Active Learning for Object Detection

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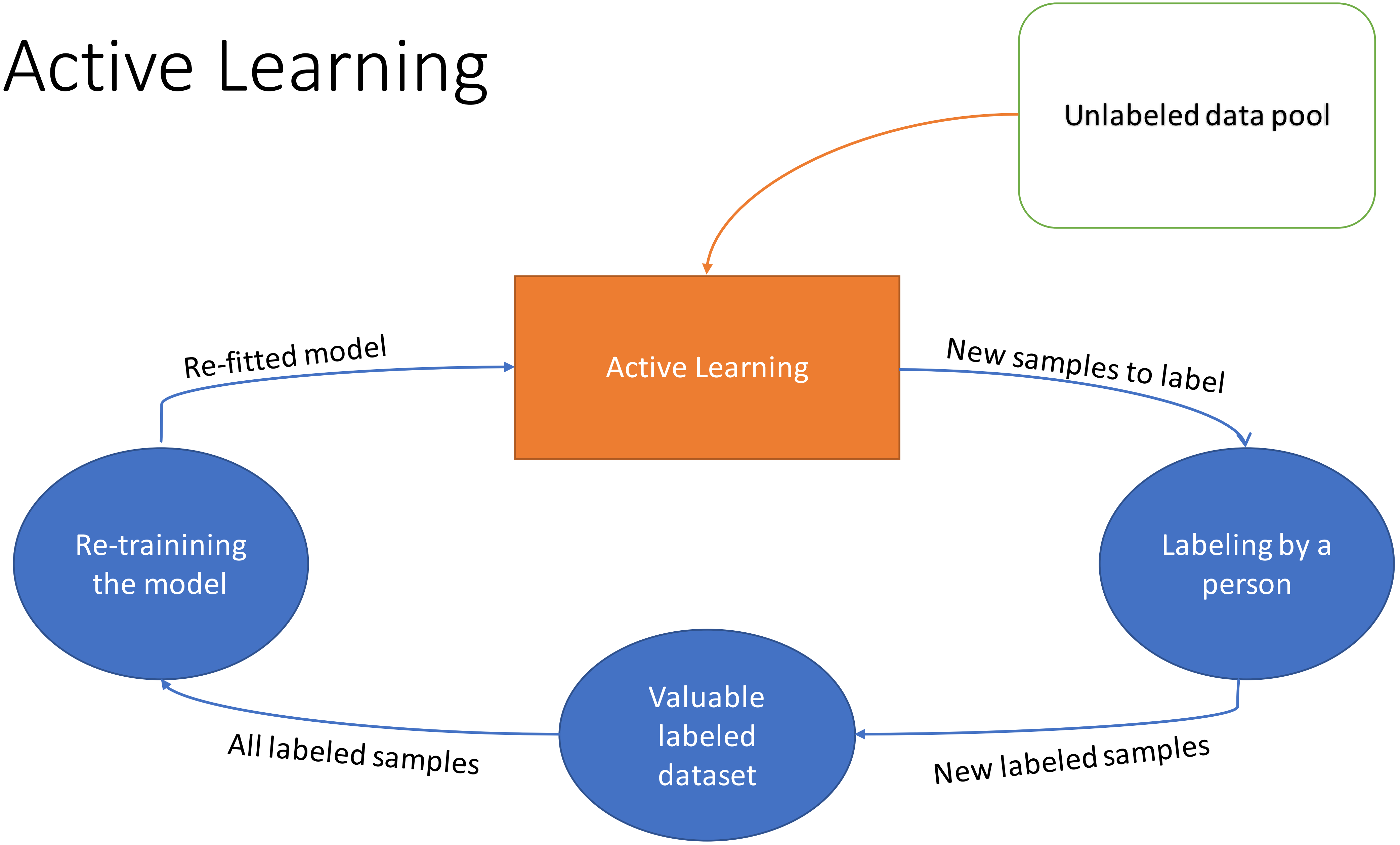
Active Learning



MI-AOD: Multiple Instance Active Learning for Object Detection

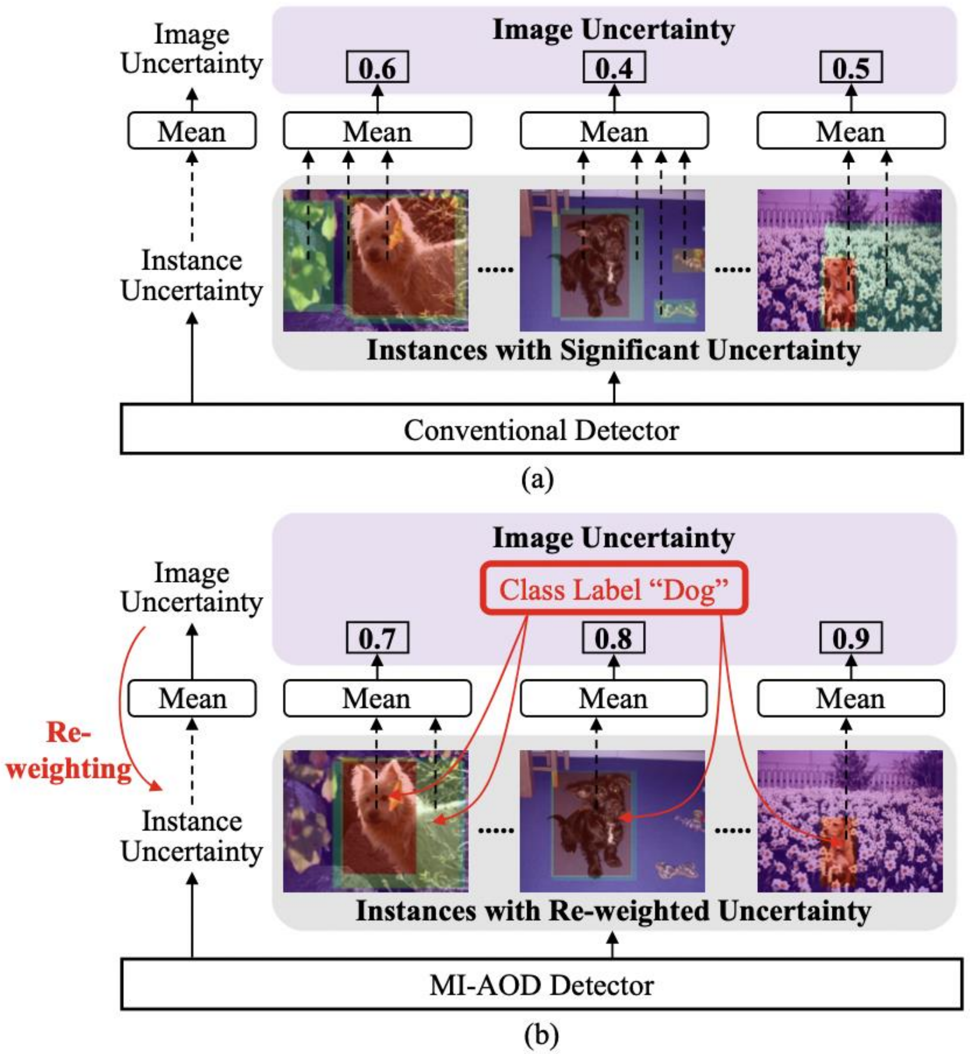


Figure 1. Comparison of active object detection methods. (a) Conventional methods compute image uncertainty by simply averaging instance uncertainties, ignoring interference from a large number of background instances. (b) Our MI-AOD leverages uncertainty re-weighting via multiple instance learning to filter out interfering instances while bridging the gap between instance uncertainty and image uncertainty. (Best viewed in color)

MI-AOD Loss Function

$$\underset{\Theta \setminus \theta_g}{\operatorname{argmin}} \mathcal{L}_{max} = \sum_{x \in \mathrm{X}_L} l_{det}(x) - \sum_{x \in \mathrm{X}_U} \lambda \cdot l_{dis}(x),$$

where

Function to modify:

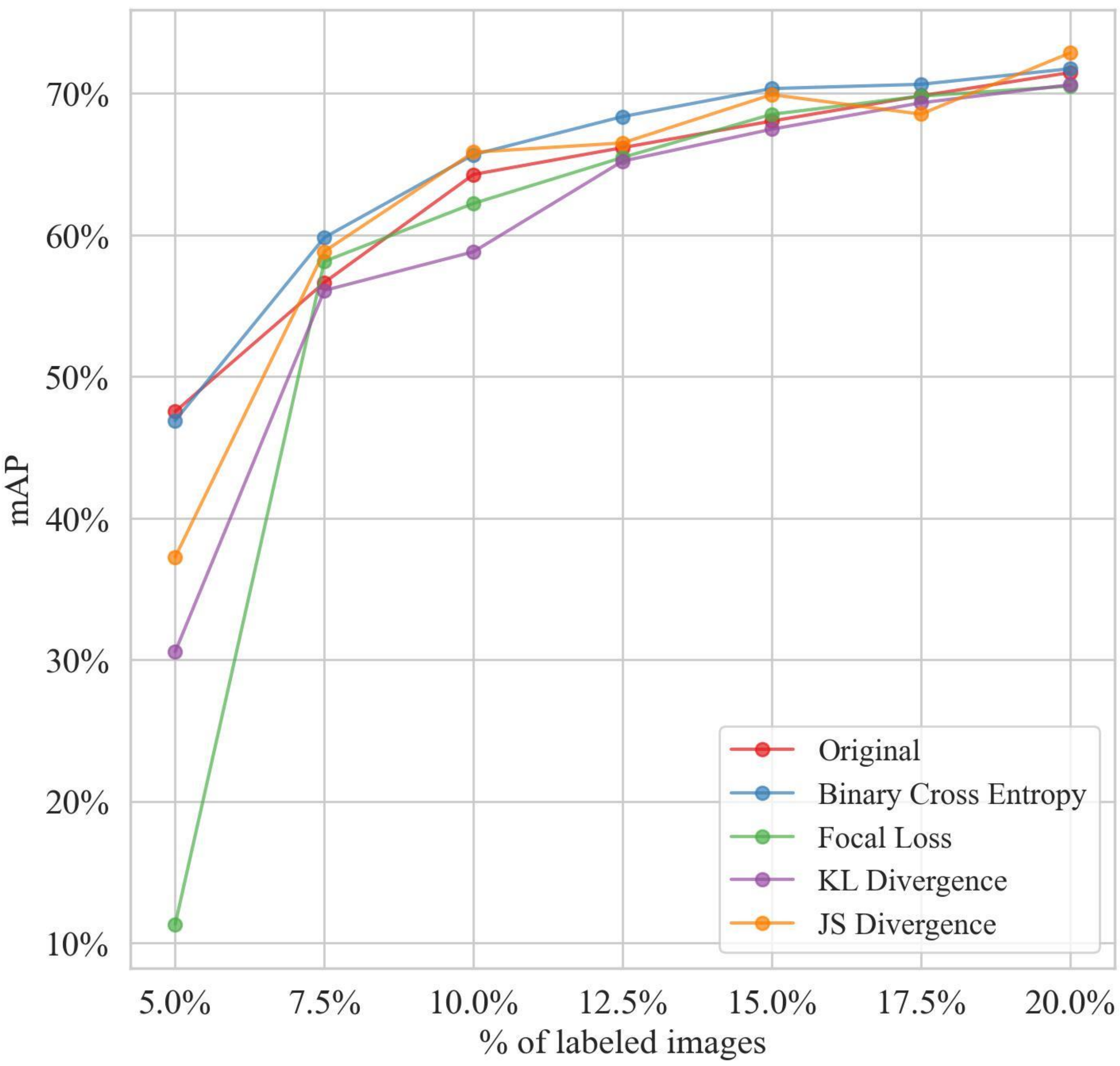
$$l_{dis}(x) = SSE(x) = \sum_i \left(\hat{y}_i^{f_1} - \hat{y}_i^{f_2}\right)^2$$

$l_{dis}(x)$ denotes the prediction discrepancy loss and $l_{det}(x)$ is a detection loss. $\hat{y}_i^{f_1}$, $\hat{y}_i^{f_2} \in \mathbb{R}^{1 \times C}$ are the instance classification predictions of the two classifiers for the i-th instance in image x, where C is the number of object classes in the dataset, and λ is a regularization hyper-parameter determined by experiment.

Proposed metrics for uncertainty

Binary Cross Entropy:	$BCE(\hat{y}^{f_1},\hat{y}^{f_2}) = -\sum_i \hat{y}_i^{f_1} \cdot\ log(\hat{y}_i^{f_2}) + (1-\hat{y}_i^{f_1}) \cdot\ log(1-\hat{y}_i^{f_2})$
Focal Loss: where	$FL(\hat{y}^{f_1},\hat{y}^{f_2}) = \sum_i \mathrm{A}_i(\hat{y}^{f_1},\hat{y}^{f_2}) \cdot \Gamma_i(\hat{y}^{f_1},\hat{y}^{f_2}) \cdot CE_i(\hat{y}^{f_1},\hat{y}^{f_2}),$ $\mathrm{A}(\hat{y}^{f_1},\hat{y}^{f_2}) = \alpha\hat{y}^{f_1} + (1-\alpha)(1-\hat{y}^{f_1}),$ $\Gamma(\hat{y}^{f_1},\hat{y}^{f_2}) = \left(1-\left(\hat{y}^{f_1}\hat{y}^{f_2} + (1-\hat{y}^{f_1})(1-\hat{y}^{f_2})\right)\right)^{\gamma},$ $CE(\hat{y}^{f_1},\hat{y}^{f_2}) = -\hat{y}^{f_1}\ log(\hat{y}^{f_2}) + (1-\hat{y}^{f_1}) \cdot\ log(1-\hat{y}^{f_2}),$ $\alpha = const, \qquad \gamma = const$
Kullback–Leibler (KL) divergence:	$KL(\hat{y}^{f_1},\hat{y}^{f_2}) = \sum_i \hat{y}_i^{f_1} \cdot log\left(\frac{\hat{y}_i^{f_1}}{\hat{y}_i^{f_2}}\right)$
Jensen-Shannon (JS) divergence:	$JS(\hat{y}^{f_1},\hat{y}^{f_2}) = \frac{1}{2}KL\left(\hat{y}^{f_1},\frac{\hat{y}^{f_1}+\hat{y}^{f_2}}{2}\right) + \frac{1}{2}KL\left(\hat{y}^{f_2},\frac{\hat{y}^{f_1}+\hat{y}^{f_2}}{2}\right)$

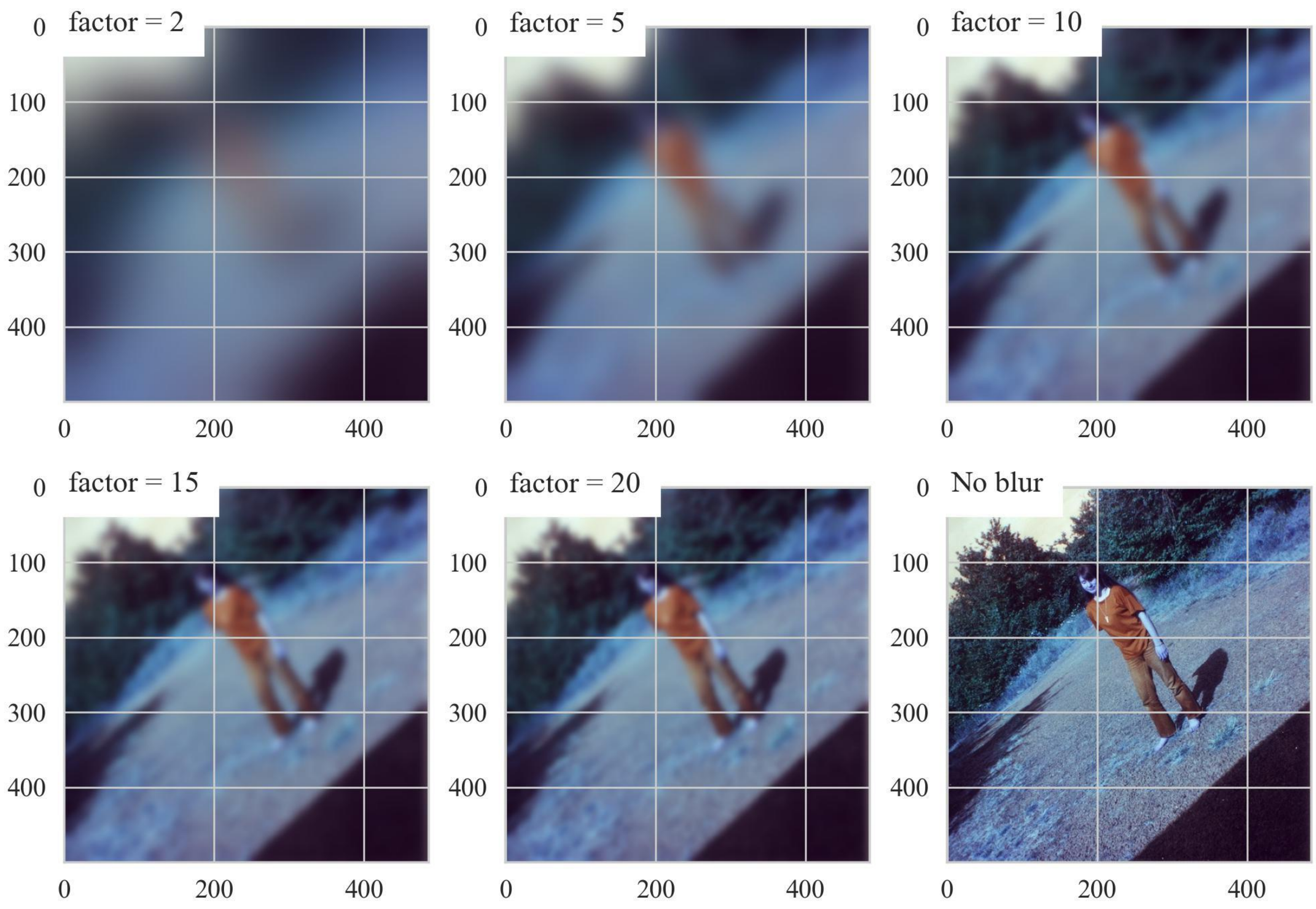
Metrics comparison and results



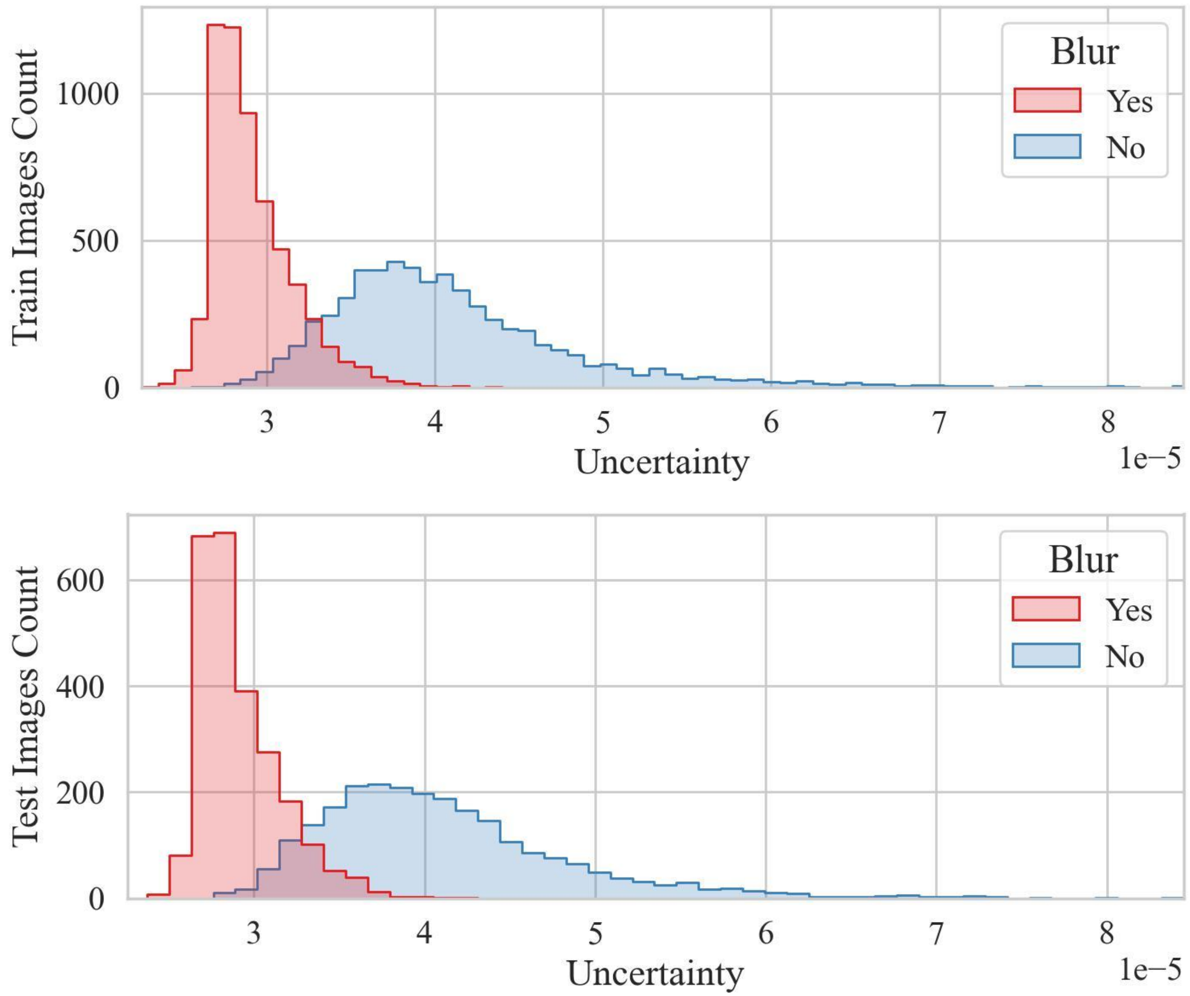
Metrics comparison and results

Labeled images ratio	mAP by metric				
	Original	Binary Cross Entropy	Focal Loss	KL Divergence	JS Divergence
0.050	0.47525	0.46891	0.11321	0.30570	0.37259
0.075	0.56642	0.59817	0.58129	0.56077	0.58834
0.100	0.64269	0.65664	0.62222	0.58810	0.65840
0.125	0.66163	0.68357	0.65470	0.65210	0.66493
0.150	0.68039	0.70334	0.68516	0.67465	0.69908
0.175	0.69820	0.70636	0.69802	0.69326	0.68530
0.200	0.71463	0.71734	0.70509	0.70604	0.72848

Testing MI-AOD for blurred images filtering

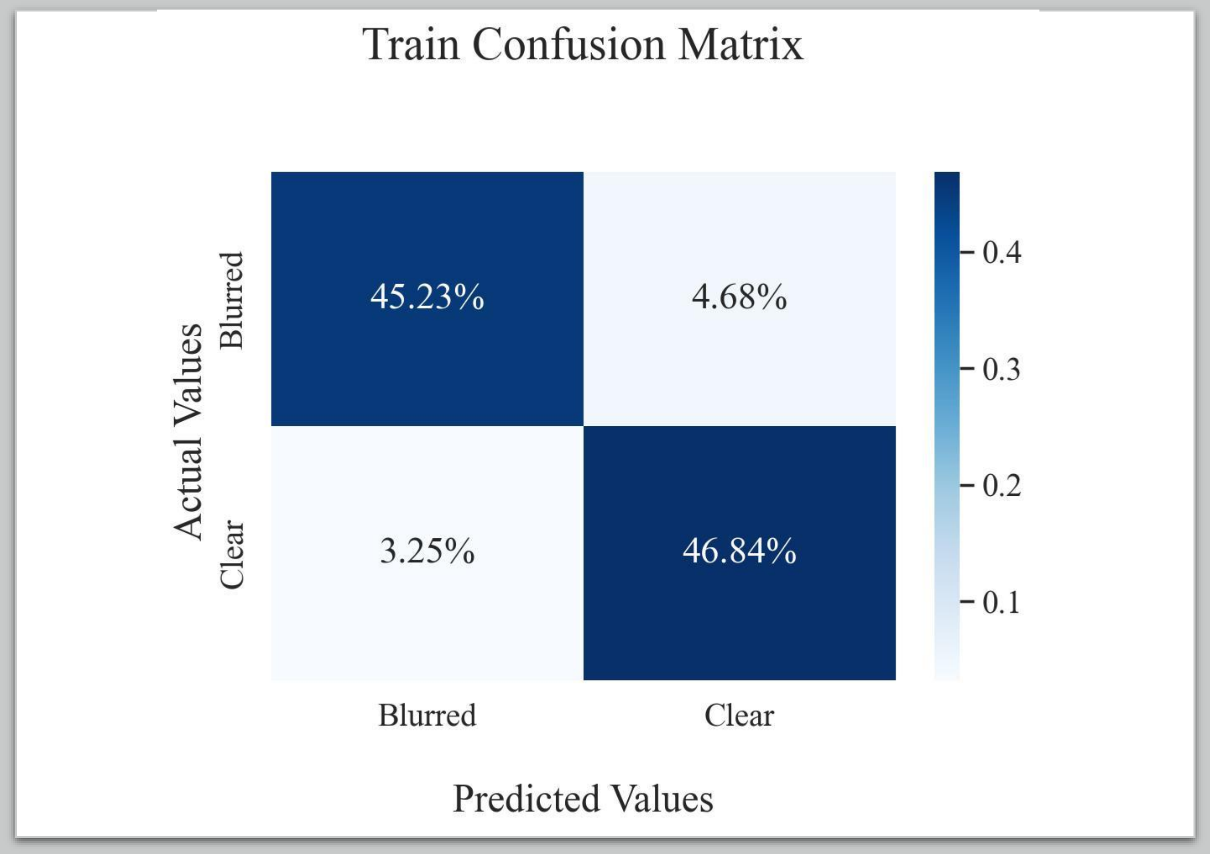


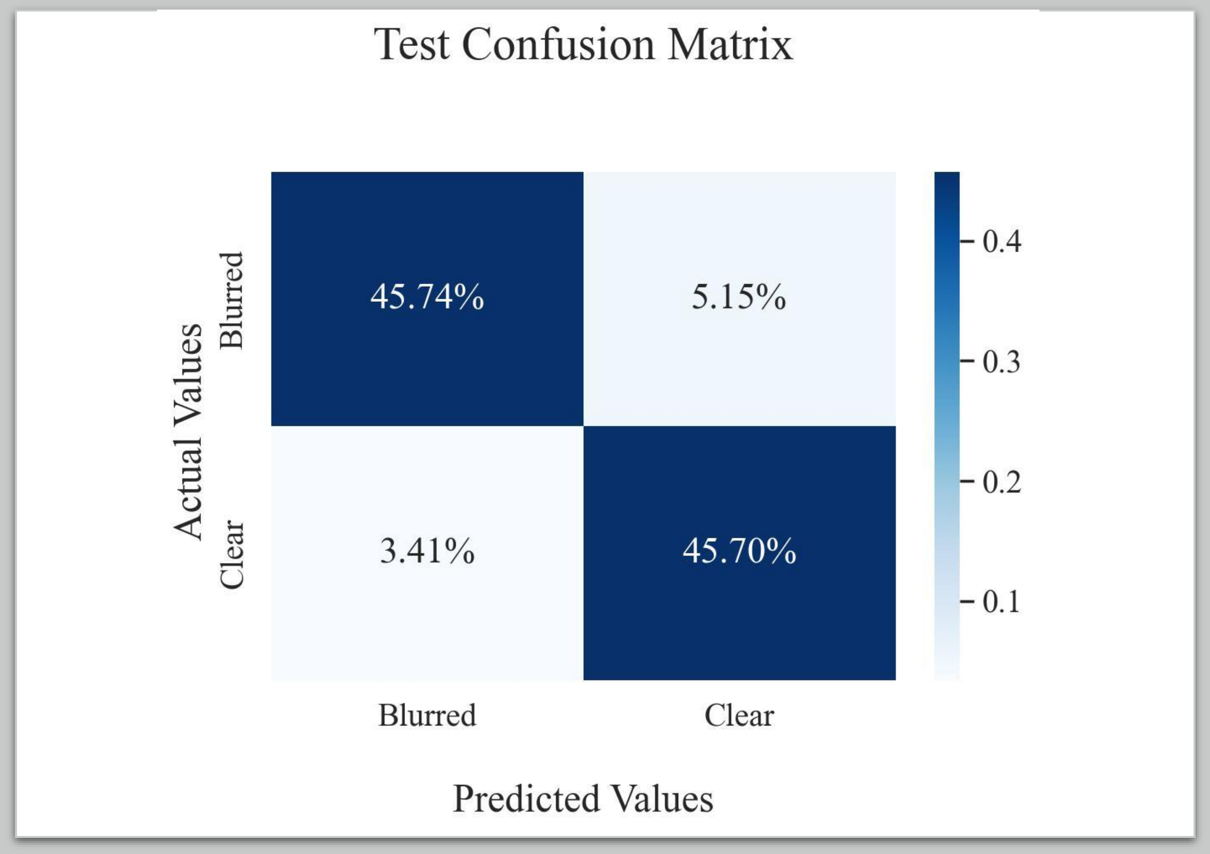
Histograms of uncertainty for blurred and clear images



Blurred image classification by uncertainty results

	Train	Test
Accuracy	0.921	0.914
Precision	0.909	0.899
Recall	0.935	0.931
F1-score	0.922	0.914





Дякую за увагу!