

Weapon Detection Using Artificial Intelligence & Deep Learning for Security Applications

¹Prof. Kanchan Umavane, ²Mr. Anil Waghmare, ³Miss. Tejaswini Rathod, ⁴Miss. Damini Lad.

¹Asst.Professor,^{2,3,4}UG Student,^{1,2,3,4}Computer Engg. Dept. Shivajirao S. Jondhle College of Engineering & Technology, Asangaon, Maharashtra, India.

¹kanchanumavane2020@gmail.com, ²anilw51992@gmail.com, ³tejaswinibrathod123@gmail.com, ⁴daminilad442@gmail.com.

Abstract -Within this project, Due to the fact that crime tends to increase at major events or in isolated, unsettling areas, security is always the first priority in every industry involved in this project. Computer vision addresses a variety of problems and is widely utilized in anomaly detection and monitoring. Video surveillance systems that can recognize and analyse situations and unexpected actions are becoming more and more Research performs automated gun (or weapon) identification using Faster RCNN and Convolution Neural Network (CNN) based SSD algorithms. Two distinct types of datasets are utilized in the proposed methodology. There were two datasets: one comprised a list of manually labelled photographs, and the other had pre-tagged images. When combined, the findings demonstrate the excellent accuracy of both methods; nevertheless, their practical use may be contingent on how well speed and accuracy are matched [1].

Keywords – Gun detection, deep learning, object detection, artificial intelligence, computer vision, RCNN, SSD

I. INTRODUCTION

Weapon or Finding anomalies the process of detecting events or objects that are anomalous, unexpected, unpredictable, or that do not fit into a pattern or are present in a dataset and hence deviate from pre-existing patterns. An irregular pattern from a set of accepted patterns is called an anomaly. As a result, anomalies are dependent upon the relevant phenomenon. Feature extraction and learning techniques or models are used in object identification to identify occurrences of different object categories the suggested implementation aims to achieve precise gun detection and classification. Another reason accuracy matters is that a false alarm might have unintended consequences. Selecting the appropriate strategy necessary to appropriately balance speed and precision. It's an illustration of the deep learning-based technique for detecting weapons. From the video input, frames are extracted. The frame differencing procedure works to produce the bounding box prior to object detection. The process of object detection and trailing ends after the dataset has been generated, trained, and sent to the object detection algorithmic program. Application-appropriate detection can be enabled for the algorithmic program (rapid RCNN or SSD) chosen for gun detection. The method encompasses a broad spectrum of detection and exploitation tasks for various machine learning models, including Single Shot Detection (SSD) and Region Convolutional Neural Network (RCNN) [1]. Artificial intelligence and Deep Learning algorithms are applied to bring about a paradigm

change. This technology uses the capacity of contemporary neural networks to identify the presence of weapons not only more efficiently and accurately than previous methods, but also more effectively. In short, this system applies Bounding Box obtained by detection of an object based on images or videos and algorithm applied to the system compared with faster RCNN. The target Convolutional neural network-based detections separated into one-stage target detection algorithm and two-stage target detection [8].

II. AIMS AND OBJECTIVE

a) Aim:

This project's goal to improve public safety and security by developing an accurate and efficient weapon detection system via the use of deep learning and AI.

b) Objective:

The principal aim of this project is to enhance public safety by developing a strong weapon detection system via the utilization artificial intelligence and deep learning. The main goal will be to create and apply a deep A learning model that is efficient and specifically designed for precise weapon detection. A variety of datasets will be employed to instruct the model, enabling optimization to reach high accuracy and efficiency it basically contains 5 objectives.

- **Data Collection:** Gather a diverse dataset of images and videos featuring various environments where weapons might be present.

- **Data Preprocessing:** Clean and preprocess the data. This might entail enhancing the dataset's variety through augmentation, standardization, and image resizing.
- **Model Development:** Create and use deep learning models for weapon detection tasks, such as CNNs, YOLO, or SSD.
- **Training and Evaluation:** Train the models using annotated data and evaluate their performance using metrics like precision, recall, and F1-score
- **Integration and User Interface:** Develop a user-friendly interface and integrate the system with existing.

III. LITERATURE SURVEY

Paper 1: (SSD) Single Shot Multi Box Detector:

We only discuss one deep neural network method for object identification in photos. Our technique, which we refer to as SSD, discretizes the bounding box output space into a group of standard boxes that span different aspect ratios by scaling each feature map point. In terms of prediction length, the network creates scores for every kind of item found in the default box and modifies the box to better suit the shape of the object. Moreover, the network integrates predictions from many feature map strategies to manage items of natural different sizes. Compared to methods that need object proposals, our SSD variant offers easier to use as it unifies all processing into a single network and completely eliminates proposal development and the ensuing step of pixel or feature resampling. Due to SSD is easy to train and integrate into systems that require a detecting component. Investigations on the ILSVRC, PASCAL VOC, and MS COCO databases demonstrate that SSD provides a single framework for both inference and training, and that it is both substantially quicker than and as accurate as approaches requiring an extra item proposal step [6].

Paper 2: Scalable Object Detection Using Deep Neural Networks:

The ImageNet Large-Scale Visual Recognition Challenge (ILSVRC-2012) is one of the image recognition benchmarks on which recently, deep convolutional neural networks have shown state-of-the-art capabilities. A network that predicts a single bounding box and a confidence score for each category of elements in the image emerged as the winner in the localization subtask. Despite being able to capture the context of the entire image around the objects, the model can manage many instances of the same object in the image without needlessly reproducing the number of outputs for each instance. It suggest using a neural network model for saliency-based detection. It allocates a single bounding box and predicts a quantity of enclosing boxes independent of class [7].

Paper 3: Anomaly Detection in Videos for Video Surveillance Application Using Neural Network:

Due to an increase in crime in busy places and shady isolated regions, security is always a top priority in all fields. An extensive array and problems are addressed by computer vision, which is extensively employed in anomalous detection and monitoring. The increasing need to safeguard people's safety, security, and property has produced a need for video surveillance systems that can recognize and comprehend situations and unusual activities. These systems are essential for intelligence monitoring. Using a technique known as anomaly detection, one can discern between different patterns and pinpoint odd patterns that appear for a short while; these patterns are known as outliers. Surveillance film may catch a wide range of probable oddities. Anomaly In video surveillance, detection entails dismantling the entire process into three stages: activity detection, image processing, and video labelers. Therefore, when it comes to real-time settings, anomaly identification in footage for use in security applications provides guaranteed outcomes. Bb - In this work, anomalies were identified in pictures and videos with a 98.5% accuracy rate [3].

IV. EXISTING SYSTEM

The process of weaponry or the ability to identify anomalies involves identifying anomalous, erratic, unexpected, or strange occurrences or objects that do not fit into a pattern or are present in a dataset and hence deviate from pre-existing patterns. An anomaly represents a pattern that differs from a collection of recognized patterns. As a result, anomalies are dependent upon the relevant phenomenon. Feature extraction and learning techniques or models are used in object identification to identify occurrences of different item categories [1]. It basically 2 Disadvantages.

- This system is not entirely automated. An administrator will confirm each gun detection alert.
- R-CNN algorithm used.

Table 1: Comparative Analysis

SR NO.	PAPER TITLE	AUTHOR NAME	Technology	Purpose
1.	Weapon Detection using Artificial Intelligence and Deep Learning for Security Application	Harsh Jain	SSD Algorithm Faster R_CNN	SSD Self-Created Image data Set
2.	SSD: Single Shot Multi Box Detector	Wei Liu et al.	Single deep neural network	SSD is Significantly More Accurate, Even when The input Image size is Less.
3.	Scalable Object Detection Using Deep Neural Networks	D. Erhan et al.	Deep Neural Networks	Model captures the whole-image context

				around the objects.
4.	Anomaly Detection in Videos for Video Surveillance Application Using Neural Network	Ruben J Franklin et.al.	Neural Networks	Anomalies were identified in pictures and movies with a 98.5% accuracy rate.

VI. PROBLEM STATEMENT

Effectively identifying and reducing possible risks posed by concealed weapons is a major concern facing public safety today. The ability of traditional security screening techniques to quickly and precisely detect hidden weapons in real-time situations is frequently compromised. This discrepancy necessitates the development of an advanced artificial intelligence and deep learning weapon detection system. Because the current systems are not sophisticated enough to offer effective and trustworthy threat detection, there may be weaknesses in different security configurations. By creating a reliable and moral weapon detection system A device capable of precisely identifying weaponry and monitor them in real time, our project seeks to close this crucial gap in public safety protocols and reduce the risks that come with bringing a hidden weapon in an array of contexts.

VII. PROPOSED SYSTEM

Precise gun detection and categorization are the main goals of the proposed implementation. Another reason accuracy matters because a false alarm might have unintended consequences. Selecting the appropriate strategy is necessary to appropriately balance speed and precision. The deep learning-based weapons identification algorithm is depicted. From the input video, frames are taken off. Before an object is detected, the frame differencing procedure works to create the bounding box. The SSD algorithm achieved unprecedented levels of accuracy and performance detection [1]. SSD speeds up the process by doing away with the need for a region-specific proposal network. SSD introduces several methods, including as standard boxes and many scales features, to address the accuracy drop. With these enhancements, SSD can now match the Faster R-precision even with images of lower quality, it increases speed even further. Around 74% on MAP and 59 fps on COCO datasets represent the average scoring.

VIII. ALGORITHM

The general idea of working of proposed system algorithms is given as follows:

Consensus Algorithm:

```
import cv2
import numpy as np
from deep_learning_model import load_model, predict_object
```

```
# Function to load the pre-trained deep learning model for object detection
def load_model():
    # Implement the model loading here
    pass
# Function to process each frame and perform object detection
def process_frame(frame, net):
    # Set parameters
    confThreshold = 0.5 # Confidence threshold for bounding box predictions
    maskThreshold = 0.3 # Mask threshold for binary masks
    # Extract frame dimensions
    frameH, frameW = frame.shape[:2]
    # Create blob from the frame
    blob = cv2.dnn.blobFromImage(frame)
    # Pass the blob as an input to the ConvNets
    net.setInput(blob)
    # Perform forward pass
    detections = net.forward()
    # Extract the bounding box and draw the box for each detected object
    for i in range(detections.shape[2]):
        confidence = detections[0, 0, i, 2]
        # Check if confidence is above the threshold
        if confidence > confThreshold:
            box = detections[0, 0, i, 3:7] * np.array([frameW, frameH, frameW, frameH])
            (startX, startY, endX, endY) = box.astype("int")
            color = (0, 255, 0) # Green color for bounding boxes
            cv2.rectangle(frame, (startX, startY), (endX, endY), color, 2)
    return frame
# Main function
def main():
    # Load the pre-trained deep learning model
    net = load_model()
    # Initialize video capture
    vs = cv2.VideoCapture("../weapon_video.mov") # Loading the video
    while True:
        # Read frame from the video stream
        grabbed, frame = vs.read()
        # Check if frame is successfully captured
        if not grabbed:
            break
        # Process each frame and perform object detection
        frame_with_boxes = process_frame(frame, net)
        # Display the frame with bounding boxes
        cv2.imshow('Weapons Detection', frame_with_boxes)
        # Check for exit command
        if cv2.waitKey(1) & 0xFF == ord('q'):
            break
    # Release the video capture object and close all windows
    vs.release()
```

```
cv2.destroyAllWindows()
if __name__ == "__main__":
    main()
End
```

IX. MATHEMATICAL MODEL

Elliptic Curve Cryptography:

A mathematical model of weapon detection using deep learning and artificial intelligence involves determining the crucial components and steps engaged in the process of detecting. The following simple mathematical representation of the weapon detection process:

1. Input:

-Let X be the input space representing video frames

- X_i represents an individual frame in the video sequence, where i is the frame index.

2. Preprocessing:

- Define a preprocessing function P that transforms the raw input frames: Preprocessed Frame $i = P(x_i)$

3. Model Representation:

-Let M represent the deep learning model used for object detection.

- For the i -th preprocessed frame, Y_i is the model's output: $Y_i = M(\text{Frame that has been prepped})$

4. Frame Differencing:

-Define a frame differencing function D to identify regions of motion between consecutive frames:

-Diff Frame $i = D(\text{Preprocessed Frame } i, \text{Preprocessed Frame } i-1)$

5. Object Filtering:

- Define a function F to filter detected objects based on relevant classes (e.g., guns): Filtered Objects $i = F(Y_i)$

6. Bounding Box Drawing:

- Define a function B to draw bounding boxes around the filtered objects: Frame with Boxes $i = B(X_i, \text{Filtered Objects } i)$

Output:

The result includes a series of frames showing the weapons' bounding boxes that were found:

Frame with Boxes 1, Frame with Boxes 2, and Frame with Boxes n] is the created film.

In security applications, it's critical to iterate on the model architecture, training data, and evaluation metrics in order to optimize performance and ensure accurate weapon detection. Moreover, privacy and ethical issues must be considered while putting these devices in place in public spaces.

X. SYSTEM ARCHITECTURE

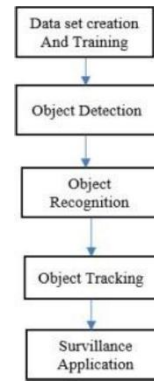


Figure 1: System Architecture

Description:

In the proposed architecture, the flow of object detection and tracking as shown in figure 1. the implementation of the system begins with training data using image processing techniques. Initially, preprocessing and feature extraction mechanisms are applied to the data, which is then stored in a database. Subsequently, sample data is provided for the detection method, wherein the system raises an alert upon spotting a weapon. The primary objectives of implementing this system include accurate gun identification and categorization, with a particular emphasis on achieving high accuracy to avoid false alarms, which could lead to undesirable consequences. Achieving a When choosing the best deployment plan, finding the ideal balance between speed and precision is essential. Deep learning serves as the foundation for the weapons identification technology. The process involves extracting frames from input videos, and while both algorithms are effective and yield satisfactory results, for real-time applications, accuracy and speed must be traded off [1]. The pre-labelled dataset (AK47) yields the best average accuracy, as seen in Figure 3. Figure 4 displays the accuracy of 74% and 91% gun identification using the cam Faster R-CNN method.

XI. ADVANTAGES

- **High Accuracy:** Deep learning models achieve superior accuracy in recognizing weapons.
- **Real-Time Processing:** Enables swift identification of weapons in live video feeds or images.
- **Scalability:** Can be deployed across various platforms and scales, from small cameras to large-scale security systems.
- **Adaptability:** Easily updated to recognize new threats or variations in weapon designs
- **Cost-Effectiveness:** Once deployed, AI-based weapon detection systems can operate autonomously with minimal human intervention, leading to long-term cost savings compared to traditional security measures that require constant manpower.

- **Integration with Existing Infrastructure:** AI-based weapon detection solutions can be integrated with existing security systems, including CCTV networks, access control systems, and alarm systems, facilitating seamless implementation without requiring significant infrastructure overhaul.

XII. DESIGN DETAILS

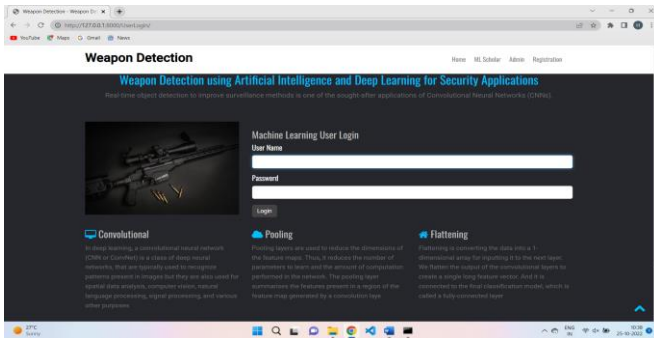


Figure 2: User Login Page

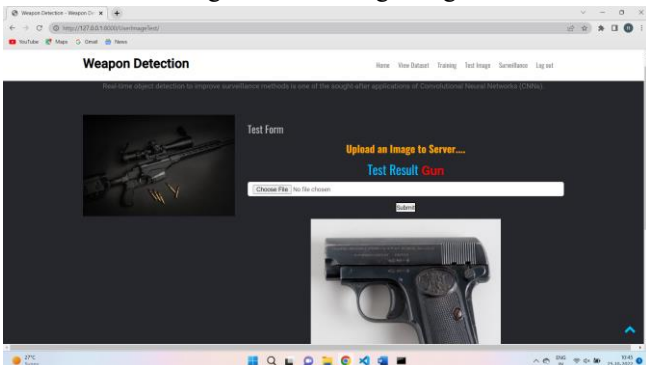


Figure 3: File Access Result

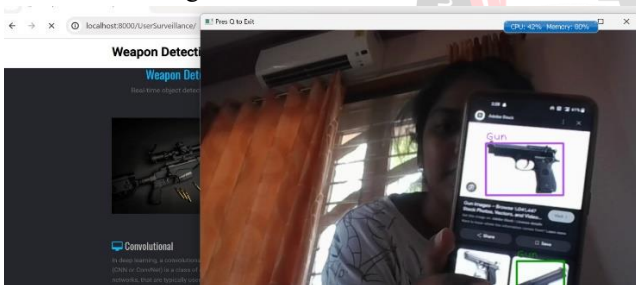


Figure 4: Weapon Detect webcam

XIII. CONCLUSION

We have attempted to put into practice “**Harsh Jain., “Weapon Detection using Artificial Intelligence and Deep Learning for Security Application”, IEEE, July, 2020**” in practice. The objective of weapon (gun) detection, pre-labelled and self-created image datasets are used to simulate Faster SSD and RCNN algorithms. While both algorithms are effective and produce good results, using them in real time requires balancing speed and accuracy. With 0.736 s/frame, the SSD algorithm provides faster speed. Faster RCNN, on the other hand, only achieves 1.606 s/frame, which is slower than SSD [2]. Faster RCNN provides improved accuracy, coming in at up to 84.6%. In contrast, SSD provides up to 73.8% accuracy, which is subpar when compared to RCNN's speed. SSD's quicker speed made it

possible for real-time detection, but quicker RCNN's greater accuracy was achieved. Additionally, by employing GPUs and expensive DSP and FPGA packages for training, it may be applied to larger datasets [1].

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