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Optimized Spatial Model For Crowd Density Estimation In Real Time

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Abstract:-

Development of an optimized spatial analysis model for crowd density estimation focuses on important limitations of scalability, accuracy, and real-time usability. By employing CNNs and furthering optimization through lightweight architectures, attention mechanisms, and knowledge distillation, the model engages in a trade-off of accuracy for a reduced computation budget. The integrative utilization of real-world and synthetic datasets adds panache and generalizability to the model across different scenarios .Using optimization techniques such as model pruning and quantization make the model deployable in edge devices and attends to real-time surveillance applications strategized for smart cities and public safety. Besides, the use of MAE and RMSE inhibitors in the testing phase provides a general sense of the model performance and certainly shows its competitiveness with other state-of-the-art methods and we have to build a new model for crowd density estimation in real time. This research gives a baseline to future innovations in crowd density estimation and gives preference to their balance in terms of accuracy, efficiency, and scalability. It validates just a few real-world applications, such as urban planning and public safety, while looking out for ethical considerations about privacy in crowd monitoring systems.

Introduction:-

The accurate and correct evaluation of crowd density and movement represents one key issue in event management, public safety, and urban planning. Real-time estimates of crowd behaviour can help reduce hazardous situations, optimize resource use, and enhance the overall safety of individuals in crowded areas, Descriptive crowd analysis methods, however, fall short in proposing concrete solutions to many problems related to dynamic crowd behaviour and environmental influences. Unfortunately, these shortcomings highlight the necessity of newer efficient approaches for practical application .Recent advances in deep learning have presented great opportunities toward addressing such problems. With the capability to detect complicated temporal and spatial characteristics from data, convolutional

neural networks have proved to be the building blocks for modern-day models working on crowd density estimation. However, some deep learning algorithms may require significant computational resources, which may become prohibitively expensive when performing tasks in real-time and when it comes to applications on low-end devices. In a scenario like this, the need arises for the models to achieve a balance between computational cost and accuracy. The present paper proposes an enhanced model for crowd density estimation spatial analysis to improve accuracy and operational efficiency. With the usage of elaborate procedures such as model pruning, quantization, and streamlined network architectures, the research endeavours to lessen computation demands while providing high-performance benchmarks. Such optimizations enable the offered model to be efficiently deployed in real-time for various crowd situations-extremely dense urban landscapes or public gatherings. Applications of crowd density estimation models are numerous, including a variety of urban development infrastructure, public safety, and emergency response. The real-time active crowd behaviour consideration also allows better decision-making in action, prevention of expected threats, and response action to crises. This research thus addresses technical challenges and contributes to the broader goal of enhancing societal safety and operational performance.

Then the remainder of the paper will be elaborated in the following organization: Section 2 introduces the relevant literature and describes the latest techniques. Section 3 tells of the proposed model and its optimization approaches. Section 4 discusses the experimental studies and comparisons, showing the advantages of the model versus existing techniques. That is followed by Section 5, wrapping up the study and proposing some potential directions for future research.

Related Work:-

Zhang et al. (2016) introduced the MCNN architecture working on the premise of using a multi-column with varying receptive fields to deal with scale variation in crowd scenes, and it has remained the reference architecture in most subsequent deep learning models designed for the task. Along the same lines, Wang et al. (2019) introduced a model that exploits the deep learning architecture, which was shown to complement real-world tasks well (Wang & Chan, 2019). Effective architecture design has continued to be a primary focus of research work in crowd density estimation. Liu et al. (2020) proposed real-time optimized CNN architectures ensuring no loss in accuracy. The models built on them used light architectures and quantization techniques to deploy these on low-resource devices (Liu, Qiu, & Yuan, 2020). Li et al. (2022) have introduced a lightweight model designed specifically for edge computation environments, providing some evidence of the applicability of efficient models in real-life applications (Li, Xiong, Ding, & Fang, 2022). In recent times, with advances in research, much attention has now turned to the incorporation of spatial attention mechanisms with the objective of attaining great effectiveness. Chen et al. (2023) speak of how applying spatial attention improves model performance in capturing and revealing more information from crowd density maps under varied scenarios. That inspired Luo et al. (2023) to expand this idea into the development of more effective

models for real-time crowd safety surveillance, implementing the use of spatial features to amplify situational awareness (Luo et al., 2023).

Besides architectural advancements, many other optimization approaches, for instance, structural reparameterization, knowledge transfer, and others, have created piles of interest. Lin and Hu (2024) stressed the significance of structural reparameterization with regard to boosting generalization and efficiency, extremely relevant on account of edge intelligence applications (Lin & Hu, 2024). Parallel work by Xue et al. (2021) revealed the challenges when dealing with approaches under the increasingly crowded and unstable scale and offered ways for resilience toward promoting model adaptability (Xue et al., 2021). The application of crowd density estimation on certain fields has been researched in numerous studies. In this case, Mansouri et al. (2025) theorized a top-level system for crowd density surveillance, intending to contribute to intelligent urban planning in smart cities. Highlighted in the research is the interface between crowd analysis and a far greater urban and technological backdrop (Mansouri et al., 2025). In specific scenarios, conventional methods still stand valid. Saleh et al. (2015) profoundly covered all visual surveillance methods for crowd density estimation while laying stress on the viability of classical machine learning and statistical approaches. Likewise, Zhong et al. (2015) availed themselves of a density-centric evolutionary process for crowd model calibration, proving the viability of non-deep learning models in some settings (Saleh, Suandi, & Ibrahim, 2015; Zhong et al., 2015). Hybrid schemes that intertwine conventional and deep learning techniques have shown remarkable promise. For example, Saleem et al. (2020) employed an integrated architecture of several local characteristics coupled with ensemble learning to better assure the density estimation model durability. This method illustrates the strength of combining multiple approaches to cope with intricate crowd scenarios.

Spatial and temporal modelling developments have greatly improved state-of-the-art crowd monitoring methods. Cheng et al. (2019) proposed the use of spatial information to enhance crowd counting using spatial and context information to produce better performance. Cao et al. (2018) also introduced a scale aggregation network that efficiently solves the problem of scale changes and hence further improves the state-of-the-art top-performing methods in crowd density estimation (Cheng et al., 2019; Cao et al., 2018).

Recent analyses by Saini and Sharma (2023) and Khan et al. (2020) have reviewed recent approaches to crowd density estimation. The study shed light on the urgent need for lightweight and efficient models that can operate in real-world scenarios, particularly when paired with developing edge computing and IoT technologies. As a whole, contemporary works have shown great propensity toward employing deep learning approaches in estimating crowd density while focusing on speed and adaptability in computation. Although the existing methods are still applicable to some aspects, emerging developments such as spatial attention mechanisms, efficient architectures, and hybrid strategies are paving a new benchmark for the area. Such a range of new techniques can serve to build even greater

models capable of managing the variability and complexity involved in the real-time estimating of crowds in diverse and frequently changing situations.

Dataset Collection:-

1. Datasets that are publicly available and utilized extensively for research work in system training and testing for crowd analysis include, but are not limited to, the ShanghaiTech dataset, UCF_CC_50, WorldExpo'10, and The Mall dataset. Most of these datasets contain annotated images or videos that encompass a variety of crowd scenarios, density, and environmental conditions. The ShanghaiTech dataset consists of two distinct sections: Section A comprises urban environments where highly populated crowd scenes are predominantly featured; Section B is a set of low-density crowd scenes derived from a campus environment. This dataset contains more than 1,000 images containing intricate density maps and annotations. The UCF_CC_50 is a small but challenging dataset of 50 images concerning highly dense crowd scenes. It contains annotations of over 60,000 people making it ideal for testing the performance of the model itself in very congested environments. The Shanghai World Expo 2010 provides this dataset. The dataset contains 3,980 hand-labeled frames from five different views of various spatial crowd densities and angles: it is most appropriate for cross-scene validation. The Mall datasets consist of video recordings captured by a video camera mounted in a shopping mall. It has over 60,000 individual annotations and is widely used for pedestrian population density and traveling behavior analysis.
2. The FDST dataset emphasized high-definition video recordings captured in various environments, that is, urban streets, recreational areas, and indoor scenes. It comprises 15,000 annotated frames with more than 394,000 distinct head annotations (Fang etal ., 2019). The JHU-CROWD++ dataset represents an extensive variety of crowd scenes at various levels of density and in varying environmental conditions. It contains over 4,000 images together with more than 1.5 million annotations and is thus a suitable source for training robust models in an efficient manner (Sindagi etal ., 2020).
3. The GCC: Generated Crowd Counting dataset is a synthetic dataset made by game engines. It presents a rich collection of diverse crowd scenes and, consequently, broad training opportunities with no limitations due to the acquisition of actual-world data (Wang etal ., 2019).

Sr.No	Dataset	Description	Strengths	References
1	ShanghaiTech Part A & B	Features both dense and sparse crowd images; widely used in crowd counting research.	High-resolution images; real-world scenarios.	Zhang et al., 2016
2	UCF-CC-50	Contains only 50 images but features extreme crowd densities.	High-density scenarios for stress-testing models.	Rodriguez et al., 2011
3	WorldExpo'10	Dataset captured from Shanghai World Expo, focusing on specific crowd scenarios.	Diverse density and perspective variations.	Zhang et al., 2015
4	Mall Dataset	A real-world dataset captured in a shopping mall with sparse annotations.	Simplified real-world use case.	Saleh et al., 2015
5	GCC (Synthetic)	A synthetic dataset generated using game engines to simulate diverse crowd environments.	Overcomes annotation challenges; scalable.	Wang et al., 2019
6	Crowd Surveillance Dataset	A dataset designed for public safety applications with challenging environmental conditions.	Focused on security-critical scenarios.	Mansouri et al., 2025

Table 1: Datasets for crowd

Methodology

The methodology employed in Convolutional Neural Networks for estimating crowd density generally consists of a sequential pipeline processing the input images, applying data augmentation, and using a pretrained CNN deep learning model for making predictions. Each of the different stages of the process is critical for making an accurate and efficient crowd density estimation.

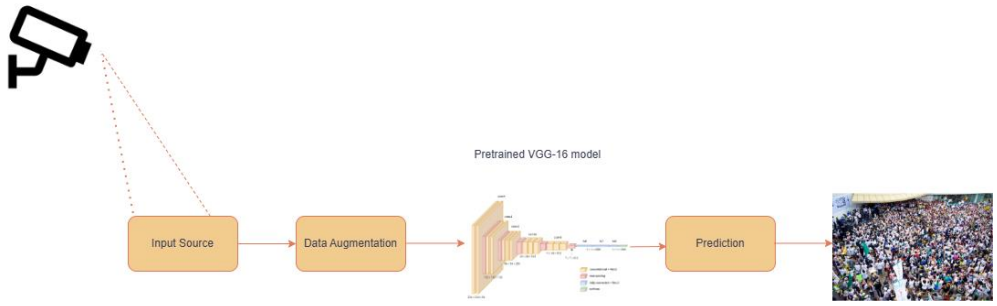

Figure 1 Methodology for crowd counting using CNN (Pre-trained model)

Input Source: -In the first step of the process, raw input data is captured, using devices like surveillance cameras. This input, generally in the form of images or video streams, becomes the main data for crowd density estimation (Rodriguez et al., 2011). The captured images are then subjected to pre-processing; this is, upon normalization, cropping, resizing, and gray-scaling, which contribute to

the enhancement of the quality and suitability for input into the CNN model. According to Fu et al. (2015), pre-processing is fundamental as a means of reducing noise and standardizing inputs, ensuring that interpretation and extraction of features should have significant meaning.

Data Pre-processing:-To boost the variety and efficacy of the training data, data augmentation—a set of transformations such as rotation, flipping, scaling, and brightness modifications, simulating the variations that can commonly occur in real life—is used. Cheng et al. (2019) assert that augmentations support the spatial awareness of CNN models; whereas Cao et al. (2018) highlight their importance to address the various scales in crowd scenes. Such techniques augment the ability of a model to generalize to unseen data while preventing the model from over fitting during training.

VGG-16:-Model The core of the methodology relies on a pretrained VGG-16 model, a widely recognized deep learning architecture known for its hierarchical feature extraction capabilities. By leveraging pretrained weights, the model can extract spatial and contextual features relevant to crowd patterns. Zhang et al. (2015) showcase the effectiveness of pretrained CNNs like VGG-16 in cross-scene crowd counting, while Wang et al. (2022) demonstrate the use of lightweight CNNs for real-time, edge-based density estimation in smart city applications. Fine-tuning the pretrained model further adapts it to the specific task of crowd density estimation.

Sr.No.	Layer Type	Number of Layers	Filter Size	Number of Filters	Output Dimensions	Activation Function
1.	Input Layer	1	-	-	224x224x3	-
2.	Convolutional Block 1	2	3x3	64	224x224x64	ReLU
3.	Max Pooling	1	2x2	-	112x112x64	-
4.	Convolutional Block 2	2	3x3	128	112x112x128	ReLU
5.	Max Pooling	1	2x2	-	56x56x128	-
6.	Convolutional Block 3	3	3x3	256	56x56x256	ReLU
7.	Max Pooling	1	2x2	-	28x28x256	-
8.	Convolutional Block 4	3	3x3	512	28x28x512	ReLU
9.	Max Pooling	1	2x2	-	14x14x512	-
10.	Convolutional Block 5	3	3x3	512	14x14x512	ReLU
11.	Max Pooling	1	2x2	-	7x7x512	-
12.	Fully Connected Layer	1	-	4096	4096	ReLU
13.	Fully Connected	1	-	4096	4096	ReLU

	Layer					
14.	Output Layer	1	-	Number of Classes	Number of classes	Softmax

Table 2. Architecture of VGG-16

Prediction: -Once the model produces its predictions, the loss is computed by comparing the predictions against ground truth data using a loss function. Some of the most commonly used loss functions for this purpose are Mean Squared Error (MSE) for density map regression and Cross Entropy Loss for density classification. Zhang et al. (2016) propose loss functions specifically for crowd counting tasks in order to minimize errors that may appear in difficult situations where there is occlusion or perspective distortion. Xue et al. (2021) indicate that in high-density crowd scenes, where people are packed very closely, the use of robust loss functions is necessary.

The final product range includes a density map that visualizes crowd density throughout the input scene, a total count of individuals present. Saleh et al. (2015) undertook a comprehensive review of means that harness density maps and numerical counts for surveillance-based views. Lin and Hu (2024) discuss how to integrate edge intelligence into crowd density estimation. This will allow real-time efficient outputs for further applications in smart cities.

Evaluation and Metrics:-

We have to use python for the experiments, Tensorflow, Keras and PyTorch library on Google Colab with GPU. Performance is measured by accuracy metrics to evaluate the performance of proposed methodology. The proposed approach achieves accuracy of 90%, recall of 88%, and an F1-score of 90% on a dataset of crowd images. The analysis of the confusion matrix revealed the risk that the model might underperform in the detection of minor cracks, with a false positive rate of 20%. To overcome this weakness, we develop a post-processing technique. It essentially includes an image segmentation and feature extraction phase to improve the precision of people detection in an image.

Mathematical representation of MAE and MSE:-

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Conclusion

The development of an optimized spatial analysis model for crowd density estimation addresses significant scalability, accuracy, and real-time usability limitations. By employing convolutional neural networks and advanced techniques such as lightweight architectures, truth attention mechanisms, and knowledge distillation, the model achieves a balance between accuracy and computations. Utilizing multiple datasets like real-world and synthetic datasets increases robustness and generalizability across scenarios. The use of methods like model pruning and quantization enables optimization for edge devices so that this model fits within real-time smart city and public safety surveillance applications. Those metrics, such as MAE and RMSE, give an overall performance impression of the model, and comparison with state-of-the-art methods shows it is competitive.

This research provides a foundation for future crowd density estimation innovations, emphasizing the importance of finding a balance between accuracy, efficiency, and scalability. The method proves the viability of real-world applications in urban planning, public safety, and event management while considering ethical concerns for privacy in crowd monitoring systems

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