Table I
Accuracy and Predictive Values

	UNet Segmentation				CRF Segmentation			
	Acc.	CPV	DPV	NPV	Acc.	CPV	DPV	NPV
Binary Segmentation, Dice Loss								
Minimal	0.2629	0.0108	-	0.3144	0.2556	0.0086	-	
Average	0.7427	0.3962	-	0.8984	0.7440	0.3978	-	0.8987
Median	0.7580	0.3933	-	0.9464	0.7589	0.3939	-	0.9479
Maximal	0.9243	0.8968	-	1	0.9217	0.9001	-	1
Binary Segmentation, Focal Loss								
Minimal	0.3379	0	-	0.3330	0.3389	0	-	0.3322
Average	0.8308	0.4023	-	0.8513	0.8098	0.4185	-	0.8292
Median	0.8671	0.3960	-	0.8891	0.8412	0.4110	-	0.8635
Maximal	0.9785	0.9897	-	0.9965	0.9780	1	-	0.9950
Ternary Segmentation, Dice Loss								
Minimal	0.0685	0.1310	0	0	0.0622	0.1271	0	0
Average	**0.3175**	0.6830	**0.3746**	0.5127	**0.4498**	0.6819	**0.5169**	0.5132
Median	**0.3067**	0.7412	**0.3245**	0.5017	**0.4386**	0.7447	**0.5616**	0.5132
Maximal	**0.7331**	0.9992	0.9992	1	**0.9168**	0.9983	0.9947	1
Ternary Segmentation, Focal Loss								
Minimal	0.0053	0.0466	0	0	0.0534	0.0899	0.0002	0
Average	**0.3178**	0.7028	**0.2437**	0.4929	**0.5026**	0.7014	**0.4890**	0.4765
Median	**0.3012**	0.8016	**0.0771**	0.4913	**0.4952**	0.7785	**0.4911**	0.4693
Maximal	**0.7775**	0.9998	1	1	**0.9381**	1	0.9911	1

Sometimes the rates $N_1/\hat{N}_1$ and $N_2/\hat{N}_2$ are greater than 1. It may indicate situations where separate persons are detected as crowds and sparse crowds are recognized as dense crowd regions. According to our calculations, from 15% to 25% images have such values. Hence, the model might both under- and overestimate the crowd density. Also, data from Table II prove again using the CRF is crucial for ternary segmentation prediction.

Table II
Crowd Detection Rates

	UNet segmentation		CRF segmentation	
	Dice	Focal	Dice	Focal
Binary Segmentation ($N_1/\hat{N}_1$)				
Minimal	0.0097	0	0	0
Average	0.7896	0.1719	0.7909	0.1687
Median	0.8454	0.1189	0.8473	0.0872
Maximal	1.3235	0.8868	1.3235	0.9057
Ternary Segmentation ($N_2/\hat{N}_2$)				
Minimal	0	0.0402	0	0
Average	**0.5298**	0.0199	**0.8785**	0.7896
Median	**0.5215**	0	**0.9704**	0.8517
Maximal	1.2971	1	1.2971	1.2971

B. Crowd Semantics

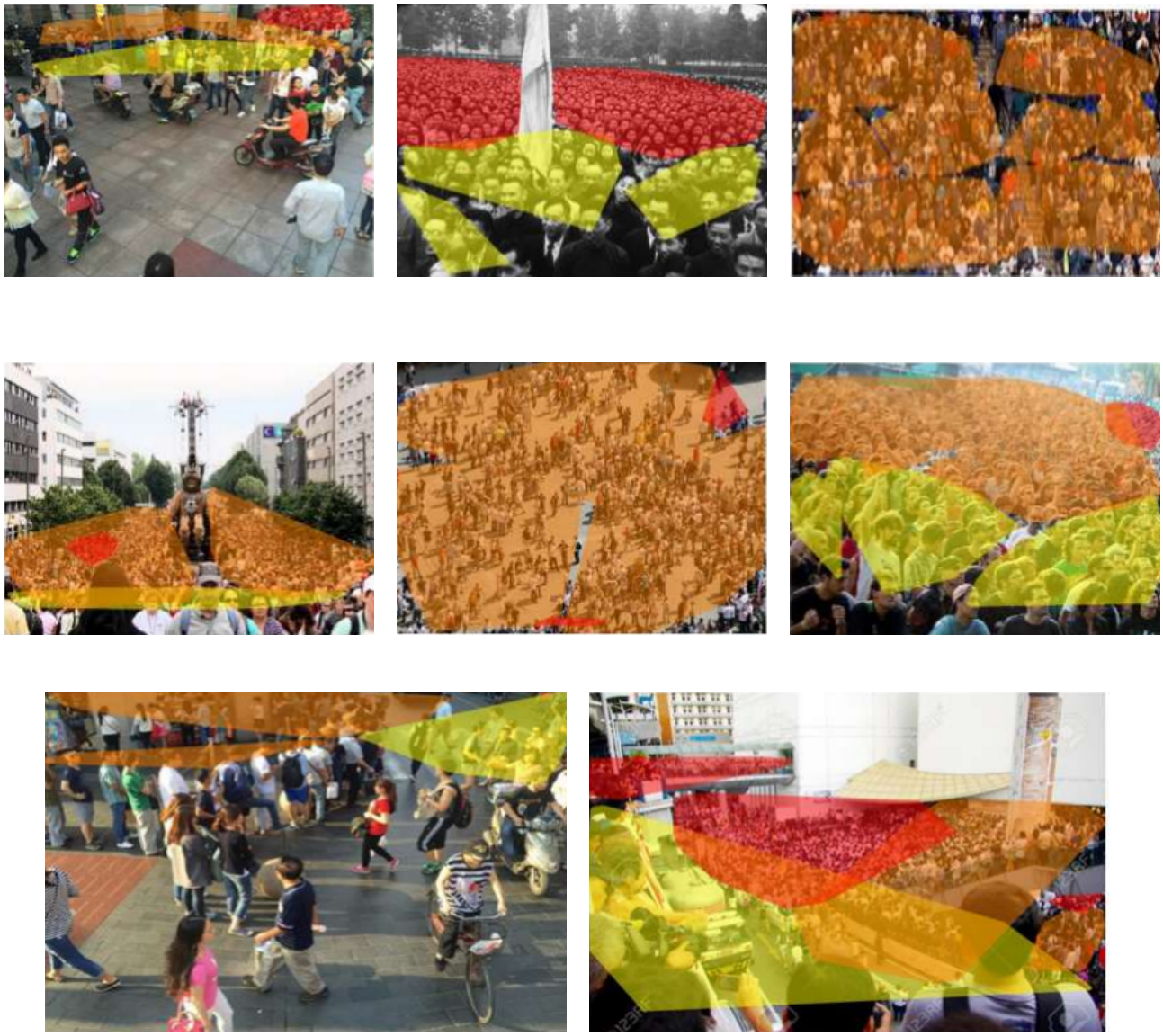
Most of the ShanghaiTech datasets images are captured by a camera observing a nearby scene from above. Hence, the typical clusterization consists of distant dense clusters, closer regular clusters, and near sparse clusters (1). However, the crowd in an image can be divided vertically if there is a tall object like a pole or a flag (Fig. 4b).

Sometimes the pattern doesn't hold, which could indicate a group with interest. Some examples where we detect a people's interest include:

- Multiple clusters with equal density spanning most of the image (Fig. 4c). Those usually present a uniform crowd with regular attention.
- A small cluster within or near a bigger one of a different type (Fig. 4, d-e). Those situations usually present a concentration of interest in particular groups within or near the crowd.
- A significant overlapping between clusters of different types (Fig. 4f). This one can indicate a spreading interest or joining the people groups. Real-time surveillance systems must detect such actions to prevent any dire situations.
- Elongated clusters presenting regular or dense crowds may indicate the presence of a queue in the region (Fig. 4g, the bottom orange cluster). If the density is high enough, some extraordinary situations might take place like queue crushes or evacuation panic which must be dealt with immediately.
- A wide sparse cluster at the bottom of the image might indicate a group of people that is very close to the observer (Fig. 4, d, h). Overlapping between the close cluster and other, distant ones is another feature of such a situation. Depending on the people's behavior, such a close group might be considered an outlier or an interest group, especially when it grows or approaches the observer.

v. Conclusions

This paper presents an approach for semantic segmentation of dense and sparse crowd images, addressing the critical



Semantic segmentation of crowds of different types: regular crowds with no attention (a, b), uniform crowd with regular attention (c),diverse crowd containing groups with increased interest (d, e), diverse crowd with a spreading group with interest (f), crowd with a queue (g), crowd with a close cluster (h)

need for accurate crowd analysis in various applications such as crowd management, surveillance, and urban planning. Our proposed method leverages a combination of UNet and CRF networks, augmented by a semi-automatic labeling technique based on Gaussian blur and thresholding methods to generate ground truth maps. Furthermore, we highlight some typical crowd behavior patterns based on clustering the people groups by their density and interconnections between them. Indicating those patterns is important for understanding crowd structures and dynamics as well as establishing crowd management and safety.

Through extensive experimentation and evaluation, we have demonstrated the effectiveness of our approach in accurately segmenting crowd images, particularly in binary segmentation tasks distinguishing crowded from non-crowded regions. While our model excels in binary segmentation, we acknowledge the challenges encountered in ternary segmentation tasks involving dense crowds, sparse crowds, and non-crowded areas. Despite this, our model shows promising results in crowd detection regardless of crowd density. Besides, we prove the necessity of CRF refinement to get better results.

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АВТОМАТИЗАЦИЯ ОЦЕНКИ ВНИМАНИЯ СКОПЛЕНИЙ ЛЮДЕЙ НА ОСНОВЕ ПОЛУАВТОМАТИЧЕСКОЙ СЕМАНТИЧЕСКОЙ СЕГМЕНТАЦИИ ИЗОБРАЖЕНИЙ С ИСПОЛЬЗОВАНИЕМ СЕТЕЙ UNET И CRF

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Семантическая сегментация изображений скоплений людей играет ключевую роль в различных приложениях, таких как управление толпой, наблюдение и городское планирование. В данной статье предложен подход к семантической сегментации изображений с плотной и разреженной толпой на основе полуавтоматической разметки, используя комбинацию UNet и условных случайных полей (CRF).

Представляется новый метод семантической сегментации для изображений скоплений людей. Сеть UNet используется для первоочередной сегментации, после которой необходимо следует её уточнение с использованием CRF. Результаты экспериментов показали, что модель лучше выявляет бинарную маску (области, занятые людьми, и фона), свободную от ошибок, чем без использования CRF. Кроме того, улучшение точности, показанной с помощью количественных и качественных результатов, превосходит существующие методы сегментации.Таким образом, предложенный подход даёт лучшие результаты по сегментации толпы в целом (без учёта типа плотности толпы), показав значительное улучшение сегментации при помощи CRF в задаче генерации сегментации толпы.

Также на основе предложенной модели сегментации выделены некоторые закономерности поведения скоплений людей. Они связаны как с плотностью внимания людей, связанным с восприятием людей и между ними, а также вероятностью возникновения чрезвычайных ситуаций.

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