Proceedings of the International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS-2024)
IEEE Xplore Part Number: CFP242B2-ART: ISBN: 979-8-3315-1809-7

Weapon Detection Identification and Classification for DCNN and YOLO-V5 Techniques

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2024 International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS) | 979-8-3315-1809-7/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICICNIS64247.2024.10823365

***Abstract*—Over 850,000 people die every year as a direct result of gun violence, yet civilians hold more than 85% of the world's weapons. Detecting weapons via manual surveillance has not been successful. It is critical to automate a system that detects weapons. A large number of convolution neural network CNN-based automated weapon identification systems have shown promising results. These methods are crucial for weapon identification but expensive. These devices produce a large amount of false negatives since monitoring videos are not high enough quality or visible enough to identify weapons. Finding the sweet spot between fast detection and a few false positives and negatives in weapon detection is the main goal of this research. In addition to defining an Area of Interest, the suggested structure uses YOLO. The models use previously processed images with backgrounds that have been blurred using a median filter. Metrics such as F1 scores, accuracy, recall, False Positive, and False Negative will be used to assess the suggested architecture. This investigation shows that YOLO-v5 can quickly identify and has a high recall rate. The deep convolution neural network DCNN required 0.17 ms for each frame, but this one only required 0.010 ms, which would indicate that security and weapon detection have good promise. Starting with a labeled collection of weapon and non-weapon photos is the initial stage in DCNN and YOLOv5 weapon detection. Use YOLOv5's ability to recognize multiple things within frames to train a real-time object localization and identification model. DCNNs categorize weapons and extract complex data effectively. DCNN classifies objects, whereas YOLOv5 detects, bounds, and tracks them. Optimize both models' hyperparameters and apply data augmentation for better performance. Install the integrated system on cutting-edge equipment for real-time weapon identification and classification.**

Keywords—weapon detection, convolution neural network, deep convolution neural network, yolo-v5, median filter

I. Introduction

There is a substantial monetary, psychological, and public health cost associated with gun violence. The annual toll from gun violence is high. Children exposed to significant amounts of violence in their neighborhoods or via media often experience psychological trauma. The mental health of children affected by gun violence, whether as victims, offenders, or witnesses, may suffer both immediately and in the future. Several studies have shown that handguns are often used in a variety of criminal acts, including robbery, theft, rape, and break-ins. A decrease in these offenses is possible via the early detection of disruptive behavior and the vigilant surveillance of suspicious activity by law enforcement authorities, which allows for swift and effective intervention. According to studies over 250,000 persons lost their lives or suffered injuries in incidents involving weapons in 2016 [1-2]. Civilians own more than 85% of the 1,013,000,000 weapons in the globe. As Forbes noted in an IBIS World story, gun sales in the US alone were expected to reach over $28 billion in 2018. There's more to identifying and handling dangerous situations than merely manually monitoring security cameras [3]. Recent years have seen impressive advancements in image recognition, categorization, and segmentation using deep learning methods and convolutional neural networks (CNNs) [4]. Modern detection models and recent technical advancements have yielded promising results, such as YOLO, DCNN, and VGG-16 [5]. Greater complexity due to partial or complete gun occlusion [6], distortion, and information degradation after transmission [7] were obstacles in weapon identification. False positives and false negatives may also occur in weapon detection systems when these delicate systems are integrated with alarms or other devices [8].

Handling non-weapon goods that are the same shape and processed in the same manner every day adds a layer of complexity to the main issues—a high frequency of inaccurate results and false negatives. Another major challenge is ensuring that the model has a low false negative rate and does not miss the weapon. Additionally, the model must accurately remove backgrounds from images and videos without giving false positives. The aforementioned models provide a considerable risk of false negatives when applied to videos. Imagine if 10 armed people attempt to attack a building; even one successful break-in might have disastrous consequences. The approaches suggested by [8-9] must be improved to increase the recognition range to include firearms and reduce the incidence of false positives and negatives.

This study suggests a model that may make use of existing models, like YOLO, which have very fast detection rates, to achieve this. By concentrating on the target area and using a Gaussian filter to exclude extraneous data, this research mostly achieved its goal of reducing the number of false positives and false negatives in the weapon identification domain. When YOLOv5s and the median filter cooperate.

YOLOv5 outperforms previous YOLO models because of its enhanced accuracy, speed, and adaptability in real-time detection tasks. The combination of the DCNN and ANN benchmarks combines the extraction of features and classification capabilities to improve the precision of detection and overall model efficiency.

A. Contribution

- Improved the accuracy and performance of the existing weapon recognition model by the use of advanced algorithmic and preprocessing techniques;
- Enhanced frame rate (FPS) for real-time application;
- Evaluated and assessed the performance of several deep learning models across diverse computer hardware.
- Improved latency, throughput, energy efficiency, and decreased memory use via network optimization.

II. Related Works

We tested the sliding window method on YouTube and were able to recognize frames with a speed of 0.19 seconds, demonstrating excellent accuracy but poor recall for video recognition. On the other hand, some research has shown that using two cameras for preprocessing and the Global Block Matching algorithm can help reduce background noise. This approach follows the Area of Interest method and significantly improves efficiency while decreasing the number of incorrect results, but it also increases the model's detection time. The effect of illumination on the detection rate of weapons, particularly cold steel blades and knives, was investigated in the research by [10], which used a CNN-based model. Although it works well inside, accuracy is reduced when used outside due to reflections and changing illumination. To improve the model's capacity to differentiate between weapons and things with comparable forms, [9] also used a technique that included training the object and class model above it. Although this method increased accuracy, recall dropped because the model mistook the characteristics of non-weapon items for those of weapons. They used region proposal networks in their study [11]. The authors developed many CNN-generated models to identify different features of weaponry, such as the trigger or the muzzle, and then combined the models to identify the occurrence of handguns in the images. This method extended detection durations but improved precision. To identify concealed weapons, research by [12-13] used a model based on a convolutional neural network (CNN) and customized images taken by passive millimeter wave (PMMW) cameras to identify gray objects that resemble pistols because of their comparable forms. Although the gadgets are useful, their exorbitant cost prevents most families from purchasing them. Using a combination of contextual neural networks, investigators in the study by [14] succeeded in learning to recognize the presence of guns, such as pistols, by training many networks to perform different tasks and then combining their results. Using a two-pass convolutional network, the enhanced RCNN [15] model rapidly detects weapons in photos from social media. Pseudo-coloring sought to improve the rate of weapon detection in single-energy X-ray images by introducing different color filters into the data [16].

Object identification in this domain makes use of a variety of techniques and deep learning models; for instance, one research [17] employed smoke from gunshots to localize the precise location of a fired weapon. Among the other topics discussed in [18] is the use of the Faster-RCNN model for object and person detection. Using support vector machines (SVMs), the authors of [19] were able to accomplish garment recognition in real time from surveillance footage. In [20], the author lays out all the steps necessary to visualize and understand convolutional networks. In a similar vein, [21] used YOLOv3 to detect items in special camera photographs that may be harmful by first figuring out the object's shape concerning its environment using temperature variations in the objects.

In a VANET environment, the primary objective of this research is to determine the efficacy of CNN-based intrusion detection systems, specifically concerning reaction time and intrusion detection accuracy [22].

The problem of misguided evaluation, misguided detection, and inconsistent attack response is a crucial litmus test for intrusion detection systems. Second only in importance to firewalls, intrusion detection (ID) has made great strides in the last few years. This study develops two separate Machine Learning methods—one supervised and one unsupervised—to detect network breaches. Unsupervised learning with self-organizing maps and supervised learning with Naive Bayes are among the offered approaches [23].

We also go over some of the potential applications of blockchain technology, like smart energy trading, encrypted communication, and transporting vehicles. All things considered, the study's findings suggest promising new avenues for smart city blockchain and edge AI applications [24].

Researchers in this study provided extensive details on their methodology. The presentation of the data and analysis is very descriptive. While bringing attention to the pressing need for better healthcare systems in the here and now, this study also suggests potential directions for future research [25].

III. Proposed Methodology

Designed to manage the false negative rate, the YOLO-v5s algorithm operates at a quicker pace than the quicker DCNN and other algorithms used in all the previously stated studies. It employs median blur to eliminate the backdrop but otherwise adheres to the area of interest technique as indicated by the literature. Further research centers on the speed of the algorithm.

As we discussed in the preceding section, the recommended framework is designed to reliably detect weapons while eliminating the drawbacks of earlier research. It is the primary objective of the model to maintain a rapid detection response while decreasing the number of false positives and negatives. The following are the components of the proposed framework: metrics for assessment of performance testing, the provided dataset, preparing the data, and model design.

A. Dataset

The positive class of handguns was supplied with 3,000 photos and Using the open-source handgun dataset from the University of Granada, boundary box documents in Pascal-VOC XML code were produced. There was prior usage of this dataset in the literature. 13000 and 90 Negative cases, or images devoid of firearms, were included in the dataset. The images were extracted from that are open-sourced from the University of Grandala and have a resolution of 100 × 100 pixels. A large portion of the 3000 gun dataset came from either the IMFDB or the COCO databases. 70% of the dataset is used for training, 20% for validation, and 10% for testing. It is the largest collection of pistol detection photos currently available, with 13500 images. The software was evaluated using YouTube movies to guarantee fair comparison with previous research studies that employed ancient action films with diverse weapon perspectives. Self-made and cropped videos are utilized in this research. The device was tested for speed and performance using a 60-second YouTube video of myth-busters playing with weapons. Roboflow, an online tool, organizes while improving images and annotated data from training. For YOLO-V5, Roboflow uploaded and transformed our VOC XML dataset into text. The YOLO model suggests pre-processing photos into 416 x 416 using Roboflow.

B. Data Preprocessing

The customized CNN model and YOLO-V5 need several preprocessing steps to be implemented. The input photographs were scaled to 240 × 240 by using PIL's image library in the DCNN model, and the YOLO-V5 database was expanded to 416 × 416 as instructed. After downloading the dataset, photos were stretched and resized using Roboflow. The background was blurred and the image was softened using a median blur. The data has to be pre-processed before algorithms using deep learning may utilize the analysis findings. Our method modifies the image dimensions to 416 × 416 for the YOLO-V5 network (32 variations) and 240 × 240 for the DCNN network before pre-processing. The second part of the pre-processing stage is to remove or blur the background of the image. The model uses the median filter function, which is faster, instead of sorting, as the Gaussian filter requires. The Gaussian filter improves images by reducing noise and keeping edges, which makes it easier to extract information for classification and recognition. More accurate detection is made possible by enhanced object delineation. Conversely, median filtering effectively gets rid of salt-and-pepper noise, keeping edges while reducing distortion during categorization.

$$\mathrm{O}(\mathrm{i},\mathrm{j}) = \mathrm{median}\{\mathrm{I}(\mathrm{i}+\mathrm{k},\mathrm{j}+\mathrm{l}) \mid (\mathrm{k.l}) \in \mathrm{W}\} \quad (1)$$

Where equation 1 is (i, j) represents the median filter's output at the position (i, j), $I(i + k, j + l)$ Encompass the next pixels contained within a window W, usually a square window around the center pixel. (i, j). W the size of the surrounding windows (e.g., 3x3, 5x5), often concentric within a sorted list of pixel intensities inside the window, the median is the middle value.

In this research, an innovative method called the GU-ME filter is presented. It combines the best features of the Gaussian and median filtering algorithms. This improves the accuracy and resilience of weapon identification and classification models by successfully eliminating noise from images while keeping critical features and edges.

C. Data Splitup for Train Model

After numerous failed attempts to upload this massive dataset to Colab, we settled on using For cloud storage, we're using Google Drive and citing the URL in our Collab notebook. This allowed us to train our model continually. We copied files from our laptop to Google Drive quickly. Our YOLO-V5 model was trained using data for testing, training, and validation. Over two-thirds of the photos were utilized for model evaluation, 20% for validation, and 10% for training. Roboflow's automatic software and literature review show this split produces the greatest outcomes, hence it was picked. Model architecture and hyperparameters for DCNN and YOLO-V5 implementations are below.

D. Data Splitup for Test Model

The testing data set consisted of 329 images using weapons and 668 photographs featuring non-weapon shootings. The Keras model library was used to load the CNN model that had been trained on 240x240 images. The test directory was made accessible to the model. The average time it took the DCNN model to assess a photo was 0.050 seconds. Without any scaling applied to the test images, the YOLO-V5 model ran quickly, requiring an average of just 0.010 seconds per image. The YOLO-V5 was put through its paces on a 25 fps YouTube video that ran for 60 seconds due to its incredible speed.

E. DCNN Model Architecture

Fig. 1 shows the design of our custom DCNN model and Fig. 2 show the system architectures. How big of a filter should the first, second, third, and final convolution layers in the model are 128 for the first, 64 for the second, and 16 for the last. We have chosen to apply Max Pooling with a 2x2 filter size after each Conv Layer in our custom CNN, and we have also explained the operation of the pooling layer. As we have said, the pooling and convolution layers have a default stride of 1.

It is possible to discreetly reject a subset of neurons known as "drop out" during preparation. In Keras, 20% is represented by a dropout value of 0.2. As a result, the neuron does not receive any more backward pass weight changes, and their role in forward pass neuron activity is momentarily eliminated. This method avoids the problem of overfitting the model. An extremely dense 128-neuron and dense 2-neuron neural network layers get the multi-dimensions after they are reduced to a one-dimensional vector. Then, the Softmax layer receives the output. Because it normalizes the scores, the softmax layer is an excellent option for displaying or using the probabilities as input to other systems.

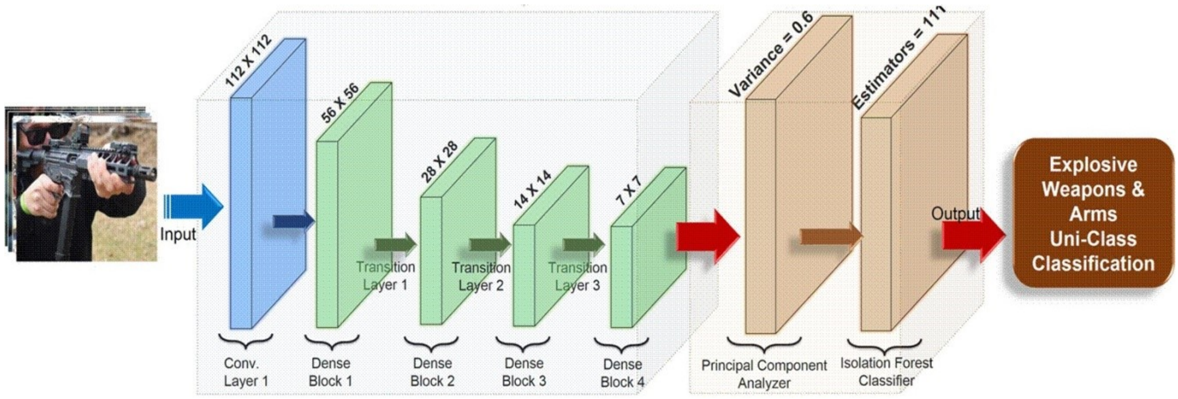

Fig. 1. DCNN Architecture

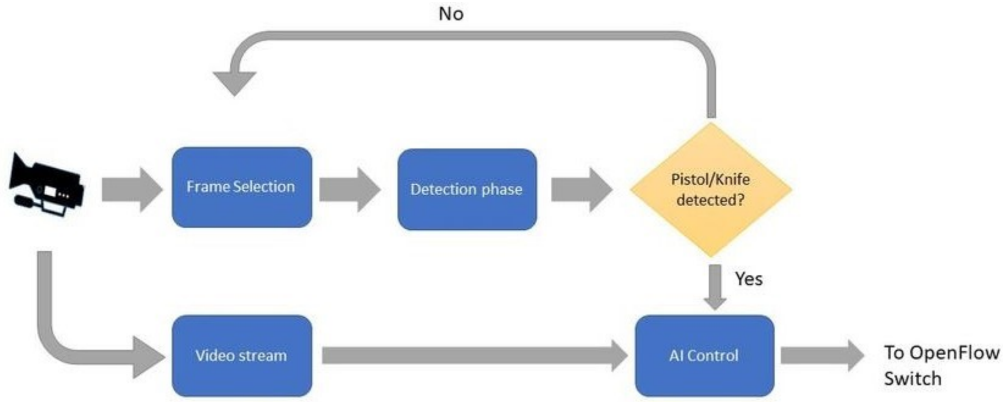

Fig. 2. System Architecture

F. *YOLO-V5 Model Architecture*

1) Video Input: A live feed from a security camera or other device initiates the system. The film is captured in real-time by the camera.

2) Frame Selection: Since it would be computationally expensive to process the whole video in real time, the system instead analyses individual frames. This reduces the computing load by separating keyframes.

3) Detection Phase: The actual AI-based detection takes place in this area. An item identification algorithm, often a model based on deep learning or a convolutional neural network (CNN), is fed the selected frames to identify weapons such as knives and firearms.

4) Decision: Pistol/Knife Detected: In this decision-making step, the algorithm determines whether a knife or firearm is present in the photo. "Yes" means that if the system detects a weapon, the procedure will proceed. Rest assured, if no weapon is detected, the system will keep watching the video stream and will return to the frames selection process.

5) AI Control: The detection of a weapon initiates an AI control system. This may be accomplished by several automated procedures, such as alerting security personnel, sounding alarms, or starting security measures.

6) Output to OpenFlow Switch: Finally, the system sends a signal to an OpenFlow switch, which might be part of a network-based safety mechanism. The OpenFlow switch has several potential applications, including traffic management and facilitating real-time communication between security and law enforcement agencies.

In the proposed system, the YOLOv5 model is a cutting-edge, fast, and accurate real-time object identification model. Utilizing features such as auto-learning bounding boxes and anchor optimization, it employs a lightweight design with better performance. YOLOv5 is quite good at finding firearms in complicated settings with low latency.

G. *Performance Enhancement:*

- To improve weapon detection and classification using DCNN and YOLOv5, use advanced data augmentation techniques such as scaling, rotation, and background alterations.
- For faster and more accurate training, employ transfer learning with pre-trained weights. Adjust learning rates and anchor box sizes for better detection.
- Combine quantization with model pruning for quicker inference and less processing.
- Ensemble learning can combine DCNN and YOLOv5 predictions for improved outcomes.
- Edge devices with GPUs or TPUs can compute the optimized model in real-time and identify weapons efficiently.

H. *Yolo Role:*

- YOLO's real-time object detection, which is ideal for dynamic scenarios due to its fast speed and

accuracy, is a key component of weapon identification.
- It creates precise bounding boxes to locate and identify weapons in images or videos, enabling efficient monitoring and quick responses in high-security scenarios.

I. Reliability:

- Both DCNN and YOLOv5 need an extensive data set with a wide range of weapon kinds, perspectives, and configurations to achieve reliable weapon recognition and classification.
- Put models through their paces in real-world settings often and make use of cross-validation approaches.
- To enhance detection results while decreasing false positives and negatives, use heterogeneity and ensemble learning.

J. Security Enhancement:

- Encrypted data transmission and secure model deployment on edge devices may improve the security and manipulation resistance of weapon detection.
- Use adversarial training to defend against spoofing attempts and confirm detections using multi-layer authentication.
- Models must be updated often with real-world data to maintain their effectiveness and manage emerging threats.

K. Real-Time Detection:

- Make use of YOLOv5's low-latency, high-speed object detection capabilities to accomplish real-time weapon detection. For quicker inference, optimize the model using methods like pruning, quantization, and efficient backbone networks.
- To speed up processing, deploy the model on edge devices that include GPUs or TPUs.
- Streamline data flow using pipeline parallelism and accelerate inference with lightweight frameworks like TensorRT.
- Furthermore, makes use of video frame skipping to zero in on important frames, guaranteeing fast and precise detection—essential for real-time applications.

L. Reduce Complexity:

To reduce complexity for streamline the firearm detection procedure using YOLOv5 and DCNN:

- Use lightweight DCNN variations like YOLOv5-Nano or MobileNet to reduce the computational load.
- Sort the qualities that are most important for classification and eliminate those that are not.
- Reduce the accuracy and eliminate any unnecessary layers to maximize the model's size and speed.
- Use transfer learning to reduce computational load and training time.
- Deploy optimized models for low-complexity inference in real-time on edge devices using frameworks such as TensorRT.
- Optimize the data's preprocessing to prevent unnecessary computation.

M. Precision Enhancement:

- By guaranteeing high-quality annotated datasets that include a variety of weapon kinds and settings.
- To increase the resilience and generalizability of the proposed model, use sophisticated data augmentation.
- It may adjust YOLOv5's anchor boxes and hyperparameters to get better object localization results.
- To improve classifications and reduce false positives and negatives, combine ensemble learning with DCNN.

Measures like recall, F1-score, and mean average precision (mAP) are used to assess the model's performance in terms of detection accuracy and classification efficiency. The models are tested on various datasets to determine detection time by measuring latency per frame using YOLOv5 and the hybrid DCNN-ANN architecture.

IV. Results and Discussion

The proposed model's performance on the 608 images test set to that of similar research that trained on the same dataset and used 3000 pistol photographs alone. Our YOLO-V5s model performs OK with the given dataset and processes, although it produces more false positives than the DCNN model. Conversely, with a recall rate of 0.990, we stand out.

The proposed model is 19 times faster than the baseline, on average, it takes just 0.010 seconds to process a single frame or image. The YOLO-v5s version satisfies the demand for weapon detection systems by providing quicker detection rates. We compared our model's performance to the best results using a similar video with the same frames. In comparison to the DCNN, our model achieves better results when it comes to video correctness, with a recall of 0.929 and a precision of 0.922. Even while the DCNN did somewhat better on images, its performance plummeted by over 20% when applied to the video dataset, according to the findings. Finally, compared to the DCNN published in the literature, which scores between 0.17 and 0.19 s per average frame, the photos perform better in terms of time, with a score of 0.010 s per frame.

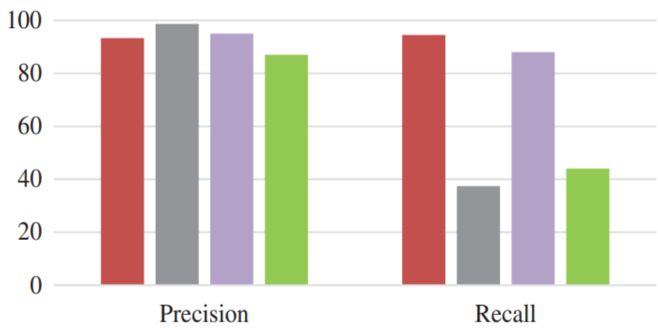

Fig. 3. Precision and Recall Performance

As seen visually in Figure 3, the proposed model performed better in terms of recall rate than the prior research. The closest result in the literature with pre-processing is 88%. Because missing weapons results in a greater human cost, recollection is more important in the context of weapon identification than it is in other contexts for this research. The total F1 score shows that the model performs better overall when compared to previous experiments that used preprocessing techniques and DCNN.

Figure 4 presents the F1 score of the various research articles clearly and concisely using our Yolo-v5s model. Compared to the DCNN model, ours performs better in videos 2 and 4, and this performance gap widens in video 5. When it comes to video 3, YOLO-v5 produces 2% better outcomes The framework that was previously published in the scientific journals depended on pretreatment to isolate the intended region.

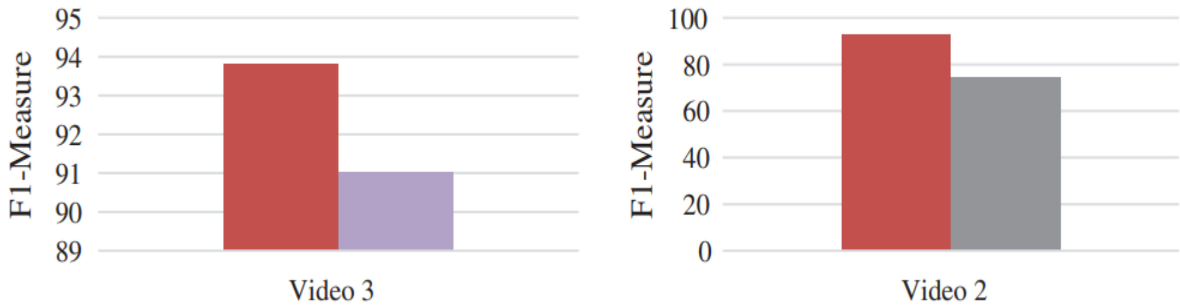

Fig. 4. F1-Score Comparison

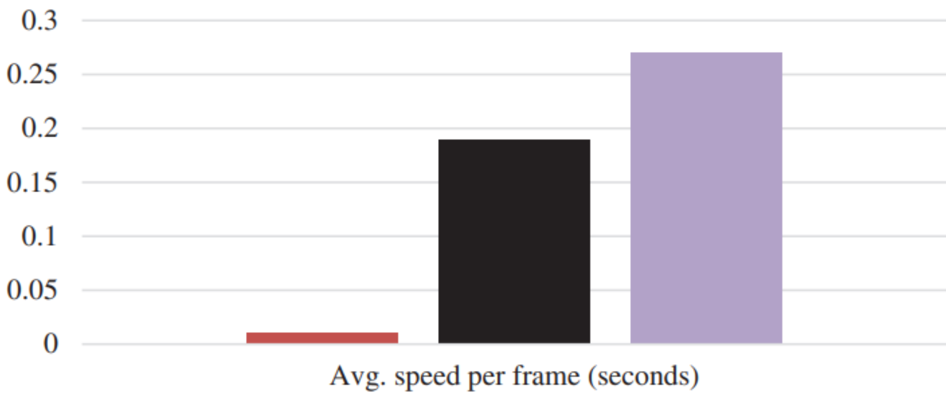

Fig. 5. Speed per second for proposed work

The comparison between the Yolo-v5 model and other existing models for weapon identification is shown in Figure 5. The accompanying figure shows that the average frame speed of DCNN is 0.17-0.19 s, which is more than ten times quicker than the 0.010 s frame speed of the YOLO-v5 model.

V. Conclusion

The findings point to a new paradigm for fast handgun identification that may be useful for alarm-based monitoring systems. To complete the unfinished business of weapon detection in a published research publication, we used state-of-the-art models like YOLOv5s, which produced very efficient results. To improve our F1-score even further, we Gaussian blurred the backdrop as a pre-processing step. The researchers at the University of Granada have made public a dataset that includes 13,000 negative class photos and 500 postal photographs. Our YOLO-v5s model was 93% accurate and 94% recalling when tested on YouTube videos; when tested on images, it was 99% accurate and 81% precise. Based on these results, our model stands out as the best option. In particular, when compared to the DCNN model used in previous research, our model outperformed it in terms of recall score and the frame rate is 19 times quicker at 0.010 s.

Compared to DCNN with ANN, YOLOv5 outperforms real-time object detection because of its efficiency, speed, and scalability. Since it does a great job at recognizing weapons with little delay, it works well in dynamic scenarios. There are several benefits, including low processing cost, optimal inference, and high accuracy. Although YOLOv5 excels in the extraction and classification of features, it may struggle to recognize small objects against complex backgrounds, in comparison with DCNN-ANN models. Research in the future may look at ways to improve YOLOv5's recognition of small objects, develop hybrid architectures for more accurate detection, and find ways to reduce false positives without sacrificing real-time processing speeds.

Acknowledgment

Author Contribution: All authors contributed equally to this work.

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