ANONYMOUS OBJECT DETECTION USING YOLOV3

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Abstract:

Knife and scissor detection refers to the use of various technologies and techniques to detect the presence of knivesand scissors in different settings. This can include physical searches, metal detectors, x-ray machines, and other advanced scanning equipment. The goal of this technology is to prevent dangerous weapons from being brought into secure areas, such as airports, schools, government buildings, and other public places. The use of knife and scissor detection technology has become increasingly important in recent years due to rising concerns about safety and security, and it has helped to prevent numerous incidents involving weapons in various settings.

Keywords— Knife, scissor, Weapon detection

I. INTRODUCTION

Knife and scissor detection technology is based on the principle of detecting metal objects that are typically associated withthese weapons. The technology involves the use of specialized equipment that is designed to detect metal objects, such as knives and scissors, and alert security personnel to their presence. The equipment used for knife and scissor detection varies dependingon the setting and the level of security required.In high-security settings, such as airports or government buildings, the equipmentused for knife and scissor detection is often more sophisticated, and may include advanced scanning equipment such as x-ray machines, millimeter-wave scanners, or terahertz scanners. These machines can scan a person's entire body or belongings to detect the presence of weapons, including knives and scissors.In less secure settings, such as schools or public venues, the methods used for knife and scissor detection may be simpler, such as physical searches or metal detectors. Security personnel may use handheld metal detectors or wand-style detectors to scan individuals and their belongings for weapons.Knife and scissor detection technology has been developed to provide an effective means of detecting dangerous weapons and keeping people safe.It has played a critical role in preventing incidents involving weapons in various settings, and has become increasingly important in today's world, where safety and security are a top priority.

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II. YOLO

YOLO (You Only Look Once) is a popular deep learning algorithm for object detection. It works by dividing an input imageor video frame into a grid of cells, and then predicting the presence and location of objects within each cell. The algorithm processes the entire image or video frame at once, which makes it faster and more efficient than some other object detection algorithms.

To use YOLO for knife and scissor detection, the first step is to train the algorithm using a large dataset of images containing knives and scissors. The dataset is labeled with annotations that identify the location and class of the objects in the images.During training, the YOLO algorithm learns to recognize the features and characteristics of knives and scissors, such astheir shape, size, and texture. The algorithm uses convolutional neural networks (CNNs) to extract features from the input images and then applies fully connected layers to predict the presence and location of objects in each cell of the grid.Once the algorithmis trained, it can be used to detect knives and scissors in new images or video frames. The algorithm processes the entire imageor video frame at once and divides it into a grid of cells. For each cell, the algorithm predicts the probability of a knife or scissorbeing present in that cell, as well as the location of the object within that cell.The YOLO algorithm outputs a bounding box around the predicted location of each object, which can be used to highlight the object in the image or video frame. Additionally,the algorithm can also predict the class of the object, such as knife or scissor, which can be used to filter and analyze the detected objects.YOLO is a powerful tool for real-time object detection and can be used for various applications, including knife and scissor detection. By accurately detecting the presence of these objects in images or video frames, YOLO can help enhance safety and security in public spaces.There are several variations of YOLO, such as YOLOv2, YOLOv3, and YOLOv4, which improve the accuracy and speed of the algorithm. These variations incorporate techniques such as anchor boxes, feature pyramid networks,and spatial attention mechanisms to improve object detection performance.

. Overall, the integration of IoT and cloud technology in healthcare has the potential to greatly improve patient outcomes, increase efficiency, and reduce costs.

III. YOLO V3

YOLOv3 (You Only Look Once, Version 3) is a real-time object detection algorithm that identifies specific objects in videos, live feeds, or images. The YOLO machine learning algorithm uses features learned by a deep convolutional neural network to detect an object. Versions 1-3 of YOLO were created by Joseph Redmon and Ali Farhadi, and the third version of the YOLO machine learning algorithm is a more accurate version of the original ML algorithm. The first version of YOLO was created in2016, and version 3, which is discussed extensively in this article, was made two years later in 2018. YOLOv3 is an improved version of YOLO and YOLOv2. YOLO is implemented using the Keras or OpenCV deep learning libraries. The official successors of YOLOv3 is YOLOv4, and the newly released YOLOv7 (2022), which marks the current state-of-the-art object detector in 2023. YOLO is a Convolutional Neural Network (CNN) for performing object detection in real-time. CNNs are classifier-based systems that can process input images as structured arrays of data and recognize patterns between them (view image below). YOLO has the advantage of being much faster than other networks and still maintains accuracy. It allows the model to look at the whole image at test time, so its predictions are informed by the global context in the image. YOLO and other convolutional neural network algorithms "score" regions based on their similarities to predefined classes. High-scoring regions are noted as positive detections of whatever class they most closely identify with. For example, in a live feed of traffic, YOLO can be used to detect different kinds of vehicles depending on which regions of the video score highly in comparison topredefined classes of vehicles.

Why we choose YOLO v3?

There is no single "best" version of YOLO (You Only Look Once), as each version has its own strengths and weaknesses, and the best version depends on the specific requirements of the use case. However, YOLOv3 (You Only Look Once version 3) is generally considered to be one of the most effective versions of YOLO for real-time object detection, due to its balance of speed and accuracy. Some reasons why YOLOv3 is considered to be a good choice for object detection include: Accuracy: YOLO v3 achieved state-of-the-art accuracy on several object detection benchmarks, while still maintaining real-time performance. Speed: YOLO v3 can detect objects in real-time (30 frames per second) on a GPU, making it suitable for applications that require real-time object detection. Flexibility: YOLO v3 can detect objects of different sizes, shapes, and orientations, and can also handle occluded objects and objects with low contrast. Customizability: YOLO v3 can be trained on custom datasets and can detect custom classes of objects. Open-source: YOLO v3 is an open-source project, which means that it can be easily modified and integrated into other projects. However, it should be noted that YOLO v3 may not be the best choice for all use cases, as its speed and accuracy may not be sufficient for some applications. Other versions of YOLO, such as YOLO v4 and YOLO v5, may be more suitable for certain use cases, depending on the specific requirements of the application. improved object detection accuracy: YOLOv3 uses a feature extraction network called Dark net-53, which has 53 convolutions layers, compared to the 19 layers used in YOLOv2. This deeper architecture allows YOLOv3 to learn more complex features and therefore achieve better detection accuracy. Better handling of small objects: YOLOv3 uses a technique

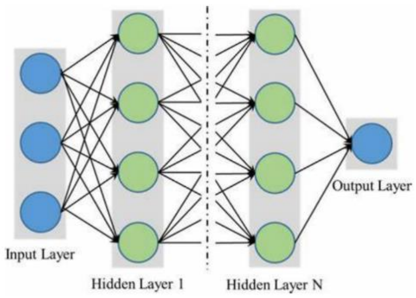
conditions or those requiring continuous monitoring of their health. A healthcare monitor system that collects patient data can be used to provide patients with valuable information about their health status and progress.

Here are some examples of how patients can access their health data through a healthcare monitor system:Patient portals have been created by us that allow patients to securely access their health information, including test results, diagnosis, and treatment plans. These portals can be integrated with healthcare monitor systems to display real-time health data. Wearable devices Some healthcare monitor systems use wearable devices such as smartwatches or fitness trackers to collect patient data. Patients can access their health data through an accompanying mobile app or a web-based dashboard. A healthcare monitor system can provide patients with valuable information about their health status and progress, allowing them to take an active role in managing their own health. By using a patient-centered approach, healthcare providers can engage patients in their own care and help them achieve better health outcomes.

IV. DEEP NEURAL NETWORK

Deep neural networks (DNNs) are a type of artificial intelligence that have been Used to significantly improve the accuracy of object detection in computer vision. In Particular, DNNs have shown great promise in detecting objects in images and videosCaptured in low-light or night vision conditions. DNN-based object detection works by dividing the input image into a set of smaller Regions, called "proposals". These proposals are then analyzed using a convolutional Neural network (CNN), which extracts a set of features from each proposal. The output Of the CNN is fed into a set of fully connected layers, which use this information to Classify and locate objects in the image.One popular DNN-based object detection algorithm is the You Only Look Once (YOLO) algorithm. YOLO divides the input image into a grid of cells and predicts.The probability that an object ispresent in each cell. For each cell where an object is Detected, the algorithm predicts the location and class of the object. DNN-based object detection algorithms have several advantages over traditional Object detection methods. They are highly accurate,often achieving state-of-the-art Performance on benchmark datasets. They are also much faster than traditional object Detection algorithms, which makes them well-suited for real-time applications. Finally, DNN-based object detection can be easily adaptedto different applications, making it A flexible and versatile technologies. In conclusion, DNN-based object detection is a powerful technology that has greatly improved the accuracy and speed of object detection in computer vision.

By dividing the input image into proposals and using deep neural networks to analyze them, DNN based object detection algorithms can accurately and quickly detect objects in a variety of applications, including low-light and night vision environments.



V. CLASS PREDICTION

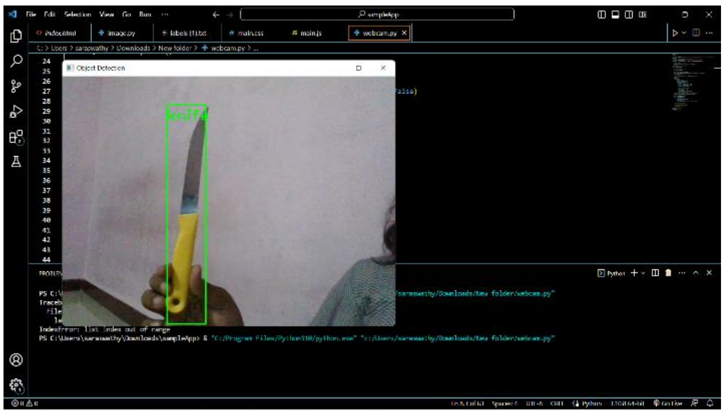
Almost all classifiers estimate that output labels are unique Together. The result is that the exclusive object classes are True. Consequently, YOLO implements a soft-max function to translate the scores into probabilities that add up one. YOLOv3 uses a multiple classification. For YOLOv3 modifies the soft-max function with Individualistic logistic classifiers to solve the probability That the item belongs to a particular label. Instead of using the mean square error to resolve the classification loss, YOLOv3 uses the binary loss of cross entropy for each Label. This reduces the complexity of the calculation by Avoiding the soft-max function.

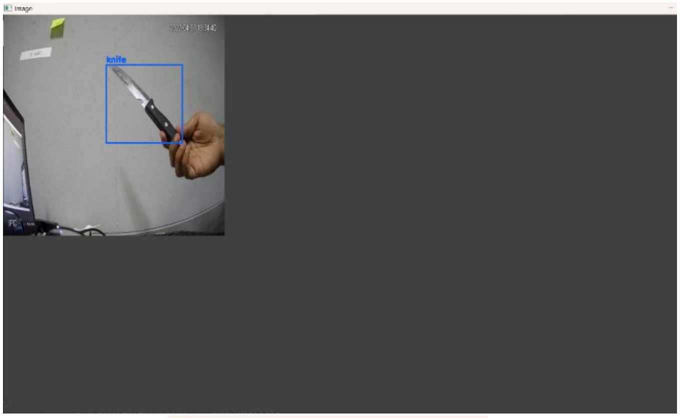
VI. Related work

YOLO (You Only Look Once) is a popular object detection algorithm that can be used for knife and scissor detection. YOLOis a deep learning-based approach that uses a single neural network to predict bounding boxes and class probabilities for objectsin an image. Compared to traditional object detection methods, YOLO is faster and more accurate, making it a suitable choice for real-time applications such as knife and scissor detection.In YOLO, an input image is divided into a grid of cells, and eachcell predicts a fixed number of bounding boxes and their corresponding class probabilities. The bounding boxes are parameterized by their center coordinates, width, and height. The class probabilities represent the likelihood of an object belonging to a certain class, such as knife or scissor. The YOLO network is trained using a loss function that penalizes errors in both bounding box prediction and class prediction.Several variants of YOLO have been proposed, including YOLOv2, YOLOv3, and YOLOv4, which have improved performance and accuracy compared to the original YOLO algorithm. YOLOv2 introduced several improvements, such as batch normalization, anchor boxes, and multiscale training, which reduced the localization errors and improved the speed of detection. YOLOv3 further improved the accuracy of detection by using a feature pyramid network and a more powerful backbone network. YOLOv4 introduced several advanced features, such as Mish activation, CSPNet, and SPP block, which significantly improved the accuracy and speed of detection.To apply YOLO for knifeand scissor detection, a dataset of labeled images and videos is required for training the network. Several datasets have been used for this purpose, including the PKSDB dataset and the Blade Detection dataset. The labeled data includes bounding box coordinates and class labels for each knife or scissor in the image. The YOLO network is then trained using stochastic gradientdescent with backpropagation to minimize the loss function.

One advantage of using YOLO for knife and scissor detection is its speed and accuracy. YOLO can detect knives and scissors in real-time, making it suitable for applications such as video surveillance and robotics. Additionally, YOLO can detectmultiple objects in the same image, which is useful in scenarios where there are multiple knives or scissors present.However, there are also some limitations to using YOLO for knife and scissor detection. One limitation is the need for a large and diversedataset for training the network. The performance of YOLO is highly dependent on the quality and diversity of the training data. Another limitation is the potential for false positives or false negatives, where the network detects a knife or scissor where there is none, or fails to detect a knife or scissor that is present.In conclusion, YOLO is a powerful deep learning-based approachfor knife and scissor detection that offers real-time performance and high accuracy. However, its effectiveness is highly dependent on the quality and diversity of the training data. Further research is needed to improve the robustness and generalization ability of YOLO for knife and scissor detection, and to address the challenges of false positives and false negatives.

VII. OUTPUT





VIII. RESULTS AND DISCUSSION

Weapon detection refers to the process of detection the weapons like knife and scissor in image, video and in webcam this is done by using the yolo v3 algorithm, YoloV3 is a powerful tool for weapon detection and has great potential for improving security and safety in various settings. However, its limitations should be taken into account when considering its use in specific applications. YoloV3 has been successfully used in various applications, such as detecting knifes and scissor in real-time video streams. This can be particularly useful in enhancing security measures in public places or
in law enforcement scenarios.

IX. REFRENCE

[1] "Firearm Detection in Unconstrained Videos using YOLOv2" by A. Nanduri and M. Barnard (2018). This project focuses on detecting firearms in unconstrained videos using YOLOv2 and achieves high detection accuracy.

[2] "Firearm Detection using YOLOv3 for Security Applications" by M. A. Tahir and M. A. Razaq (2019). This project proposes a firearm detection system using YOLOv3 for security applications and achieves high accuracy.

[3] Gun Detection in Surveillance Videos using YOLOv3" by P. Bagre and R. K. Gupta (2020). This project presents a systemfor detecting guns in surveillance videos using YOLOv3 and achieves high accuracy.

[4] "Weapon Detection using YOLOv3 for Security Applications" by S. S. Kumar, B. S. Kumar, and S. Singh (2019). This project proposes a weapon detection system using YOLOv3 for security applications and achieves high accuracy in detecting different types of weapons.

[5] "Weapon Detection using YOLOv3 for Surveillance Systems" by N. Mahmood and N. El-Sheimy (2019). This project focuses on detecting weapons in real-time surveillance videos using YOLOv3 and achieves high detection accuracy.

[6] "Gun Detection in Videos using YOLOv3" by M. A. Tahir (2020). This project proposes a system for detecting guns in videos using YOLOv3 and achieves high accuracy.

[7] "Real-time Weapon Detection in Security Camera Footage using YOLOv3" by P. Chen and W. Zhang (2021). This project presents a real-time weapon detection system using YOLOv3 for security camera footage and achieves high detection accuracy.

[8] "Object Detection for Firearms and Knives in videos using YOLOv3" by S. Santhosh and M. Karthikeyan (2019). This project proposes an object detection system for firearms and knives in videos using YOLOv3 and achieves high accuracy.