A Study on Fine-Grained Motorcycle Classification for Intelligent Transportation Systems

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INTRODUCTION

Problem: Accurate motorcycle identification is crucial for security and forensics, yet it's an overlooked area in fine-grained vehicle classification research. The effectiveness and specific challenges of recognizing motorcycle make and model remain poorly understood.

Objectives:

- To benchmark deep learning models for Fine-Grained Motorcycle Classification (FGMC).
- To pinpoint the fundamental obstacles for accurate FGMC.

DATA

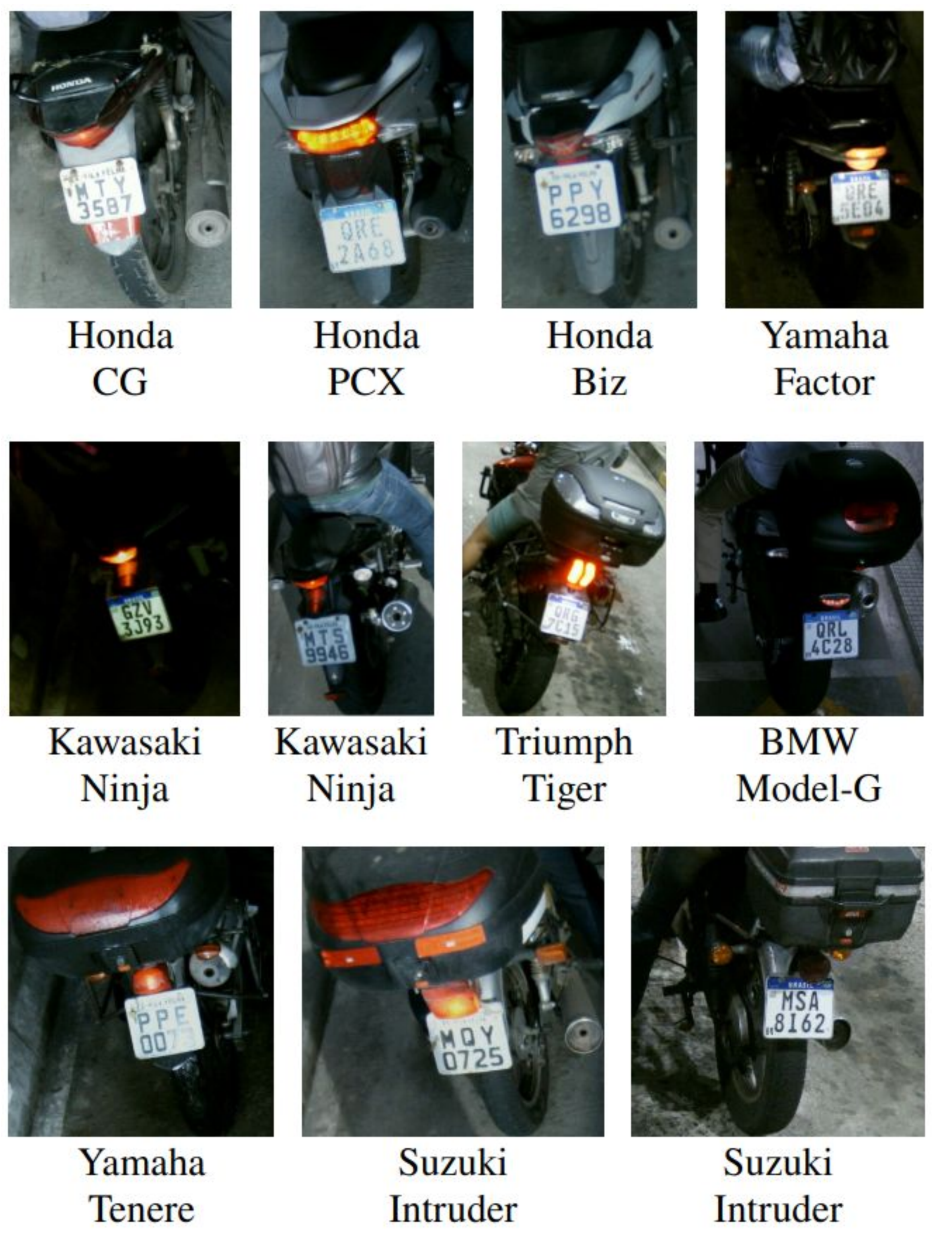
Source: RodoSol-ALPR dataset.

Preprocessing: Image selection & motorcycle cropping.

Annotation: License plates were used to get motorcycle data from a vehicle database.

Datasets:

- *MotorcycleMake:* 6,230 images across 7 classes.
- *MotorcycleModel:* 5,827 images across 29 classes.



RESULTS

Classification Performance

Comparison of deep learning models using two training protocols: standard (p1) and balanced sampling (p2). Results are averaged over 10 runs, with standard deviation in parentheses. The best outcomes are shown in bold.

Models trained with protocol (p1)

Model	*MotorcycleMake* mi-acc	*MotorcycleMake* ma-acc	*MotorcycleMake* F1	*MotorcycleModel* mi-acc	*MotorcycleModel* ma-acc	*MotorcycleModel* F1
EfficientNet-V2 [27]	**95,37 (0,59)**	**77,09 (3,51)**	**80,35 (2,29)**	**94,62 (0,59)**	**85,50 (2,13)**	**86,83 (1,74)**
MobileNet-V3 [28]	93,49 (0,50)	73,69 (2,59)	77,53 (2,36)	91,88 (0,74)	78,69 (3,05)	80,67 (2,59)
ResNet-50 [29]	90,50 (1,24)	57,61 (6,71)	59,31 (7,69)	92,80 (0,73)	81,16 (2,71)	82,39 (2,42)
ResNet-101 [29]	89,48 (0,64)	54,08 (2,23)	55,71 (3,10)	92,18 (1,17)	80,00 (3,18)	81,60 (3,34)
SwinTransformer-V2 [30]	76,92 (0,98)	37,35 (3,45)	41,99 (4,42)	67,73 (1,85)	36,22 (2,11)	40,47 (2,34)
ViT-B16 [31]	79,15 (0,82)	46,10 (3,67)	52,08 (3,64)	70,60 (1,06)	44,07 (1,53)	48,60 (2,00)
YOLOv11-nano-cls [32]	93,25 (0,58)	71,91 (2,99)	75,88 (2,86)	91,18 (1.00)	77,54 (3,86)	78,90 (2,90)

Models trained with protocol (p2)

Model	*MotorcycleMake* mi-acc	*MotorcycleMake* ma-acc	*MotorcycleMake* F1	*MotorcycleModel* mi-acc	*MotorcycleModel* ma-acc	*MotorcycleModel* F1
EfficientNet-V2 [27]	**94,65 (0,62)**	**77,55 (4,14)**	**81,19 (3,64)**	**93,29 (0,60)**	**81,21 (2,24)**	**83,97 (2,02)**
MobileNet-V3 [28]	91,42 (0,47)	70,11 (3,36)	74,72 (2,52)	90,65 (0,49)	76,08 (2,59)	79,14 (1,96)
ResNet-50 [29]	92,05 (1,11)	71,95 (3,43)	75,52 (2,96)	91,64 (0,73)	78,58 (3,18)	81,30 (2,45)
ResNet-101 [29]	91,16 (1,19)	70,62 (1,88)	74,07 (1,87)	90,61 (1,13)	76,30 (2,64)	78,67 (2,10)
SwinTransformer-V2 [30]	70,39 (3,10)	14,22 (0,24)	12,16 (0,73)	24,74 (13,8)	03,54 (0,43)	01,56 (0,56)
ViT-B16 [31]	70,50 (2,70)	14,25 (0,06)	11,91 (0,08)	23,47 (13,4)	17,10 (13,5)	12,96 (12,0)
YOLOv11-nano-cls [32]	91,87 (0,82)	71,38 (3,93)	73,36 (3,25)	89,39 (1,44)	76,25 (2,70)	77,48 (2,73)

Challenges

Models from the same manufacturer, especially when they target the same market segment.

Yamaha Factor

Yamaha Fazer

Daytime images provide clearer visual details, while nighttime views are more limited.

Daytime Nighttime
Honda Pop-100

Daytime Nighttime
Kawasaki Ninja

CONCLUSION

Key takeaways: FGMC is a viable and emerging research area for the vehicle classification community. The biggest hurdles are severely imbalanced data and poor performance in adverse conditions.

Next steps: Focus on expanding the dataset, and integrating this system with license plate recognition to improve motorcycle identification.

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