

# Night-time Lightweight Vehicle Detection Algorithm Based on Knowledge Distillation



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## Introduction

To address the issues of blurred visual features in nighttime images, susceptibility to noise interference, low detection efficiency, and high computational costs and memory usage, we propose a lightweight model based on knowledge distillation.

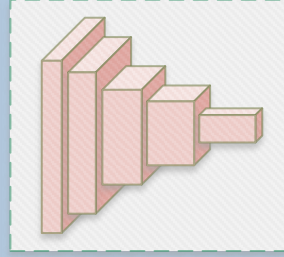
There are three methods of night detection: two-stage algorithms based on image enhancement, augmentation algorithms based on semi-supervised/unsupervised, and domain adaptation-based methods. They have their own advantages and disadvantages.

## Method

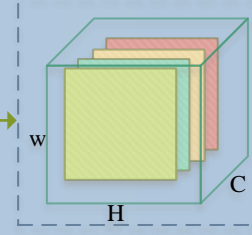
Our method is based on the following techniques:

- Knowledge distillation: The core idea is to let a small model imitate the behavior of a large model, so that the small model can also achieve performance close to that of a large model.
- LSCD: By using GN convolution, the number of parameters can be greatly reduced, which makes the model lighter
- MP: This parallel structure not only improves the computational efficiency, but also avoids the information loss that may be caused by a single method.

## Teacher Model



## Channel distribution distillation



## Student Model

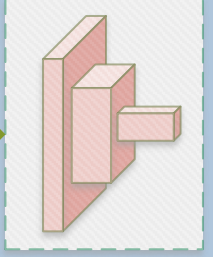


Fig. 3. Channel-wise Knowledge Distillation.

## MP

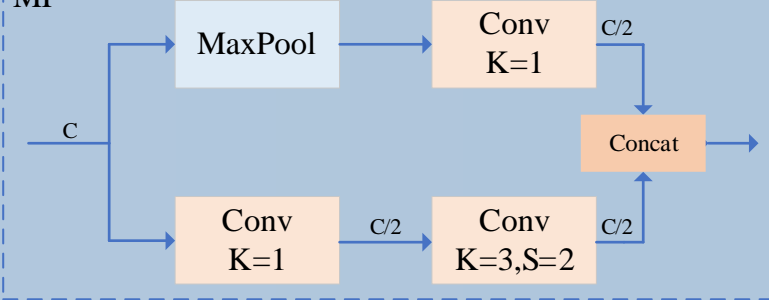


Fig. 4. MaxPooling with Convolution (MP).

## Loss Function

EMASlide Loss function:

$$f(x) = \begin{cases} 1 & x \leq \mu - 0.1 \\ e^{1-\mu} & \mu < x < \mu + 0.1 \\ e^{1-x} & x \geq \mu \end{cases}$$

$$u_t = du_{t-1} + (1-d)x_t$$

$$d(t) = \text{decay} \times (1 - e^{-t/\tau})$$

where  $\mu$  is the average of the IoU values of all bounding boxes, the  $\mu_t$  is the IoU mean value at the current moment,  $\mu_{t-1}$  is the IoU mean value at the previous moment, and  $d$  is a function that changes over time.

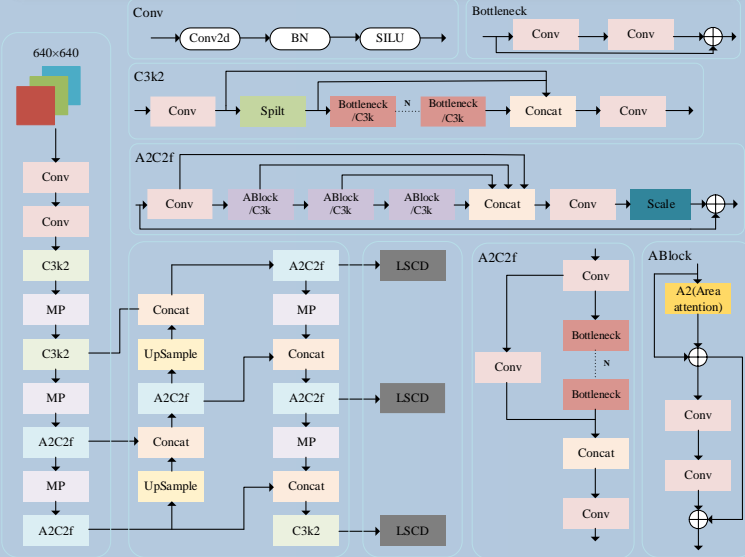


Fig. 1. YOLO-LME network model.

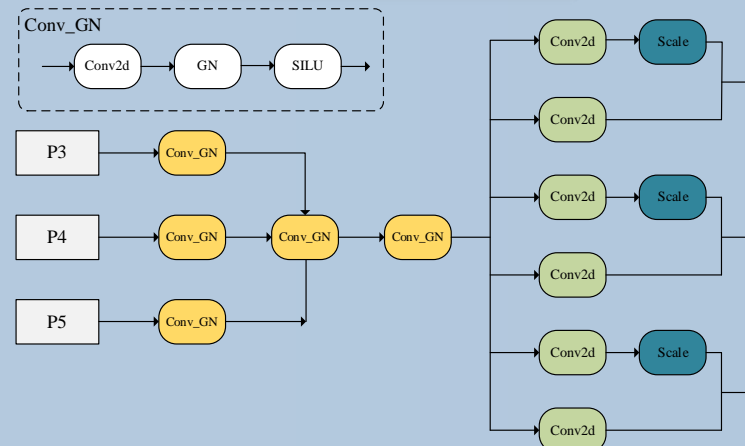


Fig. 2. LSCD detection head.

TABLE 1. RESULTS ON THE SELF-BUILT DATASET

Models	$mAP@50\%$	$mAP@95\%$	$Params/10^6$	GFLOPs	FPS
YOLOv5s	86.5	57.7	9.11	23.8	129
YOLOv8n	85.4	56.8	3.01	8.1	166
YOLOv10n	85.1	56.4	2.27	6.5	170
YOLOv11n	85.2	56.6	2.58	6.3	134
YOLOv12n	85.5	56.7	2.56	6.3	107
YOLOv12s	87.6	58.9	9.23	21.2	103
YOLOv12s+	88.3	59.6	9.26	21.4	92
ours	87.8	58.4	2.05	5.1	78