CROWD DENSITY AND BEHAVIOUR ANALYSIS

Minor project report submitted in partial fulfilment of the requirement for the degree of Bachelor of Technology

in

Computer Science and Engineering

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CERTIFICATE

I hereby certify that the work which is being presented in the project report titled "Crowd Density And Behaviour Analysis" in partial fulfilment of the requirements for the award of the degree of B.Tech in Computer Science and Engineering and submitted to the Department of Computer Science And Engineering, Jaypee University of Information Technology, Waknaghat is an authentic record of my own work carried out during the period from January 2024 to May 2024 under the supervision of Dr.VIPUL KUMAR SHARMA, Department of Computer Science and Engineering, Jaypee University of Information Technology, Waknaghat.

The matter presented in this project report has not been submitted for the award of any other degree of this or any other university.

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This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

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ABSTRACT

Crowd density and behavior analysis in urban environments are crucial for various applications, from public safety to urban planning. However, traditional methods often struggle with accurate density estimation and understanding complex behavioral patterns. To address these challenges, this study proposes a novel approach leveraging Convolutional Neural Networks (CNN). By employing deep learning techniques, our framework aims to process images containing crowds, extracting intricate features essential for accurate density estimation. Specifically, CNN, a state-of-the-art crowd counting architecture, is utilized for its ability to handle highly congested scenes with varying crowd densities. To ensure the robustness and generalizability of our model, we utilize a diverse dataset comprising crowd scenes captured under various conditions, including different vantage points and lighting.

The proposed methodology consists of two primary stages: crowd density estimation and behavior analysis. In the density estimation stage, CNN processes input images to generate density maps, offering pixel-wise estimations of crowd density. Subsequently, our behavior analysis module utilizes the generated density maps to infer crowd behaviors, identifying patterns such as dispersion, aggregation, and movement dynamics. Moreover, privacy-preserving measures are integrated into the framework to address ethical implications, ensuring individual anonymity while facilitating effective crowd analysis. Experimental results demonstrate superior performance in accuracy and computational efficiency compared to existing methods, showcasing the scalability and adaptability of our approach for real-world deployment in diverse urban environments. This comprehensive framework not only enhances crowd management strategies but also contributes to advancing the understanding of crowd dynamics in urban settings, with potential applications across various domains

In addition to its practical applications, the proposed framework holds promise for fostering a deeper understanding of societal dynamics within urban environments. By unraveling the intricate interplay between crowd density and behavior, our approach sheds light on the underlying mechanisms driving collective human interactions. Through the lens of CNN, we gain insights into the social dynamics that shape urban spaces, from the formation of spontaneous gatherings to the propagation of information and ideas. This holistic perspective not only enriches our comprehension of urban phenomena but also lays the groundwork for informed policy interventions and community-centric initiatives. By leveraging the power of data-driven insights, we pave the way towards more resilient, inclusive, and vibrant urban ecosystems, where the pulse of the crowd becomes a catalyst for positive change.

Chapter 01: INTRODUCTION

1.1 Introduction

The research addresses the challenge of accurately estimating crowd density and analyzing crowd behavior in various contexts, such as public spaces, events, and transportation hubs. Traditional methods of crowd analysis often lack the precision and scalability needed to handle the complexities of crowded environments, leading to inefficiencies in crowd management and safety protocols. Additionally, manual crowd monitoring and analysis are labor-intensive, subjective, and prone to errors, making it difficult for stakeholders to make data-driven decisions in real-time scenarios.

Furthermore, the dynamics of crowd behavior, including movements, interactions, and spatial distributions, pose significant challenges for existing crowd analysis techniques. Factors such as occlusion, perspective distortion, and varying crowd densities further complicate the accurate estimation of crowd density and the extraction of meaningful insights into crowd behaviors. Additionally, the need to balance privacy considerations with effective crowd monitoring adds another layer of complexity to the problem.

Moreover, with the increasing frequency of large-scale events, urbanization, and population density, the demand for robust and scalable crowd analysis solutions has become more urgent. Efficient crowd management strategies are essential for ensuring public safety, optimizing resource allocation, and enhancing the overall experience of individuals within crowded environments. Therefore, there is a critical need for innovative approaches that leverage advanced technologies, such as computer vision and machine learning, to address the challenges of crowd density estimation and behavior analysis effectively.

Hence, the primary objective of this research is to develop a comprehensive framework for crowd density estimation and behavior analysis using cutting-edge techniques like Convolutional Neural Networks (CNN) and CSRNet. Specifically, the research aims to address the following key challenges: (1) enhancing the accuracy and scalability of crowd density estimation in diverse environments, (2) capturing and interpreting complex behavioral patterns exhibited by crowds, and (3) ensuring the ethical and privacy-aware deployment of crowd analysis methodologies. By developing novel computational methods and validating them using real-world crowd datasets, the research endeavors to advance the state-of-the-art in crowd analysis and contribute to more effective crowd management strategies and public safety measures.

1.2 Objectives

1. **Primary Objective: Revolutionize Crowd Analysis Methodologies**
    - Leverage advanced deep learning techniques, particularly Convolutional Neural Networks (CNN).
    - Address limitations of traditional methods in density estimation and capturing crowd behaviors.
    - Develop a robust framework for accurate crowd density estimation and behavior analysis.
    - Provide a powerful tool for applications in public safety, infrastructure planning, and event management.
    - Enable stakeholders to make informed decisions based on comprehensive crowd dynamics analyses.
2. **Framework Goals**
    - Ensure scalability and generalizability using diverse datasets of crowd scenes under various conditions.
    - Achieve superior accuracy and computational efficiency compared to existing methods.
    - Establish a new standard in crowd analysis methodologies.
    - Empower stakeholders with actionable insights for proactive decision-making.
    - Contribute to the advancement of scientific knowledge in crowd dynamics.
    - Foster a deeper understanding of societal interactions and lay the groundwork for future research and innovation.
    - Create a transformative impact on crowd perception, analysis, and management in modern contexts.
3. **Secondary Objective: Foster Interdisciplinary Collaboration and Knowledge Exchange**
    - Bridge the gap between deep learning techniques and crowd analysis.
    - Facilitate dialogue and collaboration among researchers, practitioners, and policymakers from diverse fields.
    - Disseminate findings and methodologies through workshops, conferences, and knowledge-sharing initiatives.
    - Promote transparency and inclusivity in the research process.
    - Ensure the framework is accessible and adaptable to a wide range of stakeholders and contexts.
    - Foster a culture of collaboration and openness to maximize research impact.
    - Pave the way for future advancements in the field of crowd analysis.

1.3 Motivation

Moreover, the rapid advancements in technology, particularly in the field of deep learning, present an unprecedented opportunity to revolutionize the way we perceive and analyze crowds. Convolutional Neural Networks (CNN), in particular, have emerged as powerful tools for image processing tasks, showcasing remarkable capabilities in crowd counting and density estimation. By harnessing the potential of these cutting-edge techniques, we aim to develop a novel framework that can transcend the limitations of traditional methods, offering superior accuracy, efficiency, and scalability in crowd analysis.

Beyond the technical advancements, our motivation also stems from a broader societal imperative to enhance the safety, efficiency, and inclusivity of urban environments. From managing large-scale events to optimizing public transportation systems, the ability to accurately predict and respond to crowd dynamics is critical for ensuring the well-being and quality of life of individuals in urban settings. By advancing the state-of-the-art in crowd analysis methodologies, we aspire to empower stakeholders with actionable insights that can drive positive change and foster more resilient, livable, and sustainable cities.

Furthermore, the interdisciplinary nature of this research provides an additional layer of motivation. By bridging the gap between deep learning techniques and crowd analysis, we aim to foster collaboration and knowledge exchange among researchers, practitioners, and policymakers from diverse fields. Through interdisciplinary dialogue and collaboration, we believe that our research has the potential to catalyze innovation, drive positive societal impact, and pave the way for future advancements in the field of crowd analysis.

1.4 Language Used

Python will serve as the main programming language for the creation and training of our suggested machine learning system for detecting lung diseases. Python is a great option for this project since it offers a large selection of machine learning packages and frameworks.

Some of the crucial Python modules and libraries that will be utilised in this project include the following

1. **Numpy:** Matrix multiplication, a frequent numerical operation and computation in machine learning techniques, is supported by the NumPy library.
2. **Pandas:** This package offers assistance with data manipulation and analysis, including feature extraction, preprocessing, and data cleaning—all of which are crucial for creating precise machine learning models.
3. **OpenCV:** This library offers support for a variety of image processing tasks, including picture enhancement, segmentation, and feature extraction. It is an open-source computer vision and image processing toolkit.
4. **Tensorflow:** Deep learning models like ResNet50 and Inception may be built and trained using TensorFlow, a well-liked machine learning library.
5. **SimpleITK:** This library offers assistance with medical image analysis and is especially helpful for processing data from medical imaging, like CT scan images.
6. **PyTorch**: It is an open-source machine learning library for Python, providing a flexible and dynamic framework for building and training neural networks. It offers tensor computation with strong GPU acceleration and supports various deep learning algorithms and techniques.
7. **Matplotlib:** Large datasets may be easily analyseds and understood thanks to the support for data visualisation provided by the Matplotlib package.

We will be able to preprocess the CT scan pictures, extract useful features, and train precise machine learning models utilising ResNet50, CNN, and Inception architectures by utilising these Python modules and tools. The efficacy of the suggested approach will be ensured by our ability to visualise and evaluate the findings of our tests.

1.5 Technical Requirements (Hardware)

The complexity and amount of the dataset, as well as the machine learning techniques employed for analysis, determine the technological requirements for hardware in lung disease diagnosis. Larger, more intricate datasets and computationally demanding algorithms, in general, need for more potent technology. For a machine learning analysis to detect lung diseases, the following general technical prerequisites may be required:

1. **CPU**: For quicker machine learning algorithm execution and parallel data processing, a multi-core CPU is advised.

2. **RAM**: For machine learning analysis, at least 16GB of RAM is advised, however 32GB or more RAM may be required depending on the size of the dataset.

3. **Storage**: The dataset size might vary, although huge volumes of data are often needed to train machine learning models. Consequently, it is advised to use a high-capacity hard drive or solid-state drive (SSD).

4. **GPU**: Graphics processing units (GPUs) can speed up computations for machine learning and shorten the time needed to train and test models. A GPU is not necessary for all machine learning methods, though. In general, GPUs are necessary for the effective training of deep learning algorithms like ResNet50, CNN, and Inception.

5. **GPU Memory**: In addition to having a powerful GPU, sufficient GPU memory is crucial, especially when dealing with large datasets and complex neural network architectures. A GPU with at least 8GB of memory is recommended for deep learning tasks, but for more demanding applications, such as training large convolutional neural networks (CNNs) or recurrent neural networks (RNNs), GPUs with 16GB or more memory may be necessary to prevent memory overflow issues.

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1.6 Deliverables/Outcomes

The primary deliverable of this research endeavor is the development of a robust and scalable framework for crowd density estimation and behavior analysis using Convolutional Neural Networks (CNN) . This framework will be accompanied by comprehensive documentation, including detailed technical specifications, implementation guidelines, and usage instructions, to facilitate its adoption and integration into existing systems and workflows. Additionally, we aim to produce a peer-reviewed research paper detailing the methodology, experimental results, and insights gained from our analysis, contributing to the body of knowledge in the field of crowd analysis and deep learning.

Furthermore, we intend to provide open-access access to the dataset used for training and evaluation purposes, ensuring transparency and reproducibility in our research methodology. This dataset will be meticulously curated to encompass diverse crowd scenes captured under various environmental conditions, facilitating rigorous testing and validation of our framework across different scenarios and contexts. By making the dataset publicly available, we aim to foster collaboration and enable researchers and practitioners to benchmark their own approaches against our proposed framework.

In terms of tangible outcomes, we anticipate that our framework will significantly advance the state-of-the-art in crowd analysis methodologies, offering superior accuracy, efficiency, and scalability compared to existing methods. This, in turn, will empower stakeholders across various domains, including law enforcement agencies, urban planners, and event organizers, with actionable insights for proactive decision-making and effective crowd management. Moreover, we expect our research to stimulate further innovation and interdisciplinary collaboration in the fields of deep learning and crowd analysis, paving the way for future advancements and applications in related domains.

Additionally, we envision broader societal impacts stemming from our research, including enhanced public safety, improved urban planning strategies, and more inclusive and resilient urban environments. By providing stakeholders with the tools and knowledge to better understand and manage crowd dynamics, we aim to contribute to the creation of safer, more livable, and sustainable cities. Ultimately, our deliverables and outcomes seek to translate cutting-edge research into real-world solutions that positively impact communities and societies at large.

Chapter 02: Feasibility Study, Requirements Analysis and Design

2.1 Feasibility Study

2.1.1 Problem Definition

The research addresses the challenge of accurately estimating crowd density and analyzing crowd behavior in various contexts, such as public spaces, events, and transportation hubs. Traditional methods of crowd analysis often lack the precision and scalability needed to handle the complexities of crowded environments, leading to inefficiencies in crowd management and safety protocols. Additionally, manual crowd monitoring and analysis are labor-intensive, subjective, and prone to errors, making it difficult for stakeholders to make data-driven decisions in real-time scenarios.

Furthermore, the dynamics of crowd behavior, including movements, interactions, and spatial distributions, pose significant challenges for existing crowd analysis techniques. Factors such as occlusion, perspective distortion, and varying crowd densities further complicate the accurate estimation of crowd density and the extraction of meaningful insights into crowd behaviors. Additionally, the need to balance privacy considerations with effective crowd monitoring adds another layer of complexity to the problem.

Moreover, with the increasing frequency of large-scale events, urbanization, and population density, the demand for robust and scalable crowd analysis solutions has become more urgent. Efficient crowd management strategies are essential for ensuring public safety, optimizing resource allocation, and enhancing the overall experience of individuals within crowded environments. Therefore, there is a critical need for innovative approaches that leverage advanced technologies, such as computer vision and machine learning, to address the challenges of crowd density estimation and behavior analysis effectively.

2.1.2 Problem Analysis

The analysis of crowd density and behavior presents a multifaceted challenge, influenced by the dynamic and complex nature of crowd dynamics in diverse environments. At the heart of this challenge lies the necessity to accurately estimate crowd density amidst various spatial and temporal scales. Crowds often exhibit heterogeneous density distributions, influenced by factors such as the layout of the environment, time of day, and the presence of obstacles or attractions. Traditional methods for density estimation may struggle to adapt to these fluctuations, leading to inaccuracies in crowd size assessments.

Moreover, understanding and interpreting crowd behavior pose additional complexities. Crowd behaviors are inherently dynamic and influenced by a myriad of factors, including social dynamics, environmental stimuli, and individual motivations. Identifying patterns within these behaviors, such as crowd dispersion, convergence, or unusual activity, requires algorithms capable of analyzing both spatial and temporal data in real-time. Additionally, ensuring the ethical and privacy considerations of crowd analysis methodologies is paramount, necessitating the development of frameworks that prioritize data anonymization and consent mechanisms.

Scalability and adaptability are also critical factors in addressing the challenges of crowd analysis. In scenarios such as large-scale events or urban environments with diverse crowd dynamics, traditional methods may struggle to process the sheer volume of data generated. This can result in computational bottlenecks and delays in decision-making processes. Therefore, there is a clear need for innovative approaches that leverage emerging technologies, such as deep learning and computer vision, to enable real-time analysis and scalable deployment of crowd analysis solutions.

2.1.2.1 Literature Review

1. **LCDnet: a lightweight crowd density estimation model for real-time video surveillance** By Muhammad Asif, Hamid Menouar and Ridha Hamila was published on 6 March 2023.

   Findings: Computer vision researchers have developed numerous CNN-based models for crowd counting and density estimation. They proposed to use LCDnet, a lightweight crowd density estimation model, and a curriculum learning (CL) training method. LCDnet is very effective and achieve very good accuracy on benchmark dataset.

2. **Crowd Density Estimation and Mapping Method Based on Surveillance Video and GIS** By Xingguo Zhang ,Yinping Sun, Qize Li , Xiaodi Li and Xinyu Shi was published on 8 February 2023.

   Findings: Traditional crowd counting methods struggle with accuracy and visualization in large scenes. They proposed CDEM-M, a method combining surveillance video and GIS for improved crowd density estimation. CDEM-M fills crowd polygons with points for visualization, enabling effective crowd supervision in location like mall, stations and sports venues.

3. **A Survey of Recent Advances in CNN-based Single Image Crowd Counting and Density Estimation** By Vishwanath A. Sindagia and Vishal M. Patel was published on 8 March 2017.

   Findings: Crowd counting and density estimation have diverse applications in surveillance, safety, and planning. Deep learning and CNNs have revolutionized the field, overcoming challenges like occlusion and scale variation. This paper surveys recent CNN-based approaches, highlighting their strengths and weaknesses while identifying potential areas for future research. Furthermore, we discuss the merits and drawbacks of existing CNN-based approaches.

4. **Crowd Density Estimation Method Using Deep Learning for Passenger Flow Detection System in Exhibition Center** By Jun Xiang and Na Liu 2 was published on 18 February 2022

   Findings: This paper proposes a crowd density estimation method using deep learning for passenger flow detection systems in exhibition centers. Based on the pixel difference symbol feature, be, the difference amplitude feature and gray feature of the central pixel are extracted to form the CLBP feature to obtain more crowd group description information

5. **Crowd Density Estimation using Imperfect Labels** By Ridha Hamila , Muhammad Asif Khan and Hamid Menouar was published on 18 May 2021

   Findings: Density estimation is one of the most widely used methods for crowd counting in which a deep learning model learns from head-annotated crowd images to estimate crowd density in unseen images. Typically, the learning performance of the model is highly impacted by the accuracy of the annotations. A significant amount of works exist on crowd counting using perfectly labeled datasets but none of these explore the impact of annotation errors on the model accuracy.

6. **Estimation of crowd density in surveillance scenes based on deep convolutional neural network**

   By Shiliang Pu,Tao Song, Yuan Zhang and Di Xie was published on 22 December 2016

   Findings: As an effective way for crowd monitoring, control and behavior understanding, crowd density estimation is an important research topic in artificial intelligence applications. In this paper, They propose a new crowd density estimation method by deep convolutional neural network (ConvNet)..

2.1.3 Solution

Addressing the challenges of crowd density and behavior analysis requires the development of a comprehensive and adaptable framework that leverages advanced technologies and methodologies. The proposed solution involves the integration of deep learning techniques, particularly Convolutional Neural Networks (CNNs) and CSRNet, with innovative data processing and analysis algorithms.

At the core of the solution is the utilization of CNNs for accurate crowd density estimation from images. These neural networks are trained on diverse datasets containing crowd scenes captured under various conditions, allowing them to learn complex spatial patterns and adapt to different environmental factors. The use of CSRNet architecture further enhances density estimation accuracy, enabling pixel-wise estimations of crowd density with minimal computational overhead.

In addition to density estimation, the solution incorporates advanced algorithms for behavior analysis, enabling the identification and interpretation of complex crowd dynamics. By analyzing temporal sequences of density maps generated by CNNs, the framework can detect patterns such as crowd dispersion, convergence, and anomalous behaviors. This behavioral analysis module is designed to provide actionable insights for crowd management strategies and public safety measures.

2.2 Requirements

2.2.1 Functional Requirements

The functional requirements of the proposed crowd density and behavior analysis framework encompass a range of capabilities aimed at achieving accurate, efficient, and scalable crowd analysis in various real-world environments. These requirements define the essential functionalities and features that the framework must possess to fulfill its objectives effectively.

- **Image Processing and Preprocessing**: The framework should support robust image processing techniques to preprocess input images, including resizing, normalization, and noise reduction, to ensure consistency and quality in the data fed into the analysis pipeline.

- **Crowd Density Estimation:** The framework should include algorithms for crowd density estimation from images, leveraging deep learning techniques such as Convolutional Neural Networks (CNNs). The density estimation module should be capable of generating density maps that provide pixel-wise estimations of crowd density within the scene.

- **Behavioral Analysis:** The framework should incorporate algorithms for behavioral analysis to detect and interpret crowd dynamics from density maps. This includes identifying patterns such as crowd dispersion, convergence, and flow dynamics, as well as anomalous behaviors that may indicate potential safety or security threats.

- **Real-time Processing:** The framework should be designed to perform crowd analysis in real-time, enabling rapid decision-making and response to dynamic crowd situations. This requires efficient algorithms and optimized computational resources to minimize processing latency.

- **Scalability:** The framework should be scalable to handle large-scale events and crowded environments with varying levels of complexity. This involves the ability to process high-resolution images and analyze dense crowds while maintaining performance and accuracy.

- **Integration with Existing Systems:** The framework should be compatible with existing crowd management systems and infrastructure, allowing for seamless integration and interoperability. This includes support for standard data formats and protocols to facilitate data exchange and communication between different systems.

- **User Interface and Visualization:** The framework should provide an intuitive user interface for interacting with the analysis results and visualizing crowd density maps and behavioral patterns. This includes features such as interactive dashboards, data visualization tools, and customizable display options.

- **Privacy and Security:** The framework should incorporate privacy-preserving measures to protect individual privacy rights while conducting crowd analysis. This includes anonymization techniques, data encryption, and access control mechanisms to safeguard sensitive information and comply with privacy regulations.

- **Customization and Adaptability:** The framework should be customizable and adaptable to different use cases and environments, allowing users to tailor the analysis pipeline and algorithms to their specific needs. This includes configurable parameters, modular components, and extensible architecture to accommodate future enhancements and requirements.

2.2.2 Non-Functional Requirements

In addition to the functional requirements outlined earlier, the proposed crowd density and behavior analysis framework must also adhere to various non-functional requirements to ensure its effectiveness, usability, and reliability in real-world deployments. These non-functional requirements encompass aspects such as performance, scalability, usability, security, and maintainability.

Performance: The framework should exhibit high performance in terms of processing speed and efficiency, enabling real-time analysis of crowd dynamics. It should minimize latency and response times to provide timely insights for decision-making purposes.

Accuracy: The framework should demonstrate high accuracy in crowd density estimation and behavioral analysis, ensuring reliable and trustworthy results. This involves minimizing errors and inaccuracies in density maps and behavioral patterns to enhance the effectiveness of crowd management strategies.

Scalability: The framework should be scalable to accommodate varying levels of data volume and complexity, allowing it to handle large-scale events and crowded environments without compromising performance or accuracy. It should scale horizontally and vertically to meet increasing demand and workload requirements.

Usability: The framework should be user-friendly and intuitive, requiring minimal training and expertise for users to interact with and operate effectively. It should provide clear and concise feedback, guidance, and documentation to assist users in navigating the system and interpreting analysis results.

Security: The framework should adhere to stringent security measures to protect sensitive data and ensure the privacy of individuals within the crowd. This includes encryption of data transmission, access control mechanisms, and compliance with data protection regulations to mitigate security risks and vulnerabilities.

Reliability: The framework should be reliable and robust, capable of operating consistently under varying conditions and environments. It should minimize downtime, errors, and system failures to maintain continuous availability and reliability in critical crowd management scenarios.

Maintainability: The framework should be designed for ease of maintenance and updates, allowing for seamless integration of new features, bug fixes, and enhancements. It should adhere to coding best practices, modular architecture, and version control to facilitate software maintenance and evolution over time.

Compatibility: The framework should be compatible with a wide range of hardware and software environments, ensuring interoperability and seamless integration with existing systems and infrastructure. It should support standard protocols and data formats to facilitate data exchange and communication with external systems.

Ethical Considerations: The framework should adhere to ethical guidelines and principles in crowd analysis, prioritizing fairness, transparency, and accountability in decision-making processes. It should ensure the responsible use of data and algorithms, respecting individual privacy rights and societal values.

2.3 Data-Flow Diagram (DFD)

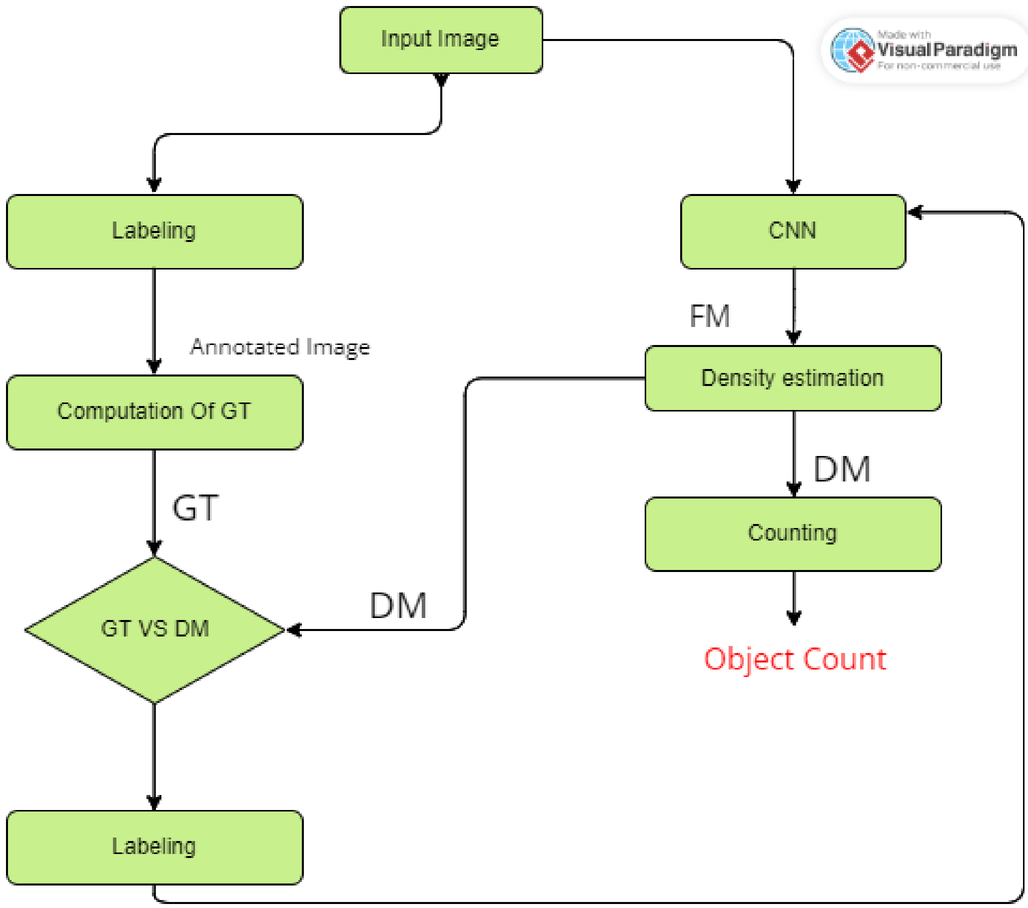


Fig. 2.3.1 Data – flow diagram

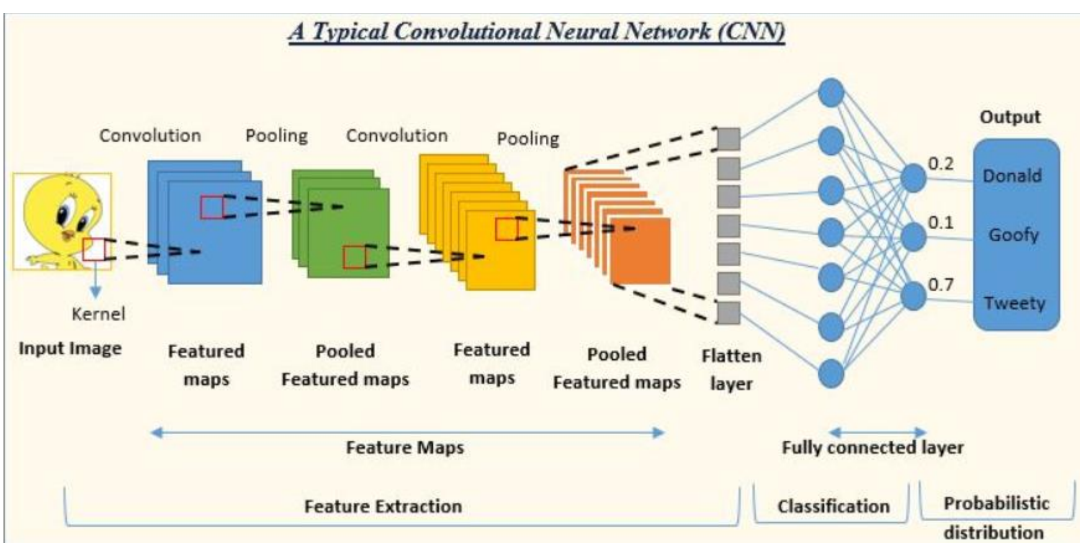


Fig. 2.3.2 CNN Architecture

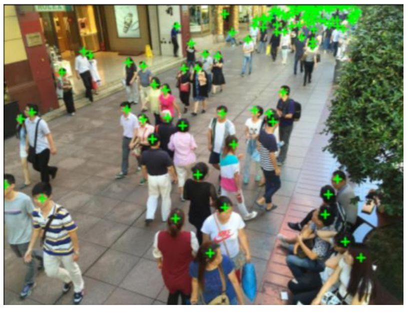
Chapter 03: IMPLEMENTATION

3.1 Date Set Used in the Minor Project

The ShanghaiTech dataset is a comprehensive resource for developing and evaluating crowd counting algorithms, essential in computer vision. It is divided into two parts: Part A and Part B. Part A consists of 482 images, primarily collected from the internet, featuring highly congested scenes. Part B includes 716 images captured from the busy streets of Shanghai, with relatively sparse crowds. Together, the dataset contains 1,198 images annotated with over 330,000 labeled individuals.

Part A's images generally depict highly dense and diverse crowd scenarios, making it challenging for algorithms to detect and count individuals accurately. In contrast, Part B features more structured crowd scenes with lesser density, resembling real-world urban environments. This distinction allows researchers to test their models against varied crowd densities and compositions, ensuring robustness and versatility in real-world applications.

The dataset annotations include detailed head annotations for each individual, enabling precise training and validation of counting models. This meticulous labeling helps in developing advanced deep learning models capable of handling the intricacies of crowd counting in different settings. The ShanghaiTech dataset has become a benchmark in the field, frequently cited in academic research and used for competitions aimed at advancing crowd counting technologies.



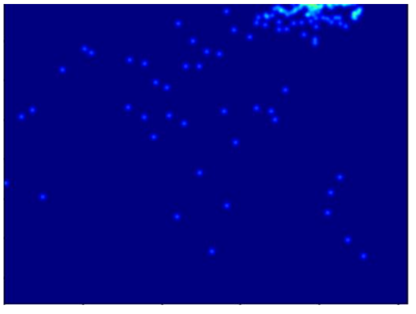


Fig 3.1.1 Test image　　Fig 3.1.2 Ground-truth　　Fig 3.1.3 Estimation

3.2 Date Set Features

3.2.1 Types of Data Set

1. **Training Dataset**: Used to train the machine learning models. It includes images and their corresponding annotated density maps to help the model learn how to count individuals in various crowd scenarios.
2. **Validation Dataset:** Used during the training process to evaluate the model's performance and adjust hyperparameters. This set ensures that the model generalizes well to unseen data and prevents overfitting.
3. **Testing Dataset:** Used after the model has been trained to evaluate its final performance. This set provides an unbiased evaluation of the model's accuracy and effectiveness in counting individuals in different crowd densities and configurations.

3.2.2 Number of Attributes and description of the data set

1. **Image ID**: A unique identifier for each image in the dataset, ensuring easy reference and management.
2. **Image Data**: The actual visual data of the crowd scenes. These images depict varying crowd densities and are critical for training and testing crowd counting models.
3. **Density Maps**: Annotated density maps that correspond to each image, providing pixel-level density information of the crowd. These maps are essential for developing algorithms that can estimate crowd sizes accurately.
4. **Number of People**: The count of individuals in each image, offering a ground truth for model validation and evaluation.

Overall, the dataset contains 1,198 images with over 330,000 labeled individuals, providing extensive data for training and validating crowd counting algorithms. This dataset is instrumental for developing models that can accurately estimate the number of people in varying crowd densities and configurations.

3.3 Design of Problem Statement

The aim of the project "Crowd Density and Behavior Analysis" is to develop an accurate and efficient system to estimate crowd density and analyze crowd behavior using video and image data. This system leverages the power of convolutional neural networks (CNN) and transfer learning to address challenges associated with manual crowd monitoring and analysis, which are often time-consuming, subjective, and prone to variability among observers.

Manual methods of crowd density estimation and behavior analysis suffer from limitations such as inconsistent results, the need for extensive human labor, and the inability to process large volumes of data quickly. As a result, there is a need for an automated system that can provide real-time, precise analysis of crowd density and behaviors to assist in public safety, event management, and urban planning.

Utilising deep learning techniques, specifically CNN and transfer learning, to extract meaningful features from video and image data to estimate crowd density and analyze crowd behavior. CNNs are known for their ability to effectively capture spatial hierarchies in images, making them suitable for tasks involving visual data. Transfer learning allows us to leverage pre-trained models on large datasets, improving the performance of our model even with limited labeled data specific to crowd analysis.

This system aims to provide reliable and interpretable results that can aid authorities in making informed decisions related to public safety and event management. By automating the process of crowd density estimation and behavior analysis, the system reduces the need for extensive human intervention, minimizes subjectivity, and enhances the ability to monitor large-scale events or high-density public areas efficiently.

The successful implementation of this project will result in a robust tool capable of generalizing across various environments and conditions, handling variations in video quality, and offering insights that can improve crowd management strategies. This will ultimately contribute to safer and more efficient management of public spaces and events.

3.4 Algorithm of the Project Problem

The objective of the project "Crowd Density and Behavior Analysis" is to create an efficient system for estimating crowd density and analyzing crowd behavior using video and image data. The system follows several key stages:

1. **Data Preprocessing:** Initially, the dataset of image data capturing different crowd scenarios is loaded along with the associated labels. The dataset is then split into training and testing sets. Preprocessing steps such as resizing images to a standard size, normalizing pixel values, and performing data augmentation (e.g., rotation, flipping, and zooming) are applied to enhance the quality and variety of the training data, ensuring optimal model performance.
2. **Model Training**: For model training, pre-trained CNN architectures are utilized. These models are initialized with weights from large-scale datasets. The top layers of these models are modified to fit the specific task of crowd density estimation and behavior analysis by adding layers such as a global average pooling layer, a dense layer with an appropriate number of units, a dropout layer to prevent overfitting, and a final dense layer with an appropriate activation function (e.g., softmax for multi-class classification). The models are then compiled with suitable optimizers, loss functions, and evaluation metrics, and trained using the training dataset, optimizing the parameters through iterative forward and backward propagation.
3. **Model Evaluation**: The performance of the trained models is evaluated using the testing dataset, with metrics such as mean squared error(MSE), mean absolute error (MAE) Grid mean absolute error(GAME) etc. used to measure the models' ability to correctly estimate crowd density and analyze behavior. Classification reports and confusion matrices are generated to provide a detailed assessment.
4. **Visualization:** Visualization of the models' performance is achieved using matplotlib, including plots of model accuracy and loss across epochs, bar graphs comparing the accuracy of different models (e.g., VGG16, ResNet50, and InceptionV3)etc. These graphical representations offer insightful perspectives on the models' performance and their precision in estimating crowd density and analyzing behavior.

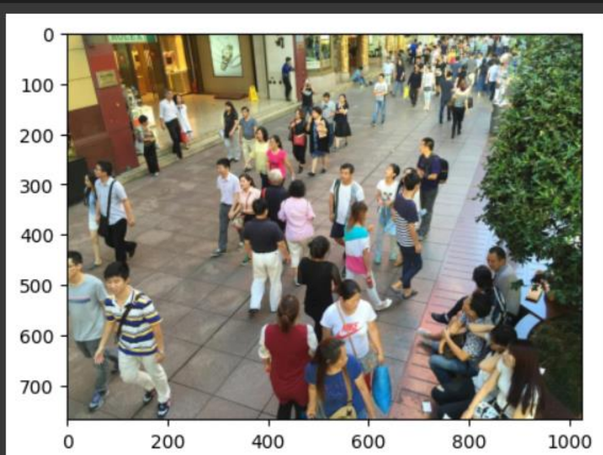
5. **Prediction/Testing:** Finally, the trained models are used to make predictions on new, unseen image data. These models can estimate crowd density and identify specific behavioral patterns present in the data, enabling real-time analysis and classification of crowd behaviors. This comprehensive approach ensures proper data processing, accurate model training and evaluation, and effective utilization of results for practical applications.

3.5 Screen shots of the various stages of the Project

```
[ ] import zipfile
    zip_ref = zipfile.ZipFile('/content/drive/MyDrive/Colab Notebooks/archive.zip', 'r')
    zip_ref.extractall('/content')
    zip_ref.close()
```

Fig 3.5.1 Importing dataset

```
path_img_ex = '/content/ShanghaiTech/part_B/train_data/images/IMG_7.jpg'
image_ex = cv2.cvtColor(cv2.imread(path_img_ex),cv2.COLOR_BGR2RGB)
figure = plt.figure(figsize=(5,5))
plt.imshow(image_ex)
plt.show()
```



```python
path_gt_ex = "/content/ShanghaiTech/part_B/train_data/ground-truth/GT_IMG_7.mat"
gt_ex = loadmat(path_gt_ex)
print('type: ', type(gt_ex))
gt_coor_ex = gt_ex.get('image_info')[0][0][0][0][0]
figure = plt.figure(figsize=(5,5))

for x_cor, y_cor in gt_coor_ex:
    cv2.drawMarker(image_ex, (int(x_cor), int(y_cor)),(0, 255, 0),thickness=3)

plt.imshow(image_ex)
plt.title("Image and Coordinate")
```

```
type:  <class 'dict'>
Text(0.5, 1.0, 'Image and Coordinate')
```


```python
density_map_ex = gen_density_map_gaussian(image_ex, gt_coor_ex, 5)

figure = plt.figure(figsize=(10,5))
plt.subplot(1,2,1)
image_ex = torch.tensor(image_ex/255, dtype=torch.float)
plt.xlabel(image_ex.shape)
plt.title('GT: '+str(gt_coor_ex.shape[0]))
plt.imshow(image_ex)

plt.subplot(1,2,2)
plt.xlabel(density_map_ex.shape)
plt.title('DM: '+str(np.sum(density_map_ex)))
plt.imshow(density_map_ex, cmap="jet")

print('max1 : ', image_ex.max())
print('max2 : ', density_map_ex.max())
print('min1 : ', image_ex.min())
print('min2 : ', density_map_ex.min())
```

```
max1 :  tensor(1.)
max2 :  0.029189795
min1 :  tensor(0.)
min2 :  0.0
```

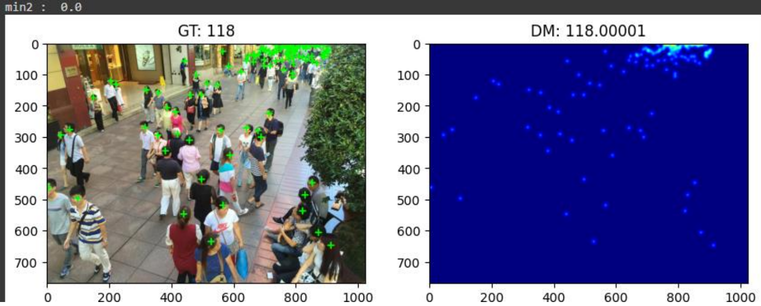


Fig 3.5.2 Exploring dataset

Data Loader

Create a data loader extract the key 'image_info' in MAT to obtain the coordinates of people location. Then use the gen_density_map_gaussian to create the density map of each image. In addition, take the dimension of the coordinate matrix as number of people, which can be used for model loss function. Downsample is applied in order to fit the shape of density map at output of training model.

```
class DataLoader(Dataset):
    def __init__(self, root_dir, gt_downsample=4, shuffle=False):
        self.root_dir = root_dir
        self.gt_downsample = gt_downsample
        self.shuffle = shuffle


        self.img_names = [filename for filename in os.listdir(os.path.join(root_dir, 'images')) if filename.endswith('.jpg')]

        if self.shuffle:
            random.shuffle(self.img_names)

       self.n_people = {}
        self.DMs = {}
        for image_filename in self.img_names:
            img_path = os.path.join(root_dir, 'images', image_filename)
            GT_filename = 'GT_' + image_filename.split('.')[0] + '.mat'
            path_GT = os.path.join(root_dir, 'ground-truth', GT_filename)
            GT = loadmat(path_GT).get('image_info')[0][0][0][0][0]
            img = cv2.cvtColor(cv2.imread(img_path), cv2.COLOR_BGR2RGB)
            self.DMs[img_path] = gen_density_map_gaussian(img, GT, 5)
            self.n_people[img_path] = GT.shape[0]


    def __len__(self):
        return len(self.img_names)

    def __getitem__(self, index):
        img_path = os.path.join(self.root_dir, 'images', self.img_names[index])  # Include the directory path
```

```
for i, (img, gt_dmap, n_people) in enumerate(dataset):
  plt.figure(figsize=(10, 5))
  plt.subplot(1,2,1)
  plt.xlabel(img.shape)
  plt.title('GT: ' + str(n_people))
  plt.imshow(img.permute(1, 2, 0))

  plt.subplot(1,2,2)
  plt.xlabel(gt_dmap.shape)
  plt.title('DM: ' + str(np.sum(gt_dmap.numpy())))
  plt.imshow(gt_dmap.permute(1, 2, 0), cmap="jet")
  plt.show()

  if i > 0:
    print('type of img: ', type(img))
    print('type of dmap: ', type(gt_dmap))
    print('shape of img: ', img.shape)
    break
```

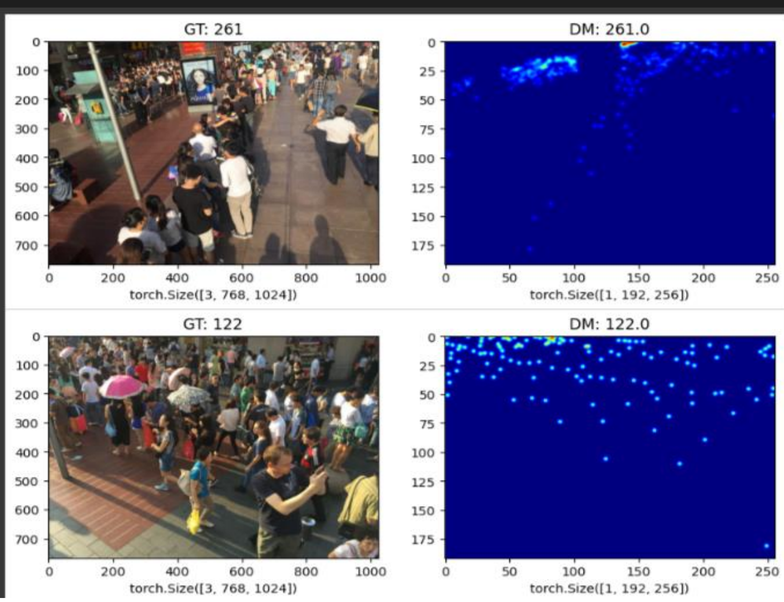


Fig 3.5.3 Data loader

Create Model for Neural Network

Build a multi-column convolutional neural network for density map prediction.

The multi-column CNN consists of multiple parallel CNN columns, each processing the input data independently and at different resolutions. In the proposed architecture, the 1st column is with lowest resolution (with largest kernel size), and lowest depth; 2nd column has incresing resolution (smaller kernel size), and larger depth, and so on.

Each CNN column learns to extract features that contains different aspects from the input data. After feature extraction, the outputs from the all CNN columns are combined by concatenation. The combined features are passed through a single convolutional layer to generate the final output.

```
[ ] class MC_CNN(nn.Module):
        def __init__(self):
            super().__init__()
            self.column1 = nn.Sequential(
                nn.Conv2d(3, 8, 9, padding='same'),
                nn.ReLU(),
                nn.MaxPool2d(2),
                nn.Conv2d(8, 16, 7, padding='same'),
                nn.ReLU(),
                nn.MaxPool2d(2),
                nn.Conv2d(16, 32, 7, padding='same'),
                nn.ReLU(),
                nn.Conv2d(32, 16, 7, padding='same'),
                nn.ReLU(),
                nn.Conv2d(16, 8, 7, padding='same'),
                nn.ReLU(),
            )

            self.column2 = nn.Sequential(
                nn.Conv2d(3, 10, 7,padding='same'),
                nn.ReLU(),
                nn.MaxPool2d(2),
                nn.Conv2d(10, 20, 5,padding='same'),
                nn.ReLU(),
                nn.MaxPool2d(2),
                nn.Conv2d(20, 40, 5,padding='same'),
                nn.ReLU(),
                nn.Conv2d(40, 20, 5,padding='same'),
```

Fig 3.5.4 Creating CNN model

Getting data ready for traning, validation, and testing

```
batch_size = 8
device = 'cuda:0' if torch.cuda.is_available() else 'cpu'

train_root_dir = "/content/ShanghaiTech/part_B/train_data"
init_training_set = DataLoader(train_root_dir, gt_downsample=4, shuffle=True)

# split part of the training set as validation set
train_size = int(0.9 * len(init_training_set))
val_size = len(init_training_set) - train_size

train_indices = list(range(train_size))
val_indices = list(range(train_size, len(init_training_set)))
train_dataset = torch.utils.data.dataset.Subset(init_training_set, train_indices)
val_dataset = torch.utils.data.dataset.Subset(init_training_set, val_indices)

train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
val_loader = torch.utils.data.DataLoader(val_dataset, batch_size=batch_size, shuffle=False)

test_root_dir = "/content/ShanghaiTech/part_B/train_data"
test_set = DataLoader(test_root_dir, gt_downsample=4, shuffle=False)
test_loader = torch.utils.data.DataLoader(test_set, batch_size=batch_size, shuffle=False)

print("Number of batches in train_loader:", len(train_loader))
print("Number of batches in val_loader:", len(val_loader))
print("Number of batches in test_loader:", len(test_loader))
```

```
Number of batches in train_loader: 45
Number of batches in val_loader: 5
Number of batches in test_loader: 50
```

Training Phase

Define a cost function that considering:

- Difference between density map and predicted image
- Difference between sum of predicted image (refering number of people) and the ground truth number of people

```
[ ] class CombinedLoss(nn.Module):
        def __init__(self, weight_dmap=0.8, weight_sum_gt=0.2):
            super().__init__()
            self.weight_dmap = weight_dmap
            self.weight_sum_gt = weight_sum_gt
            self.img_loss = nn.MSELoss()
            self.gt_loss_mse = nn.MSELoss()
            self.gt_loss_mae = nn.L1Loss()

        def forward(self, logits, batch_dmap, batch_gts):
            batch_gts = batch_gts.float()
            img_loss = self.img_loss(logits, batch_dmap)
            gt_loss_mae = self.gt_loss_mae(torch.squeeze(logits.sum(dim=(2,3))), batch_gts)
            gt_loss_mse = self.gt_loss_mse(torch.squeeze(logits.sum(dim=(2,3))), batch_gts)

           # print('logits : ', torch.squeeze(logits.sum(dim=(2,3))))
           #print('gts     : ', batch_gts)
           #print('MAE:   ', gt_loss_mae)

            combined_loss = self.weight_dmap * img_loss + self.weight_sum_gt * gt_loss_mae
            return combined_loss, gt_loss_mae
```

```
        print('>> VAL:   Epoch {} | mae:      {:.6f}'.format(epoch, val_mae))

        if val_loss < best_val_loss:
            best_val_loss = val_loss
            best_nr_epoch = epoch
            torch.save(model.state_dict(), './crowd_counting.pth')


        train_losses.append(tr_loss)
        train_mae_losses.append(tr_mae)
        val_losses.append(val_loss)
        val_mae_losses.append(val_mae)

    print('best training MAE: ', train_mae_losses[best_nr_epoch])
    print('best val MAE:      ', val_mae_losses[best_nr_epoch])
```

```
Epoch 0:
>> TRAIN: Epoch 0 | tr_loss:  19.210991
>> TRAIN: Epoch 0 | mae:      96.054238
>> VAL:   Epoch 0 | val_loss: 10.340457
>> VAL:   Epoch 0 | mae:      51.702087
Epoch 1:
>> TRAIN: Epoch 1 | tr_loss:  7.807290
>> TRAIN: Epoch 1 | mae:      39.036272
>> VAL:   Epoch 1 | val_loss: 14.204311
>> VAL:   Epoch 1 | mae:      71.021338
Epoch 2:
>> TRAIN: Epoch 2 | tr_loss:  5.880530
>> TRAIN: Epoch 2 | mae:      29.402501
>> VAL:   Epoch 2 | val_loss: 1.837369
>> VAL:   Epoch 2 | mae:      9.186727
Epoch 3:
>> TRAIN: Epoch 3 | tr_loss:  4.765747
>> TRAIN: Epoch 3 | mae:      23.828603
>> VAL:   Epoch 3 | val_loss: 4.044452
>> VAL:   Epoch 3 | mae:      20.222138
Epoch 4:
>> TRAIN: Epoch 4 | tr_loss:  2.999079
>> TRAIN: Epoch 4 | mae:      14.995277
>> VAL:   Epoch 4 | val_loss: 3.890103
>> VAL:   Epoch 4 | mae:      19.450395
best training MAE:  29.402501021491158
best val MAE:       9.18672685623169
```

Fig 3.5.5 Model Training

```python
best_model = MC_CNN().to(device)
best_model.load_state_dict(torch.load('./crowd_counting.pth'))
criterion_mae = nn.L1Loss()  # Use L1Loss for MAE
criterion_mse = nn.MSELoss()  # Use MSELoss for MSE

test_loss_mae_acc = 0.0
test_loss_mse_acc = 0.0
with torch.no_grad():  # Use no_grad to disable gradient computation
    for batch_img, batch_dmap, batch_gts in test_loader:
        batch_img, batch_dmap, batch_gts = batch_img.to(device), batch_dmap.to(device), batch_gts.to(device)

        logits = best_model(batch_img)
        loss_mae = criterion_mae(torch.squeeze(logits.sum(dim=(2,3))), batch_gts)
        loss_mse = criterion_mse(torch.squeeze(logits.sum(dim=(2,3))), batch_gts)

        # Keep running statistics
        test_loss_mae_acc += loss_mae.item()
        test_loss_mse_acc += loss_mse.item()

# Calculate average losses
test_loss_mae = test_loss_mae_acc / len(test_loader.dataset)
test_loss_mse = test_loss_mse_acc / len(test_loader.dataset)

# Print results
print('TEST:  test_MAE: {:.3f}'.format(test_loss_mae))
print('TEST:  test_MSE: {:.3f}'.format(test_loss_mse))
```

```
TEST:  test_MAE: 9.937
TEST:  test_MSE: 1442.158
```

Fig 3.5.6 Model Evaluation

```python
# Get some random validation images
dataiter = iter(test_loader)
ex_images, _, ex_gts  = next(dataiter)


# Show images and density map

pred_dms = best_model(ex_images.to(device))
plot_corresponding_pairs(ex_images.cpu(), pred_dms.cpu(), 'twilight')

# Print labels
print(' '.join('%5s' % ex_gts[j].item() for j in range(batch_size)))
```


```
21   90   26   96   81   65   261   165
```

Fig 3.5.7 Prediction

Chapter 04: RESULTS

4.1 Discussion on the Results Achieved

The "Crowd Density and Behavior Analysis" project aimed to develop an efficient system for estimating crowd density and analyzing crowd behavior. The results achieved through this project highlight the effectiveness of using deep learning models, specifically CNN architectures, in combination with transfer learning techniques.

The line graph would have epochs on the x-axis and the corresponding model Weight loss and MAE on the y-axis. As the epochs increase, the Error rate should ideally decreace while the model loss decreases, indicating improved performance.

First for 5 Epochs

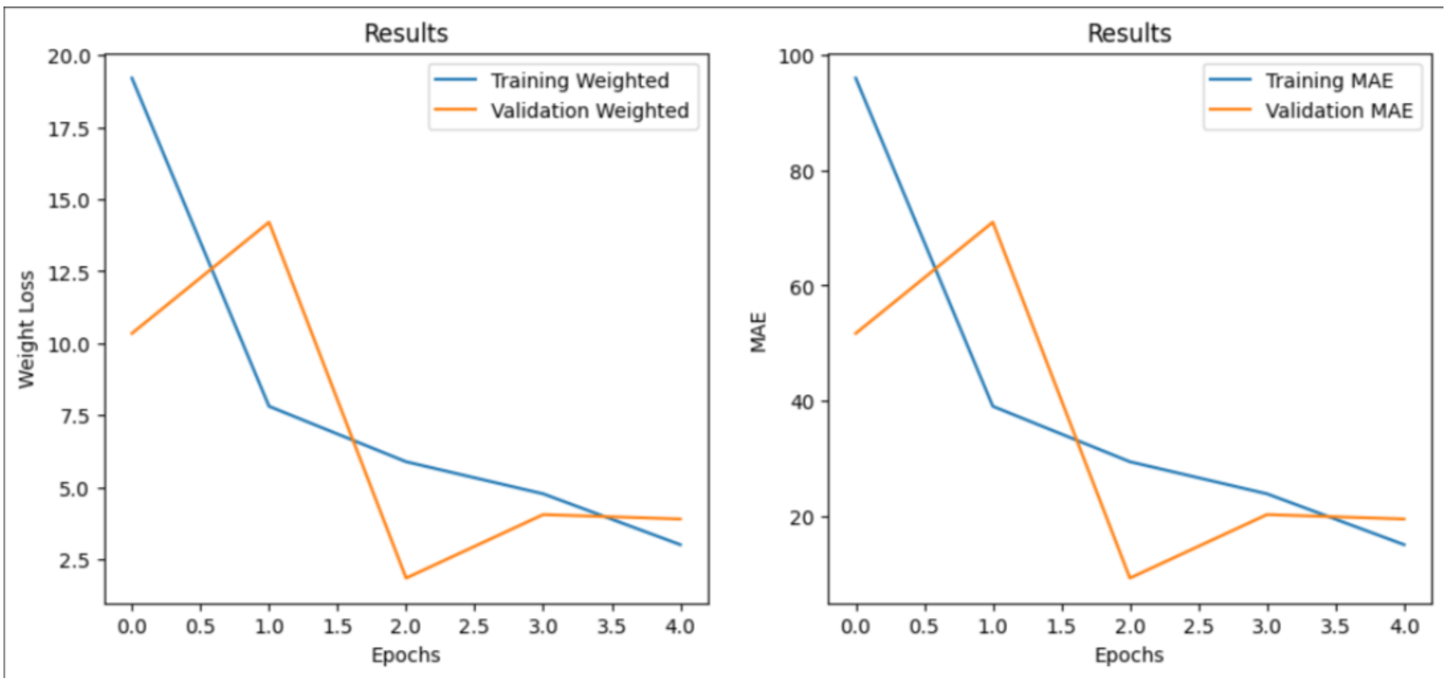


Fig 4.1.1 For 5 Epochs

For 15 Epochs

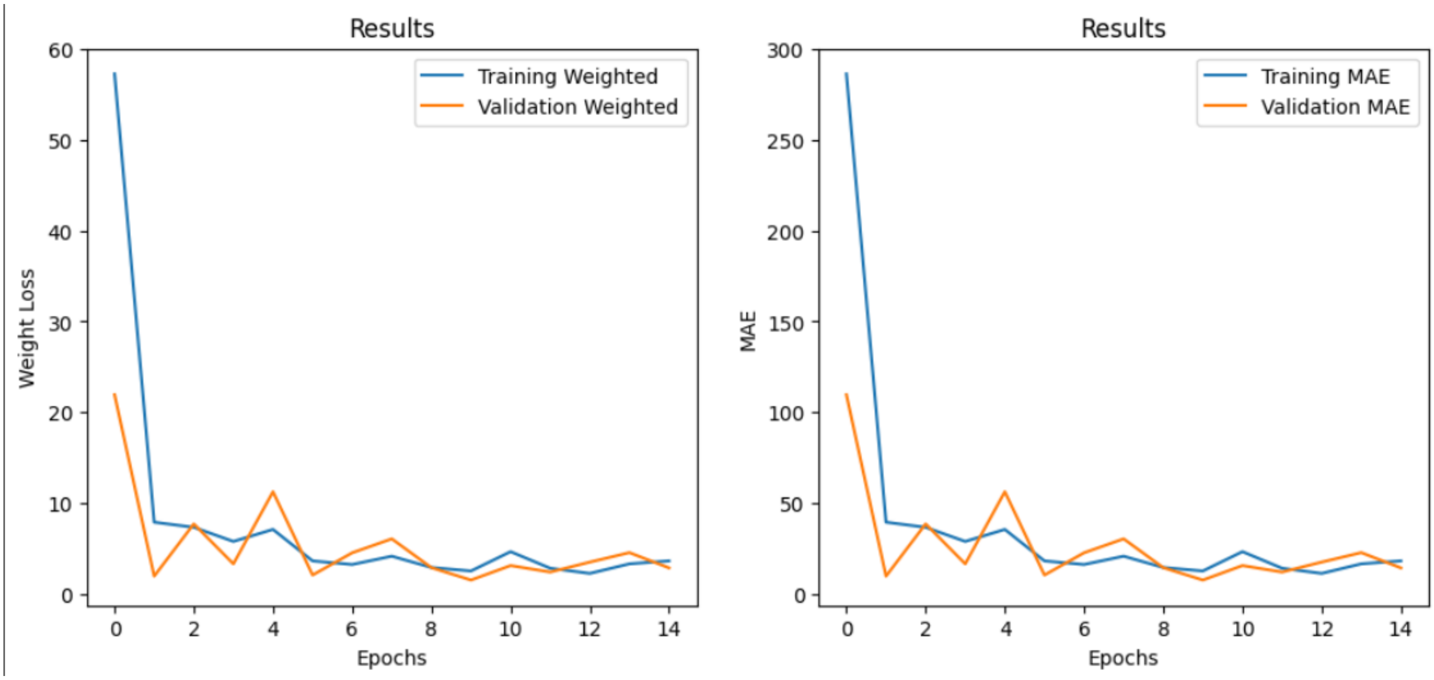


Fig 4.1.2 For 15 Epochs

Here we can see as epochs increase, the Error rate is ideally decreace while the model loss decreases, indicating improved performance

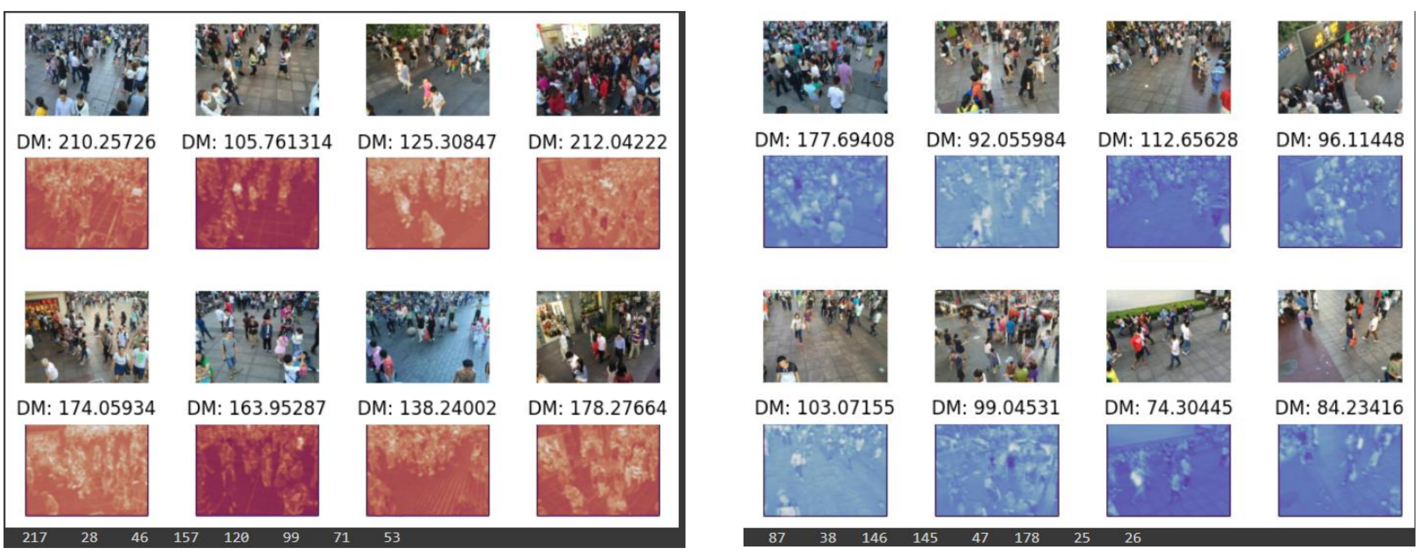


Fig 4.1.3 Test result after 15 epochs vs 5 epochs

Now, Let’s discuss Comparison of different error:

Method	NO. of epoch’s	Training	Validation	Testing	
		MAE	MAE	MAE	MSE
MCNN	5	29.4025	9.1867	9.937	1442.158
MCNN	15	12.6022	7.5920	9.847	1115.069

From the comparison of different errors, it is evident that increasing the number of epochs from 5 to 15 improves the model's performance in terms of both MAE and MSE across training, validation, and testing datasets. The training and validation MAEs show significant reduction, indicating better learning and generalization. The testing MAE and MSE also improve, though the improvements are more modest. These results suggest that further training beyond 15 epochs might continue to enhance model performance, potentially reducing errors even further. However, it is essential to monitor for overfitting, ensuring that the model maintains its ability to generalize well to unseen data.

While the results achieved in this project demonstrate the potential of using CNNs and transfer learning for crowd density estimation and behavior analysis, overall error is still rather little high, indicating significant room for improvement. Future work should focus on addressing these issues to improve model performance and ensure accurate predictions of crowd behaviors and densities.

4.2 Application of the Minor Project

The "Crowd Density and Behavior Analysis" project has several practical applications across various domains. By leveraging advanced deep learning techniques, this project provides a robust solution for real-time analysis of crowd density and behavior, which can be utilized in multiple fields to enhance safety, management, and planning.

1. **Public Safety and Event Management:** Real-time crowd density estimation helps ensure safety during large gatherings like concerts and sports events. It enables timely interventions to prevent overcrowding and accidents by monitoring crowd movements and identifying potential hazards.
2. **Urban Planning and Smart Cities**: Urban planners can use this project to design public spaces that handle high foot traffic efficiently. By understanding crowd behaviors, planners can optimize the layout of parks, squares, and transportation hubs to minimize congestion**.**
3. **Transportation Management:** Transportation systems benefit from real-time crowd density data to manage passenger flow in subways, train stations, and airports. This improves overall efficiency and helps identify and alleviate bottlenecks, enhancing passenger experience.
4. **Disaster Management:** During emergencies, real-time crowd data supports effective evacuation planning and response. Understanding crowd movements helps disaster response teams manage large crowds safely and reduce the risk of casualties.
5. **Healthcare Facilities:** Hospitals can use crowd density estimation to manage patient and visitor flows, especially during health crises. This helps maintain social distancing, optimize emergency departments, and reduce infection spread by monitoring waiting areas and movements.

4.3 Limitation of the Minor Project

Despite the promising results and practical applications of the "Crowd Density and Behavior Analysis" project, there are several limitations that need to be addressed:

1. **Variability in Lighting Conditions:** The performance of the model can be significantly affected by varying lighting conditions. Poor lighting or shadows in the images can lead to inaccurate density estimations analysis. Enhancing the robustness of the model to handle diverse lighting conditions is necessary.
2. **Occlusions and Overlapping Individuals:** In crowded scenes, individuals often overlap or are occluded, making it difficult for the model to accurately estimate the number of people . Developing advanced techniques to handle occlusions and differentiate between overlapping individuals is a critical challenge.
3. **Limited Generalization:** The model may not generalize well to different environments or crowd scenarios that were not present in the training dataset. Ensuring the model's robustness across diverse settings requires a more extensive and varied dataset, which may be difficult to obtain.
4. **Real-Time Processing Limitations:** Although the project aims for real-time analysis, processing high-resolution video data in real-time can be computationally intensive. Improving the efficiency of the model to ensure real-time performance without sacrificing accuracy is an ongoing challenge**.**
5. **Dependence on Data Quality:** The accuracy of the model heavily relies on the quality of the training data. Noisy or low-quality data can lead to poor model performance. Ensuring high-quality, annotated datasets is essential for training effective models.
6. **Ethical and Privacy Concerns:** Using video surveillance for crowd monitoring raises ethical and privacy issues. Ensuring that the system complies with privacy laws and ethical guidelines, and addressing public concerns about surveillance, is crucial for the acceptance and deployment of the technology.

4.4 Future Work

The "Crowd Density and Behavior Analysis" project has shown promising results, but several areas for future work can enhance its performance and broaden its applications. Additionally, behavior analysis was not fully explored in this project, which provides an opportunity for further research and development.

1. **Improving Model Robustness:** Future work should focus on improving the model's robustness to handle diverse environmental conditions such as varying lighting, weather conditions, and different times of the day. This could involve incorporating advanced data augmentation techniques and training on more diverse datasets to ensure consistent performance across different scenarios.
2. **Enhancing Real-Time Processing:** Optimizing the model for real-time processing without compromising accuracy is an important area of future work. This could involve exploring lightweight model architectures, improving computational efficiency, and leveraging hardware acceleration techniques such as GPUs and TPUs.
3. **Advanced Behaviour Analysis:** Integrating advanced behaviour analysis capabilities into the system is a significant area for future development. This includes detecting and predicting complex behaviors such as panic, aggression, or unusual movements. Techniques such as recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and other temporal analysis methods could be employed to understand and predict crowd behavior over time.
4. **Integration with Other Systems:** Exploring the integration of the crowd density and behavior analysis system with other public safety and management systems can enhance its utility. For example, integrating with emergency response systems, smart city infrastructure, and transportation management systems can provide comprehensive solutions for crowd management and safety.

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