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Thermal-Image Landmine Detection using MobileNetV3 and YOLOv8 Ensemble Deep Learning

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Abstract: Post-conflict landmine detection requires precise and implementable solutions in resource-constrained scenarios. In this work, thermal pictures captured by drones with infrared sensors are used to identify landmines using ensemble deep learning. To improve safety-critical reliability, the suggested system combines a lightweight MobileNetV3 classifier with a YOLOv8 object detector. Thermal pictures are preprocessed and enhanced to improve resistance against background, lighting, and mine appearance, and the dataset is split into training, validation, and test sets for fair evaluation. While YOLOv8 is taught to identify suspected mines using bounding boxes, MobileNetV3 is designed for binary mine/no-mine classification by transfer learning. To reduce false negatives in humanitarian demining, an ensemble technique integrates the predictions of both models. Experimental results show that the ensemble outperforms the individual models in terms of safety-oriented parameters for thermal imaging detection quality, accuracy, precision, and recall. The study found that a lightweight ensemble of MobileNetV3 and YOLOv8 on thermal images can improve aircraft landmine identification in real-world circumstances.

Index terms *- — YOLOv8, thermal drone imaging, object detection, deep learning, real-time detection, Flask web application, UAV-based monitoring, bounding box detection, hazardous area identification, and landmine localization*

1. INTRODUCTION

Landmines, one of the worst war leftovers, continually threaten civilian lives and socioeconomic progress. There are millions of landmines and explosive bombs underground, inflicting environmental damage, deaths, and injuries. Deminers risk their lives and time to find landmines using metal detectors, trained animals, and physical probing. Researchers have worked at safer, more advanced landmine detecting technologies to overcome these constraints. Early research showed that innovative biological sensing devices may identify explosive residues without human intervention [1].

Landmine detection research have increased due to remote sensing advances. Multispectral and hyperspectral imaging can identify surface and shallow-buried landmines by detecting minor spectral variations between disturbed soil and the rest of the environment [2]. Synthetic aperture radar (SAR) aboard UAVs can detect hidden landmines with lower risk and more coverage than ground-based sensors [3]. Unmanned and robotic humanitarian demining is more appealing since hovercrafts and robotic vehicles with mine detecting sensors may pass through dangerous areas [4].

In recent years, deep learning has become a strong tool for problem solving using extensive sensor data and boosting recognition precision. CNNs can detect discriminative information in aerial and thermal pictures, making them useful for landmine detection. Landmines' heat-retaining and material structure creates a temperature differential between soil and thermal pictures, making thermal imaging appealing. However, even deep learning-based landmine detection systems lack datasets, cannot be controlled by environmental impacts, are more likely to give false negatives, and require lightweight trained models that can be implemented on UAV platforms with minimal processing power.

Real-world observations of landmines show that one channel or sensory model cannot perceive them. Instead, hybrid and ensemble deep learning techniques should integrate model capabilities to improve resilience and safety-oriented performance measures [5]. Based on these findings, this research proposes an ensemble deep learning framework for thermal-image-based landmine identification using a lightweight MobileNetV3 classifier and YOLOv8 object detector. Combining classification and detection outputs and employing UAV-acquired thermal imagery decreases false negatives and improves humanitarian demining accuracy and efficiency.

2. LITERATURE SURVEY

a) Advancements in Landmine Detection: Deep Learning-Based Analysis With Thermal Drones:

In order to improve safety and effectiveness in demining operations, improvements in detecting technology are required due to the widespread hazard of landmines in conflict-affected areas. Furthermore, as many conflict-affected areas lack the financial resources or technological infrastructure to implement costly and sophisticated detection technologies, the creation of a solution that can be used successfully in both resource-rich and resource-poor situations is crucial. In this research, a deep learning-based method for landmine identification using unmanned aerial vehicles with thermal imaging sensors is presented. By utilizing the MobileNetV3-Large architecture and expanding upon it, we suggest a machine learning model that is both lightweight and powerful, which may be viewed as a quick, safe, and economical way to identify landmines. Using a special dataset of 2,700 thermographic photos taken by a DJI Matrice 100 drone equipped with a Zenmuse XT infrared camera, we assessed our method. We overcome one of the main obstacles in landmine identification by improving the model's capacity to generalize across various terrains and mine types through careful data pre-processing and augmentation techniques. Our model's assessment on a carefully selected test set shows encouraging results, with training accuracy of 96.97%, validation accuracy of 97.19%, and test accuracy of 96.14%. These measures show the model's ability to outperform existing thermal techniques in actual demining operations, in addition to demonstrating its efficacy in finding landmines from thermal photos. This encourages the use of deep learning technology and unmanned aerial vehicles to address environmental and humanitarian issues.

b) UAV-based detection of landmines using infrared thermography:

In areas of the world afflicted by violence, landmines continue to pose a serious concern, killing innocent people. Remarkably, somebody person is killed by these deadly explosives every ninety-five minutes (Landmines Monitor 2022 2022), with a large percentage of victims being innocent bystanders. Landmine detecting techniques now in use are ineffective, expensive, and dangerous for both the operator and the integrity of the system. In order to uncover these concealed threats, we offer a new, practical, safe, and economical method in this study. Our suggested technique combines a thermal camera and an unmanned aerial vehicle (UAV) to take high-resolution pictures of minefields. After that, these photos are sent to a base computer, where a cutting-edge image processing technique is used to determine whether landmines are present. Notably, our method achieves an amazing detection accuracy of over 88% and operates very well, especially in the nighttime. When compared to current approaches that are limited by their design constraints, these results show a great deal of potential.

c) Deep learning-based detection of surface and buried landmines:

The local community frequently has to learn to live with the fear of landmines, which are explosive weapons that can lie dormant for years and have catastrophic repercussions. Landmine removal, or even just locating them, is hazardous and difficult operation that frequently calls for expensive machinery and highly qualified personnel. In order to make it simpler and faster to locate landmines and enable communities to live without being at risk from them, rapid, dependable, and easily accessible procedures are needed. This study explores the potential applications of innovative thermography and machine learning (ML) techniques for the detection of hidden and surface landmines. It also draws attention to important environmental issues related to picture acquisition and the precautions that should be taken to reduce the possibility of getting photos that may be challenging to utilize. A realistic and difficult dataset is utilized to evaluate an ML model that uses a Convolutional Neural Network (CNN) and YOLOv8 to determine how well it can find landmines in infrared (IR) photographs. The CNN predicts the right answer 92.31% of the time, yielding impressive results that highlight the potential of this innovative approach.

d) How to Implement Drones and Machine Learning to Reduce Time, Costs, and Dangers Associated with Landmine Detection:

Unpiloted aerial systems (UAS), sometimes known as drones, and deep learning algorithms are two quickly developing technologies that are transforming scientific problem solving.One These two technologies are combined in our work to provide a potent auxiliary tool for the identification of scatterable landmines. Due to their tiny size, unpredictable minefield direction, and vast area of impact upon deployment, these bombs have historically presented difficulties for clearance efforts. In order to quickly evaluate large regions for landmine contamination, minefield direction, and potential minefield overlap, our previous work concentrated on creating a dependable UAS that could detect and identify individual components of

PFM-1 minefields. We created and implemented a machine learning workflow utilizing a region-based convolutional neural network (R-CNN) in our most recent proof-of-concept research to automate the detection and classification process, attaining a 71.5% detection success rate.Two In further experiments, we increased the size of our dataset and raised the CNN's detection accuracy of PFM-1 anti-personnel mines from visual (RGB) UAS-based footage to 91.8%. The purpose of this study is to acquaint the demining community with the advantages and disadvantages of unmanned aerial systems (UAS) and machine learning, and to propose the use of these technologies as a crucial supplementary first-look area reduction method in humanitarian demining operations. As part of this endeavor, we want to offer comprehensive guidance on how to apply this method for area reduction and non-technical survey (NTS) assistance of verified and suspected hazardous areas with the least amount of funds and resources.

e) Comparing Surface Landmine Object Detection Models on a New Drone Flyby Dataset:

Traditional landmine detecting techniques are costly, hazardous, and time-consuming. Due to the tiny, soda-can-sized surface landmines that have lately become common, using deep learning-based object recognition algorithms on drone footage is intriguing but presents a number of difficulties. Since the majority of object detection research focuses on the analysis of ground video surveillance pictures, there is presently no scientific evaluation of the best machine learning models for this problem in the literature. We initially build a bespoke dataset using drone photos of POM-2 and POM-3 Russian surface landmines to aid in the training of comprehensive models and promote research for surface landmine identification. We train, test, and compare four distinct computer vision foundation models—YOLOF, DETR, Sparse-RCNN, and VFNet—using this dataset. For drone photos obtained from 10m AGL, all four detectors perform well overall, with YOLOF leading other models with a mAP score of 0.89 and DETR, VFNET, and Sparse-RCNN mAP values all around 0.82. Additionally, YOLOF takes 56 minutes to train on an Nvidia V100 computing cluster. Lastly, this study provides landmine image, video, and model datasets to facilitate further surface landmine detection research.

3. METHODOLOGY

i) Proposed Work:

The proposed method uses thermal images from UAV-mounted infrared cameras to identify landmines using ensemble deep learning. The system uses a binary classifier based on MobileNetV3 and a YOLOv8 object detector to handle a range of detection problems. Thermal pictures from UAV surveys are scaled, normalized, and data are added to improve resilience under different soil and ambient conditions. MobileNetV3 is perfect for resource-constrained airborne platforms since it uses global feature extraction and quick mine/no-mine classification, whereas YOLOv8 uses bounding box predictions to identify possible landmines.

The suggested approach uses ensemble fusion to integrate the predictions of both models in order to improve the reliability of safety-critical humanitarian demining. An OR-based ensemble method flags a landmine whenever either model identifies a threat, maximizing recall and minimizing false negatives during human clearance operations. For automated surveys, the highest performance, outstanding accuracy, and high-quality identification are achieved by combining MobileNetV3 and YOLOv8 confidence ratings in a weighted Ensemble Average method. Because of its dual-mode ensemble design, the system is safe, accurate, scalable, and useful for real-world UAV-based landmine detection.

ii) System Architecture:

The system design, a modular UAV-based landmine detection pipeline, enables effective data collecting, processing, and decision-making. A drone with a thermal infrared camera takes thermal pictures of possible landmine sites at various heights. In order to boost thermal contrast and lower noise, an image preprocessing module at the ground station or onboard processing unit resizes, normalizes, and enriches the raw thermal pictures. The processed photos are supplied into two concurrent deep learning modules, MobileNetV3 classification and YOLOv8 object identification, for both local object localization and global classification.

An ensemble fusion module combines the results of both deep learning models after inference. While MobileNetV3 assesses whether or not a mine is present, YOLOv8 generates bounding boxes with confidence scores for landmines that are discovered. Ensemble techniques, which employ fail-safe OR logic for maximum recall and weighted averaging for best accuracy, are used to integrate these predictions. Operators get detection warnings, annotated thermal pictures, and confidence metrics from the final judgment module. This architecture enables real-time speed, scalability, safe deployment, and resource-efficient UAV platforms in humanitarian demining operations.

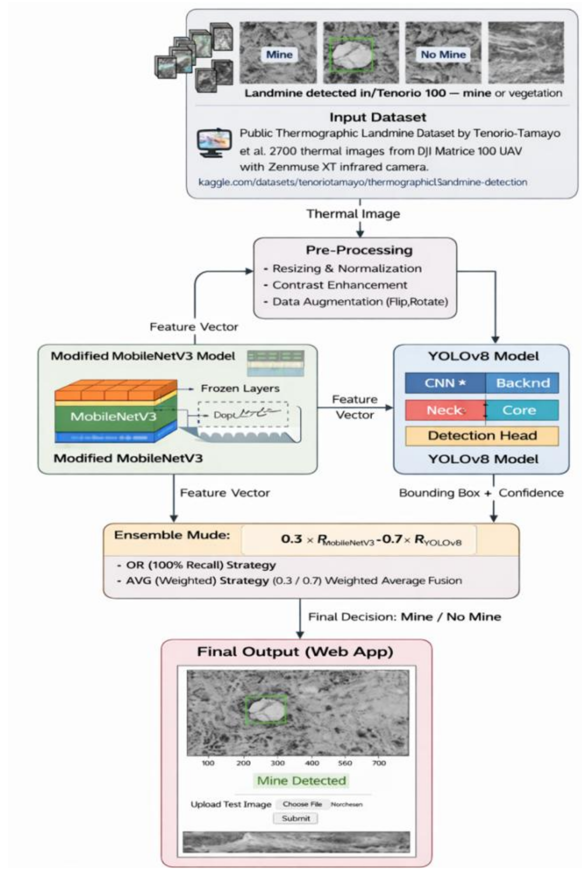

Fig1 proposed architecture

iii) Modules:

1. Data Acquisition Module

In this module, a UAV equipped with an infrared camera records a thermal image of the area. It supplies the system with a realistic input of data by running the mine and non-mine scenarios at different elevation and weather conditions.

2. Data Preprocessing Module

Scaling, normalisation and supplementation of thermal images is done to minimise noise and maximise contrast. This module renders the model resistant to variation in the illumination, temperature of background and soil texture.

3. MobileNetV3 Classification Module

This module model is a fine-tuned MobileNetV3 binary-classifier which is used to identify a thermal image as mine or no-mine. It is lightweight in structure, thus facilitating the process of deployment and inference of low-resource UAV systems.

4. YOLOv8 Detection Module

The bounding boxes and YoloV8 level of confidence are the methods that find landmines. Mine location The information gained in this module entails geographical data to enable safe navigation and clearance.

6. Decision and Visualization Module

The final module generates annotated thermal images, score of confidence, and detection alerts. The findings can be used in decision making of automated landmine survey operators and humanitarian demining.

iv) Algorithms:

1. Modified MobileNetV3-Large (Binary Classification)

MobileNetV3 is a lightweight convolutional neural network that can classify mine and no-mine based on thermal images. The project builds on an already trained MobileNetV3 backbone with transfer learning, global average pooling, and fully connected layers consisting of ReLU-activated and sigmoid-activated layers. This is an appropriate method in extracting discriminative thermal qualities at minimum processing cost that will be employed in the operation of UAVs and edge devices.

2. YOLOv8 (Object Detection and Localization)

YOLOv8 is a single-stage object detector a model used in detecting landmines on thermal images. It needs real-time prediction of bounding box and confidence score that is enabled by mining spatial localization. YOLOv8 with its enhanced architecture is beneficial to enable the use of aerial surveys in real-time and to make an accurate detection and quick inference.

4. EXPERIMENTAL RESULTS

Training, validation, and testing of experimental thermographic landmine data were separated into equal mine and no-mine categories. Accuracy, precision, recall, and reliability detection were some of the safety criteria utilized to evaluate performance. The MobileNetV3 classifier's fit in binary classification, high inference rate, and reproducible results on the validation and test sets made it suitable for usage with lightweight UAVs. Thermal photos showed surface and shallow-buried landmines with YOLOv8 accuracy; however, low contrast circumstances caused a false negative.

Integrating the outputs of the YOLOv8 and MobileNetV3 was necessary to ensure that these flaws were addressed using ensemble approaches. Ensemble OR's 100% recall ensured that no landmine situations were missed during high-risk humanitarian demining operations. Weighted Ensemble Average is more accurate (98.10) than the individual models (MobileNetV3 and YOLOv8 are the best weighted, 0.3 and 0.7, respectively), which made the weighted Ensemble Average approach particularly intriguing. These results show that the ensemble design, which minimizes false negatives and increases detection reliability, has made automated UAV-based land mine surveys more effective and feasible.

Accuracy: A test's accuracy is its capacity to distinguish healthy from ill cases. Find the percentage of instances with genuine positives and negatives to assess test accuracy.

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: Classification accuracy or positive cases constitute precision. The formula for accuracy is:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

Recall: A model's recall measures its ability to recognize all appropriate machine learning class instances. The ratio of accurately predicted positive observations to total positives indicates a model's class instance detection skill.

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

mAP: Mean Average Precision ranks quality. It considers the number and order of relevant ideas. Calculating MAP at K uses the arithmetic mean of each user or query's Average Precision (AP).

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

$$AP_k = \text{ the AP of class } k$$

$$n = \text{ the number of classes}$$

F1-Score: A high F1 score suggests an accurate machine learning model. Integrating recall and precision improves model correctness. Accuracy measures how often a model predicts a dataset correctly.

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

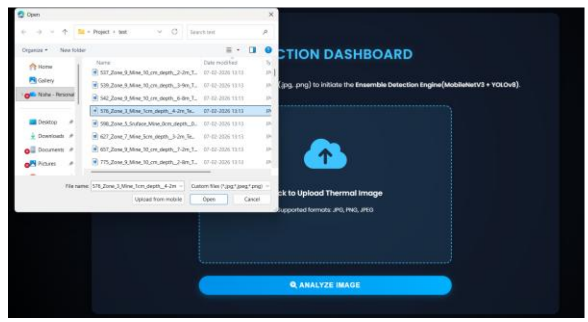

Fig2 Uploaded image

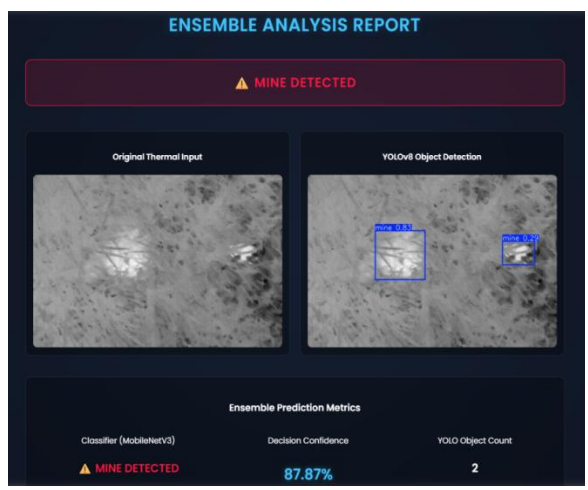

Fig3 Recognized traffic sign

5. CONCLUSION

The study presents a reliable and effective deep learning architecture to identify landmines using

UAV thermal images and a lightweight MobileNetV3 classifier and YOLOv8 object detector for classification and spatial localization. The models operated well under difficult thermal imaging conditions such soil kinds, burial depth, and noise thanks to significant preprocessing, dataset partition, and transfer learning.

The final test data shows that the MobileNetV3 classifier has a high classification accuracy of 95.58, 95.10 precision, 97.14 recall, and 96.11 F1-score, indicating that it can identify landmines. High recall means the model can detect most landmines, which is crucial in a safe humanitarian demining operation.

The YOLOv8 detector has good localization performance with 95.58 precision, 94.17 recall, 94.87 F1-score, and 97.59 accuracy on the test set. The results show that YOLOv8 can identify and localize landmines in thermal photos while balancing accuracy and false alarms.

In general, MobileNetV3 and YOLOv8's combined classification and object detection architecture is reliable and computationally efficient for real-time UAV landmine detection. The proposed approach may be expanded, executed, and adapted to humanitarian demining settings, reducing field operator danger and safety.

6. FUTURE SCOPE

Real-time detection and operational scope can be improved in the landmine detecting system. LiDAR, hyperspectral, and ground-penetrating radar data combined with thermal imaging should enhance mine identification, especially in obstructed or low-metal mines. Advanced deep learning architectures with lightweight optimization will enable quicker and wider coverage on resource-constrained UAVs. An automated drone navigation system with on-board processing reduces human interaction, improving safety. Adding predictive analytics for high-risk zones and automated reporting will speed up decision-making and humanitarian clearance, making landmine detection in various situations safer and more thorough.

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