## 1. Dataset Structure

Downloaded and extracted

• Raw: data/CCPD2019/

• Subsets:

Sub-Dataset	Description	Image Number
CCPD-Base	Ordinary license plate picture	200 k
CCPD-FN	License plate is relatively close or far from the camera's shooting position	20 k
CCPD-DB	Brighter, darker or unevenly lit license plate areas	20 k
CCPD-Rotate	License plate tilted 20 to 50 degrees horizontally, -10 to 10 degrees vertically	10 k
CCPD-Tilt	License plate tilted 15 to 45 degrees horizontally and 15 to 45 degrees vertically	10 k
CCPD-Weather	License plate photographed in rain, snow and fog	10 k
CCPD-Challenge	The more challenging pictures in the plate detection recognition task	10 k
CCPD-Blur	Blurred plate images due to camera lens shake	5 k
CCPD-NP	Picture of a new car without plates fitted	5 k

# 2. Yolov5 setup and train

- YOLOv5 repo cloned and configured
- YAML file created with train/val paths
- Generate YOLO-style proto-labels
- YOLO training script uses CCPD2019 raw images
- Labels generated using filename metadata
- Outputs YOLO-style .txt files per image
- Trained weights saved for cropping step

# 3. Cropping

- Crops license plates using YOLOv5 bounding boxes
- Output images are 144×48 RGB crops
- Used as input for recognition models (baseline, PDLPR)

- - > ccpd\_base\_crops
  - > ccpd\_base\_val\_crops
  - > ccpd\_blur\_crops
  - > ccpd\_challenge\_crops
  - > ccpd\_db\_crops
  - > ccpd\_fn\_crops
  - > ccpd\_np\_crops
  - > ccpd\_rotate\_crops
  - > ccpd\_tilt\_crops
  - > ccpd\_weather\_crops

# 4. Baseline Pipeline

#### Input

• Source: Cropped license plate images (RGB) 48 × 144 pixels

#### **Tokenizer**

- Converts CCPD-encoded filenames (e.g., "0\_0\_22\_27\_27\_33\_16") to license plates (e.g., "皖A04025")
- No <SOS> or <EOS> tokens are used in CTC; blank index (0) is reserved

#### Feature Extraction: CNN+ Bi-GRU

- 3× convolutional blocks with BatchNorm + ReLU + MaxPooling
- Final output reshaped into sequence for temporal modeling
- Output: Tensor of shape (batch\_size, width/8, channels × height/8)

#### **Sequence Modeling**

Bidirectional GRU (3 layers):

- Captures left–right temporal dependencies
- Input: flattened feature maps
- Output: sequence of features for classification

#### Decoder

 Fully-connected linear layer maps each timestep to logits over character classes (including blank)

#### **Loss Function**

 CTC Loss (Connectionist Temporal Classification): Allows flexible alignment between predicted sequence and ground truth and does not require character-level alignment or segmentation

#### Inference

- Greedy decoding with collapsing repeated characters and removing blanks
- Ground truth derived directly from filename structure (CCPD encoding)

## Input

#### **Tokenizer**

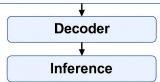
- Converts CCPD-encoded filenames (e.g., "0\_0 2\_ 27\_27\_33\_16") to license plates (e.g., "張A04025)
- No <SOS> or <EOS> tokens are used in CTC; blank index (0) is reserved

### **Feature Extraction**

- 3 × convolutioional blocks with BatchNorm + RELU + MaxPooling
- Final output reshaped into sequence for temporal modeling
- Output: Tensor of shape (batch\_size, width/8, channels × height/8)

### **Sequence Modeling**

- Bidirectional GRU β layers):
  Captures left–right temporal dependencies
- Input: flattened feature maps
- Output: sequence of features for classification



## 5. PDLPR Pipeline

#### Input

• Source: Cropped license plate images (RGB) 48 × 144 pixels

#### Tokenizer

 Converts plate strings (e.g., "京A12345") to integer sequences, including special tokens like <S0S> and <E0S>.

#### **Feature Extraction: IGFE (Improved Global Feature Extractor)**

- Based on CNN with:
  - Focus structure (YOLOv5-inspired) for spatial slicing without information loss
  - ConvDownSampling instead of pooling to preserve semantic content
  - ResBlocks to increase feature richness and stability
- Output: Feature map of shape (batch\_size, 512, 6, 18)

#### Encoder

- Flattens feature map to sequence: (batch\_size, 27, 512)
- Adds fixed sinusoidal positional encodings
- Passes through a stack of Transformer encoder blocks with:
  - Multi-Head Self-Attention
  - Feedforward layers
  - Residual connections + LayerNorm

#### **Decoder: Parallel Transformer Decoder**

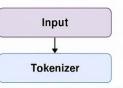
- Uses a stack of Transformer decoder blocks
- During training learns to attend to encoder features and previously decoded tokens.
  It uses masked Multi-Head Self-Attention to prevent attending to future tokens, enabling parallel computation during training.

#### **Loss Function**

 CTC Loss (Connectionist Temporal Classification): Used for sequence recognition

#### Inference

• The model iteratively predicts the next token.



 Converts plate strings, "萧A12345") to integer sequences, including special tokens <SOS> and <EOS>

#### **Feature Extraction**

- Based on CNN (improved Global Feature Extractor)
  Based on a CNN with:
  - Focus structure (YOLOV5-inspired) for spatial slicing without information ioss
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  - Feedforward layers
  - Residual connections+ LayerNorm

### Decoder

Uses a stak of \* Transformerr Decoder
 Used for sequence recognition, especially for arainalls-

Inference

## 6. Results – Baseline

### Base:

- Plate similarity (Leveshtein): 99.6 %
- Throughput : 3972.7 FPS (plates/s)

## **Averages on all sub-datasets:**

- Plate similarity (Leveshtein): 77.7%
- Throughput: 4128.2FPS (Plates/s)

## 7. Evaluation PDLPR

### Base:

Plate accuracy: 99.60 %Char accuracy: 99.83 %

• Throughput : 2968.5 FPS (plates/s)

## **Averages on all sub-datasets:**

Plate Accuracy: 76.47%Char Accuracy: 92.81%

• Throughput: 2845.7 FPS (Plates/s)