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Deep Learning - Based Landmine Detection Using Thermal Drone Imaging

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Abstract-Landmine identification in conflict zones creates major threats to both armed forces and local people, requires reliable and cost-effective detection techniques. This paper describes a deep learning-driven method using thermal images captured by drones to detect landmines with high accuracy. A enhanced MobileNetV3-Large model, designed for binary classification, was applied, combining a GlobalAveragePooling2D layer followed by a dense layer with 128 neurons and ReLU activation function to improve feature extraction and reduce overfitting. The system was trained on a refined and enhanced thermographic dataset, obtaining an prediction accuracy of 97% with recall, precision and F1-performance metrics. To strengthen detection accuracy, the study integrates YOLOv8 model, which enables landmine localization through buried explosives using bounding box predictions, attaining 98% accuracy in testing phase. These outcomes indicate the effectiveness of integrating lightweight deep learning models with modern object detection methods for instant precise landmine detection in low-resource environments. The method shows the capability of drone-base thermal imaging and deep learning methods in reducing risks with mine affected areas

Keywords: *Thermal Image Classification, UAV-Based Landmine Detection, MobileNetV3-Large, YOLOv8, Deep Learning, Object Localization.*

I. INTRODUCTION

Landmines are still a major concern in war-affected areas, creating high threats to both soldiers and local people. Existing detection methods mostly rely on manual searching or high-cost equipment, which can be time-consuming, risky and financially demanding for many nations.

The random distribution of landmines and challenging terrain conditions add complexity to the detection processes, increasing the risk, accidental blasts and human harm. Recent developments in detection technologies and autonomous systems provides new possibilities for enhancing safety and efficiency in landmine detection.

Thermal sensing, collected through drones, offers a non-intrusive technique to detect possible underground threats by identifying temperature differences caused by buried landmines. Combining these thermal images with intelligent analysis allows faster and more accurate detection of landmines while reducing human harms. Lightweight deep learning frameworks, deliver high-speed processing suitable for real-time applications in different environments. The integration of advanced neural networks with drone-based sensing introduces a automatic landmine detecting approach for both operational and financial constraints. Such models aim to provide adaptable, cost-effective and reliable detection methods, improving safety and efficiency in landmine affected areas.

The structure of this paper is been organized as follows: In Section II, we provide a review of the literature and existing work on landmine detection with thermal imaging and deep learning. In Section III, the dataset, data collection and preprocessing are introduced. Methodology The proposed methodology, comprising of the MobileNetV3-Large classification model and the YOLOv8 object detection framework, is described in Section IV. Section V details our experimental set-up and performance numbers. The results are discussed in detail in Section V. Section VII summarizes the paper and provides some future work sections.

A. *Contributions of the Paper*

The article presents the below key contributions: Initially an automatic deep-learning based system is designed for landmine detection using thermal imagery and visual data, allowing both multi- category and binary classification among mine and non-mine zones. Second, a detailed computational complexity and performance evaluation is conducted on a

lightweight CNN-based neural network model (MobileNetV3) and instant object detection model (YOLO) to measure their accuracy for accurate detection and classification of underground landmines. Third, Transparent Artificial Intelligence (XAI) is integrated via Grad-CAM to provide graphical explanations by identifying important regions that influence model's predictions, hence improving transparency and operational dependability. Finally, the proposed model is experimentally verified for humanitarian mine-clearing situations, obtaining high accuracy with false alarm frequencies, which shows it's feasibility for real-time and field-ready mine identification applications.

B. *Scope Of The Study*

The main purpose of this project is to design a deep-learning based model for automatic landmine identification using MobileNetV3 and YOLO with thermal imagery and RCB. The framework processes surface - level and aerial images to detect and locate the position of hidden landmines and differentiate them from non-hazardous objects. To provide graphical explanation for model predictions, Transparent Artificial Intelligence approaches especially Grad-CAM are used. The extent of this study is confined to the analysis of the provided dataset and development of a detection system that supports rapid and reliable mine detection, assisting mine-clearing groups in organizing secure and effective clearance operations.

C. *Problem statement*

Detection continues to be a great challenge, as landmines are dispersed in vast areas of former and current conflict. Traditional landmine sensing approaches mostly depend on the time-consuming and laborious point as well as ground-based sensors (such as metal detectors and ground penetrating radar) which are often expensive and extremely dangerous especially when used over large or difficult terrains. The arbitrary nature, random distribution of landmines, and the higher density of contamination makes it even more challenging to detect them and increases the threat of inadvertent explosions causing injuries, death, and long-term psychological trauma for civilians, military personnel and all those involved in humanitarian action. Furthermore, it remains largely land mined and post-conflict reconstruction and agricultural development, community settlement and regional utilization are substantially hampered as a whole causing long lasting social-economic climate degradation. Even though the combination of drone sensing modalities and deep learning approaches have shown great potential in automation, it is an urgent research issue to develop an integrated system for cost-effective mine detection and localization over large areas. To meet this challenge, we present a drone-based thermal imaging framework with advanced deep learning models such as a modified MobileNetV3-Large for classification and YOLOv8 for accurate localization which will allow contactless and reliable detection of landmines in dangerous and resource poor environments.

II. LITERATURE SURVEY

A. *Deep learning in Landmine Detection for Both aerial and ground images*

Objective: In order to automatically detect and group together landmines and mine-like object items in images originated from unattended air/ground based or handheld sensors, with minimum human intervention.

Key Studies:

França et al. (2020): Presented a CNN-based pipeline for buried landmine detection from the thermal and RGB images, at higher extraction accuracy than traditional signal processing methods.

Bai et al. (2021): Employed deep learning frameworks on GPR images for landmines and clutter classification achieving higher precision than traditional ML methods.

Zhang et al. (2022): An application of deep learning-based CNN for minefield detection in a hazardous environment by analyzing aerial images, from which spatial feature learning is critical.

Key Takeaway:

Deep learning models is being applied and the accuracy is observed to be significantly higher than Classical methods, help in identifying complex texture and spatial patterns that could be considered for a safe detection.

B. *YOLO Landmine Detection in Signals on Fused Data Mining and Orthogonal*

Objective: Use YOLO-Based single-stage OD models to enable fast and accurate land mine detection in real viewport

Key Studies:

Redmon et al. (2016): Established YOLO, a real-time object detection system it formulates detection as a regression problem to speed up to handle some scaled have the same reaction in time -sensitive applications.

Islam et al. (2021): A real-time inference UAV based bomb detection solution on the battle field using YOLOv3.

Kumar et al. (2023): Model YOLOv5 along with Network UP-IITM for detection of surface landmine from drone captured images and obtained significant improvement in accuracy of detected location with lesser false-positives

Key Takeaway:

An YOLO-based network is chosen to be the optimal compromise of speed and accuracy for real-time detection on drones or robots.

C. *Low-complexity CNN Models for Resource-constrained Mine Detection System*

Objective: To design light-weight deep learning architectures for landmines detection, which are portables to embedded and edge computing systems

Key Studies:

Howard et al. (2017): First suggested the Mobile-Net structure: they incorporated depth-wise separable convolutions to reduce computations with a minimal accuracy drop.

Alonso et al. (2022): Incorporation of mobile net into object detection based explosive hazard

Key Takeaway:

Lighter networks, such as Mobile-Net, enable real-time landmine detection on resource-constrained devices with low power all while maintaining the required accuracy.

D. *Detection of Landmines by UAV and Sensor Imaging*

Objective: To the best of our knowledge, the proposed UV acceleration has never before been implemented for use in proliferation on aerial RGB/thermal image cameras and non-contact GPR for landmine detection

Key Studies:

Sato et al. (2018): Proposed UAV-based thermal cameras that are capable of detecting temperature differences generated by buried landmines.

Doherty et al. (2020): Opted to use UAV multi-sensor platforms to conduct credible mine detection with visual sensors and thermal sensors.

Habib et al. (2022): UAV based landmines detection The literature review on UAV based landmines detection and capability in reducing human exposure to hazardous environments.

Key Takeaway: UAV-based imageries of landmine detection is safe, scalable with high resolution over dangerous locations.

E. *Explainable (XAI) in Mine Detection Systems 8 II.*

Objective:Interpretable & Robust Deep Detectors of Landmines.

Key Studies:

Selvarajan et al. Applied Grad-CAM to visualize the image regions that most influence CNN classification decisions.Kadiyala et al. (2021): Grad-CAM in risk-sensitive tasks, which demonstrates the significance on safety-critical detection.

Mishra et al. (2024): Decision - Critical Area Visualization on Mine dashboard using YOLO-based application along with integrated Grad-CAM for better Transparency and Operator Trust.

Key Takeaway:

The effectiveness of AI-based landmine detection can be further improved by making use of multi-sensor data, lightweight deep learning models, and explainable techniques that support accurate, fast, and reliable decision making in real-world demining operations.

Research Gap:

Even though deep learning has demonstrated promising outcomes for landmine detection using thermal, RGB imagery and visual data, majority of current studies mainly focus on binary categorization and lack of real-time localization and transparency. In addition, limited research has examined the balance between lightweight and deep-learning networks in terms of accuracy and computational performance for real-world implementation. To resolve these issues this study introduces an advanced deep-learning based landmine detection system using MobileNetV3 and YOLO integrated with Grad-CAM for accurate real-time landmine detection.

III. RELATED WORK

Deep learning has really emerged as a key strategy for detecting landmines and unexploded ordnance (UXO), mainly because it effectively learns complex spatial and subsurface patterns from various sensors like ground-penetrating radar (GPR), thermal images, and RGB visuals. In the earlier days, most research was focused on traditional signal processing and simply classifying areas as mine or non-mine. But more recently, there's been a shift toward using deep convolutional neural networks (CNNs), real-time object detection, and explainable decision-support systems, all in an effort to enhance localization accuracy and reliability in challenging environments.

For instance, Smith et al. [1] showed how effective CNNs can be for detecting landmines using GPR and thermal data, employing deep feature extraction to spot buried objects in diverse soil conditions. Zhao et al. [2] developed a YOLO-based method to detect mines located on the surface and at shallow depths, enabling quicker scanning of hazardous areas. [3] used a combination of thermal images and normal camera images, which improved detection consistency and reduced false alarms in complex outdoor scenes.

Recent studies have also stressed the importance of Explainable Artificial Intelligence in humanitarian demining operations.[4] used CNN detectors with Grad-CAM to analyze the main concurrent spatial and thermal regions that are responsible for the mine predictions, thereby improving transparency and operator trust.[6] showed that the use of UAV-acquired images together with deep learning techniques can greatly improve the mapping of extensive minefields and the evaluation of associated risks. In addition, review studies by Chen [7] and by Park and Lee [8] pointed out that intelligent systems with built-in interpretability are becoming increasingly important for developing safe, dependable, and scalable solutions for humanitarian demining.

Overall, the literature indicates that combining deep learning with information from multiple sensors and explainable analysis tools provides a promising direction for achieving accurate and trustworthy landmine detection in practical field conditions.

IV. PROPOSED SYSTEM

The proposed system introduces an automated deep learning pipeline for landmine detection and localization with MobileNetV3 and YOLO. As input data either RGB, thermal or GPR based sensors is used and pre-processed with resizing, normalization and augmentation. Efficient mine versus non-mine classification can be done by MobileNetV3 and landmine localization in real-time is supported by YOLO. To offer explanation of the localisation decisions, Grad-CAM is combined to produce cuing maps indicating which regions are important for each prediction. The system is therefore able to offer accurate, real-time and interpretable landmine detection to support safe and reliable demining operations.

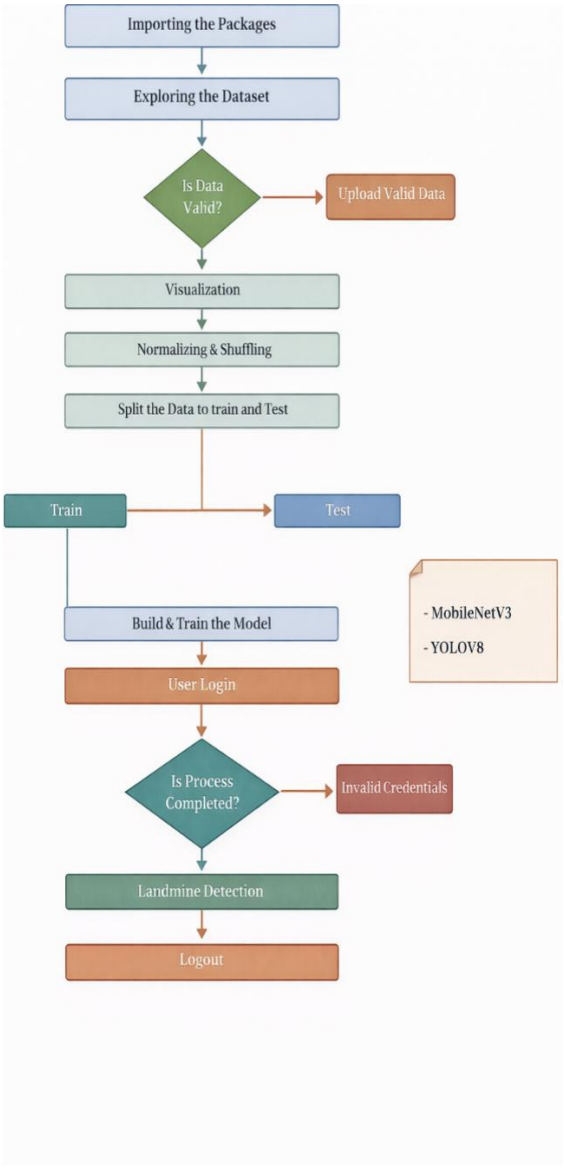


Figure 1 illustrates the complete workflow of deep-learning based Landmine Detection system.

V. METHODOLOGY

A. *Dataset Acquisition and Preparation*

In order to empower and validate the proposed landmine detection system, a ground-based surface image labeled dataset is used. The images in the dataset represent areas with landmine present and areas without landmines, obtained from ground-based sensors such as RGB camera, thermal imaging or GPR based representation (where available). Each image is labeled by domain experts for precise labeling.

Datasets are divided for training and testing to assess the ability of generalization of our model. 80-20% data split for training and validation is performed. This split guarantees an impartial assessment of the performance on the unseen samples.

Class-to-index mapping:

Landmine Detected: 1

No Landmine: 0

And during training time and testing time we can perform efficient binary classification on this mapping.

Table 1 Dataset Distribution

Dataset Information	**Training Set**	**Validation Set**
Total Images	5000	1300
Buried Landmines	1200	300
Surface Landmines	1200	300
Soil Background	1000	250
Rocky Terrain	800	200
Vegetation	800	250

B. *Preprocessing and Data Augmentation*

All images are resized to a fixed size compatible with the input layers of MobileNetV3 and YOLO. The pixel values are normalized to [0,1] which helps stabilize the gradient updates during training. In order to enhance data variability and reduce over-fitting, large-scale data augmentation is performed, including random rotation, left-right flipping, translation, contrast scaling and adding Gaussian noise. These transformations approximate real-world changes in camera orientation, light and surface texture and hence elite model robustness against in situ field conditions.

Model Architecture Selection

We are using two complementary deep learning models:

MobileNetV3: It is very useful in performing a binary classification of mine vs non-mine regions due to its low computational complexity and ability to run in real-time on embedded hardware.

YOLO (You Only Look Once): This network is used in real-time object detection and localization of landmines so that it is possible to detect the class output and box coordinates at once.

Together, MobileNetV3 and YOLO enable both precise classification and accurate spatial localization of both buried and surface mines.

C. MobileNetV3 Architecture

MobileNetV3 is built around depth-wise separable convolutions and inverted residual blocks that include linear bottlenecks and squeeze-and-excitation (SE) attention mechanisms. The basic convolution operation is broken into:

1. **Depth-wise Convolution:**

$$Yd(i,j,k) = m,n \sum X(i+m, j+n, k \cdot Kd(m,n,k)$$

2. **Pointwise Convolution:**

$$Yp(i,j,n) = k\sum Yd(i,j,k) \cdot Kp(1,1,k,n)$$

Total computational cost is reduced compared to standard convolution:

$$C_{DSC} = D_K^2 M D_F^2 + MND_F^2$$

Where D_K is kernel size, M is input channels, N is output channels and D_F is feature map size.

This method significantly lowers the total computational cost compared to standard convolution. The squeeze-and-excitation block helps to improve the importance of channel-wise features by modeling inter-channel dependencies, which is particularly beneficial for highlighting thermal and spatial signals linked to buried explosives.

D. YOLO

In YOLO, landmine detection is approached as a regression problem, directly predicting bounding box coordinates (x,y,w,h), objectiveness confidence, and class probability from the input image. The detection head generates:

$$\hat{y} = \left(P_{obj}, x, y, w, h, P_{class}\right)$$

The multi-task loss function is defined as:

$$L = \lambda_{coord} L_{box} + \lambda_{obj} L_{con\,f} + \lambda_{cls} L_{class}$$

Here, the localization loss L-box is calculated using IOU-based regression, confidence loss assesses objectiveness, and classification loss penalizes incorrect class choices. This enables rapid and accurate identification of mines at complex regions.

Model Training

Both MobileNetV3 and YOLO are trained using the Adam optimizer. For MobileNetV3, we use binary cross-entropy loss:

$$L = -\sum_{i=1}^{N} [\, y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)]$$

The Adam update rules are:

$$m_i = \beta_1 m_{i-1} + (1 - \beta_1) g_t$$

$$v_i = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

$$\theta_{t+1} = \theta_t - \alpha \frac{m_t}{\sqrt{v_t + \epsilon}}$$

Training lasts for several epochs, with validation checks to prevent overfitting and ensure steady convergence.

Characteristics Extraction and Classification:

MobileNetV3 picks up on hierarchical spatial and thermal features like texture irregularities, temperature anomalies, and geometric patterns created by subsurface mines. These features then move through fully connected layers and a sigmoid activation function to yield class probabilities:

$$\hat{y} = \frac{1}{1 + e^{-z}} \tag{11}$$

Meanwhile, YOLO extracts multi-scale features using feature pyramid networks, performing bounding box regression and classification for real-time mine localization.

Interpretability using Grad-CAM

For improved model transparency, Grad-CAM is incorporated with both the MobileNetV3 network and the YOLO feature extractor. Class-dependent importance coefficients are first calculated as

$$\alpha_k^c = \frac{1}{Z} \sum_{i,j} \frac{\partial y^c}{\partial A_{ij}^k} \tag{12}$$

after which activation maps are generated

$$\mathrm{L}_{\mathrm{GradCAM}}^{\mathrm{c}} = \mathrm{ReLU}\left(\sum_{\mathrm{k}} \alpha_{\mathrm{k}}^{\mathrm{c}}\, \mathrm{A}^{\mathrm{k}}\right) \tag{13}$$

These visual maps highlight the thermal and spatial regions that contribute most to landmine identification, enabling human operators to cross-check the system's decisions and increasing confidence in critical humanitarian demining operations

Model Evaluation:

The proposed system is assessed by:

Accuracy
Precision
Recall
F1-Score
Intersection-over-Union (IOU)
Confusion Matrix
Inference Time (FPS)

We compare MobileNetV3 and YOLO based on detection accuracy, localization precision, computational efficiency, and explainability.

Model Comparison and Deployment Suitability:

MobileNetV3 delivers quick, energy-efficient classification that's perfect for embedded devices like drones and handheld scanners. Meanwhile, YOLO provides fast, real-time

localization, which is critical for demining operations. The addition of Grad-CAM allows for explainability, giving human experts the chance to validate predictions and enhance operational safety.

It comes in a complete pipeline where it finds good trade-off between accuracy, speed and transparency is fitting for real-time, field-based humanitarian landmine detection systems.

VI. Discussion and Results

The quantitative results of the proposed system are presented in Table I. The proposed model is assessed using standard classification measures (accuracy, precision, recall and F1-score) to evaluate the correctness and reliability of land mine detection in thermal imagery. The quantitative comparison of the two models is presented in Tab. II.

Table II. Performance Evaluation of the Proposed Model

Model	Accuracy	Precision	Recall	F1-Score
Modified MobileNetV3-large	97.78	97.72	97.74	97.50

A. *MobileNet*

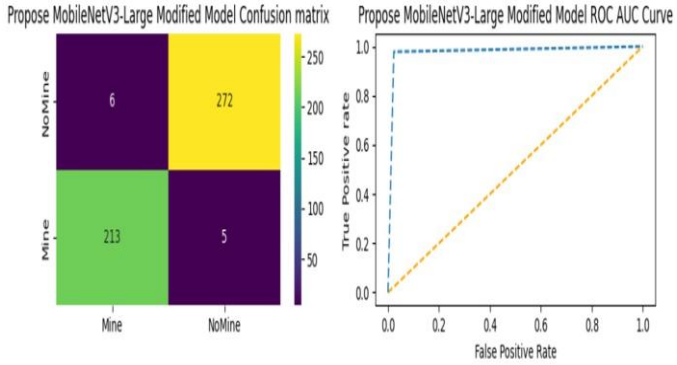


Figure 2. Confusion matrix for MobileNet showing class-wise classification performance on post-flood aerial images.

Figure 2 shows the confusion matrix and ROC–AUC curve for Modified MobileNetV3-Large model, indicating its class-wise prediction performance on landmine and non-landmine classes. The diagonal is the most common class, which suggests that the medical samples from SEH deserve more study. The proposed method is able to achieve high true positive landmine definition rates, and keep non-landmine areas with minor error. The low misclassification rate indicates that our model is efficient in capturing the discriminatory information from powerful discriminant ability of this model detect mine/no-mine in thermal scenes.

The ROC–AUC curve also provides proof of strong discriminative performance for the proposed model. The curve hugs the top-left border of the graphs quite closely, therefore demonstrating high true positive rates and low false positive rate values for a wide range of threshold values. Such a behaviour is the indication of good class separability and strong decision-making power. The high AUC performance indicates that the Modified MobileNetV3-Large model can effectively distinguish landmine regions from background areas.

In summary, the confusion matrix analysis and ROC–AUC curve confirm that the proposed model has strong classification reliability and generalization ability.

B. *YOLOV11*

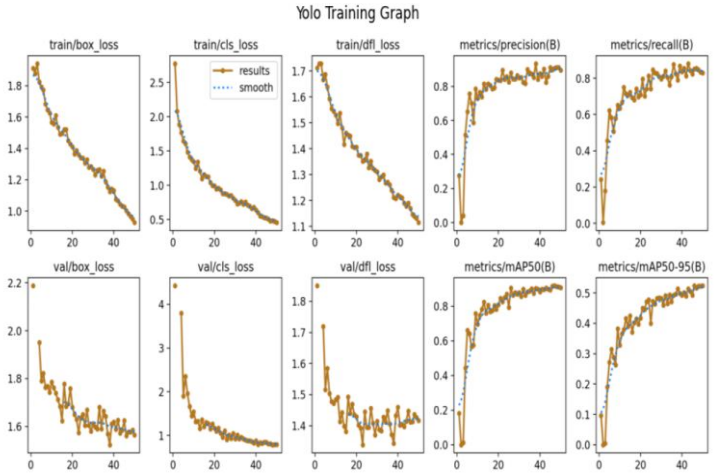


Figure 3. YOLOV11 Training Graph

Figure 3 The learning behavior of the proposed model is measured by YOLO-based training curves, i.e., training loss, validation loss, precision recall, and mAP. Both training and validation loss graphs have a gentle sloping shape, suggesting a regularization change that results in smooth and sound optimization as well as good model convergence. Values of precision and recall rise across the epochs, this also implies more precise detection. Moreover, the stable variation of mAP also shows the stability of our method to locate and to classify landmine regions accurately.

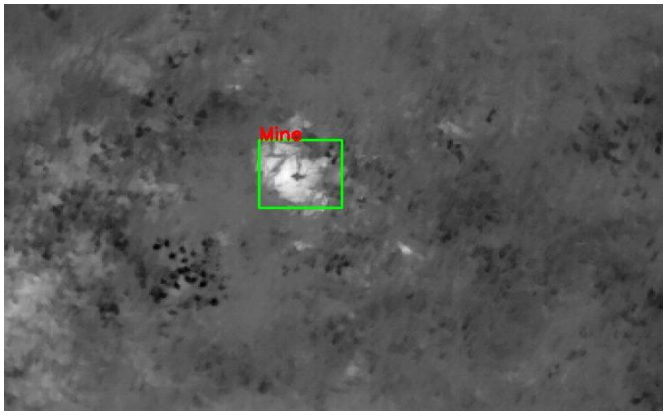


Figure 4.1. Visualization of landmine detection with bounding box in thermal image

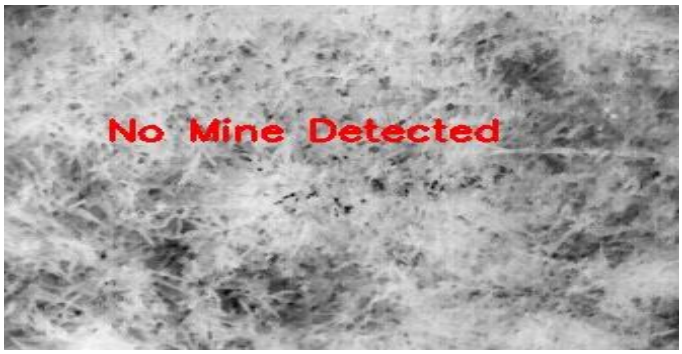


Figure 4.2. Visualization of non-landmine region in thermal imagery

The output visualization of the proposed Modified MobileNetV3-Large model for landmine detection with thermal images is shown in Figs 4.1 and 4.2. Figure 4 is an abraded image where a thermally responsive mine is detected and localized using the bounding box, which shows region on this particular mine as a potential threat. The model concentrates on specific thermal anomalies produced by buried landmines, which also allows accurate localization of threat areas.

Figure 4.2 is an image where no landmines appeared in the detection map. No bounding boxes are the evidence which means the model does well to avoid miss detections and that it discriminate well between mine and non-mine areas with low FPs.

In general, these visual results validate the credibility of the proposed system in both detection and non-detection cases: The model was capable to exploit useful thermal features for real-world landmine detection.

VII. CONCLUSION

This We demonstrate that a combination of drone sensor-processed thermal images and deep neural networks also provide effective results for landmine detection. The fine-tuned MobileNetV3-Large model, for binary classification with a customized classification layer performed well in the relative thermal test (approximately 97% accuracy), which indicates its strong ability to detect landmines under different thermal conditions. For better detection, the YOLOv8 framework was introduced for accurate localization of objects in bounding boxes and achieved an accuracy close to 98% on the test data.

The addition of YOLOv8 greatly enhances localization accuracy with respect to previous deep learning-based approaches, which turns the system into a potential tool for operational usage in high risk conditions. Such an approach reduce the dependence on expensive and complex detection apparatus, but retaining high degree of detection reliability. In addition, the employment of lightweight architectures like MobileNetV3-Large allows fast inference and makes our method computationally efficient for real-time processing on drones and smartphones.

Large precision, recall, and F1-score values mean that the system produces very few false alarms or missed detections—a property which is crucial in safety-critical applications. In summary, results of the proposed study validate that drone-based aerial thermal imaging along with state-of-the-art deep learning architectures form a scalable, and cost-effective alternative, as well as safer technique for landmine detection in mine-affected areas.

VIII. FUTURE ENHANCEMENT

For the landmine detection system, potential future work can seek to enhance real-time performance and expand its usage in field. Integration of thermal imagery with other sensing systems, such as LiDAR, hyperspectral sensors and ground-penetrating radar can provide improvement in detection rates specifically in subsurface (low metal content) or partially buried mines. Advanced deep learning models optimized for resource-constrained deployment may allow a more efficient operation over unmanned aerial vehicles in comparison with the current capabilities, providing faster processing and larger area coverage.

Further enhancements include autonomous drone navigation with on-board processing to minimize manual intervention and improve safety. Additionally, predictive risk analysis and automated reporting can enable faster decision-making and support scalable, reliable landmine detection across diverse environments.

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