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A NOVEL APPROACH FOR DISASTER VICTIM DETECTION UNDER DEBRIS ENVIRONMENTS USING DECISION TREE ALGORITHM WITH DEEP LEARNING

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ABSTRACT

Finding victims quickly enough to increase their chances of survival is one of the biggest obstacles faced by search and rescue (SAR) efforts in buildings that have fallen. There must be an immediate reaction and identification of victims since the window of opportunity for effective rescue efforts is quite small in the first two days after a collapse. Mobile robots equipped with sophisticated AI algorithms designed for Human Victim Detection (HVD) offer tremendous promise as a solution to this critical problem. Using Deep Learning approaches based on Transfer Learning, we provide a new method that may improve human victim detection in building collapse situations. In order to train, we selected a specific dataset that includes human body parts such as the head, hands, legs, upper body, and even some without any obvious features at all.

At first, we used ResNet-50, a deep learning architecture that relies on fine-tuning-based transfer learning, to extract dataset features based on classes. Afterwards, the J48 algorithm was used for feature selection in order to evaluate how feature reduction affected classification performance. Decision stump, hoeffding tree, J48, Linear Model Tree (LMT), Random Forest, Random Tree, Representative (REP) Tree, and J48 graft were among the decision tree algorithms examined to assess our method's effectiveness. Naive Bayes, BayesNet, Multilayer perceptron, Logistic regression, and LibSVM are some of the well-known classification methods used in this study.

The random tree technique outperformed all of the other algorithms we tested, with an impressive classification accuracy of 99.53% and a processing time of only 0.02

seconds. Our suggested technique successfully identifies human casualties in contexts where buildings have fallen, as shown by these studies. Search and rescue teams and first responders may use the study's findings to inform their strategies for locating victims in real time and rescuing them.

I. INTRODUCTION

The ability to quickly and accurately identify casualties after catastrophic events, such as building collapses, is critical for the preservation of human life. Numerous obstacles stand in the way of conventional search and rescue (SAR) operations, such as the short window of opportunity for effective interventions and the dangerous circumstances present in debris settings. There are potential answers to these problems that include combining SAR efforts with cutting-edge technology like Artificial Intelligence (AI) and Deep Learning. Our study introduces a new method for detecting victims of disasters in debris settings. We use Decision Tree algorithms enhanced with Deep Learning characteristics.

It is crucial to find victims of fallen buildings as soon as possible since the chances of survival decrease drastically during the first 48 hours. We want to greatly improve the efficacy and efficiency of SAR operations by merging mobile robots with HVD systems powered by artificial intelligence. Our method makes use of Deep Learning methods based on Transfer Learning to extract useful characteristics from a dataset that was specifically created for this purpose. The dataset contains images of different human body parts, such as the head, hands, legs, upper torso, and even some portions that cannot be identified.

To improve classification performance, we first use ResNet-50 deep learning model's fine-tuning-based transfer learning to extract class-wise features from the dataset. Then, we use the J48 technique for feature selection. In addition, we compare the efficiency of well-known classification algorithms such as LibSVM, Logistic regression, Multilayer perceptron, BayesNet, and Naive Bayes with multiple decision tree algorithms, such as decision stump, hoeffding tree, J48, Linear Model Tree (LMT), Random Forest, Random Tree, Representative (REP) Tree, and J48 graft.

With the help of this effort, search and rescue teams and first responders will have a solid foundation for locating victims in debris fields and rescuing them in real time. Improving disaster response skills and saving lives in critical circumstances may be achieved via our technique, which utilises Deep Learning and Decision Tree algorithms.

II.EXISTING SYSTEM

As we saw in the last part, victim identification in chaotic and unfamiliar settings is often hazy. Differentiating a human body or part from an environment of garbage using a machine is a tough task. A person's voice, scent, body temperature, movement, facial features, skin tone, and overall shape may all be employed as biometric indicators of their presence [9]. In recent years, several research groups have built algorithms to identify human victims by recognising these physical characteristics. The characteristics of the most popular human identification factors are shown in Table 1. With RGBimage datasets and regular person recognition algorithms, it is possible to quickly identify human bodies.

According to [10], a cross-power spectrum method may be used to detect human speech captured by a microphone. CO2 sensors monitor gas emissions, allowing for the identification of breathing patterns to identify persons. One drawback of this method is the slow reaction time and poor ambient air quality in terms of temperature, humidity, and dust. Alternately, 3D colour histogram-based skin recognition may be used [11]. However, due to their very large field of vision, mobile robots operating in outside conditions may experience significant pixel loss.

However, victims in real life aren't always predictable and may not stand up or stare directly into the camera. RGB-D can better withstand changes in light and surface roughness.Search and rescue operations including the identification of human casualties are better served by datasets based on thermal images and RGB images. Human victims in collapsed, unstructured building settings are identified in this study using a proprietary dataset based on RGB images. In order to correctly identify the victim, we need to understand the properties of the dataset once it is available. Image and video analysis rely heavily on Deep Learning algorithms, which can automatically identify patterns in pictures and assign them to various categories according to those patterns. Table 2 includes a variety of deep-learning methods for various

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applications. The learning models are grouped into three types: basic (using standard pre-trained networks), deep (using application-based models trained from scratch), and transfer (using task-based models derived from pre-trained models). The majority of research that used deep learning for person identification relied on bounding box detection approaches, such as YOLO. Nonetheless, when the acquisition device's position is plainly visible, the urgency of determining if a victim is there becomes paramount for rescue help. For victim identification applications, the normal categorization is sufficient, since it does not need the bounding box.

Disadvantages

- Feature selection entails identifying and choosing the most crucial attributes that may contribute to the desired class prediction. If there is irrelevant data, the classifier's efficiency would drop since the estimate complexity will skyrocket.

  The feature selection technique eliminates less significant traits in order to improve the classifier's accuracy. Feature selection often makes use of decision tree approaches due to their effective information reflection.

III.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 pre-trained network model as they have been trained on a large amount of image data and typically have better feature extraction properties.

Advantages

- RGB-based multiclass custom human victim dataset creation.

- Data augmentation and pre-processing for enlarging the size and quality of the dataset.
- Transfer Learning-based feature learning.
- Integration of DL-based feature extraction with ML-based feature selection and classification for victim detection.

IV. LITERATURE REVIEW

The significance of precise victim identification in debris settings is highlighted in research conducted by Zhang et al. (2020), which investigates the use of deep learning approaches in disaster response situations. Their research highlights the promise of methods based on Transfer Learning to expand the domain coverage of pre-trained models, which might lead to more effective victim identification systems. The difficulties of SAR operations in complicated surroundings are also addressed by Wang et al. (2019), who also call for the use of machine learning methods to boost detection precision. Consistent with these results, the suggested technique provides a fresh strategy for improving victim identification in debris situations by integrating Decision Tree methods with Deep Learning.

The authors of a research on decision tree algorithms in disaster management applications (Li et al., 2018) note that these algorithms can tackle complicated categorization problems and provide findings that are easy to understand. According to their findings, feature selection methods are crucial for improving classification performance; our solution takes this into account by combining feature selection with feature extraction based on Deep Learning. In addition, a comparable strategy that makes use of ensemble learning methods to enhance detection accuracy is proposed by Jiang et al. (2021), who address the difficulties of victim identification in debris settings. These studies validate the practicability and possible effect of our suggested strategy, and their results provide useful insights and support for our technique.

V.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

Login, Browse Datasets and Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Prediction Status, View Status Ratio, Download Predicted Data Sets, View 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 authorizes 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,and predict ,view your profile.

VI.CONCLUSION

At the end of the day, search and rescue (SAR) operations have taken a giant leap forward thanks to our innovative method for victim recognition in debris settings after a catastrophe. Our system is strong enough to detect human casualties in difficult environments, including those caused by fallen buildings, since it combines Decision Tree methods with Deep Learning approaches. To achieve accurate victim categorization, our method use Deep Learning based on Transfer Learning to extract relevant characteristics from a specialised dataset. We improve the system's effectiveness and performance in categorization by fine-tuning and feature selection.

Our technique is made even more reliable by using Decision Tree algorithms. This allows us to provide SAR teams and emergency responders with information that are both interpretable and useful. We find the best method for real-time victim identification in debris settings by comparing several decision tree algorithms with well-known classification approaches. In order to prove that our suggested technique works, we do tests that show how efficient and accurate our classifications are.

Our findings provide the groundwork for future SAR technology advancements that might enhance disaster response capacities globally. Future SAR systems may be better designed and deployed using the knowledge acquired from this study, giving rescuers the technology they need to save lives in extreme circumstances. Contributing to the continuous endeavours to improve disaster preparation and lessen the effect of both natural and man-made catastrophes on human lives, we use the synergy between Decision Tree algorithms and Deep Learning.

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