# **Real time crowd counting using deep learning**

Sougandhika Narayan, Adithya S.R, Anupa M.B, Chandrashekhar, Jaswanth G

<sup>1</sup>Assistant Professor,<sup>2</sup>Student, <sup>3</sup>Student, <sup>4</sup>Student, <sup>5</sup>Student <sup>1</sup>Department of Computer Science and Engineering, <sup>1</sup>K S School of Engineering and Management, Bengaluru, Karnataka, India

Abstract - - Counting the number of peoples or objects in videos or photos is known as crowd counting. Numerous daily activities, including urban planning, healthcare, disaster management, public safety, and defense , can benefit from this process. The studies are being conducted in this area. This paper discusses a few crowd-counting methods using convolutional neural networks traditional neural networks and other deep learning concepts. Through computer Intelligence, it monitors and predicts the count of people in overcrowded areas. Numerous issues, including occlusion, perspective and scale distortion, and uneven dispersion, affect crowd-counting techniques. Calculation complexity rises in crowd density. The majority of crowd-countingtechniques entail estimating density. An idea of the spatial distribution is provided by density estimation.

Index Terms - Crowd analysis, Deep Learning, Crowd counting, Convolutional neural network, Density estimation

## **I. INTRODUCTION**

In the present world Numerous real-world applications, including resource management (such as the provision of food and water), traffic control, security, and disaster relief, depend on crowd counting. The conventional techniques for counting a crowd, like manual counting, keeping track of each person's countusing registers, and using sensors, are time-consuming, and they can cause inaccurate results, because of people constantly moving bodies. As a result, techniques for the crowd counting that rely on CCTV video feeds or live data feeds have evolved. Crowd behavioranalysis is complex because it has both physiological and dynamic characteristics. Humans can extract useful information on behavior patterns in the surveillance area, monitor the crowd for abnormal situations in real time, and provide the potential for immediate solutions. However, there are several limitations to the simultaneous observation of various signals in high-density crowds. So there so many technologies were introduced in the field of crowd analysisto overcome this limitation.



Fig 1. A crowd scenario

## **II APPLICATION AND CROWD COUNTING CHALLENGES**

Crowd counting has several uses, it is the following:

- (a) For public space design: Design should maximize the safety of crowd movements and gatherings.
- (b) Counting Attendance: This is useful for keeping track of attendance in workplaces or educational institutions.
- (c) Disaster Management: To avoid crowding during public gatherings.
- (d) System for gathering intelligence: it can be implemented in a variety of industries to shorten queue lengths. Challenges with Crowd Counting:
- (a) Imperceptible objects
- (b) lot of clutter
- (C) bad lighting
- (d) dimensions and viewpoint

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#### **III. MOTIVATIONS**

Managing live crowds, especially non-organized ones, presents unique challenges for Crowd counting, Behavior Monitoring, and Analysis Systems. It has the successful applications in organized crowd scenarios, dealing with the unpredictability of non-organized crowds remains an tough challenge in research. This system relies on various factors like light conditions, occlusion, noise, and head positions. Developing effective models in this field requires extensive training data, yet there is a scarcity in fetching datasets for crowd management. Challenges include difficulties in recognizing individual objects when they converge and dealing with non-uniform arrangements, termed clutter, which is akin to visual noise. In essence, crowd analysis and behavior analysis face hurdles in accurately analyzing and monitoring the behaviors of non-organized crowds due to their unpredictable nature and the intricacies associated with factors like clutter and limited training data.

#### IV. GOALS

• Accurate Crowd Counting:

Developing the machine learning models that can accurately count the number of individuals in crowded scenes, accounting for variations in crowd density, lighting conditions, and diverse camera perspectives.

• Real-Time Processing:

Design algorithms and models that can process and analyze video streams or image sequences in real time. This is crucial for applications where timelyinformation about crowd size is essential, such as in emergency response or event management.

• Handling Non-Organized Crowds:

Address the complexities associated with non-organized crowds, where individuals may move unpredictably and exhibit diverse behaviors. The aim isto develop the models that can effectively handle the challenges posed by the dynamic nature of such crowds.

•Scalability and Adaptability:

Designing the systems that can scale to handle crowds of varying sizes, from small gatherings to large-scale events. Additionally, the models should be adaptable to different settings and scenarios without significant retraining.

•Integration with Surveillance Systems:

Explore the integration of real-time crowd-counting systems with existing surveillance infrastructure. This includes compatibility with CCTV cameras, drones, orother monitoring devices commonly used in public spaces.

• Robustness to Environmental Factors:

Creating the models that are compatible to environmental challenges, including variations in lighting, occlusions, and different forms of noise. The goal is ensuring the system's performance is reliable in various real-world conditions.

# **V** METHODOLOGY

• Data Collection and Preprocessing:

Collect a diverse dataset of images or video sequences containing crowded scenes. Ensure that the dataset covers a huge range of crowd densities, lighting conditions, and scenarios.

• Network Architecture Selection:

Choosing a deep learning architecture suitable for crowdcounting. Common architectures including ConvolutionalNeural Networks (CNNs), Fully Convolutional Networks (FCNs), and more recent models designed specifically for crowd counting, such as the CSRNet or the MCNN (Multi-column CNN).

• Training:

Train the selected deep learning model using the annotated dataset. This involves feeding the input images into the network and adjusting the model's weights through backpropagation to minimize the chosen loss function.

• Fine-Tuning:

Fine-tune the model on the specific characteristics of our target environment or application. This step helps the model adapt to the nuances of real-world scenarios.

• Validation and Testing:

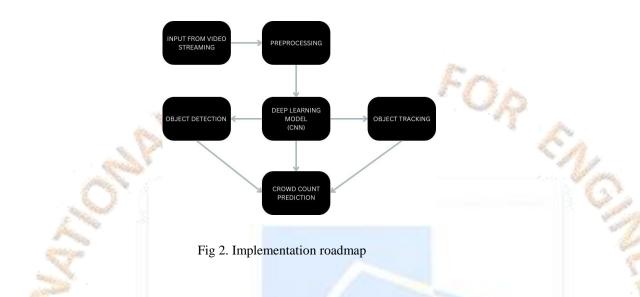
Evaluate the trained model on a separate validation setto ensure it generalizes well to unseen data. Fine-tuneparameters if necessary. Finally, test the model on an independent test set to assess its real-worldperformance.

#### • Integration with Real-Time Systems:

Integrate the trained model into a real-time system. Depending on the application, this could involve deploying the model on edge devices, integrating withexisting surveillance systems, or setting up a dedicated infrastructure for real-time processing.

#### • Continuous Monitoring and Updating:

Implementing mechanisms for continuous monitoring the system's performance in real-world scenarios. If necessary, update the model periodically to account for changes in the environment or crowd behavior.



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