COMPARATIVE ANALYSIS OF DEEP LEARNING APPROACHES: REAL TIME CROWD DENSITY ESTIMATION

Nitin Kumar Saini[1], Dr. Ranjana Sharma[2]

[1]Research Scholar, Teerthanker Mahaveer University, Moradabad (U.P.), India.
nitin.scholar@tmu.ac.in
[2]Associate Professor, Teerthanker Mahaveer University, Moradabad (U.P.), India.
ranjana.computers@tmu.ac.in

ABSTRACT

These days, a lot of surveillance and emergency systems are closely related to crowd control, which makes things difficult, especially when the crowd size is unknown. This problem provides as a springboard for investigating density- or count-based crowd estimating techniques. A key issue in many applications, such as traffic management, biology, security, and surveillance, is the density of populated places. In addition to giving a thorough overview of the various methods and strategies used in earlier research to estimate crowd size, this study also seeks to identify the datasets that were used in these studies. A comparative study of relevant works is provided, highlighting the advantages and disadvantages of each methodology. This identifies important directions for future research in the field of congested area estimate.

KEYWORDS: *Deep Learning, CNN, Crowd Counting*

1. INTRODUCTION

This In our everyday lives, surveillance systems are now commonplace. They are used in a variety of places, including malls [3], bank offices [1], and traffic monitoring [2]. Each environment has a different goal for which a surveillance system is used. In particular, this research explores the use of surveillance technologies for crowd size estimation. Estimating crowd density aims to provide valuable insights into the dynamics of congested situations, facilitating a thorough behavioural analysis for improved safety, security, and management strategies. The use of computer vision techniques is a typical feature of these systems. Most systems work with frames from video streams, although some are devoted to single-image calculations. Several interdisciplinary research domains are covered by crowd analysis, such as computer vision, biology [4], physics [5], and psychology [6], and public safety. In this research paper we also discuss about real time crowd density estimation and temporal analysis of crowd counting.

1.1.Crowd Density can be used in different fields for research: -

- Public Safety and Security: By organizing major gatherings, events, and protests, crowd density statistics can help guarantee that the necessary security and safety precautions are taken.
- Tourism: Recognizing trends of population density in tourist locations can help with visitor flow management, cultural site preservation, and environmental impact reduction.
- Transportation: By analysing population density in major hubs for travel, such train and bus terminals, schedules, layouts, and flow can be improved while easing congestion and providing a better experience for passengers.
- Metropolitan Planning: By comprehending the density of people living in metropolitan areas, urban planners can create public places, transit networks, and infrastructure that are more effectively able to support the population.

This paper's structure is set up as follows: Part1 gives the introduction paper and Part 2 lists the different datasets that researchers use to evaluate their approaches. A thorough analysis of the methods used for crowd density estimation is given in Part 3. A comparative study of earlier methods for crowd density estimation is done in Part 4 and Part 5, the conclusion, provides a summary based on issues that have been found but need more research.

2. DATASETS

Datasets are playing a vital role in computer vision. In computer vision processing datasets are essential requirement to proposed design. The datasets used by earlier research to assess methods for estimating busy areas are listed in this section. Although some studies generate their own datasets, most studies use pre-existing, well-known datasets.

In particular, the focus of this section is on standard datasets that are frequently used in the field of crowded zone analysis.

- WorldExpo'10 Datasets [7]: The scale of this dataset, which includes many sequences devoted to crowd counts, is noteworthy. Compared to other datasets, it has a greater quality (576*720) and includes a significant number of prototypes (1132 video clips) and scenes (108). Moreover, a hundred of camera recorded videos and images for crowd counting.
- UCSD dataset [8]: 2000 frames taken from live streaming videos make up this dataset. Notable for having only one camera capture each frame, which results in a limited variety of scenes. This dataset's frames have a lesser resolution (158*238).
- UCF_CC_50 [9]: Approximately 63,000 pedestrians are tagged in 50 frames of the UCF_CC_50 dataset, which is more than the UCSD dataset.
- ShanghaiTech dataset [10]: The ShanghaiTech dataset presents 1198 photos of a large crowd, with 330,165 pedestrians classified. Part A of these photos was collected at random from the internet, while Part B is made up of pictures taken on the streets of Shanghai.
- Make3D [9]: The 2272*1704 resolution of the Make3D dataset is used for single-frame scene depth estimates and feature learning. More than a thousand scenarios are included, including both indoor and outdoor spaces. UCF-QNRF [11]: With over 1.25 million annotations over 1535 photos, the UCF-QNRF dataset provides a variety of perspectives and takes density and lighting changes into account. This dataset's data comes from Google searches and Hajj photos.
- MALL [12]: The MALL dataset, which spans 2000 frames and includes 62,325 pedestrians, comes from a 2012 CCTV camera installed in a shopping centre. It has components from the actual world, like people, booths, indoor plants, and glass object reflections.

Table 1. Description of different datasets.

Sr.No	Datasets		Resolution	Number of scenes	Total Number of persons	Average Crowd Count
1.	WorldExpo'10		4440000	108	199923	50.2
2.	UCF_CC_50		50	50	63974	1279.5
3.	UCSD		2000	-	49885	24.9
4.	ShanghaiTech	Part A	482	-	241677	501.4
		Part B	716	-	88488	123.6
5.	UCF-QNRF		5841726	1535	12000	815
6.	MALL		307200	2000	60000	-

3. CROWD DENSITY ESTIMATION METHODS

3.1. Counting by Regression: - When there is a lot of background noise and a large number of people, counting using detection techniques become less accurate. Regression counting is used to solve these issues. By mapping features extracted from local picture patches to the count, this method does away with the requirement for segmentation or individual tracking [23]. Firstly, low-level features like edge and foreground details are retrieved, and these features are mapped to the count to create a regression model. Specifically, this approach seeks to improve counting precision in intricate and congested settings.

3.2. Counting by Detection: - The spatial information that photographs naturally contain was ignored by many earlier techniques. On the other hand, by creating a mapping between item density maps and local features—with a focus on density—this method incorporates spatial information. Rather than teaching every person one-on-one, this approach tracks multiple people at once [23]. It allows for a more sophisticated understanding of the interactions between local features and item density in a crowded context by acknowledging the possibility of non-linear mapping.

3.3. Counting by Density: - Although prior methods effectively tackled obstacles like blockage and crowding, numerous approaches disregarded crucial spatial data in favour of a worldwide headcount. Density estimation is a prevalent feature in crowd counting systems, which is visually represented by density maps in photos with ground truth (GT) and forecasts. In addition to providing a count, these density estimates also reveal details about the spatial distribution of persons. A unique loss function that was created to count both pedestrians and bacterial cells using datasets specifically made for each—the cell dataset and the pedestrian dataset, respectively—was introduced in a substantial way in this sector. [23] An efficient example-based method was presented for the visual object counting (VOC) problem, which counts quickly while maintaining almost perfect accuracy.

4. LITERATURE REVIEW

This paper we have to discuss different research paper which is based on the crowd density estimation and temporal analysis of crowd counting and estimation for this research we have to follow various steps to select the paper which are as follows:-

- The first step is to filter the papers based on the abstract and title.
- Step two: Remove duplicate publications that employ the same techniques inside the same dataset.
- The third step involves approving papers that meet the required standards, which include being written in English, having known authors, having been reviewed, being developed, and being discussed.

In this research, the analysis of dense scenes usually focuses on determining the density or counting the number of people in the scene.

S. Lin et al. [13] an intelligent technique for head detection using an SVM classifier was presented. First, the frame is subjected to a noise reduction phase. This is followed by an extraction stage that involves normalization and Haar wavelet transformation. The next step is the matching phase, where the SVM classifier is used to classify the retrieved features into head or non-head classes. The estimated accuracy obtained is between 90% and 95%, especially for photos with about 125 people in them. The results of the experiment highlight the importance of setting the camera position to the ideal angle of 72.5 degrees, which is established by the camera sensor's location in relation to the crowd plane. It is important to note that the suggested approach makes the assumption that every human head is the same size and distributed evenly.

Khan et.al. [14] The innovative Loop Closure Detection (LCD) system for LiDAR point clouds in Simultaneous Localization and Mapping (SLAM) applications, called LCDNet, is presented in this work. In contrast to earlier deep learning techniques, LCDNet is very good at finding loop closures, which are important for reducing cumulative drift in SLAM systems, especially in difficult situations like reverse loops. With the use of imbalanced optimum transport theory, LCDNet, which consists of a common encoder, a global descriptor-based location identification head, and a unique differentiable relative pose head, achieves better performance. Its considerable benefit over current methods is demonstrated by extensive assessments on real-world autonomous driving datasets, particularly in handling reverse loops. Robust generalization across various sensor configurations in unknown urban areas is demonstrated through integration into a LiDAR SLAM library.

Liang et.al. [15] We are pleased to present CrowdCLIP, our novel unsupervised approach to crowd counting, which makes use of a special understanding of the intrinsic relationship between count text and crowd patches. Taking use of the recent CLIP vision-language model's success, CrowdCLIP is a first in using vision-language proficiency to address counting difficulties. By using ranking text prompts during training, size-sorted population patches are aligned, hence enhancing the learning process of the image encoder via a multi-modal ranking loss. To handle picture patch variety, our method combines a simple yet powerful progressive filtering algorithm to find viable crowd patches and maps them to the language space with different counting intervals during testing. Extensive experiments on difficult datasets show that CrowdCLIP performs better than previous unsupervised counting methods [6].

Wang R .et.al.[16] Urban surveillance requires efficient crowd management; nevertheless, labeled training sample scarcity complicates crowd counting operations. This paper presents an Automatic Augmentation Framework for Counting (AAC) based on deep reinforcement learning to improve the performance of the model. The AAC system iteratively refines a data augmentation strategy by pre training and using the Deep Deterministic Policy Gradient (DDPG) algorithm on a segmented validation dataset. Performance is improved by fine-tuning the model using the optimal augmentation action. Furthermore, a novel crowd counting dataset representing Hajj settings is presented called HaCrowd. Five crowd counting models are used in augmentation studies on a variety of datasets, including

HaCrowd, to show how AAC may produce adaptable and dataset-specific augmentation strategies that greatly enhance model performance.

Wang C.et.al. [17] Precise counting of people in situations with high population density is essential for anomaly detection and video monitoring. Nevertheless, existing approaches suffer from issues like sparse training data, significant occlusions, and cluttered surroundings. Numerous current methods are less effective in densely crowded settings with insufficient training samples because they rely on auxiliary detectors or manually created features like SIFT and HOG. Our study presents an end-to-end deep Convolutional Neural Network (CNN) regression model that learns features on its own to address this. To reduce background noise, we improve training data by adding negative examples with 0 counts. The experimental results show that our method outperforms the state-of-the-art techniques in terms of mean count performance and absolute difference variance.

M.fu.et.al. [18] this paper presents ConvNet, an enhanced version of the Convolutional Neural Network (CNN) with the goal of increasing crowd density estimation speed and accuracy. Using a two-stage CNN cascade, the author suggests cutting some network connections in order to speed up calculations. The PETS_2009 dataset is the subject of the experimentation, and the technique is limited to 42x40 image sizes. The mistake rate has decreased to 3.2%, according to the data. Unfortunately, the author does not go into great depth on the acceleration that this optimization technique achieves.

C.Zhang et.al. [19]A deep Convolutional Neural Network (CNN) is used by C. Zhang et al. [16] to estimate crowd density/count, especially for scenes that haven't been observed before. The pre-trained CNN model is adjusted to conform to the features of the target scene as part of the authors' data-driven methodology. Furthermore, they present a new dataset with 108 frames that includes about 200,000 people. A comparison study is carried out, taking into account alternative datasets, in order to evaluate the effectiveness of their methodology in various scenarios.

Y. Zhang et al.'s [20] Multi-column CNN architecture (MCNN) is used to estimate crowd density from a single image. Any size or resolution of input image can be used with the MCNN. With different-sized filters, the CNN picks up characteristics unique to each column. The real density map for the input image is then produced using a geometry-adaptive kernel. The authors present a brand-new dataset with 1198 photos that cover a variety of difficult scenarios. A mean absolute inaccuracy of 1.07% is shown in the experimental data, demonstrating the efficacy of their method in crowd estimate.

C. Shang et al.'s goal [21] is to use an end-to-end Convolutional Neural Network (CNN) to directly count crowds from input photos. Using a pre-trained CNN on the image, their method estimates crowd numbers using both global and local information. Local counting is facilitated by the recurrent network layers, which map pertinent features. This method shortens the training period, and the local count enhances the precision of the outcomes derived from local areas. A comparative analysis with other databases illustrates the thorough assessment of their crowd counting strategy and the efficacy of their methodology.

The "Crowdnet" paradigm is introduced by L. Boominathan et al. [22], who use a deep Convolutional Neural Network (CNN) to estimate crowd density. Applying both shallow and deep characteristics to static photos, Crowdnet produces useful results that are enhanced with semantic data. The authors recommend expanding the training dataset to include more than 100 samples in order to improve accuracy. They conduct evaluations using the UCF CC 50 dataset and present and analyse the results of their strategy.

5. Methodology of Crowd Density Estimation with different approaches

In this paper we have to discuss different methodology of crowd density estimation which is as follows: -

[7] The Multi-Column based Architecture (MCNN) was suggested by Zhang et al. to handle crowd density in images with different densities and viewpoints Fig.1. By employing three columns with varying receptive field sizes, it guarantees resilience to changes in object scale. They presented an innovative technique for creating ground truth crowd density maps that takes perspective distortion into account and estimates Gaussian kernel spread parameters using average distances between people. Without using perspective maps, this approach adds distortion information. They also created the ShanghaiTech crowd dataset, which addresses real-world issues not covered by previous datasets. It consists of 1198 photos with 330,000 tagged heads.

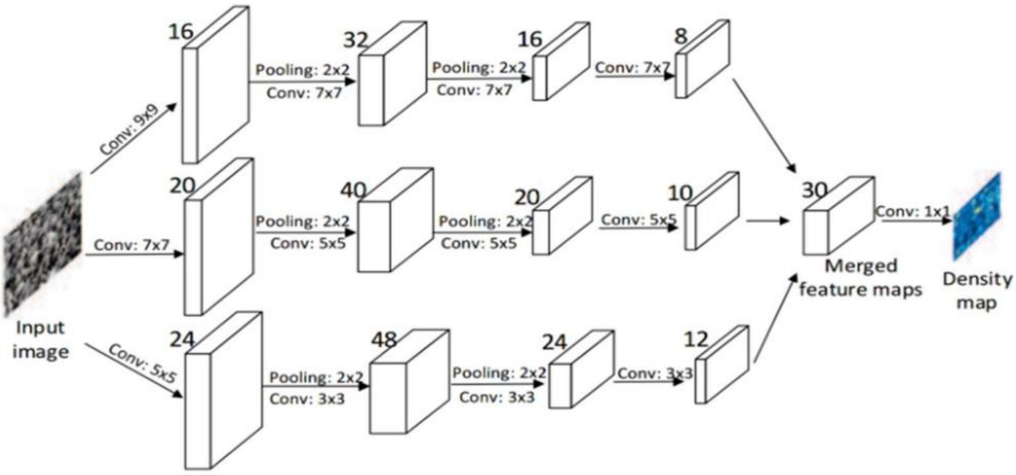

Fig.1. Overview of MCNN by Zhang et.al.[7]

[25] A Mixture of CNNs (MoCNN) was proposed by Kumagai et al. to solve the problem of crowd count prediction in images with different looks. The architecture consists of a gating CNN and several expert CNNs with specific knowledge of various scene appearances. This gating CNN uses the appearance of the input image to dynamically pick the best expert CNN. Expert CNNs forecast crowd sizes, and gating CNNs forecast individual expert probability. Then, based on these probabilities, a weighted average of the predicted counts from each expert CNN is calculated, improving the accuracy of count prediction even in the presence of appearance fluctuations.

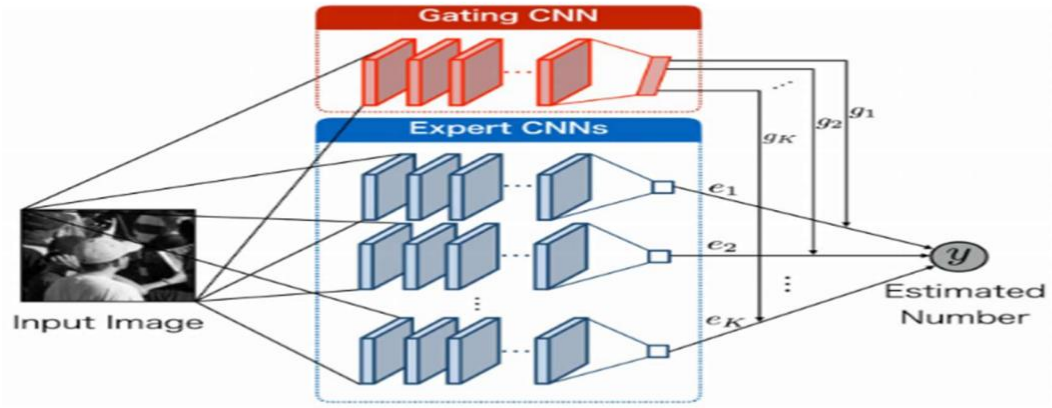

Fig.2.Overview of the Mixture of CNN (MOCNN) for crowd counting by [25]

[23] [26] several layers are usually included in the architecture of a convolutional neural network (CNN) with global density feature, which is intended to extract features from input images and integrate global density data. Convolutional layers are frequently used first to capture local patterns and characteristics, and then pooling layers are added to minimize spatial dimensions while maintaining crucial information. In order to gather data from throughout the entire image and enable the network to detect global density features, it may then add more layers, such as fully linked layers or global pooling layers. These layers are essential for combining data from the whole picture instead of just certain areas.

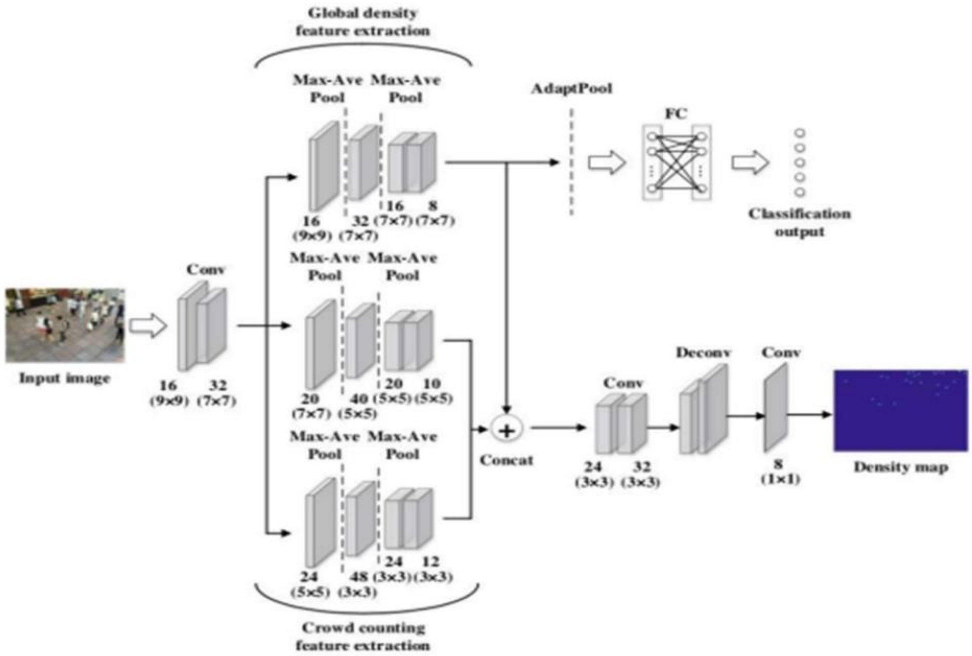

Fig.3. Overview of Density based methodology for crowd counting [23] [26]

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6. DESCRIPTION

The The most significant studies are covered in this part in order to highlight the advantages and limitations of each work. Next, to demonstrate accuracy, a comparison based on various results metrics is emphasized. This section concludes with a presentation of the field's evolution based on the quantity of publications over the last five years. It is best to showcase earlier works in accordance with their qualities, advantages, and disadvantages. Numerous researches are described in Table II according to the input type, application type, employed methodology, dataset, real-time processing, limits, and benefits.

Table 2. An overview of the main methods used to calculate or measure crowd density

Author	Inputs	Application	Approach	Dataset	Benefits	Limits	Real-time
[13]	Image/different position	Pedestrians	End-End deep model CNN	UCFCC	Reduce the mean and the deviation of AD and NAD	Only 1300 per/image	NA
[14]	Image512x640	Pedestrians /Surveillance/CAR	CNN	DroneRGBT	Improve Accuracy	head annotations	Yes
[15]	Image	Pedestrians	CNN /Encoder and Decoder	UCF-QNRF,JHU Crowd+,ShangaiTech,UCF-CC50	Improve performance	Localization	NA
[16]	Image	Pedestrians	CNN/DNN	HaCrowd	Accuracy	NA	NA
[17]	Image/different position	Pedestrians	End-End deep model CNN	UCFCC	Reduce the mean and the deviation of AD and NAD	Only 1300 per/image	NA
[18]	Image 42x40	Pedestrians	Optimized 2CNN layers	Pets-2009	speed up processing and increase the correct rate	Complicate algorithm and limited dataset	NA
[19]	Image 158x238	Pedestrians	CNN	New dataset WorldExpo'10 UCSD UCD_CC50	Applied for unseen scene	NA	NA
[20]	Image/arbitrary	Pedestrains	Multi-column CNN	New dataset WorldExpo'10 UCSD UCD_CC50	Improve estimation density	NA	NA
[21]	Image 640x480	Pedestrains	CNN based on local and global mapping	New dataset WorldExpo'10 UCSD UCD_CC50	Decrease the time processing	NA	NA
[22]	Image 225x225	Pedestrains	Deep Learning and shallow	UCF_CC50	Increase Accuracy	Insufficient number of training image	Yes

3. CONCLUSIONS

Researchers continue to face difficulties in precisely measuring the density of people in dense locations. This work has examined several avenues for future study on crowded zones with an emphasis on methodologies, measurements, and datasets. Improvements to the dataset are required; these should include adding more scenes and representing more than 500,000 pedestrians. These enhancements are essential for honing the outcomes from the assessment stage. Methods still need to be improved, especially in terms of lowering inaccuracies between estimated and real crowd counts. It is crucial to investigate ways to facilitate camera movement and to integrate data from various sources. Moreover, the real-time limitation is recognized as a crucial element for upcoming studies in this field. Applications for crowd density estimation can be found in many different fields, such as bacterial cell microscopy, packed car traffic, mall crowds, and pedestrian counts. The increasing number of publications published in databases such as Web of Science, IEEE Xplore, and Science Direct indicates that this domain is still an ongoing and open problem, even with its widespread use. The Web of Science database shows a noteworthy increase in the domain's prominence from 85 articles in 2015 to 148 articles in 2019. This is reflected in the publication trend. Additionally, a 25% increase in published articles between 2018 and 2019 is shown by the IEEE Xplore database. Since 2018, there has been a

20% evolution in published papers, as indicated by the Science Direct database. These figures highlight the domain's significance as well as the continuous difficulties with crowd assessment. This comprehensive investigation shows that real-time restrictions and accuracy of crowd size prediction still need to be improve.

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Authors

Nitin Kumar Saini received the master’s degree from Teerthanker Mahaveer University Moradabad in 2022 and pursuing Ph.D. at Teerthanker Mahaveer University Moradabad. He is currently Research Scholar in the Department College of Computing Science and Information Technology (CCSIT).His research area is Deep Learning. He is member of IEEE.

Ranjana Sharma received the master's degreee from Uttrakhand Technical University Dehradun in 2014 and Ph.D. at from Uttrakhand Technical University Dehradun in 2021, India. She is currently working as an Associate Professor with the Department of Computer Science Engineering, College of Computing Sciences and Information Technology (CCSIT), Teerthanker Mahaveer University.She has more than 17 years of teaching experience. she has published more than 30 papers in peer-reviewed reputed journals, conferences, and book chapters. She has 14 publications in Scopus indexed journals, SCI indexed journals, book chapters, or conference proceedings. She is member of IEEE since 2019 and She is Editors member in smart-2023. Her research area are machine learning and Remote sensing ,data science .She has received the award “Excellence in Researcher award ” by the chief minister of uttrakhand which is conducting coer college in 2022. She received “National Builder award” in the field of education by the commissioner of Moradabad in 2023.