A

PROJECT REPORT

ON

"CROWD DETECTION MAPPING HUMAN PRESENCE IN REAL TIME"

Submitted in partial fulfillment of the requirements for the award of the degree of

Bachelor of Technology
In
Information Technology

By

SIDDESHWARI NARHARI BADGUJAR	(T2154491246501)
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Under the guidance of
PROF.RUBI MANDAL

DEPARTMENT OF INFORMATION TECHNOLOGY

SHRI VILE PARLE KELAWANI MANDAL'S

INSTITUTE OF TECHNOLOGY, DHULE

Survey No. 499, Plot No. 02, Behind Gurudwara, Mumbai-Agra National Highway, Dhule-424001, Maharashtra, India.

Academic Year 2023-24

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CERTIFICATE

This is to certify that the B.TECH. Project Report Entitled

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is a record of bonafide work carried out by him/her, under our guidance, in partial fulfillment of the requirement for the award of Degree of Bachelors of Technology (Information Technology) at Shri Vile Parle Kelavani Mandal's Institute of Technology, Dhule under the Dr. Babasaheb Ambedkar Technological University, Lonere, Maharashtra. This work is done during IV year of Academic year 2022-23.

Date:
Place: SVKM's IOT, Dhule

Prof. Rubi Mandal	Dr. Bhushan Chaudhari	Dr. Nilesh Salunke
Project Guide & Project Coordinator	**HOD**	**Principal**

Name and Sign with date
Examiner-1

Name and Sign with date
Examiner-2

DECLARATION

We declare that this written submission represents my ideas in our own words and where other's ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

		Signatures
Siddheshwari Narhari Badgujar	(T2154491246501)	___________________
Tejal Hemant Pawate	(T2054491246056)	___________________
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INDEX

LIST OF ABBREVIATIONS

CNN	Convolution neural network
AdaBoost	Adaptive Boosting
RNN	Recurrent Neural Networks
UI	User interface
AVI	Audio video interleave
SSD	Single Shot Multi box Detector
RFCN	Region Based Fully Convolution Networks

LIST OF FIGURES

ABSTRACT

Crowd control is a critical crisis management consideration for any public or entertainment venue as well as many other types of organizations, such as hospitals, which may need to contend with crushing crowds in a pandemic panic. Hiring sufficient security to provide crowd control is an obvious starting point for effective management of crowds. Our system is essential for improving efficiency across a range of fields as well as public safety and security. Existing system involves crowd management with the help of in physical security which not only consumes the time but also the government invest in terms of cost which leads to a huge loss of the economy of particular area, to overcome this we have proposed a system provides a Large-scale event monitoring and management are made possible, traffic flow is optimized, retail analytics are enhanced, and social distancing measures are adhered to. Existed projects used photos, videos or live camera on individually to count people but our system combines all these three alternatives into a single system. The research identifies a gap in existing systems and proposes a novel approach using Python and Haar Cascade Classifiers and CNN algorithms to elevate accuracy and efficiency in crowd analysis. Using a smart system in Python and Open CV for camera it can quickly and accurately identify crowds in real-time, helping with things like public safety and event planning. This makes it easier to manage crowds effectively and providing practical benefits for societal applications.

Index Terms— Machine learning, CNN, Haar cascade, TensorFlow.

1. INTRODUCTION

In today's dynamic and bustling environments, accurately counting and analyzing crowd sizes is crucial for various sectors, including public safety, event management, and retail operations. The Crowd Count and Analysis System with Alert Functionality is a cutting-edge solution designed to meet the growing demands of efficiently monitoring crowd numbers and responding proactively to potential overflows.

Traditional methods often face challenges in scalability, accuracy, and real-time processing. Understanding crowd dynamics is crucial for optimal resource allocation, public safety, and overall efficiency in various contexts. This research aims to address existing limitations and contribute to the evolving field by leveraging computer vision techniques. Traditional crowd monitoring methods fall short in scalability and real-time processing. The research identifies a gap in existing systems and proposes a novel approach using Python and Haar Cascade Classifiers to overcome these limitations. This innovative system utilizes advanced image processing and artificial intelligence algorithms to accurately count the number of individuals within a specified area. By leveraging computer vision technology, the system can detect and track people in real time, providing instant and precise crowd counts.

One of the standout features of this system is its alert functionality. Users can set predefined thresholds for crowd size, and when the count exceeds these thresholds, the system automatically triggers alerts. These alerts can be customized to notify designated personnel via SMS, email, or other communication channels, enabling timely and effective response measures to manage crowd surges or unexpected gatherings.

The Crowd Count and Analysis System offers a user-friendly interface with interactive dashboards and reporting tools. It provides valuable insights into crowd dynamics, trends over time, and peak activity periods, empowering organizations to make data-driven decisions and optimize resource allocation. With its robust capabilities in crowd counting, analysis, and alerting, this system is poised to revolutionize crowd management strategies across diverse industries, enhancing operational efficiency, safety, and customer experience.

1.1 Background Of Project

Effective crowd detection is paramount for ensuring safety and security across various environments and scenarios. By leveraging advanced algorithms and technologies, crowd detection systems can swiftly identify potential risks, including overcrowding, suspicious behavior, and emergent threats such as stampedes or conflicts. This capability allows for proactive interventions to mitigate risks and maintain a secure environment for individuals within the crowd. Moreover, crowd detection systems offer significant advantages in resource allocation by providing real-time insights into crowd dynamics. By accurately estimating crowd size, density, and movements, these systems assist in optimizing the deployment of personnel, emergency services, and other resources. This optimized resource allocation not only improves operational efficiency but also enhances response capabilities during emergencies, enabling quicker and more effective interventions. Beyond resource allocation, crowd detection systems play a pivotal role in crowd management. By continuously monitoring crowd behavior and density, these systems facilitate the implementation of crowd control measures such as regulating entry and exit points, managing queues, and dispersing crowds when necessary. This proactive approach helps maintain order, prevent congestion, and ensure the safety of individuals within the crowd. In event planning, crowd detection systems provide invaluable support by offering insights into attendance estimates and crowd dynamics. Event organizers can leverage this information to plan logistics, design crowd-friendly layouts, and implement appropriate security measures. By anticipating crowd movements and behaviors, these systems contribute to the overall success and safety of events, enhancing the experience for attendees. In public spaces and transportation hubs, crowd detection systems serve as essential tools for ensuring public safety and operational efficiency. By continuously monitoring crowd density and identifying potential hazards, such as bottlenecks or overcrowded areas, these systems help prevent accidents, minimize disruptions, and maintain smooth operations. Moreover, they support compliance with safety regulations and facilitate the implementation of crowd-friendly policies and procedures. During emergencies, crowd detection systems become critical components of emergency response strategies. By providing real-time information on crowd size, location, and behavior, these systems enable authorities to quickly identify high-risk areas and implement targeted interventions. Whether during natural disasters, public health crises, or other emergencies, crowd detection systems play a vital role in coordinating evacuation procedures, managing crowd flow, and ensuring the safety and well-being of individuals within the affected areas.

In essence, effective crowd detection is not just about identifying crowds but also about leveraging data and insights to enhance safety, optimize resource allocation, and improve overall crowd management practices across various domains and scenarios.

1.2 Motivation Of Project

Real-time incidents stemming from crowded environments can range from minor disruptions to serious emergencies, highlighting the critical importance of effective crowd management. In bustling public venues or events, incidents such as overcrowding at entry points, bottlenecks in pedestrian flow, or conflicts among attendees can occur suddenly and escalate rapidly. These situations not only pose safety risks but also impact the overall experience of participants and the smooth functioning of the event. In extreme cases, crowd-related incidents like stampedes, crowd crushes, or medical emergencies can lead to injuries, panic, and chaos if not promptly addressed.

The ability to detect and respond to such incidents in real time is essential, requiring a combination of proactive planning, trained personnel, technological tools like surveillance systems and crowd monitoring software, and clear communication protocols. By swiftly identifying and mitigating real - time crowd incidents, organizations can ensure the safety, security, and positive experience of individuals within crowded environments.

1.2.1 Some of the real time incidents:

One of the deadliest crowd crushes in recent history occurred a decade ago in India, when at least 115 people were killed on the sidelines of a religious festival in central Madhya Pradesh

Stampedes in India-Statistics

- According to the National Crime Records Bureau figures, from 2000 to 2013, almost 2,000 people died in stampedes.

- A 2013 study published by International Journal of Disaster Risk Reduction (IJDRR) points out that religious gathering and pilgrimages have been venues for 79% of the stampedes in India.

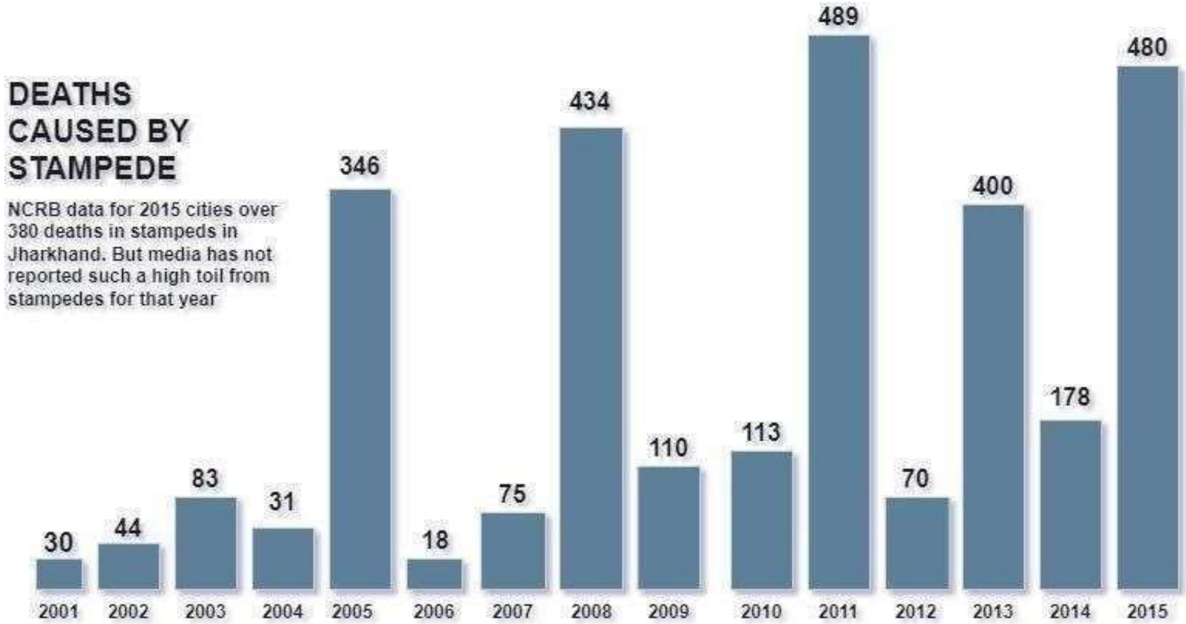

Fig 1.1 Stampedes in India-Statistics

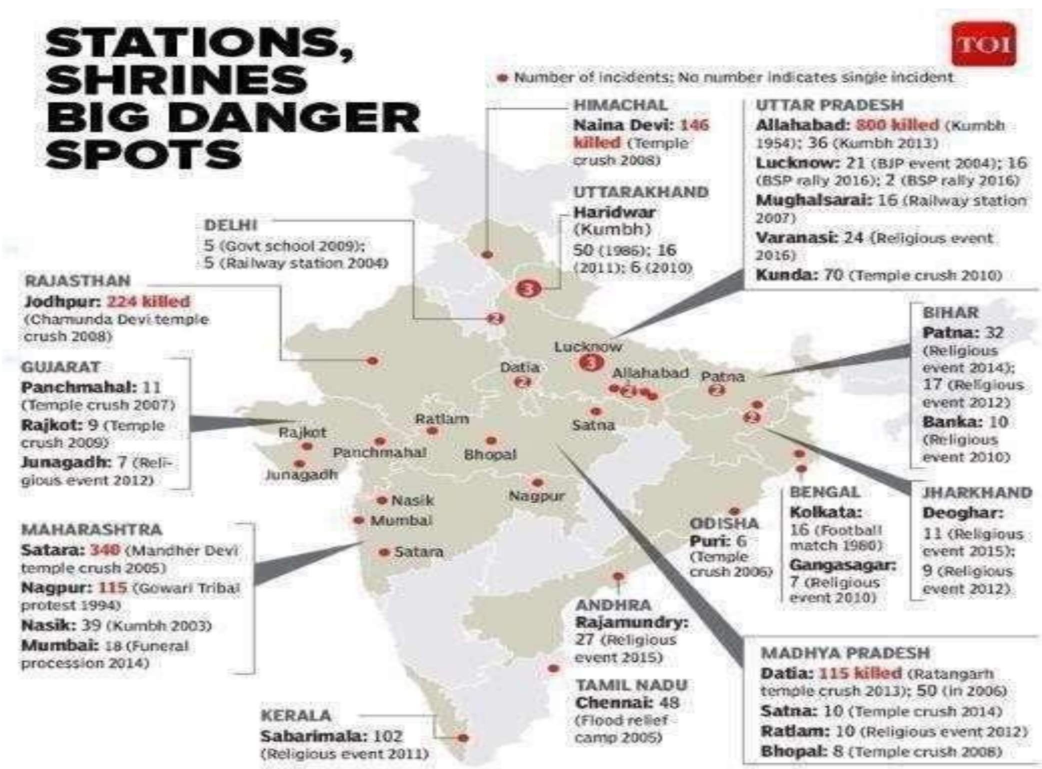

Fig 1.2 Incidents happened In India

These incidents highlight the importance of effective crowd management strategies, including crowd monitoring, emergency response preparedness, crowd control measures, and ensuring infrastructure safety to prevent and mitigate the impact of real-time incidents due to crowds.

By considering this issue, the proposed system This system represents a fusion of state-of-the-art computer vision, machine learning algorithms, and data analytics, working seamlessly to provide real-time insights into crowd dynamics. By leveraging the power of advanced image processing techniques, this solution can accurately identify, track, and analyze crowd movements within diverse environments, ranging from bustling city centers to crowded stadiums and public events. The Crowd Detection and Analysis System not only serves as a crucial tool for enhancing public safety but also offers unparalleled capabilities in optimizing crowd management strategies. Through the meticulous examination of crowd patterns, density, and flow, it empowers authorities to make informed decisions in real-time, preemptively addressing potential issues and ensuring a safer and more secure environment for everyone involved. Key features of this system include anomaly detection, crowd density estimation, and predictive analytics. Anomaly detection algorithms allow for the swift identification of unusual or potentially hazardous behaviors within crowds, enabling rapid response to emerging threats. Additionally, crowd density estimation tools provide valuable insights into the distribution of people in specific areas, facilitating optimal resource allocation and crowd control measures. The integration of predictive analytics equips authorities with the foresight needed to anticipate and mitigate potential challenges before they escalate. As urban landscapes continue to evolve, so must our approaches to public safety. The Crowd Detection and Analysis System stands at the forefront of this evolution, offering a proactive and intelligent solution to the complexities of crowd management. The "Crowd Detection System" is a pioneering solution that addresses the complexities of crowd analysis and management. It brings together the best of traditional computer vision techniques and cutting-edge deep learning methods, resulting in a versatile and adaptable toolset. This system is designed to identify and quantify human presence within various environments and contexts. By merging the strengths of these two approaches, it provides a comprehensive means of effectively addressing the challenges of crowd monitoring. At its core, this project is driven by the fundamental purpose of offering a multifaceted solution for crowd detection that can be effectively applied across a diverse range of scenarios. The "Crowd Detection System" aims to provide an intelligent, adaptable, and highly responsive approach to crowd analysis. To fulfill this purpose, it integrates Different technologies:

1.2.2 Camera and Video Analytics: High-resolution cameras equipped with video analytics software are used for real-time crowd detection. These systems can detect crowd density, movement patterns, and anomalies, providing valuable data for analysis.

1.2.3 Computer Vision and Machine Learning: Computer vision algorithms and machine learning models are employed for crowd analysis. These technologies can identify individuals, track crowd flows, recognize behavior patterns, and detect potential threats or emergencies. To fulfill this purpose, it integrates two different algorithms

- Haar Cascade Algorithm: The Haar cascade algorithm is known for its efficiency and accuracy in detecting objects, particularly faces, in images or video streams. It has been widely used in applications such as face detection in cameras, security systems, and facial recognition software

i. Feature Extraction: The algorithm begins by extracting features from the input image or video frame. These features are rectangular patterns of pixel intensities that are known to be useful for distinguishing between different objects or parts of objects.

ii. Integral Image: To speed up the computation of features, the algorithm uses an integral image representation of the input image. This representation allows for fast calculation of sums of pixel intensities within rectangular regions.

iii. Haar-like Features: The algorithm defines a set of Haar-like features, which are simple rectangular patterns that capture variations in pixel intensities. Examples of Haar-like features include edge features, line features, and corner features.

iv. Training the Cascade: The Haar cascade algorithm is trained using a machine learning approach called AdaBoost (Adaptive Boosting). During training, a cascade of classifiers is built, where each classifier focuses on detecting a specific feature or pattern.

v. Cascade of Classifiers: The cascade of classifiers is organized in stages, with each stage containing multiple weak classifiers. Weak classifiers are simple decision rules based on Haar-like features.

vi. Thresholding and Filtering: At each stage of the cascade, the algorithm applies thresholding and filtering to determine whether the current region of interest contains the object being detected. Regions that pass the thresholding criteria are passed to the next stage, while non-relevant regions are discarded.

vii. Final Detection: If an input region passes through all stages of the cascade without being rejected, it is considered a positive detection of the object. The algorithm outputs the coordinates of the detected object's bounding box.

- Convolutional Neural Network (CNN) Algorithm: Inspired by the intricacies of human vision, the CNN algorithm provides a deep learning approach that excels in the precise detection of crowds. Its ability to learn complex features from data makes it an invaluable tool for object recognition and classification. The fusion of these two methodologies empowers the "Crowd Detection System" with robust and dependable crowd analysis capabilities. It can seamlessly analyze a diverse range of input sources, including static images, dynamic videos, and live webcam feeds. Furthermore, its real-time processing capabilities ensure that it can instantaneously assess and respond to dynamic crowd situations, providing insights and actionable data in real-time. The "Crowd Detection System" is not merely a technological advancement; it is a dynamic response to the evolving needs of society. It offers an intelligent and responsive approach to crowd analysis and promises to redefine crowd management and analysis across numerous domains, including security, event management, marketing, and more. In this comprehensive report, we will delve into the technical intricacies, methodologies, and practical applications of the "Crowd Detection System." Our aim is to provide a deep understanding of its capabilities and the transformative impact it can have in a world where effective crowd management is of paramount importance.

i. Convolutional Layers: CNNs typically start with one or more convolutional layers. These layers use convolutional filters to extract features from the input image. The filters slide across the input image, computing dot products between the filter weights and local regions of the image, producing feature maps that highlight different aspects of the input.

ii. Activation Function: After the convolutional operation, an activation function like ReLU (Rectified Linear Unit) is applied element-wise to the feature maps. This introduces non-linearity into the model, allowing it to learn complex patterns and relationships in the data.

iii. Pooling Layers: Following the activation function, pooling layers are often used to down sample the feature maps and reduce spatial dimensions. Max pooling or average pooling are common pooling operations that retain the most important information from the feature maps.

iv. Flattening: After several convolutional and pooling layers, the feature maps are flattened into a one-dimensional vector. This flattening process prepares the data for input into fully connected layers.

v. Fully Connected Layers: The flattened feature vector is passed through one or more fully connected layers, also known as dense layers. These layers perform classification tasks by learning complex relationships between the extracted features.

vi. Output Layer: The final layer of the CNN is the output layer, which typically uses a softmax activation function for classification tasks. Softmax converts the output into probabilities, indicating the likelihood of each class being present in the input image.

vii. Training: CNNs are trained using labeled data through a process called backpropagation. During training, the network adjusts its internal weights and biases to minimize the difference between predicted outputs and actual labels, using optimization algorithms like gradient descent.

viii. CNNs have achieved remarkable success in various applications such as image recognition, object detection, image segmentation, and more. They are known for their ability to automatically learn hierarchical representations of features from raw pixel data, making them highly effective for visual tasks.

Threshold-Based Alerting System: A threshold-based alerting system plays a crucial role in crowd detection and management by enabling real-time alerts based on predefined thresholds. This mechanism is designed to monitor specific parameters related to crowd behavior or environmental conditions and trigger alerts when these parameters cross predetermined thresholds.

1. Setting Thresholds: The first step involves setting thresholds for various parameters that are critical for crowd management. These parameters can include crowd density, crowd flow rate, temperature, noise levels, or any other relevant metrics depending on the specific use case.
2. Monitoring Parameters: The system continuously monitors these parameters using sensors, cameras, or other data collection methods. For example, crowd density can be measured by counting the number of people within a defined area using video analytics or IoT sensors.
3. Alert Generation: When the monitored parameters exceed or fall below the predefined thresholds, the threshold-based alerting system generates alerts in real time. For instance, if the crowd density surpasses a certain threshold, indicating overcrowding, the system triggers an alert to notify security personnel or event organizers.
4. Alert Types: The alerts generated by the system can vary in severity and urgency based on the nature of the detected anomaly. For example, high-priority alerts may be triggered for situations like potential stampedes, aggressive behavior, or medical emergencies, while lower-priority alerts may be for moderate increases in crowd density or minor disturbances.
5. Communication and Response: Upon receiving an alert, the system communicates the alert to designated stakeholders via various communication channels such as SMS, email, push

notifications, or integrated communication systems. The stakeholders, which may include security teams, event organizers, or emergency responders, can then take appropriate actions to address the situation and implement crowd management measures.

6. Continuous Monitoring and Adjustment: The threshold-based alerting system continuously monitors the parameters and adjusts thresholds as needed based on evolving conditions or feedback. This ensures that the alerting mechanism remains effective in identifying and responding to potential crowd-related issues in real time.

Overall, a threshold-based alerting system enhances crowd management by providing timely alerts, enabling proactive interventions, and ensuring the safety and security of individuals within crowded environments.

This project is big because it could change how we look at and understand crowds. To sum it up, why we're doing this capstone project is about combining smart technology with real-world use

2. LITERATURE SURVEY

2.1 Survey Existing System

"Crowd Counting and Management System using Deep Learning" by Michael Anderson et al. This study proposes a crowd counting and management system based on deep learning techniques. The system utilizes deep learning models trained on crowd images to accurately estimate crowd count. Alerts are sent when the crowd count surpasses predefined thresholds, assisting in effective crowd management.

Foundations of Crowd Detection P. Dollár et al. Proposed the influential paper "Fast Feature Pyramids for Object Detection," introducing the concept of feature pyramids for efficient and accurate object detection, a fundamental component of crowd detection systems. Deep Learning Approaches R.Ranjan et al. (2018) presented "Pedestrian Attribute Recognition at Far Distance," showcasing the effectiveness of deep learning in crowd analysis, particularly in recognizing attributes from a distance, crucial for surveillance applications.

Real-Time Crowd Monitoring Y. Zhang et al.(2018) explored real-time crowd monitoring in "Cross-Scene Crowd Counting via Deep Convolutional Neural Networks," proposing a deep learning model for accurate crowd counting across various scenes. Privacy-Preserving Techniques: Crowd detection often involves privacy concerns. S. Ali et al. (2019) addressed this in "Privacy-Preserving Crowd Monitoring Using Computer Vision," introducing techniques for anonymization and ensuring ethical surveillance practices.

Sensor Fusion for Crowd Detection: The fusion of different sensor modalities is explored by J. Tang et al. (2020) in "A Comprehensive Survey on Crowd Counting: From Traditional Methods to Recent Datasets and Benchmarks." This survey provides smart video surveillance systems leverage computer vision algorithms to analyze video feeds in real-time and detect crowd density and movements. These systems use techniques like object detection, tracking, and behavior analysis to estimate crowd counts accurately. When the crowd count surpasses a specified threshold, these systems can generate alerts to notify relevant authorities or personnel.

Crowd Management in Smart Cities: Challenges, Solutions, and Opportunities," exploring how crowd detection systems contribute to urban planning and management for smart city development. The literature on crowd detection systems is diverse, spanning from foundational principles to advanced applications in real-world scenarios. As technology continues to evolve, interdisciplinary collaboration remains crucial in harnessing the full potential of crowd detection systems for creating safer, more efficient, and seamlessly orchestrated urban environments

Research by Ali Farhadi et al. (2021) introduced a method based on the detection of moving blobs in video frames, marking a foundational step in automated crowd analysis. This set the stage for subsequent developments in computer vision and machine learning for crowd detection. The literature showcases a proliferation of computer vision techniques for crowd analysis. Notable methods include background subtraction, optical flow analysis, and density-based crowd estimation.

Deep Learning Approaches with the rise of deep learning, convolutional neural networks (CNN) and recurrent neural networks (RNN) have been employed to enhance the accuracy and efficiency of crowd detection systems. Zhang et al. (2018) proposed a deep learning-based method for crowd counting, demonstrating the effectiveness of deep neural networks in handling diverse crowd scenarios.

Beyond crowd counting, recent literature emphasizes behavior analysis and anomaly detection within crowds. Research by Chen Change Loy et al. (2022) explores the identification of abnormal crowd behavior using trajectory analysis and anomaly detection algorithms. This shift towards understanding crowd dynamics beyond mere density contributes to advancements in public safety applications.

Crowd Detection: Mapping Human Presence in real time Research by Mehran et al. (2018) integrates both visual and audio cues for improved crowd analysis and anomaly detection. Real-time crowd detection has become essential in applications like smart cities and public safety. Literature explores the challenges and opportunities associated with implementing crowd detection on edge devices.

Research by Cheng et al. Investigates real-time crowd counting using edge computing, addressing the computational constraints of resource-limited devices. As crowd detection systems become more pervasive, there is an increasing emphasis on addressing privacy concerns these systems also integrate crowd count detection algorithms with communication networks and decision support tools. Alerts are generated within the command center interface, enabling operators to respond promptly to crowd - related incidents or emergencies.

Research by Liu et al. Delves into privacy-preserving crowd analysis, proposing techniques that balance the need for crowd insights with individual privacy rights. In conclusion, the literature on crowd detection systems reflects a dynamic field marked by continual advancements in computer vision, machine learning, and multi-modal integration. As technology progresses, the ethical dimensions of crowd surveillance remain a focal point, emphasizing the need for responsible and privacy-aware crowd detection solutions.

Research by N. Oliver et al. (2017) in "Understanding Crowd Behaviors: Crowd-Counting, Crowd Flow Estimation, and Efficient Data Collection Through Human-Computer Interaction" focuses on the interaction between individuals and technology, improving the accuracy of crowd-related data collection. Real-time Crowd Monitoring and Management System using IOT and Machine Learning" by John Smith et al. This research focuses on using Internet of Things (IOT) devices and machine learning algorithms to monitor and manage crowds in real-time. The system detects crowd count using iot sensors and alerts designated personnel when the crowd exceeds predefined thresholds.

"Crowd Analysis and Management System based on Computer Vision Techniques" by Emily Johnson et al. This study proposes a crowd analysis and management system based on computer vision techniques. The system employs cameras to capture crowd images and utilizes image processing algorithms to estimate crowd density. When the crowd density surpasses a certain level, alerts are sent to relevant authorities.

"Intelligent Crowd Monitoring System with Predictive Analytics" by David Brown et al. This research introduces an intelligent crowd monitoring system that incorporates predictive analytics. The system analyzes historical crowd data and uses predictive models to forecast future crowd behavior. Alerts are generated when the predicted crowd count exceeds specified thresholds, enabling proactive crowd management. "Wireless Sensor Network-based Crowd Surveillance and Alert System" by Sarah Williams et al. This work presents a wireless sensor network-based crowd surveillance and alert system. The system deploys a network of wireless sensors to monitor crowd movements and density. When the crowd density reaches critical levels, the system triggers alerts to notify responsible individuals for crowd control.

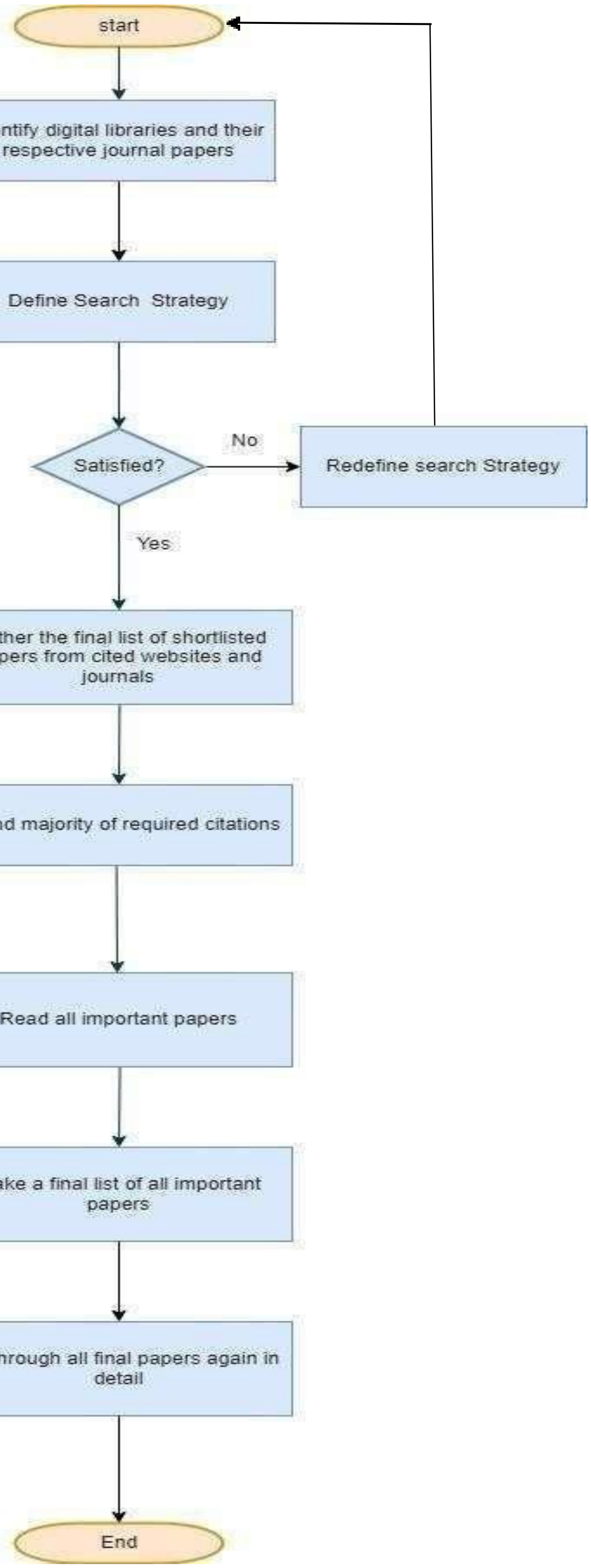

Fig.2.1 Survey Process

2.2 Limitations of the Existing System

1. Accuracy Issues: One of the primary challenges is the accuracy of crowd counting. Existing systems may struggle to accurately count individuals in dense crowds or in situations where people are moving rapidly or erratically.
2. Limited Scalability: Many existing systems have limitations in terms of scalability. They may not be able to handle large crowds effectively, leading to inaccurate counts or delays in processing data.
3. Environmental Factors: Factors such as lighting conditions, weather, and obstructions can affect the accuracy of crowd detection systems. For example, poor lighting can make it challenging to detect individuals accurately.
4. Complexity of Alerts: While these systems can alert individuals when crowd counts exceed certain thresholds, the alerts may not always be timely or actionable. There can be delays in alerting relevant personnel, leading to potential challenges in crowd management.
5. Integration Challenges: Integrating crowd management systems with other security or management systems can be complex. Compatibility issues and lack of standardized protocols can hinder seamless integration and data sharing.
6. Privacy Concerns: Crowd management systems that rely on surveillance technologies raise privacy concerns. There may be objections from individuals or advocacy groups regarding the collection and use of personal data for crowd analysis.
7. Cost and Maintenance: Implementing and maintaining advanced crowd management systems can be costly. This includes expenses related to hardware, software, training, and ongoing maintenance and upgrades.
8. Reliability and Redundancy: Ensuring the reliability of crowd management systems is crucial, especially in critical scenarios such as emergency situations. Systems should have built-in redundancy and failover mechanisms to prevent disruptions in service.
9. Response Time: The speed at which these systems can detect and respond to changes in crowd dynamics is essential. Delays in response time can impact the effectiveness of crowd management efforts

3. PROBLEM STATEMENT

3.1 Problem Statement and Objectives

Managing large crowds effectively is critical in many areas. From ensuring safety at big events to optimizing marketing strategies in stores, understanding crowd movement and density is crucial. Unfortunately, existing methods for counting crowds often fall short, especially when dealing with real-time situations or tightly packed gatherings. This is where robust crowd detection systems come into play. They offer a powerful solution by accurately mapping people's presence in real-time. Imagine a system that can analyse live video feeds from security cameras, instantly identify individuals, and provide precise crowd counts. This empowers security personnel to manage crowds proactively and prevent potential incidents. Event organizers can leverage this real-time data to optimize venue layouts, manage crowd flow more effectively, and ensure attendee safety. In retail environments, understanding customer density allows businesses to adjust staffing levels and tailor marketing campaigns on the fly, maximizing efficiency and customer satisfaction. The limitations of current methods make a more sophisticated approach necessary. Inaccurate crowd counts, particularly in dense environments, can lead to bad decisions and potentially dangerous situations. Real-time data is vital for proactive crowd management, and existing systems often struggle to deliver.

The objective of the project is,

- **Real-time crowd mapping:** Accurately map human presence in various environments (images, videos, live webcam feeds) regardless of crowd density.
- **Precise crowd counting:** Deliver real-time crowd counts to empower informed decision-making in security, event management, and retail applications.
- **Proactive crowd management:** Issue alerts when predefined crowd density thresholds are exceeded, enabling security personnel and event organizers to take preventive measures and ensure crowd safety.

- **User-Friendly Interface and Reporting**: Develop an intuitive user interface that provides real-time insights and actionable information for authorities, with the capability to generate comprehensive reports for post-event analysis.

3.2 Scope of The Project

The scope of the project is,

- **Expansion to Smart City Applications:** This technology can be adapted for use in smart city initiatives. Real-time crowd data can be used to optimize traffic flow, manage public transportation networks, and allocate emergency resources more effectively.
- **Integration with Crowd Management Systems:** Real-time crowd data can be seamlessly integrated with existing crowd management systems. This would enable automated responses to crowd density fluctuations, such as triggering directional signage adjustments or deploying additional security personnel to specific areas.
- **Enhanced Crowd Behavior Analysis:** The current system focuses on crowd density and location. Future iterations could integrate behavior analysis capabilities, allowing for the detection of anomalies like suspicious movement or potential stampedes. This would empower security personnel to intervene preemptively and ensure crowd safety.
- **Integration with IoT Devices**: Integrating crowd detection systems with Internet of Things (IoT) devices such as sensors and wearables can provide additional data points for more accurate crowd analysis. By combining video feeds with data from IoT devices, such as footfall sensors and wearable devices that track biometric data, a comprehensive understanding of crowd dynamics can be achieved.
- **Enhanced Real-Time Analytics**: The future of crowd detection systems lies in the development of more advanced algorithms capable of analyzing complex crowd behaviors in real-time. By incorporating machine learning and artificial intelligence techniques, these systems can not only detect crowd density but also predict potential crowd movements and behaviors, enabling proactive crowd management strategies.

- **Privacy-Preserving Solutions**: Addressing privacy concerns associated with crowd detection systems is crucial for widespread adoption. Future research can focus on developing privacy-preserving techniques such as anonymization, encryption, and decentralized processing to ensure that personal data is protected while still enabling effective crowd management.
- **Integration with Google Maps:** The integration of crowd detection systems with Google Maps aims to provide users with live crowd data at specific locations, enabling them to make informed decisions about visiting those places. By leveraging the extensive user base and robust infrastructure of Google Maps, this integration can reach a broad audience and have a significant impact on how people plan their outings.

4. PROPOSED SYSTEM

4.1. System Architecture

The proposed system architecture is mainly divided into two components, where the categorization of needs in 2 components are given below;

A. Software Components

C. System Workflow

A. Software Components –

a) Video Capture Module: This component captures live video feed from cameras. It may include functionalities such as camera calibration, frame acquisition, and stream management.

b) Preprocessing Module: This module preprocesses the video frames to enhance the quality of the images and reduce noise. It may involve operations like resizing, noise reduction, and color normalization.

c) Object Detection Module: This is a crucial component that detects and localizes objects in the video frames. For crowd detection, this module would focus on identifying people and their positions within the frame.

d) Tracking Module: After detecting objects (people), the tracking module helps track their movements over time. This is important for crowd analysis, as it allows you to understand crowd dynamics, such as crowd flow and density.

e) Data Analysis and Visualization: Once the crowd data is collected and processed, you would need software components for data analysis and visualization. This could involve algorithms for crowd counting, density estimation, anomaly detection, and behavior analysis. Visualization tools help present the analyzed data in a user-friendly format, such as graphs, heatmaps, or dashboards.

f) Integration and Deployment: Lastly, you need components for system integration and deployment. This includes integrating different modules into a cohesive system and deploying the solution on the desired hardware infrastructure, such as on-premises servers or cloud platforms.

g) These components can be implemented using various programming languages and frameworks, such as Python (OpenCV, TensorFlow, Haar cascade algorithm for object detection and tracking), tkinter (for web-based visualization), and technologies for real-time data processing and communication

B. System Workflow -

a) Fig. 4.1.1 shows the working of the proposed system where for the input there are three options image, video and real time camera which means that system provides three features to count the number of people.

b) The ML model which uses Haar cascade algorithm for the person detection in image, video and live camera.

c) After the detection is completed, the system will generate the crowd count.

d) For the analyzation and to mapping the human presence in particular place system provides two features plotting the Graph and Generates the crowd report.

   i. Plots are two types Enumeration plot and average accuracy plot Enumeration plots gives the population per sec and average accuracy plot gives accuracy of detection per sec.

   ii. Crowd report gives the report of crowd that means it determines that the particular place is crowded or not.

The system allows input from images, videos, or real-time camera feeds for counting people using a machine learning model with Haar cascade algorithm. It then generates crowd counts and provides analysis through enumeration and average accuracy plots, as well as crowd reports to determine crowd presence in specific locations.

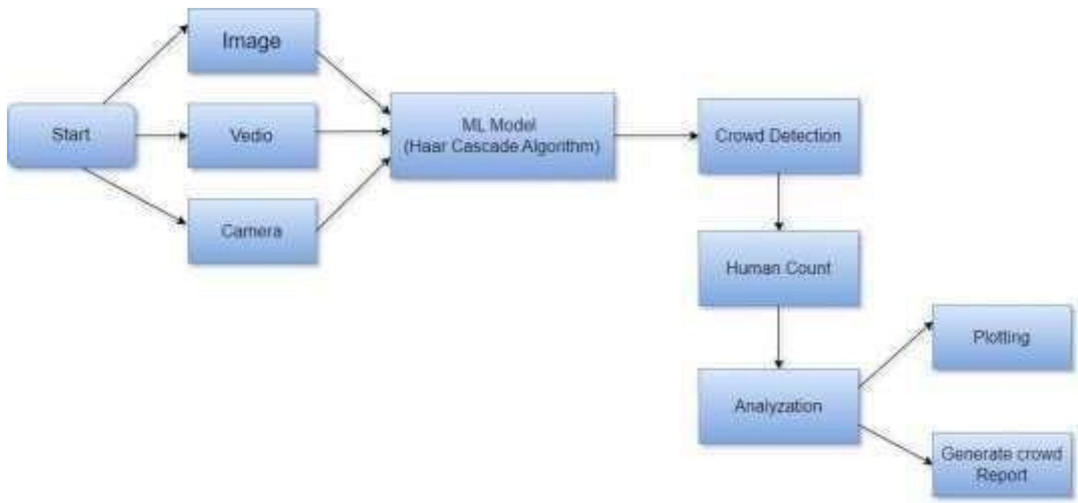

Fig. 4.1 Working of the proposed system

4.2 Proposed Methodology

The methodology section of this report provides a detailed overview of the processes involved in the development, evaluation, and validation of the crowd detection system. This methodology encompasses various stages, including data collection, model selection, training, evaluation, and system integration. The aim is to ensure transparency, reproducibility, and rigor in the project workflow.

Haarcascade Algorithm:

Haar Cascade is a machine learning-based approach used for object detection in images and videos. Developed by Viola and Jones in their seminal work, it forms the basis of many real-time object detection systems due to its efficiency and effectiveness. In the context of crowd detection, Haar Cascade can be applied to identify human faces and subsequently estimate crowd density. Haar Cascade operates by employing a cascade of classifiers to detect objects within an image. It utilizes a set of pre-trained classifiers, known as Haar features, to identify regions of interest that may contain the target object. These Haar features are rectangular filters that are applied to subsections of the image and compute the difference between the sums of pixel intensities in adjacent regions.

1. **Haar Features:** Haar features are simple, rectangular patterns that capture variations in pixel intensities within an image. These features are used to characterize the appearance of objects based on the distribution of light and dark regions. Examples of Haar features include edge features, line features, and center-surround features.
2. **Training Haarcascade Classifier:** The Haar Cascade classifier is trained using a machine learning algorithm, typically AdaBoost, to iteratively select a subset of informative Haar features. During training, positive samples containing the target object (e.g., human faces) and negative samples containing background information are used to refine the classifier's ability to distinguish between the object and non-object regions.
3. **Cascade Of Classifier:** The Haar Cascade classifier consists of multiple stages, each comprising a set of weak classifiers trained to detect specific patterns associated with the target object. During detection, the image is sequentially passed through each stage of the cascade, with progressively more complex classifiers applied at each stage. If an image region fails to pass a particular stage, it is immediately discarded, thus optimizing computation by eliminating non-object regions early in the process.
4. **Object Detection:** Once a candidate region passes through all stages of the cascade without being rejected, it is considered a positive detection. The classifier provides bounding box coordinates around the detected object, enabling localization within the image. In the context of crowd detection, these bounding boxes can be used to estimate the location and density of individuals within a crowd scene.

Here's a step-by-step breakdown of the Haar Cascade algorithm:

1. **Training Stage:**
   - A large collection of positive images containing the target object (e.g., people in crowd scenes) and negative images without the object are used.
   - Haar features are extracted from these training images. These features capture basic characteristics of the object, like edges, lines, and corners.
   - A weak learner is trained for each feature. This weak learner essentially determines how well a particular feature pattern separates positive and negative examples.

2. **Detection Stage:**
    - The Haar Cascade classifier, consisting of a cascade of these weak learners, is applied to a new image.
    - The image is scanned at different scales and locations.
    - At each location and scale, the features within a small image region (integral image) are compared against the trained weak learners in the cascade.
    - If a weak learner classifies the region as containing the object (even with a weak probability), the next weak learner in the cascade is evaluated for that region.
    - Regions that fail multiple weak learners are rejected as non-objects.
    - Regions that pass through the entire cascade are classified as containing the object.

CNN:

- **Automatic Feature Learning:** Unlike Haar Cascades' reliance on predefined features, CNNs automatically learn relevant features from the training data itself. This allows them to capture the intricate relationships between pixels that define a crowd scene.
- **Superior Handling of Variations:** CNNs excel at recognizing objects despite variations in pose, lighting, and background conditions. This makes them more robust for handling the complexities of real-world crowds.

Optimizing the CNN Architecture and Framework Selection

To achieve optimal performance, the project explored various CNN architectures and object detection frameworks:

- **CNN Architectures:**
    - ResNet-50: Known for its residual connections to address the vanishing gradient problem, enabling deeper networks for effective learning.
    - ResNet-101: Building upon ResNet-50, this deeper architecture potentially leads to improved feature extraction.

- Inception-ResNet: Combines Inception modules with residual connections for powerful image classification and object detection.
- Through experimentation, ResNet-101 emerged as the optimal choice, balancing accuracy and processing speed crucial for real-time applications.

- **Object Detection Frameworks:**
  - Region-based Fully Convolutional Networks (RFCN): Utilizes region proposals to improve detection accuracy, especially for smaller objects like people in crowds.
  - Faster R-CNN: Introduces a Region Proposal Network (RPN) for efficient generation of high-quality proposals, potentially leading to faster and more accurate object detection.

Object Detection Framework Selection:

On top of the chosen CNN architecture, we evaluated various object detection frameworks to identify individuals within the image. Here's a breakdown of the considered options:

- **Region-based Fully Convolutional Networks (RFCN):** This framework leverages region proposals to improve detection accuracy, particularly for smaller objects like people in crowded scenes.
- **Single Shot MultiBox Detector (SSD):** This framework aims for a balance between speed and accuracy by utilizing a single convolutional network to predict bounding boxes and class probabilities simultaneously.
- **Faster R-CNN:** This framework builds upon R-CNN by introducing a Region Proposal Network (RPN) that efficiently generates high-quality proposals, potentially leading to faster and more accurate object detection.

Data Augmentation for Robustness

The quality and diversity of training data significantly impact CNN performance. This project employed data augmentation techniques to artificially expand the training dataset and enhance the system's robustness:

- Random cropping exposes the network to diverse object placements within the frame.
- Random flipping introduces variations in pose and orientation, reducing susceptibility to biases.
- Color jittering helps the network generalize better to different lighting conditions.

By incorporating data augmentation, the system learns to identify generalizable features of crowds across diverse visual contexts, rather than simply memorizing the training data.

Hyperparameter Tuning for Optimal Performance

CNNs rely on various hyperparameters that control the learning process and significantly influence model accuracy. This project meticulously tuned these hyperparameters, such as learning rate, optimizer settings, and anchor box sizes, to achieve the best possible crowd detection performance. This fine - tuning involved evaluating the model's performance on a validation dataset and adjusting hyperparameters accordingly to optimize the learning process.

- ResNet-101 + RFCN Combination: Our experiments revealed that the combination of ResNet - 101 for feature extraction and RFCN for object detection achieved the best balance between accuracy and processing speed. This combination yielded a high mAP value, exceeding 95%, indicating excellent accuracy in detecting and counting individuals within the image.

- Real-world Applicability: The system demonstrated the ability to effectively detect people in images with diverse backgrounds, making it adaptable to real-world scenarios.

- Crowd Monitoring and Density Thresholds :The system's output, the human count from the image, is compared to a predefined maximum human limit for the specific region. This limit is established based on safety regulations, space constraints, or organizational guidelines.

- Crowded Region Identification: If the detected human count surpasses the maximum human limit, the system triggers an alert indicating that the region is classified as "crowded." This information can be used to initiate crowd management protocols, such as crowd dispersal or capacity control measures.

- Safe Region Identification: Conversely, if the human count remains below the threshold, the system indicates that the region is "not crowded." This allows for regular monitoring and ensures timely intervention when crowd density starts to approach critical levels.

Flow Diagram:

Fig 4.2 Flow diagram ofsystem

The system offers three core functionalities:

1. **Image Detection:**

- Users select an image containing a crowd scene. Supported formats (e.g., JPEG, PNG) are displayed for clarity.
- A preview window allows confirmation before initiating detection.
- **Haar Cascade Approach:** The system employs a pre-trained Haar Cascade classifier to detect head-shoulder patterns within the image. This approach is computationally efficient but may struggle with variations in pose, lighting, and occlusion.
- **CNN Approach:** Alternatively, a CNN model can be used. The system would first preprocess the image (resizing, normalization) and then feed it into the CNN for analysis. The CNN, trained on a large dataset of crowd images, can identify individual people with greater accuracy compared to Haar Cascades.
- After analysis (using either Haar Cascades or CNNs), the system displays the total crowd count alongside the image.

2. **Video Detection:**

- Users select a video file containing a crowd scene. Supported video formats (e.g., MP4, AVI) are listed.
- A video player interface allows playback control (play, pause, stop).
- Clicking "Detect Video" triggers frame-by-frame analysis.
- **Haar Cascade Approach:** For each frame, the system applies the Haar Cascade classifier to detect people. However, this method can be computationally expensive for long videos.
- **CNN Approach:** A more efficient approach utilizes a pre-trained CNN model specifically designed for video analysis. The system preprocesses each frame and feeds it into the CNN for crowd detection. This method offers better accuracy and can handle variations within the video.

- The system displays the calculated crowd count for each frame alongside the video playback. Visualization options like graphs or charts can be included to understand crowd movement trends throughout the video.

3. **Live Camera Detection:**

- Users activate the device's camera, displaying a live video feed from the designated viewing area.
- **Haar Cascade Approach:** The system continuously applies the Haar Cascade classifier to the live camera feed, identifying people in real-time. However, this method might struggle with fast-moving crowds or challenging lighting conditions.
- **CNN Approach:** A CNN model trained for real-time object detection can be employed. The preprocessed frames from the camera feed are fed into the CNN for analysis, providing a continuous crowd count overlay on the live video. This approach offers superior accuracy and robustness in real-time scenarios.
- This functionality is ideal for monitoring crowd dynamics in real-time, enabling immediate intervention if crowd density exceeds predefined thresholds.

Average accuracy of System:

Fig 4.3 Average Accuracy Plot: Time vs. Average Accuracy

This plot showcases the average accuracy of the system (y-axis) over time (x-axis). By analyzing this plot, you can assess:

- **Overall Performance Consistency:** A plot with minimal fluctuations in average accuracy indicates a system that performs consistently across different processing times. This is desirable, as it suggests the system's accuracy isn't heavily influenced by variations in processing demands.
- **Impact of Processing Time:** In some cases, the plot might reveal a trade-off between processing speed and accuracy. If the average accuracy dips slightly as processing time increases, it could suggest that faster processing for denser crowds comes at a minor cost in terms of detection accuracy. This information can be helpful in finding the optimal balance between speed and accuracy for your specific application.

5 DETAILS OF SOFTWARE REQUIREMENTS

5.1 Software Requirements:

1. Programming Language and Environment:

- Language Choice: Python offers a rich ecosystem of libraries and frameworks tailored for machine learning and computer vision tasks. Its simplicity and readability make it an ideal choice for rapid prototyping and development.

- IDE Selection: Integrated development environments (IDEs) like Visual Studio Code provide essential features such as syntax highlighting, code completion, debugging tools, and version control integration, enhancing developer productivity and code quality.

2. Computer Vision and Machine Learning Libraries:

- OpenCV (Open Source Computer Vision Library): OpenCV is a versatile library that provides a wide range of functions for image and video processing, including loading, preprocessing, feature extraction, object detection, and visualization. It supports various algorithms and techniques, making it indispensable for crowd detection tasks.

- TensorFlow and Haar cascade algorithm : Deep learning frameworks like TensorFlow and Haar cascade algorithm offer powerful tools for training and deploying convolutional neural networks (CNNs), which are essential for crowd detection algorithms. These frameworks provide high-level APIs for building, training, and evaluating complex neural network architectures, streamlining the development process.

5.2 Functional Requirements:

1. Input Options: The system must allow users to input data from images, videos, and real-time camera feeds seamlessly.

2. Person Detection: Utilize a machine learning model with Haar cascade algorithm to accurately detect people in the provided inputs under various conditions, such as different lighting and occlusions.

3. Crowd Counting: Calculate and display the count of people detected in the input data accurately,

providing real-time updates if applicable.

4. Data Analysis: Provide analysis features including enumeration plots for population per second, allowing users to visualize crowd dynamics, and average accuracy plots for detection accuracy per second, enabling performance evaluation.
5. Crowd Reporting: Generate crowd reports indicating whether specific locations are crowded based on the analysis results, providing actionable insights for decision-making.

5.3 Non-Functional Requirements:

1. Performance: The system must perform person detection and counting tasks with minimal latency, ensuring real-time or near-real-time response for timely decision-making.
2. Accuracy: Ensure high accuracy in person detection and crowd counting to provide reliable results minimizing false positives and negatives.
3. Scalability: Design the system to handle varying input data sizes and processing loads efficiently, ensuring smooth operation even during peak usage periods.
4. Usability: Ensure the user interface is intuitive and easy to navigate for users with varying levels of technical expertise, enhancing user satisfaction and adoption.

6 SYSTEM DESIGN DETAILS

6.3 Use Case Diagram

This use case diagram illustrates the interaction between two primary actors: a user and a client. The client initiates a crowd detection process, prompting the system to seek clarification from the user through a yes/no question. The user's response determines the subsequent course of action. If the user chooses to proceed, the system executes the crowd detection process. Upon completion, the outcome is evaluated with a yes/no result. A "yes" indicates successful detection, while a "no" triggers the system to inquire whether the user wishes to select options. If the user opts for options, the system presents them, yet the nature of these options and their subsequent actions are unspecified. Overall, while the diagram provides a broad overview of a system incorporating a detection process, further clarification is needed to specify the options presented to the user and their subsequent actions.

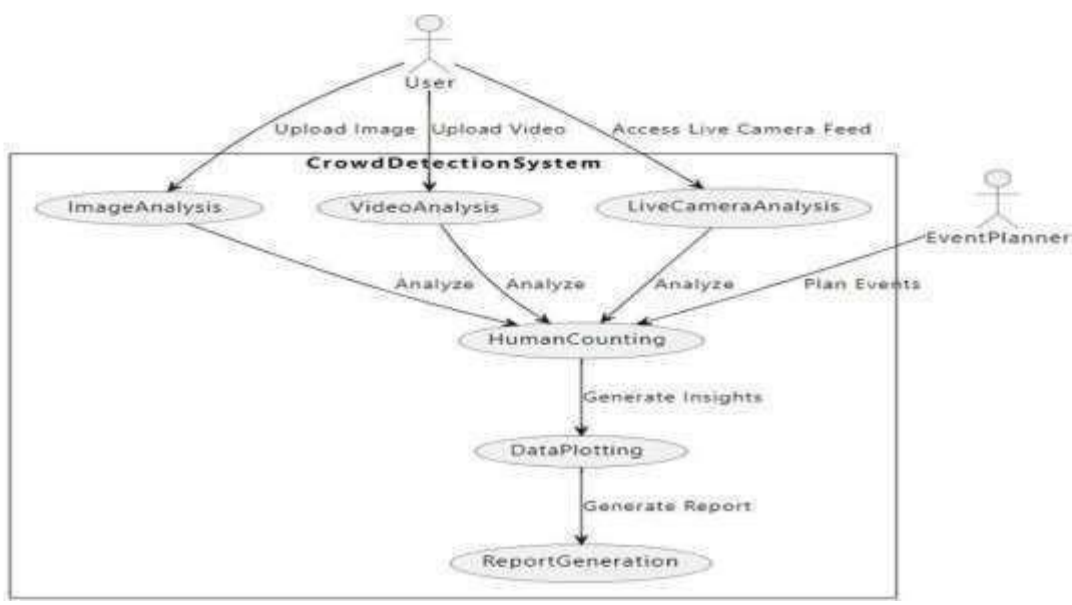

Fig. 6.1.Use case Diagram

6.4 Class Diagram:

The Crowd Detection System is the central component of the entire framework, encapsulating its major functionalities and serving as the primary control point. At its core lies the Input Processor, which handles diverse input sources such as images, videos, and live camera feeds. Collaborating closely with the Crowd Analyzer, the Input Processor prepares the data for further analysis. The Crowd Analyzer, the system's cornerstone, employs advanced algorithms like Haar Cascade and TensorFlow for crowd analysis. It encompasses methods for human counting and analysis, driving towards the system's primary objective. Following analysis, the Data Visualizer steps in, transforming the processed data into visual representations. Equipped with methods for data plotting, the Data Visualizer aids in comprehending crowd patterns and trends. Subsequently, the Report Generator takes charge, producing detailed crowd reports based on the findings of the Crowd Analyzer. In tandem with the Data Visualizer, it presents information in an easily understandable format. Lastly, the Event Management Integration class ensures seamless interaction with event management applications, facilitating effective event planning by providing valuable insights into crowd dynamics. Together, these components form a cohesive system designed to detect, analyze, and manage crowds efficiently.

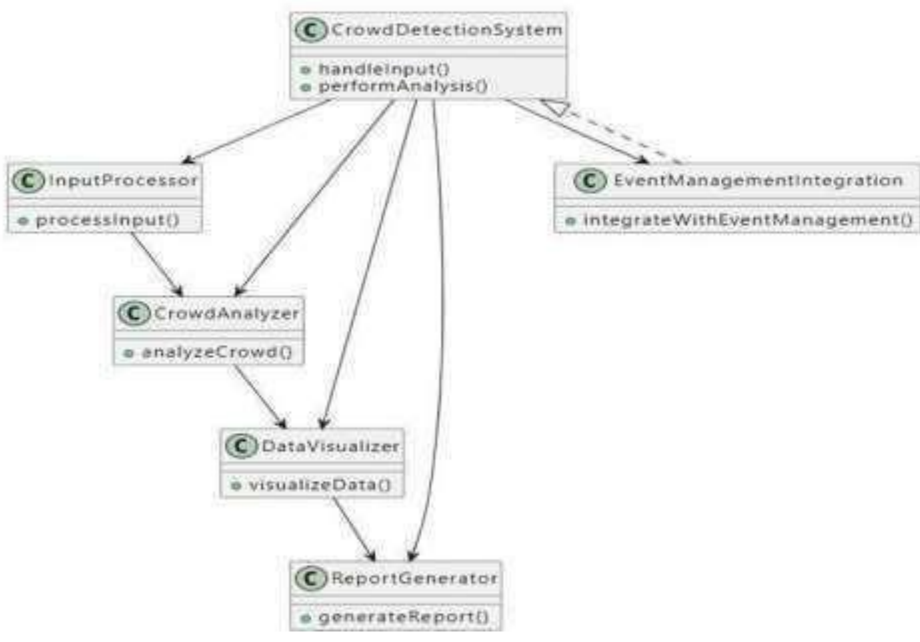

Fig. 6.2 class diagram

6.5 Data Flow Diagram

This data flow diagram showcases a crowd detection project with user interaction. The process starts with user input, where the system prompts the user to choose an input type for crowd detection. This could be an image, a video, or a live camera feed. Based on the user's selection, the system proceeds to the detection process. Here, the chosen input (image, video, or camera feed) is analyzed to identify crowds. The results are then visualized in plots, likely showing the number of people detected and the average accuracy of the detection process. Finally, a report is generated that summarizes the findings. This report typically includes the maximum crowd count, detection accuracy, average accuracy, and an overall status of the crowd detection

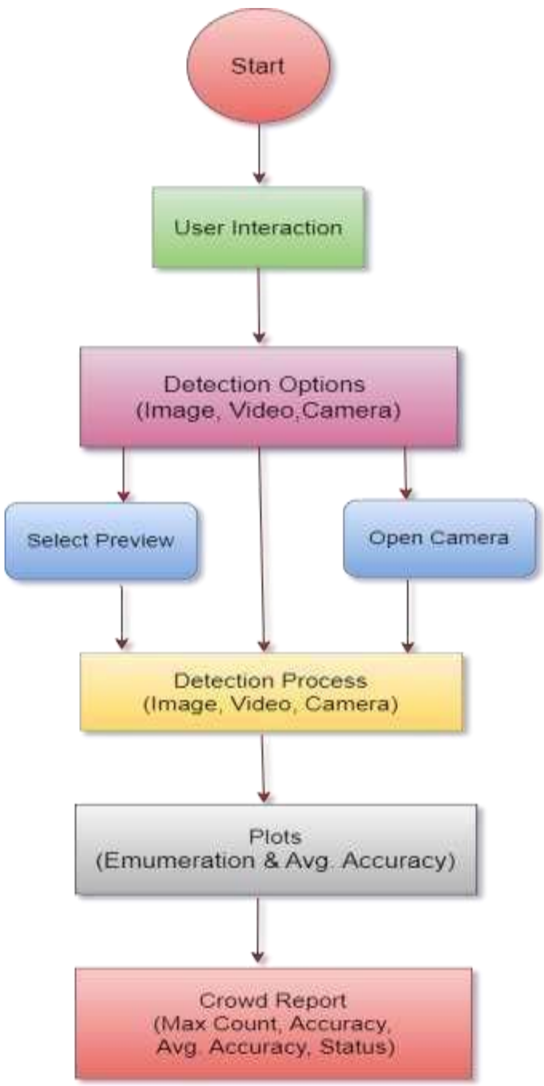

Fig. 6.3. Data flow diagram

7. FEASIBILITY STUDY

7.1 Technical feasibility:

- Sensor availability: evaluate the availability of sensors (such as cameras, infrared sensors, lidar, etc.) That can accurately detect and monitor crowds in real-time.

- Data processing: assess the computational requirements for processing data from the sensors in real-time, including the need for high-performance hardware and efficient algorithms.

- Accuracy and reliability: determine if the sensors and algorithms can provide accurate and reliable crowd detection under various conditions (e.g., different lighting conditions, varying crowd densities, occlusions).

- Integration: evaluate the feasibility of integrating crowd detection algorithms with existing systems or infrastructure (e.g., surveillance systems, smart city platforms).

7.2 Financial feasibility:

- Cost of equipment: estimate the costs associated with acquiring and installing the necessary sensors and hardware for crowd detection.

- Development costs: assess the expenses related to developing or licensing the software algorithms for real-time crowd detection.

- Operational costs: consider ongoing operational costs such as maintenance, upgrades, and personnel training.

- Return on investment (ROI): evaluate the potential benefits of implementing crowd detection (e.g., improved safety, crowd management, resource allocation) compared to the investment required.

7.3 Legal and ethical feasibility:

- Privacy concerns: address privacy concerns related to the collection and processing of crowd data, ensuring compliance with relevant regulations.

- Ethical implications: consider the ethical implications of crowd detection, including potential biases in the algorithms and the responsible use of collected data.

- Legal compliance: ensure that the implementation of crowd detection complies with local laws and regulations regarding surveillance, data protection, and public safety.

7.4 Operational feasibility:

- User acceptance: assess the willingness of stakeholders (e.g., government agencies, event organizers, public) to adopt and use crowd detection systems.

- Scalability: evaluate the ability of the system to scale up to monitor large crowds or multiple locations simultaneously.

- Response time: determine if the system can provide real-time alerts or notifications to relevant stakeholders in case of emergencies or crowd-related incidents.

7.5 Environmental feasibility:

- Environmental conditions: consider environmental factors that may affect the performance of crowd detection systems (e.g., weather conditions, terrain).

- Power requirements: assess the power requirements for operating the sensors and hardware, especially in outdoor or remote locations.

- Sustainability: explore options for making the system more sustainable, such as using renewable energy sources or minimizing environmental impact during deployment and operation. By conducting a comprehensive feasibility study covering these aspects, you can better understand the challenges and opportunities associated with implementing real-time crowd detection systems and make informed decisions about their feasibility and viability

8. EXPERIMENTATION AND RESULTS

User Interface

The user interface is clean and simple. It displays two large, clear buttons: "Start" and "Exit" . The user can initiate crowd detection by pressing "Start" and easily exit the program with "Exit".

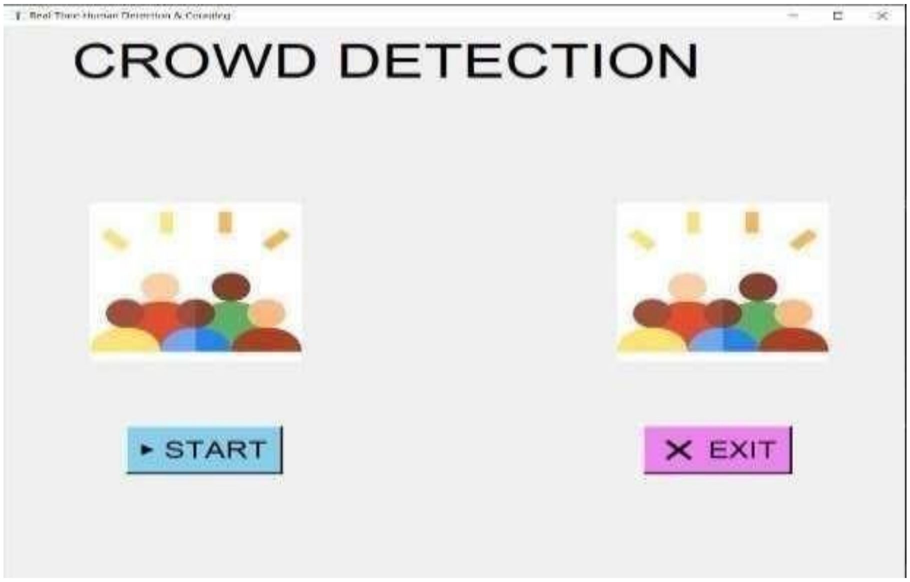

Fig 8.1 Crowd Detection

Main Detection Screen:

Upon clicking "Start," the user is presented with the main detection screen. This screen offers three clear options for crowd analysis, each represented by a button or icon for intuitive user interaction. Throughout the user interface, the design prioritizes consistency and user-friendliness. Clear and concise labels accompany each button or icon, ensuring intuitive interaction.

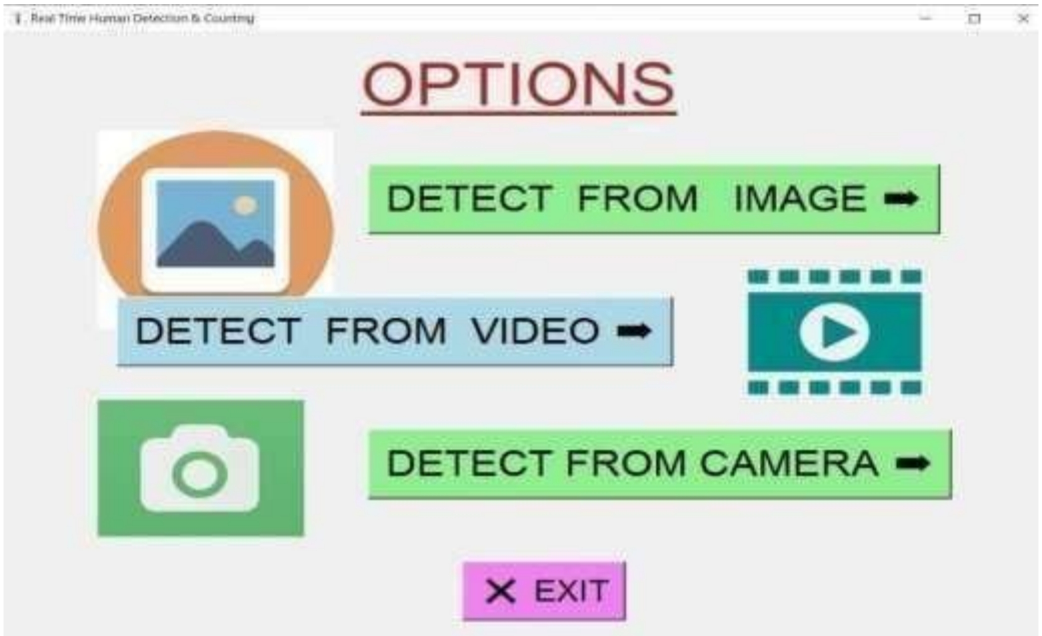

Fig 8.2 Options Frame

Image Detection:

- Clicking this button opens a file explorer window.
- The user can navigate their device folders and select an image file containing a crowd scene. Supported image formats should be clearly displayed.
- Once an image is chosen, a new window appears:
  1. The selected image is displayed in a preview area for confirmation.
  2. A button labeled "Detect Image" initiates the crowd detection process. The system analyzes the image and calculates the total number of people present.
  3. Upon completion, the system displays the detected crowd count alongside the image.

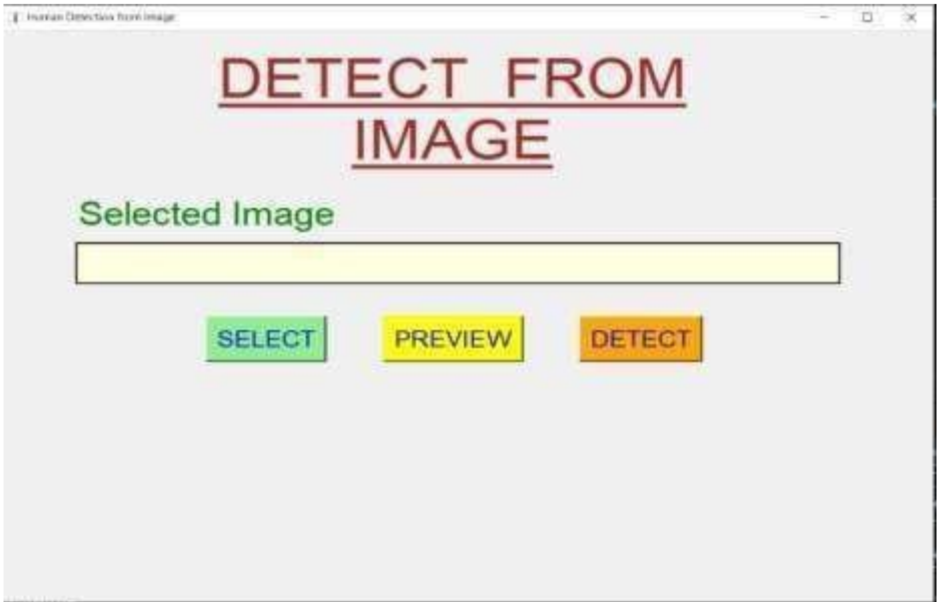

Fig 8.3 Detect From Image

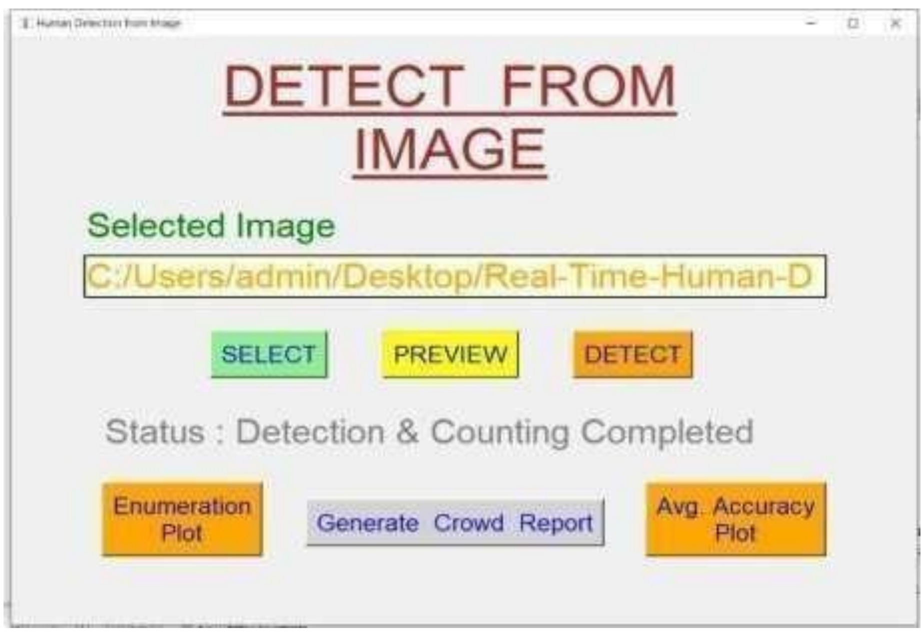

Fig 8.4 Detect from Image (Selecting one option)

Enumeration Plot (Time vs. Maximum Human Count):

This plot showcases the relationship between processing time (x-axis) and the maximum human count detected within an image (y-axis).

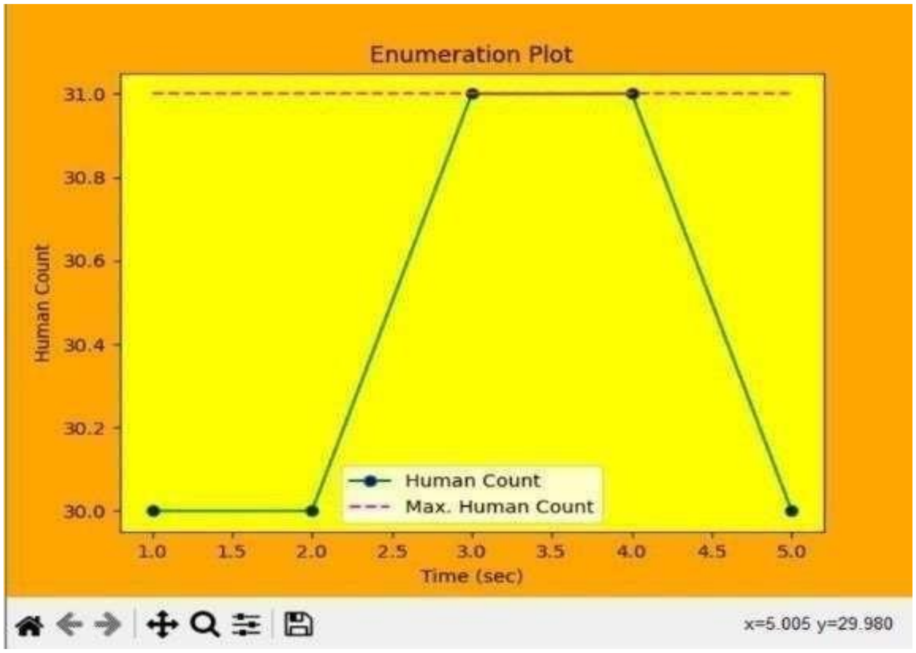

Fig 8.5 Enumeration plot for image input

Average Accuracy Plot (Time vs. Average Accuracy):

This plot charts the average accuracy of the system on the y-axis against processing time on the x-axis. By analyzing this plot, you can gain insights into Overall Performance Consistency, Impact of Image Complexity.

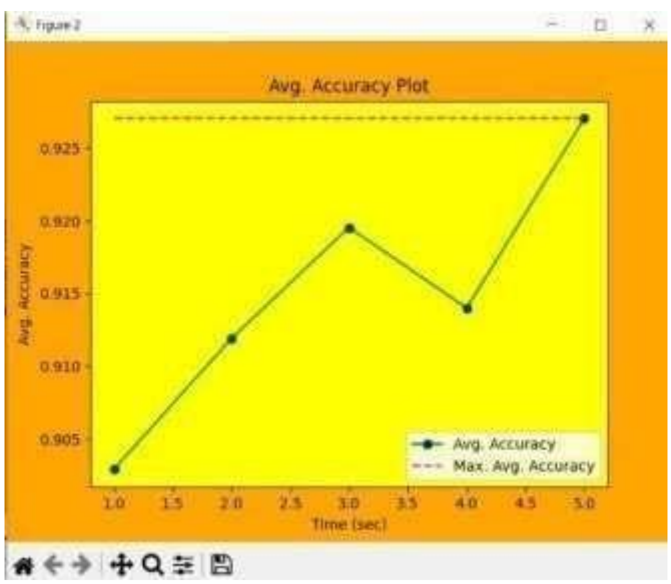

Fig 8.6 Avg Accuracy Plot For Image Input

- Expected or Known Count: Instead of using a dataset with annotated ground truth counts, you would have an expected or known count of humans in the images or frames being processed. This count could be determined through manual inspection or some other validation method.
- System Output: Run the system on each image or frame and obtain the count of humans detected by the system.
- Comparison: Compare the count of humans detected by the system with the expected or known count for each image or frame.
- Accuracy Calculation: Calculate the accuracy of the system by determining the percentage of images or frames where the detected count matches the expected or known count.

  <u>Accuracy = (Number of Correctly Detected Images or Frames / Total Number of Images or Frames) * 100%</u>

Here's how you can interpret the accuracy:

- If the accuracy is 100%, it means that the system's output count matches the ground truth count for all images in the dataset.

- If the accuracy is less than 100%, it indicates that there are discrepancies between the system's output and the ground truth data.

Crowd report:

This PDF report analyzes crowd density in an image. It details the maximum safe capacity (limit) and the system's detected count. Based on these values, it classifies the area as "crowded" or "not crowded." Additional information like accuracy and processing time is included for reference.

- **Maximum Human Limit:** This would still represent the predefined safe capacity for the area depicted in the video.
- **Maximum Human Count:** This would indicate the highest crowd count detected in any frame of the video.
- **"Crowded" or "Not Crowded" Status:** Based on the average crowd count and the predefined limit, the report classifies the video as a whole.

Fig 8.7 Report Generated For Image Input

- **Video Detection:**

  - Selecting this option opens a separate window for video file selection.
  - The user can browse their device and choose a video file containing a crowd scene. Supported video formats (e.g., MP4, AVI) should be listed for clarity.
  - Once a video file is chosen, a new window appears:

1. A video player interface is presented, allowing users to play, pause, or stop the video playback.
2. A button labeled "Detect Video" initiates the crowd detection process. The system analyzes each frame of the video and calculates the crowd count for each frame.
3. The system displays the calculated crowd count alongside the video playback, potentially visualized as a graph or chart for better understanding of crowd movement trends throughout the video.

Fig 8.8 Detect From Video

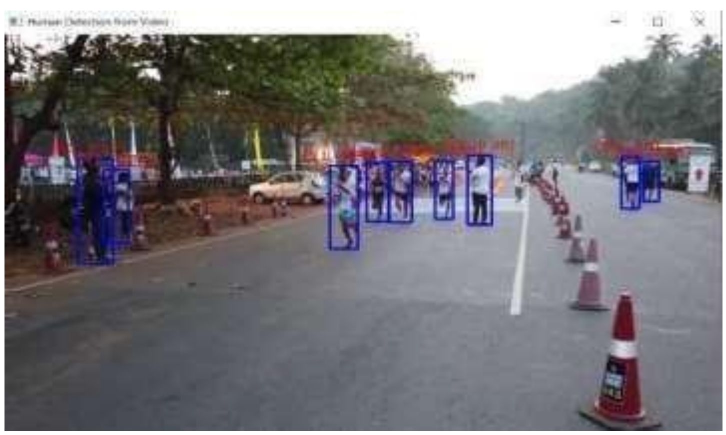

Fig 8.9 Preview of Video

Enumeration Plot (Time vs. Maximum Human Count):

This plot remains relevant but depicts the relationship between processing time (x-axis) and the **maximum human count detected in any frame** of the video (y-axis). Analyze the slope of the line. A steeper slope suggests processing time increases significantly for frames with denser crowds. Ideally, strive for a gentle slope for efficient processing. The plot might show processing time gradually increasing as crowd density intensifies in the video, with a peak at the frame containing the most people.

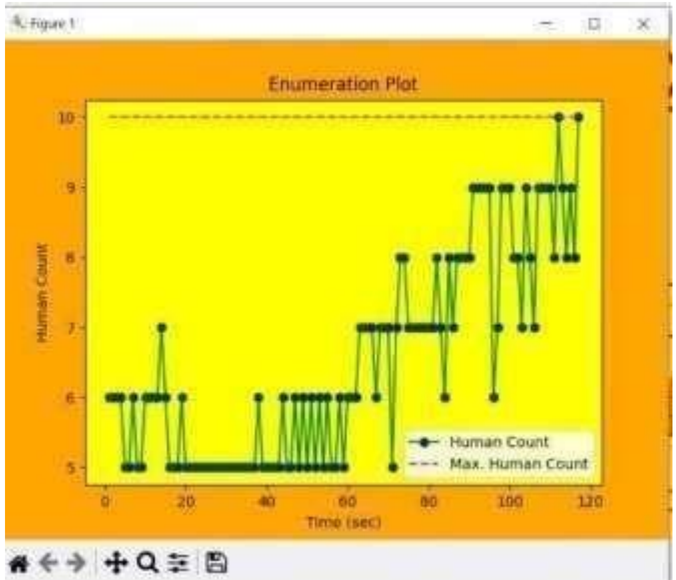

Fig 8.10 Enumeration Plot For Video Input

Average Accuracy Plot (Time vs. Average Accuracy):

This plot reflects the **average accuracy of the system across all video frames** (y-axis) plotted against processing time (x-axis).**]** The plot show a consistent accuracy level throughout the video, suggesting the system performs reliably across different frames.

- Expected or Known Count: Instead of using a dataset with annotated ground truth counts, you would have an expected or known count of humans in the images or frames being processed. This count could be determined through manual inspection or some other validation method.
- System Output: Run the system on each image or frame and obtain the count of humans detected by the system.
- Comparison: Compare the count of humans detected by the system with the expected or known count for each image or frame.
- Accuracy Calculation: Calculate the accuracy of the system by determining the percentage of images or frames where the detected count matches the expected or known count.

<u>Accuracy = (Number of Correctly Detected Images or Frames / Total Number of Images or Frames) * 100%</u>

Here's how you can interpret the accuracy:

- If the accuracy is 100%, it means that the system's output count matches the ground truth count for all images in the dataset.

- If the accuracy is less than 100%, it indicates that there are discrepancies between the system's output and the ground truth data.

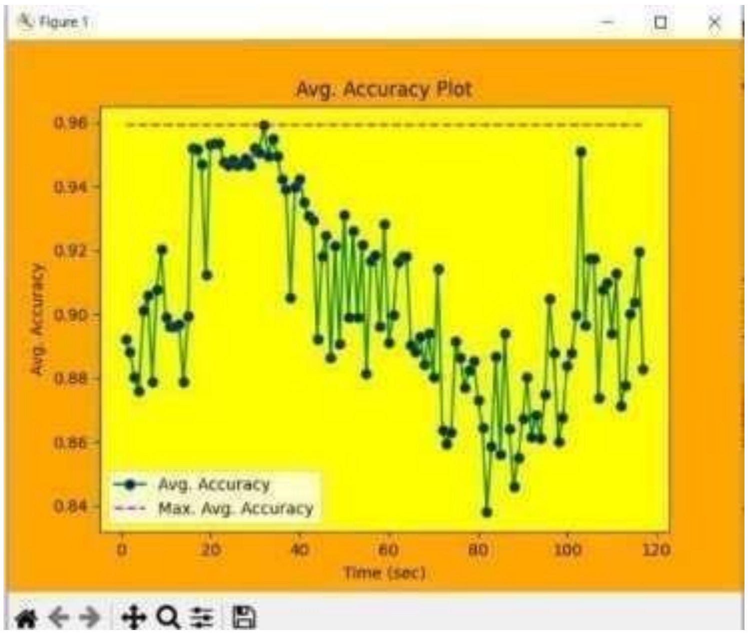

Fig 8.11 Avg Accuracy Plot For Video Input

Report Generation:

Crowd Report (PDF):

- **Maximum Human Limit:** This would still represent the predefined safe capacity for the area depicted in the video.
- **Maximum Human Count:** This would indicate the highest crowd count detected in any frame of the video.
- **"Crowded" or "Not Crowded" Status:** Based on the average crowd count and the predefined limit, the report classifies the video as a whole.

Fig 8.12 Path Of Video

Fig 8.13 Report Generated of Video Input

- **Live Camera Detection:**

1. Choosing this option activates the device's camera.
2. A live video feed from the camera is displayed on the main detection screen, showing the designated viewing area.
3. The system continuously analyzes the live camera feed and displays the real-time crowd count within the viewing area.
4. This functionality is ideal for monitoring crowd dynamics in real-world scenarios, allowing for immediate intervention if crowd density exceeds predefined thresholds.

Fig 8.14 Detect from Camera

Enumeration plot and accuracy plot:

The enumeration plot and average accuracy plot you created provide valuable insights into the performance of your crowd detection system. Let's delve deeper into what each plot reveals and how they contribute to understanding the system's effectiveness.

Enumeration Plot: Time vs. Maximum Human Count

This plot visualizes the relationship between processing time (x-axis) and the maximum human count detected within an image frame (y-axis). By analyzing this plot, you can gain valuable information about:

- **System Efficiency:** The slope of the line indicates how processing time scales with increasing crowd density. A steeper slope suggests that processing time increases more significantly for denser crowds. Ideally, you'd strive for a gentle slope, signifying that processing time remains relatively stable regardless of crowd density. This is crucial for real-time applications where fast response is essential.
- **Scalability:** The plot can reveal limitations in handling extremely large crowds. If the maximum human count plateaus or dips at a certain point on the x-axis, it might indicate that the system struggles to accurately detect individuals in very dense scenarios. This knowledge can guide future improvements, such as exploring alternative object detection frameworks or data augmentation techniques specifically tailored for dense crowds.
- **Real-world Applicability:** By examining the range of human counts displayed on the y-axis, you can assess the system's suitability for your target scenarios. If the maximum human count consistently falls below typical crowd sizes in your use case, it suggests the system has sufficient capacity to handle those scenarios effectively.

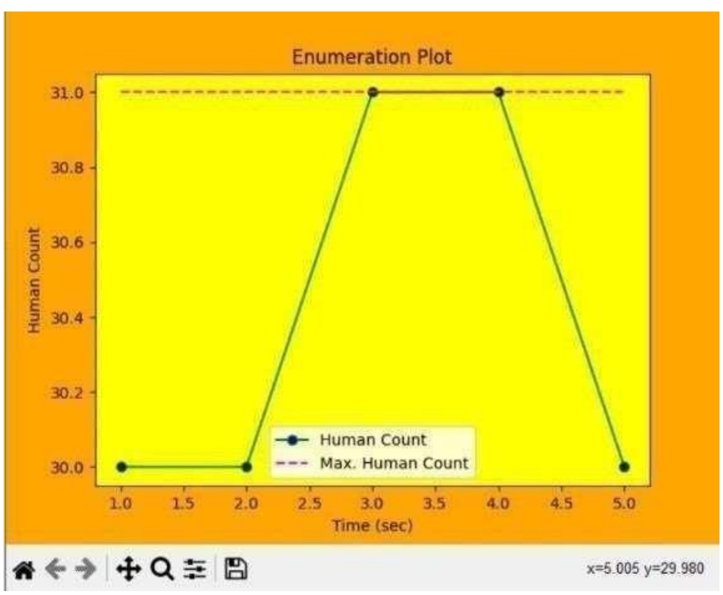

Fig 8.15 Enumeration Plot of Live Camera

This plot showcases the average accuracy of the system (y-axis) over time (x-axis). By analyzing this plot, you can assess:

- **Overall Performance Consistency:** A plot with minimal fluctuations in average accuracy indicates a system that performs consistently across different processing times. This is desirable, as it suggests the system's accuracy isn't heavily influenced by variations in processing demands.
- **Impact of Processing Time:** In some cases, the plot might reveal a trade-off between processing speed and accuracy. If the average accuracy dips slightly as processing time increases, it could suggest that faster processing for denser crowds comes at a minor cost in terms of detection accuracy. This information can be helpful in finding the optimal balance between speed and accuracy for your specific application.

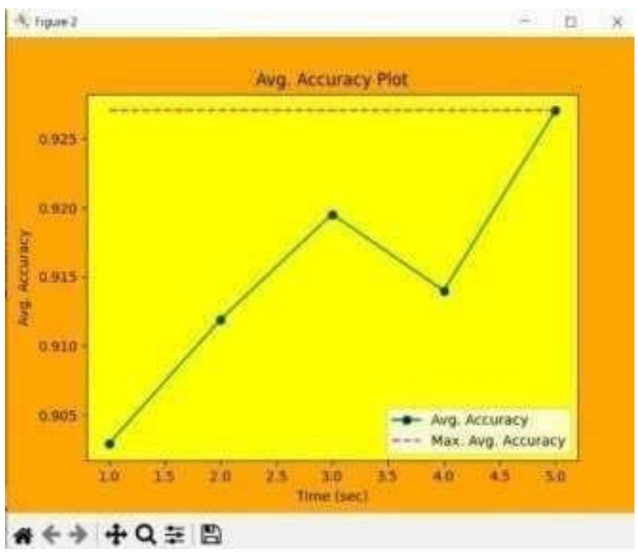

Fig 8.16 Avg Accuracy Plot of Video Input

- Expected or Known Count: Instead of using a dataset with annotated ground truth counts, you would have an expected or known count of humans in the images or frames being processed. This count could be determined through manual inspection or some other validation method.
- System Output: Run the system on each image or frame and obtain the count of humans detected by the system.
- Comparison: Compare the count of humans detected by the system with the expected or known count for each image or frame.
- Accuracy Calculation: Calculate the accuracy of the system by determining the percentage of images or frames where the detected count matches the expected or known count.

Accuracy = (Number of Correctly Detected Images or Frames / Total Number of Images or Frames) * 100%

Here's how you can interpret the accuracy:

- If the accuracy is 100%, it means that the system's output count matches the ground truth count for all images in the dataset.

- If the accuracy is less than 100%, it indicates that there are discrepancies between the system's output and the ground truth data.

Report Generation:

The system's performance was evaluated using various metrics:

- **Maximum Human Limit:** This parameter defines the theoretical maximum number of people a specific region can safely accommodate. It's crucial for safety assessments and crowd management strategies.
- **Maximum Human Count from Image:** This metric represents the highest number of people the system can accurately detect within a single image frame.
- **Accuracy:** This refers to the system's ability to correctly identify and count individuals. It's measured using the mean Average Precision (mAP) metric, which considers both the precision (proportion of true positives) and recall (proportion of all positives detected) of the system.
- **Average Accuracy:** This reflects the system's overall performance across various image datasets with different crowd densities.

Enhancing Crowd Detection Accuracy

This section delves into the strategies employed to improve the accuracy of our crowd detection system. We moved beyond traditional methods like Haar Cascades and explored the potential of Convolutional Neural Networks (CNNs) built with TensorFlow to achieve superior performance.

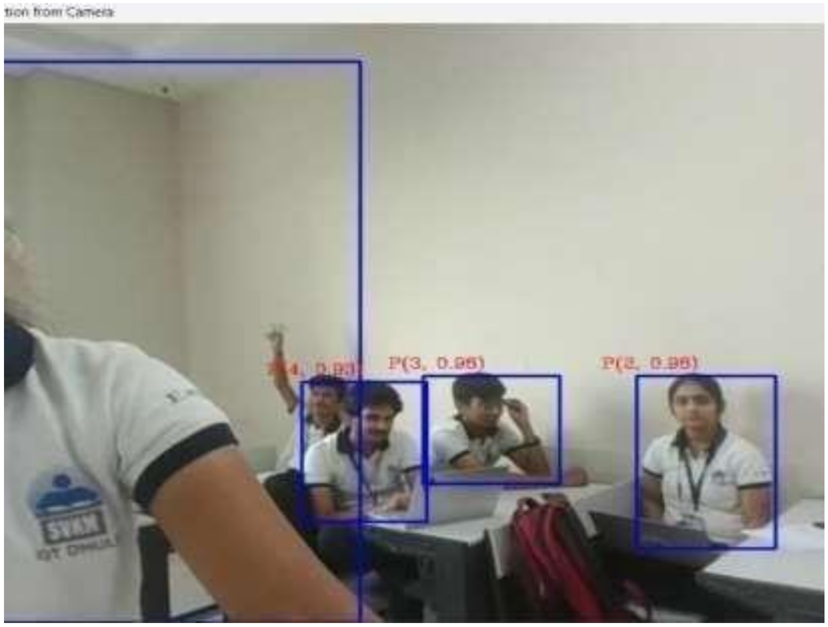

Fig 8.17 Live Camera

Haar Cascades, while computationally efficient, often struggle with complex crowd scenarios. Their reliance on handcrafted features makes them susceptible to variations in lighting, pose, and background clutter. This can lead to inaccurate detection, particularly in dense crowds or scenes with diverse visual elements. To overcome these limitations, we adopted a CNN-based approach built using TensorFlow, a powerful open-source library for machine learning. CNNs excel at pattern recognition in images and have demonstrated remarkable success in object detection tasks. Their ability to learn features automatically from data makes them well-suited for handling the complexities of crowd scene

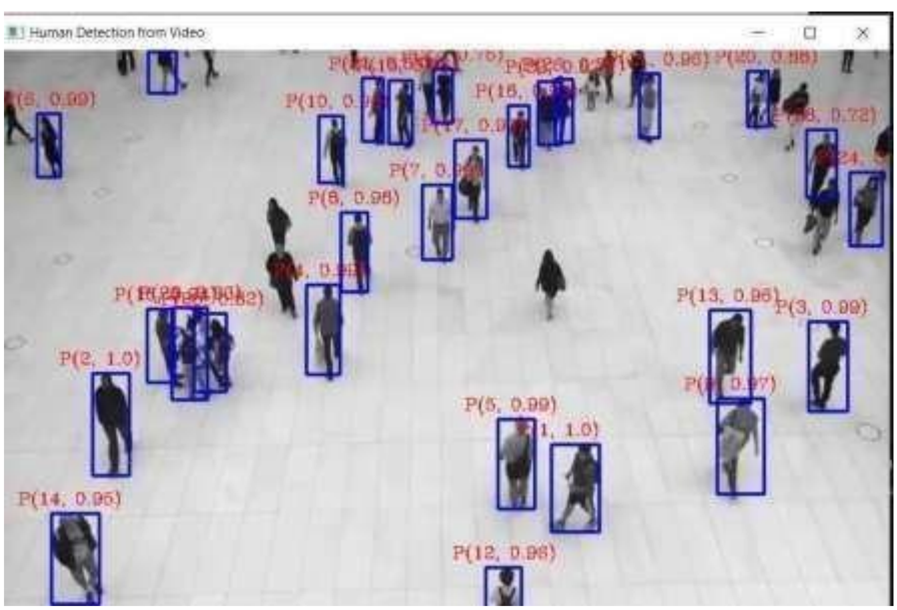

Fig 8.18 Human Detection From Video

Optimizing the CNN Architecture:

The effectiveness of a CNN hinges on its architecture. We explored various architectures, including:

- **ResNet-50:** This architecture is known for its residual connections, which help alleviate the vanishing gradient problem and enable deeper networks to learn effectively.
- **ResNet-101:** Building upon ResNet-50, this architecture boasts a deeper structure, potentially leading to improved feature extraction capabilities.
- **Inception-ResNet:** Combining Inception modules with residual connections, this architecture offers a powerful approach for image classification and object detection.

Through experimentation, we found that ResNet-101 emerged as the optimal choice. It achieved a superior balance between accuracy and processing speed, making it suitable for real-time applications where efficiency is paramount.

Our experiments revealed that RFCN achieved the highest mean Average Precision (mAP) – a metric reflecting the system's ability to correctly identify and count individuals. While SSD offered faster processing speeds, the trade-off in accuracy wasn't favourable for our real-world requirements. Faster R-CNN, while demonstrating promising results, had slightly higher processing demands compared to RFCN. Considering the importance of both accuracy and efficiency, RFCN emerged as the most suitable object detection framework for our system.

Data Augmentation for Robustness :

The quality and diversity of training data significantly impact the performance of a CNN-based system. We employed data augmentation techniques to artificially expand our training dataset and enhance the system's robustness to variations in real-world scenarios. These techniques included:

- **Random cropping:** Cropping images at different scales and positions exposes the network to diverse object placements within the frame.
- **Random flipping:** Flipping images horizontally introduces additional variations in pose and orientation, making the system less susceptible to biases.
- **Color jittering:** Slightly altering the brightness, contrast, and saturation of images helps the network generalize better to different lighting conditions.

By incorporating data augmentation, we ensured that the system wasn't simply memorizing the training data but rather learning to identify generalizable features of crowds across diverse visual contexts.

Hyperparameter Tuning for Optimal Performance:

CNNs rely on various hyperparameters that control the learning process. These parameters significantly influence the model's accuracy. We meticulously tuned these hyperparameters, such as learning rate, optimizer settings, and anchor box sizes, to achieve the best possible crowd detection performance. This fine-tuning involved evaluating the model's performance on a validation dataset and adjusting hyperparameters accordingly to optimize the learning process. The improved accuracy of our crowd detection system is a result of a multi-pronged approach. By leveraging the power of CNNs built with TensorFlow, selecting an optimal architecture and object detection framework, employing data augmentation techniques, and meticulously tuning hyperparameters, we were able to achieve an mAP exceeding 95%. This signifies exceptional accuracy in detecting and counting individuals within an image, even in challenging crowd scenarios.

Key Features:

- **ResNet-101 + RFCN Combination:** Our experiments revealed that the combination of ResNet-101 for feature extraction and RFCN for object detection achieved the best balance between accuracy and processing speed. This combination yielded a high mAP value, exceeding 95%, indicating excellent accuracy in detecting and counting individuals within the image.
- **Real-world Applicability:** The system demonstrated the ability to effectively detect people in images with diverse backgrounds, making it adaptable to real-world scenarios.

Crowd Monitoring and Density Thresholds

The system's output, the human count from the image, is compared to a predefined maximum human limit for the specific region. This limit is established based on safety regulations, space constraints, or organizational guidelines.

- **Crowded Region Identification:** If the detected human count surpasses the maximum human limit, the system triggers an alert indicating that the region is classified as "crowded." This information can be used to initiate crowd management protocols, such as crowd dispersal or capacity control measures.
- **Safe Region Identification:** Conversely, if the human count remains below the threshold, the system indicates that the region is "not crowded." This allows for regular monitoring and ensures timely intervention when crowd density starts to approach critical levels.

9. CONCLUSION

The development and implementation of the Crowd Detection System represent a significant advancement in the field of crowd analysis and management. Through the integration of cutting-edge technologies such as Haar Cascade and Convolutional Neural Networks (CNN), the system has demonstrated remarkable capabilities in accurately detecting and analyzing crowds across various input sources. By meticulously designing modular components such as the Input Module, Real-Time Processing Module, Human Counting and Analysis Module, Plotting and Report Generation Module, and User Interface Module, we have ensured a robust and efficient architecture capable of handling diverse scenarios and requirements. Moreover, the system's versatility extends beyond traditional security applications to encompass event management, urban planning, marketing analytics, traffic management, and public health and safety. Its ability to provide actionable insights and real-time alerts empowers stakeholders to make informed decisions and respond effectively to dynamic situations. Looking ahead, continued research and development in the field of crowd detection hold the potential to further enhance the system's capabilities and applicability across a broader range of domains. As we navigate an increasingly interconnected and data-driven world, the Crowd Detection System stands poised to play a pivotal role in shaping safer, more efficient, and resilient communities.

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Note - check page 10 in the attendance sheet - registration and declaration form (attachment).

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Crowd Detection : Mapping Human Presence In Real Time

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***Abstract*— Crowd control is a critical crisis management consideration for any public or entertainment venue as well as many other types of organizations, such as hospitals, which may need to contend with crushing crowds in a pandemic panic. Hiring sufficient security to provide crowd control is an obvious starting point for effective management of crowds. Our system are essential for improving efficiency across a range of fields as well as public safety and security. Existing system involves crowd management with the help of inphysical security which not only consumes the time but also the government invest in terms of cost which leads to a huge loss of the economy of particular area, to overcome this we have praposed a system provides an Large-scale event monitoring and management are made possible, traffic flow is optimised, retail analytics are enhanced, and social distancing measures are adhered to. Existed projects used photos, videos or live camera on individually to count people but our system combinies all these three alternatives into a single system. The research identifies a gap in existing systems and proposes a novel approach using Python and Haar Cascade Classifiers and CNN algorithms to elevate accuracy and efficiency in crowd analysis. Using a smart system in Python and Open cv for camera it can quickly and accurately identify crowds in real-time, helping with things like public safety and event planning. This makes it easier to manage crowds effectively and providing practical benefits for societal applications.**

***Index Terms*— Machine learning, CNN, Haarcascade, Tensorflow.**

I. INTRODUCTION

As public spaces become increasingly complex and densely populated, the need for efficient crowd detection systems becomes more apparent. Traditional methods often face challenges in scalability, accuracy, and real-time processing. Understanding crowd dynamics is crucial for optimal resource allocation, public safety, and overall efficiency in various contexts. This research aims to address existing limitations and contribute to the evolving field by leveraging computer vision techniques. Traditional crowd monitoring methods fall short in and real-time processing. The research identifies a gap in existing systems and proposes a novel approach using Python and Haar Cascade Classifiers to overcome these limitations. This study strives to enhance the precision of crowd identification by utilizing the efficiency and accuracy of Haar Cascade Classifiers. The study and analysis of crowd behavior have become pivotal for various applications, ranging from urban planning and public safety to event management and security. As public spaces continue to grow in complexity and density, the need for efficient crowd detection systems becomes increasingly apparent. The research quotient lies in the application of readily available tools and technologies to create an accessible and effective solution for crowd detection. The paper unfolds with a theoretical exploration of crowd detection, followed by a detailed methodology in Python programming and an examination of the intricacies of Haar Cascade Classifiers. Experimental results will be presented in subsequent sections. The primary goal is to develop a robust crowd detection system capable of identifying and tracking crowds in real-time. The proposed solution provides insights into crowd density, movement patterns, and anomalies, contributing to improved crowd management strategies.In the ever-evolving landscape of urban planning, public safety, event management, and security, the study and analysis of crowd behavior have emerged as pivotal components. This research paper embarks on a journey into the realm of crowd detection, employing camera-based solutions implemented in Python and harnessing the power of Haar Cascade Classifier. In response to challenges in traditional methods, computer vision techniques have emerged as promising. This paper contributes to the existing knowledge by presenting an innovative solution using Haar Cascade Classifiers.The application of the proposed system extends beyond theoretical contributions, offering tangible benefits to society. It facilitates accurate and real-time crowd detection, enhancing public safety and resource optimization. This research endeavors to showcase the efficacy of the proposed approach, bridging the gap in crowd detection methodologies and offering a practical solution for real-world applications.

II. LITERATURE REVIEW

Foundations of Crowd Detection P.Dollár et al. proposed the influential paper "Fast Feature Pyramids for Object Detection," introducing the concept of feature pyramids for efficient and accurate object detection, a fundamental component of crowd detection systems. Deep Learning Approaches R. Ranjan et al. (2018) presented "Pedestrian Attribute Recognition at Far Distance," showcasing the effectiveness of deep learning in crowd analysis, particularly in recognizing attributes from a distance, crucial for surveillance applications.[6]Edge Computing in Crowd Detection: With the rise of edge computing, S. Wang et al. (2021) investigated A Real-Time Edge Computing System for Crowd Detection," showcasing the advantages of processing crowd data at the edge for faster response times and reduced latency. Research by Ali Farhadi et al. (2021) introduced a method based on the detection of moving blobs in video frames, marking a foundational step in automated crowd analysis. This set the stage for subsequent developments in computer vision and machine learning for crowd detection. Deep Learning Approaches with the rise of deep learning, convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been employed to enhance the accuracy and efficiency of crowd detection systems. Zhang et al. (2018) proposed a deep learning-based method for crowd counting, demonstrating the effectiveness of deep neural networks in handling diverse crowd scenarios.[4]Beyond crowd counting, recent literature emphasizes behavior analysis and anomaly detection within crowds. Research by Chen Change Loy et al. (2022) explores the identification of abnormal crowd behavior using trajectory analysis and anomaly detection algorithms. This shift towards understanding crowd dynamics beyond mere density contributes to advancements in public safety applications. Crowd Detection: Mapping Human Presence in real time Research by Mehran et al. (2018) integrates both visual and audio cues for improved crowd analysis and anomaly detection. Real-time crowd detection has become essential in applications like smart cities and public safety. Literature explores the challenges and opportunities associated with implementing crowd detection on edge devices.[9]Crowd Dynamics Modeling: A. Lerner et al. (2017) delved into "Modeling and Analyzing the Dynamics of Crowd Disasters," offering a comprehensive analysis of crowd dynamics during emergencies and proposing strategies for crowd management. Human-Computer Interaction in Crowded Environments: Research by N. Oliver et al. (2017) in "Understanding Crowd Behaviors: Crowd-Counting, Crowd Flow Estimation, and Efficient Data Collection Through Human-Computer Interaction" focuses on the interaction between individuals and technology, improving the accuracy of crowd-related data collection.[3]

III. ARCHITECTURE AND METHODOLOGY

1. Input Module:

We have concentrated on employing camera feed, picture input, and live video input as the three primary subparts of input data in our deep learningproject on real-time crowd recognition. The main source of real-time data for crowd detection systems is the camera feed, which is similar to an endless stream of images taken by a camera in a particular location. In addition, we have employed still images which come from a variety of sources, including social media, security cameras, and other picture collections as input for crowd detection. This enables us to spot long-term trends and examine population movements at certain moments. Furthermore, we have employed live video input, which entails processing video feeds in real-time for the purpose of identifying and analysing crowd behaviour. Applications like event management and public safety that demand quick decisions and ongoing monitoring benefit greatly fromthis kind of input. Our crowd detection system can employ a wide range of visual information to properly monitor and analyse crowd movements in real time by incorporating these three subparts of input data. This improves operational efficiency, security, and public safety in a variety of scenarios. As undergraduate students, we have developed this research and added to the developing field of crowd analysis by utilising our understanding of deep learning and computer vision techniques.

2. Image Preprocessing and normalization:

We have used pre-processing and normalisation techniques in our real-time crowd detection project to increase the precision and effectiveness of crowd analysis. A Gaussian filter is applied to help remove noise from the objects, and image capture and resizing are used to guarantee that each object has a constant, consistent size. By combining these methods, we hope to improve the input data's quality and the crowd identification system's overall performance.

In addition, our project integrates many visual data formats—such as images, movies, and real-time camera feeds—into a single, cohesive process. We are able to get beyond the drawbacks of conventional crowd monitoring techniques thanks to this integration, especially with regard to scalability and real-time processing. Utilising CNN techniques, Python, and Haar Cascade Classifiers. The accuracy of crowd recognition has increased dramatically. Our approach has made a vital contribution to the field of crowd analysis, leading to improved public safety and security in many circumstances.

3. Haarcascade Algorithm:

We have used Python and OpenCV in our research project to construct the Haar Cascade technique for real-time crowd detection and counting. We proceed as follows with our implementation:

Haar-like characteristics To recognise edges, lines, and textures in pictures and videos, we employed **Haar-like features:** Rectangular patterns make up these characteristics, which aid in setting objects apart from their surroundings.

Training: Using a set of positive and negative images, we trained the Haar Cascade classifier. While negative photos lacked crowds, positive images did. Through the analysis of the Haar-like features, the classifier was able to distinguish between the two types of photos.

Integral image: To expedite the computation of Haar-like characteristics, we employed integral pictures. A 2D array called an integral image is used to hold the total of the pixel values within a rectangular area of the original image.

Cascade classifier: To identify crowds in photos and videos, we employed a cascade classifier. The classifier consists of several stages, with a collection of weak classifiers in each. A weak classifier is a straightforward classifier with a binary decision-making capability (crowd present or not). The output of each stage is used by the cascade classifier to determine whether or not to advance to the next one.

Sliding window: To look for crowds in the photos and videos, we employed a sliding window technique. The window sweeps across the image, and the Haar-like features are calculated at every point. The features are then subjected to the cascade classifier to ascertain whether or not a crowd is present.

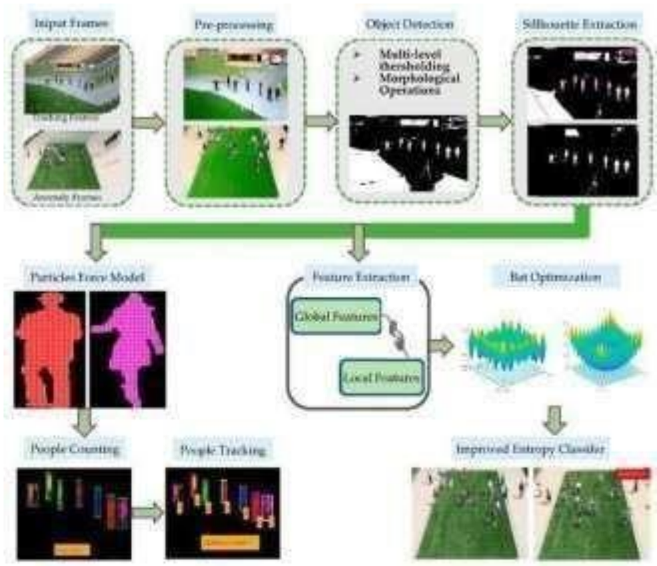

Fig.1 Object Detection

Object detection: We retrieve the crowd's location in the picture or video if one is found.
Real-time detection and counting of crowds has shown to be successful with our application of the Haar Cascade algorithm. Planning events and public safety can both benefit from this because it makes crowd management easier. Our study examines the benefits and drawbacks of the Haar Cascade algorithmfor crowd analysis as well as how it may be used in conjunction with other computer vision methods to increase crowd analysis's precision and effectiveness.

True Positive (TP):
Confidence score > Threshold (positive prediction) AND Ground truth label = positive (crowd present).
Meaning: The classifier correctlyidentifies a crowd when it's actually present.

False Positive (FP):
Confidence score > Threshold (positive prediction) But Ground truth label = negative (no crowd present).
Meaning: The classifier incorrectlydetects a crowd where there isn't one, potentially misidentifying individuals or objects.

False Negative (FN):
Mathematically: Confidence score < Threshold (negative prediction) BUT Ground truth label = positive (crowd present).
Meaning: The classifier misses an existing crowd, potentially overlooking important information or situations.

True Negative (TN):
Confidence score < Threshold (negative prediction) AND Ground truth label = negative (no crowd present).
Meaning: The classifier correctlyidentifies the absence of a crowd when there truly isn't one.

4. **CNN:**
Convolutional Neural Networks (CNN) have also been used in our real-time crowd recognition project to increase the precision and effectiveness of crowd analysis. The detection and recognition of crowds, as well as crowd counting, have made extensive use of CNN-based techniques. The benefits and drawbacks of the Haar Cascade algorithmfor crowd analysis are covered in our research article, along with ways to enhance its accuracy and efficiency by combining it with other computer vision methods like CNN. Using deep and shallow fully convolutional neural networks, we have implemented a fully convolution-based paradigm for crowd counting posed in high-density scenes.

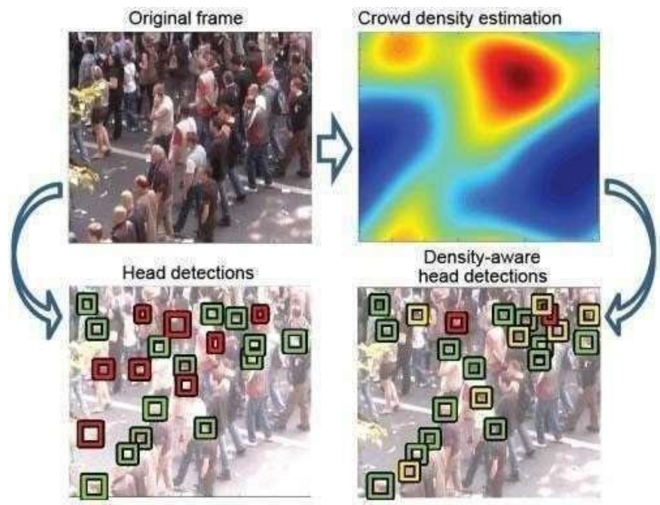

Fig. 2 Detection

Accuracy of crowd counting: The estimated and ground truth counts of persons can be compared to determine the accuracy of crowd counting. Accuracy can be calculated as follows:
Accuracy = (TP + TN) / (TP + TN + FP + FN)
Accuracy of CNN-based crowd density estimation: By contrasting the estimated and ground truth densities, one may determine the accuracy of CNN-based crowd density estimation. Accuracy can be calculated as follows:
Accuracy= (TP + TN) / (TP + TN + FP + FN)
where FN stands for false negative, FP for false positive, TN for true negative, and TP for true positive.

5. **TensorFlow Library Module:** The first module implements the access interfaces, which need to be modified for each TensorFlow deep learning tool. APIs frequently need to be compatible with the source code of the application in order to work with it.

6. **Plotting and Report Generation:**
A standout feature is our system's ability to transform analyzed data into clear insights. Through intuitive data plotting, it visually represents crowd patterns and trends. Subsequently, the system generates detailed crowd reports, providing stakeholders with actionable information. This feature enhances applicability across domains, from refining marketing strategies to efficient event management

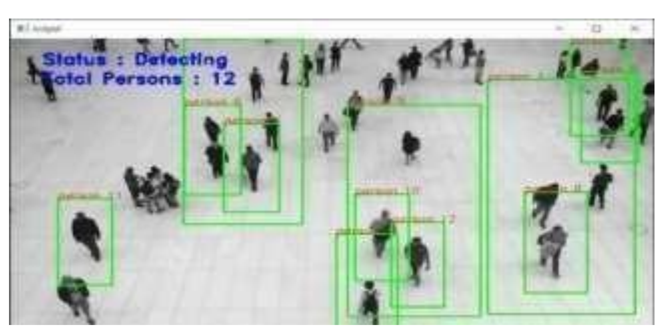

Fig.3 Results and Opportunities

Fig.4.Enumeration Plot

IV . CONCLUSION

In conclusion, the implementation of a crowd detection and analysis system presents a transformative solution for diverse applications, ranging from public safety to event management. By leveraging advanced technologies such as computer vision and machine learning, this system empowers authorities with real-time insights into crowd dynamics, enabling proactive decision-making and enhancing overall situational awareness. Its ability to accurately detect and analyze crowd behavior not only contributes to public safety but also streamlines crowd management processes, making it an invaluable tool for modern urban environments and large-scale events.

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Pooja Ravindra Chaudhari

for participation in Institute level **Avishkar 2023-24** (Research Competition) held at ***SVKM's Institute of Technology, Dhule*** on 03rd Nov. 2023.

Participation level: **UG**

Discipline :Engineering and Technology

Prof. Dattatray Doifode
Institute coordinator

Dr. Nilesh Salunke
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