IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 13, Issue 3, March 2024

DOI: 10.17148/IJARCCE.2024.13328

WEAPON DETECTION In A CRIME SCENE USING CONVOLUTION NEURAL NETWORK

K. Mohan Krishna[1], A. LikhithaReddy[2], G. Sri Sai Meghana[3], Ch. Rohith Varma[4], G. Velugondaiah[5]

Assistant Professor, CSE, Vasireddy Venkatadri Institute of Technology, Guntur, India[1]

Student, CSE, Vasireddy Venkatadri Institute of Technology, Guntur, India[2-5]

Abstract: Due to an increase in crime during big events or in isolated, suspicious areas, security is always a top priority in every field. Computer vision is widely used in abnormal detection and monitoring to address a variety of issues. The need for video surveillance systems that can identify and analyze scenes and anomalous events has grown due to the increased demand for the protection of personal property, safety, and security. These systems are essential for intelligence monitoring. This project uses Faster RCNN techniques and a convolution neural network (CNN) based YOLO Module to provide automatic gun (or) weapon detection. Two kinds of datasets are used in the suggested implementation. There was one dataset with pre-labeled photos and another with a collection of manually labeled images. The algorithms yield tabular results with good accuracy; however, the trade-off between speed and precision may determine how these algorithms are applied in practical scenarios.

Keywords: Weapon detection, convolutional neural network, image classification, object detection, computer vision.

I. INTRODUCTION

The process of identifying irregular, unexpected, unpredictable, or uncommon events or items, which deviate from established patterns within a dataset, is known as anomaly detection. In this context, feature extraction and learning models or algorithms are employed for object identification to recognize occurrences of various item categories. The primary objective of the proposed implementation is accurate gun detection and categorization.

Frames extracted from the input video are utilized, and prior to object detection, bounding boxes are generated through the frame differencing process. A dataset is created, trained, and then fed into the object detection algorithm, based on the appropriate detection method selected for the gun detection application, whether it be rapid RCNN or SSD. The approach addresses the detection problem by employing various machine learning models such as Region Convolutional Neural Network (RCNN) and Single Shot Detection.

II. LITERATURE SURVEY

[1] Sheen et al. proposed a concealed weapons detection (CWD) method based on a three-dimensional millimeter (mm) wave imaging technique for identifying hidden weapons at airports and other secure locations on the body.

[2] Z. Xue et al. suggested a CWD technique utilizing fusion-based multi-scale decomposition, integrating colour visual imagery with infrared (IR) imaging for concealed weapons detection.

[3] R. Blum et al. recommended a CWD method incorporating visual and IR or mm wave imagery using a multi-resolution mosaic technique to highlight concealed weapons within target images.

[4] E. M. Upadhyay et al. proposed a CWD technique employing image fusion, combining IR and visual images to detect concealed weapons, particularly in scenarios with over and underexposed areas. Their approach involved applying a homomorphic filter to visual and IR images captured under different exposure conditions.

[5] The concept of automated image processing for public security applications has been widely recognized and studied.

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Closed-circuit television (CCTV) systems played a crucial role in advancing such work, first utilized in 1946 in Germany to monitor the launch of the V2 rocket.

[6] Although CCTV had earlier applications, significant advancements occurred in the last two decades, enabling visual object recognition and detection for surveillance and security purposes. The development of the Charge-Coupled Device (CCD) in 1973 facilitated the widespread deployment of surveillance cameras by 1980.

[7] In 2003, Royal Palm Middle School in Phoenix employed facial recognition technology for the first time to track missing children.

[8] Several object detection algorithms have been proposed in computer vision to enhance surveillance systems. These algorithms have found applications in various sectors such as anomaly detection, deterrence, human detection, and traffic monitoring. R. Chellapa et al. briefly discussed object tracking and detection in surveillance cameras.

[9] J.S. Marques proposed distinct techniques for evaluating the effectiveness of different object recognition algorithms. B. Triggs et al. described the histogram oriented gradient (HOG) method, which emerged as a novel architecture for feature extraction, primarily used in human detection applications.

[10] In 2005, the sliding window technique was introduced for recognizing number plates, employing a sliding window for segmentation and a neural network for character recognition on the number plate.

[11] The development of CCTV systems led to the introduction of firearm detection algorithms, first proposed by L. Ward et al. in 2007. They also implemented a surveillance system in 2008, featuring an accurate pistol detection model for RGB images.

However, their method failed to detect various pistols in the same scene. Their approach involved removing non- related items using the K-means clustering algorithm and applying the SURF (Speeded-Up Robust Features) method for point of interest detection. Darker introduced the concept of a SIFT-based weapon detection algorithm, utilizing motion segmentation for Region of Interest (ROI) estimation.

[12] Rohith Vajhala et al. proposed the technique of knife and gun detection in surveillance systems. They had used HOG as a feature extractor along with backpropagation of artificial neural networks for classification purposes. The detection was performed using different scenarios, first weapon only and then using HOG and background subtraction methods for human before the desired object and claimed to have an accuracy of 83%.

[13] Verma et al. had also used the deep learning technique to detect weapons and used the Faster RCNN model. The work was performed on imfdb, which in my opinion is not suitable to train a model for real-time case. They claimed to have an accuracy of 93.1% on that dataset but in the case of weapon detection, only achieving higher accuracy is not enough, and precision and recall must the considered.

[14] The work of Siham Tabik et al. was closely tied to the actual situation. They employed region proposal and sliding window techniques in Faster RCNN to detect firearms in real time. The region suggestion method produced the best results. The region suggestion approach processed the image in 140ms at 7 frames per second, whereas the sliding window took 14 s per image.

[15]. The goal of Jose Luis Salazar González et al.'s effort was to obtain results in real time. They trained Faster-RCNN using Feature Pyramid Network and Resnet50 after extensive experimentation with a variety of datasets. This advances the state of the art by 3.91%.

III. METHODOLOGY

The proposed implementation primarily emphasizes the accurate detection and classification of guns, prioritizing precision due to the potential consequences of false alarms.

Two datasets were utilized: one comprising pre-labeled images, and the other manually labeled images. Results were tabulated, showcasing favorable accuracy for both algorithms. However, the practical application of these algorithms in real-world scenarios may involve a trade-off between speed and accuracy.

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Object Recognition:

Object recognition involves predicting the actual category of an image by assigning high probabilities to the respective class. Convolutional Neural Networks (CNNs) are employed for efficient execution of this process. Numerous state-of-the-art classification and detection algorithms utilize CNNs as a backend for their tasks**.**

Image Classification:

This task entails feeding an image through a classification model, which slides a kernel/filter across the entire image to generate feature maps. The model then predicts the label based on the extracted features' probabilities.

Object Localization:

Object localization determines the precise location of an object within an image, providing its associated height, width, and coordinates.

Object Detection:

Combining aspects of the aforementioned algorithms, object detection identifies bounding boxes with associated coordinates (x and y) and dimensions (width and height), along with the class label. Non-maximum suppression is employed to filter out boxes below a specified threshold, yielding the following results: bounding box and probability.

Classification and Detection Approach:

Two approaches are employed in the proposed work for classification and detection models:

- **Sliding Window/Classification Models:**

This method involves moving a window over an image to select different areas, utilizing an object recognition model to identify each frame patch covered by the window.

- **Region Proposal/Object Detection Models:**

This technique employs an image's bounding boxes as input and outputs proposals for areas in the image most likely to contain objects**.**

Training Mechanism: Training begins with defining the problem, acquiring the necessary dataset, applying preprocessing techniques, and then training and evaluating the dataset.

Evaluation involves assessing performance metrics such as accuracy, precision, recall, and F1-score on a separate test dataset. Successful evaluations result in saving the trained weights as a classifier, while incorrect evaluations prompt the application of backpropagation and gradient descent algorithms.

Evaluation:

Evaluate the trained models using performance metrics like accuracy, precision, recall, and F1-score on a separate test dataset**.**

Implementation:

An interactive application is developed to allow users to input weapon images and classify them using the trained models.

Validation:

The application's performance is validated by testing it with various weapon images and evaluating its accuracy in detecting weapons.

By following this proposed methodology, a robust and efficient system for weapon detection can be developed.

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PROBLEM STATEMENT:

In areas with high crime rates attributed to firearms or knives, particularly where their possession is permitted, one effective strategy for prevention is the detection of dangerous objects such as handguns and knives in images and videos. To address this need, we propose an automatic weapon detection system designed for surveillance and control purposes. Our approach emphasizes early detection of these weapons using deep learning techniques applied to real-time video security.

DESIGN:

SYSTEM REQUIREMENTS:

A. **HARDWARE REQUIREMENTS**:

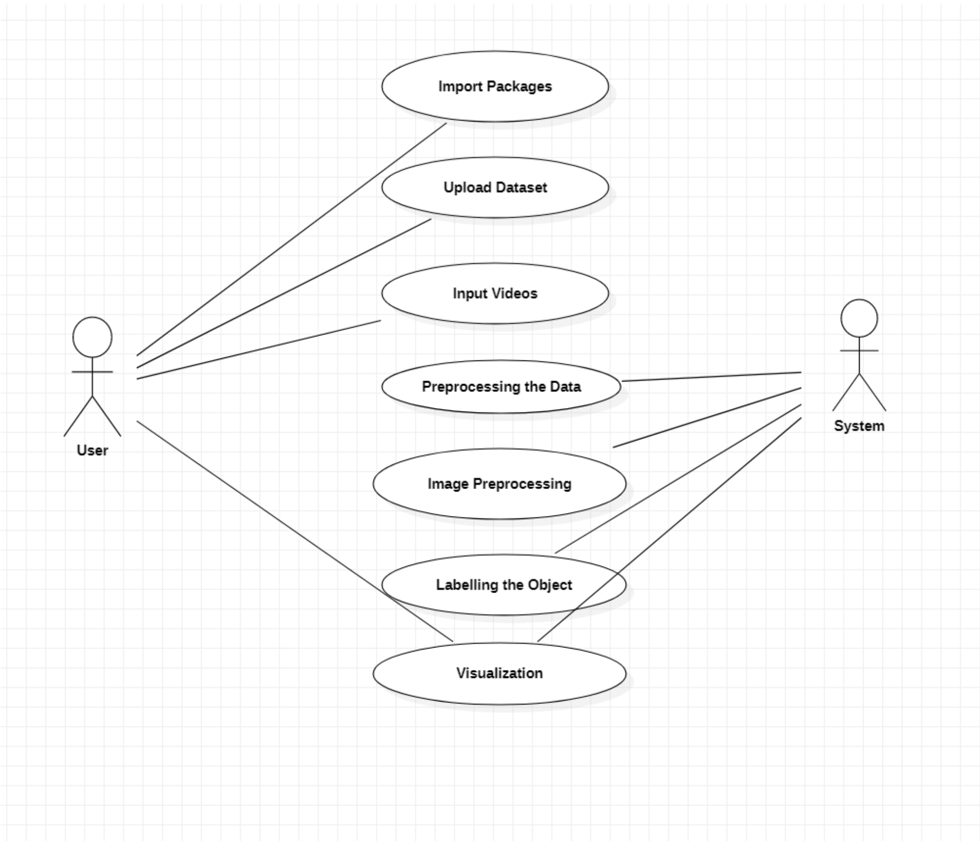
- operating System: Windows, Linux
- Processor: inteli3 or more
- RAM: 4 GB
- Hard Disk: 250 GB

B. **SOFTWARE REQUIREMENTS**:

- Python idle 3.7 version
- Jupiter
- Kaggle
- Anaconda 3.7

DIAGRAMS:

- **USECASE DIAGRAM**



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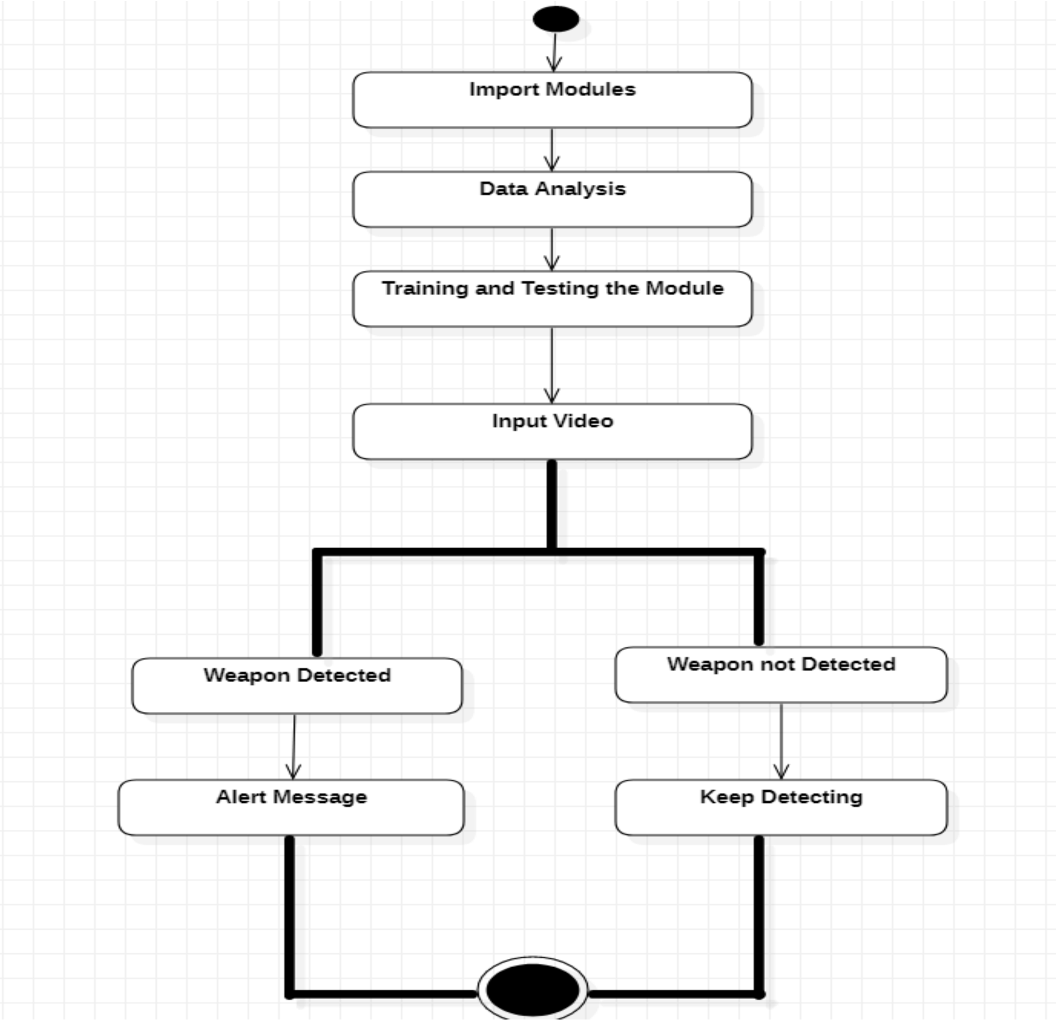
- **ACTIVITY DIAGRAM:**



IMPLEMENTATION:

import cv2
import numpy as np

Load YOLO

net = cv2.dnn.readNet("yolov3_training_2000.weights", "yolov3_testing.cfg") classes = ["Weapon"]
layer_names = net.getLayerNames()

layer names[i - 1] for i in net.getUnconnectedOutLayers() = output_layers colors = np.random.uniform(0, 255, size =(len(classes), 3))
Function to prompt user for file name or start webcam def get_input():

file_name = input("Enter file name to detect weapon (e.g., 'ak47.mp4'), or press 'Enter' to start webcam: \n") if file_name == "":
file_name = 0 # Start webcam if no file name provided return file_name

Capture video from file or webcam cap = cv2.VideoCapture(get_input()) while True:
_, img = cap.read()

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```
height, width, channels = img.shape

blob = cv2.dnn.blobFromImage(img, 0.00392, (416, 416), (0, 0, 0), True, crop=False) net.setInput(blob)
outs = net.forward(output_layers)

# Perform Non-Maximum Suppression to get bounding boxes

# NOTE: 'boxes', 'confidences', and 'class_ids' variables are not defined in the provided code snippet # They need to be defined elsewhere in your code
indexes = cv2.dnn.NMSBoxes(boxes, confidences, 0.5, 0.4) # Print if weapon detected in frame
if indexes == 1:

print("Weapon detected in frame")

font = cv2.FONT_HERSHEY_PLAIN

for i in range(len(boxes)): if i in indexes:
x, y, w, h = boxes[i]

label = str(classes[class_ids[i]]) color = colors[class_ids[i]]
cv2.rectangle(img, (x, y), (x + w, y + h), color, 2) cv2.putText(img, label, (x, y + 30), font, 3, color, 3)
cv2.imshow("Image", img) key = cv2.waitKey(1)
if key == 1:

break cap.release()
cv2.destroyAllWindows()
```

ALGORTITHM

Step 1: Upload Dataset
Take the software dataset(Images of guns).

Step 2: Data Pre-processing
Filter dataset according to requirements and create a new dataset which has attributes according to analysis to be done.After performing Data Pre-processing we are dividing dataset into the Train and Test datasets

Step 3: Perform Image pre-processing on dataset from here we use various Machine Learning models.

Step 4:Apply The CNN Based Algorithm.

Step 5:Train The Model Through CNN Approaches

Train the model with Training Data then analyze dataset over classification algorithm .The SSD(Single Shot Detection) and RCNN(Region based Convolution Neural Networks) approaches are implemented . The Detection and Classification are implemented.

Step 6: Run The Model

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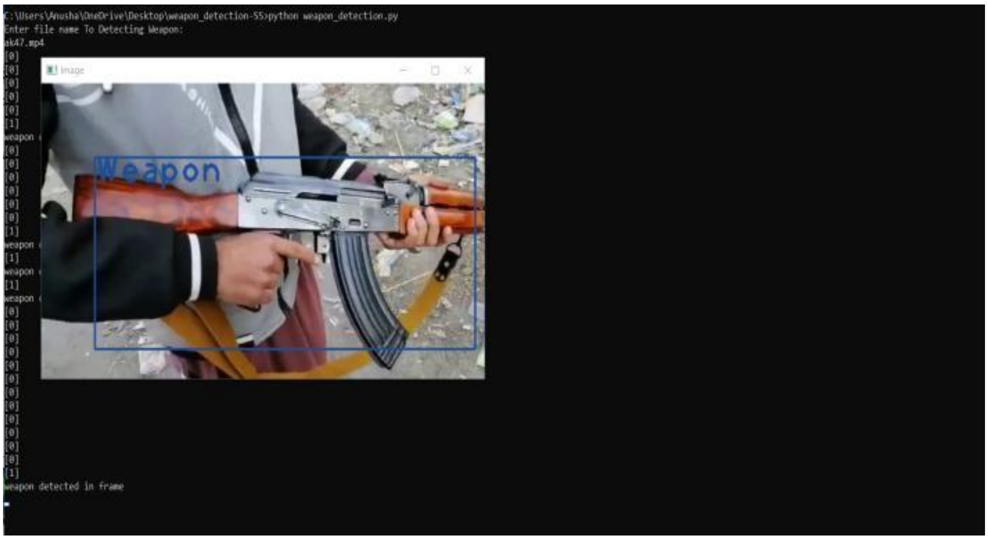
IV. RESULTS

The Figure represents the Command Prompt which we are using to execute our code.

After the code execution we get the Following Outputs:



If there is no weapon then the following output looks like:

The below image is the result of the above CCTV video input.

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V. CONCLUSION

Security is a major concern in various environments, especially in crowded events or isolated areas where crime rates are rising. With an increasing demand for safety, security, and protection of personal property, the deployment of video surveillance systems has become essential. These systems play a crucial role in recognizing and interpreting scenes, as well as detecting anomaly events, which are vital for intelligence monitoring. This project is designed to detect weapons using Recursive Convolutional Neural Networks (RCNN).

VI. LIMITATIONS

Convolutional Neural Networks (CNNs) present significant challenges for weapon detection due to their requirement for complex image processing. The deployment of CNNs may be hindered by the extensive computational resources needed for training and inference, especially in locations with limited access to high-performance computing. Additionally, identifying firearms in photos can be challenging due to variations in appearance, position, lighting, and occlusions. Addressing these challenges requires robust training data and advanced model architectures. These factors collectively contribute to reduced efficiency and accuracy in weapon identification using CNNs. Despite these challenges, CNN-based weapon detection systems continue to improve due to ongoing advancements in deep learning methods and hardware capabilities.

HARDWARE REQUIREMENTS

Deep learning models, especially CNN based weapon detection models demand significant computational resources, advancements in hardware technology and optimization techniques can mitigate some of these challenges, making deployment feasible even in resource-constrained environments.

FUTURE SCOPE

Currently, the project is implemented to display an alert message stating "Weapon Detected in Frame" upon detection. However, in the future, we plan to integrate sensors to emit a beep sound upon weapon detection. This enhancement aims to reduce time complexity while providing an audible alert.

ACKNOWLEDGEMENT

We extend our heartfelt gratitude to **Dr. N. Lakshmi Prasanna**, our esteemed Project Coordinator and Associate Professor at VVIT Institute. Her insightful guidance and unwavering support propelled us to delve deeper into the intricacies of our project.

Additionally, we express our sincere appreciation to **Mr. K. Mohan Krishna**, our dedicated Project Guide and Assistant Professor at VVIT Institute. His continuous support and mentorship have been invaluable throughout our journey.

Both **Dr. N. Lakshmi Prasanna** and **Mr. K. Mohan Krishna** have demonstrated dedication, patience, and commitment towards our project. Their profound knowledge and constructive feedback have played a pivotal role in shaping the outcome of our project.

We are deeply grateful to them for their contributions, which have been instrumental in our success.

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REFERENCES

[1] The July 2019 shootings at the Christchurch mosque. Wikipedia has it accessible online at https://en.wikipedia.org/wiki/Christchurch_mosque_shootings

[2]. CCTV" was written by W. Deisman. It was released in 2003 by the Royal Canadian Mounted Police's Research and Evaluation Branch Community Contract and Aboriginal Policing Services Directorate in Ottawa, Ontario, Canada.

[3] "Video surveillance of public places" authored by J. Ratcliffe. It was published in 2006.

[4] "Automated detection of firearms and knives in a CCTV image" authored by M. Grega, A. Matiolałski, P. Guzik, and M. Leszczuk. The journal "Sensors" published it on pages 47 of Volume 16, Issue 1, January 2016

[5] An incident in July 2019 where China's CCTV surveillance network captured a BBC reporter in just 7 minutes. It is available online at the following link: https://techcrunch.com/2017/12/13/china-cctv-bbc-reporter/

[6] The author of "CCTV Operational Requirements Manual 2009," K.MacLennan-Brown, J. Gattuso, and N. Cohen. Published in 2009 by the Home Office Scientific Development Branch in St. Albans, United Kingdom

[7] G. Flitton, T. P. Breckon, and N. Megherbi wrote "A comparison of 3D interest point descriptors with application to airport baggage object detection in complex CT imagery". Pages 2420–2436 of Volume 46, Issue 9 of the journal "Pattern Recognition" published it in September 2013.

[8] A method for automatically identifying concealed weapons in images. 2009's Fifth Annual Workshop on Cyber Security and Information Intelligence Research (CSIIRW) was where it was presented. R. Gesick, C. Saritac, and C.-C. Hung are the authors.

[9] G. K. Verma and R. K. Tiwari's "A computer vision based framework for visual gun detection using Harris interest point detector" It appeared in Volume 54, Pages 703–712, of "Procedia Computer Science" in August of 2015.

[10] A computer vision framework that uses SURF (Speeded Up Robust Features) for visual gun identification. A presentation of it took place in January 2015 at the International Conference on Electrical, Electronics, Signals, and Communication Optimization (EESCO).G. K. Verma and R. K. Tiwari are the authors.

[11] The authors of the paper are Xiao, Z., Lu, X., Yan, J., Wu, L., and Ren, L. The paper is titled "Automatic detection of concealed pistols using passive millimeter wave imaging". It was presented at the IEEE International Conference on Imaging Systems and Techniques (IST). The conference took place in September 2015.

[12] Three-dimensional millimeter-wave imaging for detection of concealed weapons. In September 2001, it was published in the IEEE Transactions on Microwave Theory and Techniques. D. M. Sheen, D. L. McMakin, and T. E. Hall are the writers.

[13] Xue, Z., Blum, R. S., and Li, Y. "Fusion of visual and IR images for concealed weapon detection". It was presented at the Fifth International Conference on Information Fusion in July of 20

[14] The article "Multisensor concealed weapon detection by using a multiresolution mosaic approach" was written by D. S. Forsyth, R. Blum, Z. Xue, and Z. Liu. In September 2004, it was presented at the IEEE 60th Vehicular Technology Conference (VTC-Fall).

[15] R. Maher's work "Modeling and signal processing of acoustic gunshot recordings". In September 2006, it was presented at the 4th IEEE Signal Processing Education Workshop and the IEEE 12th Digital Signal Processing Workshop.