A2 - Team Business Insight Report: Computing Ground Sign Awareness

Team 1

Patrick Nielsen, Abhishek Rathi, Constantin Wiese, Nithin Babu, Lidia Schwarz

MBAN Dual Degree, Hult International Business School – SF Campus

DAT-7471: Business Analysis with Unstructured Data

Professor Thomas Kurnicki

04/08/2024

Word count ex. Front-page, references & appendices: 1475

Computing Ground Sign Awareness

The first use of land mines dates back to the American Civil War, but it was first widely used during World War II (Smithsonian, 2016). More than 250,000 people alive today have been injured by landmines, and civilians are injured at least as frequently as military personnel. There are presently over 100 million active landmines across the world, with an additional 5000 put in place every day, while each year more than 10,000 people are killed or injured by landmines every year (Joss, 1997). Moreover, it will take 1,1000 years to clear all the world's landmines if no new mines are laid (United Nations, 2023). Hence, the questions are:

1. How can the lethality of landmines be reduced for both military and civilian personnel?
2. How can the demining process be sped up?

This paper will present a concept, demo, and use case of an object localization model, which addresses the above questions.

Classification

Mines and improvised explosive devices (IEDs) can be segmented into two categories based on their deployment: above and below-surface deployment. Above-surface deployment typically occurs when time is short and dispensed from land vehicles, aircraft, or artillery (International Committee of the Red Cross, 1997). Below-surface deployment is done manually to conceal the landmine; hence, it is not detectable, and other proxy indicators must be used to detect it. These indicators are referenced as ground signs awareness (Geneva International Centre for Humanitarian Demining, 2020).

Classification - Mines

The model will only classify anti-personnel mines as these are the most widespread and pose the most significant risk to military and civilian personnel. On the other hand, anti-vehicle mines require several hundred pounds of pressure to activate, making them less of a risk to civilians. Twenty of the most widespread anti-personnel mines have been included in the dataset to handle the in-class variation of landmines. Moreover, an intentional intra-class imbalance has been put on the soviet era and butterfly landmines as these are the most widespread mine types.

Classification - Ground Signs

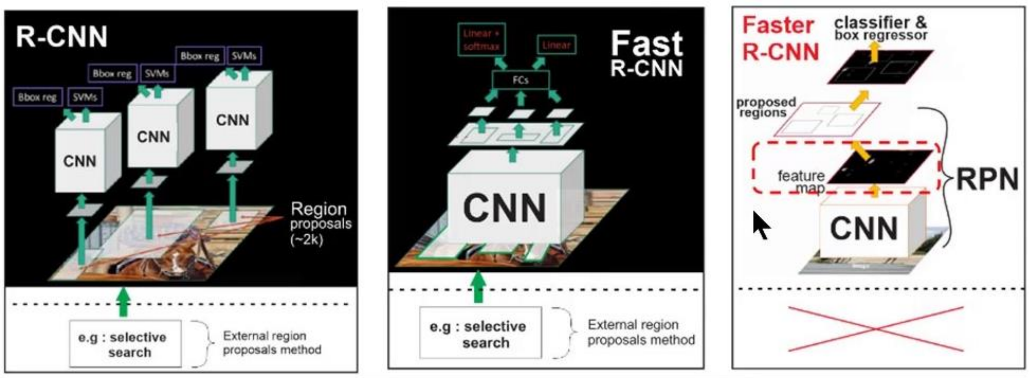
The model's ground signs list is based on the Geneva International Centre for Humanitarian Demining Handbook and the United States Marine Corps Counter IED SOP. The Ground sign intra-class variation includes minefield markers, disturbance, discardables, color change, degree of regularity, flattening, markers, and components (USMC, 2008). Moreover, the dataset has been varied on background noise, view, and scale to make the model more robust.

Model Selection

To solve the object localization problem, the Faster R-CNN model has been selected. The model extends the original R-CNN and Fast-RCNN, which operates more efficiently because it integrates the regional proposal step into the network architecture.

The model implements a regional proposal network to generate proposals, eliminating the requirement for external proposal methods like the ones needed in earlier models, such as selective search. It shares the convolutional layers with the detection and network, allowing it to generate proposals based on a sliding window over the image. Next, the model performs Region of Interest Pooling to extract a fixed-size feature from each of the proposals. Lastly, these features are passed to a connected network to classify objects and refine the bounding box.

This architecture makes the model more accurate, faster, and efficient compared to the previous models. However, this also increases the complexity and computational resources, making it harder to implement, train, and resource-heavy. Moreover, lightweight architecture models such as YOLO can be faster due to their multi-stage processes.



	R-CNN	Fast R-CNN	Faster R-CNN
Test time per image	50 seconds	2 seconds	0.2 seconds
Speed-up	1x	25x	250x
mAP (VOC 2007)	66.0%	66.9%	66.9%

Figure 1 - R-CNN model comparison (Li & Karpathy, 2014)

Use Case Discussion

The object localization model can have multiple applications, separated into two categories: military and civilian use.

Military Use

Landmine detection equipment such as the US PSS-14 man-born mine detector and the US Husky vehicle-mounted mine detector have been part of military doctrine for many years. These devices combine metal detection and radar capabilities to detect mines (Military, 2024; ArmyTechnology, 2020). However, the disadvantage of these technologies is that they allow military personnel to advance very slowly and be physically present, making them vulnerable to direct and indirect hostile fire.

For instance, the object detection model can be integrated into soldier helmet cams or vehicle optics, allowing the detection of potential threats in a larger area than a ground-based sensor. This increases the speed at which troops can advance. Moreover, the model can be integrated into unmanned aerial vehicles (UAVs), enabling troops to perform reconnaissance of routes prior to advancement, thereby eliminating the need for soldiers' physical presence.

Civilian Use

For civilian purposes, the model can be embedded into drones to cover large areas and detect high, low, and no-concentration mines, redirecting demining efforts to the most critical locations, making the demining more efficient, and speeding up the demining initiatives.

Model Performance

Summary

Our analysis of an object localization model for mine detection reveals key areas for enhancement. Despite successfully identifying several anti-personnel mines, a significant number were missed, and ground sign detection proved ineffective. We recommend augmenting the dataset, refining ground sign classification, and adjusting model thresholds to improve precision and recall. Prioritizing recall is crucial, as missing mines pose a greater risk than false positives. Implementing these changes will boost the model's effectiveness and safety in demining operations.

Confusion Matrix interpretation

The model correctly identified fifteen anti-personnel mines, but 12 were missed. Accurate detection is crucial for the safety of demining operations, as missing mines can result in casualties. To address this, it is recommended to enhance the model with more data and improve feature detection capabilities for mines.

Regarding false alarms, the model experienced 20 instances where non-objects were misclassified as anti-personal mines and two instances where they were incorrectly classified as ground sign mines. False alarms can lead to inefficiencies and unnecessary costs in demining operations. To reduce the number of false positives, the recommendation is to adjust the model's thresholds and improve its precision.

Ground sign detection posed a significant challenge, as no ground signs were detected. To improve detection, incorporating more diverse ground sign data into the model and re-evaluating the features used for identification is advised. Further, breaking down ground signs into smaller subcategories could significantly enhance model accuracy. Different types of ground signs, like mine markers and disturbances, are classified together, leading to sizeable intra-class variation. By creating specific subcategories, the model can more easily learn to distinguish between these variations, improving its detection capabilities.

Regarding model reliability, the current model has issues with incorrectly classifying non-objects as mines and missing ground signs, which underlines the importance of reliability for adoption in both military and civilian demining applications. Implementing cross-validation and robustness checks against diverse environments is recommended to enhance reliability.

Safety concerns were highlighted due to 12 anti-personal mines and ten ground signs not being detected, which are classified as false negatives. Each undetected mine represents a potential threat to life in a demining context. To mitigate this risk, it is crucial to prioritize reducing false negatives through improving model sensitivity and validation processes, ensuring a safer operation environment.

Performance Metrics

For Anti-Personal Mines: At an IoU threshold of 0.5, the model's average precision is 0.5082, showing it can detect mines with a moderate level of accuracy when the criteria are lenient. However, at a higher IoU threshold of 0.75, precision falls to 0.1779, indicating that the model's ability to localize mines accurately is significantly reduced.

For Ground Signs, the model's average precision is notably low at 0.0167 for an IoU of 0.5, decreasing to 0 at an IoU of 0.75. This performance indicates the model's current struggle to recognize ground signs effectively, crucial for pinpointing potential minefields. A significant factor contributing to this low precision is the considerable variation in ground signs, making it challenging for the model to identify them accurately. To enhance the model's capability, increasing the dataset with more samples and diversifying the categories of ground signs can be highly beneficial. More samples would provide the model with a broader spectrum of examples to learn from, while additional classes would help reduce intra-class variation, leading to more accurate detection and identification.

Precision-Recall

The Precision-Recall curve for an IoU of 0.5 illustrates the trade-off between precision and recall. Initially, the model shows high precision but low recall. This pattern signifies that while the model's predictions of mines are frequently correct, it fails to detect numerous present mines. As efforts to increase recall (identifying more actual mines) are made, the precision decreases, leading to more false positives (incorrectly identifying objects as mines).

In this context, recall becomes more critical than precision. The paramount concern in mine detection is to avoid missing any mines, as each undetected mine represents a potentially life-threatening risk. Therefore, prioritizing recall ensures that fewer mines are missed, albeit at the expense of increased false positives. In practical terms, it is more acceptable to investigate and clear false alarms than to overlook actual mines, making recall the primary focus to enhance the safety and effectiveness of demining efforts.

Literature Review or Background

Army Technology (2020). *Husky Vehicle Mounted Mine Detector (VMMD)*. ArmyTechonology. https://www.army-technology.com/projects/husky-vehicle-mounted-mine-detector/?cf-view

Geneva International Centre for Humanitarian Demining (2020). *IED INDICATORS AND GROUND SIGN AWARENESS HANDBOOK*. GICHD. https://www.gichd.org/fileadmin/uploads/gichd/migration/fileadmin/GICHD-resources/rec-documents/IED_indicators_and_grounds_sign_awareness_handbook__EN.pdf

International Committee of the Red Cross (1997). *Anti-personnel Landmines Friend or Foe?*. ICRC. https://www.icrc.org/en/doc/assets/files/other/icrc_002_0654.pdf

Joss, D., M. (1997). *Anti-personnel lindmine injuries: a global epidemic*. IOS Press. Work, vol. 8, no. 3, pp. 299-304, 1997. https://pubmed.ncbi.nlm.nih.gov/24441894/

Military (2024). *PSS-14 Mine Detector.* Miliatary.com. https://www.military.com/equipment/pss-14-mine-detector

Smithsonian (2016). *Birth of the landmine*. National Museum of American History. https://americanhistory.si.edu/explore/stories/birth-landmine

United States Marine Corps (2007). *2401-CIED-1001/7/8 Counter Improvised Explosive Devices (IED)*. USMC. https://www.trngcmd.marines.mil/Portals/207/Docs/FMTBE/Student%20Materials/MCECST/E_Counter_IED_SO.pdf?ver=m9Cn_6kTDm1Cp_oj-17z9g%3D%3D

United Nations (2023). *The deadly legacy of landmines*. UN. https://news.un.org/en/story/2023/04/1135252

Appendix

Model Diagnostics

Model

Model ID	A-MINESCLASSIFICATION-rKPeILd9-YY61G0KZ-s2-pp1-m1
Model type	Object detection
Target	labels
Classes	Anti Personal Mines Ground Signs
Trained on	2024/04/02 20:31
Columns (train set)	5
Rows (train set)	80
Train/validation split ratio	0.8
Pretrained Model	FASTERRCNN
Fine-tuned backbone layers	0 / 5
Optimizer	Adam
Learning rate scheduler	On plateau
Initial learning rate	1.000e-4
Final learning rate	1.000e-4
Weight decay	0
Batch size	2
Epochs scheduled	5
Epochs trained	5
Epochs till Best Model	3
Early stopping	Enabled
Early stopping min delta	0
Early stopping patience (in Epochs)	5
Code Env	INTERNAL_object_detection_v1
Python version	3.6.8

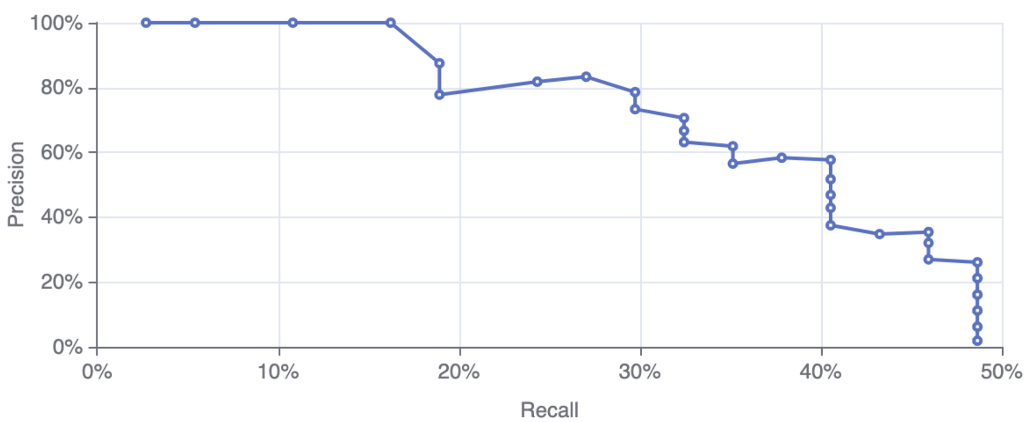
Confusion Matrix

Ground Truth \ Predicted	Anti Personal Mines	Ground Signs	Not Detected
Anti Personal ...	15	0	12
Ground Signs	0	0	10
Not an object	20	2	0

Performance Metrics

Filter class...	Average Precision (IoU=0.5)	Average Precision (IoU=0.75)	Average Precision (all IoUs)
All classes	**0.2624**	**0.0890**	**0.1151**
Anti Personal Mines	**0.5082**	**0.1779**	**0.2242**
Ground Signs	**0.0167**	**0.0000**	**0.0061**

Precision-Recall



Specific Mis-classification cases -

Figure 1 - In this image, a shoe is classified as an anti-personal mine.

Figure 2 - The model fails to detect this anti-personal mine, as few samples like this image were available in the training data.

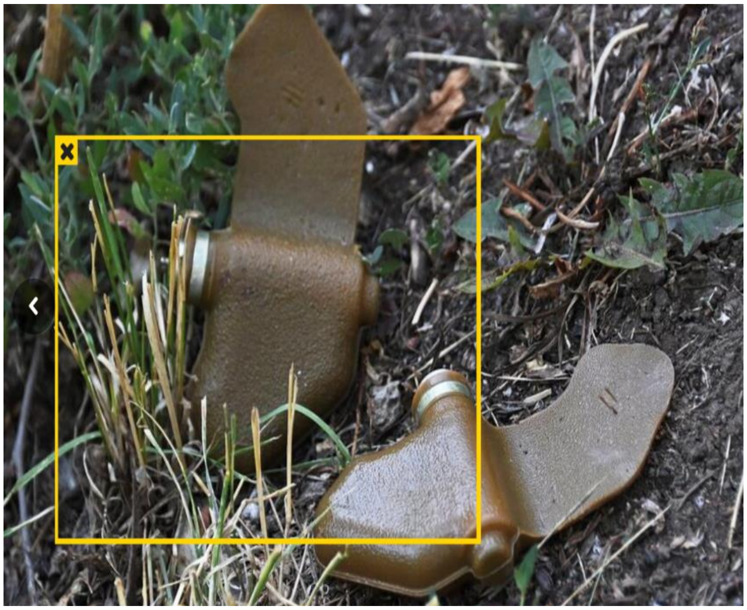


Figure 3 - In this case, the model has difficulty distinguishing between closely placed similar objects, which leads to overlapping bounding boxes and misclassification.

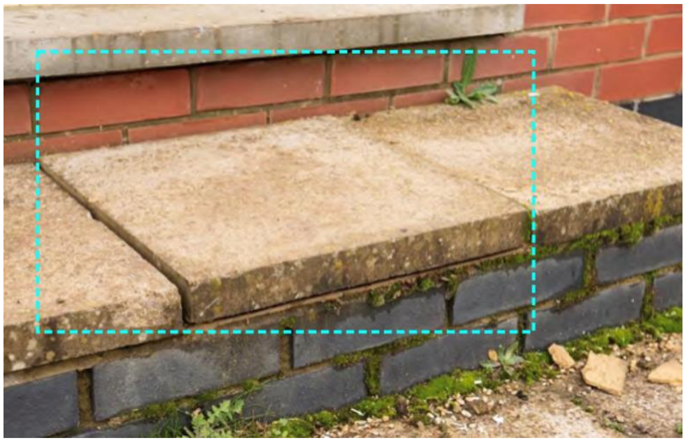


Figure 4 - The model fails to identify this removed tile ground sign mine as no such images were in the training data.

Figure 5 - In this case, the model has failed to identify far away anti-personal mines as they appear smaller in the image, potentially below the resolution threshold that the model can predict.

Figure 6 - Model is not able to recognize this mine, as there were none like this in the training data.

Dataiku Workflow