LPLC: A Dataset for License Plate Legibility Classification

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Motivation

- ALPR remains unsolved for challenging scenarios
 - Adversarial environments, poor equipment, transmission compression
- Super-resolution (SR) presents new challenges
 - Good images get degraded: which images should undergo SR?
- Real-world systems deal with untreatable large amounts of data
 - How much of it can or should be discarded?





Quality vs. Legibility



Good quality images (top right) may feature illegible LPs and vice-versa (bottom right)

A single image may contain both legible and illegible LPs.







Legibility Example









The Dataset

- Real-world radar images from the Brazilian state of Paraná
- Annotated attributes:
 - 4-corner bounding box
 - Plate OCR (characters)
 - Legibility class (4 levels)
 - Vehicle and plate occlusion flags
- For for various ALPR tasks outside of Legibility Classification





The Dataset – Instances and Attributes









The Dataset – Instances and Attributes







The Dataset – Instances and Attributes







Legibility Levels









Legibility Levels

LPs by Legibility		Other Attributes			
Class Number		Class True		False	
Perfect	5,617	Occluded	12,586	101	
Good	3,641	Valid	12,359	328	
Poor	1,825	OCR 11,083		1,604	
Illegible	1,604	\rightarrow Total LPs	12,687		

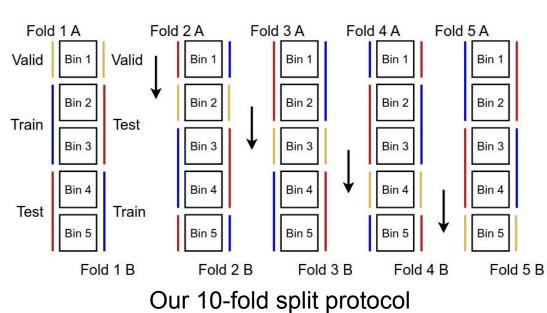
Images by Time of Day		Images by Attributes		
Class	Number	Has at Least One	Number	
Morning Afternoon Evening Night	3,830 2,556 2,585 1,239	Legible LPs Non Occluded LPs Valid Vehicles → Total Images	9,684 10,195 10,030 10,200	







Legibility Classification



Madal	Class				O 11
Model	Perfect	Good	Poor	Illegible	Overall
ResNet-50 ViT b-16 YOLO11m-cls	84.54% 85.74% 88.37%	67.98% 68.00% 65.83%	56.70% 58.80% 59.42%	72.97% 73.67% 74.47%	74.51% 75.48% 76.79%

Class

	Model	Legibility Recognition (Legible vs. Poor)	Full Recognition (Legible, Poor, Illegible)		
	ResNet-50	92.56%	87.23%		
}	ViT b-16	93.16%	87.78%		
	YOLO11m-cls	92.71%	86.25%		

Average test Micro-F1 score for the three legibility protocols

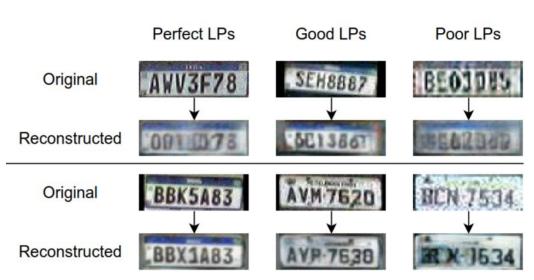






Super-resolution

Out-of-the-box SR showcases poor cross-dataset performance



GAN Model	OCR Results With SR	Class			Taka1
GAN Model		Perfect	Good	Poor	Total
	Better	98	108	108	314
LCOFL-GAN [9]	Equal	494	308	170	972
	Worse	5,012	3,206	1,523	9,741
	Better	211	276	160	647
Real-ESRGAN [15]	Equal	5,180	2,683	572	8,435
	Worse	213	663	1,069	1,945
	Better	108	98	45	251
LPSRGAN [10]	Equal	264	209	115	588
	Worse	5,232	3,315	1,641	10,188









Future Work

- A proper ALPR SOTA comparison
 - In traditional tasks
- Better SR methods for a cross-dataset scenario



Thank you for your attention!

Please visit us at: github.com/lmlwojcik/lplc-dataset

Our dataset is public for **research** purposes



GitHub





