Enhanced Sustainable Crowd Monitoring and Risk Assessment System

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Abstract—In today's digital age, many locations still rely on traditional approaches to count crowds, such as manual register maintenance, people counters, and sensor-based counting at entrances. However, these methods prove inadequate in areas where the movement of people is sporadic, highly unpredictable, and constantly changing. These methods are timeconsuming and tedious. This Application checks the total count of people and gives the count of people in closer proximity. When the closer proximity count is near to total count it might lead to stampedes or accidents. This System also helps us to monitor the people with more risk based on their distance between each other. In this project we use neural network based predefined model for better accuracy. YOLOv3 algorithm adopts an architecture which detects each person in crowd, spot location with a bounding box, and does the counting. Deploying it on current surveillance systems and drones used by police to monitor large areas can help to prevent stampedes by allowing automated and better tracking of activities happening in the area. It can also be used to alert police in case .It offers real-time insights into the area of anuncontrollable situation in a particular area.

KEYWORDS

Object detection, You Only Look Once, Bounding boxes, Risk analysis, Machine learning, Proximity analysis, sustainable.

1. INTRODUCTION

The main focus of our research project is to develop and implement a real-time people counting system for visual surveillance, which holds immense significance for crowd and security control. This system plays a crucial role in closely monitoring the number of individuals at various public gatherings, ensuring their health and safety. Crowd management presents unique challenges due to the behavior of people in crowds, leading to potential disasters like collapses and overcrowding. To prevent such incidents, effective crowd control strategies are essential. Crowd surveillance adopts two primary approaches: macroscopic and microscopic. Macroscopic methods analyze entire crowd scenes, encompassing crowd density, counting, and flow estimation. These techniques efficiently handle dense crowds and provide insights into general crowd behavior. On the other hand, microscopic techniques focus on individual objects within a crowd, offering more precise information about crowd conditions, even in sparse populations. Combining both approaches allows for a comprehensive understanding of crowd dynamics. Unmanned aerial vehicles (UAVs) have emerged as a valuable tool for crowd control through recent technological advancements. Aerial photography provides elevated viewpoints, enabling the creation of discrete density maps. These maps categorize different crowd areas as dense, medium, sparse, or empty, offering valuable insights into crowd conditions and distribution. In the context of social distancing, crowd counting and action recognition technology play a pivotal role. The densitybased approach is particularly useful in reducing errors and miscounts. Long-term occupancy and congestion maps are generated to analyze pedestrian spatial patterns, identifying areas with social distancing violations. Heatmaps further aid in identifying highrisk areas where compromises are frequent. These short-term and long-term occupancy maps become essential tools for identifying high-risk areas within crowded scenes, providing valuable insights into crowd behavior and sustainable adherence to social distancing guidelines. By employing proactive crowd control measures based on these insights, risks can be reduced, and public spaces can be kept safe. Thus accurate crowd counting and efficient crowd management strategies are vital for ensuring safety in crowded environments. The integration of macroscopic and microscopic approaches, along with occupancy maps, density- based techniques, and heat map analysis, allows for a comprehensive understanding of crowd behavior and the identification of high-risk areas. By implementing these measures, authorities can strengthen crowd control, reduce risks, and proactively safeguard the health of individuals in public spaces.

2. REQUIREMENT ENGINEERING

2.1 Software Requirements : The product viewpoint and features, operating system and operating environment, graphics requirements, design limitations, and user documentation are all part of the functional requirements or overall description papers.

The application of requirements and implementation restrictions provides an overall picture of the project in terms of what areas of strength and weakness exist and how to address them.

- Operating System: - Windows 10
- Technology: Python
- Software: Visual Studio Code

2.2 Hardware Requirements : The minimum hardware requirements vary greatly depending on the product being produced

by an Enthought Python / Canopy / VS Code user. Apps that require big arrays/objects in memory will demand more RAM, but applications that require several calculations or activities to be performed rapidly would require a faster CPU.

- Operating system: Windows, Linux
- Processor: minimum intel i3
- Ram: minimum 4 GB
- Hard disk: minimum 250GB

3. RELATED WORK

The paper titled “Object tracking and counting in a zone using YOLOv4, DeepSORT and Tensor flow”.[1] introduces a system that addresses the challenge of tracking multiple objects in a frame. It comprises three stages: detection, identification, and tracking of objects in a specific zone. YOLO is used for object detection, classifying objects into 80 categories for accurate identification. The system incorporates motion prediction with an estimation model and utilizes Kalman filters for tracking moving objects. DeepSORT is employed to track objects by associating newly detected objects with those from the previous frame. The integration of YOLO, DeepSORT, and TensorFlow creates an efficient and precise system forobject tracking and counting.

The paper "Human Crowd Detection for City Wide Surveillance".[2] by Dushyant Kumar Singh, Sumit Paroothi, Mayank Kumar Rusiac, and Mohd. Aquib Ansari presents an autonomous solution for detecting and analyzing human crowd behavior in public spaces. The system aims to reduce the workload of individuals and enhance law enforcement's effectiveness in monitoring city areas. Object detection techniques are used for real-time detection of human pedestrians and unusual behaviors like violent crowd behavior or trespassing in restricted areas. The system incorporates violent flow descriptors and SVM classification for crowd behavior analysis and includes a real-time information dissemination component to promptly address crowd violence. This integrated system enables early detection and resolution of security threats in public spaces.

In the paper "Single-Pixel Thermopile Infrared Sensing for People Counting".[3] authors Ashish Pandharipande, Abhishek Murthy, Erik Hagenaars, and Geert Leu propose a novel people counting method using a single-pixel thermopile and a passive infrared sensor. The method accurately measures object temperatures in environments with multiple people through a developed thermopile signal model. People counting is achieved using cumulative sum (CUSUM) change detection in the object temperature signal, analyzing the differential mean temperature in detected changes to estimate the number of people present. Enhancements are made through decision fusion with an infrared vacancy sensor, resulting in high accuracy. The method is validated using both simulated and real-world data, showing minimal counting errors.

4. PROBLEM STATEMENT

In the past, manual registers were used to keep track of the number of people in a crowd. However, with advancements in technology, the focus has shifted towards developing systems that not only detect people in a crowd but also manage the associated risks. Currently, the existing systems primarily concentrate on the detection of individuals and ensuring safety measures. However, there is now a growing emphasis on accurately counting the number of people present in a crowd and actively maintaining this count. This involves incorporating live video feeds and real-time detection of crowds into the existing framework.

5. TECHNOLOGY

Python is a versatile and efficient programming language known for its simplicity and userfriendliness. It works well with other languages, making it a popular choice in various applications. Created by Guido van Rossum in the late 1980s and early 1990s, Python is based on languages like ABC, C, C++, and Unix shell. It is open-source and widely used in Dialogflow and as the foundation for many software projects. Python is maintained by a core development team, with Guido van Rossum still contributing significantly to its development. It is commonly used in build control, testing, and automation tasks by software engineers.

Figure 1. Python

6. IMPLEMENTATION

Modules

Processing Video Frame : We utilized the powerful open-source library, OpenCV, to process our video. OpenCV offers a wide range of tools for image and video processing tasks. When dealing with videos, it's important to understand that they are made up of discrete frames, each represented as a matrix of pixels. The pixels in each frame can be represented in different color models, such as grayscale, RGB, or multispectrum. OpenCV provides the necessary functionalities to manipulate and analyze these frames, enabling us to perform various image and video processing operations sustainably.

Detecting People: In our project, we employ the YOLOv3 algorithm for detecting people in video frames. YOLOv3 utilizes the powerful DarkNet-53 architecture. The YOLO model is renowned for its effectiveness in deep learning-based object detection, providing fast performance, making it suitable for real-time applications. In our custom implementation, we utilize YOLO's unique design for human detection. The algorithm analyzes input images and simultaneously estimates bounding boxes (tx, ty, tw, th), confidence scores, and probabilities for multiple classes (P1, P2, ..., Pc). Our focus is on extracting relevant box information, item reliability, and class labels to accurately identify individuals. The YOLO model was trained on the COCO dataset, containing 80 different categories, including humans.

Distance Calculation: The distance between individuals is determined using their center of gravity derived from box sensing. These centroids represent the points in the middle of each individual's bounding box. Additionally, we added an angle that helps calculate the distance between individuals at different points. By taking the angles into account, we can calculate the distance between people even if they are not looking directly at each other. This angle will help to adjust the distance according to the direction or angle of the neighboring people.

Declaration of Results:

The system detects people and measures the distance between them. Depending on how close they are, the checkboxes change color to show their close relatives. If people are very close to each other, a red box is shown, otherwise, a green box is shown. In addition to all detected persons, the system also monitors people in high-risk and safe places. If the number of people at risk is more than half of the total, an alarm is given and an audible warning is given.

7. RESULTS

In this particular setup, the video frame is deliberately angled to capture street views, aiming to enhance sustainable distance measurement accuracy. By transforming the perspective view into a topdown perspective, more precise distance estimations can be achieved. The video sequences are displayed in a vertical layout, with each pedestrian represented by a designated box, enabling efficient crowd monitoring and individual tracking within the recorded footage. To visually illustrate proximity between pedestrians, two distinct colors are used for the boxes. Red boxes indicate pedestrians whose distance from others falls below the acceptable threshold, serving as a visual alert for instances of insufficient social distancing. On the other hand, green boxes represent pedestrians adhering to safe distancing guidelines, facilitating easy identification and continuous monitoring of compliant individuals. This setup and visual representation offer a comprehensive approach to analyzing crowd dynamics, assessing individual proximity, and monitoring adherence to safe distance guidelines. It provides valuable insights into pedestrian interactions and contributes to a safer and well-regulated environment.

Figure 2. Video Feed Detection 2

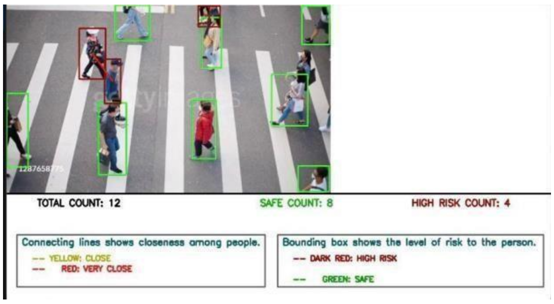

Figure 3. Video Feed Detection 2

8. CONCLUSION AND FUTURE ENHANCEMENTS

The proposed methodology introduces a human crowd surveillance system using Deep Neural Networks and computer vision. The system estimates the distance between people in realtime video streams and identifies non-compliant pairs with red frames and lines. The validation of the method on a pedestrian video demonstrates its effectiveness in applying crowd management strategies to prevent disasters by identifying high-risk individuals. The system generates alerts with beep sounds for the monitoring system when risks are detected. The implementation utilizes the YOLO object detection algorithm and spatial relationship calculations to identify individuals, assess their proximity, and determine their risk levels. It counts the total number of people, high-risk individuals, and safe individuals in the frame. The crowd analyzer assists in monitoring compliance with social distancing guidelines, managing crowds, and assessing overcrowding risks. The implementation also includes a warning and sound notification for situations where the number of people exceeds a certain threshold or high-risk individuals exceed half of the total count, enhancing real-time risk detection. Overall, the human crowd analyzer demonstrates the effective application of computer vision for crowd analysis, contributing to safety in crowded environments. One possible way to enhance the project even further would be to incorporate a notification system that sends alerts to the mobile phone of the individual responsible for monitoring the crowd.

9. REFERENCES

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