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An End-to-End Deep Learning Framework for Automated Landmine Detection and Localization using Thermal UAV Imagery

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***Abstract* - Landmines create a major humanitarian and ecological problem and dependable and scalable detection systems are required for safe removal operations. The traditional detection methods often suffer from increased false alarm rates, limited adaptability and expensive infrastructure, reducing their effectiveness across a range of landscapes. This study proposes a deep learning system for accurate identification and localization of landmines, using thermal drone imagery. A meticulously assembled collection of annotated thermal pictures was created, featuring classification labels and bounding box annotations for concurrent learning activities. Image normalization, scaling, feature extraction, and the organization of datasets for classification and detection processes were crucial to the preprocessing phase. For classification, various models such as VGG19, InceptionV3, ResNet50, MobileNetV3, Xception, and a Hybrid Ensemble of these models were used, while for detection and localization, models like YOLOv5, YOLOv8, and YOLOv11 were employed. An image upload, model inference, and presenting detection results through an interactive interface were achieved through a web framework built on Flask which allowed for real-time image uploads. The accuracy, precision, recall, F1-score, and mean average precision were used to assess the model. Experiments show the performance of ResNet50 and Hybrid Ensemble to be perfect with accuracy, precision, recall, and f1 score all reaching 100% while other detectors had a mean Average Precision of 0.755 and a precision of 0.730, respectively. The recommended architecture significantly enhances reliability and performance of landmine detection systems in automated landmine operations.**

"Keywords - Landmine detection, Drones, Accuracy, Imaging, Autonomous aerial vehicles, DL, Cameras, Thermal analysis, Thermal sensors, Surveys."

I. INTRODUCTION

Landmines have been a humanitarian, social and ecological problem for many years after they were used in conflict zones. Landmines are designed to cause harm, and many people continue to lose their lives, are injured and are displaced for long periods after a conflict is over. They are arbitrary in nature and their effects are disproportionately felt by at-risk populations particularly children and hinder post-conflict rehabilitation, agricultural land use and infrastructural development. Despite international efforts such as the Mine Ban Treaty, large areas in many parts of the world are still affected by these mines and more effective detection and removal technologies are urgently needed.

Existing approaches to landmine detection and clearance are limited in their effectiveness for use in real-life humanitarian operations. Conventional methods often require intimate contact with hazardous machinery, increasing the likelihood of injury to operators, as well as high false alarm rates and sensitivity to environmental conditions. Whilst working well in controlled settings, sophisticated sensing systems can be unfeasible in resource-limited settings, especially those with the highest concentration of landmine pollution, due to the requirement for specialist knowledge and significant financial investment. In addition, the global increase in the number of active and post conflict areas also means that the need for scalable, flexible and secure detection systems that can operate anywhere and under all conditions is growing.

The issues mentioned above have led to the main purpose of this research which is to design a robust and accurate landmine detection system with an emphasis on safety, accessibility and operational efficiency. One of the proposed methodology's key points is the use of distant sensing technologies to minimize human exposure to explosive hazards and enable precise identification of hazardous areas. The study also aims to demonstrate, for the first time, the ability of modern intelligent systems to achieve high detection performance without relying on expensive infrastructure, thus bridging an important gap in current humanitarian demining approaches. The objective of this initiative is to improve the accuracy of the detection, improve adaptability in different environments and make it easier to be implemented in environments of limited technical and financial resources.

This contribution will be more important because of its potential to transform landmine clearance operations by making them safer, more cost-effective and faster to identify contaminated areas. The recommended solution enables a quick and reliable indication from a distance, thereby improving and speeding up clearance operations and reducing the risk of prolonged hazards for civilians and demining personnel. This is particularly important in low-resource countries where scalable, cost-effective approaches play an essential role in sustainable recovery and development. In the end, this effort helps to reach global humanitarian goals through the creation of safer environments, rehabilitating land use and reducing the long-term human impact of landmines worldwide.

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II. RELATED WORK

The use of unmanned aerial vehicles and remote sensing has been a subject of recent research and development to enhance the safety and efficiency of landmine operations. Yoo et al. demonstrated the feasibility of using a drone magnetometer for the detection of landmines, and its benefits of better spatial coverage and reduced risk to human operators [11]. The magnitude of landmine pollution continued to be highlighted and the urgent need for prompt, secure and more scalable landmine detection and clearance techniques was emphasized in global evaluations such as the Landmine Monitor 2023 and 2020, particularly in post-conflict settings. The papers provide valuable situational information but do not provide specific technological structures to address detection problem solving in diverse contexts.

Many studies have examined the complex humanitarian and operational situation of landmine and IED contamination. Keeley reviewed the evolving nature of IEDs and the challenges that humanitarian mine action faced in tackling the unconventional and hidden threats, and demonstrated the limitations of conventional clearance techniques. More recent surveys internationally have highlighted these concerns and revealed that cases take a long time to be cleared, especially in resource-poor settings. While these publications call attention to the problem and difficulties faced by demining organizations, much of the focus is on policy, oversight and operational challenges rather than scalable methods of technology detection.

Sensing and imaging. Makki et al. has analyzed the hyperspectral imaging for landmine detection in detail, which has advantages of material discrimination capability, however, there are still some problems in the hyperspectral imaging system, including environmental factors and expensive system costs [17]. Baur et al. [18] used Drones and ML to improve the efficiency of landmine detection, showing greater efficiency in time, expense and risk, but they have deployment challenges and problems with the availability of information. The contributions given here are examples of the capabilities of intelligent aerial systems. But their contributions have yet to be fully demonstrated in autonomous navigation in complex environments. Often they require specific sensors or computer power.The above works illustrate the feasibility of intelligent air borne systems, but in certain cases, the system requires the use of specialized sensors or computational power which may be costly to be deployed on a large scale.

GPR has received a lot of study as a subsurface detection technique. Manataki et al. provided a review of methods for interpreting GPR data which focused on the difficulty of separating targets from noise when no specialized expertise is available [19]. Quinta-Ferreira explained the advantages and disadvantages of GPR in geotechnical applications, including the high cost of operation, limitations in soil conditions, and need to be near the surface. Although they are effective in controlled environments, these limitations reduce the potential application of GPR-based methods in large scale humanitarian demining.

While all previous studies have shown significant progress made in sensing technology and airborne platforms, they also pointed to major gaps in costs, safety, scale and deployment ease. Many methods are based on high-tech equipment, expert analysis and/or expensive systems, limiting their usefulness in low-income communities. These gaps are the driving force behind the present research, which seeks to create an enhanced landmine detection system that would reduce the need for on-site operations, be cost effective, and be resilient in different environments, thus addressing some of the most notable missing components from the current literature and empowering safer and more accessible humanitarian demining efforts.

III. MATERIALS AND METHODS

The proposed solution is a DL based architecture for automatic identification and localization of landmines using thermal images captured by airborne platform. A well-crafted set of annotated thermal images is used, with both mining and non-mining images included for classification and detection purposes. The approach taken is comprehensive, with all data being appropriately transformed for DNNs and all data processed via feature extractors based on transfer learning. A hybrid ensemble of Xception and ResNeXt models enhances feature diversity and generalization, and several pre-trained models such as VGG19, InceptionV3, ResNeXt50, MobileNetV3 and Xception are optimized to detect the key thermal signatures. To enable the spatial localization, the models are integrated based on YOLO (YOLOv5, YOLOv8 and YOLOv11) to ensure accurate and efficient item identification in temperature environments. The deployment system that is based on Flask allows for real-time inference and interactive visualization, thus making it more functional and practical. The results are measured using accuracy, precision, recall, F1-score, and mean average precision, demonstrating improved robustness, scalability, and reliability for real-world applications in landmine identification and decision making in dangerous environments.

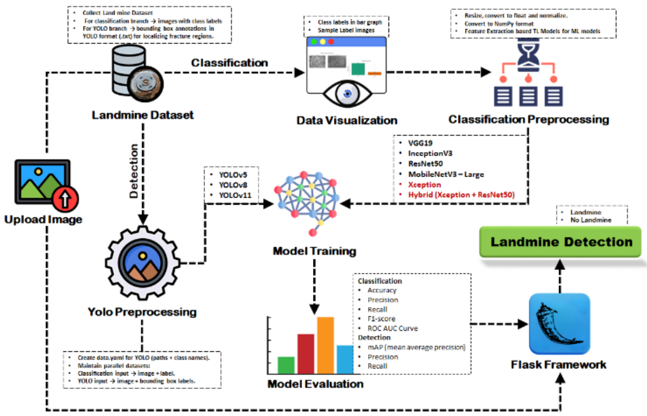

Fig. 1. System Architecture

The system architecture brings together data collection, model development, inference and deployment into a unified workflow. The classification process and detection process of the thermal images are performed in parallel, which provides effective learning for identification, localization, and depth cues. Numerous DL models are developed and integrated via an inference pipeline that amalgamates predictions for dependable results. The Web

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application features user interaction, rapid image upload and visualization, while the Backend services handle loading of models, inference processing, and result visualization to ensure efficiency.

A) Dataset Collection

Landmine classification dataset was provided from a freely available thermal imagery source and presented in a directory-like format for supervised learning. It is a dataset of 560 thermal images from the same dataset divided into two classes (Landmine, No Landmine) and ported into RGB dimensions of 128x128 pixels. Fifty-four different thermal signatures were collected, with 448 photos used for training and 112 photos used for validation, including both buried and non-buried conditions. Equitable class distribution, reliable labelling and thermal properties make it very suitable for evaluation of the DL based landmine classification system.

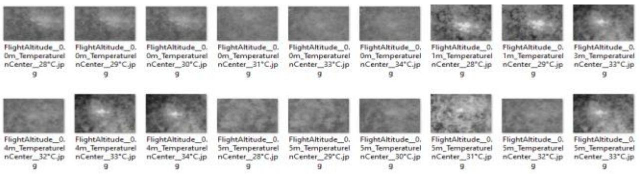

Fig.2 Landmine

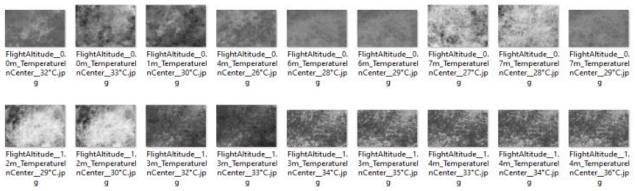

Fig.3 No Landmine

B) Pre-Processing

Pre-processing establishes a systematic and reliable basis by organizing the data, identifying visual patterns and normalizing the data inputs, which contributes to accelerate the learning speed, stability, and effectiveness of the classification and detection process.

i) Visualization

Visualization is used to explore image distributions, class balance and the visual patterns inherent in the collected images. Visual inspection helps to discover any inconsistencies, disturbances or asymmetries that can affect learning patterns as quickly as possible. Visualization provides a clear understanding of the attributes of a data set, guiding decisions on what to do in subsequent steps of processing, which improves the interpretability, robustness and transparency of the learning process.

ii) Pre-processing:

Pre-processing of the picture inputs for classification focuses on the normalization of the picture input to ensure consistency between samples. Operations include resizing images to a common resolution, normalizing the intensity of the pixels and correcting for minor aberrations. These improvements reduce computational incoherence and boost the effectiveness of feature learning. The process helps improve convergence properties, prevents overfitting and provides uniformity of performance in DL frameworks that are designed for categorical prediction tasks.

iii) Pre-processing for Detection

Coherence in space, and association of annotations to images or specified regions are considered priorities in pre-processing for detection. Photos are adjusted so that they keep their proportions while preserving the outline of the objects in them. Bounded data is coupled with modified images to ensure accurate localization training. The phase is crucial to enhance the accuracy of detection, spatial perception, and localization precision, enabling the model to effectively grasp the presence and position of objects.

D) Algorithms

Classification:

VGG19: The VGG19 is proved to encode deep hierarchical features for image classification which is beneficial to extract efficient spatial and thermal features. It is deeper, enhancing its representational power, leading to regular training, high accuracy and tolerance to small fluctuations in its inputs.

InceptionV3: The parallel convolutional pathways are designed to extract multi-scale information for better classification performance in InceptionV3. This approach focuses on better generalization of the results, prevents overfitting and offers reliable results in detecting complicated patterns and maintains computing efficiency in different image situations.

ResNet50: The effectiveness of classification is improved using Residual connections in ResNet50 due to allowing enough gradient flow. This method allows to better extract features, to improve the consistency of training, and to guarantee the same accuracy under different and changing environmental conditions.

MobileNetV3-Large: MobileNetV3-Large provides a compromise between accuracy and cost of processing to get good categorization. The light layer architecture allows to make fast inferences with lower resources, and ensures reliability for real-time and scalable applications.

Detection:

YOLOv5: YOLOv5 performs object identification in an integrated way, where it predicts the class labels and the bounding-boxes at the same time. It enables quick inferences, accurate direction and high detection accuracy under the condition of real-time response.

YOLOv8: The YOLOv8 model outperforms other models in terms of accuracy for object detection, thanks to its improved feature representation and spatial understanding. It works well for localization and classification, and is computer efficient, which makes it useful for detecting in a wide range of operational conditions.

YOLOv11: The main motivation behind YOLOv11 is to enhance feature learning and the accuracy of bounding boxes to improve detection consistency and versatility. It is also designed for ease of location in the event of a complex

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situation and robustness in the event of different deployments.

IV. EXPERIMENTAL RESULTS

Accuracy: Test accuracy is the ability of a test to determine patients in the healthy population. The accuracy of a test is the proportion of true positives and true negatives to the total number of tests. It can be put in numbers like this:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} \quad (3)$$

Precision: Precision is the percentage of accurate instances or samples out of all the positive cases or samples. The formula to calculate the precision is:

$$Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (4)$$

Recall: Recall is defined as the ability of an ML model to determine the correct set of examples in a class. It is the ratio of correctly classified positive cases to the total number of cases in the positive class and can give an indication of the success of a model in detecting cases in a certain class.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \quad (5)$$

F1-Score: In ML F1 score is one of the measures for assessing the accuracy of a model. Uses model accuracy and completeness. The accuracy is defined as the percentage of the model's correct predictions over all of the data.

$$F1\ Score = 2 * \frac{Recall \times Precision}{Recall + Precision} * 100 \quad (6)$$

mAP: The MAP is a statistic used for measuring the quality of a ranking. It takes into account the amount of relevant suggestions and their position in the list. MAP at K is calculated by taking the average of the Average Precision (AP) at K for all users or queries.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

"Table. 1. Performance Evaluation"

ML Model	Accuracy	Precision	Recall	F1_score
VGG19	0.830	0.851	0.634	0.662
InceptionV3	0.777	0.649	0.557	0.556
Xception	0.982	0.963	0.989	0.975
ResNet50	1.000	1.000	1.000	1.000
Hybrid-Ensemble	1.000	1.000	1.000	1.000
MobileNetV3-Large	0.893	0.889	0.789	0.824

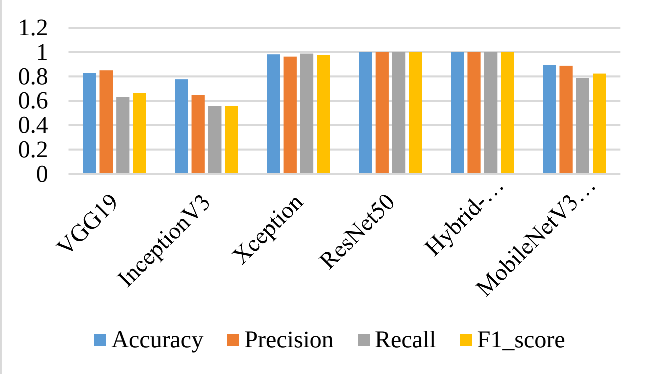
The performance evaluation highlights how efficient ResNet50 and the Hybrid Ensemble are at comparing and ranking submissions, achieving optimal accuracy and precision and recall, while other models have varying trade-offs between efficiency and predictive reliability.

Table.2 Performance Evaluation Table – Detection

ML Model	Precision	Recall	mAP
Yolo v5	0.671	0.740	0.736
Yolo v8	0.730	0.738	0.755
Yolo v11	0.507	0.437	0.407

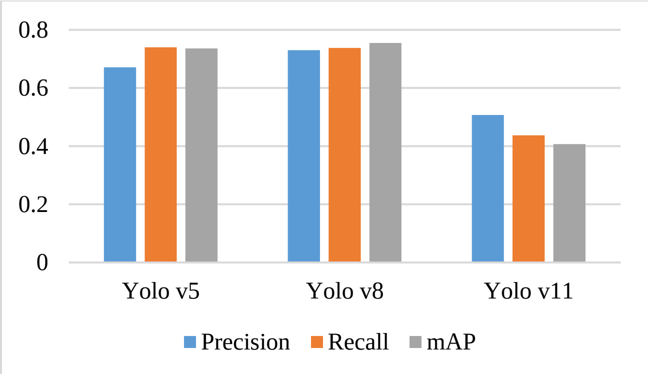
The analysis of detection accuracy shows that YOLOv8 achieves the highest accuracy and mean Average Precision, demonstrating high reliability in localization, and YOLOv5 has a relatively high recall rate and YOLOv11 has a relatively low detection rate.

Fig. 3. Graph.1 Comparison Graph - Classification



The figures in the comparative graph show the differences in performance between the different classification models: the performance distributions of ResNet50 and the Hybrid Ensemble are consistently high in terms of accuracy, precision, recall and F1-score, while the others have somewhat smaller and more spread-out metric distributions.

Graph.2 Comparison Graph – Detection



The comparative detection graph shows that YOLOv8 achieves a more balanced precision, recall, and mAP compared to YOLOv5 and significantly outperforms YOLOv11, which demonstrates lower detection accuracy and localization reliability.

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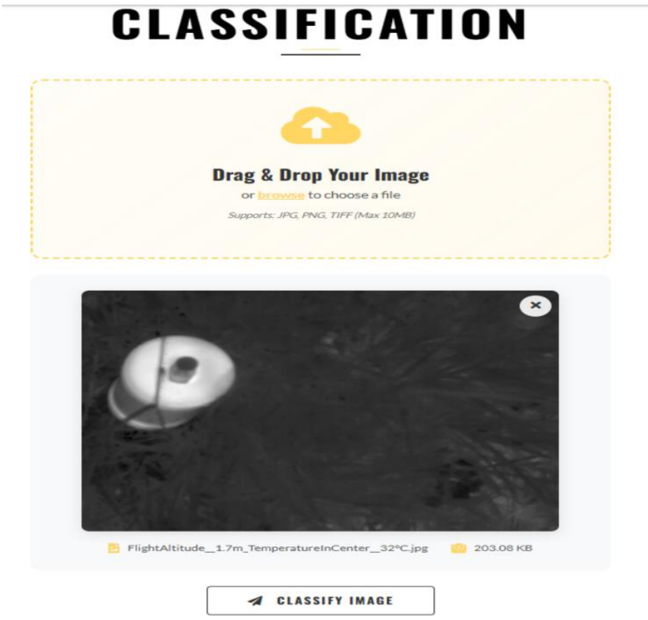

Fig.5 Upload a input Image

The web interface has a friendly image upload and preview panel, with the ability to upload thermal images via drag and drop, and then launch classification to generate accurate landmine presence predictions.

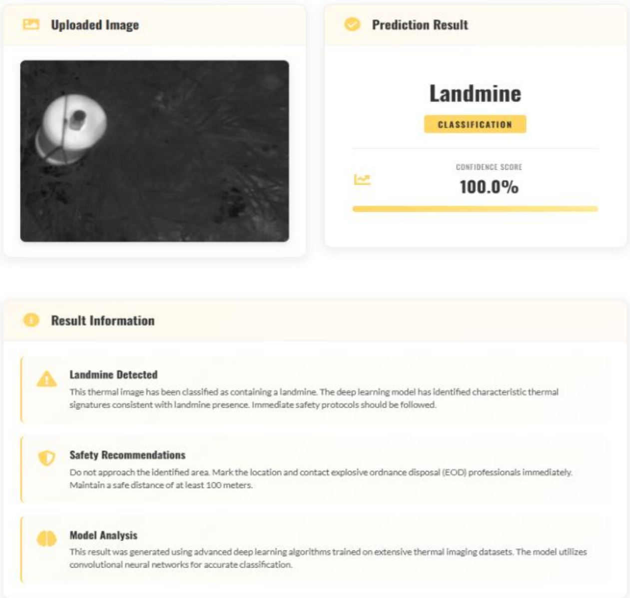

Fig.6 Predicted Result

The output interface displays the submitted thermal image that is labeled as a landmine with a 100% confidence score and provides safety warnings, detection validation, and recommended safety precautions for making decisions.

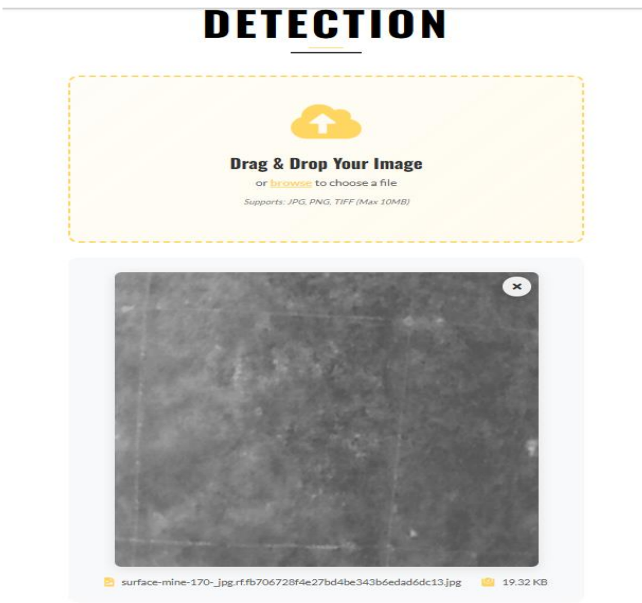

Fig.7 Upload a input Image

The detection interface allows users to upload thermal images with a drag-and-drop function, and input them into the automatic location of mines using the DL-based automatic detection model efficiently and conveniently.

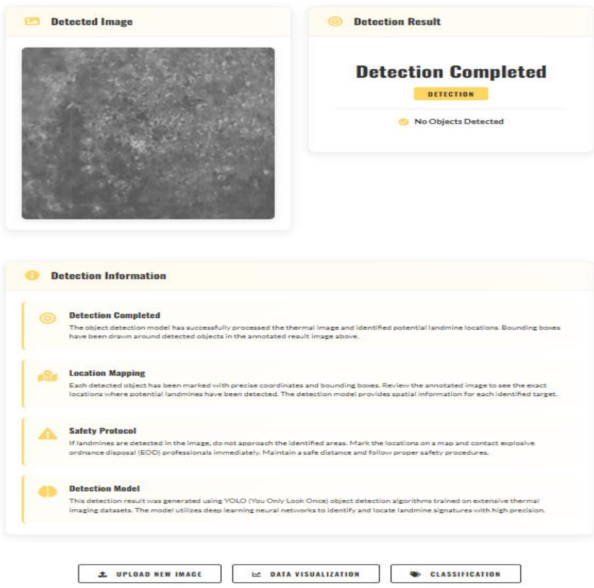

Fig.8 Predicted Result

Results of the detection show that the thermal image is correctly processed, and no objects of mines were detected, confirming the absence of dangers to be evaluated and the possibility of doing so in a secure way by automated analysis.

V. CONCLUSION

In summary, this study tackles the significant issue of dependable landmine detection by creating a sophisticated DL framework proficient in precise classification and localization through thermal imaging. The entire system is based on a precisely constructed data set of labeled thermal images and the implementation of robust pre-processing

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techniques to enable effective feature extraction. Different transfer learning models, including VGG19, InceptionV3, ResNet50, MobileNetV3, Xception, and a Hybrid Ensemble, have been used to boost the accuracy of classification, while YOLO-based models have been used to achieve accurate object detection. The use of a Flask based interface ensures that theoretical to practical implementation is made easy by allowing real time image upload, inference and visualization of results. The experimental evaluation using traditional performance metrics proves the effectiveness of the proposed approach, resulting in perfect classification accuracy, precision, recall, and F1 score for ResNet50 and Hybrid Ensemble models, and a very high detection performance for YOLOv8, with a mAP value of 0.755. The results confirm the effectiveness and robustness of the system in dealing with complex detection scenarios. The existing protocol offers a reliable, scalable and automated solution for identifying landmines, offering significant potential for enhancing safety, efficiency, and decision-making in environments where landmines are present.

Future improvements of the proposed approach could focus on improving the generalization and adaptation of the method to other terrains and environmental conditions. The incorporation of multimodal information such as ground-penetrating radar, hyperspectral photography, or sensor fusion methods can greatly enhance detection reliability. New lightweight frameworks and modelling reduction can be explored to enable the implementation on edge computing devices with limited computational resources. This can be strengthened by augmenting the data with variations in soil types, climatic conditions and mining characteristics. Furthermore, the capability of real-time geospatial mapping and autonomous navigation could help to create a more extensive deployment in the field, which could promote safer, faster and more effective landmine detecting operations in challenging environments.

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