An Enhanced Weapon Detection System using Deep Learning

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Abstract: **Considering a growing number of criminal acts, there is an urgent need to introduce computerized command systems in security forces. This study presents a novel deep learning model specifically developed for identifying seven different categories of weapons. The suggested model utilizes the VGGNet architecture and is implemented utilizing the Keras architecture, which is built on top of the TensorFlow framework. The model is trained to recognize several types of weapons, including assault rifles, bazookas, grenades, hunting rifles, knives, handguns, and revolvers. The training procedure involves creating layers, executing processes, saving training data, determining success rates, and testing the model. A customized dataset, consisting of seven different weapon categories, has been meticulously chosen and organized to support the training of the proposed model network. We do a comparative study using the newly created dataset, specifically comparing it with established models such as VGG-16, ResNet-50, and ResNet-101. The suggested model exhibits exceptional classification accuracy, obtaining a remarkable 98.40%, outperforming the VGG-16 model (89.75% accuracy), ResNet-50 model (93.70% accuracy), and ResNet-101 model (83.33% accuracy). This research provides a vital viewpoint on the effectiveness of the suggested deep learning model in dealing with the complex problem of weapon classification, presenting encouraging outcomes that could greatly improve the capabilities of security forces in countering criminal activities.**

Keywords: Deep learning, armed weapon detection, machine learning, object detection, convolutional neural networks

I. INTRODUCTION

Surveillance cameras have become prevalent in the modern era of improved science and technology as an essential instrument for preventing crime [1]. Security professionals must diligently oversee the installation of many camera systems in various locations [2,3].

Traditionally, post-incident analysis involves security guards arriving at the scene, examining recorded images, and collecting essential evidence [4]. Consequently, the need for proactive systems at crime scenes has been emphasized [3,5,6]. This research advocates the creation of a system that makes use of software to quickly notify security staff when it detects dangerous things, enabling immediate action to avert potential crimes [4,7]. Hence, it has to be essential to develop a system that has the ability to learn and identify potentially dangerous things [8].

The profound importance of deep learning in enhancing the execution of tasks inside protection control systems is generally recognized [3]. Deep learning is a specific area within machine learning that utilizes multiple layers of non-linear processing units to gather and modify features [9,10]. Deep learning focuses on extracting representations from primary data through integrating the understanding of a number of feature levels of data [11]. An image representation entails quantifying the density metrics for each pixel and identifying features such as groups of edges and distinctive forms [12]. The Convolutional Neural Network, also known as the is the core architecture of deep learning. It consists of several layers, including the pooling, convolution, and activation operation, dropout, entirely interconnected, and layer for classification [13].

In contemporary society, illicit activities predominantly center around portable firearms [16]. Research consistently highlights the significant role that handheld guns play in various illicit activities such as theft, illegal hunting, and terrorism [17]. One proposed approach to reduce criminal activities is the establishment of surveillance systems or control cameras. This allows security units to take proactive steps at an early stage [18,19,20]. Nevertheless, the task of identifying weapons poses distinctive difficulties, such as self-occlusion, object resemblances, and complexities in the backdrop [15,16]. Self-occlusion refers to the circumstance where a portion of the weapon is blocked or hidden, while object similarities exist when non-weapon objects, like hands or clothing, bear resemblance to weapons. Background addresses refer to the difficulties related to the surroundings in which a weapon is placed [16].

This article introduces a novel deep learning model specifically developed for the purpose of accurately detecting and classifying seven specific types of weapons, namely assault rifles, bazookas, grenades, hunting rifles, knives, pistols, and revolvers. The classification performance of the proposed model is thoroughly assessed using well-established benchmarks, such as the Visual Geometry Group (VGG-16) model [21], Residual Network (ResNet50), and ResNet101 models [22]. Comparative investigation reveals that the suggested model exhibits higher accuracy and reduced loss rates compared to the VGG-16, ResNet50, and ResNet101 models. The subsequent sections of this work are organized in the following manner: Section 2 conducts a comprehensive analysis of the relevant literature. Section 3 elucidates the materials and methods employed in the study. Section 4 showcases the results of the evaluation of the classification performance. Section 5 provides an in-depth discussion. Lastly, Section 6 concludes the study by summarizing significant findings and indicating potential avenues for future research.

II. LITERATURESURVEY

The emergence of automatic handgun detection systems for surveillance and security applications have drawn considerable attention in recent years, leading to the exploration of novel techniques and methodology. This literature assessment consolidates and evaluates numerous research efforts, each making a distinct contribution to the developing field of weapon detection systems. A major study, as stated in [18], focused on generating crucial training data for an automatic handgun detection system using deep Convolutional Neural Network (CNN) classification. The study thoroughly explored the effectiveness of several categorization models, with a particular focus on the importance of reducing false positives. After analyzing two approaches to classification, one using the sliding window technique and the other using the geographic proposal approach, it was found that the region-based CNN model, which operates quickly, produced the most promising results [18].

The study [23] focused on determining the imbalance map and evaluating candidate regions from input frames using image fusion. This study intended to improve object detection in surveillance transcriptions by utilizing a cost-effective symmetrical dual-camera system, with the goal of reducing false positives. By including brightness-guided preliminary processing, which includes lowering and juxtaposing, throughout both the development and testing phases, a model was created that can accurately detect cold steel weapons[24].The successful implementation of this versatile approach showcased enhanced accuracy in recognizing objects and events in video footage.

A study on hybrid weapon detection employed fuzzy logic to create a system that can identify dangerous items, such as firearms and blades, by incorporating extra variables. This not only strengthened the accuracy of the results, but also substantially decreased the occurrence of false alarms[25]. Two new techniques were introduced in a study that exploited deep Convolutional Neural Networks (CNNs) to classify weapons [26]. The study examined the impact of adjusting the neuron count in the layer that is completely linked by utilizing the weights obtained from a trained beforehand VGG-16 model. This investigation provided useful knowledge regarding classification systems. A research that specifically targeted the identification of guns in surveillance videos [5] stationed its analysis on regions where human presence was detected. The implementation of a weapon detection system that utilizes distinct components of weapons demonstrates a focused approach to improving detection efficiency [27].

An independent inquiry[28] examined the implementation of various tiers of defense for Internet of Things (IoT) platforms. The suggested system consistently assessed multidimensional events and determined protection levels, fulfilling the requirement for a comprehensive approach to security management in dynamic situations. The study conducted real-time object detection, focusing on movable weapons such as pistols and rifles [20]. The research successfully recognized and categorized ammunition in photographs by using TensorFlow-based versions of Overfeat, a convolutional neural network (CNN) based visual extractor and data generator. A research investigation on the automated identification of firearms and swords presented algorithms to alert human operators when these items were recognized in closed-circuit telecommunications systems[29]. The project aimed to prioritize practicality by minimizing false alarms and creating a system that can promptly issue notifications in hazardous situations.

Clustering algorithms and color-based segmentation were used in the field of visual weapon registration to exclude unimportant objects from photographs. The Harris detector and rapid retina keypoint descriptor were critical in detecting pertinent objects, dealing with challenges such as partial occlusion, scaling, rotation, and the existence of several weapons[30]. A study was conducted to identify individuals who are at risk, namely those who possess handheld weapons. This study established a model that examines the interaction between humans and objects. This methodology was designed to detect hazardous incidents by identifying hidden dangerous things in possible areas of the human body [31].

To summarize, previous research has mostly focused on categorizing hidden weapons such as firearms, knives, and handheld weapons. However, this literature review highlights a significant deficiency in the current body of knowledge. As far as we know, there has been no study that

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has thoroughly examined the identification and differentiation of various types of weapons. This study tries to fill this gap by offering a complete weapon detection model that can detect a wider range of Comparison of weapon categories in relation to prior research findings, while maintaining a high level of accuracy.

III. MATERIALS AND METHODS

3.1 Dataset and Pre-Processing

A lack of a consistent dataset for weapon identification and recognition prompted the development of a distinct dataset consisting of 5214 weapon photos sourced from the internet. In order to assure the effectiveness of detecting and identifying real-life weaponery, the downloaded photographs were meticulously chosen based on their high quality and varied perspectives. An essential component of the pre-processing stage entailed minimizing extraneous elements from every weapon image. An individual analysis was conducted, utilizing several computer tools, to improve the quality and relevancy of images. This involved performing operations such as padding, Image manipulation techniques such as concealment, eliminating backgrounds, expanding, and rotation. After creating individual photographs. Each weapon class was considered individually, they were collected and arranged into a dataset. The dataset consisted of monochromatic photographs depicting assault rifles, bazookas, grenades, hunting rifles, knives, handguns, and revolvers. The Python programming language was used to convert each image to grayscale format and resize it to dimensions of 144 × 144 pixels. The photos have been classified according to their respective weapon classifications and arranged accordingly. Figure 3.1 presents graphic representations of a sample dataset. The specifics of the weapon dataset, including the categories and quantities of photographs, are outlined in Table 3.2.

Fig 3.1. Dataset containing several classes: (a) assault rifles; (b) bazookas; (c) grenades; (d) hunting rifles; (e) knives; (f) pistols; (g) revolvers.

Table 3.2 The collection contains various classes of weapons together with the corresponding number of photos for each type.

Weapon Class	Number of Images
Assault Rifle	927
Bazooka	211
Grenade	507
Hunting Rifle	849
Knife	1076
Pistol	1170
Revolver	474
Total	5214

3.2 CNN Model

Within the domain of object recognition, the CNN algorithm has emerged as the most widely employed deep learning method. The CNN method, which achieved recognition for its exceptional performance in the 2012 ImageNet Large-Scale Visual Recognition Competition, went on to be utilized in other fields. This work introduces a new model (Figure 3.3) that is built upon the VGG-16 model (Figure 3.4). The model comprises 25 layers, including convolution, pooling, dropout, rectified linear units (ReLU), flatten, fully connected, and classification layers, with a total of 337,671 parameters. Figure 3.3 provides information about a convolutional neural network model that has been created. Figure 3.4 provides information regarding the architectural design of the VGG-16 model.

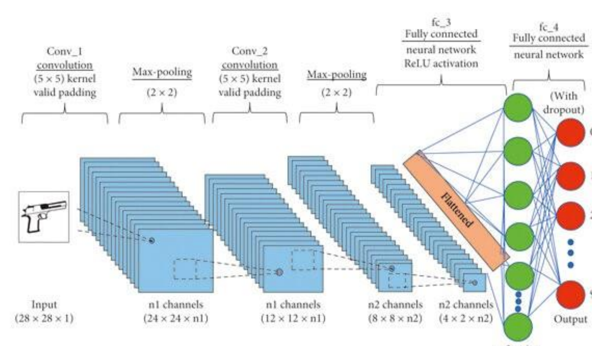

Fig-3.3 Developed convolution neural network model

The decision to utilize the suggested model instead of the standard VGG-Net model was based on its lower layer count, which makes it well-suited for training on inexpensive computers that reduce training time and processing costs, while continuing to provide excellent accuracy. The model's architecture comprises two convolutional layers and an ultimate pooling layer, which are applied to grayscale input images. The pooling layer utilizes a 2-step 2 × 2 filter matrix to generate a new matrix value by shifting across the input matrix. The use of ReLU activation functions in convolution layers guarantees the

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efficiency and speed of the network. Applying a dropout layer of 25% after each pooling layer helps prevent the technique of memorization. The techniques of convolution, pooling, and flattening are applied iteratively in succeeding layers with varying parameters and filter channel values. The process of organizing neurons into an array involves flattening and completely linking layers, resulting in a final layer that is entirely linked and composed of 2048 neurons. The classification layer utilizes the softmax activation function to produce outputs ranging from 0 to 1, which belong to seven distinctive weapon categories. The greatest output value reveals the predicted weapon type.

Fig 3.4 VGG-16 Model

3.3 Media and Libraries Used

The suggested model was generated using the Keras library, which has been built on TensorFlow. Additional libraries, including NumPy, Matplotlib, PIL, Os, OpenCV, Sklearn, and Imageio, were also leveraged. TensorFlow, a freely available software library, provided as the interface for training and executing machine learning algorithms. The Python programming language was utilized to write the programs for implementing and testing the model. The model training was executed on a PC that had an Intel Core i7-9750H 2.60 GHz processor, Nvidia GeForce GTX 1650 graphics card, and 8 GB RAM. The primary objective of the study was to further improve the accuracy, sensitivity, and specificity rates by employing Convolutional Neural Networks (CNN) while at the same time decreasing the loss rates.

3.4 Training and Evaluation

The training method consisted of multiple iterations, where parameters were optimized to minimize the loss function and assure precise predictions. Evaluation of performance and mitigation of overfitting were accomplished by employing a validation set. Afterwards, the trained model was evaluated using a distinct testing dataset to measure its ability to generalize. The model's success in weapon identification and categorization was quantified using performance indicators such as precision, recall, efficiency, and F1 score.

3.5 Comparison with Existing Models

To assess the superiority of the given model, a comparative analysis was conducted against established architectures, specifically the VGG-16 model and Residual Network (Res-Net) models like ResNet-50 and ResNet-101. The examination considered parameters like reliability, inaccurate result and efficiency of computation..

3.6 Ethical Considerations

Throughout the process of developing the model, ethical considerations were given the highest priority. The utilization of internet-acquired photographs complied with copyright restrictions, and diligent measures were taken to ensure the database's inclusiveness and absence of prejudice. The study focused on promoting the prudent utilization of technology for surveillance and safety objectives, taking into account the possible ramifications on society.

IV. RESULTS AND DISCUSSION

4.1 Model Comparison and Training

The study conducted experiments utilizing seven different weapon types, comparing the proposed model with well-established architectures such as VGG-16, ResNet-50, and ResNet-101 models. The dataset was partitioned into training (60%), testing (20%), and validation (20%) subgroups for every single model, following the guidelines provided in Table 4.1. The models were trained with consistent parameters, including the activation function (ReLU), mini-batch size (32), dropout rate (0.25), optimization technique (Adamax), and number of epochs (30).

TABLE 4.1 WEAPON DATASET DIVISION

Dataset	Percentage
Training	60
Testing	20
Validation	20

The evaluation of the VGG-16 model (Figure 4.2a) revealed a comparatively slower learning rate, achieving a success accuracy of 90.12% only after 30 epochs. In contrast, the ResNet-50 model (Figure 4.2b) demonstrated swift learning and attained a success accuracy rate of 94.25%. The ResNet-101 model, shown in Figure 4.2c, attained an accuracy of 84.43%, which was considerably inferior to that of the ResNet-50 model. The model depicted in Figure 4.2d exhibited rapid learning, achieving an excellent accuracy of 98.32% after 30 epochs. The effectiveness of a neural network as a whole depends on its structure and parameter configurations. Despite having fewer layers and parameters, the recommended model

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outperformed the VGG-16, ResNet-50, and ResNet-101 models. The reduced complexity facilitated faster data processing, training, and testing, leading to enhanced accuracy in achieving desired outcomes and reduced rates of failure.

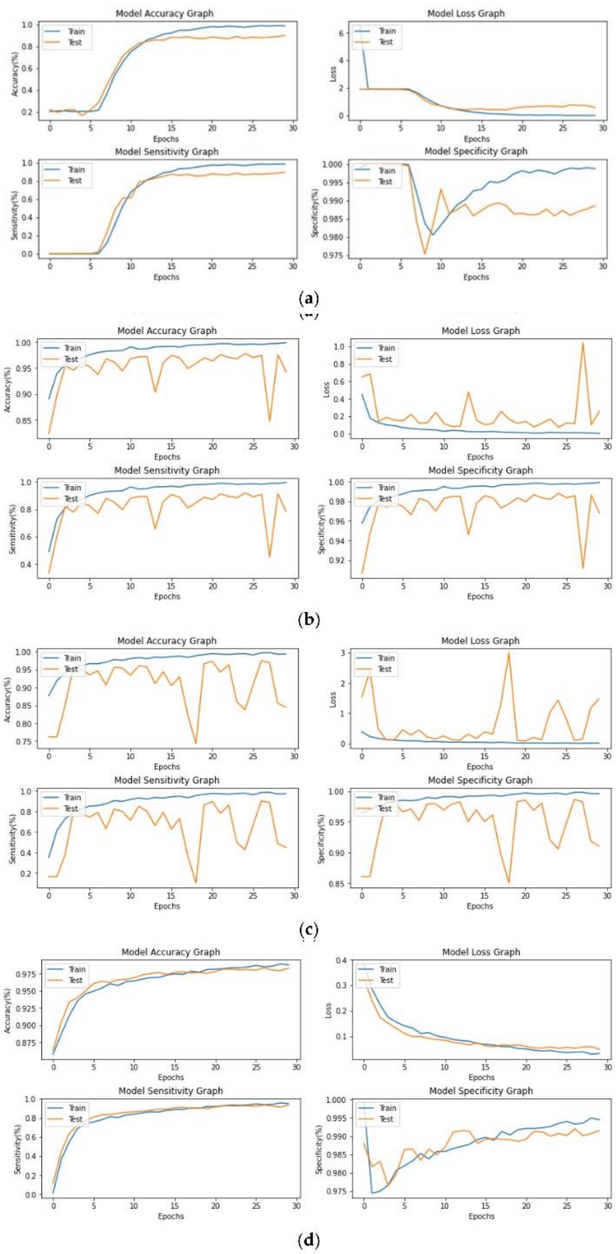

Fig 4.2 The graphs depict the variations observed during training for four different models: (a) VGG-16, (b) ResNet-50, (c) ResNet-101, and (d) the suggested model.

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4.2 Model Evaluation and Comparison

In order to thoroughly assess the models, a meticulous comparison was carried out, taking into account reliability, specificity, sensitivity, and loss factors (Table 4.3).The proposed model consistently outperformed alternative models, achieving an impressive success rate of 98.40%. The model outperformed the VGG-16, ResNet-50, and ResNet-101 models, which achieved success rates of 89.75%, 93.70%, and 83.33% respectively.

Table 4.3 Training success rates of the VGG-16, ResNet-50, and ResNet-101 models and the proposed model.

Measures	VGG-16 Values	ResNet-50 Values	ResNet-101 Values	Proposed Model Values
Accuracy	89.75%	93.70%	83.33%	98.40%
Sensitivity	89.71%	76.48%	41.05%	92.89%
Specificity	98.84%	96.55%	90.44%	99.28%
Loss	6.38	2.79	1.615	0.52

The superiority of the suggested model is apparent in its accelerated learning, enhanced precision, and lower error rates. This highlights the increased effectiveness achieved by optimizing the model architecture for weapon detection.

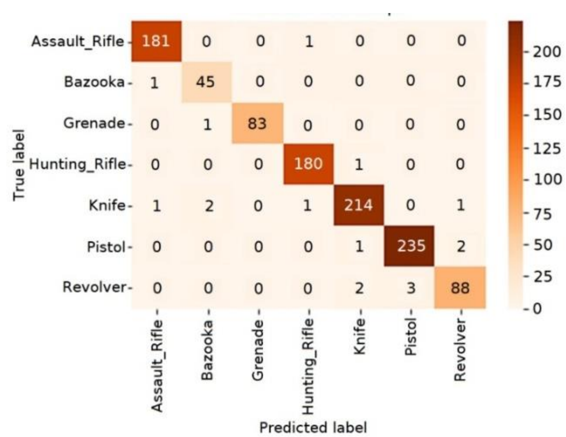
4.3 Confusion Matrix Analysis

The correctness of the suggested approach was evaluated by analyzing its effectiveness using a confusion matrix (Figure 4.4). Remarkably, assault weapons and hunting rifles demonstrated the highest levels of accuracy in categorization, achieving a remarkable 99.45%. In contrast, pistols (94.62%) and bazookas (97.72%) exhibited noticeably lower rates of success.

The little decline in performance, particularly in the context of pistols, can be ascribed to the optical resemblances they bear to firearms. The suggested model's high overall accuracy of 98.40% demonstrates its effectiveness in accurately differentiating between different weapon categories. The proposed model showcases its ability to achieve exceptional accuracy in many real-world weapon detection settings.

Fig 4.4 Confusion Matrix Graph

4.4 Performance Evaluation with Real-Life Data



To assess its feasibility, the suggested model underwent testing utilizing images depicting different categories of weaponry being employed against human subjects. The test data were collected from the web, and the region proposal approach was utilized to validate accuracy.

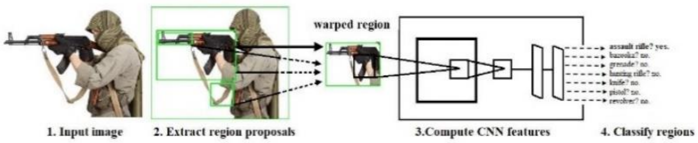


Fig. 4.5 Region proposal approach

The proposed model demonstrated practical adaptability through the utilization of the region suggestion approach [38]. The model successfully identified areas with potential weapons and achieved a satisfactory accuracy in appropriately categorizing them.

4.5 Mean Average Precision (mAP Evaluation)

To assess the performance of the proposed model, the mean average precision (mAP) metric was utilized (Table 4). The mean Average Precision (mAP) scores for each and every weapon class serve as a clear indication of the model's efficacy in accurately detecting and categorizing weapons. The mean average precision (mAP) routinely surpasses 97%, demonstrating the model's high accuracy in detecting various weapon categories in real-world situations.

4.6 Sample Test Results

The effectiveness of the suggested approach for multiple armament categories is demonstrated by the empirical investigation's results (Figure 7). The images exemplify the model's proficiency in precisely categorizing firearms in various circumstances and environments, hence strengthening its suitability for real-world use. This project entailed the creation of an artificial intelligence model utilizing deep learning methodologies.The model was specifically engineered to autonomously handle safety measures and possesses the capability to identify and categorize seven unique varieties of firearms. The proposed model outperformed existing models, such as VGG-16, ResNet-50, and ResNet-101, achieving an excellent accuracy rate of 98.40%. The model's decreased total number of layers and parameters resulted in improved processing, training, and testing speed, rendering it a viable solution for real-time weapon identification.

The model's ability to detect potential weapon locations was assessed using an area suggestion method, which examined its practical adaptability. The mAP values provided additional validation of the model's precision in categorizing various weapon classes. The suggested model demonstrated its superiority through a comparison with current studies, exhibiting greater accuracy rates in comparison to similar firearm detection systems. The model's ability to detect many weapon types simultaneously makes it an advanced solution for safety and monitoring applications.

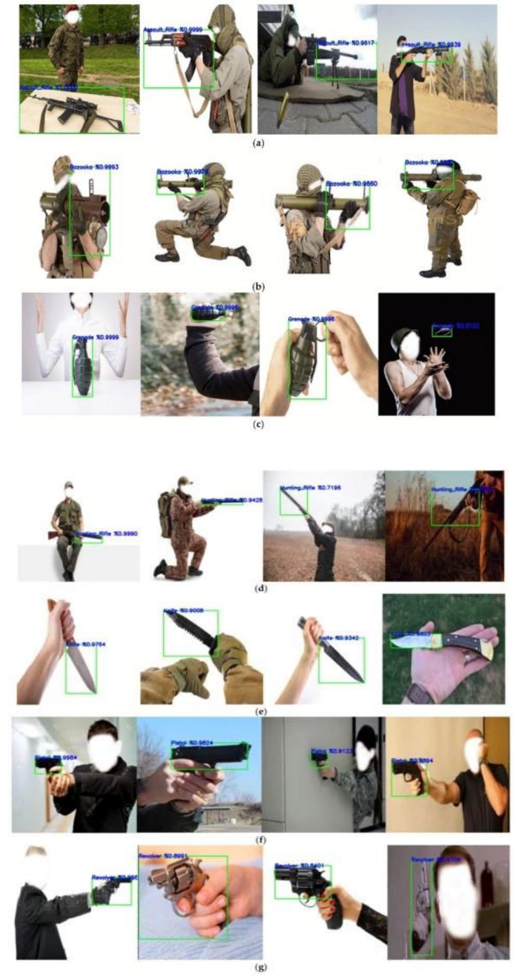


Fig 4.6 The test results for many classes are as follows: The following weapons are included in the list: (a) assault rifles; (b) bazookas; (c) grenades; (d) hunting rifles; (e) knives; (f) pistols; (g) revolvers.

In summary, the created model is a very efficient tool for independent security systems, demonstrating the capability to improve safety measures in various situations. The study highlights the significance of effective and precise weapon detection models, which contribute to the wider domain of machine vision for safety purposes.

Table 4.7 The mean average precision (m AP) of the weapon pictures utilized in the dataset.

Weapon Class	**Number of Images**	**AP (%)**	**m AP (%)**
Assault Rifle	123	91.7	87.3 m AP @0.5 Io U
Bazooka	96	87.5	
Grenade	105	89.2	
Hunting Rifle	112	90.8	
Knife	88	82.5	
Pistol	128	88.3	
Revolver	90	80.8	
Total	742		

V. CONCLUSION

In the current context of increasing illegal activity, it is crucial to have the ability to independently detect and identify firearms on individuals by analyzing surveillance footage, without the need of individual involvement. Precise categorization and identification of weapons are crucial for effectively anticipating and deterring criminal activities, allowing relevant authorities to take preventive steps. Portable or handled firearms are important tools in a variety of illicit operations, such as stealing, illegal hunting, and crimes of violence. It is crucial to recognize these weapons in order to predict potential criminal elements in security camera photographs and provide immediate and necessary actions. This work introduces an innovative model specifically created to identify and categorize seven different types of weapons, utilizing the VGG-Net architecture. A novel dataset comprising these weapon categories was compiled for the aim of training and assessing. Comparative analyses were performed using established models, namely VGG-16 (with a success accuracy of 89.75%), ResNet-50 (with a success accuracy of 93.70%), and ResNet-101 (with a success accuracy of 83.33%). These analyses demonstrated the superior effectiveness of the proposed model, which achieved an excellent success rate of 98.40%. Additional assessments entailed doing tests on the model using photos depicting humans carrying firearms. The utilization of the region suggestion approach facilitated the generation of novel images, hence enabling the creation of realistic testing scenarios. The model demonstrated exceptional performance by precisely identifying weapon photos against various backdrops. Overall, the suggested model serves as a significant resource for addressing security weaknesses and improving the effectiveness and efficiency of security personnel in different contexts. The study's conclusions can be directly applied to different circumstances, which increases its uniqueness and potential impact. The expected contributions are providing guidance and inspiration for similar research, namely in the field of independent security units. Future research could prioritize the development of a robust infrastructure for autonomous robot warriors that possess the capability to autonomously detect and interpret data that is entered. These automated entities possess the capability to promptly alert security troops, examine the information in immediate form utilizing security surveillance systems, and enhance categorization precision. Additionally, future research efforts could prioritize the identification of firearms with a coating, thereby enhancing the capabilities of weaponry detection equipment.

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