SVTR: Scene Text Recognition with a Single Visual Model

constiution: Baidu Inc., Fudan University, China
conference: IJCAI 2022
github: https://github.com/PaddlePaddle/PaddleOCR
reference: https://arxiv.org/pdf/2205.00159v2.pdf

> **PP-OCRv3**
> Introduction: PP-OCRv3, proposed by PaddleOCR team, is further upgraded on the basis of PP-OCRv2. The overall framework of PP-OCRv3 is same as that of PP-OCRv2. The base model of recognition network is replaced from CRNN to SVTR, which is recorded in IJCAI 2022.
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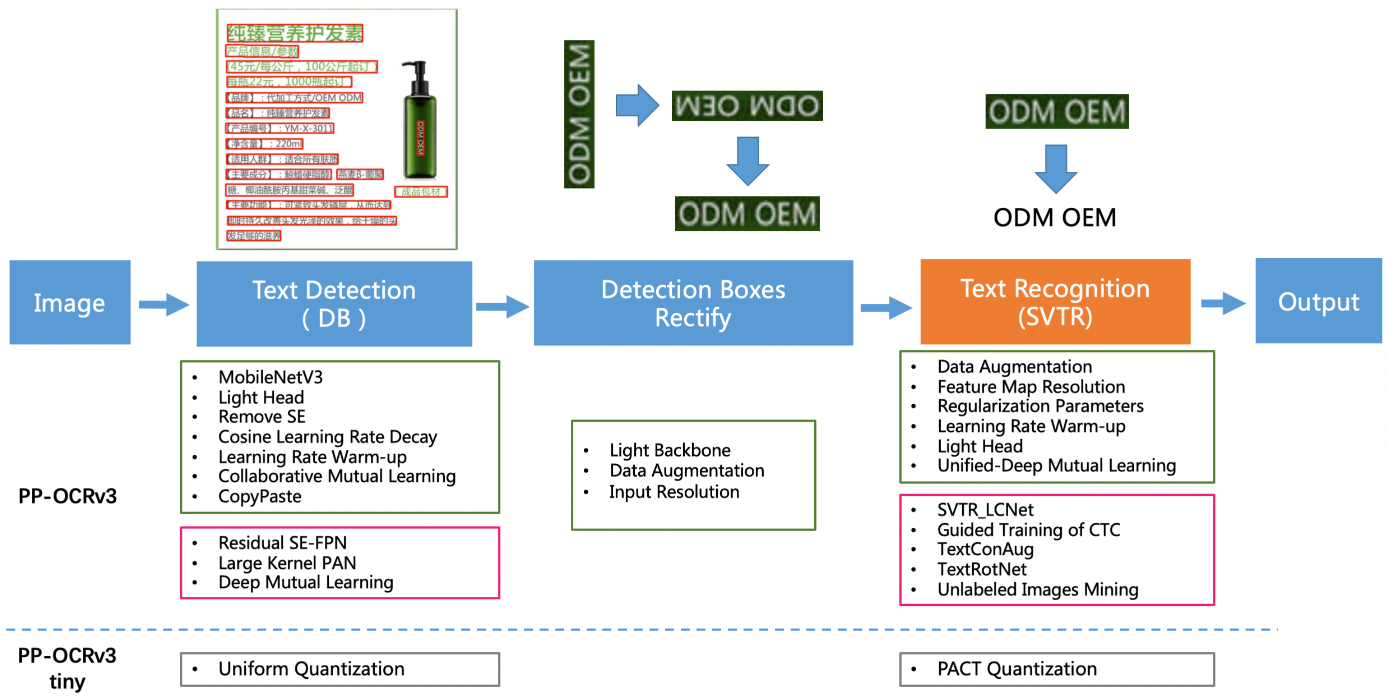
> 
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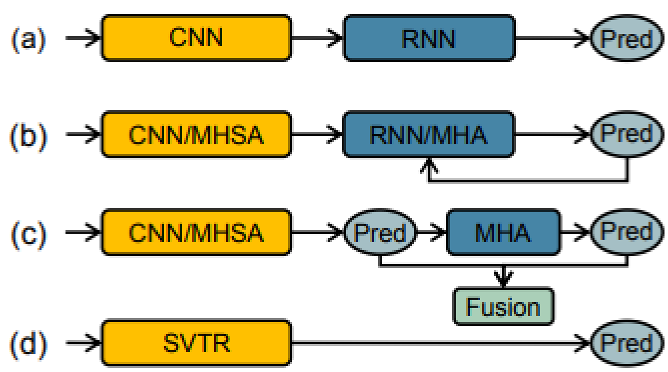
> There are 9 optimization strategies for text detection and recognition models in PP-OCRv3, which are as follows.
> In terms of effect, when the speed is comparable, the accuracy of various scenes is greatly improved:
> - In Chinese scenarios, PP-OCRv3 outperforms PP-OCRv2 by more than 5%.
> - In English scenarios, PP-OCRv3 outperforms PP-OCRv2 by more than 11%.
> - In multi-language scenarios, models for more than 80 languages are optimized, the average accuracy is increased by more than 5%.

Abstract

- In this study, we propose a Single Visual model for Scene Text recognition within the **patch-wise** image tokenization framework, which dispenses with the **~~sequential modeling~~** entirely.
- The method, termed SVTR, firstly decomposes an image text into small patches named **character components**.
- **Global and local mixing** blocks are devised to perceive the inter-character and intra-character patterns, leading to a multi-grained character component perception. Thus, characters are recognized by a simple linear prediction.

> 
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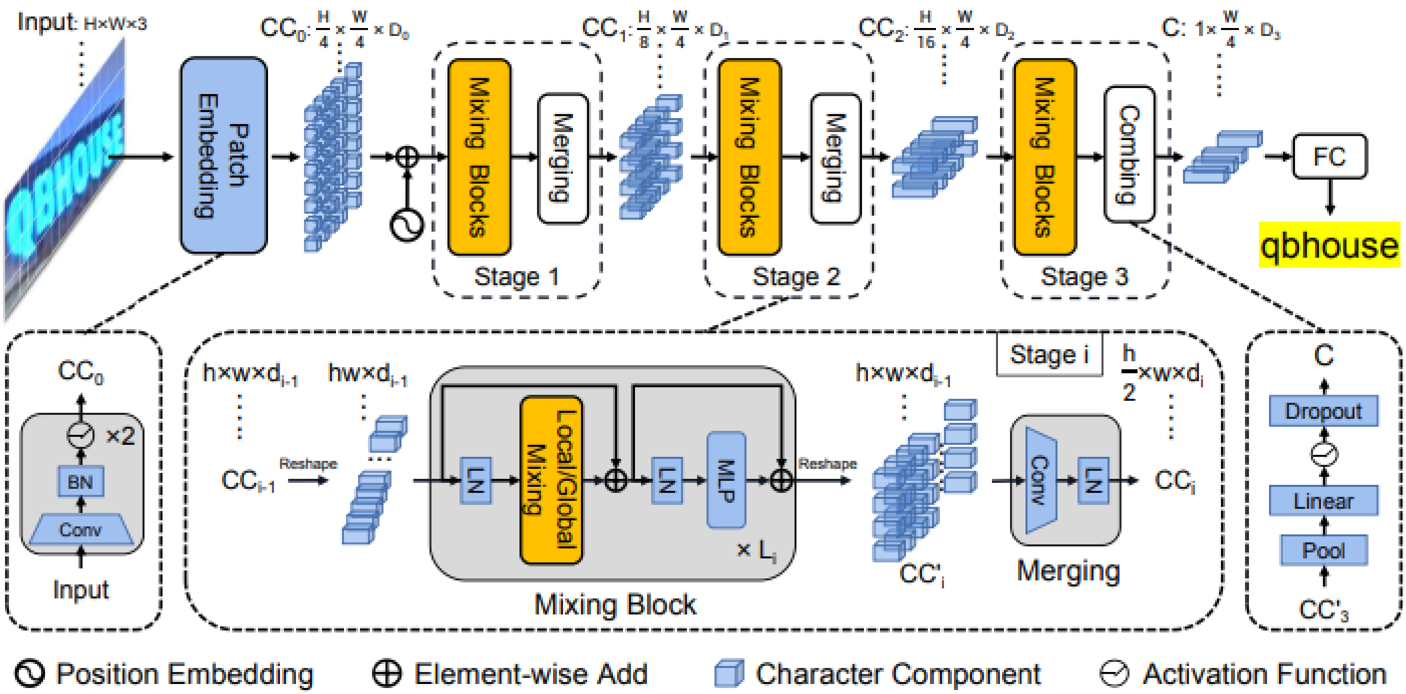
> Figure 1:
> (a) CNN-RNN based models.
> (b) Encoder-Decoder models. MHSA and MHA denote multi-head self-attention and multihead attention, respectively.
> (c) Vision-Language models. (e.g. SRN, ABINet)
> (d) Our SVTR, which recognizes scene text with a single visual model and enjoys efficient, accurate and cross-lingual versatile.

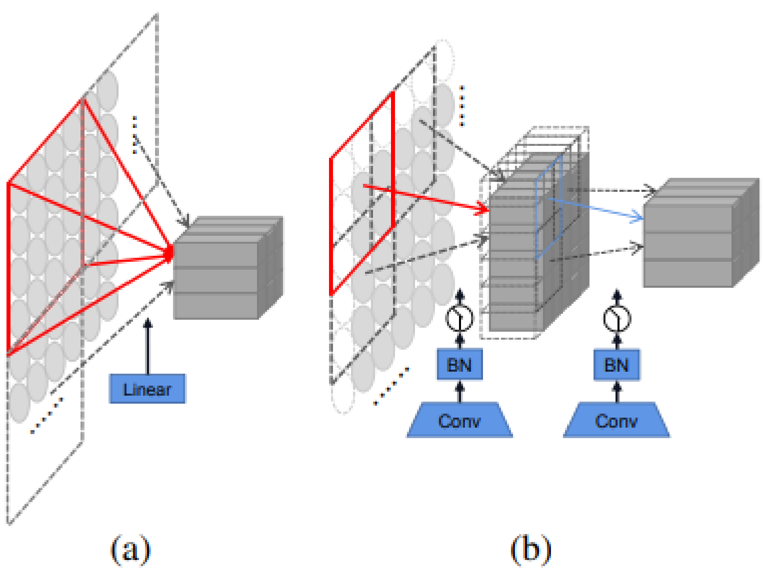
Method

Overall Architecture



> Figure 2: Overall architecture of the proposed SVTR. It is a three-stage height progressively decreased network. In each stage, a series of mixing blocks are carried out and followed by a merging or combining operation. At last, the recognition is conducted by a linear prediction.

Progressive Overlapping Patch Embedding

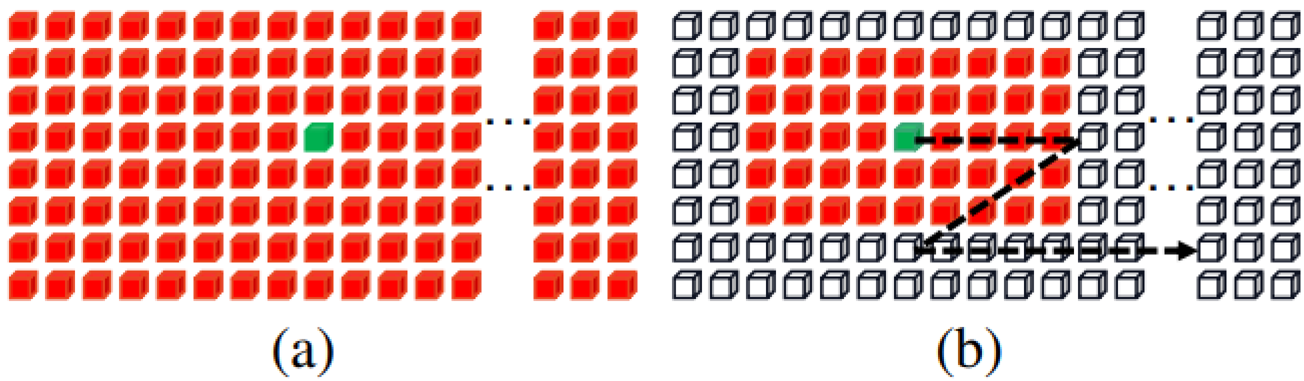


> Figure 3: (a) The linear projection in ViT [Dosovitskiy et al., 2021]. (b) Our progressive overlapping patch embedding.

- There exists two common one-step projections for this purpose, i.e., a 4×4 disjoint linear projection (see Figure 3(a)) and a 7 × 7 convolution with stride 4.

- Alternatively, we implement the patch embedding by using two consecutive 3 × 3 convolutions with stride 2 and batch normalization, as shown in Figure 3(b).
- The scheme, despite increasing the computational cost a little, adds the feature dimension progressively which is in favor of feature fusion.

Mixing Block



> Figure 4: Illustration of (a) global mixing and (b) local mixing.

- Since two characters may differ slightly, text recognition heavily relies on features at character component level.
- We argue that text recognition requires two kinds of features:
  1. The first is local component patterns such as the **stroke-like** feature. It encodes the morphology feature and correlation between different parts of a character.
  2. The second is intercharacter dependence such as the correlation between different **characters** or **between text and non-text** components.
- Therefore, we devise two mixing blocks to perceive the correlation by **using self-attention with different reception fields**.

Merging

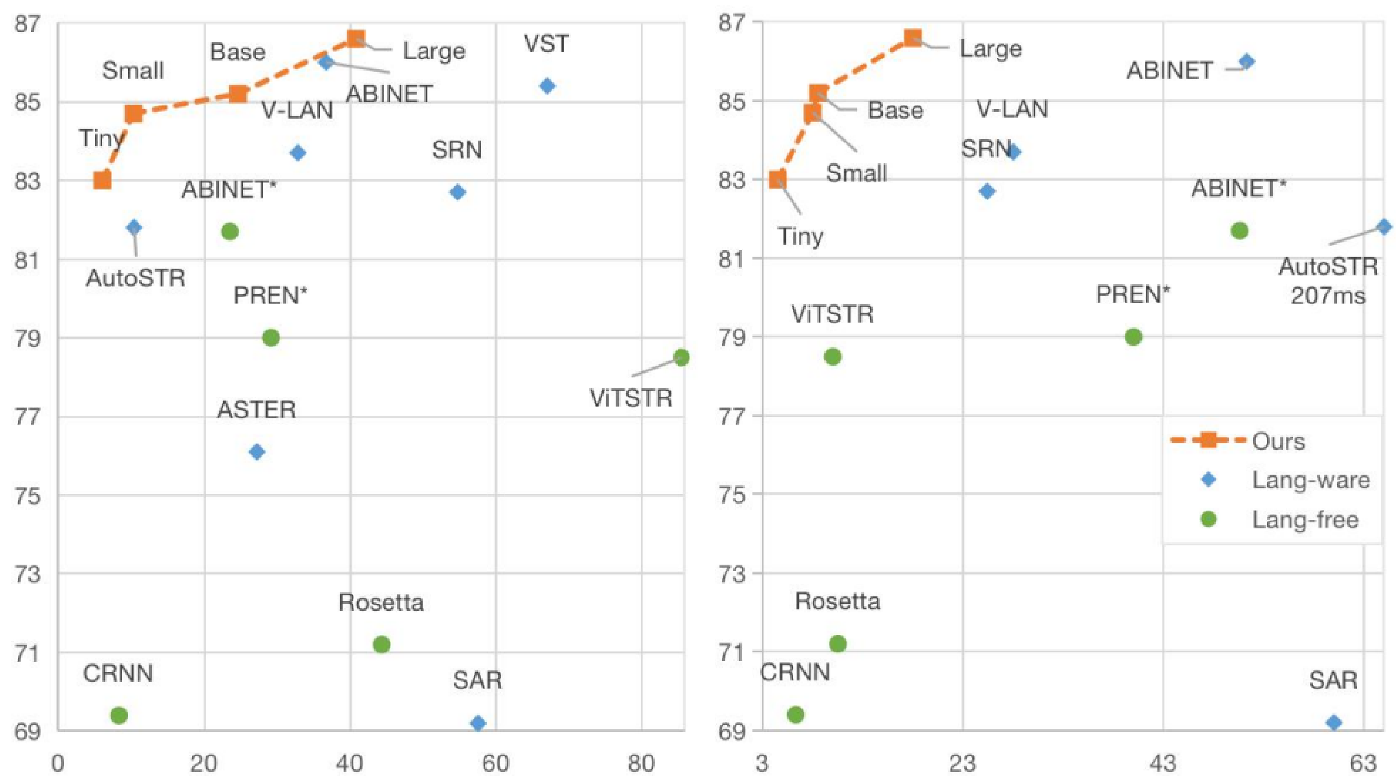
- It is computational expensive to maintain a constant spatial resolution across stages, which also leads to redundant representation.
- we employ a 3×3 convolution with stride 2 in the height dimension and 1 in the width dimension, followed by a layer norm, generating an embedding of size $\frac{h}{2} \times w \times d_i$.
- The merging operation halve the height while keep a constant width. It not only **reduce the computational cost**, but also build a **text-customized hierarchical structure**.

Combining and Prediction

- It pools the height dimension to 1 at first, followed by a fully-connected layer, non-linear activation and dropout.
- By doing this, **character components are further compressed to a feature sequence**, where each element is represented by a feature of length D_3.
- Compared to the merging operation, the combining operation **can avoid applying convolution** to an embedding whose size is very small in one dimension, e.g., with 2 in height.

Experiments

The Effectiveness of Patch Embedding



> Figure 5: Accuracy-parameter (M) and Accuracy-speed (ms) plots of different models on IC15.

Comparison with State-of-the-Art

	method	English regular			English unregular			Chinese	Params	Speed
		IC13	SVT	IIIT5k	IC15	SVTP	CUTE	Scene	(M)	(ms)
Lan-free	CRNN[Shi *et al.*, 2017]	91.1	81.6	82.9	69.4	70.0	65.5	53.4	8.3	6.3
	Rosetta[Borisyuk *et al.*, 2018]	90.9	84.7	84.3	71.2	73.8	69.2	-	44.3	10.5
	SRN*[Yu *et al.*, 2020]	93.2	88.1	92.3	77.5	79.4	84.7	-	-	-
	PREN*[Yan *et al.*, 2021]	94.7	92.0	92.1	79.2	83.9	81.3	-	29.1	40.0
	ViTSTR[Atienza, 2021]	93.2	87.7	88.4	78.5	81.8	81.3	-	85.5	11.2
	ABINet*[Fang *et al.*, 2021]	94.9	90.4	94.6	81.7	84.2	86.5	-	23.5	50.6
	VST*[Tang *et al.*, 2022]	95.6	91.9	95.6	82.3	87.0	91.8	-	-	-
Lan-aware	ASTER[Shi *et al.*, 2019]	-	89.5	93.4	76.1	78.5	79.5	54.5	27.2	-
	MORAN[Luo *et al.*, 2019]	-	88.3	91.2	-	76.1	77.4	51.8	28.5	-
	NRTR[Sheng *et al.*, 2019]	94.7	88.3	86.5	-	-	-	-	31.7	160
	SAR[Li *et al.*, 2019]	91.0	84.5	91.5	69.2	76.4	83.5	62.5	57.5	120
	AutoSTR[Zhang *et al.*, 2020]	-	90.9	94.7	81.8	81.7	84.0	-	10.4	207
	SRN[Yu *et al.*, 2020]	95.5	91.5	94.8	82.7	85.1	87.8	60.1	54.7	25.4
	PREN2D[Yan *et al.*, 2021]	96.4	94.0	95.6	83.0	87.6	91.7	-	-	-
	VisionLAN[Wang *et al.*, 2021]	95.7	91.7	95.8	83.7	86.0	88.5	-	32.8	28.0
	ABINet[Fang *et al.*, 2021]	**97.4**	93.5	96.2	86	89.3	89.2	-	36.7	51.3
	VST[Tang *et al.*, 2022]	96.4	**93.8**	**96.3**	85.4	88.7	**95.1**	**-**	64.0	-
Ours	SVTR-T (Tiny)	96.3	91.6	94.4	84.1	85.4	88.2	67.9	6.03	4.5
	SVTR-S (Small)	95.7	93.0	95.0	84.7	87.9	92.0	69.0	10.3	8.0
	SVTR-B (Base)	97.1	91.5	96.0	85.2	**89.9**	91.7	71.4	24.6	8.5
	SVTR-L (Large)	97.2	91.7	**96.3**	**86.6**	88.4	**95.1**	**72.1**	40.8	18.0

> Table 4: Results on six English and one Chinese benchmarks tested against existing methods, where CRNN and Rosetta are from the reproduction of CombBest [Baek et al., 2019]. Lan means language and * means the language-free version of the corresponding method. The speed is the inference time on one NVIDIA 1080Ti GPU averaged over 3000 English image text.