Firearm Detection and Segmentation Using an Ensemble of Semantic Neural Networks

Alexander Egiazarov  
Digital Security Group  
University of Oslo  
Oslo, Norway  
alexaeg@ifi.uio.no

Vasileios Mavroeidis  
Digital Security Group  
University of Oslo  
Oslo, Norway  
vasileim@ifi.uio.no

Fabio Massimo Zennaro  
Digital Security Group  
University of Oslo  
Oslo, Norway  
fabiomz@ifi.uio.no

Kamer Vishi  
Digital Security Group  
University of Oslo  
Oslo, Norway  
kamerv@ifi.uio.no

Abstract—In recent years we have seen an upsurge in terror attacks around the world. Such attacks usually happen in public places with large crowds to cause the most damage possible and get the most attention. Even though surveillance cameras are assumed to be a powerful tool, their effect in preventing crime is far from clear due to either limitation in the ability of humans to vigilantly monitor video surveillance or for the simple reason that they are operating passively. In this paper, we present a weapon detection system based on an ensemble of semantic Convolutional Neural Networks that decomposes the problem of detecting and locating a weapon into a set of smaller problems concerned with the individual component parts of a weapon. This approach has computational and practical advantages: a set of simpler neural networks dedicated to specific tasks requires less computational resources and can be trained in parallel; the overall output of the system given by the aggregation of the outputs of individual networks can be tuned by a user to trade-off false positives and false negatives; finally, according to ensemble theory, the output of the overall system will be robust and reliable even in the presence of weak individual models. We evaluated our system running simulations aimed at assessing the accuracy of individual networks and the whole system. The results on synthetic data and real-world data are promising, and they suggest that our approach may have advantages compared to the monolithic approach based on a single deep convolutional neural network.

Index Terms—weapon detection, firearm detection, firearm segmentation, semantic segmentation, physical security, neural networks, convolutional neural networks (CNNs)

I. INTRODUCTION

According to the report “Global Study on Homicide 2019”, published by the United Nations Office on Drugs and Crime (UNODC), more than 464,000 people across the world were killed in homicides in 2017, accounting for more than five times of the number of people killed in armed conflict. Moreover, excluding homicides of unknown mechanism, more than half (roughly 54%) of homicides worldwide in 2017 were perpetrated with a firearm, and slightly more than a fifth (22%) were perpetrated with a sharp object [1]. The use of technology in law enforcement and crime prevention is developing rapidly. For example, video surveillance technology has been proved useful in aiding investigators either to identify new suspects related to a crime or to bolster evidence against current ones. In some cases, video footage can be a decisive piece of evidence in the course of a trial. Current video surveillance systems (also known as CCTV) are generally operating passively [2], which indicates that related authorities usually become aware of a crime event postliminary. For example, CCTV operators or police officers review a video footage only after a crime occurred. In addition, in cases where video surveillance technology is used for real time monitoring as a way of deterring potential crimes, an agent would have to visually detect the presence of weapons in the monitored scenes and make decisions in a very short time. Any delay or miscalculation in the decision making process of an agent could be detrimental and result even in loss of human lives. One of the most effective solutions to this problem is to enhance surveillance cameras with Artificial Intelligence (AI), where an accurate proactive crime-fighting tool can be used to detect and consequently prevent weapon crimes.

The contribution of this research is twofold. First, we apply the concept of semantic decomposition to the problem of detecting a weapon; that is, we reduce the holistic problem of detecting a whole weapon to the subset of smaller, semantically-related problems of identifying the different component parts of a weapon. Second, we apply and evaluate this approach on a weapon detection system that we developed using deep Convolutional Neural Networks (CNNs) for detecting individual parts of a firearm in images and videos.
The proposed method can be used in several applications, such as for real-time detection of weapons in places where video surveillance is available or needed (e.g., airports, stadiums, other public places), for control purposes (e.g., in the case of videos or images uploaded to social media containing graphics with weapons), and for complementing other current security technologies (e.g., metal detectors that can detect weapons concealed on an individuals body).

The paper is structured as follows. Section II presents background information and related work. Section III formalises the goal of our research and our approach to solving the problem of weapon detection via machine learning. Section IV analyses the dataset generation protocol for our study, while Section V provides details about the model we implemented. Section VI presents different simulations conducted for validating our model and assessing its performance. Section VII discusses some ethical implications related to our work. Finally, Section VIII concludes our work and outlines future developments.

II. BACKGROUND

A. Security

No region in the world is exempt from the dramatic consequences of firearms violence. The problems associated with firearms violence covers the whole spectrum of human security: ranging from high levels of individual physical insecurity (domestic and street violence, gang and criminal violence) with severe economic and social consequences for the society at large, to large scale armed conflicts in which these arms enable widespread violence and account for the majority of deaths.

B. Machine learning

Machine learning provides a set of methods and techniques for inferring patterns and relations among data. Supervised learning is the task of learning a functional relationship between a set of data and a semantic class. Given a set of samples \( x \) as vectors, where each of the vectors is associated with a label \( y \), the aim of a machine learning algorithm is to discover a function \( f : x \mapsto y \) that associates every sample to its label \( f \).

A popular family of algorithms for supervised learning is neural networks, which constitute universal approximators that can be effectively trained by backpropagation. Convolutional Neural Networks, in particular, are a sub-set of neural networks designed to process two-dimensional inputs and be invariant to translations; these networks can be used to process images and to carry out tasks such as image detection or image segmentation.

The availability of large amounts of data and computational power has recently fostered the development of deep learning algorithms, that is, the use of layered neural networks able to learn complex functions \([4]\). In particular, the success of deep CNNs on several image recognition tasks \([5]\) has made these models a common choice for solving problems of image recognition, detection and segmentation. Starting from the simple pixel representation of an image, deep CNNs automatically discover robust and increasingly higher-level features that can be used to solve challenging problems in image recognition and segmentation \([6], [7]\).

C. Related work

The problem of weapon detection in videos or images using machine learning is related to two broad research areas. The first research area focuses on addressing weapon detection using classical computer-vision or pattern-matching methods, whereas the second research area focuses on improving the performance of object detection using machine learning techniques.

- **Weapon detection:** The majority of methods used for weapon detection are based on imaging techniques, such as infrared imaging \([8]\) and millimeter wave imaging \([9]\). The most representative application in this context is luggage control in airports.

- **Object segmentation models:** Object segmentation consists of recognizing an object and finding its location in the input image. The existing methods address the segmentation problem by reformulating it into a classification problem; first a classifier is trained, and then, during the detection process, filters are run on a number of areas of the input image using either the sliding window approach \([10]–[12]\) or the region proposals approach \([13]–[16]\).

Standard machine learning approaches based on deep convolutional neural networks have also been used to try to solve the problem of detection and segmentation at the same time \([17], [18]\). However, to the best of our knowledge this is the first work focusing on firearm detection and segmentation using an ensemble of small semantic neural networks.

III. PROBLEM STATEMENT

In this paper, we tackle the problem of detecting the presence of weapons within an image. We cast this problem as an image detection/segmentation supervised learning problem: we want to learn a function that given an image as input returns the presence and the location of the weapon. Following the state of the art, we decided to use convolutional neural networks to learn such a function.

Weapon detection presents some peculiar and significant challenges. First of all, one of the main drivers of deep learning, that is the availability of data, is weak in this specific application domain. Differently from other standard image recognition problems that can exploit the availability of large standardized public datasets, we can not rely on similar resources. For this reason, we decided to collect and develop our own dataset (Section IV).

We also decided to consider a possible limitation on the other drive of deep learning, that is the availability of
significant computational resources. To face this constraint, we decided to exploit common prior semantic knowledge about weapons: since any modern firearm is composed of different identifiable parts, we decided to decompose the overall problem of detecting a single weapon in a set of smaller problems concerned with the detection of the individual component parts of the weapon itself. We thus instantiated a set of small convolutional neural networks, each one solving the simpler problem of detecting a specific component part of a weapon, and aggregated the results in a robust output (Section V). The individual networks are faster to train, requiring less computational resources and can be easily parallelized.

Training a set of smaller and potentially weaker learners finds justification in ensemble theory. It is well-known that simple weak learners (i.e., modules whose accuracy is just above a random chance threshold) may be effectively aggregated in ensemble modules whose accuracy is stronger than the individual learners [19]. This principle informs our hypothesis that aggregating potentially weak learners in the form of small dedicated networks detecting specific parts of a weapon may not only guarantee a computational advantage but also produce an ensemble system that is more robust and reliable than a single deep network.

IV. DATASET GENERATION

Due to the lack of comprehensive image libraries for firearms, we created a custom dataset. We decided to focus on a single specific type of rifle, AR-15 style rifle. The choice was made considering the popularity of this firearm in the Western part of the world, accessibility of the source images and visual diversity of different models with core features being preserved. It is worth noting that this type of firearm in addition to other rifles was used in terror attacks (mass shooting), such as in New Zealand in 2018 [20], in Las Vegas, USA in 2017 [21] and in Orlando, USA in 2016 [22]. We identified four essential component parts: barrel, magazine, butt-stock and upper-lower receiver assembly (see Figure 1).

Fig. 1: Main components of AR-15 rifle.

To generate positive instances for our dataset we queried the Google images service and retrieved 4500 instances of pictures depicting AR-15 rifles. We first processed these images manually, generating and classifying 2500 samples for each component part. Following the standards [3], we partitioned samples into training (2000 samples), validation (400 samples) and test (100 samples) sets; we then augmented our training dataset through synthetic manipulations (e.g., rotation, shearing, and scaling) to increase the total number of training samples per part to 8000. To generate negative instances, we reused the initial source set of 4500 images and extracted random samples that explicitly do not contain any firearm parts, such as background details, humans, clothing and miscellaneous items present in the source images (see for an example Figure 2).

Fig. 2: An illustrative example of the stock and a negative sample.

In total, we have five datasets, one for each component plus one composed of exclusively negative examples; all the images add up to 42500 samples. Each picture is 200×200 pixels.

V. SEMANTIC SEGMENTATION MODEL

One of the main contributions of this work is the semantic decomposition of the detection problem. Instead of directly solving the challenge of detecting a weapon, we developed a system that relies on the identification of its parts. Breaking down the problem of identifying a weapon into the problem of identifying its components simplifies the problem at hand: it provides a divide-and-conquer approach to solve a high-level problem through the solution of a set of smaller similar problems. Moreover, in this case, it also offers a simple way to deal with situations where firearms are partially concealed, lack certain distinct features or are modified.

We implement a modular array of convolutional neural networks. All the networks have the same architecture: three convolutional layers for feature extraction and three dense layers for binary classification (see Figure 3 for reference). In the convolutional section, we use layers containing 32 or 64 filters with default stride of 1×1, with ReLU activation functions, and 2×2 max-pooling. In the dense section, we use fully connected layers. We use a ReLU activation function in all layers of the network. The number of neurons in the dense layers is determined by the number of classes (four in our case). The output layer uses a sigmoid activation function to predict the probability of each component being present in the image.

Fig. 3: Architecture of the semantic segmentation model.

1 All models are implemented using Keras (https://keras.io) and TensorFlow (https://www.tensorflow.org).
activation function, except for the last layer where we rely on the softmax function to compute the output. Moreover, in the second-to-last layer, we use dropout with a probability $p = 0.5$ for regularization. The relatively small architecture allows for faster parallel tuning and training.

At runtime, in order to process an image of arbitrary size, a simple iterative algorithm based on a sliding window is used to generate cropped images of the required input size of $200 \times 200$ pixels.

We take the output of each network to carry equal weight towards the final detection decision, each one contributing 25 percent certainty about the presence of a firearm. However, the mechanism to aggregate each output in a final decision can be easily changed by the developer of the system by tweaking the contribution weight of each component of the weapon and the number of components that should be detected before raising an alert: in sensitive and critical situations, the system can be configured to raise a firearm detection alert whenever a single component part is identified; in less critical scenarios, the sensitivity (and, relatedly, the number of false positive detections) may be lowered by requiring the identification of multiple component parts before raising an alert. Notice, also, that a developer may easily decide to instantiate and aggregate different custom-designed networks; the modular design of our system allows for straightforward plugin and removal of additional networks, whose output is aggregated in the final decision.

Finally, to assess image segmentation, the outputs of the individual networks are used to produce a heatmap and a bounding box marking the region of the image where our model returned a high positive activation, thus pinpointing the location of the detected weapon in the image.

### VI. Experimental Validation

#### A. Simulation 1: Quantitative assessment of the individual networks

The first simulation assesses the performance of each component network on the test data.

- **Protocol:** After training and validating our networks, we tested each of them on the corresponding test data set composed of 100 positive and 100 negative instances. The aim of this simulation is to evaluate the accuracy achieved on the test set and to identify and understand the potential weaknesses of the system by examining the cases on which the system returned a wrong output. The output layer of the network has two nodes, one activated when the network believes a weapon is present, and one activated when the network believes a weapon is absent. Since the last layer is a softmax, the total activation of the layer is one. The threshold for weapon detection is set at 0.5. If the output of the node for the presence of a weapon is greater than 0.5, then we have a positive output; otherwise, we have a negative output.

- **Results:** Table I reports the absolute detection values on positive and negative samples for each component network along with the relative accuracy, precision and recall.

| Part name | Pos. set | Neg. set | Accuracy | Precision | Recall |
|-----------|----------|----------|----------|-----------|--------|
| Stocks    | TP: 97   | TN: 78   | 0.875    | 0.97      | 0.815  |
|           | FP: 3    | FN: 22   |          |           |        |
| Magazines | TP: 81   | TN: 84   | 0.825    | 0.81      | 0.835  |
|           | FP: 19   | FN: 16   |          |           |        |
| Barrels   | TP: 99   | TN: 54   | 0.765    | 0.99      | 0.683  |
|           | FP: 1    | FN: 46   |          |           |        |
| Receivers | TP: 82   | TN: 95   | 0.885    | 0.82      | 0.943  |
|           | FP: 18   | FN: 5    |          |           |        |

*Note:* TP stands for true positives, FP for false positives, TN for true negatives, and FN for false negatives.

The network responsible for the detection of receivers achieved 95% accuracy when tested against negative samples, but performed slightly worse in detecting the actual receivers achieving 82% accuracy. The network responsible for the detection of magazines achieved 84% accuracy against the negative samples and 81% accuracy in detecting magazines (positive samples). The network trained on barrels correctly classified 54% of the negative samples, and performed remarkably well in detecting barrels with an accuracy of 99%. The results of the network responsible for the detection of the stocks gave an 78% accuracy in
classifying correctly negative samples and 97% accuracy in detecting stocks.

c) Discussion: Overall, the performance of the individual networks is satisfying, with an accuracy ranging between 75 and 90 percent. Notice that the strength of our system relies not only on the performance of the individual networks but also on the ensembling of the results of all networks. For instance, assume that the system is set up to raise a positive detection alert if at least two of the networks output a positive signal; assume also that the average accuracy on positive samples is 0.8 (as in our simulations); then, the overall probability of the system of missing a positive sample is given by the probability of three individual networks of making a mistake in recognizing a positive sample, that is, \((1 - 0.8)^3 = 0.008\); the overall system may then reach an accuracy up to 0.992 in detecting positive samples. This result is consistent with the ensemble theory discussed in Section III.

B. Simulation 2: Evaluation of semantic segmentation

In the second simulation, we further assess the behaviour of the individual neural networks assembled into a coherent system and provide a proof of concept for the principle of semantically decompositon of the problem of weapon detection.

a) Protocol: We tested the reliability of the system by feeding images (from the datasets) of AR-15 style rifle on a noisy neutral background (e.g., an image of a concrete surface). We selected a high-quality image of the weapon and we artificially produced different sets of transformed images, such as rigid transformations of the weapon (change of orientation, scale and location) and ablative transformations of the weapon (removal and occlusion of component parts). We ended up working with both images of single component parts and images of the whole rifle. In total, we generated 14 random images that allow us to evaluate both the performance of individual networks (as we did in the previous simulation) and the performance of the whole system. For a sample of a used image, the background, and a sample ablative transformation, see Figure 4.

The setup of this simulation allows us to evaluate the performance of the network independently of possible confounding elements in the background. In other words, it allows us to assess whether the networks are able to identify their target component both in an ideal setting and under several challenging transformations of the weapon.

We evaluate the results of our simulations by assessing the detection and segmentation performance of our system. The detection is evaluated by checking whether a specific network (in case of an image of a component) or the ensemble system (in case of an image of the whole weapon) produce a positive output. The segmentation is evaluated by computing a bounding box and checking it against a manually defined ground-truth bounding box. A segmentation is deemed successful if the area of the bounding box covers the firearm or all visible parts. If the bounding box is clearly outside of the boundaries of the firearm or if it is covering a sizeable non-firearm area, then the segmentation is deemed unsuccessful.

b) Results: Testing 14 images, the system correctly detected the presence of a weapon, without generating any false negatives. The segmentation was also satisfactory, with the system successfully placing a bounding box over the firearm despite different orientations, scaling and part combinations. Figure 5 shows different sample bounding boxes computed by the system on components that are part of the rifle. Similarly, Figure 6 shows the overall bounding box computed on an image of a rifle by aggregating individual bounding boxes. Notice that the end parts, such as the barrel, while correctly identified by the individual network, were sometimes not covered in the aggregated bounding box. The reason for that is that the aggregation algorithm weighted more overlapping areas such as the central parts of the weapon.

c) Discussion: The results of this simulation are very encouraging: even though these tests were conducted on sanitized images in which potential distractors were removed, they demonstrate that the array of networks is robust enough in detecting parts of a weapon under different transformations. Removing certain parts of the rifle proves the main strength of our solution based on a set of semantic networks: even when some parts of a firearm object are obscured or concealed, our system can still detect the presence of the firearm as long as at least some of the predefined parts are present. This makes our system suitable for deployment in...
environments where detecting concealed firearms in a rapid manner can mitigate potentially harmful events.

C. Simulation 3: Evaluation on realistic video frames

In this simulation we assess the accuracy of our system by processing images obtained from a custom video stream rather than images obtained from the Internet.

a) Protocol: We processed a video stream containing a single standing person holding a AR-15 rifle. The subject is holding the rifle in three possible positions (low, medium and high). For each position, we extract 16 images showing the person holding the rifle in different degrees of rotation. The clothing of the subject and the background in the images are neutral to ensure that the rifle does not explicitly blend with the surroundings or the person. In total, we processed 48 sample images in which the weapon is presented in different rotation angles, and also situations in which certain parts of the rifle are obscured by the subject’s clothing or the way the weapon is held.

Similarly to previous simulations, we evaluate our results by computing the detection accuracy and presenting the bounding boxes of the identified objects. For each testing image, we provided a ground-truth bounding box by manually identifying the area in a frame where the rifle or parts of the rifle were visible. We quantitatively computed the overlap between the true bounding box and the predicted bounding box by evaluating the intersection between the true bounding box over the union of the bounding boxes computed by each one of our component networks.

b) Results: Table II reports the number of correct detections of the network and the number of instances where the computed bounding box overlapped at least 50 per cent the true bounding box. Images where the subject was holding the rifle at a low position, were successfully detected 13 times out of 16, even when the overlapping of bounding boxes was low (4 out of 16 with 50% or more overlap). Images where the subject was holding the rifle at a medium position, performed slightly worse, with our system correctly classifying 10 out of 16 samples, whereas there was an improvement in accuracy of the segmentation boxes with 6 out of 16 boxes overlapping equally or more than 50%. Finally, images where the subject was holding a rifle at a higher position our system achieved higher accuracy by correctly classifying 15 out of 16 images. In addition, 9 out of 16 images had their computed bounding boxes overlapping for 50% or more with the true bounding boxes.

| Position | Detection | Overlap over 50% |
|----------|-----------|-----------------|
| Low      | 13 / 16   | 4               |
| Medium   | 10 / 16   | 6               |
| High     | 15 / 16   | 9               |

Figure 7 shows a successful detection with an accurate computed bounding box. Figure 8 shows the case of a successful detection, but where the bounding box was mistakenly computed and included the head of the person holding the weapon.

c) Discussion: In this simulation, the system had the task of identifying a AR-15 rifle held by a person. Besides different orientations and angles, this scenario takes into consideration concrete distractors, such as the person itself and its clothes. The results showed that semantic segmentation modelling is indeed promising in detecting a firearm...
in different angles and positions, but nevertheless, it is still prone to misclassifying objects that bear similar color or shape to the ones that have been used to train the model. For instance, the misclassification of the black balaclava as shown on Figure 8 suggests that the negative set used during the training should include a wide variety of images to cover all possible situations and environmental features such as clothing, headwear and background details.

VII. ETHICAL CONSIDERATIONS

Use of machine learning in safety-critical situations raises ethical questions about the uses and potential misuses of learning algorithms. In our case, while our aim was to develop an effective system that may be used to help security personnel in detecting threatening situations in civil society and in intervening more promptly to prevent loss of lives, we are aware that our system may be tuned and deployed in other scenarios; in particular, it is not far-fetched to see its use within lethal autonomous weapon system (LAWS). The authors, however, discourage and condemn the use of their system in autonomous weapons.

To prevent our system from making decision autonomously, we also considered a potential extension, including a human-in-the-loop. In the context of critical AI systems designed to make potentially dangerous decisions, a simple solution adopted to prevent catastrophic errors is offered by integrating a human overseer in the decision loop of the machine [24], [25]. We considered the implementation of a human-in-the-loop system both at training time and at test time. During training, such an approach would allow a human supervisor to check and correct the actual decision of the system, it would allow the detection of common mistakes and biases in the network, and it would make it possible to transfer human insights by providing a stronger learning signal to the machine. After deployment, a human overseer would check and validate the outputs of the network and would be responsible and accountable for the final decision.

VIII. CONCLUSIONS AND FUTURE WORK

In this paper, we considered the problem of detecting the presence of weapons within images or video frames. We suggested a solution based on machine learning techniques and the principle of semantic decomposition of the problem. Instead of implementing a single complex learning module which would require large amounts of data and high computational resources, we proposed the use of multiple simple neural networks that could be cheaply trained to detect only specific components of a weapon and which could be easily aggregated to produce robust output. We tested our model on data from the same distribution as the training data (i.e., Google images), we examined it on synthetic sanitized data, and we evaluated it on out-of-sample (i.e., video frames) data. The results showed the reliability of the individual component part networks and the versatility of the overall system in integrating the outputs of the single networks.

While promising, our results are still preliminary and different directions of future developments are left open. From a practical point of view, the system may be further refined by generating more extensive and representative data sets and by considering additional components of a rifle. Another obvious extension would be to enlarge the set of detected objects from the simple AR-15 model to other rifles or, even, other weapons, such as knives. The process of aggregating the outputs of individual networks could be refined as well. In this work, we proposed a simple majority rule, and we suggested in passing other potential rules. However, the problem of producing a single output may be more formally expressed in probabilistic terms, and we could exploit other statistical models to generate outputs reporting not only a final decision but their uncertainty, as well. This work could better reconnect our research to the theory of ensemble learning as well.

[https://futureoflife.org/open-letter-autonomous-weapons/](https://futureoflife.org/open-letter-autonomous-weapons/)
Most importantly, we are considering the development of a thorough comparison between our semantic segmentation approach and standard approaches presented in the literature and based on a single deeper neural network able to identify at once the presence of weapons in an image. A fair comparison is far from trivial, as it would require the training of models with similar capacity and using equally informative data sets. We are designing such experiments with the aim to precisely evaluate the strengths and the weaknesses of the two approaches in terms of accuracy, confusion matrices, and training cost in terms of number of samples and computational time.

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