# **Context-Aware Learning for Enhancing Traffic Helmet Violation Detection**



Phan Nguyen Huu Phong

Nguyen Tien Huy

**University of Information Technology - National University of Vietnam** 

#### **Abtract**

In urban settings, vehicular accidents, particularly motorcycle incidents, significantly contribute to property damage and loss of life. This paper introduces a novel traffic helmet detection system leveraging context-aware learning to address limitations in existing methodologies under complex environmental contexts. We propose a Spatial-Channel Attention Module (SCAM) to focus on multiscale objects, demonstrating competitive real-time detection outcomes with a lightweight model of only 8.9M parameters.

#### Introduction

**Problem Statement:** Increasing traffic accidents, especially in undeveloped countries, are often due to the non-utilization of helmets.

**Challenge:** Existing models are computationally intensive and not practical for real-world application.

**Solution:** Automated helmet detection system leveraging context-aware learning to adapt to different traffic conditions.

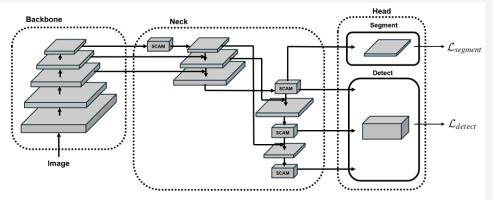
## Methodology

## 1. Proposed Dataset

**Dataset:** 91,000 annotated images from 12 cities in Myanmar.

**Automatic Segmentation:** Using Mask2Former pretrained on the CityScapes dataset to create segmentation maps.

#### 2. Network Architecture



Backbone: Extracts image features at five levels.

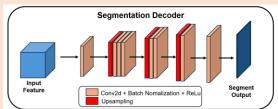
**Neck:** Aggregates information from different levels using attention modules.

**Head:** Divided into Segment Decoder (for segmentation predictions) and

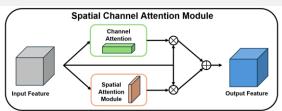
Object Detector (for final detection outputs).

#### 3. Context-Aware Learning:

Semantic segmentation is integrated into the network to provide contextual information, enhancing object detection performance.



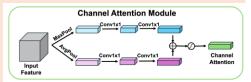
#### 4. Spatial - Channel Attention Module (SCAM)



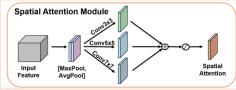
Combines channel and spatial attention mechanisms to focus on multi-scale objects.

#### **Channel Attention Module**

Recalibrates the weight of each channel and uses it to select significant channels.



#### **Spatial Attention Module**



Highlights important spatial regions, recognizing features across multiple scales.

## **Experiments:**

#### 1. Results

Method	Model	Backbone	mAP	Parameters
Transformers	Cascade R-CNN	Swin Transformer	30.4	>80M
	Faster R-CNN	Swin Transformer	27.6	>40M
	DETR	ResNet-50	27.2	41M
	Deformable DETR	ResNet-50	22.9	40M
CNN	RetinaNet	ResNet-50	25.9	34M
	YoloV7-L	ELANet	28.6	>70M
	PP-YOLOE	<b>CSPResNet</b>	18.3	52.2M
	PP-YOLOv2	ResNet-50	16.6	54.6M
Ours	Ours	Ours	18.5	8.9M

#### 2. Ablation Study

Method	mAP (%)
without SCAM	17.4
with SCAM	18.5

- 1. Our model demonstrates competitive performance with fewer parameters compared to other models.
- 2. Effectiveness of SCAM showing improvements in mAP.