Utrecht University
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Applied Data Science master thesis

Improving Parcel Security: Neutron Image-Based Detection of Illegal Objects using YOLOv4 CNN

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Abstract

Deep learning models are revolutionizing security tasks by detecting illegal objects in parcels. Enabling this technology with neutron-based images can be a powerful tool for enhanced security measures as neutron sources can penetrate materials more easily. By applying image processing techniques, data augmentaion and hyperparameter tuning, this work aims to optimize a YOLOv4 (You Only Look Once version 4) CNN (Convolutional Neural Network) deep learning model. Table 4.1 shows the performance results of this model with the proper techniques applied. Data augmentation was employed and research for the network's best configuration. As a consequence of the results obtained, an efficient and accurate system has been implemented that manages to enhance security in neutron images. In collaboration with Dynaxion Security we try to deliver a scalable and robust system that can be used in the future. By utilizing the power of YOLOv4, this system can detect and classify illegal objects with high accuracy and in real-time. The incorporation of neutron images, which capture the unique radiation signatures of objects, adds an additional layer of specificity to the detection process, making it even more reliable and effective. This broader perspective highlights the system's potential to contribute significantly to crime prevention, public safety, and security in various settings, including airports or public venues.

Contents

1. Introduction

In this master's thesis we present a illegal object detection system in collaboration with Dynaxion Security. A YOLOv4 Darknet based CNN model is proposed combined with neutron-based images. The pipeline implemented involves different tasks: data preprocessing, data preparation for training, training the deep learning model and retrieving the results, and hyperparameter selection to improve results. Data augmentation techniques are also applied in order to obtain better performance metrics.

1.1 Motivation and context of the project

Dynaxion Security is a company developing a new generation scanning system for non-invasive and fully automated substance identification for security purposes.The Dynaxion scanning system utilizes a novel Radio Frequency Quadrupole (RFQ) particle accelerator to create a beam of neutrons that is used to scan objects. By using combination of neutron and gamma-ray detectors and deep learning algorithms, substances can be identified down to their atomic level. The principal motivation behind this project is to address the need of developing an effective illegal object detection system tailored specifically for Dynaxion Security. By providing them with a state-of-the-art solution that excels in the task of illegal object detection, we aim to significantly enhance their security infrastructure and strengthen their ability to mitigate potential threats.

Moreover, this thesis seeks to contribute to the broader field of security technology by advancing the state-of-the-art in illegal object detection. Through rigorous research and experimentation, we aim to enhance the reliability, efficiency, and scalability of the detection system. The insights gained from this project can potentially benefit not only Dynaxion Security but also other security organizations facing similar challenges.

By undertaking this project, we seek to make a meaningful impact on the field of security technology while addressing the specific needs of Dynaxion Security. Through this collaboration and the new cutting-edge deep learning models, we aim to develop a illegal object detection system that sets new standards for performance and can be served as an automatic tool in the future.

1.2 Literature review

To address our motivation, the work is supported by an initial literature review. The task performed to search for articles is explained in Appendix **A**. Initially, a search was conducted for neutron-based image articles; however, no articles were found. Subsequently, a total of 53 articles using x-ray keywords were identified. Among them, 39 articles were rejected due to their irrelevance to the project or because they focused on significantly different topics compared to the subject matter of this project. So finally this search proportioned 14 articles, each and everyone of them with different characteristics that helped during the developing and analysis of the project.

From the articles researched, x-ray images are used in 11 of them as their dataset: [1]–[11]. These studies employed different types of metodologies; [3], [4], [7], [12] use Faster-RCNN for object or anomaly detection, [1], [11] have applied SIFT descriptors for their analysis, [5], [6], [8] used YOLO CNN based implementations, median filtering is used in Ref. [13] for neutron radiography, a CNN-BLS based architecture is employed in Ref. [8] and two neural networks named ZPG-Net and MFA-Net are implemented in Ref. [10] and Ref. [2] respectively. Apart from having used x-ray images, neutron detection in gamma ray images is tried in Ref. [14], and maxicolfacial fracture detection in CT images is applied in Ref. [12]. Having known the specifications of other systems, this proposal consists of a illegal object detector including neutron images and a YOLOv4 CNN deep learning model. The research study has been conducted to assess the presence of this pipeline, although it is important to note that absolute certainty regarding its non-appearance cannot be established at this time, it is important to preserve a scientific approach and acknowledge the potential for future developments.

1.3 Objectives of the project

The principal objectives and goals of this work are divided into two paths. Firstly, to develop an efficient and accurate illegal object detection system customized specifically for Dynaxion Security, with the aim of enhancing their security infrastructure. This objective is related with the field of security technology, addressing the need for an effective solution that meets the requirements of Dynaxion Security. Secondly, this thesis seeks to contribute to the broader field of deep learning in security by advancing a state-of-the-art in illegal object detection model.

Through research and experimentation, this work aims to enhance the reliability and efficiency of the detection system. By collaborating with Dynaxion Security and leveraging cutting-edge deep learning models, our project strives to develop an automatic illegal object detection system that establishes new performance standards. In order to accomplish our goals, a pipeline is developed involving: data analysis and preprocessing, YOLOv4 CNN training, result retrieving, and hyperparameter tuning and research. Taken this into account, the hypothesis of this project is wheter we can optimize the deep learning model employed for a neutron image based dataset and have a general accurate and efficient system.

Disclaimer

The data used in this study is entirely simulated, ensuring the exclusion of any privacy concerns associated with real-world personal information. Furthermore, the model developed within this research is designed to be privacy insensitive, focused on distinguishing between the legality of objects in the images. This deliberate approach was adopted as a precautionary measure to mitigate potential privacy issues in the future.

2. Data

This chapter focuses on the description and preparation that has been applied to the initial data given. We present a detailed overview of the dataset, including its source, size, and composition. Furthermore, we discuss the preprocessing techniques employed to ensure the quality of the data and suitability for training our deep learning model.

2.1 Data description

The dataset comprised a total of 2358 neutron-based images, each captured from a distinct angle using Dynaxion's system. Each image had a corresponding annotation file containing the following information about each object contained in the image: object name, material name, material legality, material category, object legality, bounding box coordinates (xmin, xmax, width and height). Figure 2.1 shows the first image of the dataset and table 2.1 contains the information needed for the bounding boxes of the image. An important fact to mention is that neutron images can be really beneficial as they can penetrate dense and shielded materials more effectively than x-ray images.

o_name	**m_name**	**m_legality**	**m_cat**	**o_legality**	**o_xdiv**	**o_ydiv**	**o_width**	**o_height**
headphone	nylon_6	legal	clothes	Objects3D	55	66	109	102
MilitaryKnife	iron	legal	metal	Illegal	524	349	35	116
HandgunColt	plastic_abs	legal	plastics	Illegal	71	396	153	67

Table 2.1: Annotation attributes for a neutron based image

The label that will be predicted is the object legality. If the object in the image is legal, it will have *Objects3D* annotated and otherwise it will have *Illegal*. Unfortunately, the initial dataset did not have the bounding boxes of the objects correctly adjusted. As it can be seen in Image 2.1, the images contain axes and additional fill in all directions. For this reason, image pro-

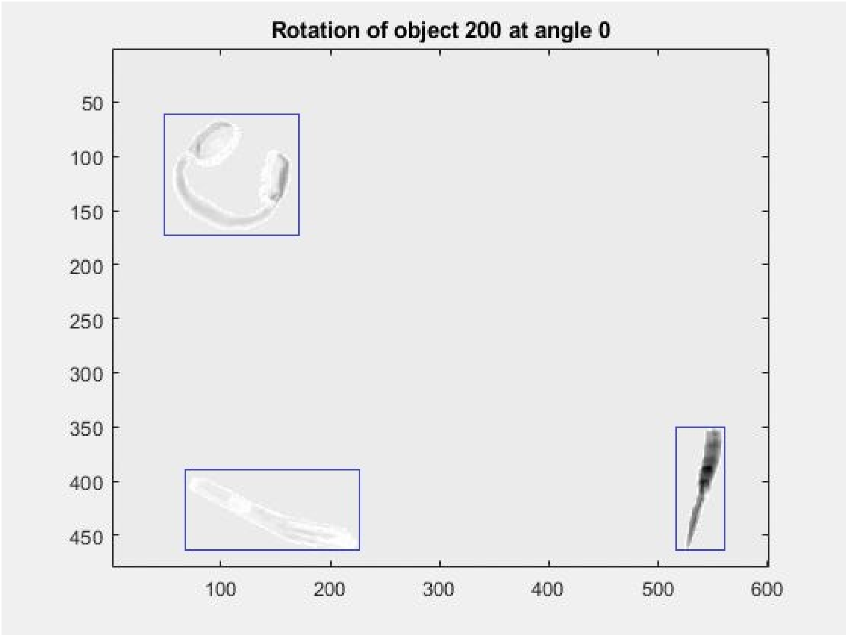


Figure 2.1: Neutron image based parcel containing 3 objects with their corresponding bounding boxes.

cessing needed to be performed in order to have a proper dataset to train the model. To address the issue of class imbalance in the dataset, data augmentation techniques were employed as part of the preprocessing pipeline. This problem can occur when the number of samples in different classes significantly varies, potentially leading to biased model performance.

2.2 Data preparation

As explained earier, data preprocessing needed to be completed in order to obtain the necessary features to train the model. This preprocessing is divided into two steps: image cropping and resizing, as well as annotation file adjusting, followed by data preparation for YOLOv4 CNN.

The initial step of our preprocessing involved detecting the relevant pixels that constitute the image and capturing their corresponding coordinates. Subsequently, we utilized this information to crop the image precisely, thereby isolating the essential content. For the final images, we applied a 416x416 resizing since it is one of the required image sizes for YOLOv4. This also included recalculating the bounding boxes that corresponded the new dimensions of the image. Finally, with the precise coordinates of the bounding boxes we were able to extract the features needed for the annotations of YOLOv4. More insight about how this data is measured and transformed is provided in Chapter 3.

2.3 Data Augmentation

In this study, class imbalance was observed in the dataset as it can be seen in 2.2, where certain classes had significantly fewer instances compared to others. More specifically 5652 examples were found from the *legal* class and 3510 from the *illegal* one. In order to reduce this problem that can lead to performance issues, data augmentation techniques were applied. By artificially expanding the size of the whole dataset through techniques such as brightness and contrast changes, the augmented dataset got more representative. This approach aimed to improve the overall performance and generalization ability of the model by providing more diverse samples for training.

Data augmentation techniques involved training the deep learning model two times more. The process is the following: the proportion of the dataset that wants to be added is selected (eg: 0.3 means that the dataset would have 30% extra images including the initial ones), this images are selected randomly and then, gamma correction changes of brightness and contrast are applied. This type of augmentation ensures that the images do not turn entirely black or white and they have a slight increase or decrease of the features selected (brightness and contrast in this case).

Figure 2.2: Class distribution histogram.

3. Method

In this study, we employed a state-of-the-art object detection model called YOLOv4, which is a Convolutional Neural Network (CNN) architecture widely recognized for its outstanding performance in real-time object detection tasks. To facilitate the implementation and training of YOLOv4, we utilized the Darknet framework as the underlying backbone.

3.1 Overview of the YOLOv4 CNN architecture

Object detection is a computer vision task that involves identifying and localizing multiple objects within an image. YOLOv4 stands for 'You Only Look Once version 4,' and it follows the one-stage, unified approach to object detection. This means that it directly predicts bounding boxes and class probabilities for all objects in a given image in a single forward pass through the neural network. As indicated earlier, our YOLOv4 approach relies on the C-based Darknet backbone approached by the following source:

`https://github.com/AlexeyAB/darknet`.

Motivated by [15], [16] and [17], the following steps include a general overview of our YOLOv4 implementation.

- **Darknet Framework**: Darknet is a neural network framework developed in C and CUDA. It provides the infrastructure for building and training deep learning models, including object detection models like YOLOv4. Darknet is known for its efficiency, making it suitable for real-time inference on both CPUs and GPUs.
- **YOLOv3**: YOLOv3, short for "You Only Look Once version 3," is a state-of-the-art object detection model known for its exceptional accuracy and real-time performance. It is used as the *Head* of the network and the whole system with these characteristics is then named

YOLOv4.

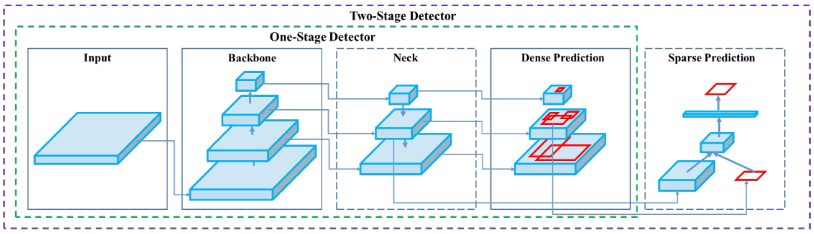


Figure 3.1: Object detector for YOLOv4. Obtained from [15]

- ***Backbone* Network**: YOLOv4 in Darknet utilizes powerful backbone networks to extract rich feature representations from input images. The default backbone network in Darknet's YOLOv4 implementation is CSPDarknet53, which is an improved version of the Darknet-53 architecture. CSPDarknet53 incorporates the concept of cross-stage partial connections (CSP) to enhance information flow and improve performance.

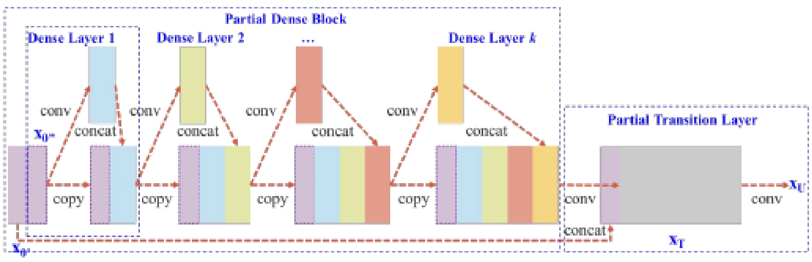


Figure 3.2: CSPDarknet53 architecture. Obtained from [17]

- **Feature Fusion**: YOLOv4 incorporates feature fusion techniques to combine features from different scales in order to handle objects of various sizes. It employs a feature pyramid network (FPN) called PANet (Path Aggregation Network), which integrates information from multiple layers with different resolutions to generate feature maps that capture both fine-grained and high-level contextual information. Thisis also called the *Neck* of the network.

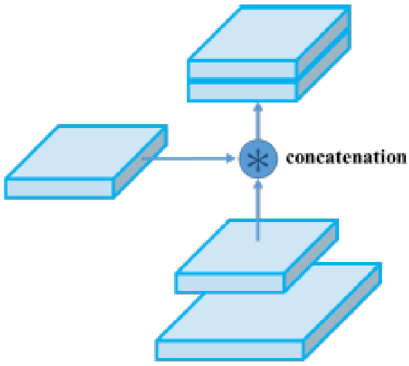


Figure 3.3: PAN for YOLOv4. Obtained from [15]

3.2 Detailed explanation of the adaptation of YOLOv4 for object legality detection

As explained in previous sections, this is not the first time that a YOLO based algorithm is used to perform illegal object detection, such as in [5] or [6]. However, the challenge in this work involves the use of neutron-based images. In this type of images you can encounter multiple objects and many of them can be either blurred, or with many unusal contrast/brighntess and rotations which can make object detection a complicated task.

In order to train the YOLOv4 object detection model effectively, a crucial part was to prepare data in the appropriate format. The YOLOv4 format requires bounding box annotations and class labels to be represented in a specific manner.

Each bounding box annotation should be described by the object's class label, along with the normalized coordinates and dimensions of the bounding box. These values represent the relative positions and sizes of the bounding boxes within the image. The formatting design should be the following: *<object-class> <x> <y> <width> <height>*, where <object-class> is the class label or index of the object. <x> and <y> are the coordinates of the center of the bounding box, relative to the width and height of the image. <width> and <height> are the width and height of the bounding box, also relative to the width and height of the image. Each line of the txt file corresponds to one object (bounding box). The workflow shown in 3.4 follows the whole process involved in illegal object detection with the dataset provided.

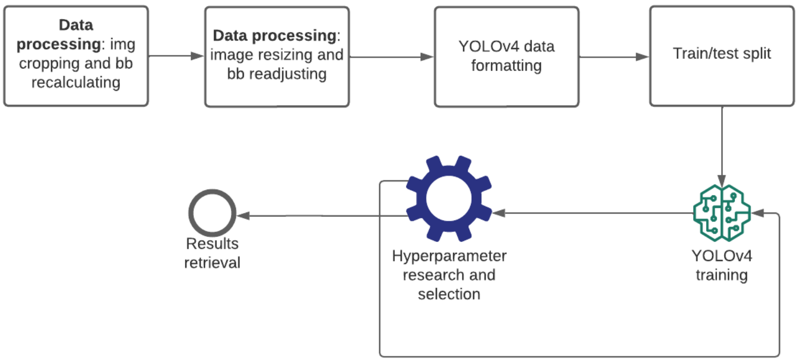


Figure 3.4: General workflow for the illegal object detection system.

3.3 Configuration and settings of the network

First of all, this project is prepared to be run in Google Colaboratory, a cloud environment in which VMs (Virtual Machines) are available to run Jupyter Notebooks. This is due to the prepared setup that it provides and the basic computational requirements that can be used in a daily basis. The tutorial in `https://github.com/AlexeyAB/darknet` has been followed in order to adapt the model to the provided dataset.

While selecting the configuration and hyperparameters for the model we carefully considered various factors mentioned in [15]. The first task when setting up the network was downloading it from the GitHub mentioned earlier. Subsequently, research needed to be done in order to modify the configuration file of the network and adapt it for the proposed problem. In order to do this, the yolov4-custom.cfg file, located in the cfg directory in the Darknet framework, was modified. The following parameters from the configuration file were set:

- **batch** = 32
- **subdivisions** = 16
- **width** = 416

- **height** = 416
- **classes** = 2 (in each of the [yolo] layers)
- **filters** = (classes + 5)x3, (in each of the [yolo] layers)
- **max_batches** = 6000 (for computational reasons)
- **steps** = 4800,5400 (for computational reasons)

3.4 Evaluation metrics used to assess the performance

Stated in [15], the metrics used in the proposed framework are the following:

- **Average Loss**: Average loss is a training metric that measures how well a model is learning to localize objects and adjust bounding box predictions during training. It is calculated based on a chosen loss function, in our case, IoU (Intersection over Union) loss. The intersection refers to the overlapping region between the predicted output and the ground truth target and the union to the combined area of the predicted output and the ground truth target.

$$IoU = \frac{\mathrm{I}}{\mathrm{I} + \mathrm{U} - \mathrm{I}} \tag{3.1}$$

- **mAP (Mean Average Precision)**: mAP is a widely used evaluation metric for object detection. It calculates the average precision across different object categories, providing an overall performance measure. Higher mAP scores indicate better detection performance across different object classes.

$$mAP = \frac{1}{N} \sum_{i=1}^{N} \text{AP}_i \tag{3.2}$$

Where N is the total number of classes and $\text{AP}(i)$ is the Average Precision for class i.

- **Precision**: Precision is the ratio of true positive detections to the sum of true positives and false positives. It measures the accuracy of object localization and helps minimize false positives, ensuring reliable predictions.

$$Precision = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{3.3}$$

- **Recall**: Recall, also known as sensitivity, is the ratio of true positive detections to the sum of true positives and false negatives. It measures the model's ability to correctly identify all positive instances, minimizing false negatives.

$$Recall = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3.4}$$

- **F1-score**: The F1-score is the harmonic mean of precision and recall. It balances both precision and recall and provides a single metric to evaluate the model's performance in terms of both false positives and false negatives.

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3.5}$$

4. Results

In this section, the final results obtained by the performed experiments are going to be shown and anayzed. They will also be compared with results in existing approaches and a final discussion about the strengths and limitations of the system.

4.1 Overview of the results

In order to obtain the results that are about to be shown in this section, a set of experiments and analysis were performed. The main goal is to achieve an optimized deep learning model that can efficiently detect illegal objects. These experiments involved training the YOLOv4 model with and without data augmentation. As explained in Chapter 2, data augmentations techniques were applied with the intention of improving the training and test results. As it can be seen in Table 4.1, three experiments were performed: model training with no data augmentation, another one with 30% of the data augmented and a final one with 60%. Best scores table (4.1) shows the best performance for the 6000 iterations in the training process. While training, when a thousand iterations are reached, the weights are saved. Finally, all of the weights files are tested and the one with the best scores is chosen. Additionally, Figure 4.1 shows the loss curve depicted in the training period (it defines the combined loss, which includes both the classification loss and the bounding box (BB) loss. A slight decreasing tendency can be observed and the final average loss with the 60% extra of data augmentation is 3.15. Results show an outstanding performance in detecting illegal objects, and by analyzing the evaluation metrics (3.2, 3.4, 3.3 and 3.5), it can be concluded that the model has not been overfitted, as both in training and evaluation metrics, the results show similar changes.

Figure 4.2 represents four test images in which the bounding boxes of

Data Augmentation	mAP	Recall	Precision	F1-score	average loss
No	0.87	0.95	0.96	0.96	3.26
30%	0.95	0.95	0.96	0.95	3.29
60%	0.97	0.96	0.96	0.96	3.15

Table 4.1: Best scores results table

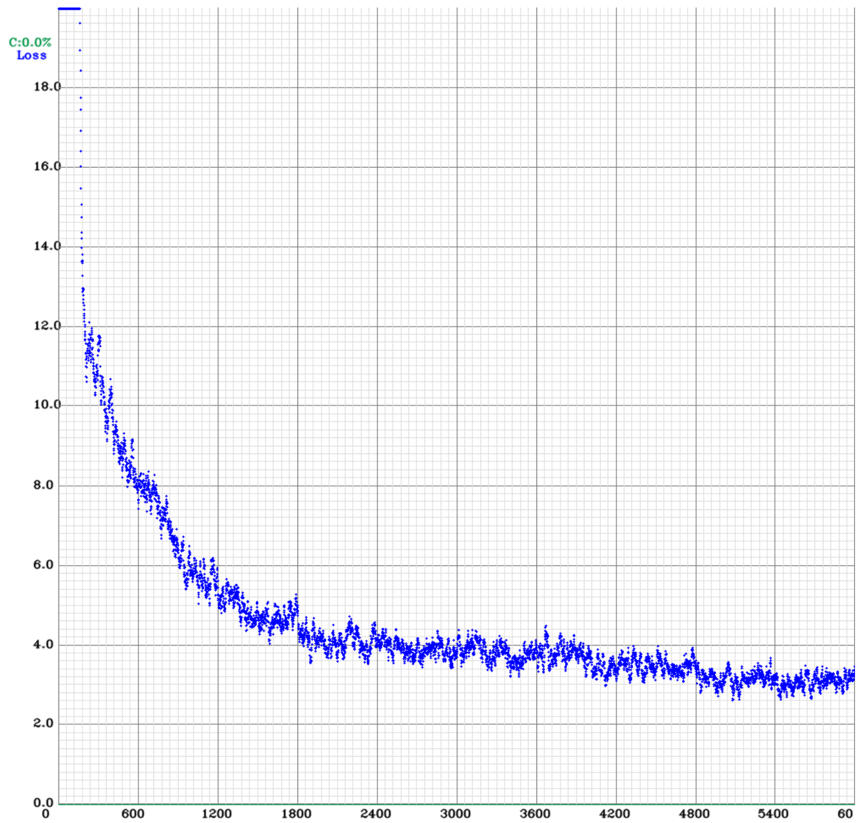


Figure 4.1: Loss chart obtained during the training of the YOLOv4 model without data augmentation.

each object in the images are depicted. The purple bounding boxes correspond to the *legal* class and the green ones to the *illegal* class. The number associated with each bounding box represents the probability of that object being from the class that it predicted. So if it is 1.00, the probability is 100%, 0.97 is 97%, etc.

4.2 Comparison with existing approaches

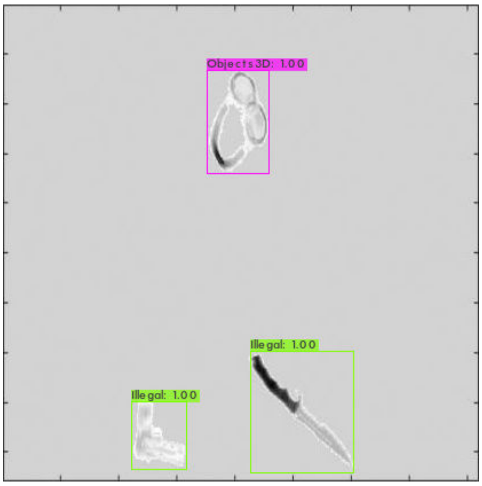
By having a look at Table 4.2, it can be analyzed that this approach overperforms most of the existing systems in all of the metrics applied. Further analysis will be made in Chapter 5.

Paper	mAP	Recall	Precision	F1-score	average loss
[9]	-	0.78	0.84	-	10.0
[10]	0.84	-	-	-	-
[11]	-	0.93	0.96	-	-
[2]	0.96	-	-	-	-
[3]	0.87	-	-	-	-
[12]	0.78	0.92	0.86	0.84	-
Our best approach	**0.97**	**0.96**	**0.96**	**0.96**	**3.15**

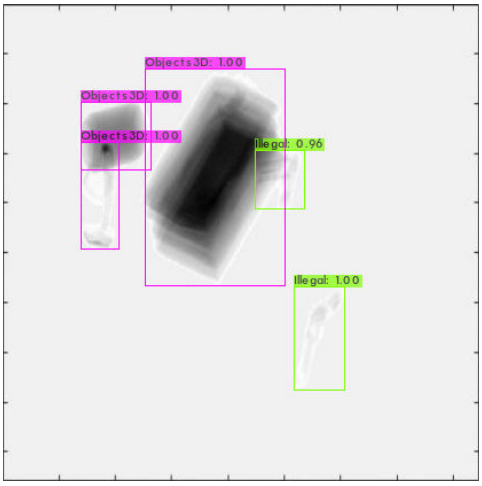
Table 4.2: Comparison table with the results of previous articles (- means that specific minformation about that metricis not provided)

4.3 Strengths and limitations of the system

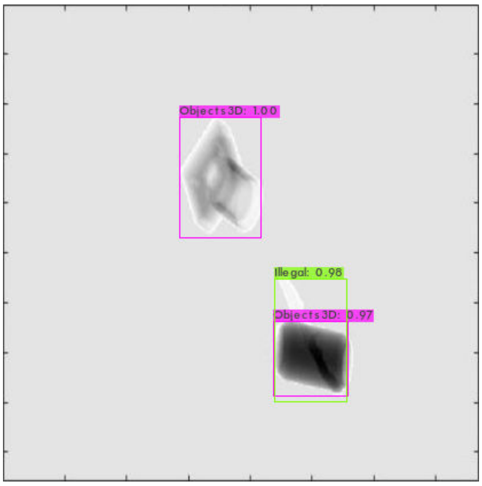
This YOLOv4 implementation offers several strengths and limitations when applied to illegal object detection. One of its main strengths is its robustness, as it has demonstrated exceptional performance in accurately detecting illegal objects. Moreover, it can be easily adapted to different datasets, enabling efficient training and detection in various environments. Another strength lies in its well-organized architecture, which promotes simplicity and effectiveness in object detection tasks. However, there are some limitations to consider. This implementation is based on the C programming language, which means that modifying certain aspects requires familiarity with the source code. Additionally, when running the model in platforms like Colab, it may suffer from performance issues, causing slower processing speeds. Another limitation is related to data storage, as the large amount of data required for training and detection can pose storage limitations.



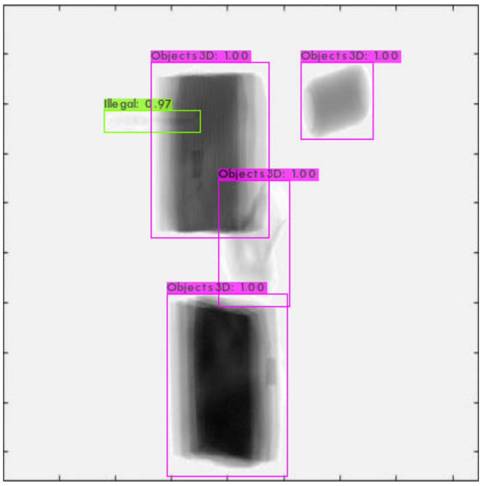
(a) **Box4**; 1 legal object, 2 illegal objects



(b) **Box993**; 3 legal objects, 2 illegal objects



(c) **Box2223**; 2 legal objects, 1 illegal object



(d) **Box2033**; 4 legal objects, 1 illegal object

Figure 4.2: Test images with their corresponding objects and bounding boxes generated.

5. Conclusion

In this chapter, as the main goals are stated and the final results obtained, an overall conclusion of this work is given out. Also a discussion about the implications of the project and room for improvement will be included.

5.1 Research objectives and results

In conclusion, this study aimed to optimize the YOLOv4 CNN model for detecting illegal objects in images by utilizing data augmentation techniques and conducting hyperparameter research and selection. The results of this study have demonstrated significant improvements in the model's performance through the augmentation of data. Moreover, the findings of this research surpass those of previous studies, particularly those conducted using X-ray images or other datasets, as the implementation of neutron images provides an advantageous perspective. Neutron images offer enhanced capabilities in penetrating dense and shielded materials, which are essential factors when detecting illicit objects. By successfully optimizing the YOLOv4 CNN model and achieving superior results, this study contributes valuable insights to the field of object detection and security. The findings suggest that further exploration of neutron images in combination with advanced deep learning techniques holds great potential for enhancing the accuracy and effectiveness of illegal object detection systems.

As it can be seen in Table 4.2, this proposal succesfully accomplished the goal of optimizing a YOLOv4 CNN in the task of illegal object detection. Many evaluation metrics are used in order to test the model and the final system returns a great set of images with the bounding boxes on each object and its predictions.

5.2 Implications and potential applications of the system

This collaboration with Dynaxion Security by developing an optimized YOLOv4 CNN model for detecting illegal objects in neutron-based images carries significant implications. Firstly, it can greatly enhance security measures in diverse settings, including airports, government buildings, and high-security facilities. By accurately and efficiently identifying illegal objects, the system effectively can mitigate potential threats and ensure safer situations. Secondly, the deployment of this system can lead to improved operational efficiency by automating the detection process. Moreover, the presence of an advanced system acts may discourage individuals from attempting to bring illegal objects into secured areas. This contributes to a safer environment and fosters public trust. However, it is important to consider legal and ethical aspects, such as privacy concerns and compliance with regulations, to ensure responsible and transparent use of the technology. One of the key ethical considerations is the responsible use of the system. A potential action that should be taken into account is establishing guidelines and protocols to govern the appropriate deployment and monitoring of the system. Regular audits and evaluations should be conducted to assess the system's accuracy, fairness, and effectiveness.

5.3 Future research and improvements

Looking ahead to future research and possibilities for advancement, there are many paths in which this study can lead. First of all, automatizing and abstracting the whole process would be the greatest step. Having a real-time security system can be really beneficial for the safety of the population in events, flights, banks, etc. Because of lack of time, further research on hyperparameter tuning or model improvement has not been possible. Since in this work, YOLOv4 c-based implementation has been used, plenty of knowledge of the source code needed to be learnt in order to optimize the model. By investing more time in this, regularization and dropout techniques can be applied in order to improve even more the permormance of the network. Additionally, more research could explore the potential of domain adaptation and transfer learning techniques to transfer knowledge from other datasets (e.g., X-ray images) to improve the model's performance on neutron images. This can help overcome potential challenges posed by the scarcity of neutron image data.

Appendices

A. Protocol for Literature Review

With the purpose of conducting a literature review for this study, a search for scientific articles is carried out as follows. We aim to cover the most relevant topics related to this study, and keywords related to these topics are chosen to perform a search on Scopus. The formulated query covers topics on xray images, object detection and threat/illegal materials articles.

Section	Keywords for the query
TITLE–ABS–KEY	"object detection" OR "object recognition"
TITLE–ABS–KEY	"X-ray*" OR "radiography"'
TITLE–ABS–KEY	"illegal materials" OR "contraband" OR "prohibited items" OR "restricted items"

Table 1: Table A1, query launched to Scopus. Covering object detection, x-ray and ilegal materials.

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