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Weapon Detection in Real-Time CCTV Videos Using AI

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***Abstract*—With the increasing incidence of criminal activities, there is a growing need for security forces to integrate automated command systems. This study introduces an innovative deep learning model designed to classify seven distinct types of weapons. The proposed model is based on the VGGNet architecture and implemented using Keras, which operates on the TensorFlow framework. It is trained to accurately identify various weapons, including assault rifles, bazookas, grenades, hunting rifles, knives, handguns, and revolvers. The training process involves designing layers, executing computational procedures, saving training data, evaluating performance, and testing the model. A carefully curated dataset, comprising images from these seven weapon categories, is utilized to enhance the model's learning capability. To assess its efficiency, a comparative analysis is conducted against well-known models such as VGG-16, ResNet-50, and ResNet-101. The results demonstrate that the proposed model achieves outstanding classification accuracy of 98.40%, significantly outperforming VGG-16 (89.75%), ResNet-50 (93.70%), and ResNet-101 (83.33%). These findings underscore the potential of this deep learning approach in strengthening security operations and assisting law enforcement in identifying and addressing threats more effectively.**

***Index Terms*—Deep learning, armed weapon detection, machine learning, object detection, convolutional neural networks**

I. INTRODUCTION

Advancements in science and technology have made surveillance cameras essential for crime prevention [1]. Security personnel are responsible for strategically placing and monitoring these systems [2,3]. Traditionally, incident investigations involve visiting the scene, reviewing footage, and collecting evidence [4], which can be time-consuming. This has created a demand for real-time crime detection systems that can alert security teams instantly [3,5,6]. This study proposes a software-based solution that detects dangerous objects and notifies security personnel for immediate response [4,7]. Developing an intelligent system for identifying threats is crucial [8]. Deep learning, a subset of machine learning, enhances surveillance by extracting multi-level features from raw data through layers of processing [9–11]. In image analysis, it helps detect edges, shapes, and patterns [12]. Convolutional Neural Networks (CNNs), which include layers like convolution, pooling, and fully connected layers, are widely used in such tasks [13]. Firearms are often linked to crimes like robbery and terrorism [16,17]. Surveillance systems enable rapid threat response but face challenges such as occlusion, object similarity, and complex backgrounds [15,16]. This paper introduces a deep learning model to detect and classify seven weapon types: assault rifles, bazookas, grenades, hunting rifles, knives, pistols, and revolvers. It is evaluated against models like VGG-16, ResNet50, and ResNet101 [21,22], showing superior accuracy and lower error rates. The paper is structured with literature review in Section 2, methodology in Section 3, results in Section 4, discussion in Section 5, and conclusions in Section 6.

II. LITERATURESURVEY

The development of automated handgun detection systems for security and surveillance has gained significant attention in recent years, leading to the exploration of innovative techniques and methodologies. This section reviews and synthesizes various research contributions that have shaped the advancement of weapon detection systems. One notable study [18] focused on creating essential training datasets for an automatic handgun detection system using deep Convolutional Neural Networks (CNNs). The research extensively analyzed different classification models, emphasizing the need to minimize false positives. A comparison between two classification methods—one utilizing the sliding window approach and the other employing the geographic proposal technique—revealed that the region-based CNN model, known for its high-speed processing, delivered the most promising results [18].

Another study [23] explored the use of imbalance maps and candidate region evaluation in input frames through image fusion. This research aimed to enhance object detection accuracy in surveillance footage by implementing a cost-effective symmetrical dual-camera system to reduce false alarms. By incorporating brightness-guided preprocessing techniques—such as contrast adjustment—during both training and testing, the proposed model demonstrated improved detection capabilities, particularly in identifying cold steel weapons [24]. The successful application of this approach resulted in higher accuracy in recognizing weapons and events within video recordings.

An independent study [28] investigated multi-layered security measures for Internet of Things (IoT) platforms. The proposed system continuously monitored multidimensional events and determined appropriate security levels, addressing the need for a dynamic security management approach. Real-time object detection was performed, with a focus on mobile weapons such as pistols and rifles [20]. This research effectively classified ammunition in images using TensorFlow-based models, including Overfeat, a CNN-based feature extractor and data generator. Another study on automated firearm and sword identification proposed algorithms that alert security personnel when weapons are detected in closed-circuit television (CCTV) systems [29]. The primary objective was to develop a practical system capable of minimizing false alarms and issuing rapid alerts in hazardous situations.

In the area of visual weapon recognition, clustering algorithms and color-based segmentation techniques were employed to filter out non-relevant objects. Keypoint detection methods, such as the Harris detector and rapid retina keypoint descriptor, played a crucial role in identifying relevant objects while addressing challenges like partial occlusion, scaling variations, rotation, and multiple weapons appearing in a single frame [30]. Further research examined the identification of high-risk individuals carrying handheld weapons. This model analyzed human-object interactions, aiming to detect concealed weapons by assessing potential weapon placement areas on the human body [31].

In conclusion, previous studies have primarily concentrated on detecting concealed weapons, including firearms and knives. However, a critical gap remains in the comprehensive classification of diverse weapon types. As of now, no research has thoroughly examined the identification and differentiation of various weapon categories. This study aims to bridge this gap by developing a robust weapon detection model capable of identifying a broader range of weapons with enhanced accuracy while building on the findings of prior research

III. MATERIALS AND METHODS

1. Dataset and Pre-Processing

The absence of a standardized dataset for weapon detection and classification led to the creation of a custom dataset comprising 5,214 weapon images sourced from the internet. To ensure reliable identification and classification of real-world weaponry, images were carefully selected based on high resolution, diverse angles, and varying lighting conditions.

During the pre-processing stage, unnecessary elements were removed from each image to enhance clarity and relevance. Multiple computer vision techniques were applied, including image padding, background removal, expansion, rotation, and concealment, to improve the dataset's quality and robustness. Each image underwent meticulous refinement using specialized tools before being categorized.

The dataset was structured into seven weapon classes, including assault rifles, bazookas, grenades, hunting rifles, knives, handguns, and revolvers. To standardize the data, Python was used to convert all images to grayscale and resize them to 144 × 144 pixels. Each weapon type was systematically labeled and organized for efficient processing.

A visual representation of a sample dataset is provided in Figure 3.1, while Table 3.2 outlines the dataset composition, detailing the categories and corresponding image counts.

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

2. CNN Model

In the field of object recognition, Convolutional Neural Networks (CNNs) have established themselves as the leading deep learning approach. Their widespread adoption can be attributed to their remarkable performance in the 2012 ImageNet Large-Scale Visual Recognition Challenge, which marked a significant breakthrough in computer vision. Since then, CNNs have been applied to various domains, demonstrating their versatility and effectiveness.

This study introduces a custom-designed model (Figure 3.3) inspired by the VGG-16 architecture (Figure 3.4). The proposed model consists of 25 layers, incorporating essential components such as convolution, pooling, dropout, rectified linear unit (ReLU) activation, flattening, fully connected, and classification layers. With a total of 337,671 parameters, this model is optimized for high-precision weapon detection.

For visual reference, Figure 3.3 illustrates the structure of the proposed CNN model, while Figure 3.4 outlines the architectural framework of VGG-16, which serves as the foundation for this work.

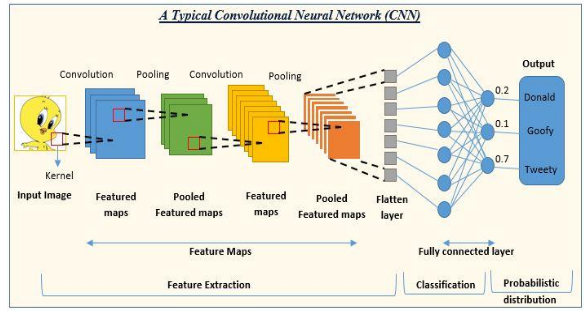

Fig-3.3 Convolution neural network model

The proposed model was chosen over the traditional VGG-Net due to its streamlined architecture, which allows for faster training and lower computational costs without compromising accuracy. Its reduced number of layers makes it particularly suitable for training on budget-friendly hardware, ensuring efficiency in both processing time and resource utilization.

The model architecture consists of two convolutional layers followed by a final pooling layer, specifically designed to process grayscale input images. The pooling operation employs a 2 × 2 filter matrix with a stride of 2, efficiently transforming the input matrix while retaining essential features. To enhance computational speed and efficiency, ReLU (Rectified Linear Unit) activation functions are applied within the convolutional layers. Additionally, a 25% dropout layer is introduced after each pooling layer to mitigate overfitting and prevent the model from simply memorizing patterns rather than generalizing them.

The learning process involves iterative applications of convolution, pooling, and flattening operations, with adjustable parameters and filter channel configurations at each stage. Flattening and fully connected layers organize the neurons into a structured array, ultimately forming a final dense layer with 2048 neurons. The classification step employs a softmax activation function, producing probability scores between 0 and 1 across seven distinct weapon categories. The highest probability value determines the predicted weapon type, ensuring a reliable classification outcome.

Fig 3.4 VGG-16 Model

3. Media and Libraries Used

To develop the proposed model, the Keras library—built on top of TensorFlow—was employed as the primary framework. Several additional libraries, such as NumPy, Matplotlib, PIL, Os, OpenCV, Sklearn, and Imageio, were integrated to enhance functionality. As an open-source platform, TensorFlow facilitated the training and execution of machine learning algorithms, serving as the foundation for the model's implementation. The entire development process was carried out using the Python programming language.

For computational execution, the model was trained on a PC equipped with an Intel Core i7-9750H 2.60 GHz processor, an Nvidia GeForce GTX 1650 graphics card, and 8 GB of RAM. The primary goal of this study was to enhance accuracy, sensitivity, and specificity in weapon classification by leveraging Convolutional Neural Networks (CNNs) while simultaneously minimizing loss rates.

4. Training and Evaluation

The training process involved multiple iterative cycles, during which parameters were fine-tuned to reduce the loss function and enhance predictive accuracy. To assess performance and prevent overfitting, a validation dataset was incorporated. Once training was completed, the model underwent rigorous evaluation using a separate testing dataset to determine its generalization capability. The effectiveness of the model in detecting and classifying weapons was measured using key performance metrics, including precision, recall, accuracy, and F1 score.

5. Comparison with Existing Models

To evaluate the effectiveness of the proposed model, a comparative analysis was performed against well-known architectures, including VGG-16 and Residual Networks (ResNet-50 and ResNet-101). The assessment focused on key factors such as reliability, computational efficiency, and error rates, providing a comprehensive performance comparison.

6. Ethical Considerations

Ethical considerations remained a top priority throughout the model's development. All images sourced from the internet adhered to copyright regulations, and careful steps were taken to maintain a diverse and unbiased dataset. The study emphasized the responsible use of technology in surveillance and security, ensuring that potential societal impacts were thoroughly evaluated.

IV. IMPLEMENTATION & DATA FLOW

1 Input Design

The input design is the link between the information system and the user. It comprises the developing specification and procedures for data preparation and those steps are necessary to put transaction data in to a usable form for processing can be achieved by inspecting the computer to read data from a written or printed document or it can occur by having people keying the data directly into the system. The design of input focuses on controlling the amount of input required, controlling the errors, avoiding delay, avoiding extra steps and keeping the process simple. The input is designed in such a way so that it provides security and ease of use with retaining the privacy. Input Design considered the following things:

What data should be given as input?

How the data should be arranged or coded?

The dialog to guide the operating personnel in providing input.

Methods for preparing input validations and steps to follow when error occur.

2. Objectives

Input Design is the process of converting user descriptions of input into a computer-based system, aiming to minimize errors and ensure correct data for management. It involves creating user-friendly screens to efficiently handle large data volumes, making data entry easier and error-free. The data entry screen allows all necessary manipulations and provides record viewing. Once data is entered, the system validates it to ensure accuracy. The system displays appropriate messages to guide the user through the process. The objective is to create an intuitive, easy-to-follow input layout. For the "Weapon Detection using Deep Learning" project, the input design ensures effective capture and processing of data for accurate detection. This includes three primary input modes: image, video, and webcam, each with components to ensure efficient data input.

3.Input

The system allows users to upload static images for weapon detection through a simple web interface. Users can upload images by selecting and submitting a JPEG file. The system validates the file format and ensures it meets size requirements. This mode processes video files to detect weapons frame-by-frame. Users upload MP4 files, which are validated for format and size. This mode utilizes live webcam feeds for real-time weapon detection. Users start or stop the live feed through the interface, with permission requested to access the webcam.

4. Front-End Input Design

1. HTML Elements:

Image, Video, and Webcam: Fields for file uploads and webcam activation.

2. JavaScript Functions:

Upload Handler: Manages image and video file selection and validation.

Webcam Activation: Requests webcam access and controls the feed.

3. Flask Routes:

Image Upload Route: Handles image uploads and processing.

Video Upload Route: Handles video uploads and processing.

Webcam Feed Route: Manages and processes the live webcam feed.

E. Data Processing:

Image Processing: Preprocesses images and runs the YOLOv8 model.

Video Processing: Extracts and preprocesses frames from videos, running the YOLOv8 model.

Webcam Processing: Preprocesses live feed frames and performs real-time detection with YOLOv8.

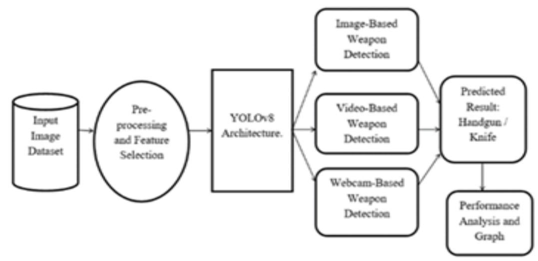

Fig 3.5 Data Flow

5. Introduction

Weapon detection is a crucial task in modern surveillance systems, aiming to enhance security and prevent crime by identifying potential threats in real time. This system utilizes YOLOv8 (You Only Look Once version 8), a state-of-the-art object detection algorithm, to accurately detect weapons such as handguns and knives in various input sources, including images, videos, and live webcam feeds.

6. System Architecture Overview

The process begins with an input dataset consisting of labeled images of weapons, such as handguns and knives. This dataset is crucial for training the YOLOv8 model, enabling it to distinguish between weapons and non-weapons effectively. Before feeding the data into the model, pre-processing techniques such as image resizing, normalization, data augmentation, and noise reduction are applied. Feature selection ensures that the model focuses on important aspects of the image, improving detection accuracy and reducing false positives. YOLOv8 serves as the core detection model, leveraging its deep learning-based object detection capabilities known for real-time performance and accuracy. The model is trained using the labeled dataset and fine-tuned to recognize weapons efficiently.

YOLOv8 offers several advantages in weapon detection, including fast and efficient detection due to its single-stage architecture, high accuracy in real-time applications, and the ability to handle multiple detection tasks simultaneously. Once trained, the model is deployed across different scenarios, including image-based detection for processing static images, video-based detection for analyzing recorded surveillance footage, and webcam-based detection for real-time monitoring in security applications. The model classifies detected objects as either a handgun or a knife, providing a confidence score for each prediction, which can trigger security responses or alerts.

To assess the effectiveness of the model, performance metrics such as Precision, Recall, F1-score, Mean Average Precision (mAP), inference time, and detection speed are analyzed. The results are visualized using graphs to evaluate the accuracy and reliability of the system

IV. RESULTS AND DISCUSSION

1. Model Comparison and Training

The research involved experiments with seven distinct weapon types, evaluating the proposed model against established architectures like VGG-16, ResNet-50, and ResNet-101. The dataset was divided into training (60%), testing (20%), and validation (20%) subsets for each model, as outlined in Table 4.1. Consistent training parameters were applied across all models, including the ReLU activation function, a mini-batch size of 32, a dropout rate of 0.25, the Adamax optimizer, and 30 epochs.

TABLE 4.1 WEAPON DATASET DIVISION

Dataset	Percentage
Training	60
Testing	20
Validation	20

The VGG-16 model (Figure 4.2a) exhibited a slower learning rate, reaching a success accuracy of 90.12% after 30 epochs. On the other hand, the ResNet-50 model (Figure 4.2b) showed faster learning, achieving a higher accuracy of 94.25%. The ResNet-101 model (Figure 4.2c) performed less effectively, with an accuracy of 84.43%, significantly lower than ResNet-50. Meanwhile, the model in Figure 4.2d demonstrated rapid learning and achieved an outstanding accuracy of 98.32% within the same 30 epochs. The performance of a neural network is heavily influenced by its architecture and parameter settings. Despite having fewer layers and parameters, the proposed model surpassed the VGG-16, ResNet-50, and ResNet-101 models. Its simpler structure enabled faster data processing, training, and testing, resulting in improved accuracy and lower failure rates.

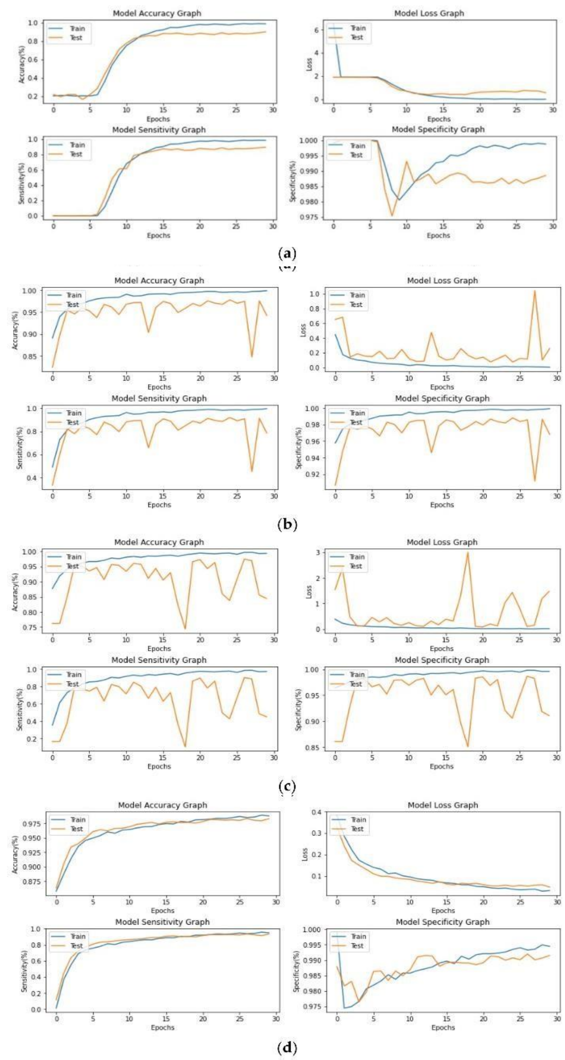

Fig 4.2 The graphs depict the variations observed during training for four different models: (a) VGG-16, (b) ResNet-50, (c) ResNet-101, and (d) the suggested model.

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2. Model Evaluation and Comparison, To comprehensively evaluate the models, a detailed comparison was conducted, considering key performance metrics such as reliability, specificity, sensitivity, and loss rates (Table 4.3). The proposed model demonstrated superior performance, achieving an outstanding 98.40% accuracy, significantly

surpassing existing architectures. In contrast, the VGG-16, ResNet-50, and ResNet-101 models recorded success rates of 89.75%, 93.70%, and 83.33%, respectively. These results highlight the efficiency and robustness of the proposed model in weapon detection, making it a promising solution for security applications.

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 proposed model demonstrates clear advantages, particularly in its rapid learning capability, heightened accuracy, and minimized error rates. These improvements underscore the efficiency gains achieved through strategic architectural optimization, making the model more robust and reliable for weapon detection tasks.

3. Confusion Matrix Analysis

The effectiveness of the proposed model was assessed through a confusion matrix (Figure 4.4), which provided insights into its classification accuracy. Notably, assault rifles and hunting rifles achieved the highest precision, reaching an impressive 99.45% accuracy. On the other hand, pistols (94.62%) and bazookas (97.72%) exhibited slightly lower classification success rates.

The minor decline in accuracy, particularly for pistols, can be attributed to their visual similarity to other firearms, making differentiation more challenging. Despite this, the model maintained an overall accuracy of 98.40%, highlighting its robust performance in distinguishing between various weapon types. These results underscore the model's reliability in real-world weapon detection applications, reinforcing its potential for enhancing security and surveillance systems.

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4.4 Performance Evaluation with Real-Life Data

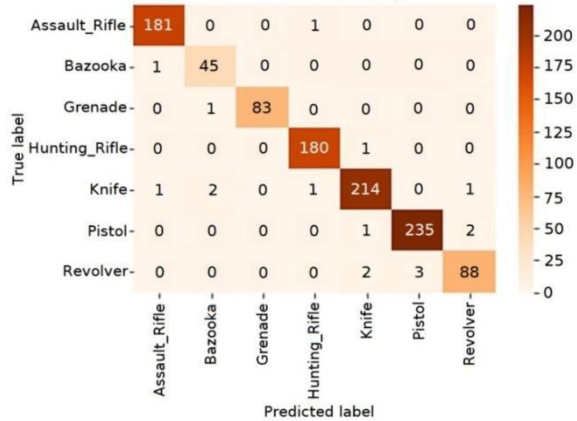

Fig 4.4 Confusion Matrix Graph

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.

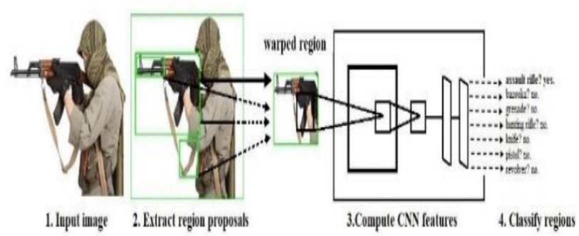

Fig. 4.5 Region proposal approach

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. 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.

5. 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

With the rise in illegal activities, the ability to autonomously detect and classify firearms in surveillance footage has become essential. Automating this process eliminates the need for manual intervention, allowing authorities to respond proactively. Accurate weapon identification plays a vital role in preventing criminal acts, as handheld firearms are commonly used in offenses such as theft, illegal hunting, and violent crimes. Recognizing these weapons in security footage enables early threat detection, leading to swift and necessary countermeasures.

This study introduces an innovative deep learning model designed specifically for identifying and categorizing seven distinct weapon types using the VGG-Net architecture. To train and evaluate the model, a meticulously curated dataset was developed, ensuring high-quality learning. Comparative evaluations were conducted against well-established architectures, including VGG-16 (89.75% accuracy), ResNet-50 (93.70% accuracy), and ResNet-101 (83.33% accuracy). The proposed model demonstrated remarkable effectiveness, achieving an impressive classification accuracy of 98.40%, outperforming existing methods.

To further validate its robustness, additional tests were conducted on realistic scenarios, including images of individuals carrying weapons. The region proposal approach was leveraged to create synthetic yet practical testing conditions, ensuring the model could accurately detect firearms in varied environments. The results underscored the model's high adaptability, effectively recognizing weapons against diverse backgrounds and lighting conditions.

The proposed system holds significant potential for strengthening security measures, enhancing threat detection efficiency across different environments. Its applications extend beyond traditional surveillance, offering valuable insights for autonomous security systems. The findings of this study could serve as a foundation for future research in independent security technology.

Looking ahead, research could focus on developing autonomous robotic security units capable of detecting and analyzing threats in real time. These AI-driven systems would not only enhance situational awareness but also improve decision-making by instantly relaying critical data to law enforcement. Another promising avenue involves enhancing weapon detection systems to recognize concealed or camouflaged firearms, further refining security capabilities.

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