A Dataset and System for Real-Time Gun Detection in Surveillance Video Using Deep Learning

Delong Qi\textsuperscript{1}, Weijun Tan\textsuperscript{1,2}, Zhifu Liu\textsuperscript{1}, Qi Yao\textsuperscript{1}, and Jingfeng Liu\textsuperscript{1}

Abstract—Gun violence is a severe problem in the world, particularly in the United States. Deep learning methods have been studied to detect guns in surveillance video cameras or smart IP cameras and to send a real-time alert to security personnel. One problem for the development of gun detection algorithms is the lack of large public datasets. In this work, we first publish a dataset with 51K annotated gun images for gun detection and other 51K cropped gun chip images for gun classification we collect from a few different sources. To our knowledge, this is the largest dataset for the study of gun detection. This dataset can be downloaded at www.linksprite.com/gun-detection-datasets. We present a gun detection system using a smart IP camera as an embedded edge device, and a cloud server as a manager for device, data, alert, and to further reduce the false positive rate. We study to find solutions for gun detection in an embedded device, and for gun classification on the edge device and the cloud server. This edge/cloud framework makes the deployment of gun detection in the real world possible.

I. INTRODUCTION

Gun violence has been a big problem around the world, especially in the countries where it is legal to carry a gun, like the United States. Every year, many innocent people are killed or harmed by gun violence in public areas \cite{1}.

There are video surveillance systems deployed in many public places, but they still require the supervision and intervention of humans. As a result, these systems cannot detect gun-related crimes fast enough to prevent the crimes. In more recent years, automatic gun detection systems have been studied \cite{2}–\cite{10}. Most of them still use surveillance video cameras, and the video streams are sent to an edge device or server to decode the video, detect guns in the video frame, and send alert (email, text message, or phone call) to personnel on duty. Others use affordable smart IP camera as an edge device, do gun detection on the camera, send the cropped gun image to server, and activate the server to send alert. The former can reuse existing surveillance video cameras, but the video streaming uses a lot of WiFi or Ethernet bandwidth, and the video processing and gun detection use expensive edge devices or servers. The latter needs to deploy new smart IP cameras, but the cameras accomplish all the video processing and gun detection, only very little data is sent to server for further processing. As a result, it is a more affordable solution than the former one.

There are a few challenges in gun detection system. First of all, it has to achieve a very high true positive (correct detection) rate (TPR), and very low false positive (false alarm) rate (FPR). In our study, we find that one major problem is how to control the false alarms, i.e., the FPR. In this prospective, gun detection remains an open problem.

The second challenge is there are no large public gun detection datasets. Almost all all researchers collect their own dataset and evaluate the performance of their algorithms on these private dataset. To our knowledge, the amount of data in their dataset is typically a few thousands, e.g., \cite{4}, \cite{6}, which is way too few. As a result, there is no way researchers can compare the performance of their algorithms to others and it is impossible to tell which algorithm is better. Our first contribution of this work is that we collect a dataset with 51K gun images. For the problem of false alarm we mentioned before, we also collect a non-gun image dataset, including images that are easily mis-detected as guns, for the study of gun/non-gun classification.

Our second contribution is to present a system for real-time gun detection and reporting. We present the image processing procedures on the edge device and the cloud server. We study to find solution for real-time gun detection on low-cost embedded edge device (e.g., smart IP camera), solution for light-weight gun classification on the edge device, and solution for more complex gun classification on the cloud server. Our focus is not to invent new detection algorithm, but to find and optimize existing algorithms for use in a practical system.

II. RELATED WORK

Among the works on gun detection \cite{2}–\cite{8}, most of them focus on applying existing CNN networks on object detection of guns. They use very complex CNN networks without considering the applications in practical system. Even though some of them call their algorithms real-time \cite{7}, \cite{8}, these algorithms use very expensive GPU machine or CPU machine, which make them not practical in large scale deployment. The work \cite{9} combines body pose with object detection to improve the detection accuracy. This additional pose detection makes it run even slower on given machine.

Another problem is the lack of large public dataset for gun detection. Most of the works use proprietary dataset, which are not only small, but also not available to other researchers. We summarize the CNN networks and datasets used in their work in Table \ref{tab:1}. Since our goal is to find a solution for embedded device, we add comments if these networks are applicable in practical systems. From the summary, we

\begin{table}[h]
\begin{center}
\begin{tabular}{|c|c|c|c|c|}
\hline
\textbf{Network} & \textbf{Dataset} & \textbf{Useful for} & \textbf{Comments} \\
\hline
VGG16 & \cite{2} & Useful for Embedded & Small, proprietary \cite{2} dataset, not suitable for practical use \\
\hline
ResNet50 & \cite{3} & Useful for Embedded & Small, proprietary \cite{3} dataset, not suitable for practical use \\
\hline
InceptionV3 & \cite{4} & Useful for Embedded & Small, proprietary \cite{4} dataset, not suitable for practical use \\
\hline
MobileNetV2 & \cite{5} & Suitable for Embedded & Light-weight, suitable for practical use \\
\hline
FaceNet & \cite{6} & Suitable for Embedded & Light-weight, suitable for practical use \\
\hline
RetinaNet & \cite{7} & Suitable for Embedded & Light-weight, suitable for practical use \\
\hline
YOLOv3 & \cite{8} & Suitable for Embedded & Light-weight, suitable for practical use \\
\hline
\end{tabular}
\end{center}
\caption{Summary of CNN networks and datasets used in the work of gun detection.}
\end{table}
observe that people really like Faster-RCNN [11], which is way more complex and slow for use in practical system. The one exception is [2], which uses a transitional image processing and a 3-layer MLP. However, it uses a very small dataset of only 3559 frame images. From this summary we see the need of a large dataset and a detection network for practical real-time applications.

In Fig. 2, we show 40 sample gun classifier images, which are cropped from the ground truth locations of the some gun images.

In Fig. 1, we show 40 sample gun detection images where the multi-scale training images are cropped from the ground truth locations of the some gun detection images.

For the concern of FPR, we also collect a large non-gun image dataset for detection and classification. Since they are non-guns, so no annotation is needed. Non-gun images are rather abundant and easy to collect. We collect 94K non-gun images from the popular ImageNet [14] and COCO [15] datasets. Furthermore, we collect objects falsely detected as guns in our system and put them in the dataset. These are hard cases and are very helpful to improve the FPR.

In Fig. 2, we show 40 sample gun classification images, which are cropped from the ground truth locations of the some gun detection images.

We deploy a few cameras in a private office and capture some gun detection data in a real scene. The data we collect this way is about a couple of thousands. We check the statistics of the gun images in the detector dataset. We look at the whole image size (width x height) and the gun bounding box size (width x height). These area indicates the resolution of the whole image and the gun object. The number of images are summarized in Table II. We use a CNN-based gun detector to roughly label the data. Finally we manually check and relabel the inaccurate labels.

We collect some images from publicly available websites of some of the papers [4], [6], [13]. Note that many of these images overlap with the first source and we have to manually clean them. The images from the video footages in [13] are used in [6]. We do not use most of them because their resolution is very low and different from real cameras.

We deploy a few cameras in a private office and capture some gun detection data in a real scene. The data we collect this way is about a couple of thousands.

Many negative samples for gun detection and classification are collected from the failed cases in our deployment cameras.

For the concern of FPR, we also collect a large non-gun image dataset for detection and classification. Since they are non-guns, so no annotation is needed. Non-gun images are rather abundant and easy to collect. We collect 94K non-gun images from the popular ImageNet [14] and COCO [15] datasets. Furthermore, we collect objects falsely detected as guns in our system and put them in the dataset. These are hard cases and are very helpful to improve the FPR.

In Fig. 2, we show 40 sample gun detection images where annotated gun bounding boxes are drew with red rectangles. In Fig. 2, we show 40 sample gun classifier images, which are cropped from the ground truth locations of the some gun detection images.

### III. Gun Detection Dataset

Before we present our gun detection system, we first present the dataset we prepare and make public for the community.

#### A. Image Sources

The sources where we collect our gun image dataset include:

- We first collect a lot of gun images from the IMFDB website [12] - a movie internet firearms database. Then we use a CNN-based gun detector to roughly label the data. Finally we manually check and relabel the inaccurate labels.
- We collect some images from publicly available websites of some of the papers [4], [6], [13]. Note that many of these images overlap with the first source and we have to manually clean them. The images from the video footages in [13] are used in [6]. We do not use most of them because their resolution is very low and different from real cameras.
- We deploy a few cameras in a private office and capture some gun detection data in a real scene. The data we collect this way is about a couple of thousands.
- Many negative samples for gun detection and classification are collected from the failed cases in our deployment cameras.

For the concern of FPR, we also collect a large non-gun image dataset for detection and classification. Since they are non-guns, so no annotation is needed. Non-gun images are rather abundant and easy to collect. We collect 94K non-gun images from the popular ImageNet [14] and COCO [15] datasets. Furthermore, we collect objects falsely detected as guns in our system and put them in the dataset. These are hard cases and are very helpful to improve the FPR.

In Fig. 2, we show 40 sample gun detection images where annotated gun bounding boxes are drew with red rectangles. In Fig. 2, we show 40 sample gun classifier images, which are cropped from the ground truth locations of the some gun detection images.

#### B. Dataset Folder Structure

The dataset folder structure is shown in Figure 3. In the top dataset folder, there are two subfolders - "detector" and "classifier", where all images for the gun detection and classification are saved. Any folder named "gun" is a folder where gun images are saved, and any folder named "other" is a folder where non-gun images are saved. In the "detector" folder, we split images to training set and test set. Users are free to re-split the training and test sets. Please note that this folder structure is the one we have when we decide to publish the dataset. The split of training and test dataset is not necessarily the one we use in our performance benchmark.

The number of images are summarized in Table II. Please note that many of the negative samples of both detector and classification are from failed cases in our study. In the gun images, majority are handgun, while a good number of them are rifles, machine guns and other types.

#### C. Annotation File Format

In the gun folders for detection, there are two sub-folders: JpegImages, and Annotations. All gun images in JGP format are saved in the JpegImages folder, and their corresponding annotation files are saved in the folder Annotations. The file names, one for JGP, and another for the annotation, are one to one mapped in the two folders.

The annotation file is in XML format. In the annotation file, the filename, dimension of the whole image, and the upper-left and lower-right coordinates of guns are given. An example of such a file is shown in Fig. 4.

#### D. Statistics of Gun Images

We check the statistics of the gun images in the detector training set. We look at the whole image size (width x height) and the gun bounding box size (width x height). These area indicates the resolution of the whole image and the gun object. We also look at the number of gun objects in every image. Shown in Fig. 4 are the statistics.

From the distribution, we notice that 1) there are two peaks in the whole image size, which correspond to the widely used image sizes in surveillance video cameras and IP cameras. There are also a very few very large images that are not shown in the distribution; 2) The sizes of the gun objects are pretty much uniform distributed, except for the very small sizes. This imposes an challenge in gun detection because there exist a lot of very small gun objects in images; 3) There are mostly one gun object in every image. Some images have two gun objects, and very few images have up to 10 gun objects in an image.

### Table I

| Ref  | Method         | dataset    | comments               |
|------|----------------|------------|------------------------|
| [2]  | MLP            | 3559       | edge + 3-layer MLP     |
| [3]  | fasterRCNN     | -          | Complex and slow       |
| [4], [5] | fasterRCNN     | 8996       | Complex and slow       |
| [6]  | M2Det          | 5000       | Complex and slow       |
| [7]  | FasterRCNN     | -          | Complex and slow       |
| [8]  | VGG16 etc.     | 3500       | Complex and slow       |
| [9]  | YoloV3+Pose    | 1745       | Complex                 |
| Ours | Simplified CenterNet | 51K        | Real-time on camera    |

### Table II

| Model     | Gun/Non-Gun(Other) | Number |
|-----------|--------------------|--------|
| Detector  | Gun                | 51,889 |
| Detector  | Other              | 154798 |
| Classifier| Gun                | 51,398 |
| Classifier| Other              | 371,078|
In the gun classification training dataset, there is always one gun object in every image. These images are all resized to 112x112.

IV. GUN DETECTION SYSTEM

Our gun detection system consists of edge devices - which are mostly smart cameras and the cloud server. The edge device does most of the video processing, gun detection, first-level gun/non-gun classification, sending gun chip image or frame to server. The server manages the device, data, alert. In addition, it has second-level gun/non-gun classification, and extra level gun action recognition, which is still in progress.

A. Gun Detection Process on Edge Device

We use low-cost smart camera as edge device. A typical example is one uses the HiSilicon-Hi3516 chip set, or the Rockchip-RK3299 chip set. We do not consider traditional IP camera since it does not have the capability to run object detection using deep learning. Streaming the video of IP camera to an expensive edge device or server is not preferred.

The gun detection process on edge device is similar to [10]. The gun detector directly takes the original high resolution video stream as input. It first runs a motion detection to determine whether there are moving objects in the video to prevent the false detection in static scene. Once motion is detected in video, gun detection is conducted on a smaller resolution video. If a gun is detected, an object
tracker is activated to track its movement. In the process of tracking, the light-weight classification network starts to run. Finally, if the tracked object is classified as a gun for more than three times, it is determined to be a gun. This tracker, classifier and some logical processing are added to minimize the false detection rate. After this, a cropped chip image of gun, a snapshot of the scene, and some Meta data such as device ID, bounding box of the gun, the timestamp, etc., are sent to the cloud, as shown in Fig. 6 [10].

B. Further Processing on the Cloud Server

After receiving the data sent from the edge device, the server begins further processing the gun chip image and the snapshot scene image. The function blocks of the server are shown in Fig. 7.

First a second level of classification, which is a more complex model than the light-weight classifier on the edge device, is run. This classifier runs on the server, so it is not restricted to use expensive hardware resources like GPU.

One extra level of function to control the FPR is to use gun action recognition. Since the server receives consecutive scene snapshots while the tracker is running, these snapshots carry temporal information of the motion of the gun and the person. These multiple scene snapshots can be used to do action recognition. Gun action is one type of abnormal action detection on videos [13]. This work is still in progress, denoted by dashed lines in Fig. 7. For more details of the action recognition, the readers are referred to [16] and more in the literature.

Other functions of the cloud server include management of device, data, reporting, and an API for web or mobile App. In the web server console, snapshot scene images of detected guns are displayed. A demonstration is shown in Fig. 8 [10].

V. CNN NETWORKS FOR GUN DETECTION AND CLASSIFICATION

In this section we present details of the CNN networks for gun detection and classification.

A. Gun Detection Network

There are a lot of great progresses in object detection including the SSD [17], YOLO family [18], Faster-RCNN family [11], the feature pyramid network [19], MMDetection [20], EfficientDet [21], transformer(DETR) [22], Centernet [23], [24], and so on. Most of them have outstanding performance but run very slowly. For real-time object detection, the YOLO3, SSD, and Centernet are a few good choices. After extensive experiments, we find that the Centernet is a good choice offering a good trade-off between performance...
and speed. We do not present the results on other networks that we have studied.

The original CenterNet uses a few backbone networks, including the Hourglass-104, DLA-34, ResNet-101, and ResNet-18 [23],[24]. We evaluate these choices on a HiSilicon-Hi3516 embedded platform, and find that their FPSs are all too slow for real-time applications. Then we go further to test different light-weight backbone networks, including the MobileNet [25] and VovNet [26]. The results are shown in Table III. We see that these backbones can mostly meet the real-time or near real-time requirement.

Next we use the VovNetv2-39 [26] as example and study different data augmentation techniques, loss function, learning rate scheme etc. to improve its detection performance. In these experiments, we use VOC2007+VOC2012 training sets as the training dataset, and use VOC2007 test set as the test dataset. Listed in Table IV are the experiment results. The best techniques are used in our gun detection performance evaluation.

Finally we test the performance of the VovNetv2-19-slim on our gun detection dataset. For comparison a couple of other networks are also evaluated. The results are presented in Table V. The IOU threshold used is 0.3. We choose this threshold because we still have the gun/non-gun classifiers on the edge device and on the cloud server. Using a small IOU threshold will improve the recall rate of gun detection, while the classifier can filter out non-gun objects.

**B. Gun Classification Network**

A light-weight gun/non-gun classifier runs on the edge device, and a more complex one runs on the cloud server. The one on the cloud sever is not restricted to use complex

| Backbone       | AP(%) | FPS |
|----------------|-------|-----|
| MobileNetv2    | 32.2  | 12  |
| VovNetv2-19-slim| 33.2  | 25  |
| VovNetv2-19    | 35.1  | 10  |
| VovNetv2-39-slim| 36.1  | 20  |
| VovNetv2-39    | 40.0  | 8   |

**TABLE IV**

Techniques to improve the CenterNet performance on VOC dataset. Training dataset = VOC2007+VOC2012 training sets, test set = VOC2007 test set.

| Technique                   | mAP(%) at IOU=0.5 |
|-----------------------------|-------------------|
| baseline                    | 74.1              |
| +multi-scale                | 75.1              |
| +Giou loss [27]             | 75.8              |
| +Cosine LR                  | 76.1              |
| +Mosaic [28]                | 76.9              |
| +FPN [19],PAN [29],RFB [30] | 78.1              |
TABLE V
THE PERFORMANCE OF THE CENTERNET GUN DETECTION AT IOU THRESHOLD = 0.3. ACC=ACCURACY, REC=RECALL, PRE=PRECISION

| Backbone         | Acc % | Rec % | Pre % |
|------------------|-------|-------|-------|
| VoVNet-v2-19_slim_light | 81.06 | 90.19 | 85.05 |
| VoVNet-v2-19_slim | 84.28 | 90.33 | 88.60 |
| Resnet18         | 84.28 | 89.88 | 88.86 |

TABLE VI
THE PERFORMANCE OF GUN CLASSIFIER AT THRESHOLD = 0.5. ACC=ACCURACY, REC=RECALL, PRE=PRECISION

| Model          | Acc(%) | Rec(%) | Pre(%) |
|----------------|--------|--------|--------|
| Resnet18       | 96.97  | 98.55  | 95.39  |
| ResNet34       | 97.57  | 99.27  | 95.89  |
| Resnet50       | 97.83  | 99.69  | 95.99  |

VI. CONCLUSION

We collect and publish a gun detection and gun classification dataset. To our knowledge this is the largest gun detection and classification dataset available for research and development purpose. We evaluate the gun detection performance on an edge device, and the gun/non-gun classification on the edge device or on the cloud server.

A work in progress is developing the gun action recognition for the cloud server. This gun action recognition is expected to reduce the FPR further.

REFERENCES

[1] “Gun violence in the United States,” https://en.wikipedia.org/wiki/Gun_violence_in_the_United_States.
[2] M. Grega, A. Miatolanski, P. Guzik, and M. Leszczuk, “Automated detection of firearms and knives in a CCTV image,” Sensors, vol. 16, 2015.
[3] Verma G. and Dhillon A., “A handheld gun detection using faster r-cnn deep learning,” Proceedings of the 7th International Conference on Computer and Communication Technology, 2017.
[4] R. Olmos, S. Tabik, and F. Herrera, “Automatic handgun detection alarm in videos using deep learning,” Neurocomputing, vol. 275, pp. 66–72, 2018.
[5] R. Olmos, S. Tabik, A. Lamas, F. Pérez-Hernández, and F. Herrera, “A binocular image fusion approach for minimizing false positives in handgun detection with deep learning information fusion,” Information Fusion, vol. 49, pp. 271–280, 2019.
[6] J. Lim, M. Jobayer, V. Baskaran, J. Lim, K. Wong, and J. See, “Gun detection in surveillance videos using deep neural networks,” Proceedings of the 2019 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference, 2019.
[7] J. González, C. Zaccaroa, J. Álvarez García, L. Morilloa, and F. Caparriníb, “Real-time gun detection in CCTV: An open problem,” Neural Networks, vol. 132, pp. 297–308, 2020.
[8] J. Lai and S. Maples, “Developing a real-time gun detection classifier,” http://cs231n.stanford.edu/reports/2017/pdfs/716.pdf.
[9] J. Ruiz-Sanquitierria, A. Velasco-Mataa, N. Valleza, G. Buenoa, J. Álvarez-García, and O. Deníza, “Handgun detection using combined human pose and weapon appearance,” in ArXiv preprint 2019.13753, 2021.
[10] Q. Yao, W. Tan, J. Liu, and D. Qi, “Edge to cloud end to end solution of visual based gun detection,” in J. Phys.: Conf. Ser. 1634 012033, 2020.
[11] S. Ren, K. He, R. Girshick, and J. Sun, “Faster r-cnn: Towards real-time object detection with region proposal networks,” IEEE Transactions on Pattern Analysis and Machine Intelligence, 2016.
[12] “Internet movie firearms database,” https://www.imfdb.org/.
[13] W. Sultan, C. Chen, and M. Shah, “Real-world anomaly detection in surveillance videos,” ArXiv preprint arXiv:1801.04264, 2018.
[14] J. Deng, W. Dong, R. Socher, L. Li, K. Li, and F. Li, “Imagenet: A large-scale hierarchical image database,” CVPR, 2009.
[15] T. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. Zitnick, “Microsoft coco: Common objects in context,” ECCV, 2014.
[16] H. Zhang, Y. Zhang, B. Zhong, Q. Lei, L. Yang, J. Du, and D. Chen, “A comprehensive survey of vision-based human action recognition methods,” Sensors, vol. 19, 2019.
[17] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C. Fu, and A. Berg, “Yolov3: An incremental improvement,” ECCV, 2016.
[18] J. Redmon and A. Farhadi, “Yolov3: An incremental improvement,” ArXiv preprint arXiv:1804.02767, 2015.
[19] T. Lin, P. Dollár, R. Girshick, K. He, B. Hariharan, and S. Belongie, “Feature pyramid networks for object detection,” CVPR, 2017.
[20] K. et al. Chen, “Mmdetection: Open mmlab detection toolbox and benchmark,” ECCV, 2020.
[21] M. Tan, R. Pang, and Q. Le, “Efficientdet: Scalable and efficient object detection,” CVPR, 2020.
[22] N. Carion, F. Massa, G. Synnaeve, N. Usunier, A. Kirillov, and Y. Zhou, “End-to-end object detection with transformers,” ECCV, 2020.
[23] K. Duan, S. Bai, L. Xie, H. Qi, Q. Huang, and Q. Tian, “Centernet: Keypoint triplets for object detection,” ICCV, 2019.
[24] X. Zhou, D. Wang, and P. Krähenbühl, “Objects as points,” in ArXiv preprint arXiv:1904.07850, 2019.
[25] M. Sandler, A. Howard, w. Zhu, A. Zhmoginov, and L. Chen, “Mobilenetv2: Inverted residuals and linear bottlenecks,” CVPR, 2018.
[26] Y. Lee and J. Park, “Centermask: Real-time anchor-free instance segmentation,” **CVPR**, 2020.

[27] H. Rezatofighi, N. Tsoi, J. Gwak, A. Sadeghian, I. Reid, and S. Savarese, “Generalized intersection over union: A metric and a loss for bounding box regression,” **CVPR**, 2019.

[28] YoloV5, ” [https://github.com/ultralytics/yolov5](https://github.com/ultralytics/yolov5).

[29] S. Liu, L. Qi, H. Qin, J. Shi, and J. Jia, “Path aggregation network for instance segmentation,” **CVPR**, 2018.

[30] S. Liu, D. Huang, and Y. Wang, “Receptive field block net for accurate and fast object detection,” **ECCV**, 2018.

[31] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” **CVPR**, 2016.