

LPLCv2: An Expanded Dataset for Fine-Grained License Plate Legibility Classification

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Motivation

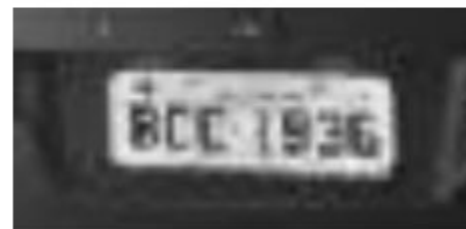
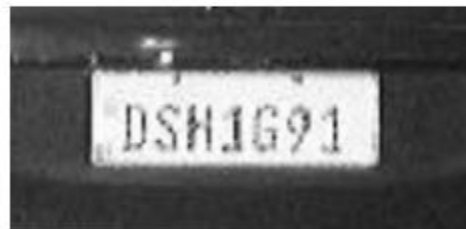
- ALPR remains unsolved in **challenging** scenarios
 - Adversarial environments, poor equipment, transmission compression
- **Super-resolution** (SR) presents new challenges
 - Good images may be degraded: which images should undergo SR?
- Real-world systems deal with unmanageable **large amounts of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

Quality vs. Legibility



High-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



Perfect

Good

Poor

Illegible

The Dataset – LPLCv2

- Real-world radar images from the Brazilian state of Paraná
- Annotated LP attributes:
 - Rectangular bounding box
 - Plate OCR (characters)
 - Legibility class (4 levels)
 - Vehicle and plate occlusion flags
 - Vehicle data (make, model, color)
- Suitable for various ALPR tasks outside of Legibility Classification

The Dataset – LPLCv2

- Real-world radar images from the Brazilian state of Paraná
- Annotated image attributes:
 - Time of day (morning, afternoon, evening, night)
 - Camera ID
 - Camera Integrity
 - Presence of rain
- Fit for various ALPR tasks outside of Legibility Classification

The Dataset – Instances and Attributes



New Recognition Challenges

- Low-resolution cameras
- Faulty cameras
- Obstructed vehicles
- Overexposed and underexposed images
- Cars at varying distances

And others...

Updates from LPLCv1

- New images
 - 12,687 -> 37,099
- Revised annotations
- Introduction of an EMA-based loss function

$$W(b) = \min\left(\frac{\max(\text{mispred}(b))}{\text{mispred}(b) + \epsilon}, M\right)$$

$$\text{smooth}(b) = \alpha * \text{confusion}(b) + (1 - \alpha) * \text{confusion}(b)$$

$$\text{mispred}(b) = \text{sum}(\text{smooth}(b)) - \text{diag}(\text{smooth}(b))$$



Dataset Statistics

TABLE I
LPLCV2 IMAGE STATISTICS.

Images by Time of Day		Images by Attributes	
Class	Number	Attribute	Number
Morning	10,998	Faulty Camera	3,690
Afternoon	12,799	Raining	770
Evening	9,157	Has Camera ID	29,965
Night	4,145	→ Total Images	37,099

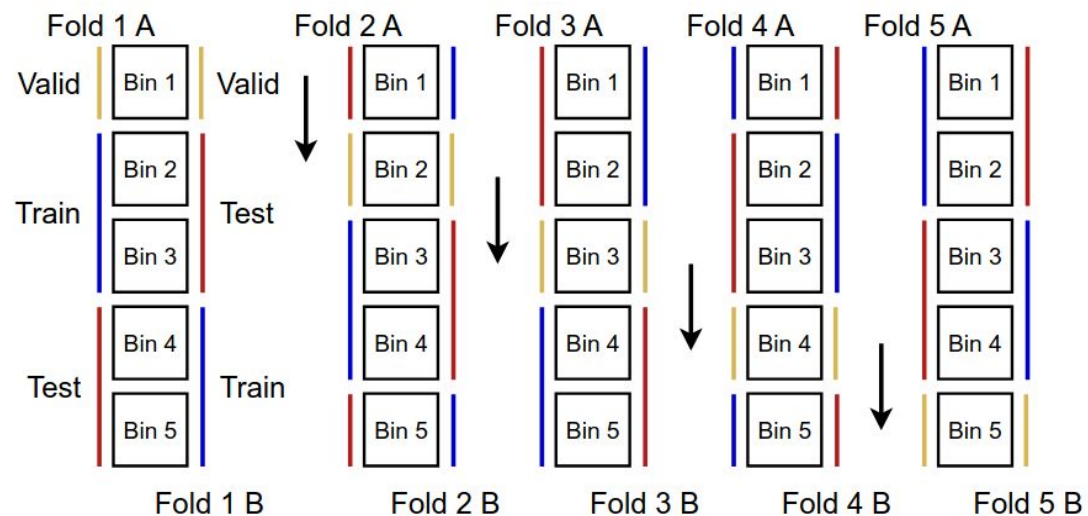
TABLE II
LPLCV2 LP STATISTICS.

LPs by Legibility		Other Attributes	
Class	Number	Attribute	Number
Perfect	18,425	Vehicle Visible	38,089
Good	10,180	Vehicle Available	25,506
Poor	7,520	LP Text Available	36,414
Illegible	5,362	→ Total LPs	41,487

Proposal Validation

- We train a ResNet50 for **legibility classification**
- We adopt the LPLCv1 results as a benchmark
 - 10-fold cross-validation protocol
- We measure the impact of the new additions:
 - Revised labels
 - New images
 - Introduction of the EMA Loss

Legibility Classification



Our 10-fold split protocol

Partition	Class				Overall
	Perfect	Good	Poor	Illegible	
LPLCv1	84.5%	68.0%	56.7%	73.0%	74.5%
+ Revised Labels	92.1%	83.1%	83.8%	88.2%	84.4%
+ More Images	92.8%	86.0%	86.0%	92.9%	88.7%
+ EMA	92.7%	86.2%	86.3%	93.0%	89.8%

Micro-F1 score in legibility classification

Evaluation Results

Ground Truth	Perfect	1980	101	1	0
	Good	167	1235	65	0
	Poor	0	89	797	68
	Illegible	0	3	42	527
		Perfect	Good	Poor	Illegible
		Prediction			

Confusion Matrix



Borderline Legibility cases

Future Work

- ALPR workflow integration
 - What is the gain in **OCR fidelity**?
- Evaluation in **cross-dataset** scenarios
 - New images and protocols

Thank you for your attention!

Please visit us at: github.com/lmlwojcik/LPLCv2-Dataset

Our dataset is publicly available for **research** purposes



GitHub

