

IMAGE SELECTION USING SELF SERVICE VISUAL ANALYTICS FOR UXO DETECTION

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Abstract : Securing border zones poses a significant challenge for military forces, with the inability to monitor continuously resulting in tragic incidents and loss of life among soldiers. The surveillance and security of border zones remain critical concerns for military forces, with the challenging task of continuous monitoring often leading to tragic incidents and casualties among deployed personnel. To address this pressing issue, this project proposes an innovative approach leveraging the You Only Look Once (YOLO) deep learning model for bomb detection. In response to escalating concerns regarding public safety and terrorism threats, there is a growing demand for robust and efficient explosive detection systems. By harnessing the capabilities of YOLO, known for its speed and accuracy in object detection tasks, this system aims to enhance security measures along border zones. The proposed bomb detection system offers the potential to mitigate risks and protect military personnel by providing real-time detection and alert mechanisms, thereby bolstering national security efforts. Through the integration of advanced technology and machine learning algorithms, this solution strives to enhance situational awareness and safeguard lives in critical border regions. By deploying advanced machine learning algorithms, the system offers the potential to mitigate risks and prevent security breaches, thereby safeguarding both military personnel and civilian populations. Through the integration of cutting-edge technology and proactive security measures, this solution seeks to enhance situational awareness and strengthen national defence capabilities in border protection effort.

IndexTerms – YOLO, Deep Learning, Image Processing, ROBOFLOW dataset, YAML File, Tensor Flow

1.1INTRODUCTION

Deep Learning is a subset of machine learning that involves training artificial neural networks with multiple layers to recognize patterns in data. Deep learning algorithms can be used for a wide range of tasks such as image and speech recognition, natural language processing, and even playing games like Go and Chess. The main advantage of deep learning over traditional machine learning approaches is its ability to automatically learn features from raw data without the need for manual feature engineering. This is accomplished by stacking multiple layers of neurons, each of which performs a nonlinear transformation of the input data. The output of one layer serves as the input for the next layer, allowing the network to gradually learn increasingly complex representations of the input data. Popular deep learning algorithms include Convolutional Neural Networks (CNNs) for image and video processing, and Generative Adversarial Networks (GANs) for generating realistic images and videos. Training deep learning models requires large amounts of labeled data and significant computational resources. However, recent advancements in hardware and software have made it

easier to train deep learning models on a wide range of applications. One of the key advantages of deep learning is its ability to handle unstructured data such as images, video, and text. 2 Convolutional Neural Networks (CNNs) are particularly effective at processing images and video, while Recurrent Neural Networks (RNNs) are better suited for sequential data processing such as natural language processing. Deep learning has had a significant impact on a wide range of industries, including healthcare, finance, and transportation. For example, deep learning algorithms are used in medical imaging to help diagnose diseases such as cancer, in finance to detect fraudulent transactions, and in transportation to improve selfdriving cars' performance. However, deep learning is not without its challenges. One of the biggest challenges is the need for large amounts of labeled data to train the models effectively. This can be particularly challenging for applications where the data is scarce or expensive to collect. Additionally, deep learning models are often black boxes, meaning it can be challenging to interpret how the model arrives at its predictions. This can be problematic for applications where interpretability is important, such as in healthcare or finance.

2.1. Method Of Learning

The current state of demining operations in conflict-affected areas, particularly in territories affected by the war and attacks in Ukraine, presents significant challenges and risks to both civilians and demining personnel. Demining is a complex, dangerous, and prolonged process characterized by the presence of explosive remnants of war (ERW) scattered across the terrain. These ERWs include landmines, unexploded ordnance (UXO), and improvised explosive devices (IEDs), posing a persistent threat to human life and hindering the safe return of civilians to their homes.

Traditionally, demining operations rely on manual detection methods, where demining personnel painstakingly search for and identify potential explosive devices using handheld detectors and visual inspections. Additionally, the reliance on manual detection methods often results in delays and inefficiencies, prolonging the process of clearing contaminated areas and delaying the return of displaced populations.

As a result, there is a pressing need for more advanced and effective detection systems that can accurately identify and localize explosive objects within the complex and challenging environments of conflict-affected areas. In recent years, object detection algorithms have emerged as promising tools for enhancing demining operations by automating the process of detecting and localizing explosive devices. These algorithms analyze visual data from images or video streams to detect objects of interest, including potential explosive devices, and determine their precise locations within the scene.

3. RESEARCH METHODOLOGY

3.1 Image Acquisition

A bomb detection system in aerial images relies heavily on the image acquisition module, which is responsible for retrieving images from satellite sources and preparing them for subsequent processing and analysis. This critical module ensures the acquisition of high-quality images necessary for accurate detection and localization of potential threats.

Images are carefully selected to provide comprehensive coverage of the designated regions, maximizing the chances of detecting any potential explosive devices.

3.2 Preprocessing

Image preprocessing is a crucial phase in the image analysis process, aimed at enhancing the quality of collected images by eliminating noise and distortions. The primary objective of preprocessing is to improve the overall quality of the photos, enabling image processing algorithms to evaluate them more accurately and efficiently.

3.3 Classification

In classification tasks, YOLO receives an image as input and processes it through multiple layers, with each layer extracting increasingly complex features from the image.

3.4 Object Detection

Object detection using YOLO involves predicting bounding boxes and class labels for each grid cell after dividing the input image into a grid. To detect bombs in aerial images, the bounding boxes and class labels predicted by YOLO are applied. The output from YOLO undergoes post-processing procedures to eliminate false detections and enhance detection precision.

3.5 Alert System

When a bomb is detected in images captured by aerial surveillance, an alarm system can be activated to promptly notify security personnel. This alarm system can be configured to send alerts through various channels, including email notifications to security guards' mobile devices.



4. RESULTS AND DISCUSS<mark>ION</mark>

Bomb detection using the YOLO (You Only Look Once) algorithm entails training a deep learning model to identify and localize explosive devices within images in real-time.

These preprocessing steps help enhance the model's ability to generalize to unseen data and improve its performance under different environmental conditions. Following preprocessing, the YOLO model is trained on the annotated dataset using a deep learning framework such as PyTorch.Upon completion of training, the trained YOLO model can be deployed to detect bombs or explosive devices in real-time within images or video stream.The model's inference process involves passing input images through the network and generating predictions for the presence and location of bombs or explosive devices. Through meticulous dataset curation, annotation, preprocessing, and training, the YOLO model can effectively contribute to efforts aimed at safeguarding lives and preventing potential disasters caused by explosive devices.

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This process commences with the assembly of a diverse dataset containing images portraying various scenarios where bombs or explosive devices may be present.

Each image in the dataset is meticulously annotated, with bounding boxes delineating the location of the bombs or explosive devices and labeled with their corresponding class ("bomb").

Bomb detection using the YOLO (You Only Look Once) algorithm entails training a deep learning model to identify and localize explosive devices within images in real-time.

5. CONCLUSION

In conclusion, leveraging the YOLO algorithm for bomb detection in aerial surveillance represents a significant advancement in enhancing security measures and mitigating risks posed by explosive threats.

By harnessing the capabilities of deep learning and computer vision, security professionals can gain valuable insights into potential threats and take proactive measures to safeguard lives and infrastructure.

The integration of YOLO-based bomb detection systems with alert mechanisms facilitates rapid response and decision-making, enabling security personnel to effectively mitigate security risks and ensure public safety.

Transparency, accountability, and adherence to ethical standards are paramount to maintain public trust and uphold fundamental rights while deploying YOLO-based bomb detection systems.

6. FUTURE WORK

Explore integration with autonomous systems, such as drones or robotic platforms, to enable mobile bomb detection capabilities for surveillance or reconnaissance missions in challenging environments.

Algorithm to implement fine-tuning pre-trained models on domain-specific datasets to improve performance in real-world deployment scenarios.

REFERENCES

[1] Ahmad, Gulzar, et al. "Intelligent ammunition detection and classification system using convolutional neural network." Computers, Materials & Continua 67.2 (2021): 2585-2600.

[2] Bhatti, Muhammad Tahir, et al. "Weapon detection in real-time cctv videos using deep learning." IEEE Access 9 (2021): 34366-34382.

[3] Bianculli, Miriana, et al. "A dataset for automatic violence detection in videos." Data in brief 33 (2020): 106587.

[4] Haq, Nazeef Ul, et al. "Orientation aware weapons detection in visual data: a benchmark dataset." Computing 104.12 (2022): 2581-2604.

[5] B. Horn, S. Cooper, and S. Deterding. Adapting cognitive task analysis to elicit the skill chain of a game. CHIPLAY '17, p. 277–289. ACM, New York, 2017. doi: 10.1145/3116595.3116640 9

[6] C. Y. Ip and A. Varshney. Saliency-assisted navigation of very large landscape images. IEEE Transactions on Visualization and Computer Graphics, 17(12):1737–1746, 2011. doi: 10.1109/TVCG.2011.231 2

[7] Khalid, Shehzad, et al. "Weapon detection system for surveillance and security." 2023 International Conference on IT Innovation and Knowledge Discovery (ITIKD). IEEE, 2023.

[8] S. Khan, E. Gunpinar, and B. Sener. Genyacht: An interactive generative design system for computeraided yacht hull design. Ocean Engineering, 191:106462, 2019. doi: 10.1016/j.oceaneng.2019.106462 2

[9] Y. Koyama, I. Sato, and M. Goto. Sequential gallery for interactive visual design optimization. ACM Transactions on Graphics (TOG), 39(4):88–1, 2020. doi: 10.1145/3386569.3392444 2

[10] Narejo, Sanam, et al. "Weapon detection using YOLO V3 for smart surveillance system." Mathematical Problems in Engineering 2021 (2021): 1-9.

[11] I. Pérez-Messina, D. Ceneda, and S. Miksch. A Methodology for TaskDriven Guidance Design. 2023. doi: 10.2312/eurova.20231094 3, 4, 9

[12] Pisantanaroj, Pattranit, et al. "Automated firearm classification from bullet markings using deep learning." IEEE Access 8 (2020): 78236-78251.

[13] J. Puchinger, G. R. Raidl, and U. Pferschy. The multidimensional knapsack problem: Structure and algorithms. INFORMS Journal on Computing, 22(2):250–265, 2010. doi: 10.1287/ijoc.1090.0344 2

[14] Ruiz-Santaquiteria, Jesus, et al. "Handgun detection using combined human pose and weapon appearance." IEEE Access 9 (2021): 123815-123826.

[15] Ruiz-Santaquiteria, Jesus, et al. "Improving handgun detection through a combination of visual features and body pose-based data." Pattern Recognition 136 (2023): 109252.

[16] D. Sacha, A. Stoffel, F. Stoffel, B. C. Kwon, G. Ellis, and D. A. Keim. Knowledge generation model for visual analytics. IEEE Transactions on Visualization and Computer Graphics, 20(12):1604–1613, 2014. doi: 10.1109/TVCG.2014.2346481 9

[17] A. Schulz, H. Wang, E. Grinspun, J. Solomon, and W. Matusik. Interactive exploration of design tradeoffs. ACM Trans. Graph., 37(4), 2018. doi: 10. 1145/3197517.3201385 2

[18] M. Sedlmair, C. Heinzl, S. Bruckner, H. Piringer, and T. Möller. Visual parameter space analysis: A conceptual framework. 20(12):2161–2170. doi: 10.1109/TVCG.2014.2346321 2

[19] E. J. Shepherd. Mapping unexploded ordnance in italy: The role of world war II aerial photographs. Conflict Landscapes and Archaeology from Above, pp. 205–218, 2016. 1

[20] Yadav, Pavinder, Nidhi Gupta, and Pawan Kumar Sharma. "A comprehensive study towards high-level approaches for weapon detection using classical machine learning and deep learning methods." Expert Systems with Applications 212 (2023): 118698.

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