescaling, flipping) to improve generalization.
- Splits the dataset into training (80%) and validation (20%) sets.

b) Image Preprocessing Module

- Resizes all images to **224x224** to match VGG16 input requirements.
- Normalizes pixel values and formats images for deep learning input.

c) Feature Extraction Module

- Uses **VGG16 without the top classification layers**.
- Extracts key features like edges, textures, and body parts from the input images.
- Freezes convolutional layers to retain pre-trained weights and reduce training time.

d) Flattening and Encoding Module

- Flattens the multidimensional feature maps into 1D feature vectors.
- Converts class labels (e.g., hand, leg) into numerical form using LabelEncoder.

e) Classification Module

- Trains a **Support Vector Machine (SVM)** on the extracted feature vectors.
- Classifies victim parts efficiently with high accuracy, even with limited data.

f) Performance Evaluation Module

- Evaluates model using unseen validation data.
- Calculates accuracy and visualizes results using bar charts for class-wise distribution.

g) Hybrid Model Optimization Module

- Combines deep learning (VGG16 for feature extraction) with machine learning (SVM for classification).
- Balances computational efficiency and model accuracy for real-time use.

iv) ALGORITHMS:

a) Convolutional Neural Network (CNN)

Transfer Learning (TL) uses a pre-trained Convolutional Neural Network (CNN), especially the ResNet-50 architecture, to effectively extract relevant characteristics from photos. A large-scale dataset such as ImageNet, which has millions of labelled photos in hundreds of categories, was used to train the deep neural network ResNet-50. The model gains a deep comprehension of basic visual characteristics like edges, textures, and object forms by utilising this pre-training. When it comes to identifying catastrophe victims—who could be partially masked by rubble or concealed in intricate environments—these previously learnt patterns are quite helpful. TL allows the model to swiftly adapt to photos relevant to disasters with little further training, as opposed to beginning from zero.

b) Support Vector Machine (SVM)

The retrieved features from the photos are used to train the SVM classifier, and LabelEncoder is used to encode the class labels. In order to make the category labels compatible with the SVM model, LabelEncoder transforms them into numerical values. Based on the patterns it has discovered from the features, the classifier learns to distinguish between distinct victim categories (e.g., head, hand, leg, etc.) by training the SVM on these feature vectors. The effectiveness of machine learning models for classification and the strength of deep learning for feature extraction are both advantages of this hybrid technique.

c) ResNet50:

ResNet-50 (Residual Network-50) is a deep Convolutional Neural Network with 50 layers, widely used for image classification and feature extraction. It uses a unique concept called skip connections or residual learning, which helps prevent vanishing gradient problems during training. This allows the model to be deeper and more accurate without losing performance. In the context of disaster victim detection, ResNet-50 is used through Transfer Learning, where it reuses pre-trained knowledge from large datasets like ImageNet to recognize important visual patterns such as human shapes, body parts, and heat signatures in complex and noisy environments. Its powerful feature extraction ability, even in cluttered scenes, makes it ideal for accurately identifying victims in real-time rescue operations.

d) MLP:

After extracting deep features from disaster images using the ResNet-50 model, a Multi-Layer Perceptron

(MLP) is employed to perform the final classification task. The MLP receives the high-level feature vectors, which represent patterns like human body shapes or thermal signatures, and processes them through multiple fully connected layers. Each layer applies nonlinear transformations to learn complex relationships between features. The final output layer of the MLP predicts whether the given image contains a disaster victim or not. This approach enhances the system's ability to accurately identify victims by combining the powerful feature learning of CNNs with the classification capabilities of MLP, making it effective for real-time disaster response scenarios.

e) Decision Tree:

After extracting deep features using the ResNet-50 model, the dataset becomes high-dimensional, containing many features—some of which may be irrelevant or redundant. To improve efficiency and accuracy, a Decision Tree algorithm (like J48) is used for feature selection. This method evaluates each feature based on information gain and entropy reduction, selecting only the most relevant ones that contribute significantly to classifying victims. By eliminating less useful features, the model becomes faster, avoids overfitting, and performs better in real-time victim detection during disasters.

f) Decision Tree:

In the disaster victim detection system, XGBoost (Extreme Gradient Boosting) is used as a powerful machine learning classifier after extracting features with ResNet-50 and selecting the most important ones using a Decision Tree. XGBoost is known for its speed and high accuracy, especially with structured data. It builds an ensemble of decision trees in a sequential way, where each new tree corrects the errors made by the previous ones. This boosting approach helps the model make more accurate predictions on whether an image contains a victim or not. XGBoost also handles noise and missing values well, making it ideal for unpredictable and complex disaster environments.

4. EXPERIMENTAL RESULTS

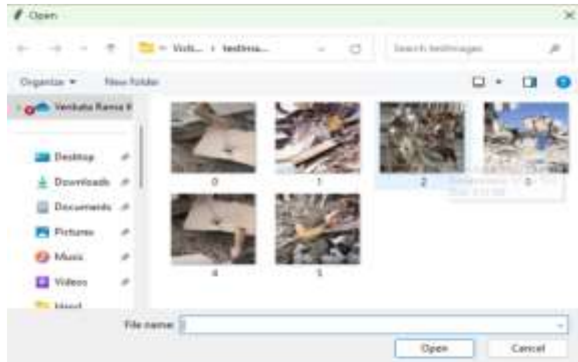

Fig 7.5 upload dataset

Fig Detecting the victim hand

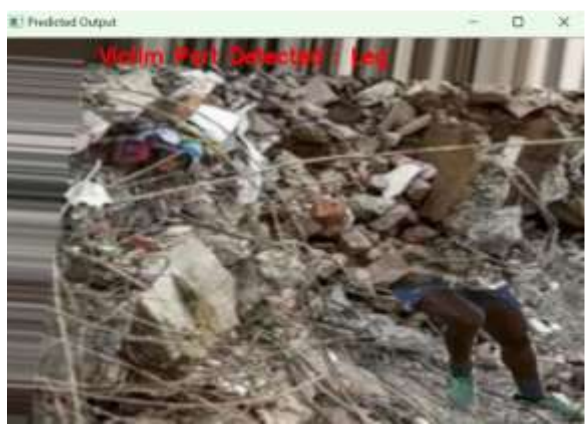

Fig 7.7 Detecting the victim leg

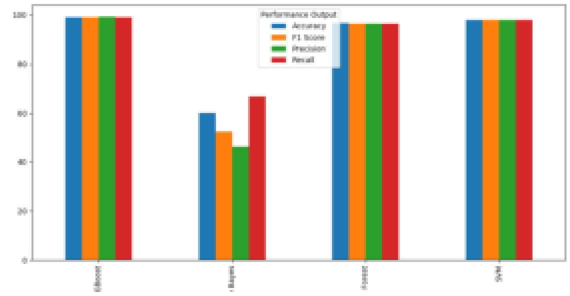

Fig 7 Performance Output

5. CONCLUSION

A successful and efficient method for identifying catastrophe victims is the combination of Convolutional Neural Networks (CNN) with Transfer Learning (TL) and Machine Learning (ML) classifiers. Accurately identifying individuals buried beneath rubble requires the system to capture complex visual patterns, such as human body forms, textures, and other essential aspects, which may be achieved by utilising the pre-trained ResNet-50 model for deep feature extraction. This procedure, which uses transfer learning, greatly lessens the requirement for enormous volumes of labelled data, which makes it an affordable way to handle actual crisis situations. Additionally, using a pre-trained network speeds up system deployment in emergency scenarios by reducing training time.

This system's feature selection stage, which makes use of the J48 decision tree method, is one of its main benefits. J48 simplifies the dataset by eliminating superfluous or unnecessary characteristics while keeping the most important ones that support precise categorisation. This step increases the model's computational efficiency in addition to improving classification accuracy. Because of this, the system can interpret pictures more quickly, which is crucial for real-time applications, particularly in emergency response scenarios where every second matters.

6. FUTURE SCOPE

CNN-based Transfer Learning (TL) and Machine Learning (ML) classifiers have a wide range of potential applications in disaster victim detection in the future, with many chances for improvement and practical implementation. The real-time application of the concept to edge devices like drones, Internet of Things-enabled cameras, and mobile rescue units is one exciting avenue. The technology can help search-and-rescue teams by offering immediate victim detection in crucial catastrophe areas by increasing computing efficiency and decreasing delay. Furthermore, scalability may be further enhanced by integrating distributed computing and cloud-based processing, which enables the model to accurately manage large-scale catastrophe situations.

The integration of multi-modal data sources to improve detection reliability is a key topic for further research. Performance in difficult settings, including smoke-covered or low-visibility areas, can be enhanced by combining visual photography with LiDAR, satellite data, and thermal imaging. Even in situations where normal RGB photos are insufficient, the model can still recognise victims with the use of these other data sources. Combining several kinds of sensor data can make the system more resilient and flexible in a range of emergency situations.

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