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Estimation of Crowd Density in Images

[1] Ravi Saharan, [2] Nishtha Kesswani, [3] Yash Chauhan

[1] [2] [3] Central University of Rajasthan, Ajmer, Rajasthan, India
Corresponding Author Email: [1] ravisaharan@curaj.ac.in, [2] nishtha@curaj.ac.in, [3] yash97097@gmail.com

Abstract— This paper presents an innovative machine learning approach designed to accurately determine the density of a crowd depicted in an image. Our primary objective is to classify images into different density categories, ranging from low to high, using a combination of image features and advanced machine learning techniques. We then apply specific methods to each density category to achieve optimal crowd size estimation. Furthermore, we propose a framework for classifying crowd density into three levels: low, medium, and high. This framework utilizes a combined CNN and RNN(LSTM) approach, taking into account factors such as security and individual comfort. It holds promise for security agencies responsible for crowd management, aiding in the prevention of crowd-related incidents. Additionally, it offers valuable insights for organizations tasked with providing accurate crowd attendance data for public events.

Index Terms—Machine learning, CNN, RNN, Crowd.

I. INTRODUCTION

Image Processing is a tool or an algorithm deploy on an image to get back improved and enhanced image or to excerpt an important information from it. It is a type of signal processing in which the image is an input and output can be image or appearances features related with it. Moreover, it is the most emerging technology used in research areas. A crowd is characterized by the gathering of numerous individuals in a disorganized or unruly manner. Consequently, crowd density refers to the number of people within a given area, typically measured in terms of individuals per square unit of area

In the contemporary world, where mass gatherings are commonplace, the demand for crowd monitoring has significantly increased. Across the globe, various open events, including musical concerts, marathons, political rallies, and similar gatherings, underscore the importance of knowing the attendance numbers for security planning and assessing the event's success. In this study, we propose a machine learning approach to estimate crowd size and categorize individuals as normal, critical, or vulnerable in terms of associated risks.

Annual crowd monitoring in video surveillance poses challenges due to the labor-intensive nature of the task and the human mind's limitations in calculating various crowd features. Our approach seeks to enhance monitoring services while introducing a new real-time feature to video surveillance. We construct a compact framework that aims to amalgamate the best existing algorithms for different image types in a comprehensive analysis, ensuring accurate result estimation. The primary focus lies in image classification, enabling the categorization of images to optimize their utilization by corresponding algorithms for precise people counting.

Fig. 1 Religious event crowd [10]

Applications:

1. Developing Service Providers in Public Places: By providing real-time data on crowd size and dynamics, intelligent visual surveillance systems support service providers in optimizing their operations and improving customer satisfaction.

2. Measuring Comfort Levels: Crowd size and density serve as indicators of comfort levels within a crowd. By monitoring these metrics, authorities can detect potential risks such as overcrowding and take preventive measures to ensure public safety.
3. Threat Detection: Crowd size and behavior analysis are critical for detecting and mitigating various threats, including rioting, protests, fights, and mass panic. By detecting anomalies in crowd behavior, intelligent surveillance systems can alert authorities to potential security threats before they escalate.

In conclusion, intelligent visual surveillance systems integrated with crowd analysis features provide numerous advantages, including boosting public safety, optimizing resource distribution, and enhancing customer experiences in public settings. With continual progress in computer vision and machine learning advancements, the potential uses of these systems are continually evolving, offering a more secure and effective outlook for monitored environments.

II. LITERATURE REVIEW

A. Review Stage

Existing technique of crowd density estimation:-

Typically, the challenge of estimating people density and crowd counting can be approached through two primary methods: Direct Approach and Indirect Approach

The Direct Approach, also known as object detection-based, involves segmenting and detecting each individual within crowd scenes, subsequently counting them using classifiers. Contrarily, the Indirect Approach, also referred to as map, measurement, or feature-based, entails counting people by measuring specific features through learning algorithms or statistical analysis of the entire crowd. This method is deemed more robust compared to direct methods.

Gao, Mingliang, et al.[15] (2024) explores crowd counting methods in the Internet of Things (IoT), covering technical goals, machine learning optimization, and deep learning models. It also examines open issues and new challenges in IoT environments.

The paper also details optimization techniques using machine learning algorithms and evaluates related factors. It emphasizes the need for further research to address the gaps in crowd monitoring within IoT environments.

Yong-Chao, et al. [14] (2024) introduces a lightweight dense crowd density estimation network aimed at optimizing the balance between counting performance and computational speed. The network comprises a feature extraction module and a feature fusion module.

Patwal, Akshita, et al.[13] (2023) driven by deep learning advancements, has led to enhanced performance and expanded real-world applications. This study evaluates various crowd counting approaches, predominantly based on CNN architecture, considering feature methods, network design, and dataset suitability.

Khan, Muhammad Asif et al. [12] (2023) introduces LCDnet, a lightweight crowd density estimation model tailored for deployment on resource-constrained embedded devices like drones, ideal for real-time surveillance applications. It details the design principles behind efficient CNN architectures and outlines three key strategies: a compact CNN model, enhanced ground truth generation leveraging head annotations and drone altitudes, and an improved training mechanism utilizing curriculum learning.

Qi Wang et al. [10] (2021) assembled a vast congested crowd counting and localization dataset known as NWPU-Crowd. This dataset consists of 5,109 images, containing a total of 2,133,375 annotated heads with corresponding points and bounding boxes.

Y. Bharti et al. [9] (2018) introduces a simple method based on image traits to estimate crowd size. Initially, the crowd is segmented into various classes, followed by the application of a specific crowd counting technique tailored to each image class. While combining these two techniques might increase time complexity, it also leads to a significant improvement in accuracy.

Yaocong Hu et al.[4] (2016) proposed a deep learning method to estimate the number of individuals in crowd images with mid-level or high-level densities. Their methodology includes partitioning the image into sections or patches, utilizing a feature-count regressor to ascertain the count of people in each patch. Submit your manuscript electronically for review.

B. Final Stage

When you submit your final version, after your paper has been accepted, prepare it in two-column format, including figures and tables.

C. Figures

As said, to insert images in *Word*, position the cursor at the insertion point and either use Insert | Picture | From File or copy the image to the Windows clipboard and then Edit | Paste Special | Picture (with “Float over text” unchecked).

III. PROPOSED MODEL

After investigating numerous methods for estimating crowd density, it becomes clear that this facet plays a crucial role in automated video surveillance. Nonetheless, the research also underscores the apparent necessity for more effective techniques within this field. The proposed work is to design a framework for crowd size estimation by classifying the images into different classes (such as high or medium, or low) based on the crowd strength and then directing it to an appropriate existing technique for crowd size estimation.

The flow chart of the work can be depicted as follows:-

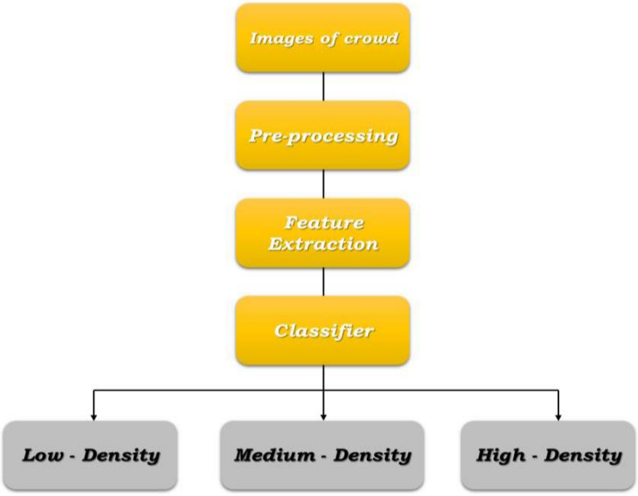

Fig 2. The diagram of proposed model

IV. EXPERIMENT SETUP AND RESULTS

Dataset

These are the datasets that are employed to train the classifier for classification for further processing.

Dataset taken from "https://www.kaggle.com/datasets/ferasoughali/mall-crowd-estimation".

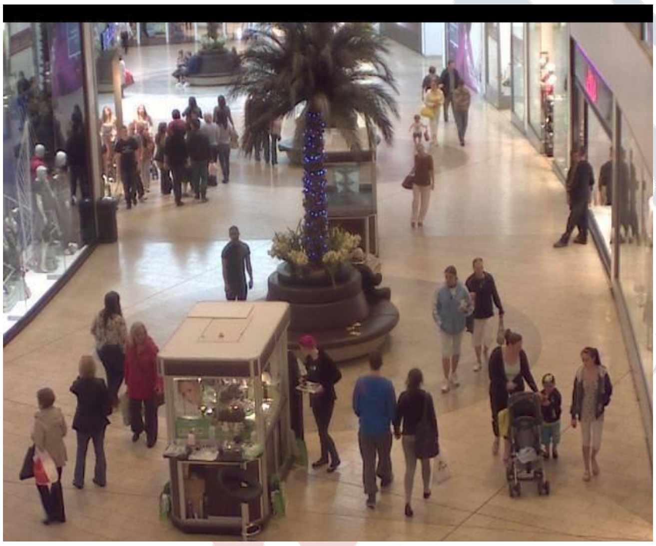

Fig 3(a). Images taken from "https://www.kaggle.com/datasets/ferasoughali/mall-crowd-estimation"

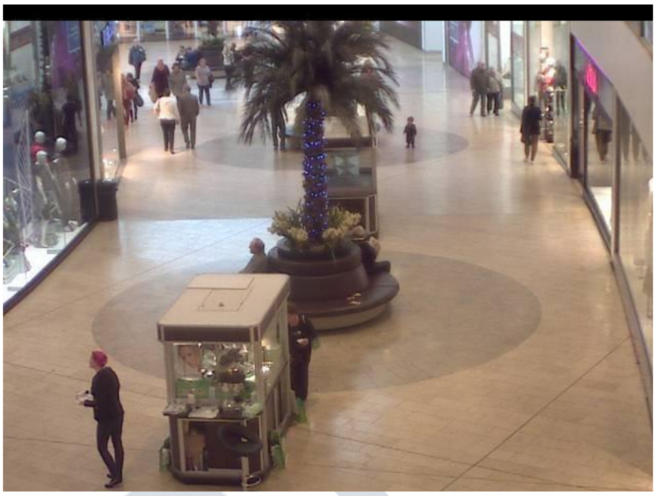

Fig 3(b). Images taken from "https://www.kaggle.com/datasets/ferasoughali/mall-crowd-estimation"

Fig3(c). Images taken from https://paperswithcode.com/dataset/jhu-crowd " http://www.crowd-counting.com/

Results

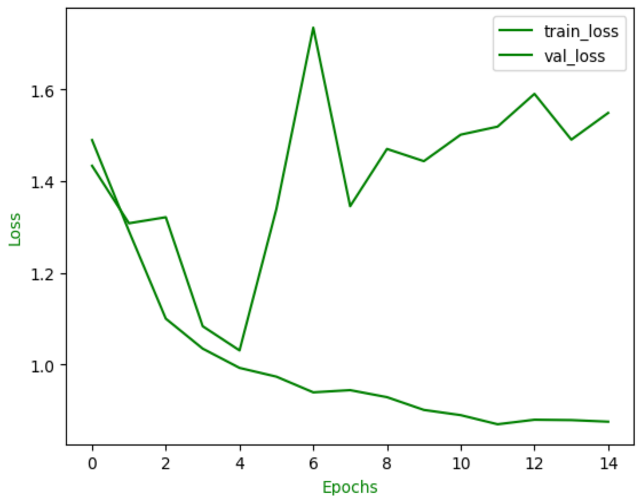

Fig 4. Images showing loss graphs (low - Density)

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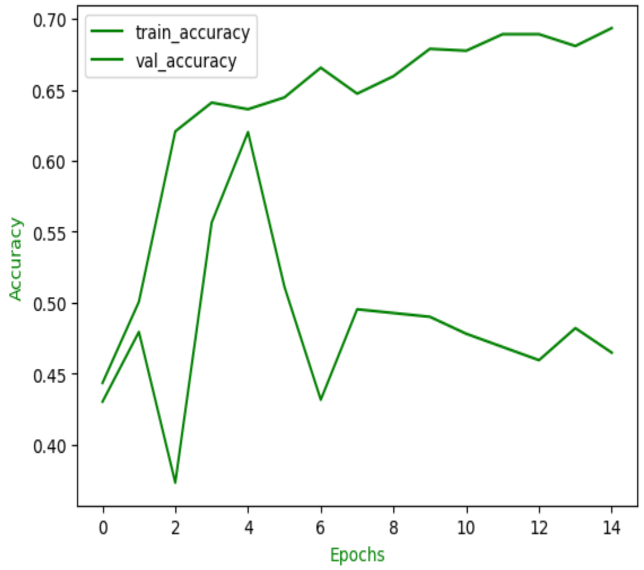


Fig 4. Images showing Accuracy graphs (low - Density)

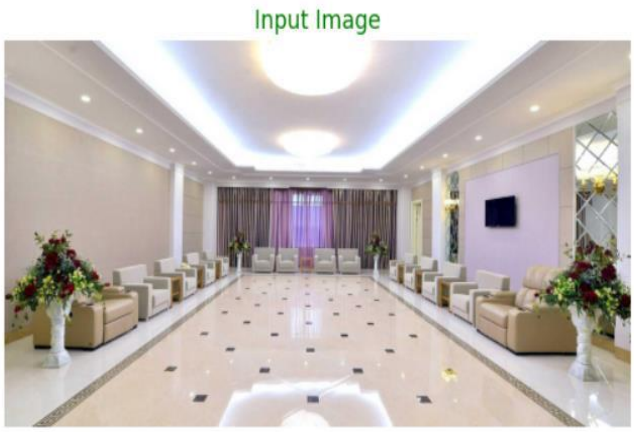
Classification Matrix :

Classification Report:

	precision	recall	f1-score	support
Low Density	0.60	0.68	0.64	235
Medium Density	0.66	0.44	0.53	324
High Density	0.61	0.85	0.71	194
accuracy			0.62	753
macro avg	0.62	0.66	0.62	753
weighted avg	0.63	0.62	0.61	753

Fig 5. Images showing classification matrix (low - Density)

Prediction:




```
1/1 [==============================] - 0s 26ms/step
The predicted label for the example image is: Low Density
```

Fig 6. Images showing result prediction (low - Density)

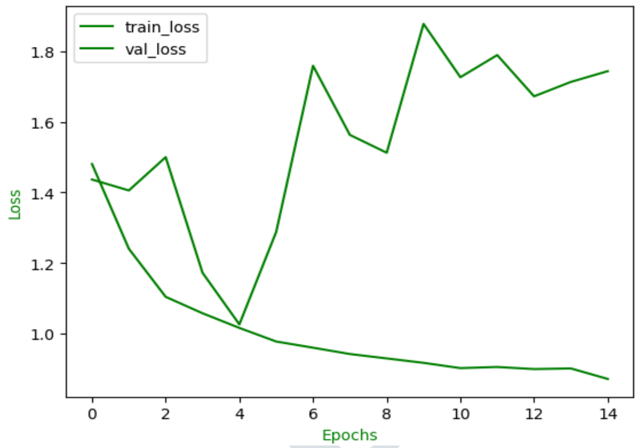


Fig.7: Images showing loss graphs (high - Density)

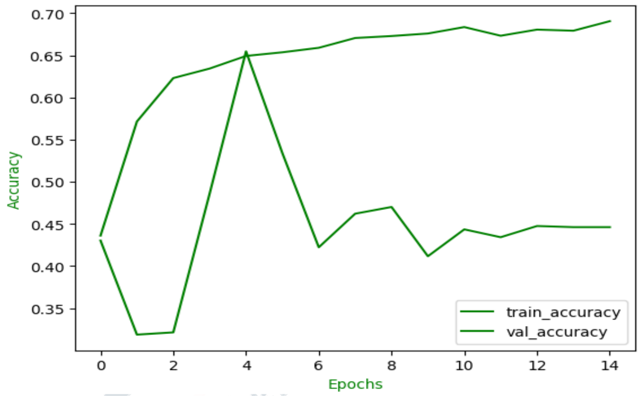


Fig.8: Images showing Accuracy graphs (high - Density)

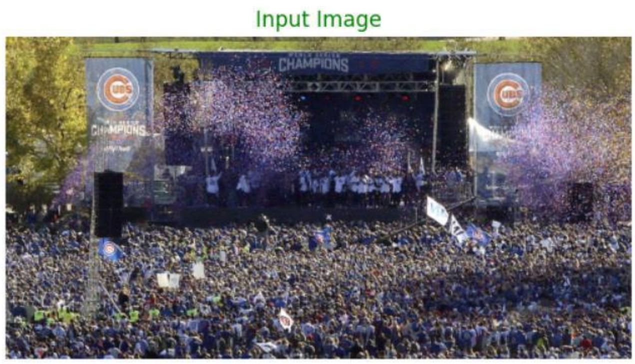
Classification Matrix:

Classification Report:

	precision	recall	f1-score	support
Low Density	0.62	0.72	0.67	235
Medium Density	0.72	0.50	0.59	324
High Density	0.63	0.83	0.72	194
accuracy			0.65	753
macro avg	0.66	0.68	0.66	753
weighted avg	0.67	0.65	0.65	753

Fig 9. Images showing classification matrix (high - Density)

Prediction:

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1/1 [==============================] - 0s 52ms/step
The predicted label for the example image is: High Density
```

Fig 10. Images showing result prediction (high-Density)

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V. CONCLUSION AND FUTURE WORK

After thorough examination of numerous articles spanning diverse perspectives, we've reached a consensus that the realm of crowd size estimation boasts a multitude of methodologies. This realization served as the impetus for crafting a comprehensive framework aimed at categorizing images into distinct types. Leveraging a machine learning approach and predefined features, our framework systematically classifies images, integrating the most effective methods suited to each image type. This approach ensures optimal results are obtained for crowd size estimation. Our methodology places a strong emphasis on refining image classification techniques to maximize the efficiency of size estimation methods. Rather than adopting conventional image classification approaches, we embraced machine learning due to the dynamic and unpredictable nature of crowd features.

Future Work

Implementing current crowd size estimation techniques involves:

- Creating software that applies the proposed framework to estimate crowd size in static images.
- Enhancing accuracy by ensuring consistent output across various image types.
- Developing a user-friendly and interactive interface for comprehensive usability.

REFERENCES

[1] A. N. Marana, S. A. Velastin, L. F. Costa, and R. A. Lotufo, “Estimation of crowd density using image processing,” in IEE Colloquium on Image Processing for Security Applications (Digest No: 1997/074), Mar. 1997, p. 11/1-11/8. doi: 10.1049/ic:19970387.

[2] Lin, Sheng-Fuu, Jaw-Yeh Chen, and Hung-Xin Chao. "Estimate of the numbers of people in crowded scenes using perspective transformation." IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans 31.6 (2001): 645-654.

[3] W. Ma, L. Huang, and C. Liu, “Advanced Local Binary Pattern Descriptors for Crowd Estimation,” presented at the Pacific-Asia Workshop on Computational Intelligence and Industrial Application, Dec. 2008, pp. 958–962. doi: 10.1109/PACIIA.2008.258.

[4] Ryan, David, et al. "Crowd counting used group tracking and local features." Advanced Video and Signal Based Surveillance (AVSS), 2010 Seventh IEEE International Conference on. IEEE, 2010.

[5] V. B. Subburaman, A. Descamps, and C. Carincotte, “Counting People in the Crowd Using a Generic Head Detector,” in 2012 IEEE Ninth International Conference on Advanced Video and Signal-Based Surveillance, Sep. 2012, pp. 470–475. doi: 10.1109/AVSS.2012.87.

[6] Y. Hu, H. Chang, F. Nian, Y. Wang, and T. Li, “Dense crowd counting from still images with convolutional neural networks,” J. Vis. Commun. Image Represent., vol. 38, pp. 530–539, Jul. 2016, doi: 10.1016/j.jvcir.2016.03.021.

[7] Rohit, V. Chauhan, S. Kumar, and S. K. Singh, “Human count estimation in high density crowd images and videos,” in 2016 Fourth International Conference on Parallel, Distributed and Grid Computing (PDGC), Dec. 2016, pp. 343–347. doi: 10.1109/PDGC.2016.7913173.

[8] Y. Yoon, J. Gwak, J.-I. Song, and M. Jeon, “Conditional marked point process-based crowd counting in sparsely and moderately crowded scenes,” Oct. 2016, pp. 215–220. doi: 10.1109/ICCAIS.2016.7822463.

[9] Y. Bharti, R. Saharan, and A. Saxena, “Counting the Number of People in Crowd as a Part of Automatic Crowd Monitoring: A Combined Approach,” in Information and Communication Technology for Intelligent Systems, S. C. Satapathy and A. Joshi, Eds., in Smart Innovation, Systems and Technologies. Singapore: Springer(2019), pp. 545–552. doi: 10.1007/978-981-13-1742-2_54.

[10] Qi Wang, Junya Gao, Wei Lin, Xuelong Li., “NWPU-Crowd: A Large-Scale Benchmark for Crowd Counting and Localization IEEE Transactions on Pattern Analysis and Machine Intelligence,” Vol. 43, Page(s): 2141 - 2149, 2021.

[11] J. Xiang and N. Liu, “Crowd Density Estimation Method Using Deep Learning for Passenger Flow Detection System in Exhibition Center,” Sci. Program., vol. 2022, p. e1990951, Feb. 2022, doi: 10.1155/2022/1990951.

[12] Patwal, Akshita, et al. "Crowd counting analysis using deep learning: A critical review." Procedia Computer Science 218 (2023): 2448-2458.

[13] Khan, Muhammad Asif, Hamid Menouar, and Ridha Hamila. "LCDnet: a lightweight crowd density estimation model for real-time video surveillance." Journal of Real-Time Image Processing 20.2 (2023): 29.

[14] Li, Yong-Chao, et al. "A lightweight dense crowd density estimation network for efficient compression models." Expert Systems with Applications 238 (2024): 122069.

[15] Gao, Mingliang, et al. "A comprehensive analysis for crowd counting methodologies and algorithms in Internet of Things." Cluster Computing 27.1 (2024): 859-873

[16] Lin, Chenxi, and Xiaojian Hu. "Efficient Crowd Density Estimation with edge intelligence via structural reparameterization and knowledge transfer." Applied Soft Computing (2024): 111366.