

Personal Mobility Safe Driving System with Knowledge Distillation

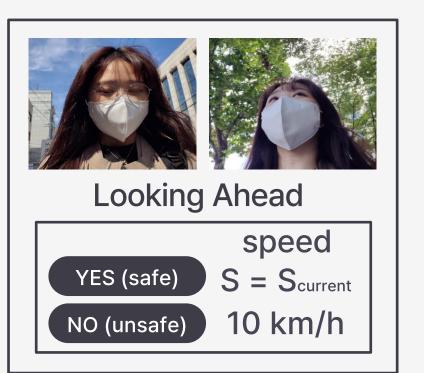
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*: contributed equally

Proposed System

User-side









Roadside





Fig 1. Summary of our proposed system.

Abstract

Issue:

Increasing number of incidents involving personal mobility devices

Key Idea:

- ✓ Deep learning (CNN)-based safe driving monitoring system for e-scooter that detects 1. Wearing a helmet, 2. Looking ahead & 3. On the sidewalk, 4. Near the intersection.
- ✓ Apply additional *lightweighting* techniques for real-time inference.

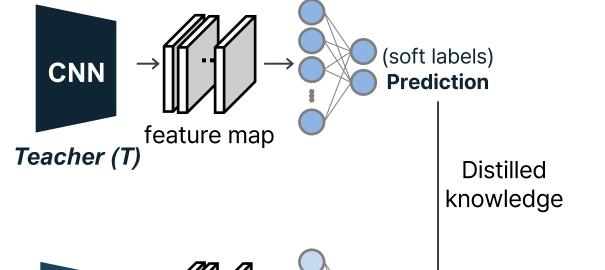
Model Implementation

Utilize standard
 Knowledge Distillation framework for fast and
 accurate inference for
 edge devices.



Student(S):
 MobileNetV3-Small &
 EfficientNet-B0

(fewer parameters for embedding)



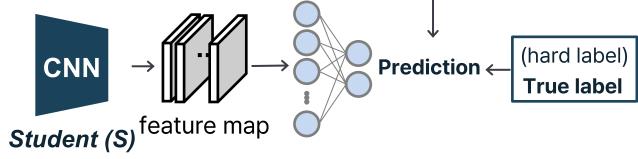


Fig 2. The architecture for the knowledge distillation

Teacher	# Params	Latency	Student	# Params	Ratio	Latency	Ratio
ResNet101	42.7M	1180ms	EfficientNet-B	0 4.1M	9.6%	364ms	30.8%
			MobileNetV3-	s 0.9M	2.1%	144ms	12.2%
VGG16	14.7M	965ms	EfficientNet-B	0 4.1M	27.9%	364ms	37.7%
			MobileNetV3-	S 0.9M	6.1%	144ms	14.9%

Table 1. Comparison number of parameters and latency between teacher and student networks. Latency is measured for one 224×224 image in yahboom jetson nano.

Introduction

- ✓ The autonomous driving market has led to increased usage of personal mobility devices (PMDs) like electric scooters.
- ✓ PMD usage has resulted in an increase in accidents and head injuries due to lack of protective equipment.
- ✓ There is a lack of research on PMD safety compared to automobiles, and current safety guidelines have weaknesses.

Quantitative Results

Datasets:

User-side - About 15,000 images of the three authors were taken near Gangnam & Seocho Station

Roadside – Manually annotated Sidewalk pedestrian image public dataset & the SDLane dataset for our tasks

Evaluation results:

Student networks show 1-5% higher accuracy compared to scratch networks in all four scenarios.

Task			Acc (%)	Task			Acc (%)
Looking Ahead	-	ResNet101	94.41%	On the	-	ResNet101	94.50%
		EfficientNet-B0	90.09%			EfficientNet-B0	91.74%
		MobileNetV3-S	90.27%			MobileNetV3-S	87.16%
	Teacher	VGG16	91.71%		Teacher	VGG16	93.58%
	Student	EfficientNet-B0	89.73%		Student	EfficientNet-B0	90.83%
		MobileNetV3-S	91.89%			MobileNetV3-S	87.16%
	Scratch	EfficientNet-B0	90.27%		Scratch	EfficientNet-B0	88.07%
		MobileNetV3-S	86.85%			MobileNetV3-S	87.16%
Wearing Helmet	-	ResNet101	93.58%	-	-	ResNet101	90.65%
		EfficientNet-B0	91.89%			EfficientNet-B0	88.79%
		MobileNetV3-S	89.74%			MobileNetV3-S	86.92%
	Teacher	VGG16	90.27%	Near the Intersection	Teacher	VGG16	86.95%
	Student Scratch	EfficientNet-B0	93.33%			EfficientNet-B0	83.18%
		MobileNetV3-S	88.47%			MobileNetV3-S	89.72%
		EfficientNet-B0	89.73%			EfficientNet-B0	87.85%
		MobileNetV3-S	86.31%			MobileNetV3-S	84.11%

Table 2. The overall accuracy of the teacher and student networks. The value marked in bold indicates the accuracy of the highest-performance student model.

Qualitative Results

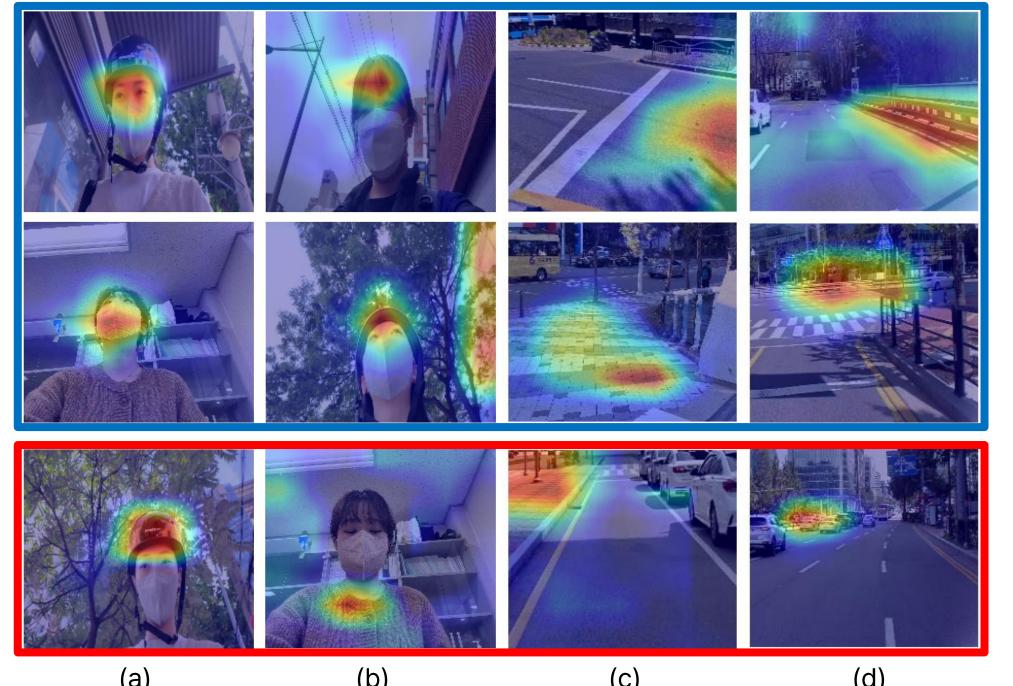


Fig 3. Grad-CAM results of the well-classified & misclassified images : (a) Looking ahead, (b) wearing helmet, (c) on the sidewalk, and (d) near the intersection.

Conclusions

Contribution:

- ✓ Propose a deep learning-based safety system for personal mobility.
- ✓ Use user-side and roadside images to check helmet usage, forward-looking behavior, and driving on sidewalks or near intersections.
- ✓ Achieve fast and accurate inference with an accuracy range of 89.72% to 93.33% within 0.36 to 0.14 milliseconds per image.
- ✓ Applicable to various road applications, including autonomous driving and delivery robots.

• Discussion:

- ✓ Datasets captured in different lighting conditions are required.
- ✓ Practical performance in actual driving scenarios is needed.