

## <u>Abstract</u>

Motivation: Multi-label image recognition is challenging due to large variations in the size and spatial location of objects, even harder when objects are occluded and small.



Specific Problem: Existing methods are complex in terms of both model and data; they do not explicitly address problem of small objects and occlusions

Model

- Multiple stages of training
- Combination of multiple learnable networks
- Relies on large language models





Data:

- High input resolution
- Complex data augmentation
- Additional data



Masked Branch (MaBr) aims to learn context based representation; Label Consistency (LaCo) models label co-occurrence.











strawberry

banana

apple

MaBr: uses nearby non-masked regions around objects to make predictions for partly visible/masked objects LaCo: learn a distribution of association across different classes "use context to infer presence of a class"

<u>Results</u>

Outperforms SOTA methods on VOC2007, MS-COCO and WIDER-Attribute.

Method	mAP	CR	CF1	Method	Input Resolution	mAP	СР	CR	CF1	OP	OR	OF1		1.0	CT1	0.01				
ResNet [15]	92.9	-	-	ResNet [15]	$448 \times 448$	79.4	83.4	66.6	74.0	86.8	71.1	78.2	Method	mAP	CFI	OFI	bicychio	bicy CO		
FeV+LV [26]	92.0	-	-	PLA [27]	$228 \times 228$	-	80.4	68.9	74.2	81.5	73.3	77.2	a consector consecto				S motorbike person	person	- DUS	
Atten-Reinforce [5]	92.0	-	-	ResNet-cut <sup>†</sup> [15]	$448 \times 448$	82.1	86.2	68.7	76.4	88.9	73.1	80.3	DHC	81 3	_	-				
RCP [25]	92.5	-	-	ML-GCN [9]	$448 \times 448$	83.0	85.1	72.0	78.0	85.8	75.4	80.3	DITE	01.5						L FILL
SSGRL [6]	93.4	-	-	MS-CMA [29]	$448 \times 448$	83.8	82.9	74.4	78.4	84.4	77.9	81.0	VA	82.9	-	-				
SSGRL (pre) [6]	95.0	-	-	KSSNet [23]	$448 \times 448$	83.1	84.0	73.2	79.0	87.8	70.2	81.5								-
ML-GCN [9]	94.0	-	-	TDPG+[31]	$440 \times 440$ $148 \times 148$	03.0 84.6	86.0	72.1	70.0	86.6	75.9	81.2	SRN	86.2	75.9	81.3	pergod	person	bottle	Lotte -
ADD-GCN [28]	93.6	-	-	CSRA + [32]	$440 \times 440$ $118 \times 118$	84.0	83.5	74.3	78.6	85.1	70.4	81.0	TH C	07.5		00.4	boat	boat	vase day	vose da
BMML† (pre) [17]	<u>95.0</u>	-	-	$O2L_R 101 \pm [22]$	$448 \times 448$	84.0	82.0	75.8	78.8	83.3	78.8	81.0	VAC	87.5	11.6	82.4				N
IDA-R101 [21]	94.3	-	-	IDA-R101 [21]	$448 \times 448$	83.8	-	-	-	-	-	-	MTT D1C	000	75 0	015				
ASL [1]	94.6	-	-	SST† [8]	$448 \times 448$	84.2	86.1	72.1	78.5	87.2	75.4	80.8	VII-B10	80.3	15.9	81.5				
MCAR [13]	94.8	-	-	P-GCN <sup>†</sup> [7]	$448 \times 448$	83.2	84.9	72.7	78.3	85.0	76.4	80.5	VITI16	077	70 1	010	ALL APP			chai
CSRA† [32]	93.7	<u>87.5</u>	88.3	KGGR† [4]	$448 \times 448$	84.3	85.6	72.7	78.6	87.1	75.6	80.9	V11-L10	0/./	/0.1	02.0	a tahaki (11 ( manan)	1 there at a man	THE STORE	TOOL TEN
KGGR [4]	93.6	-	-	ADD-GCN [28]	$576 \times 576$	85.2	84.7	75.9	80.1	84.9	79.4	82.0					person	u i person	person	PTROR!
KGGR (pre) [4]	95.0	-	-	SSGRL [6]	$576 \times 576$	83.8	<u>89.9</u>	68.5	76.8	<u>91.3</u>	70.8	79.7	VIT-L16 + $CSRA^{\dagger}$	89 6	80.4	84 9				10
SST [8]	94.5	-	-	C-Tran [16]	$576 \times 576$	85.1	86.3	<u>74.3</u>	<u>79.9</u>	87.7	76.5	81.7	TI LIO I CORT	07.0	00.4	01.7			Back and States	a solution of the
MSL-V	95.0	84.8	89.5	MCAR [13]	$576 \times 576$	84.5	84.3	73.9	78.7	86.9	76.1	81.1	VIT-L16 + MSL	90.6	80.5	85.3			- Fadlet and 14	Facher Filler 1
MSL-C	96.1	92.4	91.6	MSL-C	$448 \times 448$	86.4	90.1	76.3	80.4	89.1	80.0	82.2		- 0.0	00.0		bicycle	bicycle	k person Lau	Person Fair



Better than self-supervised method; better at heavy masking; generic and applicable to any model architecture.

Maalaina	VOC2007		Method	Masking	VOC2007	MS-COC
Masking	VUC2007	MS-COCO	MSL-V	Low	94.6	77.8
MAE [14]	95.3	85.5	MSL-V	High	95.0	79.0
MSL	96.1	86.4	MSL-C	Low High	95.0 96 1	85.1 86.4
ä.			WISL-C	mgn	70.1	00.4

e VOC2007, mAP (%) MS-COCO,	mAP (%)	Method	VOC2007, mAP (%)
94.4 76.8 <b>95.0 79.</b>	3 <b>)</b>	MCAR [13] MCAR [13] w/ MSL	94.8 95 6
93.7 84.3 96.1 86.4	3 4	SST [8]	94.5
		<u></u>	95.0

## <u>Conclusion</u>

MSL is a simple yet effective single-stage, model-agnostic learning paradigm using

Robust to heavily masked inputs; would be good at occlusions naturally.

![](_page_0_Figure_34.jpeg)

masking. Use context on both image- and label-level to infer presence of multiple objects, even in cases where object are small and occluded.

Compare to recent methods, MSL does not require:

- multiple stages of training, combination of multiple networks, reliance on large language models (LLMs)
- high input resolution, complex data augmentation strategies, additional data for pretraining

TLDR: MSL is a simple and effective single-stage model-agnostic learning paradigm for visual learning tasks. It is similar to how us humans use context to perceive the visual world. Do try it!