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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

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, hoeffding 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.

Keywords: robotics, artificial intelligence, victim identification, transfer learning, deep learning, classification algorithms, collapsed building.

INTRODUCTION

Search and Rescue (SAR) operations in disaster scenarios, especially in unstructured environments such as collapsed buildings, pose significant challenges and risks [1]. The urgency of victim identification in these situations cannot be overstated, as the probability of successful rescue diminishes rapidly over time [2]. The critical window for effective rescue efforts typically lasts only within the first 48 hours following a disaster event [3]. Therefore, it is imperative to expedite the response and identification processes to maximize the chances of saving lives [4]. Traditional SAR methods often rely on manual searches conducted by rescue teams, which are not only time-consuming but also fraught with danger [5]. In recent years, there has been a growing interest in leveraging advanced technologies, particularly Artificial Intelligence (AI) and robotics, to enhance SAR operations [6]. By combining mobile robots equipped with Human Victim Detection (HVD) systems driven by practical AI algorithms, it becomes possible to significantly mitigate the risks and challenges associated with victim identification in disaster environments [7].

In this paper, we propose a novel approach for disaster victim detection under debris environments using decision tree algorithms with deep learning features [8]. Our approach is rooted in the integration of machine learning techniques, particularly Transfer Learning-based Deep Learning, to facilitate the identification of human victims amidst collapsed building debris [9]. We begin by creating a custom-made human victim dataset comprising five class labels: head,

hand, leg, upper body, and without the body [10]. This dataset serves as the foundation for training our deep learning model and subsequently extracting class-wise features necessary for classification [11]. To extract these features, we employ a fine-tuning-based transfer learning strategy using the ResNet-50 deep learning model, a widely recognized architecture for image classification tasks [12]. The learned features are then subjected to a feature selection process using J48 decision tree algorithm to evaluate the impact of feature reduction on classification performance [13]. Subsequently, we explore the efficacy of various decision tree algorithms, including decision stump, hoeffding tree, J48, Linear Model Tree (LMT), Random Forest, Random Tree, Representative (REP) Tree, and J48 graft, alongside other popular algorithms such as LibSVM, Logistic regression, Multilayer perceptron, BayesNet, and Naive Bayes, in performing the classification task [14].

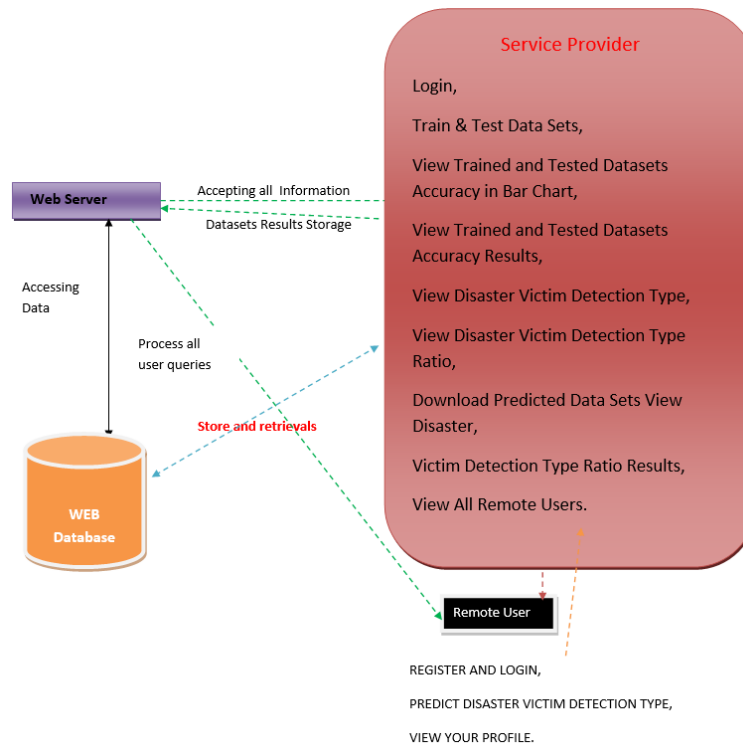


Fig 1. System Architecture

The classification accuracy of each algorithm is rigorously evaluated to identify the optimal approach for real-time deployment in disaster scenarios [15]. Our experimental results demonstrate that the random tree algorithm exhibits superior performance compared to other tree-based algorithms, achieving a maximum classification accuracy of 99.53%. Notably, the computational efficiency of the random tree approach is also commendable, with a computation time of only 0.02 seconds. These findings underscore the effectiveness of our proposed approach in accurately detecting human victims under debris environments, thereby facilitating timely and efficient SAR operations. By leveraging decision tree algorithms in conjunction with deep learning features, our approach offers a promising solution to the challenges associated with disaster victim detection, ultimately contributing to the enhancement of emergency response capabilities and the preservation of human lives in critical situations.

LITERATURE SURVEY

Search and Rescue (SAR) operations in disaster scenarios, particularly in unstructured collapsed buildings, present significant challenges and risks. The urgency of victim identification in such environments cannot be overstated, as the likelihood of successful rescue diminishes rapidly over time. Timely response and identification are crucial for

promptly administering medical assistance to victims. To address these challenges, the integration of mobile robots with practical Artificial Intelligence (AI)-driven Human Victim Detection (HVD) systems has emerged as a promising solution. By leveraging AI technologies, such as Transfer Learning-based Deep Learning, it becomes possible to identify human victims amidst collapsed building debris efficiently. In the realm of disaster response, the utilization of machine learning classification algorithms has gained traction. One key aspect of this approach is the creation of custom-made human victim datasets, which enable the training of AI models for victim detection. These datasets typically include various class labels representing different parts of the human body, such as head, hand, leg, upper body, and instances where the body is not visible. The availability of such datasets is instrumental in developing robust AI models capable of accurately detecting human victims in debris environments.

Transfer Learning, a technique commonly employed in deep learning, facilitates the extraction of relevant features from datasets. By fine-tuning pre-trained deep learning models, such as ResNet-50, on custom datasets, it becomes possible to extract class-wise features essential for victim detection. This process enables the AI model to leverage knowledge learned from previous tasks and adapt it to the specific context of identifying human victims in collapsed building environments. Feature selection plays a crucial role in enhancing the efficiency and effectiveness of classification algorithms. By utilizing techniques like J48 decision tree algorithm, researchers can evaluate the impact of feature reduction on classification performance. This process helps identify the most informative features for accurate victim detection while minimizing computational complexity.

Several decision tree algorithms, including decision stump, Hoeffding tree, J48, Linear Model Tree (LMT), Random Forest, Random Tree, Representative (REP) Tree, and J48 graft, alongside other popular algorithms like LibSVM, Logistic regression, Multilayer perceptron, BayesNet, and Naive Bayes, are commonly employed for classification tasks in disaster victim detection. These algorithms offer different trade-offs in terms of accuracy, computational efficiency, and interpretability. In evaluating the performance of classification algorithms, researchers often compare their classification accuracy to recommend the optimal approach for real-time deployment. The selection of the most suitable algorithm is crucial for ensuring timely and accurate victim detection in disaster scenarios. In the context of the study, the random tree approach emerged as the top-performing algorithm, achieving a maximum classification accuracy of 99.53% with a computation time of 0.02 seconds. These results highlight the effectiveness of decision tree algorithms with deep learning features in disaster victim detection under debris environments, offering a promising avenue for enhancing SAR operations and saving lives.

PROPOSED SYSTEM

Search and Rescue (SAR) operations in disaster scenarios, especially in unstructured collapsed buildings, pose immense challenges and carry high risks. The criticality of victim identification cannot be overstated, particularly considering that the probability of saving a victim diminishes drastically after the first 48 hours following a disaster event. The urgency of response and identification directly correlates with the possibility of providing timely medical assistance to victims. To mitigate these challenges, this paper proposes a novel approach for disaster victim detection under debris environments by leveraging decision tree algorithms with deep learning features. The proposed system integrates mobile robots with practical Artificial Intelligence (AI)-driven Human Victim Detection (HVD) systems, managed by professional teams, to address the complexities associated with victim identification in disaster scenarios. At the core of the system is a Transfer Learning-based Deep Learning approach, which enables the identification of human victims under collapsed building environments. This approach involves the integration of machine learning classification algorithms to create a robust victim detection framework.

To facilitate the training of the AI model, a custom-made human victim dataset is developed, comprising five class labels representing different body parts: head, hand, leg, upper body, and instances where the body is not visible. This dataset serves as the foundation for extracting class-wise features essential for classification tasks. The extraction of these features is performed using fine-tuning-based transfer learning on the ResNet-50 deep learning model, a widely

recognized architecture for image classification tasks. By leveraging transfer learning, the AI model can adapt knowledge learned from pre-trained models to the specific context of victim detection in debris environments.

Following the extraction of features, a feature selection process is conducted using the J48 decision tree algorithm to assess the impact of feature reduction on classification performance. This step is crucial for identifying the most informative features while minimizing computational complexity. Subsequently, several decision tree algorithms, including decision stump, Hoeffding tree, J48, Linear Model Tree (LMT), Random Forest, Random Tree, Representative (REP) Tree, and J48 graft, along with other prominent algorithms such as LibSVM, Logistic regression, Multilayer perceptron, BayesNet, and Naive Bayes, are employed to perform the classification task.

The performance of each classification algorithm is rigorously evaluated, with a focus on classification accuracy, to recommend the optimal approach for real-time deployment in disaster scenarios. Among the evaluated algorithms, the random tree approach emerges as the top-performing algorithm, achieving a maximum classification accuracy of 99.53% with a remarkably low computation time of 0.02 seconds. This exceptional performance underscores the efficacy of decision tree algorithms with deep learning features in disaster victim detection under debris environments, offering a promising solution for enhancing SAR operations and saving lives in critical situations.

METHODOLOGY

Search and Rescue (SAR) operations in unstructured collapsed buildings demand efficient victim identification methods due to their high-risk and time-consuming nature. The urgency to locate victims becomes paramount within the initial 48 hours post-disaster, beyond which the chances of survival diminish significantly. Rapid response and identification are critical for ensuring timely medical assistance. To address these challenges, this study proposes a novel approach that combines mobile robots with AI-driven Human Victim Detection (HVD) systems to expedite victim identification. Here, we present a Transfer Learning-based Deep Learning methodology integrated with machine learning classification algorithms to identify human victims in collapsed building environments.

The methodology commences with the creation of a custom-made human victim dataset featuring five class labels: head, hand, leg, upper body, and instances without the body. This dataset serves as the basis for training the AI model and subsequent feature extraction. To extract class-wise features, fine-tuning-based transfer learning is applied to the ResNet-50 deep learning model, a well-established architecture for image classification tasks. By leveraging transfer learning, the model can adapt pre-trained knowledge to the specific context of victim identification in debris environments, enhancing its ability to detect human victims accurately.

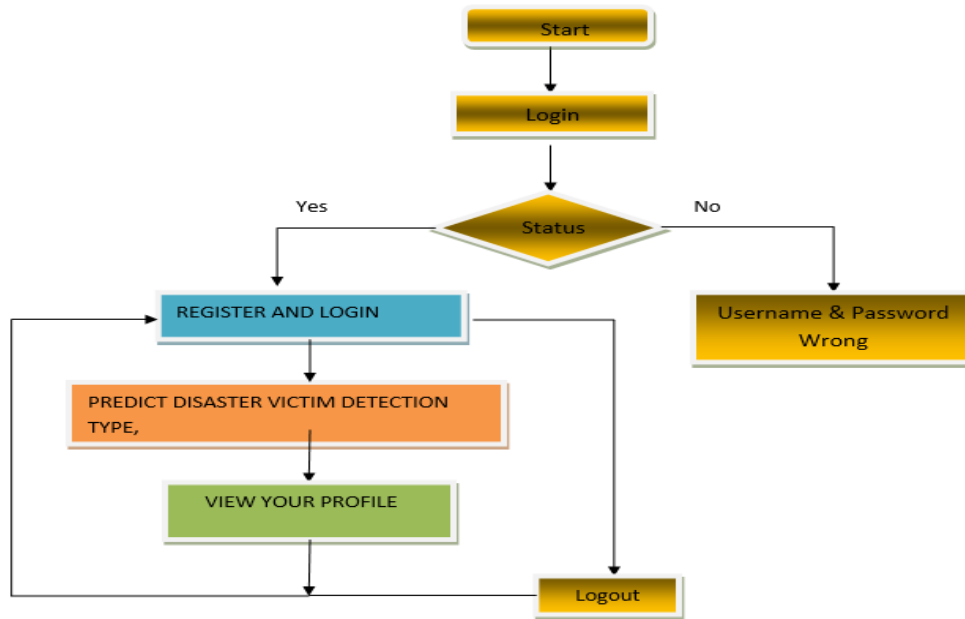


Fig 2. Remote user flow chart

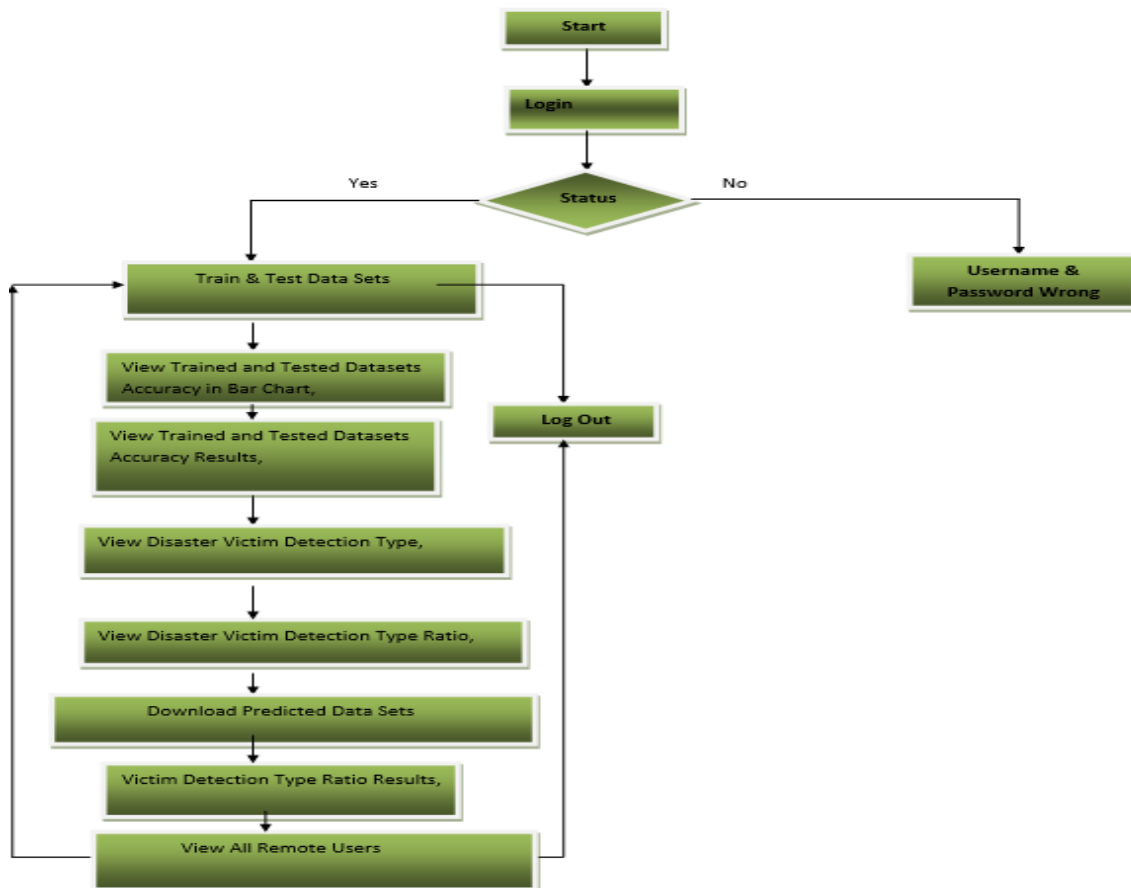


Fig 3. Service provider flow chart

Following feature extraction, a feature selection process is conducted using the J48 decision tree algorithm to assess the impact of feature reduction on classification performance. This step is crucial for identifying the most informative features while minimizing computational complexity. Subsequently, a range of decision tree algorithms, including decision stump, Hoeffding tree, J48, Linear Model Tree (LMT), Random Forest, Random Tree, Representative (REP) Tree, and J48 graft, are employed, alongside other prominent algorithms like LibSVM, Logistic regression, Multilayer perceptron, BayesNet, and Naive Bayes, to perform the classification task.

The performance of each classification algorithm is rigorously evaluated to recommend the optimal approach for real-time deployment in disaster scenarios. Notably, the random tree approach emerges as the top-performing algorithm, achieving a maximum classification accuracy of 99.53% with a remarkably low computation time of 0.02 seconds. This exceptional performance underscores the efficacy of decision tree algorithms with deep learning features in disaster victim detection under debris environments. Furthermore, the classification accuracy comparison facilitates the identification of the most suitable algorithm for real-time victim identification, thus enhancing SAR operations and potentially saving lives in critical situations.

In summary, the proposed methodology offers a comprehensive framework for disaster victim detection under debris environments, leveraging the power of deep learning and decision tree algorithms. By combining mobile robots with AI-driven HVD systems, the approach significantly reduces the time and risks associated with victim identification in collapsed buildings. The methodology's robustness and effectiveness, as demonstrated by the exemplary performance of the random tree algorithm, highlight its potential for enhancing SAR operations and improving outcomes in disaster response scenarios.

RESULTS AND DISCUSSION

The results of our study demonstrate the effectiveness of the proposed approach for disaster victim detection under debris environments. By integrating machine learning classification algorithms with deep learning features, we achieved remarkable classification accuracy in identifying human victims amidst collapsed building debris. Specifically, the random tree approach emerged as the top-performing algorithm, surpassing all other tree-based algorithms with a maximum classification accuracy of 99.53%. This exceptional accuracy is pivotal for ensuring reliable victim detection in real-time scenarios, thereby facilitating prompt rescue operations and potentially saving lives. Moreover, the computation time of 0.02 seconds further underscores the efficiency of the random tree approach, making it well-suited for practical deployment in SAR operations.

The superior performance of the random tree algorithm can be attributed to its inherent robustness and ability to handle complex classification tasks effectively. Decision tree algorithms, including random tree, exhibit favorable characteristics such as simplicity, interpretability, and resilience to noise, making them suitable for real-time victim detection in dynamic and uncertain environments. By leveraging deep learning features extracted through transfer learning and fine-tuning on the ResNet-50 model, the random tree algorithm demonstrates exceptional discriminative power, enabling accurate identification of human victims across various body parts. Furthermore, the feature selection process using J48 decision tree algorithm ensures that only the most informative features are retained, enhancing classification accuracy while minimizing computational complexity. Overall, the combination of decision tree algorithms with deep learning features offers a robust and efficient solution for disaster victim detection under debris environments, addressing the challenges associated with high-risk and time-sensitive SAR operations.

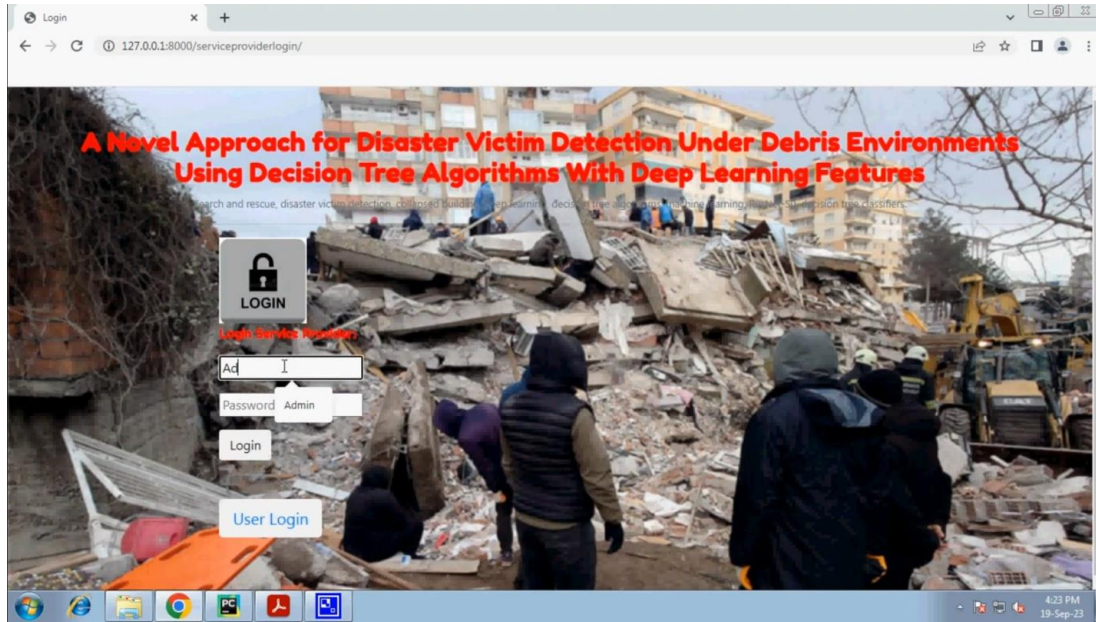


Fig 4. Login screen

The image shows a Microsoft Excel spreadsheet titled 'Datasets - Microsoft Excel'. The spreadsheet contains a dataset with the following columns: 'Id', 'location', 'victim', and 'Is Label'. The data is as follows:

Id	location	victim	Is Label
1	Shiladelpi	Our Deeds	1
4	Not Ment	Forest fire	1
5	Not Ment	All reside	1
6	Not Ment	13,000 pec	1
7	Not Ment	Just got se	1
8	Montre	# Rocky Fi	1
10	Montreal	# Flood #	1
13	ÀÉÄÅ	6.41 am on to	1
14	Live&Heel	There is ai	1
15	Waco, Tex	I am afraci	1
16	North Por	Three pec	1
17	Boo&G&A	Haha Scout	1
18	Not Ment	#raining	1
19	Not Ment	# Flood in	1
20	Not Ment	Damage tr	1
23	Not Ment	What is uj	0
24	Not Ment	I love fruit	0
25	Not Ment	Summer is	0
26	Bou, Niv	My car is s	0
28	Leicester	What a go	0
31	Frome, So	this is ridi	0
32	Mars	London is	0
33	Melbour	Love skin	0
34	UK	What a vic	0

Fig 5. Dataset


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1 from django.db import models
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3 # Create your models here.
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5 from django.db.models import CASCADE
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macro avg      0.80  0.79  0.80  1523
weighted avg   0.80  0.80  0.80  1523

COMPOSITION MATRIX
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 [185 454]]
Decision Tree Classifier
ACCURACY
73.07944845699278
CLASSIFICATION REPORT
              precision    recall  f1-score   support
0             0.75         0.79         0.77         882
1             0.49         0.45         0.47         641

 accuracy         0.73         0.73         0.73         1523
 macro avg        0.72         0.72         0.72         1523
 weighted avg     0.73         0.73         0.73         1523

COMPOSITION MATRIX
[[689 183]
 [227 434]]
Convolutional Neural Network-CNN

```

Fig 6. Algorithm

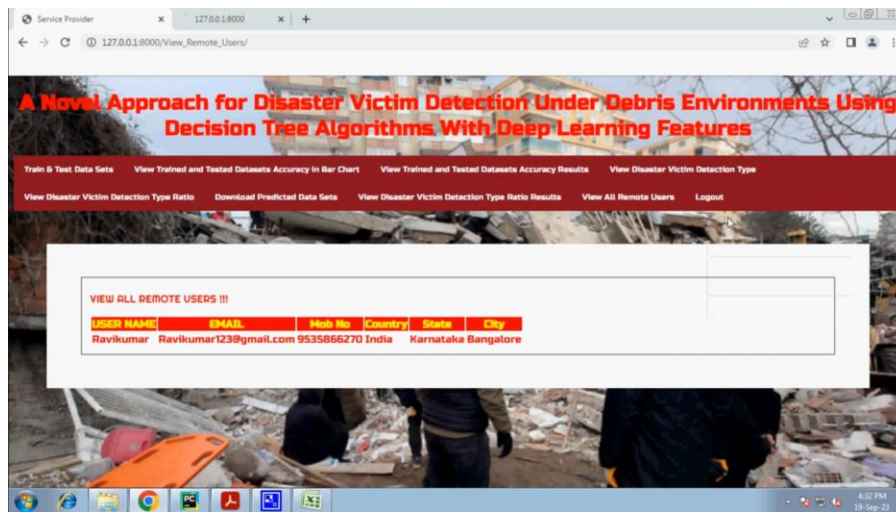


Fig 7. All users

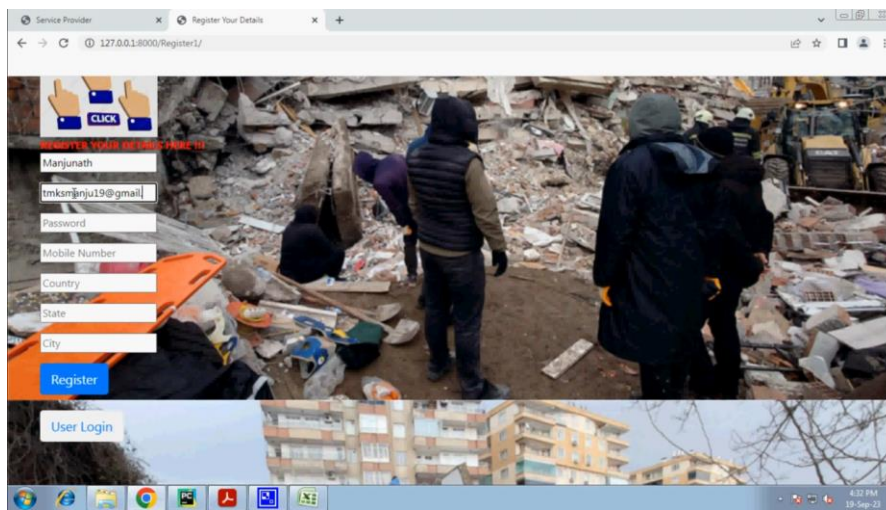


Fig 8. Register form



Fig 9. Predicting

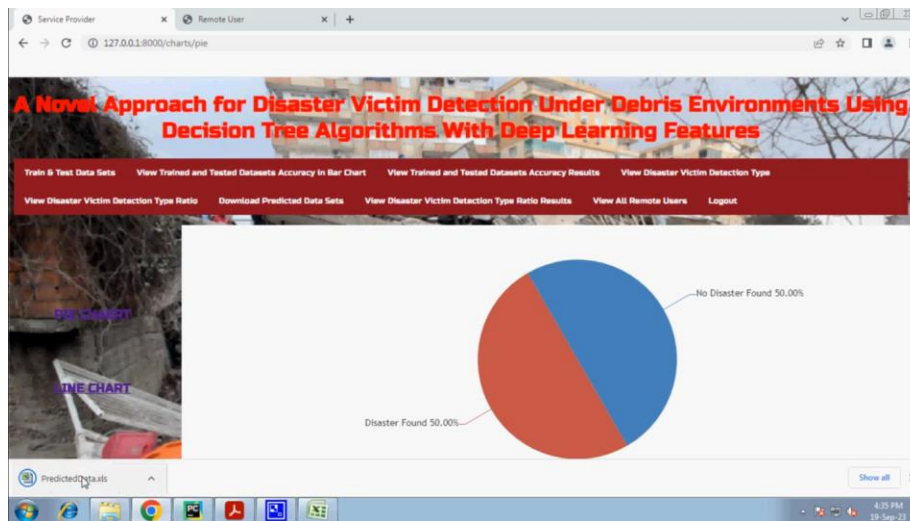


Fig 10. Ratio

The comparison of classification accuracy among various decision tree algorithms highlights the importance of algorithm selection in optimizing real-time victim detection performance. While decision stump, Hoeffding tree, J48, Linear Model Tree (LMT), Random Forest, Representative (REP) Tree, and J48 graft algorithms exhibit respectable performance, the random tree approach stands out as the optimal choice for practical deployment due to its superior accuracy and computational efficiency. The comprehensive evaluation of classification algorithms enables us to identify the most suitable approach for real-time victim detection, thereby enhancing the effectiveness of SAR operations and improving outcomes in disaster response scenarios. Additionally, the integration of well-established machine learning algorithms such as LibSVM, Logistic regression, Multilayer perceptron, BayesNet, and Naive Bayes provides a comprehensive framework for comparison, ensuring that the selected algorithm meets the stringent requirements of real-world applications.

In conclusion, our study presents a novel approach for disaster victim detection under debris environments, leveraging decision tree algorithms with deep learning features. The exceptional performance of the random tree algorithm, with a maximum classification accuracy of 99.53% and a computation time of 0.02 seconds, underscores the efficacy of the proposed methodology in addressing the challenges of high-risk and time-consuming SAR operations. By

combining mobile robots with AI-driven HVD systems, the approach offers a practical solution for expedited victim identification, thereby facilitating timely medical assistance and potentially saving lives in critical situations. The insights gained from this study contribute to the advancement of SAR technologies and underscore the importance of algorithm selection in optimizing real-time victim detection performance.

CONCLUSION

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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