Car Plate Recognition and Reconstruction with Deep Learning

Anasztazia Jovanovic, 2214842
Angeliki Spanou-Kapantoni, 2223715
Chiara Cortese, 2224681

OUTLINE

Automatic License Plate Recognition

- Automatic License Plate Recognition (ALPR) systems must accurately read plates in diverse real-world conditions, including motion blur, occlusions, and poor lighting.
- Developing robust models capable of handling such variability is essential for reliable vehicle identification.

Deep learning approaches

CTC-based end-to-end baseline

YOLOv5 and PDLPR model

Objective: evaluate and compare their performance in recognizing and reconstructing license plates

Deep learning approaches

CTC-based end-to-end baseline

YOLOv5 and PDLPR model

Challenge: Designing a custom decoder to accurately map dataset's index-based labels into valid license plate characters and structure.

Baseline Model (1/4)

- The baseline model uses a sequence modeling approach to recognize license plates as character strings.
- It only performs license plate recognition (not detection)

Baseline Model (2/4)

- Visual Feature Extraction with CNN

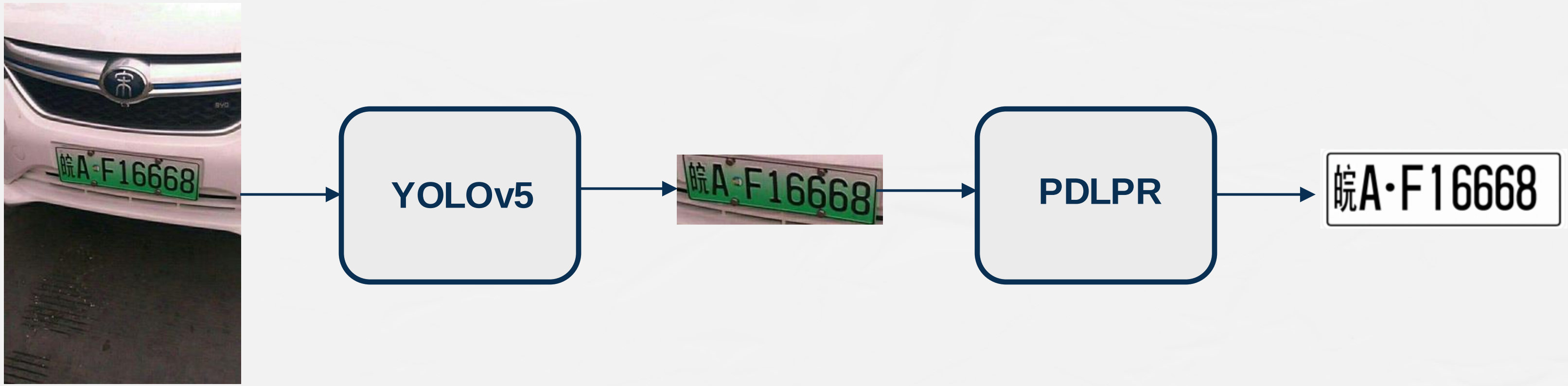
Baseline Model (3/4)

- Sequence Modeling with Bi-LSTM

Baseline Model (4/4)

- Alignment with CTC Loss

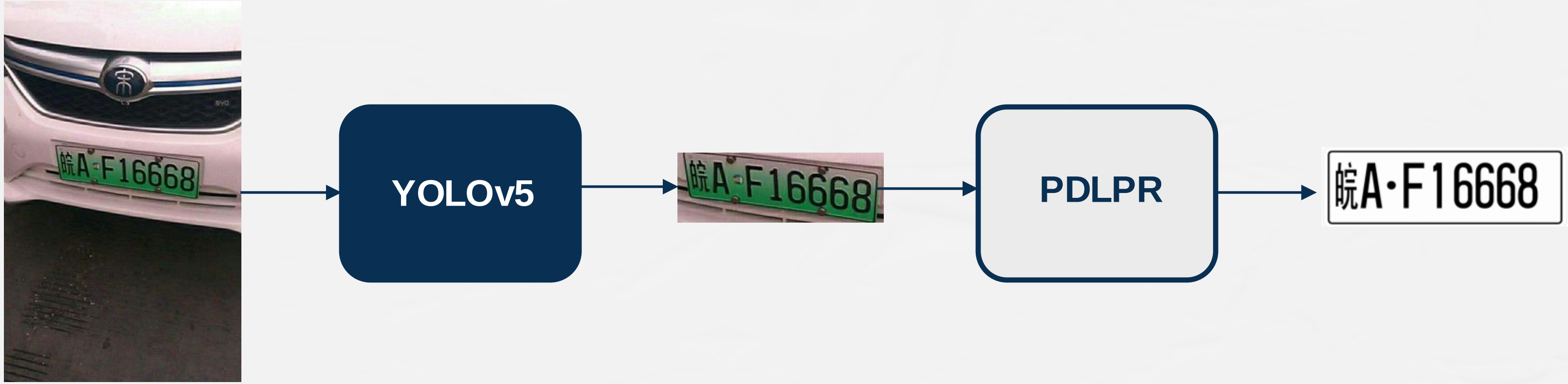
YOLOv5 and PDLPR model (1/3)



This system decomposes the task into two separate but integrated stages:

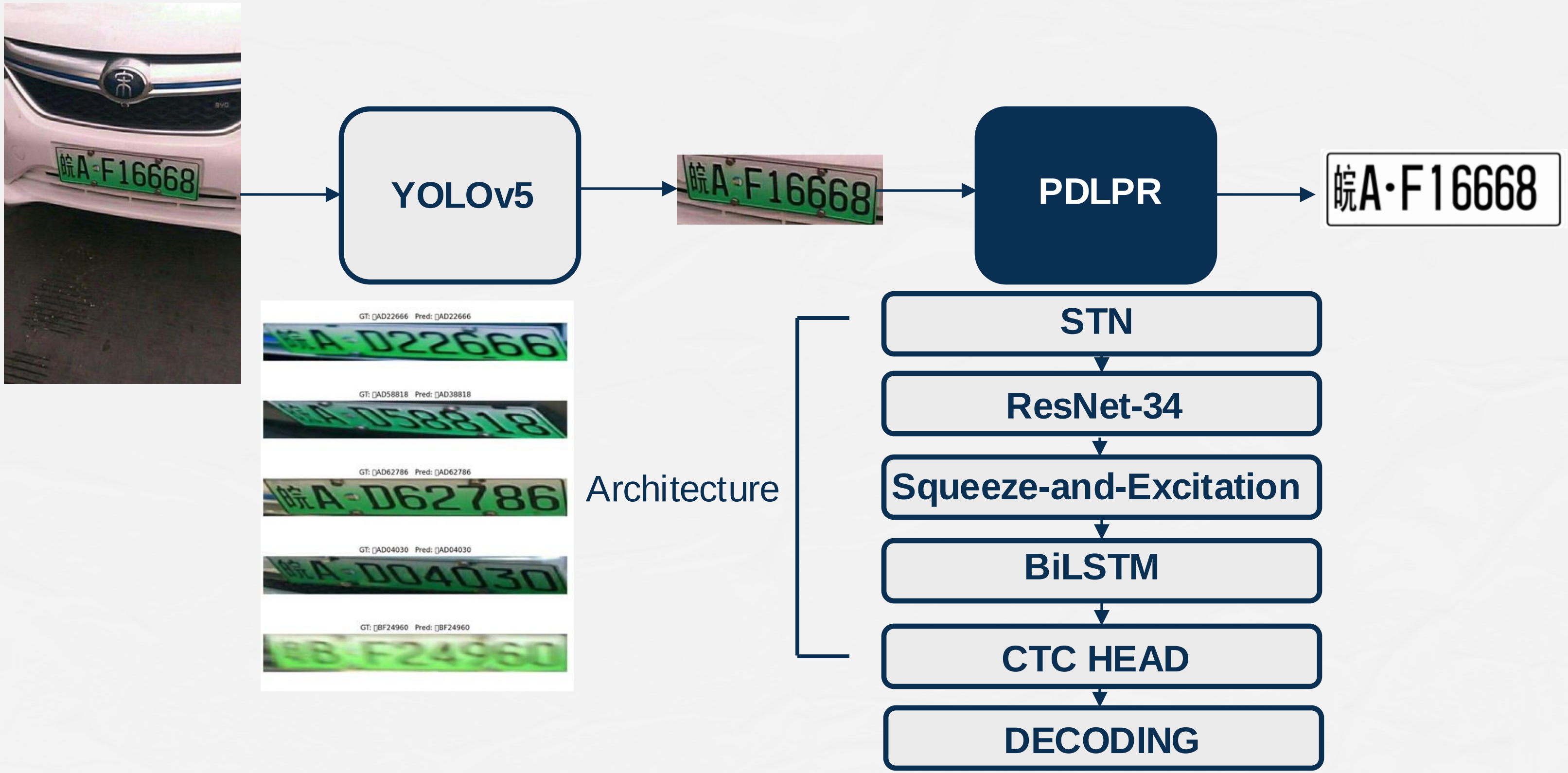
- **Detection**: YOLOv5 object detector to locate the license plate region in full car images.
- **Recognition**: PDLPR model to read the characters from the cropped plate image.

YOLOv5 and PDLPR model (2/3)



- YOLOv5 (You Only Look Once v5) is a real-time object detector.
- Trained to identify and localize license plates within full-resolution images.
- It predicts bounding box coordinates and class confidence in one forward pass.

YOLOv5 and PDLPR model (3/3)



CCPD (Chinese City Parking Dataset)

- 300k images and refined annotations
- Energy vehicle sub-dataset (CCPD-Green) that has an eight-digit license plate number.
- Each image contains a single vehicle with one license plate.

EVALUATION METRICS

- **Loss:** Measures how well the model's predicted output aligns with the ground truth.
- **Character Accuracy:** Ratio of correctly predicted characters to the total number of characters.
- **Plate Accuracy:** Measures how many full license plates were predicted completely correctly (all 8 characters).
- **F1 Score:** balanced measure of a classification model's performance (it combines precision and recall into a single value).

RESULTS: Comparison (1/5)

	Loss	Char Accuracy	Plate Accuracy	F1 score
Baseline Model	0.3161	90.43%	73.25%	90.43%
YOLOv5 + PDLPR	0.2744	93.28%	62.80%	93.28%

RESULTS: Comparison (2/5)

	Loss	Char Accuracy	Plate Accuracy	F1 score
Baseline Model	0.3161	90.43%	73.25%	90.43%
YOLOv5 + PDLPR	**0.2744**	93.28%	62.80%	93.28%

- YOLO+PDLPR generalizes better across the test data for individual predictions

RESULTS: Comparison (3/5)

	Loss	Char Accuracy	Plate Accuracy	F1 score
Baseline Model	0.3161	90.43%	73.25%	90.43%
YOLOv5 + PDLPR	0.2744	**93.28%**	62.80%	93.28%

- Per-character recognition is stronger in the ResNet-based PDLPR

RESULTS: Comparison (4/5)

	Loss	Char Accuracy	Plate Accuracy	F1 score
Baseline Model	0.3161	90.43%	**73.25%**	90.43%
YOLOv5 + PDLPR	0.2744	93.28%	62.80%	93.28%

- CTC's ability to model sequence consistency
- PDLPR's per-position classifiers making independent errors

RESULTS: Comparison (5/5)

	Loss	Char Accuracy	Plate Accuracy	F1 score
Baseline Model	0.3161	90.43%	73.25%	90.43%
YOLOv5 + PDLPR	0.2744	93.28%	62.80%	**93.28%**

- YOLO+PDLPR shows better balance between precision and recall
- It handles both false positives and false negatives more effectively

CONCLUSION

- Both models demonstrate complementary strengths, highlighting a trade-off between character precision and sequence-level consistency.
- **Baseline Model**: Simpler, end-to-end and effective at learning full-sequence patterns.
- **YOLOv5 + PDLPR**: Modular and flexible, better suited for real-world variation.

FUTURE WORKS

- Evaluate on cross-domain datasets
- Multilingual License Plate Support

REFERENCES

1. Tao, L., Hong, S., Lin, Y., Chen, Y., He, P. and Tie, Z. (2024). A Real-Time License Plate Detection and Recognition Model in Unconstrained Scenarios. Sensors, 24(9), 2791

2. Xu, Z.; Yang, W.; Meng, A.; Lu, N.; Huang, H.; Ying, C.; Huang, L. Towards end-to-end license plate detection and recognition: A large dataset and baseline. In Proceedings of the European Conference on Computer Vision (ECCV), Munich, Germany, 8–14 September 2018.

3. R. K. Prajapati, Y. Bhardwaj, R. K. Jain and D. Kamal Kant Hiran, ”A Review Paper on Automatic Number Plate Recognition using Machine Learning : An In-Depth Analysis of Machine Learning Techniques in Automatic Number Plate Recognition: Opportunities and Limitations,” 2023 International Conference on Computational Intelligence, Communication Technology and Networking (CICTN), Ghaziabad, India, 2023, pp. 527-532

THANK YOU