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REVIEWING THE IMPACT OF YOLO ON FORENSIC EVIDENCE ANALYSIS IN CRIME SCENE INVESTIGATIONS

Pooja Kolhatkar[*1], Dipak Padule[*2], Pratima Salunkhe[*3]

[*1]Department Of Forensic Science YCIS, Satara, India.

[*2,3]Software Engineer, Pune, India.

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ABSTRACT

As society grapples with an escalating crime rate, the urgency to resolve pending cases and streamline the evidence collection and analysis process has never beenmore critical. Amidst this backdrop, the advent of computer vision systems and the proliferation of data have catalysed a paradigm shift in object detection models/algorithms. This paper delves into the transformative potential of the You Look Only Once (YOLO) model, a state-of-the-art Convolutional Neural Network (CNN) architecture renowned for its swift detection capabilities, even on low-end devices.

The paper commences with an introduction and background, subsequently unfolding the innovative and descriptive approach of the YOLO model towards object detection. The spotlight is on the model's application in Forensic Evidence Detection and Analysis, underscoring its instrumental role in revolutionizing crime scene investigations. Through this exploration, the paper aims to contribute to the ongoing discourse on leveraging advanced technologies to combat crime effectively and efficiently.

Keywords: YOLO, Forensic Evidence, Object Detection, Crime Scene Investigation.

I. INTRODUCTION

The escalating crime rate is a multifaceted issue influenced by various socioeconomic factors, including poverty, inequality, lack of education, drug abuse, and systemic issues within the justice system. Crime rates can fluctuate based on geographical location and specific types of crimes, but some regions have seen increases inviolent crimes, property crimes, and cybercrimes. Main reasons behind increased crimes are corruption, high poverty levels as well as unemployment in various areas leads to crimes, economic hardship can push anyone towards criminal activities either individual attempt crime or harm self by means of suicide. Drug addiction isone of the main reason of gun wars and gang wars. Morepeople getting addicted to drugs day by day. There are various crime activities we are seeing this days. This escalating crime rate making law enforcement agencies and government officers hard to investigate crimes on time and give justice to sufferer. Various techniques has been practiced by governments to minimize crime rates and control them. But already we have lots of cases pending and need of solving them is also increased, as criminals freely living their life just because of crimes not being investigated properly. Due to this it is becoming a crucial and critical thing to implement automation in evidence analysis and crime scene investigation. And also automation in preventing crimes before happening is also required various agencies has implemented this in their areas using CCTVs in main areas.

In this review paper we are focusing on how we can use object detection model in forensic evidence analysis and crime scene investigation. We start this review with short background of object detection models/algorithms followed by state of the art object detection model YOLO, a detailed approach of object detection models towards forensic evidence analysis, short architecture of model and finally application of YOLO in forensic evidence analysis.

1. Background

History of object detection models spans several decades. Before the 2000s object detection is dependent on handcraft and traditional computer vision techniques. Methods like edge detection and histogram based approaches were used for detecting objects in images orphotos. In 2000s feature based methods are used to detect objects. In mid 2000s histogram of oriented gradients HOG emerged as best and popular method for object detection.

Deep learning revolution started in 2010s, CNN convolutional neural networks enhanced object detection

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process. The models like Alex Net, VGG and later region-based CNN r-CNN in mid 2010s significantly boosted object detection performance. In recent years single-shotdetectors (SSDs) and YOLO become more famous because of its improved performance, speed and real time detection of objects efficiently. This features makes YOLO model best for use in crime scene investigation. We will see detailed information of same in coming sections.

2. YOLO Model

The ground-breaking object detection system, "You Only Look Once" (YOLO), has made a significant impact in the realm of computer vision. This system, which was first presented by Joseph Redmon and Santosh Divvala in their 2016 paper, "You Only Look Once: Unified, Real-Time Object Detection," has been widely recognized forits innovative approach. The key feature of YOLO is itscapacity to identify and categorize objects within an image in a single sweep of a neural network. This unique attribute makes it highly effective for applications that require real-time processing.

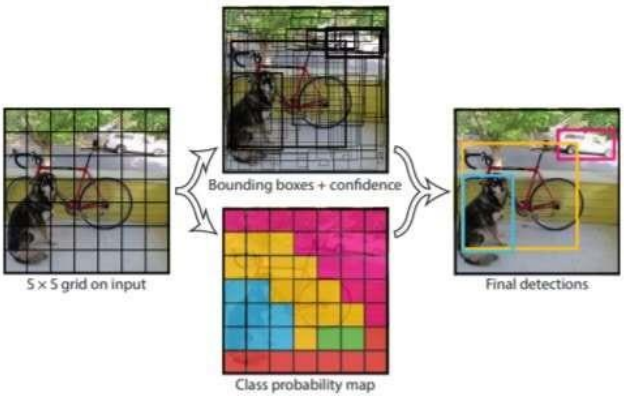

Figure. The Model [1]

1.1 YOLO's Unique Features and Principles:

1.1.1 One-Step Detection:

YOLO processes an input image by dividing it into a grid. Each cell in the grid simultaneously predicts bounding boxes, class probabilities, and confidence scores. This unique approach allows the entire image to be processed in a single pass through the neural network, making YOLO considerably faster than traditional two-stagedetectors.

1.1.2 Prediction of Bounding Boxes:

YOLO estimates bounding boxes by adjusting the coordinates of the bounding box relative to the grid cell. Each cell is tasked with predicting multiple bounding boxes. The bounding box predictions are denoted by four coordinates: the center of the box (x, y), and its width (w)and height (h).

1.1.3 Class Probability Estimation:

In addition to predicting bounding boxes, YOLO also estimates the likelihood of the object belonging to different classes for each bounding box. This is achievedusing a softmax activation function to derive class probabilities. Each bounding box is assigned class probabilities independently, and the box with the highestprobability is deemed the final prediction for that grid cell.

1.1.4 Confidence Score:

Each bounding box prediction is accompanied by a confidence score that reflects the model's certainty in theaccuracy of the prediction. The confidence score is influenced by both the precision of the bounding box andthe predicted class probabilities.

1.1.5 Use of Anchor Boxes:

To enhance bounding box predictions, especially for objects of varying scales and aspect ratios, YOLO employs anchor boxes. The model is trained to predict offsets for predefined anchor boxes, enabling it to accommodate a range of object shapes and sizes.

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1.1.6 Architectural Design:

The architecture of YOLO comprises multiple convolutional layers followed by fully connected layers. The final layer predicts bounding boxes, class probabilities, and confidence scores for each grid cell. Several versions of YOLO, such as YOLOv2, YOLOv3, and YOLOv4, have been introduced, each offering improvements in accuracy and speed.

1.1.7 Real-Time Applications:

Thanks to its ability to process images swiftly and accurately, YOLO is ideally suited for real-time applications. These include video analysis, autonomous vehicles, surveillance systems, and more.

1.1.8 Potential Limitations:

Despite its speed and efficiency, YOLO may encounter difficulties in detecting small objects in high-resolution images and can be sensitive to object occlusion.

1.2 Why YOLO is State of the ART model

1.2.1 Efficiency and Speed:

Unlike traditional object detection systems that require multiple passes through a neural network, YOLO accomplishes object detection and classification in a single pass. This makes it incredibly efficient and fast, which is crucial for real-time applications.

1.2.2 Unified Detection Framework:

YOLO's approach to object detection is unified, meaning it simultaneously predicts bounding boxes and class probabilities directly from full images in one evaluation. This differs from other methods that break the problem down into two steps—proposing regions and then classifying them.

1.2.3 Robustness to Object Scale:

By dividing the image into a grid and predicting bounding boxes and class probabilities for each cell, YOLO can detect objects of various sizes and shapes. This is further enhanced by the use of anchor boxes, which allow the model to adjust its predictions to different scales and aspect ratios.

1.2.4 End-to-End Training:

The entire YOLO model is trained in an end-to-end manner. This allows for joint optimization on both localization (finding where the objects are) and classification (identifying what the objects are), leading to better overall performance.

1.2.5 Continuous Evolution:

The YOLO architecture has seen several iterations, with each new version (such as YOLOv2, YOLOv3, YOLOv4, YOLOv5, YOLOv6, YOLOv7 and most recent and powerful YOLOv8) introducing improvements in terms of speed and accuracy. This continuous evolution and adaptation to new challenges and requirements have kept YOLO at the forefront of CNN architectures.

II. YOLO MODEL'S APPROACH TOWARDS OBJECT DETECTION

2.1 Single Pass Detection:

YOLO's primary innovation is its single pass detection mechanism. Unlike other object detection models that use a two- step process (first identifying regions of interest, then classifying those regions), YOLO performs both tasks simultaneously. It processes the entire image in one forward pass through the neural network, predicting bounding boxes and class probabilities directly from the image.

2.2 Dividing the Image into a Grid:

The first step in YOLO's detection process is dividing the input image into an S x S grid. Each grid cell is responsible for predicting an object if the object's center falls within that cell.

2.3 Bounding Box Prediction:

Each grid cell predicts B bounding boxes and confidence scores for those boxes. These bounding boxes are defined by five parameters: x, y, w, h, and confidence. The (x, y) coordinates represent the center of the box relative to the bounds of the grid cell. The width and height (w, h) are predicted relative to the whole image. Finally, the confidence score represents the probability that a bounding box contains an object (multiplied by the Intersection Over Union (IOU)between the predicted box and the ground truth).

2.4 Class Probability Prediction:

In addition to predicting bounding boxes, each grid cell also predicts C conditional class probabilities (Pr(Class_i|Object)). These probabilities are conditioned on the grid cell containing an object. They reflect the probability that the detected object belongs to a particular class (e.g., dog, car, etc.).

2.5 Handling Different Object Sizes:

YOLO uses anchor boxes to handle objects of different sizes. Anchor boxes are predefined boxes with certain shapes and sizes. During training, the model learns to adjust these anchor boxes to match the ground truth boxes.

2.6 Network Design:

YOLO uses a CNN (Convolutional Neural Network) for feature extraction. The network architecture consists of 24 convolutional layers followed by 2 fully connected layers. Different versions of YOLO use different network architectures (e.g., Darknet-19 for YOLOv2 [1]and Darknet-53 for YOLOv3).

2.7 Loss Function:

The YOLO model is trained using a multi-part loss function that includes components for classification loss, localization loss (errors in the predicted bounding box), and confidence loss (errors in the predicted probability ofobject presence).

By combining these elements, YOLO can detect objects in images with high speed and accuracy, making it a state-of-the-art model for object detection tasks.

Discussion on the innovative and descriptive approach ofthe YOLO model.

2.8 Application in Forensic Evidence Detection and Analysis

1. Object Detection and Classification for Crime Evidence Analysis: A study conducted by Alayesanmi Femi Samson, Francisca Oladipo, and Emeka Ogbuju at the Federal University Lokoja, Nigeria, developed an object detection model based on the YOLO Convolutional Neural Network (CNN) architecture to detect objects at a crime scene without human involvement1 [2]. The model was trained on a dataset of 5 classes of objects with 1,173 custom images common to indoor crime scenes [1]. The system achieved an average accuracy of 67.84% at 0.013 confidence thresholds [3] The model was deployed on an Android-based forensic case documentation mobile application to review its effectiveness in real-time [2]
2. Real-Time Detection and Identification of Suspects in Forensic Imagery: Advanced versions of YOLO, such as YOLOv8, have been used for real-time detection and identification of suspects in forensic imagery2 [4]. These models can process high-resolution images in real-time, making them suitable for applications that require immediate results, such as identifying suspects from surveillance footage. [5]
3. Forensic Analysis of Attacked Drone: A study proposed YOLO and Optical Flow for Forensics (YOLOFOR), an attack detection method that can perform object detection accompanied by an object's movement direction estimation model to assist forensic investigation on drone video data. [6] This methodcomprises two main components, specifically YOLOv5and Lucas Kanade [7] Explanation of how the YOLO model is revolutionizing crime scene investigations.

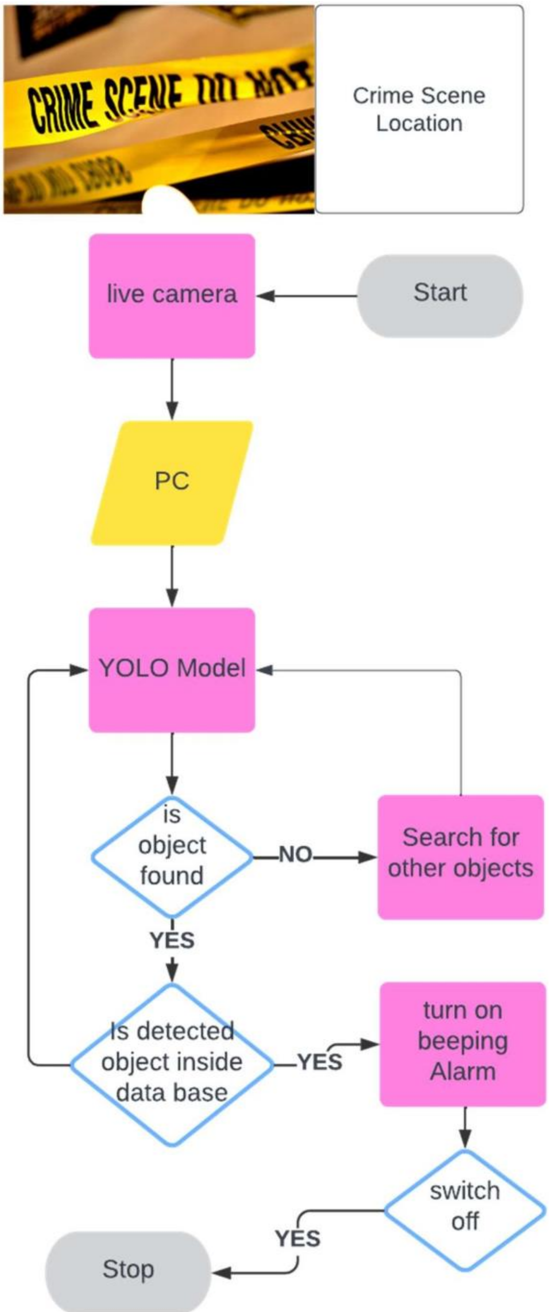

Figure: Flowchart of Application of YOLO in forensicevidence analysis

1. Real-Time Object Detection for Crime Scene Analysis: A study conducted by Alayesanmi Femi Samson, Francisca Oladipo, and Emeka Ogbuju at the Federal University Lokoja, Nigeria, developed an object detection model based on the YOLO Convolutional Neural Network (CNN) architecture to detect objects at acrime scene without human involvement1. The model was trained on a dataset of 5 classes of objects with 1,173 custom images common to indoor crime scenes1. The system achieved an average accuracy of 67.84% at 0.013confidence thresholds1. The model was deployed on an Android-based forensic case documentation mobile application to review its effectiveness in real-time [11]
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3. Real-Time Image-Based Weapon Detection: YOLOv4 models have been customized and fine-tuned to classify and position six types of harmful objects (i.e., Camera, Handgun, Rifles, Dagger, Sword, and Sticks) in real- time. [10] This approach has been used to achieve faster performance and better detection accuracy, particularly in scenarios where rapid weapon detection is critical. [10]
4. Real-Time Object Detection for Security Systems: Security systems have integrated YOLO models for real-time monitoring and analysis of video feeds, allowing rapid detection of suspicious activities, social distancing,and face mask detection [15].
5. Real-Time Object Detection for IP Cameras: The proposed model enables consistent object detection service for various input sources of YOLO, and can solvereal-time processing problems that may occur in Real Time Streaming Protocol (RTSP) used with YOLO object detection applications, when the video input source of the applications is IP cameras. [12]

III. CONCLUSION

This paper has journeyed through the developmental path of object detection models, observing their progression from manually engineered methods to the advanced era of deep learning, ultimately leading to the advent of YOLO. The distinctive features of the YOLO model, including its single-step detection process, capability to manage various object sizes, and real-time processing abilities, establish it as a crucial instrument in crime investigation.

Moreover, our examination of YOLO's uses in forensic evidence analysis has revealed a multitude of potential applications. Ranging from instantaneous object detection at crime scenes to the recognition of suspects inhigh-definition images, the incorporation of YOLO intodiverse forensic scenarios has proven its effectiveness inaccelerating investigations and improving the precision of evidence analysis.

The research explored, especially those concentrating on real-time crime scene analysis, suspect identification, weapon detection, and amalgamation with security systems, highlight the transformative capacity of YOLO. These applications not only exhibit its accuracy but also its adaptability in tackling a variety of challenges within the realm of crime investigation.

With the ongoing advancements in technology, the constant evolution of YOLO, as seen through versions like YOLOv2 to YOLOv8, emphasizes its flexibility and dedication to remain at the cutting edge of object detection models.

In summary, this paper adds to the existing dialogue on utilizing sophisticated technologies like YOLO for effective crime prevention. It underscores the importance of incorporating state-of-the-art tools in law enforcement and forensic analysis to speed up investigations, secure justice for victims, and foster safer communities.

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