Automatic Number Plate Recognition for Angle and Perspective variations

CS 5100 - Artificial Intelligence (Fall 2023) - Jonathan Mwaura

Shivam Thakker Yasha Chaurasia Krutik Bajariya Adit Shah

Description and Applications









What is Number Plate Recognition?

A technique to read and decode alphanumeric letters on license plates using optical character recognition (OCR).

Steps:

- Capturing pictures/videos of moving vehicles
- Locating vehicle
- Locating and extracting the license plate
- Using OCR algorithms for character identification

Applications:

- Security
- Ticketless Parking
- Smart Cities
- Tolling and ITS

Problem Statement



- Challenges in accurately detecting number plates:
 - 1) Varying Lighting Conditions
 - 2)Angle and Perspective variations
 - 3)Different plate designs and fonts
 - 4)Speed of the vehicle
 - 5)Weather conditions
 - 6)Inaccurate camera quality

 These contribute to the main problem in number plate detection: Quality of image/video captured

Proposed Model

Consists of 3 main steps:

1) Vehicle Detection

 License plate detection by unwarping images using Affine Transformation.

3) OCR

Vehicle Detection

- Used YOLOv2 model, reason:
 - Fast execution
 - Good precision and recall

 Tilted images have a very small LP size to vehicle bounding box ratio

Leads to poor accuracy

Solution: Resize the image

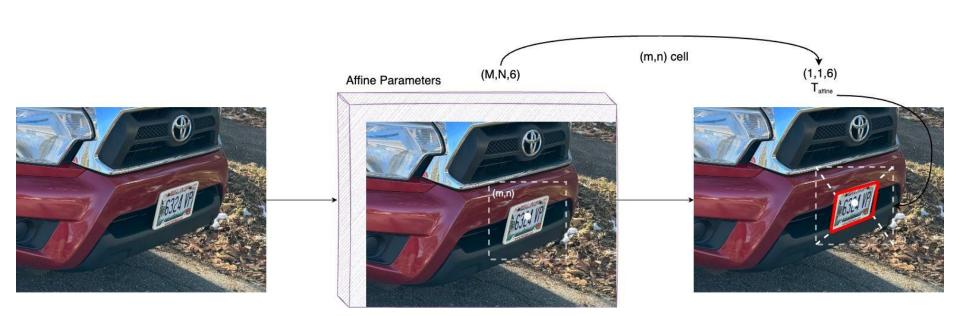
AFFINE TRANSFORMATION

The affine transformation method is commonly employed to address geometric distortions or deformations that arise from less-ideal camera angles.

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} * \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x' \\ y' \end{bmatrix}$$

Affine transformation functionalities are:

- 1. Scaling
- 2. Shear
- 3. Rotation
- 4. Reflection



Loss Function

- Aim: Estimate 8 feature-map parameters
- Feature-map elements-
 - 2 representing object/not object probability (m₁, m₂)
 - 6 representing affine transformation parameters (m₂ to m₈)

- 2 parts of loss function:
 - 1. Probability of presence of the object at any point (x, y) Determined by logloss function

$$f_{prob}(h, w) = logloss(I_{obj'}, m_1) + logloss(1 - I_{obj'}, m_2)$$
, where

$$I_{obj} = \begin{cases} 1, & \text{if (h, w) has object,} \\ 0, & otherwise \end{cases}$$

2. Error between the affine transformed points of a square with (h, w) as the center w.r.t normalised actual LP corner points

$$f_{affine}(h, w) = \sum_{i=1 \text{ to } 4} |T_{hw}(q_i) - Original image points|,$$

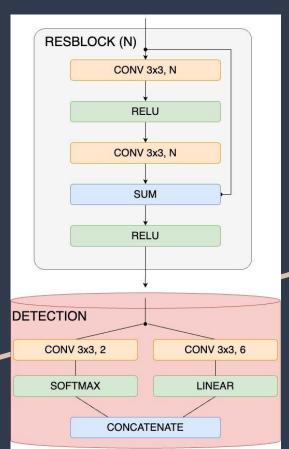
where, q_i be the center points of unit square vertices centered at origin, and,

$$T_{hw}(q) = \begin{bmatrix} max(m_3, 0) & m_4 \\ m_5 & max(m_6, 0) \end{bmatrix} \cdot q + \begin{bmatrix} m_7 \\ m_8 \end{bmatrix}$$

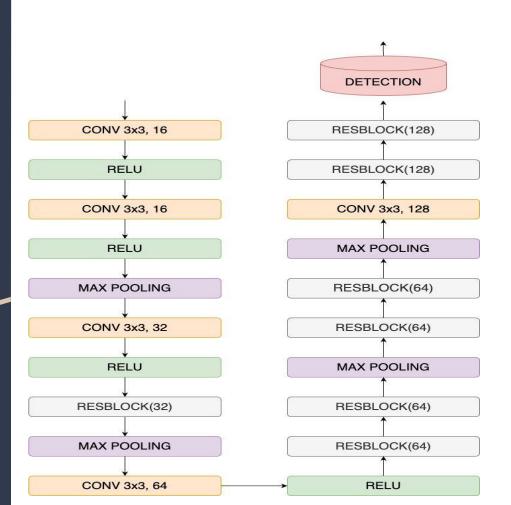
Final loss = $\sum_{h=1 \text{ to H}} \sum_{w=1 \text{ to W}} [f_{prob}(h, w) + I_{obj}(h, w) \cdot f_{affine}(h, w)],$

where, H - height of image; W - width of image

License Plate Detection



Network Architecture



Dataset and Training Details

Dataset	# images
Open ALPR (EU)	104
Open ALPR (BR)	108
AOLP	611
UFPR-ALPR	60

Training - 40% (353 images)

Validation - 40% (353 images)

Testing - 20% (177 images)

- Data augmentation steps
 - Scaling
 - Rotation
 - Translation
 - Colorspace
 - Aspect Ratio

Performed OCR to extract number plate using YOLO model.

Ran 10,000 iterations, took 12 hours.

- Machine specs
 - Macbook Pro M3 Pro Chip
 - 11-core CPU
 - 14-core GPU
 - 18GB Unified Memory

Evaluation Functions





Extraction Rate =
$$\left(\frac{Number of Successfully Extracted License Plates}{Total Number of Input Images}\right) \star 100\%$$

Recognition Rate =
$$\left(\frac{Number\ of\ Correctly\ Recognized\ Characters}{Total\ Number\ of\ Characters\ Processed}\right)\star\ 100\%$$

Results

Dataset	Recognition Rate (Ours)
ALPR (EU)	94.65%
ALPR (BR)	82.91%
AOLP	94.78%
UFPR	74.66%

Dataset	Extraction Rate
ALPR (EU)	99.08%
ALPR (BR)	97.39%
AOLP	98.19%
UFPR	98.79%

Results

Comparing our results on AOLP dataset based on recognition rate

Papers	Recognition Rate
Hiu Li etal. [4]	95.57%
Ibtissam Slimani [5]	96.11%
Ours	94.78%

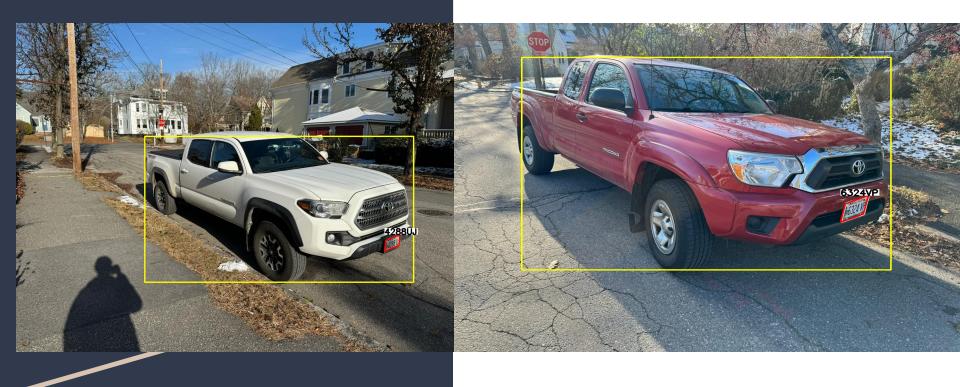
Comparing our results on UFPR dataset based on recognition rate

Papers	Recognition Rate
Sighthound [1]	62.50%
Open ALPR [2]	54.72%
Ours	74.66%

Comparing our results on AOLP dataset based on extraction rate

Papers	Extraction Rate
Yuan etal. [6]	91.27%
Ibtissam Slimani [5]	96.72%
Ours	98.19%

Results



Future Work

- After detecting the license plate and unwarping it,
 - Add GAN model to increase the image quality.
 - Current model has high extraction rate.
 - Limitations of current model miss detects the characters due to low image quality.
 - Eg Considers I as 1

 Can extend the work for detecting motorcycle LP as it encounters challenges such as changes in aspect rate and layout.

References

1) S. Z. Masood, G. Shu, A. Dehghan, and E. G. Ortiz, "License plate detection and recognition using deeply learned convolutional neural networks," CoRR, vol. abs/1703.07330, 2017. [Online]. Available: http://arxiv.org/abs/1703.07330

2) OpenALPR Cloud API, http://www.openalpr.com/cloud-api.html

3) Silva, S.M., Jung, C.R.: "Real-time brazilian license plate detection and recognition using deep convolutional neural networks." In: 2017 30th SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI). pp. 55–62 (Oct 2017).

https://doi.org/10.1109/SIBGRAPI.2017.14

4) H. Li, P. Wang, M. You, C. Shen "Reading car license plates using deep neural networks" Image Vis Comput (2018), https://doi.org/10.1016/j.imavis.2018.02.002

- 5) Ibtissam Slimani, Abdelmoghit Zaarane, Wahban Al Okaishi, Issam Atouf and Abdellatif Hamdoun, "An automated license plate detection and recognition system based on wavelet decomposition and CNN"
 LTI Lab, Department of Physics, Faculty of Sciences Ben M'Sik, Hassan II University Of Casablanca, Morocco https://doi.org/10.1016/j.array.2020.100040
- 6) Y. Yuan, W. Zou, Y. Zhao, X. Wang, X. Hu, N. Komodakis "A robust and efficient approach to license plate detection" IEEE Trans Image Process (2017), https://doi.org/10.1109/TIP.2016.2631901