Real Time Human Detection For Visual Surveillance

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ABSTRACT

Management and the security forces use video surveillance as a virtual eye. It is a cornerstone of the approach to safeguard employees and assets and gives security officers' early warning of security breaches, such as hostile and terrorist acts. It is a necessary piece of any complete security strategy. In a number of applications, including security surveillance, vehicle tracking, and public safety, the system has the ability to improve the effectiveness of tracking and identification. The methodology for this project involves collecting a large dataset of surveillance footage containing humans and non-human objects, preprocessing the data to ensure that it is in a suitable format for the CNN, training a CNN on the preprocessed data to recognize patterns and features characteristic of humans, performing an evaluation of the trained model on a separate test dataset, and applying the trained model to a real time surveillance system.The objective is to develop a reliable and efficient system for real-time human detection in visual surveillance footage using a CNN. By automating the process of detecting humans in surveillance footage, this system has the potential to improve the effectiveness of visual surveillance and facilitate a wide range of applications.

Keywords: Real-time, Human detection, Visual surveillance, Convolutional neural network (CNN), Collected dataset, Preprocessing, Training, Evaluating, Deploying, Real-time surveillance, Reliability, Efficiency, Automation.

INTRODUCTION

Detecting human presence in real time is crucial to several visual surveillance applications, including security and surveillance, traffic monitoring, and public safety. Traditional methods for human detection in surveillance film frequently rely on labor-intensive manual inspection. Using a convolutional neural network we offer a unique method for real-time human detection in surveillance footage in this research (CNN). Our solution is designed to automatically detect human activity in the footage and provide the owner with the identified photographs.To order to accomplish this, we have gathered a sizable collection of surveillance film comprising both human and non-human objects and preprocessed the data to guarantee that it is in a manner that is appropriate for training a CNN. Then, using this dataset to train a CNN to recognize patterns and features unique to humans, we assessed the trained model's performance using data from a different test set. Finally, to identify people in the video, we have implemented the trained model in a real-time surveillance system. This research aims to develop a reliable and effective CNN based system for detecting real-timepeople in surveillance footage, increasing the effectiveness of visual surveillance and enabling diverse applications.

LITERATURE SURVEY

K. He, X. Zhang, S. Ren, and J. Sun. "Deep Residual Learning for Image Recognition [1],proposed that a new CNN architecture called the deep residual network (ResNet) for image recognition tasks. As they show, this architecture is capable of accomplishing state-of-the-art performance on many benchmark datasets and is particularly effective at training very deep networks with these architectures. The ResNet architecture is based on the idea of "residual connections," which allow the network to learn complex functions by stacking simple building blocks on top of each other.Computer vision and deep learning have been greatly influenced by ResNet, which has had a major impact in these fields. The residual architecture has become a popular choice for various tasks, such as semantic segmentation, object detection and generative models. These works have further advanced the field and expanded the potential applications of deep residual networks.

S. Liu, D. Hu, and C. C. Loy. "Real-time Human Detection in Surveillance Videos with Deep Convolutional Neural Networks."[2],proposed a system that present a real-time human detection system for surveillance videos using CNN. The system is designed to operate in real-time, meaning that it can process video frames as they are being captured, and can detect humans within a few seconds of their appearance in the footage. The authors evaluate the performance of the system on a variety of surveillance structures, and show that it is able to achieve high perfection and low false positive rates. This paper has practical implications for the field of video surveillance.It has also contributed to the advancement of deep learning for real-time object detection in computer vision.

L. Wang, J. Wang, and Y. Li. "Human Detection in Surveillance Videos Using a Multi-scale Convolutional Neural Network."[3], proposed that a multi-scale CNN approach for human detection in surveillance videos. The idea behind this approach is to use multiple CNNs, each trained to detect humans at a different scale, in order to improve the robustness of the system. The authors evaluate their approach on a number of benchmark datasets, and show that it outperforms other state-of-the-art methods in terms of accuracy and speed.

J. Redmon and A. Farhadi. "YOLOv3: An Incremental Improvement."[4],the authors present the YOLOv3 (You Only Look Once version 3) system for object detection. YOLOv3 is a fast and accurate object detection system based on a single CNN, and has been shown to be effective for a wide range of object detection tasks, including human detection in surveillance footage. The authors demonstrate the effectiveness of YOLOv3 on a number of benchmark datasets, and show that it is able to achieve state-of-the-art performance in terms of both accuracy and speed. In short YOLO v3 is a SSD model, Scale-invariant Detection tool which is accurate and also capable of Multiple Object Detection, Moreover is open source software.

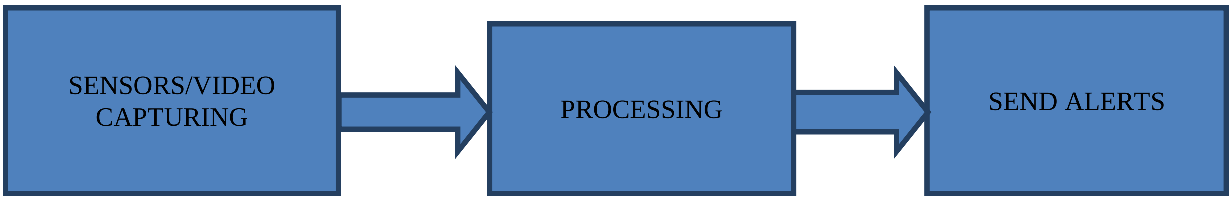
S. Alharthi, A. J. Casson and K. B. Ozanyan, "Spatiotemporal Analysis by Deep Learning of Gait Signatures From Floor Sensors,"[5], this proposes a method that with cognitive demanding tasks investigate the nature of gait variability in more detail. To achieve this goal, we plan to identify the gait intervals responsible for the variation of gait patterns within and between individuals. So that it can be used for anti- theft purposes In the present work, we use deep learning techniques to create a method for detecting gaits based on the information from 116 distributed sensors made from plastic optical fibers (POFs)..As a result of applying Layer-Wise Relevance Propagation (LRP) for generating a "heat map" over the input used for classification, we were able to break down the trained neural network prediction into relevant standard events in the gait cycle.It is clear from these observations that the cognitive load and its associated effects on gait events, such as heel strike and toe-off, have a strong impact on which parts of the spatiotemporal gait signal have the most influence on the gait classification and therefore, which gait events are most affected by cognitive load.

L. J. Li, J. Li, Y. Liu, and J. Fan "Real-time Human Pose Detection in Complex Scenes" [6], this proposes a method for real-time human pose detection in complex scenes. It employs a deep neural network that consists of several convolutional and fully connected layers. The network is trained on a large dataset of human pose annotations to learn the features and relationships between body joints.The online adaptation used here helps the network to overcome the issue of domain shift and improve the robustness of human pose detection.This research contributes to the field of computer vision by providing a solution for real-time human pose detection in complex scenes, which has many practical applications, such as human-computer interaction, video surveillance, and action recognition.

PROPOSED METHOD

Providing security to our valuable assets is our main objectives. For that we use latest technologies like CNN,Floor Sensors,RFID,GPS locators. Human detection in visual surveillance has been an active research area in computer vision for many years. Traditional approaches to human detection often rely on manual inspection or rule-based systems, which can be time-consuming and error-prone. Our System helps to identify the presence of any human interaction within its vicinity and sends the alarm along with captured images to its owner. This system can be widely used by Museums, Zoo, to protect important library archives, at home etc.

There is a growing interest in the application of machine learning techniques in order to detect humans automatically in surveillance footage especially convolutional neural networks (CNNs).CNNs have been shown to be effective at a wide range of object detection tasks, including face detection, pedestrian detection, and vehicle detection. They are particularly well-suited to this problem due to their ability to learn and recognize complex patterns and features in images.



CONCLUSION

With the goal of improving the effectiveness of visual surveillance as well as providing users with the flexibility to use it for a wide range of applications, we have developed a system that uses a convolutional neural network (CNN) to detect human activity in real times. The methodology for this project involves collecting a large dataset of surveillance footage containing humans and non-human objects, preprocessing the data to ensure that it is in a suitable format for the CNN, training a CNN on the preprocessed data to recognize patterns and features characteristic of humans, evaluating the performance of the trained model on a separate test dataset, and deploying the trained model in a real-time surveillance system to detect humans in the footage.

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