Bayesian Uncertainty Models for Occluded Landmine Detection - Literature Review

31-03-2025

Greg Salmon, MSc AI for Sustainable Development, UCL, ucabgws@ucl.ac.uk

Abstract

Despite being effective, traditional landmine detection approaches are slow, dangerous, and costly. An emerging strategy involves utilizing unmanned aerial vehicles (UAVs) equipped with sensors and cameras to detect landmines using various machine learning techniques. Success has been found in applying deep learning models, such as You Only Look Once (YOLO) and Region-based Convolutional Neural Network (RCNN), to landmine detection. An underlying obstacle with this approach arises as occlusions such as terrain and vegetation impact the accuracy of the predictions when based solely on imagery [1]. Moreover, the adaption of these techniques into current demining operations largely depends on the trustworthiness of the model. Specifically, quantifying generalization of the model to unseen data is paramount, as it provides a measure of risk and reliability. Little research has been focused on quantifying model uncertainty within the domain of landmine detection, despite being adopted in the broader domain of object detection. This review plans to address the aforementioned gap in research by analyzing relevant studies to identify potential approaches to both detection techniques through occlusion and uncertainty quantification of machine vision models.

Project Aims and Objectives

This literature review highlights the intersection of Bayesian learning, occluded landmine detection, and machine vision through systematically identifying key literature within each domain. Additionally, this research focuses on uncovering the answers to several research questions, namely:

1. What level of vegetation coverage (none, low, moderate, high, and total) renders state of the art (SOTA) machine vision models incapable of achieving trustworthy accuracies?
2. In what capacity has Bayesian uncertainty estimation been applied to the domain of machine vision, and more specifically to landmine detection?
3. What model architecture achieves the highest general accuracy across different studies?

In addressing these questions, the feasibility of estimating uncertainty for landmine detection will be better understood. Additionally, this research serves as the foundation for a dissertation focused on implementing this technique.

Background

Machine Vision

Deep machine vision strategies can largely be broken down into two distinct architectures: one-stage and two-stage. The primary strategy of two stage detection is to provide general candidate regions in the first stage, and then refine these candidates into a final class and bounding box prediction during the second stage [2]. Common two-stage techniques include RCNN, Spatial Pyramid Pooling Networks (SPPNet), Fast RCNN, Faster RCNN, and Feature Pyramid Networks (FPN) [2].

One-stage detection strategies combine both candidate proposals and bounding box predictions into a single step. The most common one-stage architecture to date is YOLO, which launched the one-stage research domain by proposing a single neural network to predict both classes and bounding boxes [3].

Both one-stage and two-stage architectures have their strengths and weaknesses. Generally, two-stage architectures achieve higher accuracies compared to one stage methods, but lack the speed of one stage detection.

Uncertainty in Machine Vision

An underlying issue with object detection with machine vision is quantifying epistemic (model) and aleatoric (data) uncertainty. Aleatoric uncertainty is a result of inherent noise within the data, and is irreducible. Epistemic uncertainty is a result of limited data, and can be reduced through collecting more data. These two uncertainties can be estimated through exact Bayesian inference.

An issue arises when applying exact Bayesian inference to deep learning problems. The true posterior can become intractable for multiple reasons, one being model complexity. An approach to handling this dilemma is turning to variational inference, a method used to approximate the posterior distribution of weights [4].

Using variational inference, a Bayesian Convolutional Neural Network (BayesCNN) can be used to quantify uncertainty [5]. Rather than learning a single weight value for each neuron in a neural network, a BayesCNN learns the probability distribution for each weight [5]. This ultimately allows for uncertainty quantification, improved regularization, potentially increased performance on small datasets, and reduced risk of overconfident predictions [5].

Machine Vision for Camouflaged Object Detection

Outside the domain of landmine detection, machine vision has been applied to camouflaged object detection (COD). Zhang et al. [6] propose an uncertainty estimation strategy for camouflaged objects, focused on the identification of various animals. Putatunda et al. [7] discuss the fusion of a vision transformer architecture with depth estimation to identify camouflaged objects, both military and civilian. These studies can be related to the domain of landmine detection as most landmines are designed to blend into their environment.

Machine Vision for Landmine Detection

Landmine detection techniques predominantly consist of biological, electromagnetic, optical, mechanical, acoustic, nuclear, and magnetometer systems [8]. Metal detecting and ground-penetrating radar (GPR) are used often for detection of occluded or buried mines [9]. Metal detection is a slower, human operated strategy. While being effective for identifying landmines with metal traces, metal detectors fail to identify mines designed without metal. GPR is another growing technique with success. The benefit of using GPR is it provides high accuracy in identifying non-metallic landmines. However, GPR is susceptible to identifying non-landmine items such as buried rocks and soil clusters, which can impede landmine removal. Moreover, rover based GPR sensors generally work best on flat, even terrain and struggle in denser conditions [8].

To overcome these limitations, UAV mounted sensing methods have been considered. Specifically, thermal and hyperspectral imagery can be used for identification of landmines. Combined with modern machine vision algorithms such as YOLO or RCNNs, airborne landmine detection systems have achieved precision rates of up to 0.97 on certain datasets [10]. There are limitations to landmine detection from imagery. Specifically, vegetation and terrain occlusion pose a significant barrier to the efficacy of the method [11].

Critical Evaluation

From a keyword search combining machine vision, landmine detection, and Bayesian statistics, roughly 1,269 articles were retrieved (**Tables 1, 2, 3**). Of these articles, a majority are out of scope for the dissertation (**Figure 2**). Ultimately, 10 publications are considered for this evaluation, which fit the criteria and quality assessment outlined (**Tables 4, 5**). These articles largely fall into three domains: meta analyses, detection by imagery in ideal conditions, and detection by imagery in occluded conditions.

Meta Analyses

Kischelewski et al. (2024) [9]: The authors focus on comparing landmine risk prediction to landmine detection research. Of the 100 identified sources discussing landmine clearance operations, 93 focused on landmine detection and only 7 focused on risk prediction. The authors come to three main conclusions: risk prediction is understudied, there is an opportunity to combine both prediction and detection into holistic operations, and there is room for improvements in current risk prediction areas. The study provides a comprehensive discussion of current and past detection methods.

Barnawi et al. (2022) [8]: Provide a comprehensive literature review for landmine detection, clearly outlining the history of landmine detection, past techniques, and deep learning approaches to the task. Additionally, specific machine learning techniques are highlighted for each detection strategy. Open issues and challenges are mentioned, specifically discussing concerns regarding noise, clutter, false alarms, and landmine signature issues.

Ideal Environment Detection

Luo et al. (2024) [12]: The authors take the approach of UAV based landmine detection using the Faster RCNN architecture. They built a custom dataset with imagery collected at altitudes of 10m, 20m, and 30m. The dataset includes diverse terrains, but there is no mention of specifically utilizing vegetation occlusion. After training, the authors used a held out test dataset and achieved an average precision of 0.712. A key insight identified is the dropoff of model ability as the pixel size of the target decreases – a result of higher altitude.

Sharifuzzaman et al. (2024) [13]: The authors propose a Bayesian approach to object detection utilizing an adapted RCNN architecture. The paper does not focus on landmine detection, but rather the development of a machine vision model with uncertainty capabilities. Several other contributions are mentioned, but do not directly relate to landmine detection. The paper addresses research question #2, as the proposed Bayesian RCNN can be adapted to landmine detection. Additionally to uncertainty quantification, the authors mention the model's ability to mitigate overfitting, as the model draws parameters from a distribution rather than a single value.

Mishchuk and Podorozhniak (2024) [14]: Mishchuk and Podorozhniak discuss the balance of accuracy and detection speed for object detection. The authors compare two SOTA machine vision models, YOLO and Real-Time Detection Transformer (RTDETR). YOLO, as described earlier, is efficient as it uses a single neural network for processing images. RTDETR achieves high accuracy at the cost of increased compute, as it utilizes a transformer architecture to enhance detection capabilities. Ultimately the authors conclude YOLO is a more balanced model for reducing the number of false positives, and RTDETR models achieve less correct predictions. However, they also mention RTDETR performs better with small objects. Ultimately, the authors conclude accuracy and performance are mostly a result of image resolution, and both YOLO and RTDETR achieve higher accuracy with better resolution, at the cost of performance.

Occluded Environment Detection

Agrawal-Chung and Moin (2024) [10]: The authors propose a novel dataset for landmine detection, created using thermal and RGB imagery taken from DJI-Mini3 drone. Specifically, the authors captured footage at varying altitudes and vegetation coverage. They tested four models, YOLOF, DETR, Sparse-RCNN, and VFNet on the dataset and identified YOLOF to perform best at all altitudes. Additionally, they noticed the FLIR thermal camera was only useful at the lowest altitude due to poor resolution. The authors do not discuss model performance in regards to vegetation coverage, which is important to consider.

Baur et al. (2024) [11]: The authors propose a model to predict detection probability based on natural vegetation coverage. Specifically, the authors define methods to measure the effect of vegetation occlusion on model recall utilizing synthetic data. The authors find landmine detection recall using the YOLOv8 model has a the steepest decline at 36% occlusion, and determine that 15% occlusion the uncertainty becomes dominated by the vegetation coverage, rather than model noise. Additionally, the authors test their hypothesis using real-world environments, spanning from no coverage to high coverage. This paper is relevant to research question #1, as it identifies the direct impact of vegetation occlusion for landmine detection.

Popov et al. (2021) [15]: Popov et al. approach the landmine detection problem by fusing thermal and multispectral imagery. Additionally, they train the model with four methods, namely generalized likelihood ratio test (GLRT), Bhattacharyya distance, spectral similarity, and logistic regression. Ultimately, the authors use these statistical methods to provide probabilistic detection estimates to landmine detection, which can be more efficient compared to traditional demining practices.

Putatunda et al. (2023) [7]: Putatanda et al. focus on the broader domain of camouflaged object detection (COD). They designed their model to be deployed using edge devices – which can process data at the source, rather than sending it back to centralized servers. The key advantage of this strategy is that this model could be implemented in the field which is essential for quick decision making in environments such as minefields and warzones. The model combines depth estimation with image recognition, as camouflaged objects may be at a different depth than their environment. The COD model does not show significant improvements in recall specifically for mine detection. When checking the F1 score of the mine class, an inconsistency was identified. Given the precision and recall, the recorded F1 score for each model was reported higher than the true F1 score when using the equation:

$$F1\ Score\ =\ \frac{2 \bullet Precision \bullet Recall}{Precision + Recall}$$

(Equation 1)

Despite this inconsistency, the results remain the same – incorporating depth is shown to have little improvements for mine detection.

Zhang et al. (2023) [6]: Zhang et al. implement uncertainty estimation for COD. The paper does not directly address landmine detection, however the techniques used in this domain can be applied to demining methods. Common COD models struggle with both epistemic and aleatoric uncertainty. The authors implement a Predictive Uncertainty Estimation Network (PUENet), which consists of a Bayesian framework and a module to approximate uncertainty. The approach outperforms SOTA COD models and additionally promotes model explainability. This paper addresses research question #2, as it provides a powerful Bayesian uncertainty quantification method for a camouflaged machine vision task.

Conclusion

All three research questions are addressed through the available research. Baur et al. [11] addresses research question #1, by outlining a potential strategy for determining vegetation coverage, suggesting that 15% occlusion is where vegetation plays into a model's uncertainty. Research question #2 is addressed by Sharifuzzaman et al. [13], Baur et al. [11], and Zhang et al. [6], as each proposes a method for quantifying model uncertainty based on data provided. Finally, research question #3 is addressed by most papers, however, Zhang et al. [6] outperforms most models on a large dataset, and implements a Bayesian uncertainty approach. A limitation identified is a lack of standardized datasets for benchmarking landmine detection models. Certain models perform well on the specific dataset used, but may have difficulty transferring to a separate dataset. Understanding the generalizability of these models is paramount for demining efforts. The papers discussed in this literature review serve as the foundation for the broader project of building a Bayesian uncertainty model for occluded landmine detection, which is an important step towards building safe and trustworthy deep learning strategies for landmine detection.

References

[1] T. Edwards, M. Nibouche, and D. Withey, "Deep learning-based detection of surface and buried landmines," in *2024 30th International Conference on Mechatronics and Machine Vision in Practice (M2VIP)*, Oct. 2024, pp. 1–6. doi: 10.1109/M2VIP62491.2024.10746152.

[2] Z. Zou, K. Chen, Z. Shi, Y. Guo, and J. Ye, "Object Detection in 20 Years: A Survey," Jan. 18, 2023, *arXiv*: arXiv:1905.05055. doi: 10.48550/arXiv.1905.05055.

[3] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," May 09, 2016, *arXiv*: arXiv:1506.02640. doi: 10.48550/arXiv.1506.02640.

[4] C. Blundell, J. Cornebise, K. Kavukcuoglu, and D. Wierstra, "Weight Uncertainty in Neural Networks," May 21, 2015, *arXiv*: arXiv:1505.05424. doi: 10.48550/arXiv.1505.05424.

[5] K. Shridhar, F. Laumann, and M. Liwicki, "A Comprehensive guide to Bayesian Convolutional Neural Network with Variational Inference," Jan. 08, 2019, *arXiv*: arXiv:1901.02731. doi: 10.48550/arXiv.1901.02731.

[6] Y. Zhang, J. Zhang, W. Hamidouche, and O. Deforges, "Predictive Uncertainty Estimation for Camouflaged Object Detection," *IEEE Trans. Image Process.*, vol. 32, pp. 3580–3591, 2023, doi: 10.1109/TIP.2023.3287137.

[7] R. Putatunda, M. A. Khan, A. Gangopadhyay, J. Wang, C. Busart, and R. F. Erbacher, "Vision Transformer-based Real-Time Camouflaged Object Detection System at Edge," in *2023 IEEE International Conference on Smart Computing (SMARTCOMP)*, Jun. 2023, pp. 90–97. doi: 10.1109/SMARTCOMP58114.2023.00029.

[8] A. Barnawi *et al.*, "A comprehensive review on landmine detection using deep learning techniques in 5G environment: open issues and challenges," *Neural Comput Appl*, vol. 34, no. 24, pp. 21657–21676, 2022, doi: 10.1007/S00521-022-07819-9.

[9] B. Kischelewski, G. Cathcart, D. Wahl, and B. Guedj, "AI for ERW Detection in Clearance Operations -- The State of Research," Oct. 31, 2024, *arXiv*: arXiv:2411.05813. doi: 10.48550/arXiv.2411.05813.

[10] N. Agrawal-Chung and Z. Moin, "Comparing Surface Landmine Object Detection Models on a New Drone Flyby Dataset," *CoRR*, vol. abs/2410.19807, 2024, doi: 10.48550/ARXIV.2410.19807.

[11] J. Baur, K. Dewey, G. Steinberg, and F. O. Nitsche, "Modeling the Effect of Vegetation Coverage on Unmanned Aerial Vehicles-Based Object Detection: A Study in the Minefield Environment," *Remote Sens.*, vol. 16, no. 12, 2024, doi: 10.3390/rs16122046.

[12] C. Luo, H. Jiang, H. Li, and D. He, "Landmine Detection Based on Faster R-CNN in UAV Platform," in *2024 7th World Conference on Computing and Communication Technologies (WCCCT)*, Apr. 2024, pp. 119–123. doi: 10.1109/WCCCT60665.2024.10541463.

[13] S. A. S. M. Sharifuzzaman *et al.*, "Bayes R-CNN: An Uncertainty-Aware Bayesian Approach to Object Detection in Remote Sensing Imagery for Enhanced Scene Interpretation," *Remote Sens.*, vol. 16, no. 13, 2024, doi: 10.3390/rs16132405.

[14] V. Mishchuk and A. Podorozhniak, "Analysis of Trade-Offs Between Accuracy And Speed of Real-Time Object Detectors for the Tasks of Explosive Ordnance Detection," in *2024 IEEE 5th KhPI Week on Advanced Technology (KhPIWeek)*, Oct. 2024, pp. 1–5. doi: 10.1109/KhPIWeek61434.2024.10878035.

[15] M. O. Popov, S. A. Stankevich, S. P. Mosov, O. V. Titarenko, M. V. Topolnytskyi, and S. S. Dugin, "Landmine Detection with UAV-based Optical Data Fusion," in *IEEE EUROCON 2021 - 19th International Conference on Smart Technologies*, 2021, pp. 175–178. doi: 10.1109/EUROCON52738.2021.9535553.

Appendix

Tables

Table 1

Data Source	Type	Date of search	Years covered by search	Justification
IEEE Xplore Digital Library	https://ieeexplore.ieee.org/Xplore/home.jsp Digital library	27/03/2025	2015-2025	Contains extensive collection of peer reviewed computer science publications
Arxiv	https://arxiv.org/ e-Print archive	27/03/2025	2015-2025	Preprints for latest research, many deep learning landmine detection techniques are less than 5 years old
ACM Digital Library	https://dl.acm.org/ Digital Library	27/03/2025	2015-2025	Covers core computer science topics and contains wide selection of applied papers
DBLP	https://dblp.org/ Computer science bibliography	27/03/2025	2015-2025	Contains comprehensive selection of computer science papers and seminal papers

Table 2

TERM	Synonymous Groups of Keywords - All Possible
A: Machine Vision	**IEEE Xplore, Arxiv, ACM Digital Library:** “machine vision” OR “computer vision” OR “YOLO” OR “CNN” OR “R-CNN” OR RCNN OR one*stage OR two*stage **DBLP:** vision|yolo|cnn$\|rcnn$|detection
B: Landmine detection	**IEEE Xplore, Arxiv, ACM Digital Library:** “Landmine detection” OR “landmine” OR “explosive ordnance” OR “UXO” OR “minefield” OR “buried explosive” OR “humanitarian demining” OR “remote explosive sensing” OR “PFM-1” OR “explosive remnants of war” **DBLP:** landmine|uxo$|minefield|explosive|demining
C: Bayesian	**IEEE Xplore, Arxiv, ACM Digital Library:** “Bayesian” OR “bayes” OR “uncertainty quantification” OR “uncertainty estimation” OR “probabilistic” OR “probability” OR “informed” **DBLP:** Bayesian|bayes|uncertainty|probabilistic|probability|informed

Table 3

ID	Source	Search Query	Justify	Results
IEEE Xplore				
101	IEEE Xplore	A	Broad search of machine vision	293,641 results
102	IEEE Xplore	B	Broad search of landmine detection	2,115 results
103	IEEE Xplore	C	Broad search of Bayesian statistics	498,198 results
104	IEEE Xplore	A AND B	Considering machine vision applied to landmine detection	348 results
105	IEEE Xplore	B AND C	Considering any Bayesian approach to landmine detection	320 results
106	IEEE Xplore	A AND C	Considering any Bayesian approach to machine vision	26,559 results
107	IEEE Xplore	A AND B AND C	Narrowest search to combine machine vision, Bayesian approaches, and landmine detection	59 results
ACM Digital Library				
201	ACM Digital Library	A	Broad search of machine vision	68,140 results
202	ACM Digital Library	B	Broad search of landmine detection	216 results
203	ACM Digital Library	C	Broad search of Bayesian statistics	367,801 results
204	ACM Digital Library	A AND B	Considering machine vision applied to landmine detection	29 results
205	ACM Digital Library	B AND C	Considering any Bayesian approach to landmine detection	205 results
206	ACM Digital Library	A AND C	Considering any Bayesian approach to machine vision	64,456 results
207	ACM Digital Library	A AND B AND C	Narrowest search to combine machine vision, Bayesian approaches, and landmine detection	29 results
Arxiv				
301	Arxiv	A	Broad search of machine vision	56,891 results
302	Arxiv	B	Broad search of landmine detection	52 results
303	Arxiv	C	Broad search of Bayesian statistics	413,011 results
304	Arxiv	A AND B	Considering machine vision applied	6 results

			to landmine detection	
305	Arxiv	B AND C	Considering any Bayesian approach to landmine detection	14 results
306	Arxiv	A AND C	Considering any Bayesian approach to machine vision	16180 results
307	Arxiv	A AND B AND C	Narrowest search to combine machine vision, Bayesian approaches, and landmine detection	0 results
		DBLP		
401	DBLP	A	Broad search of machine vision	328,819 results
402	DBLP	B	Broad search of landmine detection	855 results
403	DBLP	C	Broad search of Bayesian statistics	123,923 results
404	DBLP	A AND B	Considering machine vision applied to landmine detection	326 results
405	DBLP	B AND C	Considering any Bayesian approach to landmine detection	21 results
406	DBLP	A AND C	Considering any Bayesian approach to machine vision	4,659 results
407	DBLP	A AND B AND C	Narrowest search to combine machine vision, Bayesian approaches, and landmine detection	5 results

Table 4

	Criteria	**Justification**
Inclusion	a) Studies assessing accuracy and F1 score of machine learning models for detecting landmines b) Studies utilizing top down imagery (RGB, hyperspectral, thermal) for landmine detection c) Studies conducted between 2015-2025 d) Academic journals or conferences	a) Need similar metrics to compare models across papers b) Only interested in UAV based imagery techniques c) Studies specifically focused on either one-stage or two-stage detection d) Interested in only sources with credibility
Exclusion	a) Studies that do not report quantitative or comparable results for model performance b) Studies focused on non-visual sensor data (magnetic, GPR, chemical analysis) c) Studies which implement land based robotics (rovers, walking robots) d) Studies which do not implement image detection algorithms	a) Incomparable if lacking common metrics b) Out of scope for this study c) Only interested in top-down aerial imagery d) Traditional techniques are not considered in this study (metal detection, prodding)

Table 5

Quality Criteria	Evaluation Questions
Study Design	• Is the study reproducible? • Does the study address the research questions appropriately? • Does the study make any assumptions about the data (time of day for data collection, lighting conditions, etc.)? • Is the study theoretical or immediately applicable?
Sample Selection	• Does the dataset contain an appropriate amount of samples? • Is the dataset balanced? • Do the samples represent varied environments (desert, plains, forests)?
Data Collection	• Is the dataset available? • Is the data collection process described? • Are the measurement instruments publicly available?
Data Analysis	• Is exploratory data analytics described? • Are results of EDA displayed?
Ethics	• Are ethical considerations, such as the risk of false negatives in landmine detection addressed? • Are there any assumptions that may add risk to human safety?
Generalizability	• Can the study be easily adapted to real world scenarios? • Does the study solve a problem that can make an impact in current landmine detection technologies?

Table 6

Study ID	Study Characteristics	Study Data	Study Methods	Study Results	Study Conclusions
Agrawal-Chung and Moin (2024) [10]	Evaluates and compares four SOTA machine vision models on novel drone footage dataset	Custom dataset consisting of RGB and thermal images and footage from drones Landmines used are POM-2 and POM-3 surface mines Varied conditions, no occlusion to heavy occlusion	Trained and compared YOLOF, DETR, Sparse-RCNN, and VNet models Used 320 images for training and 70 images for testing No mention of validation	YOLOF model performed the best compared to the other models with mAP of 0.89 YOLOF had fastest training time Performance for all models improved at low altitudes Drone speed has no influence on detection accuracy	All models performed well, and YOLOF shows promise for being a good candidate for landmine detection Thermal imaging struggles with vegetation obstruction
Barnawi et al.	Comprehensive literature review	Analyze types of detection systems	Compares different detection	Deep learning improves detection	Identified several open challenges,

(2022) [8]	for landmine detection using deep learning Discusses the state of multiple different sensing technologies	such as biological, electromagnetic, optical, mechanical, acoustic, nuclear and magnetometer	performances across different systems	probability for most sensing technologies GPR is the most widely used UAV applications are effective strategies to address issue	namely noise, clutter, false alarms, dis-localization of landmine signatures, and missing landmine signatures Security of data transmission is important
Baur et al. (2024) [11]	Identify impacts on vegetation coverage for landmine detection Quantify detection uncertainty using coverage percentage	Varied levels of vegetation Synthetic dataset designed to mimic varying levels of vegetation Additional 8 real-world minefield environments for empirical tests	Designed model to estimate detection accuracy based on occlusion using YOLOv8 Created algorithm to estimate vegetation height and coverage	Determined significant decrease in recall as vegetation increases, following sigmoid shape Designed uncertainty maps based on UAV imagery	Vegetation becomes significant driver of uncertainty at 15% occlusion, and grows onwards
Kischelewski et al. (2024) [9]	Literature review and meta analysis for ERW detection strategies Compares prediction vs detection strategies	Analyzed 100 sources from an initial search of 1,558 papers	Filtered by year, empirical studies, and peer reviewed articles Categorized data into detection or prediction	93 papers discuss detection, while only 7 discuss prediction Only 16 papers discuss image based detection techniques, with 13 being hyperspectral and 10 being thermal	Risk prediction is understudied Combining risk prediction and landmine detection can provide probability of finding ERW
Luo et al. (2024) [12]	Aerial landmine detection using Faster R-CNN model with various backbone networks	Collected optical and infrared images at altitudes of 10m, 20m, and 30m Includes 14,314 optical images and 4,487 infrared images Diverse scenes, no mention of occlusion	Discussed image augmentation techniques to improve generalization Implement a Faster R-CNN with specific architecture decisions mentioned	Used recall and average precision as main metrics Achieved average precision of 0.712 for testing Additionally analyzed average precision of targets with pixel values >10,000, achieving an average precision	Accuracy of landmine detection drops as altitude increases Address risk of false positives from detection

				of 0.985	
Mishchuk and Podorozhniak (2024) [14]	Analyzes trade-offs between accuracy an inference time in real-time object detection Compares performance of YOLOv8 and RTDETR models	Uses randomly selected subset from the COCO validation dataset Large imbalance towards “person” compared to other classes No mention of occlusion	Compared YOLOv81 and YOLOv8x to RTDETR-L and RTDETR-X Comparison metrics: mAP@0.5, mAP@0.75, Precision, Recall, and object size mAPs Compared performance over different resolutions	RTDETR achiever higher mAP rates, but have significantly higher false positive rates YOLOv8 models maintain consistent balance between correct predictions and detected objects Performance decreases on small objects with lower resolution	Clear tradeoff between accuracy and performance high resolutions provide enable better accuracy, while lower resolution enables faster processing Suggest to maximize object size in images to improve detection accuracy
Popov et al. (2021) [15]	Fusion of multispectral and thermal imagery to improve landmine detection reliability Utilize a range of probabilities for determining whether a landmine is detected	Custom dataset with imagery collected using quadcopter Thermal and multispectral images Potentially buried landmines	Implemented four landmine detection methods: GLRT, Bhattacharyya distance, spectral similarity, and logistic regression If obtained estimate was below lower threshold, determined no landmine If between lower and upper threshold, an expert would be consulted If above upper threshold, the model would assume there is a landmine in the image without expert approval	Logistic regression had the lowest probability of false alarm, despite having a relatively lower probability of landmine detection Detection improved with multiple sensors compared to single-sensor approaches	Data fusion significantly improved model performance System can be incorporated into early stages of mine clearance operations
Putatunda et al. (2023) [7]	Propose lightweight model for camouflaged object detection	Synthetic data generated to overcome lack of camouflaged datasets - army assets and traffic assets	Utilize modified YOLOv5 model with vision transformers for improved feature extraction Multimodal	Achieve highest overall performance with proposed model Consistent results across both datasets	Suggest integrating RGB and depth improves camouflage detection Can be deployed

		Utilize camouflage	approach combining both RGB and depth maps	Inconsistency with precision and recall not resulting in same F1 score as study	on edge devices
Sharifuzzaman et al. (2024) [13]	Implementation of Bayesian object detection using Bayes R-CNN Attempts to incorporate uncertainty quantification and reduce overfitting, information loss, and limited background information	Use DIOR and HRSC2016 datasets Contain complex backgrounds for testing detection robustness No mention of occlusion	Propose four implementations: Multi-Resolution Extraction Network, Bayesian convolutional layers, Multi-Level Feature Fusion Module, and Bayesian Distributed Lightweight Attention Module Enhances low-resolution inputs with super-resolution step	DIOR mAP: 74.6% HRSC2016 mAP: 91.23% Outperformed existing SOTA solutions for both datasets 99% accuracy for background classification	Successfully provided uncertainty estimations Combined approach proved better than existing approaches
Zhang et al. (2023) [6]	Addresses model and data uncertainty in camouflaged object detection Introduced Bayesian approach for uncertainty quantification	Used several COD datasets, including COD, COD10K, CAMO, CHAMELEON, and NC4K Utilize camouflage and occlusion	Proposed novel model PUENet, which combines Bayesian Conditional VAE, Predictive Uncertainty Approximation, and Selective Attention Module	PUENet outperformed SOTA COD models across multiple metrics and several different benchmarks	Successfully addressed both model and data biases Provided accurate predictions, including segmentation Achieved sampling free uncertainty estimation

Figures

Figure 1

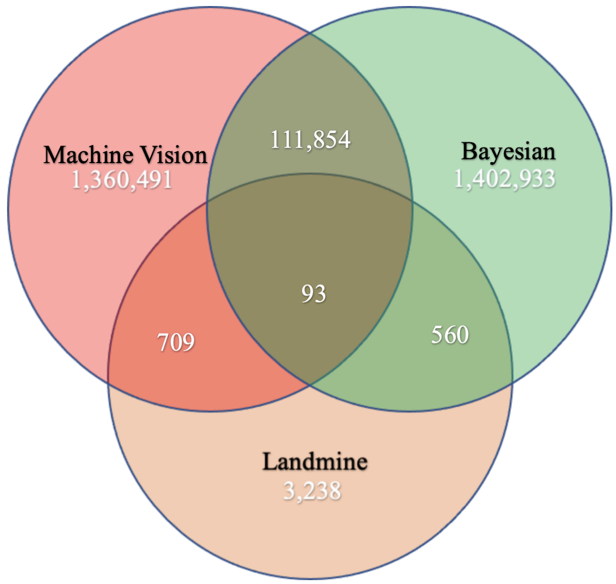

Figure 2