Optimization Approach for Prediction in MPCount Algorithm

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1 Implementation

This section provides an overview of the modifications made to the MPCount algorithm to optimize both prediction speed and memory efficiency for high-resolution images.

In this approach, downsampling and convolutional integration were introduced to enhance efficiency. Unlike the previous patch-based method, which divided images into patches and processed each independently, downsampling reduces spatial resolution, preserving density distribution while lowering pixel processing requirements. Convolutional integration further facilitates local averaging in the downsampled image, significantly reducing computational complexity and making it suitable for real-time applications in large-scale counting tasks.

2 Results

The following tables compare the performance metrics (processing time and prediction accuracy) of the original and optimized versions of the MPCount algorithm on various datasets. Here processing time refers to the time taken in prediction and testing on a particular dataset.

Table 1: Comparison of Processing Time for Original and Optimized Model

Model Trained On	**Testing On**	**Original Time (MM:SS)**	**Optimized Time (MM:SS)**
ShanghaiTech Part A	ShanghaiTech Part B	02:25	00:54
ShanghaiTech Part B	ShanghaiTech Part A	01:03	00:35
UCF-QNRF	ShanghaiTech Part A	01:03	00:33
UCF-QNRF	ShanghaiTech Part B	02:25	00:54

Table 2: Comparison of Prediction Accuracy (MAE, MSE) for Original and Optimized Model

Model Trained On	**Testing On**	**Original (MAE, MSE)**	**New algorithm (MAE, MSE)**
ShanghaiTech Part A	ShanghaiTech Part B	11.39, 19.73	97.90, 126.29
ShanghaiTech Part B	ShanghaiTech Part A	102.60, 183.04	286.07, 427.19
UCF-QNRF	ShanghaiTech Part A	64.89, 108.80	260.87, 401.71
UCF-QNRF	ShanghaiTech Part B	12.62, 24.65	98.09, 126.48

3 Analysis of Results

We have achieved a significantly faster prediction algorithm, with the time required for processing reduced to less than half compared to the original model. This improvement highlights the effectiveness of our optimized approach, making it well-suited for real-time applications where speed is essential.

The increase in Mean Absolute Error (MAE) and Mean Squared Error (MSE) in the optimized approach is primarily attributed to the following factors:

- The downsampling process enhances computational efficiency by reducing the number of pixels processed. While this speeds up predictions, it can smooth out fine-grained details, potentially leading to inaccuracies in regions with intricate density variations. Despite this, the method retains an accurate representation of overall density distribution, which is ideal for real-time applications where speed is critical.
- The convolutional integration step introduces an approximation in density summation, balancing speed and accuracy. While this approach simplifies the computation, it can result in slight increases in MSE and MAE, as it focuses on rapid estimation of the overall count. This trade-off between speed and minor accuracy loss makes the optimized method well-suited for scenarios that prioritize quick response times.