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Enhancing Security with Smart Surveillance and Detecting Weapons in Real Time using Deep Learning

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ABSTRACT*:* *In today's world, security and safety are crucial for a country's economic prosperity, particularly in attracting investors and tourists. Although Closed Circuit Television (CCTV) cameras are widely used for surveillance, they still heavily rely on human intervention for detecting illegal activities like robberies. This study addresses this challenge by employing state-of-the-art deep learning algorithms to automatically detect harmful weapons in CCTV footage. Utilizing approaches like sliding window/classification and region proposal/object detection, algorithms such as YOLOv5, YOLOv6, YOLOv7, YOLOv8, and Faster RCNN are leveraged. A custom dataset, compiled from various sources including manual collection and GitHub repositories, was created due to the absence of a standard dataset for real-time scenarios. Emphasizing precision and recall over accuracy, YOLOv5 stands out as the most effective algorithm, achieving an impressive F1-score of 91% and a mean average precision of 91.73%, surpassing previous benchmarks. This research contributes to enhancing security measures by providing an automated system for weapon detection, thus fostering a safer environment and facilitating economic growth.*

Keywords *–deep learning, YOLO (you only look once),CNN.*

1. INTRODUCTION

In today's interconnected world, the issue of crime, particularly crimes involving handheld weapons, has become a critical concern for societies across the globe. The prevalence of violence perpetrated with firearms has contributed significantly to a rise in crime rates in numerous countries. This surge in criminal activity not only threatens the safety and security of individuals but also undermines the stability necessary for societal progress. Whether aiming to attract investors, foster economic growth through tourism, or simply ensure the well-being of citizens, maintaining law and order is paramount. However, the proliferation of handheld weapons, particularly in regions where firearm ownership is

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legal, poses a significant challenge to achieving this goal.

The impact of crime extends far beyond its immediate victims, affecting entire communities and even reverberating on a global scale. In today's era of instantaneous communication and social media, the dissemination of information, whether accurate or not, can rapidly influence public perception and behavior. Consequently, incidents of violence can quickly escalate, fueling fear, anxiety, and distrust within society. Moreover, psychological studies indicate that individuals exposed to hate speech or incendiary rhetoric may be susceptible to radicalization or impulsive acts of violence, especially if they have access to firearms [1].

Recent years have witnessed several high-profile incidents of mass violence perpetrated with handheld weapons, capturing international attention and sparking debates on gun control and public safety. One such tragic event occurred on March 15, 2019, in Christchurch, New Zealand, when a gunman attacked the Al-Noor Mosque during Friday prayers, leaving 44 innocent worshippers dead [2]. Just minutes later, another attack claimed the lives of seven more civilians, highlighting the devastating impact of such acts on communities [3].

The Christchurch massacre is not an isolated incident but part of a broader pattern of gun-related violence observed in various parts of the world. The United States, in particular, has experienced numerous active shooter incidents, including the infamous Columbine High School shooting, which resulted in 37 victims, and the tragic assault carried out by Anders Breivik on Utøya Island in Norway, where 179 individuals lost their lives [4]. Similarly, Europe has witnessed its share of violence, such as the attack on the Charlie Hebdo newspaper, which claimed 23 lives [5].

Statistics from the United Nations Office on Drugs and Crime (UNODC) paint a sobering picture of the prevalence of gun-related crimes in different countries. For instance, Belgium records a rate of 1.6 gun-related crimes per 100,000 people, while the United States reports a significantly higher rate of 4.7 per 100,000. Mexico, facing pervasive issues of organized crime and drug trafficking, experiences an alarming rate of 21.5 gun-related crimes per 100,000 individuals [6]. These figures underscore the urgent need for effective measures to address the proliferation of firearms and mitigate the associated risks to public safety.

In conclusion, the escalation of crime, particularly crimes involving handheld weapons, poses a significant threat to societal well-being and progress. The ease of access to firearms, coupled with factors such as social media influence and psychological vulnerability, contributes to the perpetuation of violence on a global scale. High-profile incidents like the Christchurch massacre serve as stark reminders of the devastating consequences of unchecked gun violence. Addressing this multifaceted issue requires comprehensive strategies encompassing legislative reforms, law enforcement efforts, and community engagement initiatives. Only through concerted action can societies hope to create safer, more peaceful environments conducive to sustainable development and prosperity.

2. LITERATURE REVIEW

The rapid advancement of technology has revolutionized various aspects of society, including the field of security and surveillance. In recent years,

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researchers have explored innovative approaches to detect and mitigate the threat posed by weapons in public spaces. This literature survey examines several studies focusing on weapon detection using a combination of deep learning, computer vision, and image processing techniques.

Bhatti et al. present a method for weapon detection in real-time CCTV footage using state-of-the-art deep learning algorithms [1]. Given the lack of standard datasets for real-time scenarios, the authors constructed their dataset by collecting images from various sources, including their own cameras, the internet, and YouTube CCTV videos. They employed a range of deep learning models such as VGG16, Inception-V3,Inception-ResnetV2,SSDMobileNetV1, Faster-RCNN Inception-ResnetV2 (FRIRv2), YOLOv3, and YOLOv4. By leveraging these algorithms, they achieved promising results in detecting harmful weapons, thereby addressing the pressing need for effective surveillance measures.

Ruiz-Santaquiteria et al. propose a novel method that integrates visual appearance analysis of handguns with 2D human pose information to enhance detection accuracy [2]. By combining these two modalities within a unified architecture, the model can effectively identify handguns even in challenging scenarios such as varying camera distances and lighting conditions. The utilization of 2D human pose estimation aids in localizing hand regions, which are crucial for detecting concealed weapons. Experimental results demonstrate significant improvements over previous approaches, underscoring the efficacy of the proposed combined model in handgun detection.

Narejo et al. introduce a weapon detection system based on the YOLO V3 object detection model, trained on a custom dataset [3]. Unlike traditional convolutional neural networks (CNNs), YOLO V3 offers superior performance and efficiency without requiring intensive computational resources. The authors emphasize the potential of their approach to enhance security and mitigate the risk of violent incidents in public spaces. By deploying the proposed system in surveillance infrastructure, authorities can proactively identify and prevent threats, thereby safeguarding human lives and ensuring public safety.

Jain et al. focus on the application of convolutional neural networks (CNNs) for automatic weapon detection in surveillance scenarios [4]. By implementing SSD and Faster RCNN algorithms, the authors demonstrate the efficacy of deep learning techniques in recognizing firearms in crowded or high-risk environments. Their study emphasizes the importance of intelligent monitoring systems equipped with anomaly detection capabilities to address the evolving challenges of security and public safety. Although both algorithms exhibit commendable accuracy, their practical deployment necessitates a trade-off between speed and precision.

Thaiparnit et al. propose a weapon detection system based on x-ray image processing, leveraging the Canny Edge Detector algorithm [5]. Despite the absence of x-ray cameras, the authors obtained images from the internet to develop and evaluate their approach. By employing image processing techniques to analyze suspicious objects, the system can identify potential threats and trigger timely notifications. The study demonstrates promising results, with the template matching algorithm achieving an 80% accuracy rate in detecting weapons.

In summary, the studies reviewed in this survey showcase the diverse approaches to weapon detection, ranging from deep learning-based models to image processing techniques. By harnessing the power of artificial intelligence and computer vision, researchers aim to bolster security measures and safeguard public spaces against the threat of violence. However, further research is needed to address the challenges of real-world deployment and ensure the scalability and robustness of these detection systems.

3. METHODOLOGY

The modern world is very concerned with security and safety. A nation's ability to attract foreign investment and tourism depends on how safe and secure its environment is. However, even if Closed Circuit Television (CCTV) cameras are employed for surveillance and to keep an eye on actions like robberies, they still need human oversight and involvement. We require a system that can instantly identify these criminal acts. Even with cutting-edge deep learning algorithms, quick processing power, and sophisticated CCTV cameras, real-time weapon detection remains a significant barrier. The challenge is made more difficult by observing from different angles and being obscured by the gun's owner and those nearby.

Disadvantage

- Still require human supervision and intervention.
- Weapon detection in real-time is still a serious challenge.

The goal of this effort is to create a safe environment by utilizing CCTV footage as a source to identify dangerous weapons using cutting-edge open-source deep learning algorithms. To eliminate false positives and false negatives, we have built binary classification using pistol class as the reference class and created relevant confusion items inclusion idea. Since there was no standard dataset for the real-time scenario, we created our own by taking shots of weapons with our own cameras, manually gathering images from the internet, extracting data from YouTube CCTV recordings, and using GitHub repositories. Sliding window/classification and region proposal/object detection are the two methods applied. The algorithms YOLOV5, YOLOV6, YOLOV&, and Faster RCNN are a few that are employed.

Major Advantages:

- Precision and recall count the most rather than accuracy when object detection is performed so these entire algorithms were tested in terms of them.
- Yolov5 stands out best amongst all other algorithms and gave a F1-score of 91% along with a mean average precision of 91.73% higher than previously achieved.

MODULES:

- Data exploration: using this module we will load data into system
- Processing: Using the module we will read data for processing
- Splitting data into train & test: using this module data will be divided into train & test
- Building the model – RCNN, Yolov5, Yolov6 , Yolov7 &Yolov8
- Deep learning algorithms- InceptionV3, VGG16 & CNN
- User signup & login: Using this module will get registration and login

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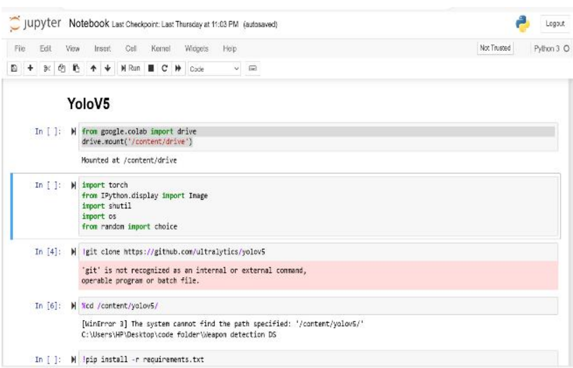
- User input: Using this module will give input for prediction
- Prediction: final predicted displayed

4. IMPLEMENTATION

ALGORITHMS:

YOLOV5: YOLOv5 uses the same head as YOLOv3 and YOLOv4. It is composed from three convolution layers that predicts the location of the bounding boxes (x, y, height, width), the scores and the objects classes.



YOLOV6: YOLOv6 is a single-stage object detection framework dedicated to industrial applications, with hardware-friendly efficient design and high performance.

Faster RCNN: Faster R-CNN is a single-stage model that is trained end-to-end. It uses a novel region proposal network (RPN) for generating region proposals, which save time compared to traditional algorithms like Selective Search. It uses the ROI Pooling layer to extract a fixed-length feature vector from each region proposal.

YOLOV7: The version YOLOv7-X achieves 114 FPS inference speed compared to the comparable YOLOv5-L with 99 FPS, while YOLOv7 achieves a better accuracy (higher AP by 3.9%). Compared with models of a similar scale, the YOLOv7-X achieves a 21 FPS faster inference speed than YOLOv5-X.

InceptionV3: The Inception V3 is a deep learning model based on Convolutional Neural Networks, which is used for image classification. The inception V3 is a superior version of the basic model Inception V1 which was introduced as Google Net in 2014. As the name suggests it was developed by a team at Google.

VGG16: VGG-16 is a convolutional neural network that is 16 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals.

CNN: The Convolutional Neural Network (CNN or ConvNet) is a subtype of Neural Networks that is mainly used for applications in image and speech recognition. Its built-in convolutional layer reduces the high dimensionality of images without losing its information. That is why CNNs are especially suited for this use case.

5. EXPERIMENTAL RESULTS

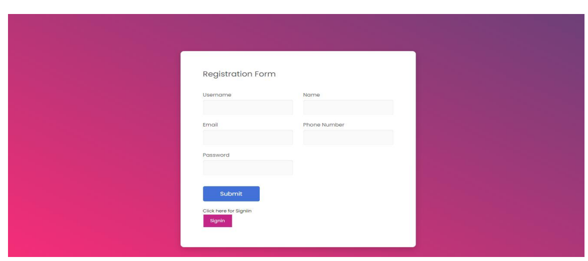


Fig 1 signup

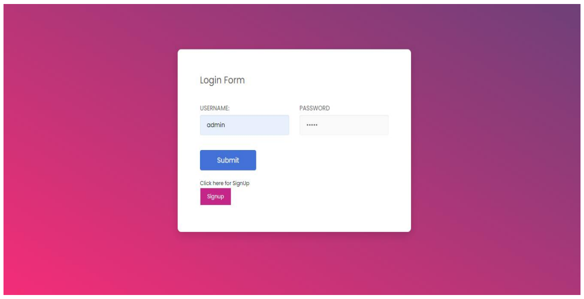


Fig 2 sign in

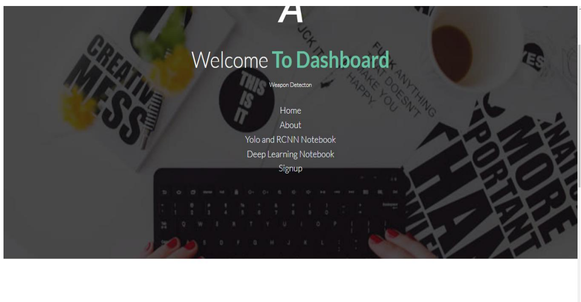


Fig 3 home page

Fig 4 upload input image

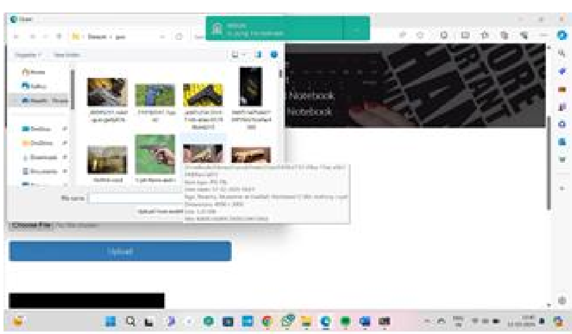


Fig 5 upload input image

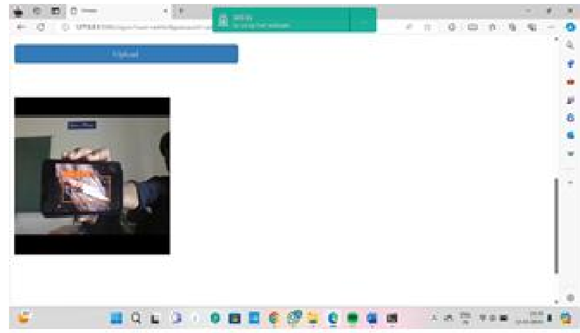


Fig 6 predicted result

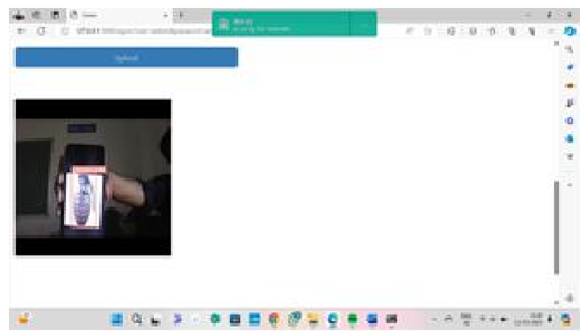


Fig 7 predicted result

6. CONCLUSION

The YOLOV5 strategy, which depends on a solitary neural network to recognize objects, was introduced in this review. We see from pictures, records, and live news appropriating the YOLOV5 judgment. This plan acts better distinguished to various methods when used to many fields, at the time of common photos. The strategy can be ready for the 10,000 foot view and is easy to utilize. The classifier is limited to a particular district when region proposition techniques are utilized. YOLOV5 expects restrictions while utilizing the whole picture. Moreover, it expects less bogus advantages behind the scenes. This solicitation estimation is from an overall perspective more conceivable and speedier to use

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long term than past ones.

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