Research Article

DETECTION OF CRIME SCENE OBJECTS FOR EVIDENCE ANALYSIS USING DEEP LEARNING TECHNIQUES

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ABSTRACT: Research on the detection of objects at crime scenes has flourished in the last two decades. Researchers have been concentrating on colour pictures, where lighting is a crucial component, since this is one of the most pressing issues in computer vision, with applications spanning surveillance, security, medicine, and more. However, nighttime monitoring is crucial since most security problems cannot be seen by the naked eye. That's why it's crucial to record a dark scene and identify the things at a crime scene. Even when its dark out, infrared cameras are indispensable. Both military and civilian sectors will benefit from the use of such methods for nighttime navigation. On the other hand, IR photographs have issues with poor resolution, lighting effects, and other similar issues. Surveillance cameras with infrared (IR) imaging capabilities have been the focus of much study and development in recent years. This research work has attempted to offer a good model for object recognition by using IR images obtained from crime scenes using Deep Learning. The model is tested in many scenarios including a central processing unit (CPU), Google COLAB, and graphics processing unit (GPU), and its performance is also tabulated.

KEYWORDS: Object Detection, Deep Learning, COLAB, CNN, Crime Scene

1. INTRODUCTION

In crime scene object detection, a wide range of computer vision applications, including autonomous driving, cutting edge driving assistance systems, robotic visions, augmented reality, etc., make object identification a significant and active area of research. The primary goal of object detection is to locate and categorize particular items in still photographs and moving pictures. The process of focusing on an object involved in the vision process, such as visual tracking, human re-identification, and semantic segmentation, is typically seen as an essential step. The semantic object detection technique makes use of several geometric patterns as proof to spot intriguing objects in pictures or movies. The patterns of forms that display a comparable category of objects are used to train the object recognition models to distinguish between distinct categories.

However, because the characteristics of basic item forms, object positions, and angles of view vary widely, it is challenging for a system to reliably identify every appearance of an object. Multiple object detection uses similarities between the succession of photos or videos determine the movement of things. Target objects are first identified in multiple object detection and the technique is then followed to assess the itinerary of the items using the results of the detection. The journey of many objects is formed by semantic object detection with detection, which utilizes associated data from the existing track and fresh identification from each frame. Thus, a sequence of detections with distinct identities is produced as a result of data association. Recognition of salient objects might be difficult when they have similar appearances.

This study develops an algorithm to categorise different crime scene photographs and to recognise different things in them. A video that is composed of photographs from crime scenes is taken into account and divided into frames. The frame rate range for video is between 45 to 120 frames per second, or 7200 pictures per minute. When processing any video, this step is frequently taken. A seven-layered convolutional neural network is used to run the video after receiving the photos, and it typically recognises the images based on the trained images. The current algorithms effectively identify items in some labeled photos, but they needed to be given positions, classes, and background distributions. However, when the objects were manually annotated, the assignment process was tedious and time-consuming.

The handcrafted features of the old sliding window object identification approach had limitations that made it difficult to reliably recognize the items. Additionally, CNN succeeded in object detection by outperforming the conventional method. But because of difficult conditions including object occlusion, more fluctuation in object scale, and dim lighting, the CNN detector was not able to attain acceptable accuracy.

2. LITERATURE SURVEY

Fu et.al. developed a region-based Convolutional Neural Network Framework for arbitrary and multi-scale item recognition in remote sensing pictures The feature fusion architecture was developed in order to extract detection characteristics based on the Region of Interest (RoI). To acquire the precise position of arbitrarily oriented objects, the Oriented Region Proposal Network (RPN-O) was constructed, and RoI pooling was utilised to avoid orientation changes. Because the established CNN architecture proved resistant to objects in remote sensing images, anchors with additional scales and angles were added to aid RPN in object detection[11]. However, the created feature fusion method was unable to identify comparable appearances and suffered from identifying the backdrop of images, which hampered object identification performance.

Cai and Vasconcelos created a cascade Region-based CNN approach for increasing the quality of object detection and segmentation. Inference uses the cascade to remove mismatched detectors and improve hypothesis quality. The resampling strategy increases hypothesis quality greatly by giving a positive training set with similar sizes for each detector and reducing over fitting. The created method, however, maximized the diversity of samples utilized to forecast the masked object because the segmentation procedure was a patch-based operation with a larger number of highly overlapping instances.

3. SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

The existing system of the project, "Detection of Crime Scene Objects using Deep Learning Techniques," employs deep learning methodologies for object recognition in crime scenes. It primarily focuses on addressing low-light and nighttime monitoring challenges by utilizing infrared (IR) images. These images capture crucial evidence that is often invisible to the naked eye. The project acknowledges the limitations of IR images, such as poor resolution and lighting effects. It aims to provide a robust model that can effectively recognize objects in IR images. The model's performance is evaluated across various computing platforms, including central processing units (CPUs), Google COLAB, and graphics processing units (GPUs), with results being systematically tabulated for assessment.

LIMITATIONS OF EXISTING SYSTEM

Poor Resolution in IR Images: Infrared (IR) images used in the system often suffer from poor resolution, which can lead to difficulties in accurately identifying and classifying objects in the crime scene.

Lighting Effects and Artifacts: IR images may contain various lighting effects and artifacts, which can introduce noise and distortions in the data, potentially impacting the system's detection accuracy.

3.2 PROPOSED SYSTEM

The proposed system for the project, "Detection of Crime Scene Objects using Deep Learning Techniques," aims to enhance object detection in crime scenes by addressing the limitations of the existing system. It intends to improve object recognition in low-light conditions, particularly during nighttime, by refining the utilization of infrared (IR) images. The system will focus on implementing advanced deep learning architectures and techniques, such as state-of-the-art convolutional neural networks (CNNs) and object tracking algorithms, to enhance the accuracy and speed of object detection. It will also introduce sophisticated image enhancement and noise reduction methods for preprocessing IR data. Furthermore, the proposed system will prioritize real-time monitoring, alerting, and reporting features to provide timely information to law enforcement. Enhanced security measures and data privacy safeguards will be integrated, and extensive testing across various hardware configurations will ensure robust performance. Overall, the proposed system aims to offer a more reliable and effective tool for crime scene analysis and object recognition.

4. SYSTEM ARCHITECTURE

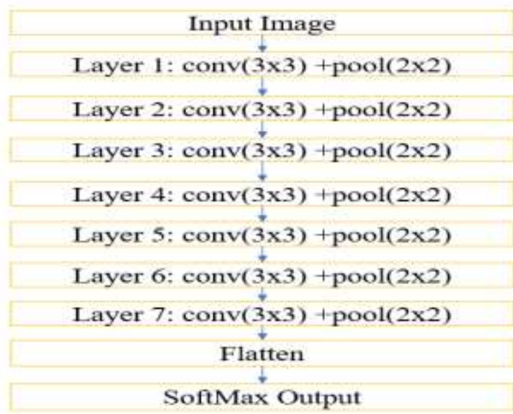

Fig. 1. Convolution Neural Network Architecture

5. METHODOLOGY

The suggested CNN architecture is displayed in Fig. 1 below. An infrared image measuring 640 by 480 pixels serves as the input. The architecture is made with the knowledge that the image is vulnerable to illumination, low resolution, and other influences, making it challenging for the image to effectively process and recognize the item. Therefore, this design consists of Seven Convolution layers with Max-pooling, One Flatten, and the Soft Max activation function. 32 filters are used in the first convolution layer, and 100 filters, each measuring 3 x 3, are used in the remaining six hidden layers. Max-pooling is also carried out with a scale of 2 x 2 at every layer. Following that, the convolution layers are flattened and normalized using the Soft Max step. All layers employ the activation function "ReLu" and the output range is varying from 0 to infinity. The activation function of ReLu is given by the equation

$$f(x) = \max(0,x) \qquad \text{……………(1)}$$

The proposed model is evaluated based on various evaluation metrics such as Precision, Recall, F-Score, and Accuracy

6. MODULES

Data Collection Module: This module is responsible for gathering and preprocessing data, including infrared images from crime scenes. It might involve data acquisition from surveillance cameras or other sources.
Preprocessing Module: image preprocessing, which could include tasks like noise reduction, image enhancement, and format standardization to Improve data quality.
Deep Learning Model Module: The core of the system, this module includes the deep learning architecture for object detection and recognition in IR images. It may involve techniques like convolutional neural networks (CNNs) or other deep learning models.
Training Module: Training the deep learning model on labeled datasets to make it capable of recognizing objects specific to crime scenes. This module may involve data augmentation, hyper parameter tuning, and model optimization.
Object Detection Module: Utilizing the trained model to detect objects in real-time IR images or video streams from crime scenes. This module may include post-processing steps to refine object detection results.

7. RESULTS

8.CONCLUSION

The development of crime scene photographs will facilitate their use in numerous security and surveillance applications. According to the experimental results, the suggested CNN architecture outperforms in terms of accuracy, and using GPUs would cut processing time by 90%. As a result, the suggested model produced remarkably precise findings. However, by recognizing and identifying the object, there is still room for development. Additionally, it's crucial to comprehend the scene. The same effort can be expanded to find undersea objects that will be helpful for defence.

FUTURE SCOPE: These advances may help to increase the precision and efficacy of crime prediction models by leveraging large datasets and sophisticated algorithms. Although there is a lack of literary wisdom on how these technologies can be used to solve the problem of crime prediction, despite the advancements in this sector. Thus our findings help to understand the implications of various ML and DL techniques. Also, our mentioned datasets and future directions will help the existing research community to pursue their research in the area of crime prediction.

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