TABLE A.I: Comparison of algorithms in the CBC dataset. CBC consists of 360 images with 3 classes, including RBC, WBC and Platelets, containing objects with different classes. We divide three local sets with train/test ratio of 8:2.

Method	mAP	Recall	
FedAvg	46.33±0.01	$67.62 \pm 0.02$	
FedProx	44.56±0.01	$66.24 \pm 0.01$	
FedPer	44.05±0.01	$65.51 \pm 0.02$	
MOON	45.28±0.01	$66.13 \pm 0.01$	
DCFL( $\mu$ =5)	44.86±0.01	$66.73 \pm 0.02$	
$DCFL(\mu=1)$	47.23±0.01	$68.95 {\pm} 0.01$	

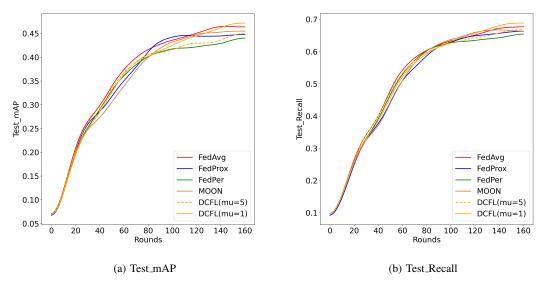


Fig. A.1: The test mAP and recall of algorithms in the CBC dataset. (a) and (b) represent mAP and recall, respectively. DCFL still performs better than other algorithms in the CBC dataset.

TABLE A.II: Ablation study of two key components: hyper-parameter  $\mu$  and multi-scale representations learned from different layer combinations. We investigate four modes of layer combinations. Although the mAP with M1 and  $\mu$ =5 is higher than that with layer1 and  $\mu$ =1, we still consider the combination of layer1 and  $\mu$ =1 to be he superior one, given the computational cost and time.

Mode	Layer1	Layer2	Laver3	μ=0.5		<i>μ</i> =1		μ=5	
			Layers	mAP	Recall	mAP	Recall	mAP	Recall
M1				48.71±0.01	$62.20 \pm 0.01$	47.61±0.05	$62.41 \pm 0.03$	55.79±0.82	66.62±0.54
M2	$\checkmark$	$\checkmark$		51.66±0.13	$65.25 \pm 0.10$	49.03±0.13	$62.98 \pm 0.11$	47.42+0.05	$61.31 \pm 0.03$
M3	$\checkmark$		$\sqrt{}$	52.43±0.12	$66.17 \pm 0.11$	47.86±0.01	$61.80 \pm 0.01$	50.01±0.17	$62.42 \pm 0.15$
M4		$\checkmark$		47.90±0.04	$61.87 {\pm} 0.03$	51.28±0.14	$66.15 \pm 0.12$	45.12±0.51	$59.46 \pm 0.28$

TABLE A.III: Ablation study of varying number of representation scales. Our multi-scale design S1 (K=2) outperforms the other two single-scale settings of S2 and S3 (K=1).

Mode	Scale1	Scale2	mAP	Recall
S1			54.04±0.09	67.94±0.07
S2	$\sqrt{}$		51.23±0.15	$65.58 \pm 0.12$
<b>S</b> 3		$\checkmark$	50.90±0.05	$64.87 \pm 0.04$