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Weapon Detection Using Faster R-CNN

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Abstract: As criminal activities continue to rise, ensuring security has become a top priority across various sectors. Computer vision technology is being extensively employed to address this problem by detecting and monitoring abnormalities. Video surveillance systems capable of identifying and analyzing scenes and detecting anomalous events have become increasingly essential to safeguard personal belongings, ensure safety, and enhance security. Such systems play a crucial role in intelligence monitoring. In this study, we implemented automatic weapon (or gun) detection using Faster RCNN techniques. Two datasets were utilized: one consisting of pre-labeled photos, and the other a collection of manually labeled images. Upon analyzing the data, both algorithms yielded highly precise outcomes. However, the practicality of these systems in real-world scenarios will ultimately depend on the trade-off between time and accuracy.
Keywords: FRCNN, SSD, Deep learning, Object Detection, Python implementation.

I. INTRODUCTION

Identifying unexpected events or objects is central to the process of detecting weapons or anomalies., unpredictable or do not conform to a specific pattern. Anomalies are deviations from accepted patterns. A key component of this procedure is the use of feature extraction as well as educating models or algorithms.to recognizes occurrences of various item categories. When it comes to gun detection, the primary objective is to identify and classify firearms accurately. It is crucial to ensure accuracy to prevent erroneous warnings that might trigger undesirable responses, making it vital to select a strategy that balances speed and precision. To detect objects frames are taken out of the video input.. The frame differencing process generates a bounding box once an object is detected. Subsequently, A dataset is produced., trained, and inputted into the object identification method predicated on the chosen detection method for gun detection. Numerous machine learning models, including Region Convolutional Neural Network (RCNN) and Single Shot Detection (SSD), are used to address the detection problem.

II. LITERATURE REVIEW

Ref Ref Wei Liu [7] SSD creates default boxes out of the bounding box's output space. at numerous aspect ratios and sizes per feature map point. Predictions from several feature maps are combined to handle objects of different sizes efficiently. Even with a reduced input image size, SSD attains noticeably more accuracy than previous single-stage methods. D. Erhan [3] Superior to deep convolutional neural networks in image recognition, winning challenges like ILSVRC-2012. Our saliency-inspired model predicts bounding boxes and scores for object detection, handling multiple instances per class. It produces competitive results with little evaluations on VOC2007 and ILSVRC2012. Ruben J Franklin [4] Security is crucial, especially in crowded or isolated areas. Computer vision helps detect anomalies for safety. Video surveillance is essential for monitoring scenes and anomalies. Anomaly detection swiftly identifies outliers in videos. Our paper achieves 98.5% accuracy in anomaly detection.. Abhiraj Biswas's research [1] forms the basis for object classification in neural network-based video recordings, streamlining image processing tasks. Feature extraction as well asmatching, which were first presented in Pallavi Raj [12], are widely used in practically all domains, from exploratory research to biomedicine. SURF, FAST, MSER, and Harris Corner Detector are several of the algorithm combinations that are used to extract, describe, and match the features of the input image and the target image. Mohana [8] Developed an integrated system using Mobile-Net SSD to manage visual data and detect weapons efficiently. Hazards are identified via ARM-based algorithms and deep neural networks. A convolutional neural network is used for analysis by a Raspberry Pi module that records live broadcasts. In questionable locations, Mobile-Net SSD enhances item detection while lowering crime rates.Yojan Chitkara [2] A model removes background to detect foreground in sports.It categorizes players by teams and colors through feature extraction. Kalman Filters track player positions, handling shadows and lighting changes. Results: 84% motion detection, 100% object detection, and tracking accuracy.

III. PROPOSED METHODOLOGY

This work uses SSD together with Faster RCNN techniquesto perform automatic detection of guns (or other weapons).Two kinds of datasets are employed in the suggested implementation.

A dataset containing pre-labeled images was contrasted with another dataset consisting of manually labeled images. Two datasets were tested out, one with pre-labeled photos and the other without. consisting of manually labeled images. The results were tabulated, showing that both algorithms achieved high accuracy. However, the selection of algorithm for real-world applications may depend on the balance between speed and accuracy.

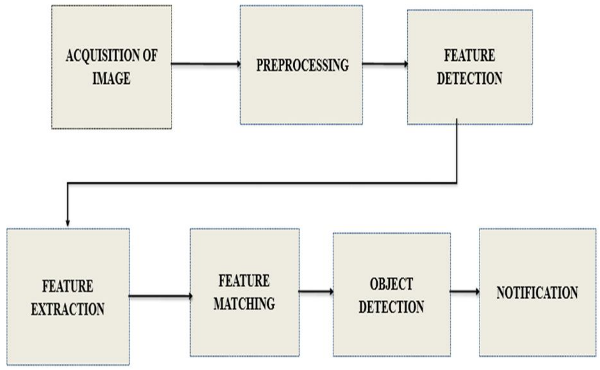

Fig.1: Block diagram of weapon detection

A. *SSD Architecture*

During training, SSD aligns anchor boxes with the fundamental object bounding boxes. The anchor box with the most overlap predicts the object's class and location, eliminating the requirement for region proposal network and speeding up the process. Technologies like basic boxes and features with many scales maintain accuracy despite these enhancements.

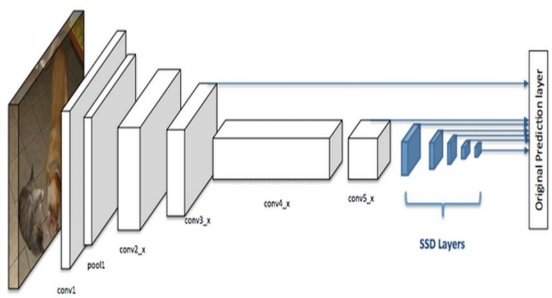

Fig.2:Architecture of SSD

B. *FRCNN ALGORITHM*

Faster R-CNN is a sophisticated object detection model that outperforms Fast R-CNN by combining a CNN with a region proposal network (RPN).It utilizes shared convolutional features and region proposals generated by the RPN during end-to-end training to identify abnormalities. The model follows image processing stages like importing, pre-processing, analysing, and outputting results. For training, labeled images are used, with 70% for training and 30% for testing purposes. The ammo dataset is trained using the Single Shot Detector (SSD) model to increase accuracy and precision, undergoing 2669 iterations to ensure a loss of less than 0.05

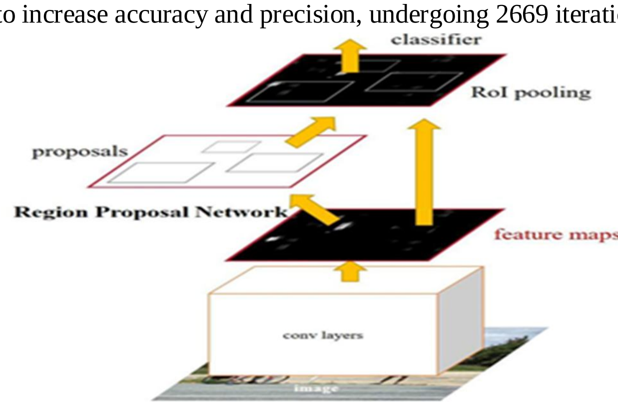

Fig.3:Architecture of FRCNN

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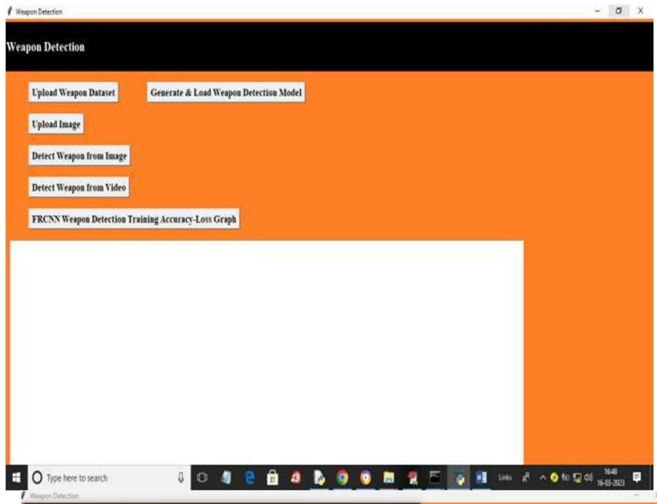
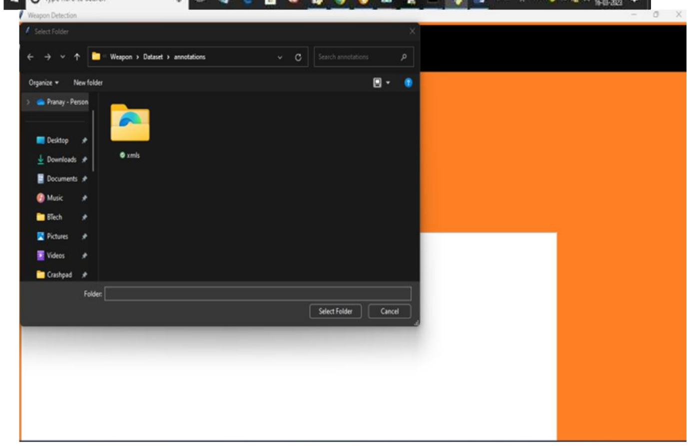
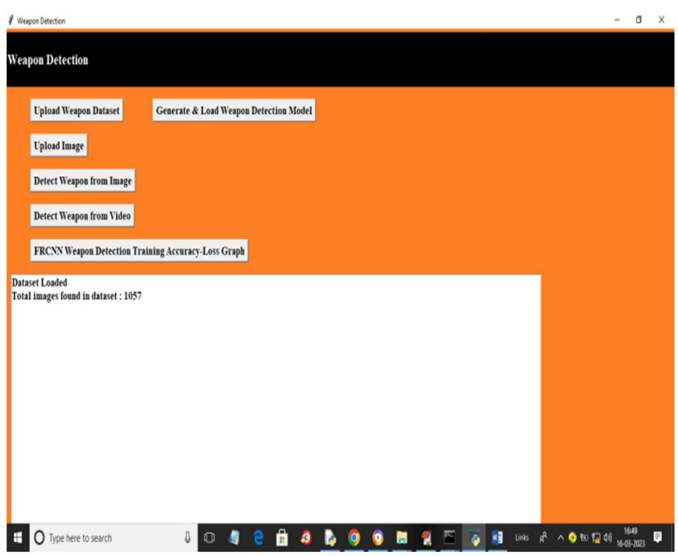
IV. RESULTS & ANALYSIS

Double-clicking the "run.bat" file will launch the project and display the screen below.





Click the "Upload Weapon Dataset" button in the above screen to upload the dataset and obtain the output below.



Click the "Select Folder" button to import the dataset and obtain the output below. In the above panels, select and upload the whole XML folder with annotated bounding boxes and picture paths.

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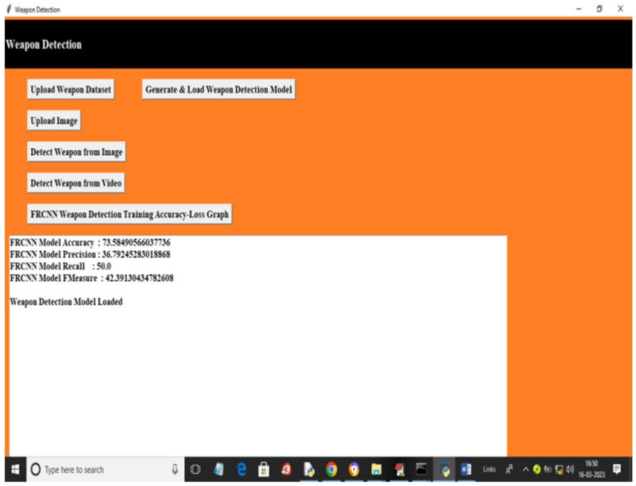
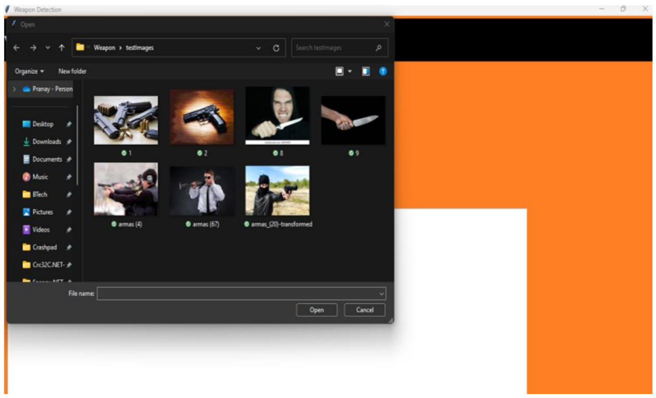
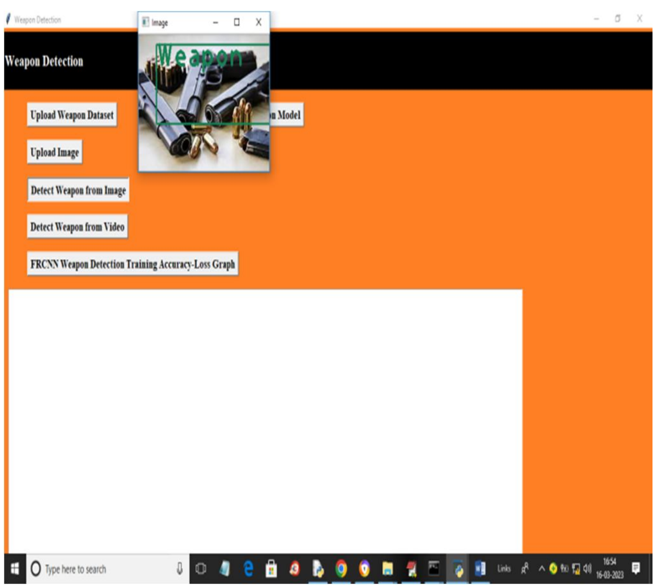


1057 weapon photos have been loaded from the dataset on the screen above. Click the "Generate & Load Weapon Detection Model" button to instruct the FRCNN model and obtain the output below.

The FRCNN model loaded in the screen above, and its accuracy was 73%.We may now view additional metrics. Click the "Upload Image" button to upload a picture and receive the output shown below.



Choose and upload an image from the screen above, then click the "Open" and "Detect Weapon from Image" buttons to obtain the output shown below.



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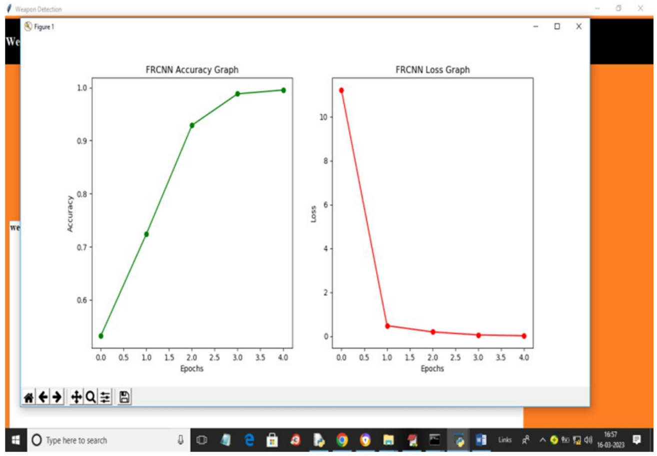

The following training graphs show x-axis training epochs and y-axis accuracy and loss values. The green line represents the accuracy, which typically increases with age, while the red line indicates the loss, which generally decreases over time. If you have additional pictures to upload and test.

V. CONCLUSION

Pre-labeled and self-generated image datasets are simulated using SSD along with Faster RCNN algorithms for weapon detection. Although there is a compromise between accuracy with speed, both algorithms are effective, with the SSD algorithm being faster at 0.736 s/feet. The speed of Faster RCNN, which is only 1.606s/frame, is not as fast as SSD. More accurately, Faster RCNN provides an accuracy of 73.6. The accuracy of SSD is only 65.8%, which is considered below average when contrasted with Faster RCNN. SSD and Faster R-CNN are both object detection algorithms, with SSD offering faster real-time detection while Faster R-CNN delivers higher accuracy. However, Faster R-CNN has an advantage in handling higher datasets by utilizing advanced hardware such as GPUs, DSPs, and FPGAs for efficient training.

VI. FUTURE SCOPE

Future research entails expanding the quantity of data sets., given that the data set can include contain several kinds of weapons like hand grenades, etc. With a comprehensive 3D data set containing object orientation, deep learning models could identify weapons pointed toward humans. This technology, by revealing concealed objects, has the potential to significantly improve weapon detection for law enforcement. Moreover, It is practicable to use on bigger datasets by utilizing GPUs as well as high-end DSP and FPGA kits.