AI-DRIVEN CROWD DENSITY ESTIMATION FOR SMART PUBLIC SAFETY MONITORING

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Introduction:

1. In contemporary In today's cities, a lot of people often gather in places like train stations, stadiums, markets, festivals, and religious events. When too many people are in one place, it can be very dangerous because it can cause traffic jams, panic, or even stampedes. It can be hard and take a lot of time to watch over crowded places by hand with security guards or regular CCTV systems.
2. Recent advances in computer vision and artificial intelligence have made it possible to automatically look at pictures and videos to learn about how people act in crowds. You can use crowd density estimation methods to figure out how many people are in a certain area and find areas that are very crowded. This information can help the people in charge of public spaces do a better job of managing them.
3. Before, crowd monitoring mostly relied on counting by hand or simple object detection. But these methods don't work very well when there are a lot of people in a small space or when visibility is limited. Instead of finding each person individually, modern deep learning methods like convolutional neural networks can make density maps that show how many people are in a certain area.
4. This project aims to create an AI-based system that uses surveillance images or video feeds to figure out how many people are in a crowd. The system will make density maps and heatmaps to show where people are in a scene. The system can help authorities find dangerous situations early and take steps to make cities safer and better run by keeping an eye on crowd levels all the time.

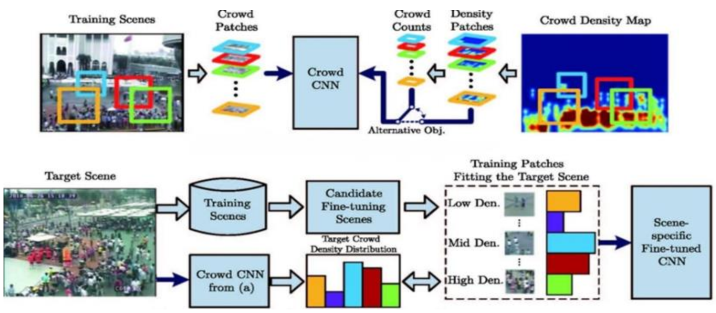

Figure 1: CSRNet Working

Objectives:

1. To create a system that can determine how many people are in a crowded area.
2. To process surveillance photos and videos using computer vision techniques.
3. To create density maps that show how people are distributed throughout a specific area.
4. To produce heatmaps that show areas with dense crowds.
5. To categorize densities of crowds into safe and unsafe categories.
6. To create an ideal user interface to show the outcomes of crowd analysis.
7. To send out early warnings when crowd density surpasses predetermined safety thresholds.
8. To create a system that enables real-time surveillance in public spaces.

Methodology:

1. Deep learning models, computer vision approaches, and real-time video processing techniques will all be used in the implementation of the suggested system. There will be multiple phases to the development process.
2. In order to train and test the system, appropriate crowd datasets will first be gathered. Images with varying crowd densities can be found in publicly accessible datasets like ShanghaiTech and UCF crowd datasets, which will be utilized for testing. Annotated photos from these datasets are used to train machine learning models for density estimation.
3. OpenCV will be used to preprocess the images prior to model training. Reducing noise, normalizing pixel values, converting images into appropriate formats, and resizing images to a standard resolution are examples of preprocessing procedures. These procedures enhance the quality of the input data and aid in the model's discovery of significant patterns.
4. A deep learning model built on the CSRNet architecture will be the system's primary component. Density estimation and crowd counting are two common uses for this model. It extracts significant visual characteristics from images using convolutional neural networks. The network creates density maps in which the concentration of people in a scene is represented by pixel intensity.
5. Following the creation of density maps, the system will sum the values in the density map to determine the overall crowd count. After that, a color-based heatmap that graphically depicts crowded areas will be created from the density map. Areas with higher density will appear in warmer colors while low-density areas will appear in cooler colors.
6. Tkinter and other Python libraries will be used to create a graphical user interface. Users will be able to view the crowd analysis results and upload pictures or videos using this interface. The estimated crowd size, density level, and heatmap visualization will all be shown on the interface.
7. Lastly, threshold values for classifying different levels of crowd density will be established. When the crowd density exceeds a certain limit, the system will generate alerts to notify users about potentially unsafe crowd conditions.

Result and Conclusion:

1. In conclusion, the creation of a useful system that can calculate crowd density from photos or video streams is the project's anticipated outcome. After analyzing surveillance data, the system will create density maps that show how people are distributed in a specific area.
2. Visual heatmaps that show areas with high crowd concentration will be generated by the model. Authorities will be able to swiftly identify areas that need attention with the aid of these heatmaps. Additionally, the system will classify the crowd level according to predetermined thresholds and estimate the total number of people in the scene.
3. The project intends to increase crowd monitoring efficiency by fusing artificial intelligence with video surveillance systems. The system will help event planners and security staff spot possible threats before they become serious.
4. The project shows how public safety applications can benefit from AI-based crowd analysis. It can be applied in a variety of settings, including public spaces, transit hubs, and big events where crowd control is crucial.
5. All things considered, the developed system will offer a workable method for enhancing safety in crowded settings through automated monitoring and early overcrowding situation detection.

References:

1. [1] A. B. Chan, Z. S. J. Liang, and N. Vasconcelos, “Privacy preserving crowd monitoring: Counting people without people models or tracking,” in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2008.
2. [2] V. Rabaud and S. Belongie, “Counting crowded moving objects,” in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2006.
3. [3] A. Marana, S. Velastin, L. Costa, and R. Lotufo, “Estimation of crowd density applying texture analysis,” Safety Science, 1997.
4. [4] D. Kong, D. Gray, and H. Tao, “A viewpoint invariant approach for crowd counting,” in Proc. Int. Conf. Pattern Recognition (ICPR), 2006.
5. [5] Y. Zhang, D. Zhou, S. Chen, S. Gao, and Y. Ma, “Single-image crowd counting via multi-column convolutional neural network,” in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2016.
6. [6] D. Sam, S. Surya, and R. V. Babu, “Switching convolutional neural network for crowd counting,” in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2017.
7. [7] Y. Li, X. Zhang, and D. Chen, “CSRNet: Dilated convolutional neural networks for understanding highly congested scenes,” in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), pp. 1091–1100, 2018.
8. [8] B. Sindagi and V. Patel, “A survey of recent advances in CNN-based single image crowd counting and density estimation,” Pattern Recognition Letters, 2018.
9. [9] X. Liu, J. van de Weijer, and A. M. López, “Density-aware person detection in crowds,” International Journal of Computer Vision, 2019.
10. [10] J. Redmon and A. Farhadi, “YOLOv3: An incremental improvement,” arXiv preprint arXiv:1804.02767, 2018.

11. [11] S. Ren, K. He, R. Girshick, and J. Sun, “Faster R-CNN: Towards real-time object detection with region proposal networks,” in Proc. Advances in Neural Information Processing Systems (NeurIPS), 2015.
12. [12] L. Zhang, M. Shi, and Q. Chen, “Crowd counting via scale-adaptive CNN,” in Proc. IEEE Winter Conf. Applications of Computer Vision (WACV), 2018.
13. [13] H. Idrees, M. Tayyab, K. Athrey, D. Zhang, S. Al-Maadeed, and M. Shah, “Composition loss for counting, density map estimation and localization in dense crowds,” in Proc. European Conf. Computer Vision (ECCV), 2018.
14. [14] W. Marsden et al., “Crowd behavior analysis using computer vision techniques,” ACM Computing Surveys, 2020.
15. [15] S. Yang, Z. Wang, Y. Li, and K. Xu, “Real-time crowd counting via mobile lightweight CNNs,” IEEE Access, vol. 9, 2021.

Future Scope:

The future scope of this project includes:

1. There are numerous ways to expand and enhance the suggested system. Future advancements could concentrate on improving the crowd monitoring system's scalability and accuracy.
2. Integrating real-time video streams from several security cameras is one potential enhancement. This would make it possible for the system to more efficiently monitor big areas like city centers, stadiums, and transit hubs.
3. To increase the accuracy of crowd density estimation in extremely dense scenes, more sophisticated deep learning models can be investigated. The system's performance could be improved by new architectures and improved training methods.
4. The incorporation of Internet of Things (IoT) technologies is another potential extension. Security staff can receive system-generated alerts automatically via public announcement systems, control room dashboards, or mobile applications.
5. Additionally, crowd movement analysis could be added to the system. Authorities can better understand how people move within a space and effectively manage crowd control by observing the direction and speed of crowd flow.
6. By facilitating automated monitoring, safer public gatherings, and enhanced emergency response systems, this technology may eventually play a significant role in the infrastructure of smart cities.