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CROWD COUNTING METHOD BASED ON CONVOLUTIONAL NEURAL NETWORK WITH GLOBAL DENSITY FEATURE

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ABSTRACT:

Methods for counting large groups of people are a major area of study in computer vision. The multi-column convolutional neural network (MCNN) has shown noteworthy performance among them. But when dealing with irregular crowd distributions, the accuracy of crowd counting using MCNN needs improvement. This research overcomes that obstacle by enhancing the MCNN model with crowd global density characteristics. We extract global density characteristics and put them into the MCNN architecture using cascaded learning approaches. We suggest an improved MCNN architecture to retain fine-grained characteristics that are often lost during downsampling. To save more complex details, max-ave pooling is used instead of max pooling, and deconvolutional layers help to restore information that was lost during downsampling. Our suggested method improves accuracy and stability, leading to potential advances in crowd counting accuracy under different crowd distributions, as shown experimentally on datasets like UCF CC 50 and ShanghaiTech.

I INTRODUCTION

To determine how many individuals are present in each frame of a picture or video, crowd counting is utilised. Three types of crowd counting techniques can be distinguished: direct counting based on target detection, indirect counting based on feature regression, and deep learning-based crowd counting. Lin et al. [1] suggested using the Haar wavelet transform to extract the feature area of the head like contour and develop the

SVM classifier to classify the feature area in the pertinent investigations based on target detection [1]-[5]. Kowalak et al. [2] suggested using body shape and contour to identify crowds and estimate their densities. All of these techniques work well in situations with low crowd densities, but in situations with high densities, the detection accuracy will suffer. The regression correlations between picture attributes and the population size are developed for crowd

counting in the pertinent feature regression studies [6] through [10]. Low-level characteristics and Bayesian regression were suggested by Chan et al. [7] as a way to increase the resilience and adaptability of the regression model. Idrees et al. proposed a way to combine data from many sources to estimate the population of a single image was made in their paper [8], which also introduced the UCF CC 50 dataset. Deep learning-based solutions for crowd counting are steadily being presented in recent times due to the rapid growth of deep learning and large data. An approach for cross-scene crowd counting was suggested by Zhang et al. Density map and global number were the two learning objectives that were alternatively used to train it. This algorithm's implementation is based on CNN with a single column. But, given the increase in crowd size, it is inappropriate. For crowd counting, Zhang et al. suggested using the MCNN with three branch networks. Each branch network employed a different set of receptive fields, allowing the upgraded MCNN to adjust to changes in the crowd's size. They also unveiled a brand-new dataset for crowd counting called ShanghaiTech. To increase spatial resolution, Boominathan et al. suggested combining the advantages of shallow and deep convolutional neural networks.

A multi-task network that incorporated the high-level prior and density estimation was proposed by Sindagi et al. Switch-CNN was suggested for crowd counting by Sam et al. In this network, a classifier was trained, and suitable input patches were chosen for the regressor. In their proposal, Shi et al. suggested condensing multiscale features into a small single vector and using a deep supervised technique to add more supervision signal. Fu et al. suggested using the LSTM structure to retrieve the crowd region's contextual information. In order to adaptively choose the counting mode utilised at various positions on the image, Liu et al. suggested adding an attention module. The MMCNN was suggested by Yang et al. for accurate crowd counting. In order to increase the robustness of the crowd counting method, in this work the location, specific information, and scale variation were taken into account to build density map. In general, these algorithms perform well while counting crowds, however when the crowd distribution is unequal, their results are ineffective.

A branch of artificial intelligence called computer vision enables computers to recognise and comprehend the visual world, or the world of pictures and movies. Computer vision involves

classifying and identifying images captured by cameras, then drawing conclusions from them or using images to analyse events and determine the best course of action. The goal of crowd counting is to count or estimate the population of an image. There are two types of crowds: sparse crowds and dense crowds. Dense crowd counting involves counting the number of individuals in densely populated areas, whereas sparse crowd counting involves counting the number of people in spatially dispersed areas.

II.LITERATURE REVIEW

Yang Zhang et al. [4] The article presents a technique for estimating the crowd size from an image with varied crowd density and perspective. In order to do this, the article created an architecture known as the Multi-column Convolutional Neural Network (MCNN), which converts a picture into a map of crowd density. The paper's evaluation measures are MAE and MSE. In order to appropriately cover all the tough cases, the model was trained and evaluated on 4 different datasets, one of which was introduced by this research.

V. A. Sindagi and others [8] In order to learn crowd count classification and density map estimate simultaneously, the authors attempted to solve this

challenge using a new CNN architecture consisting of end-to-end cascaded networks. By categorising the crowd count into different groups, the method suggested incorporates a high-level prior into the density estimate network, which is similar to roughly estimating the total count in the image. This makes it possible for the layers of the network to accumulate globally applicable discriminative characteristics that aid in estimating density maps that are more accurate and have a smaller count error. From beginning to end, the integrated training is completed. Thorough testing on extremely difficult publicly available data sets demonstrates that the suggested method creates denser maps with lower count errors and higher quality than current state-of-the-art methods.

D. B. Sam et al. [7] The authors propose a crowd counting model that transforms a crowd scene from an input image to its density as a solution to the crowd counting problem. They have introduced a switching convolution neural network-based model to address the common issues and challenges encountered during crowd analysis, such as inter-occlusion between people caused by crowding, indistinguishability between people and the background scene or objects, high variability of camera point-of-views, etc. by utilising the image's

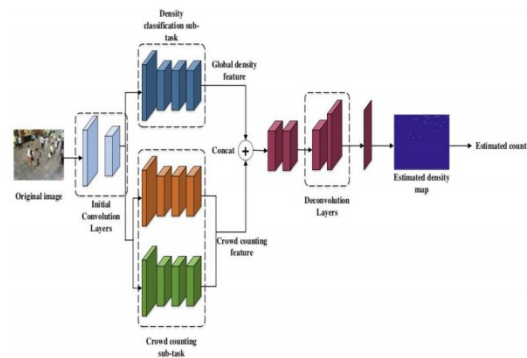
wide variation in crowd density to increase the final estimated crowd count's accuracy and localization.

P. Thanasutives et al. This paper's authors take a different tack when it comes to crowd counts. They propose a technique based on dual path multi-scale fusion networks (SFANet and SegNet), two modified neural networks. These two networks or models were given the names M-SFANet and M-SegNet. With the help of atrous pyramid pooling (ASPP), which consists of parallel atrous convolution layers with different sampling rates, the SFANet encoder is able to extract multi-scale features from the target object and integrate those features into a wider context. The context-aware-module (CAN), which is also related to MSFANet, is used by the authors to deal with scale variation in the input image further and to adaptively encode the scales of the contextual information. As a result, the developed model may be used to count people in both scenarios of dense and sparse crowds.

III.ALGORITHM FRAMEWORK

The primary framework of the suggested strategy can be separated into three sections in this paper: First, the sub-task for density classification yields the global density characteristics. These are

combined with information gleaned from the crowd counting task. Then, in order to maintain more features, max-ave pooling is introduced. Deconvolutional layers are also utilised to recover lost features during the downsampling process. Lastly, a feature map with a global density feature is used to construct the estimated density map. Estimated counting is obtained using the estimated density map. The algorithm's framework.



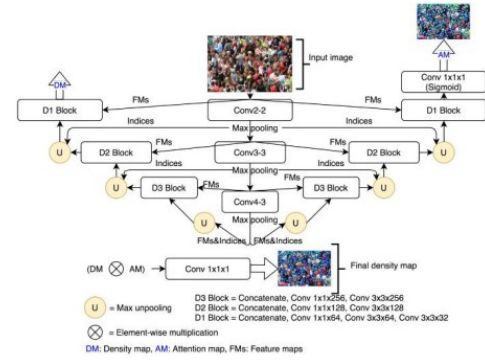
CONVOLUTIONAL NEURAL NETWORK WITH GLOBAL DENSITY FEATURE

The MCNN-based method of crowd counting has thus far shown accurate counting results. The methods for counting crowds that are currently in use, however, do not account for uneven crowd distributions. The global density characteristic is taken into consideration in order to address the issue of unequal crowd dispersion. In this study, the network is built using two methods: extracting feature maps with global

density features, and creating a denser map overall.

Working:

Convolution and deconvolution use different computation techniques. You can think of deconvolution as the convolution computation done backwards. In essence, it is an up sampling procedure. The high-dimensional characteristics will be down sampled to the low-dimensional features throughout the calculation procedure in the pooling layers. The feature map's resolution will be decreased. Each pooling region's location of the maximum in the low-dimensional feature matrix will be noted in a position set. The resolution of the feature map will be restored during the up sampling procedure in the deconvolutional layers. The maximum inside each pooling zone will be roughly restored in the high-dimensional feature matrix in accordance with the position selected after the high-dimensional feature matrix has been reconstructed. The remaining values in the high-dimensional feature matrix will be 0.



The process of convolution down-sampling and deconvolution up-sampling is shown in Fig.3. In Fig.3, when the down-sampling operation in the first convolutional layer is finished, the resolution of output feature map in the pool1 becomes half of that in the input image. When the downsampling operation of the second convolutional layer is finished, the resolution of output feature map in the pool2 becomes half of that in the pool1. That means it only keeps 1/4 resolution of the input image. Through adding two deconvolutional layers and four times up-sampling.

Method	Avg. MAE	Avg. MSE
Zhang, Y. et al. [4]	11.6	-
Sam, D. B. et al. [7]	9.4	-
Cong Zhang et al. [6]	10.7	15.0

Table: Comparison of the models reviewed in this paper on UCF_CC_50 dataset

IV.CONCLUSION

Our data suggests that crowd counting and density analysis have come a long way in recent years. Using convolutional neural network (CNN) architecture as a

foundation, this research investigated many methods for crowd density analysis and counting. The results of evaluating the techniques suggested by different authors utilising datasets from ShanghaiTech, UCF CC 50, UCSD, WorldExpo10, etc., revealed that the strategies' performance differed based on the dataset and application situation. There is a strong relationship between the quality of the dataset's preprocessing and the model's performance after receiving the processed data. The evaluation makes it quite evident that there are benefits and drawbacks to each method; in certain cases, one approach may be more appropriate than the others. The developers of these methods have refined their model via substantial study, allowing it to consistently provide accurate findings.

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