High-Performance Transformers for Table Structure Recognition Need Early Convolutions

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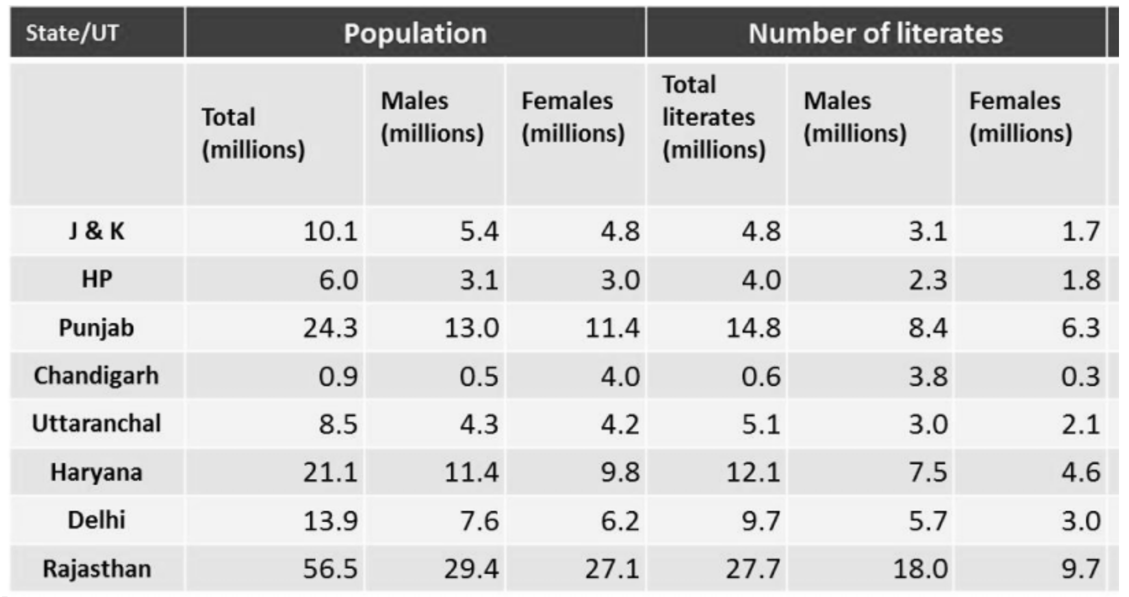
Oral Presentation at NeurIPS'23 Workshop on Table Representation Learning

Existing table structure recognition research treats task as image-to-text generation

Input Image



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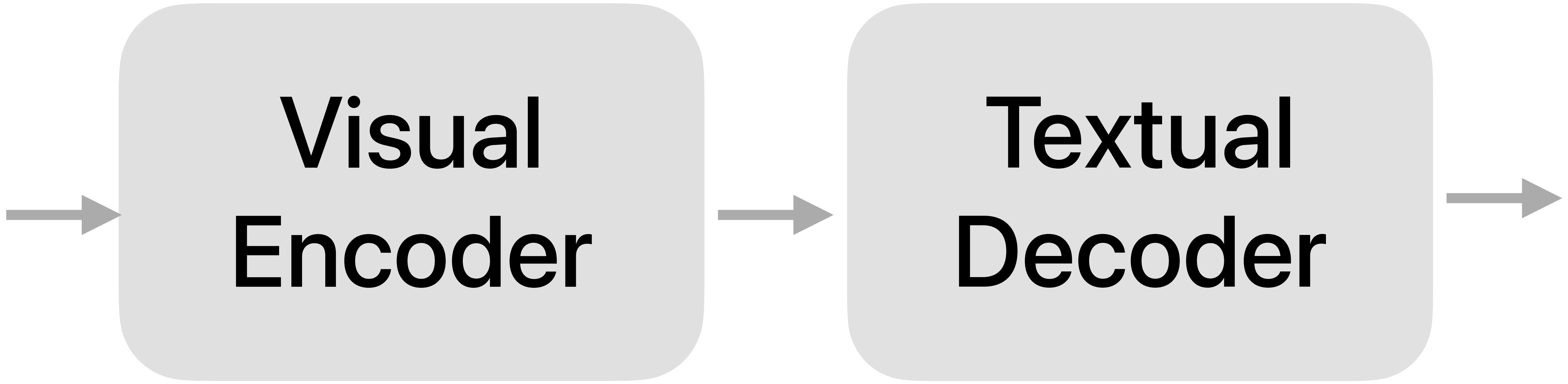
Delhi	13.9	7.6	6.2	9.7	5.7	3.0
Rajasthan	56.5	29.4	27.1	27.7	18.0	9.7



Visual Encoder

Textual Decoder

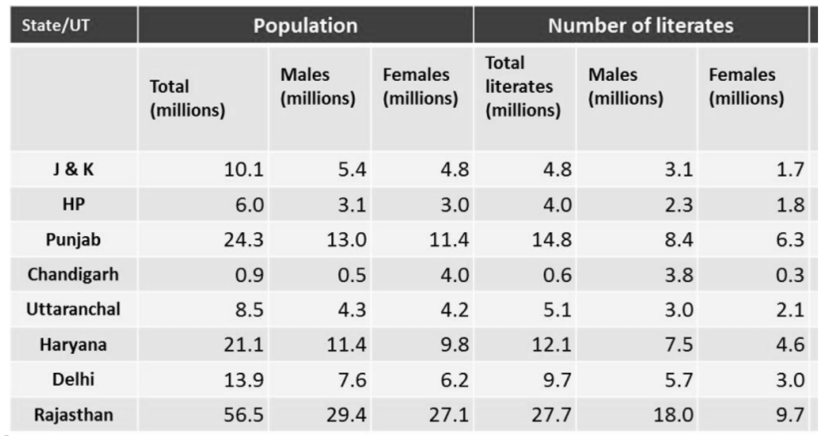
HTML Tags

<thead><tr>
<td></td>…

Model architecture in existing method:
Hybrid CNN-Transformer

- CNN backbone takes up ~50% of the total model parameters
- Significantly reduces both training and inference speed

Input Image



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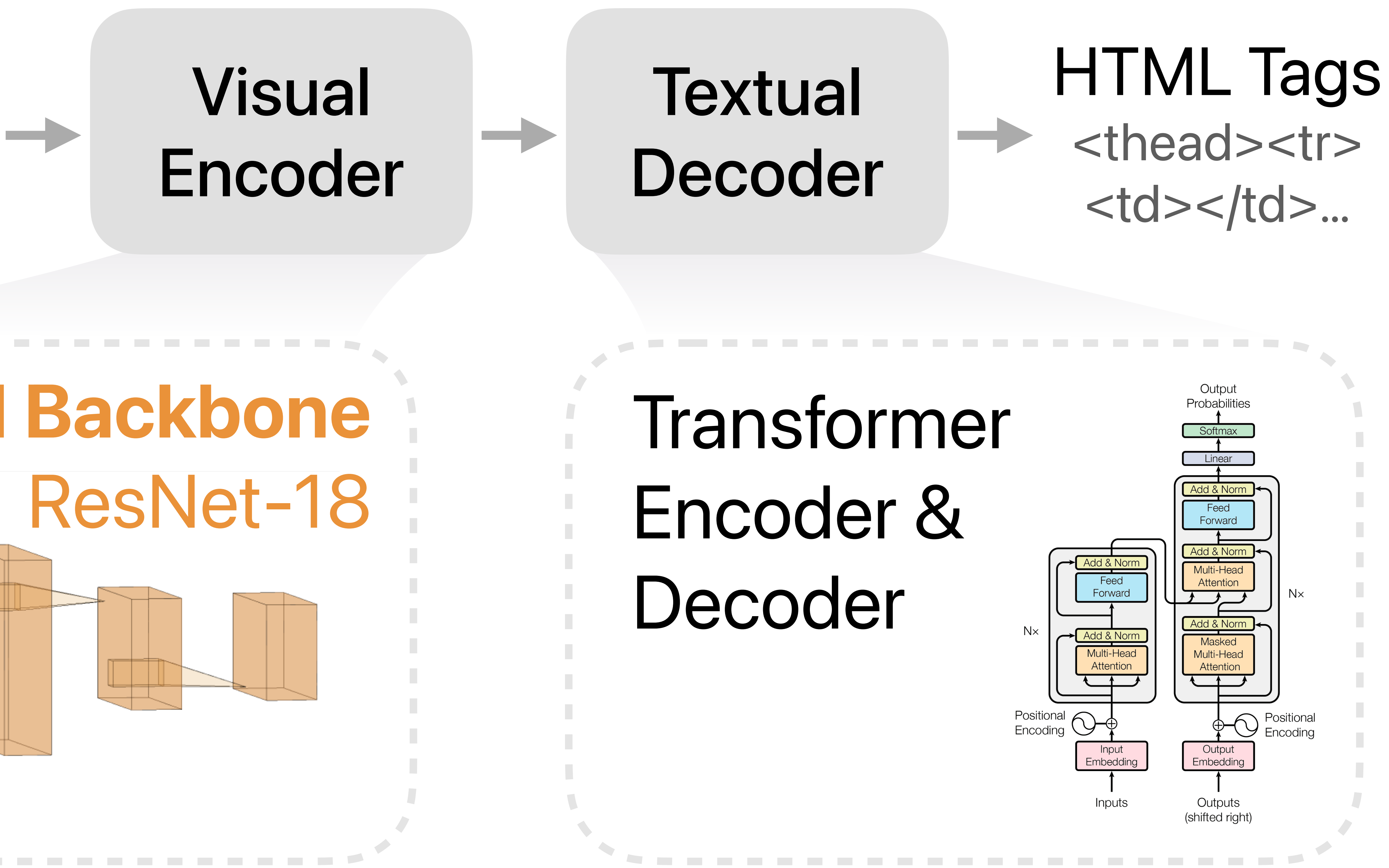

Visual Encoder

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CNN Backbone
ResNet-18

Transformer Encoder & Decoder

But hybrid CNN-Transformers seldomly used:

Vision Transformers use simple linear projection instead of CNN backbone

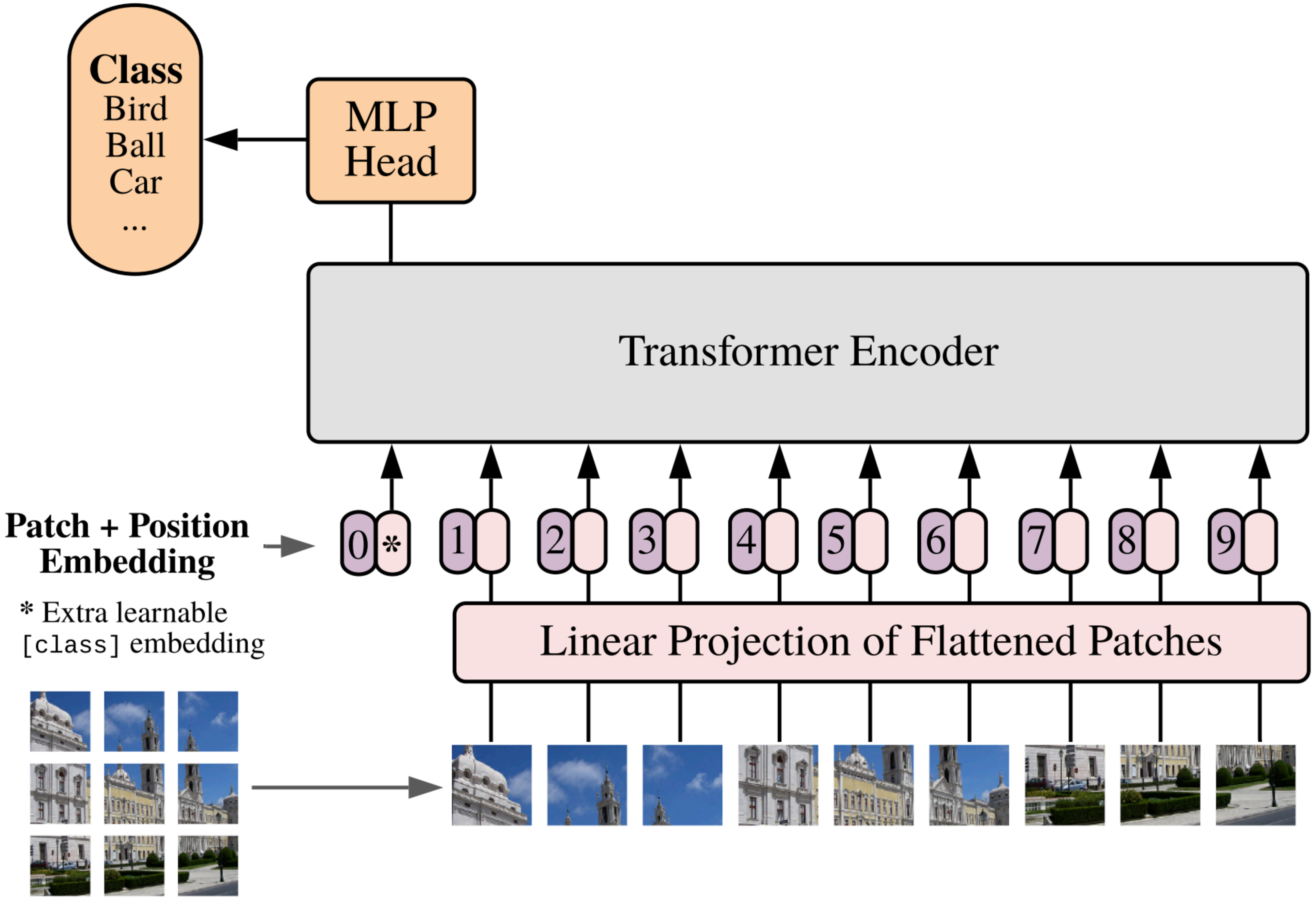
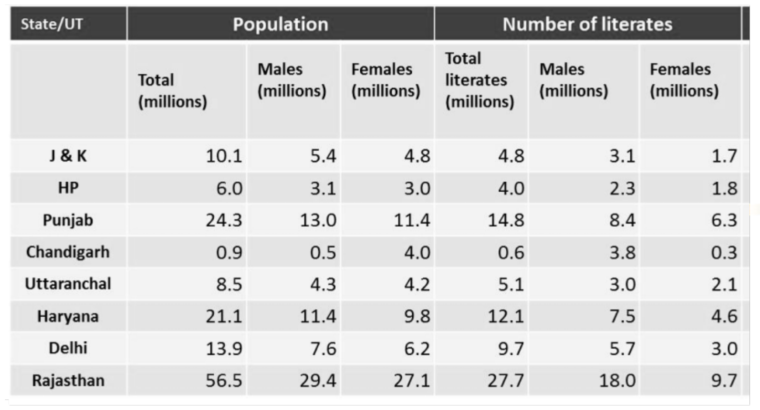

Class
Bird
Ball
Car
...
MLP Head
Transformer Encoder
Patch + Position Embedding
* Extra learnable [class] embedding
0
*
1
2
3
4
5
6
7
8
9
Linear Projection of Flattened Patches

Image credit: A. Dosovitskiy, et. al.

Can we simply employ the linear projection?

Input image



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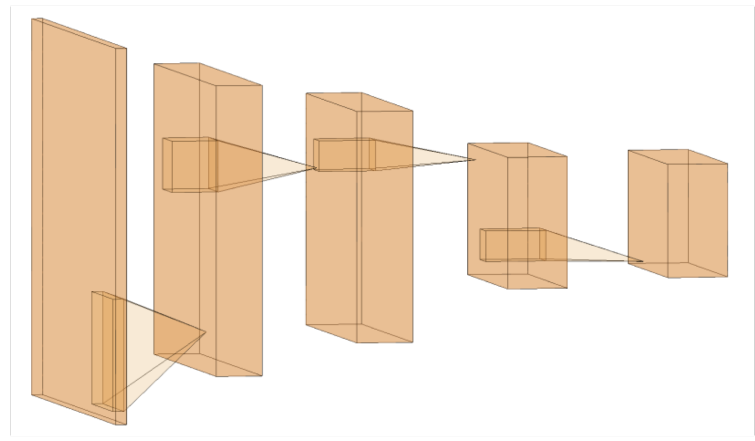
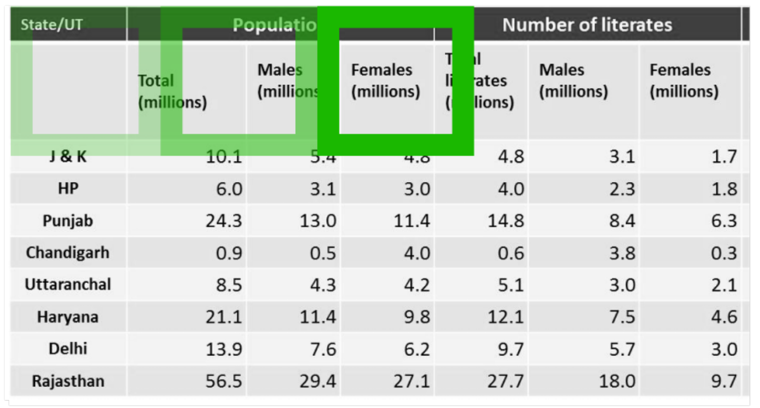
	Performance	Model Complexity
ResNet-18 CNN Backbone	High ✓ 94.50% Complex TEDS	High ✗ 28.70M #Param. 42.22G MAC
LinearProj	Low ✗ 86.62%	Lowest ✓ 22.67M 10.28G





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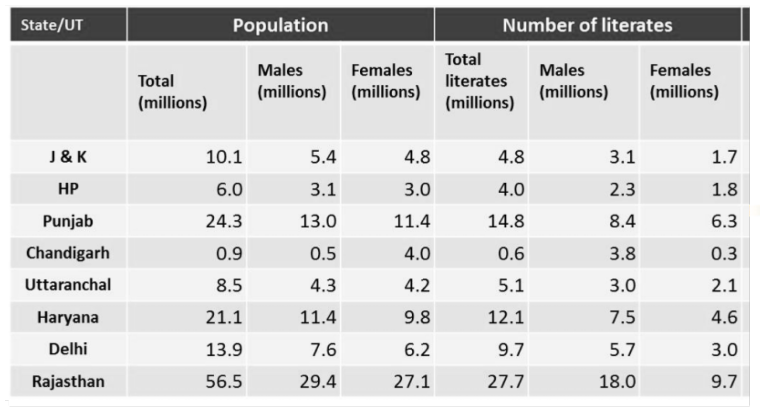
Textual Decoder

Visual Encoder Options for Table Structure Recognition

Can we simply employ the linear projection?

No, performance suffers

Input image



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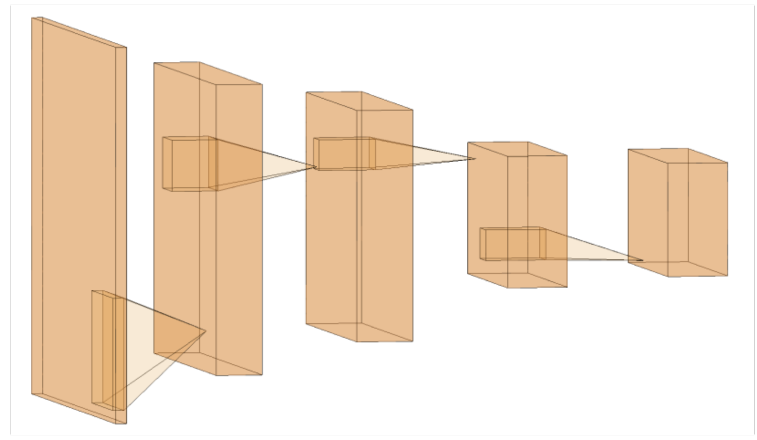
Performance

Model Complexity

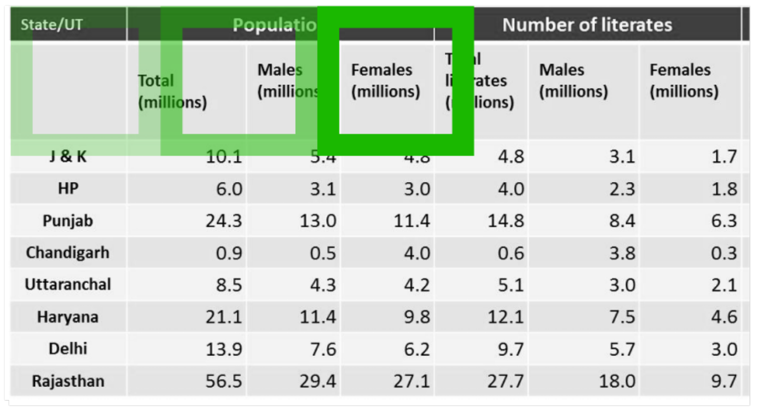
ResNet-18
CNN Backbone



High ✓
94.50%
Complex TEDS

High ✗
28.70M #Param.
42.22G MAC

LinearProj



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Low ✗
86.62%

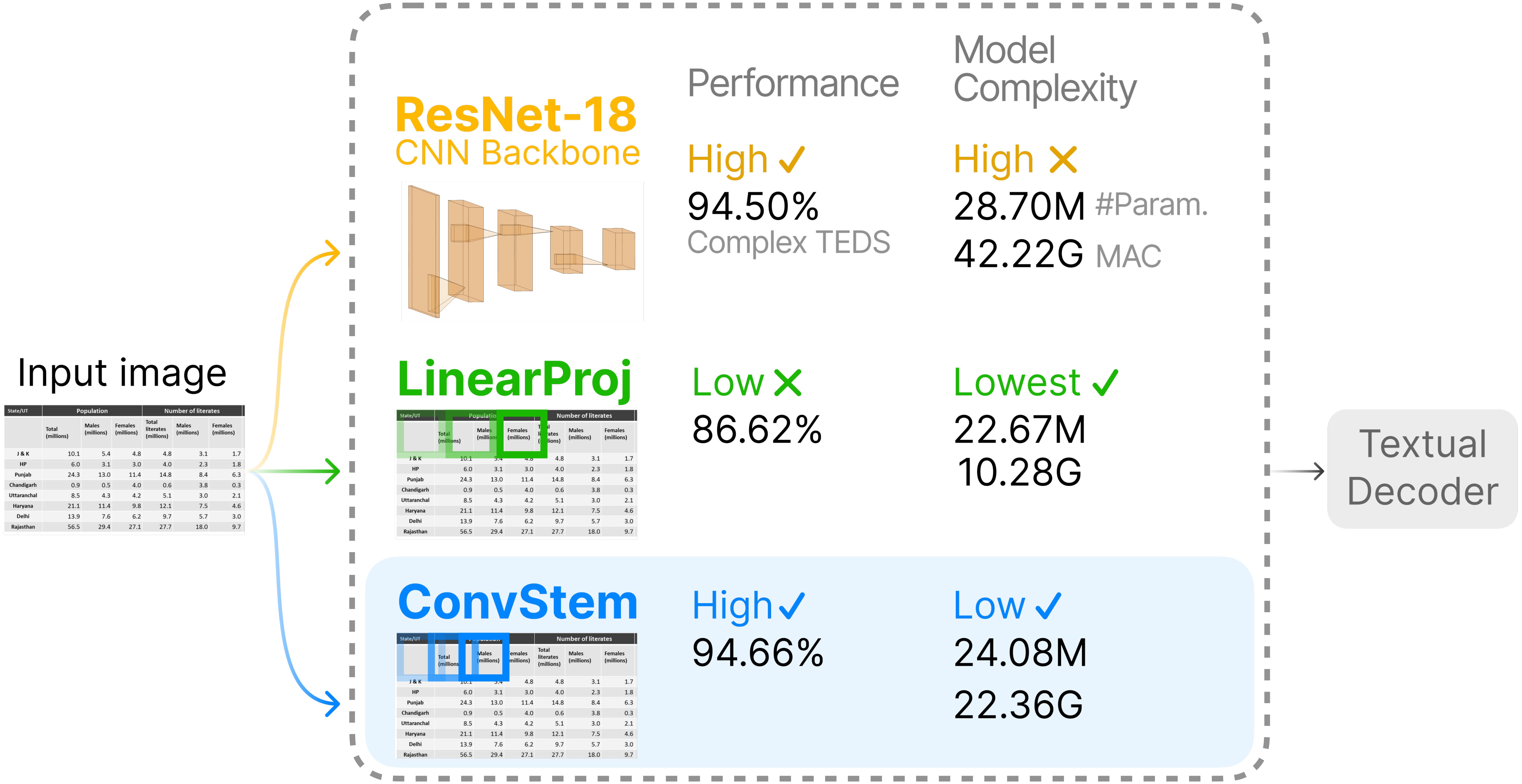
Lowest ✓
22.67M
10.28G

Textual Decoder

Visual Encoder Options for Table Structure Recognition

Our Key Contribution & Discovery

ConvStem matches CNN backbone performance with a simpler model



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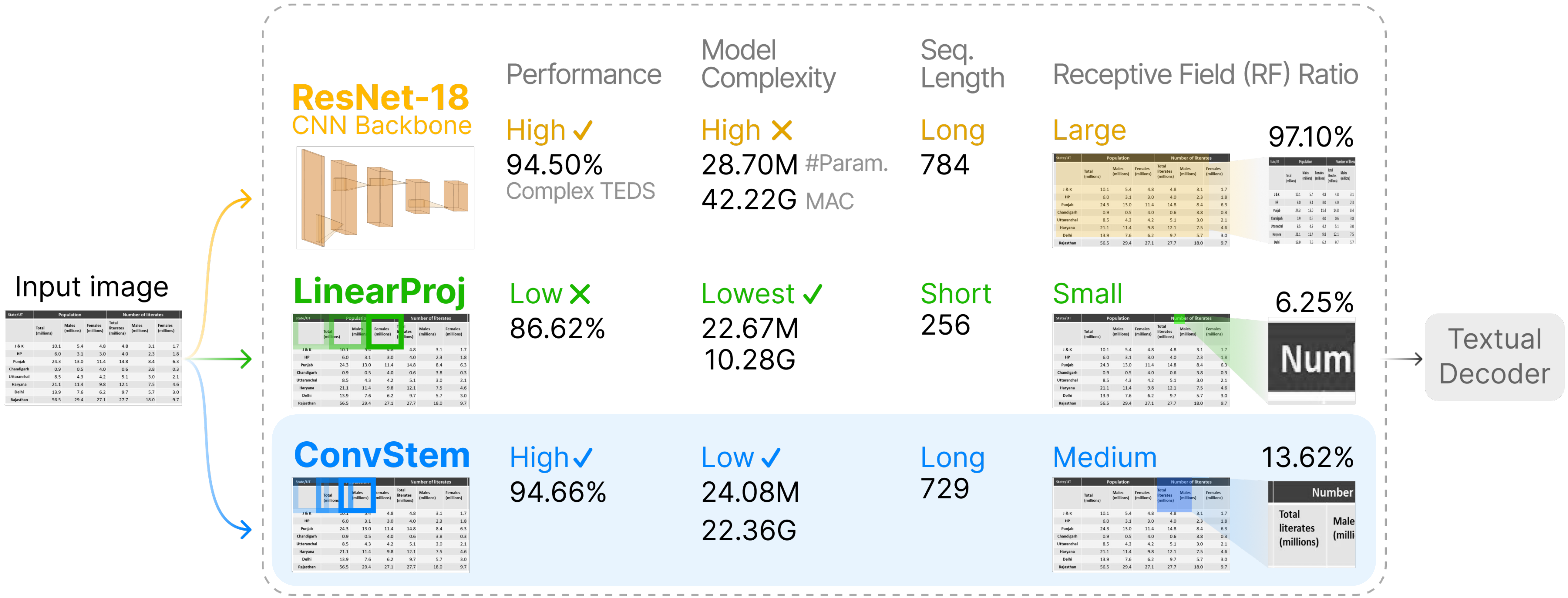
ConvStem	High ✓ 94.66%	Low ✓ 24.08M 22.36G

Textual Decoder

Visual Encoder Options for Table Structure Recognition

Why is convolutional stem effective?

Higher receptive field ratio & longer sequence length



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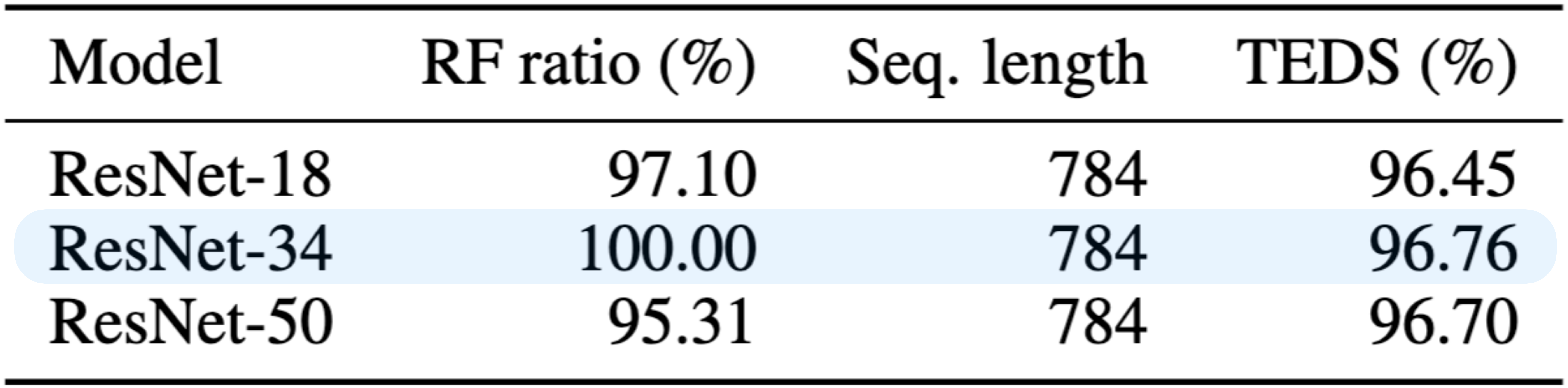
	Performance	Model Complexity	Seq. Length	Receptive Field (RF) Ratio
ResNet-18 CNN Backbone	High ✓ 94.50% Complex TEDS	High ✗ 28.70M #Param. 42.22G MAC	Long 784	Large 97.10%
LinearProj	Low ✗ 86.62%	Lowest ✓ 22.67M 10.28G	Short 256	Small 6.25%
ConvStem	High ✓ 94.66%	Low ✓ 24.08M 22.36G	Long 729	Medium 13.62%

Textual Decoder

ConvStem matches CNN backbone performance with a simpler model

CNN Backbone

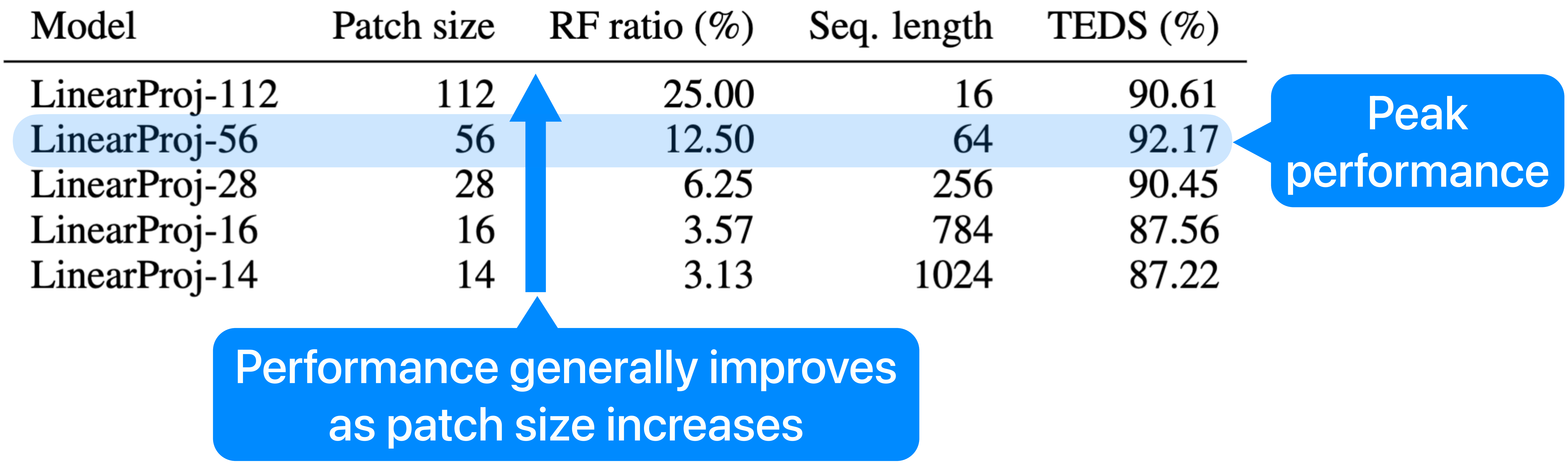
ResNet-34 has the highest TEDS due to its high RF ratio



Model	RF ratio (%)	Seq. length	TEDS (%)
ResNet-18	97.10	784	96.45
ResNet-34	100.00	784	96.76
ResNet-50	95.31	784	96.70

Linear Projection

As the patch size increases, performance generally improves, reaching its peak at a patch size of 56



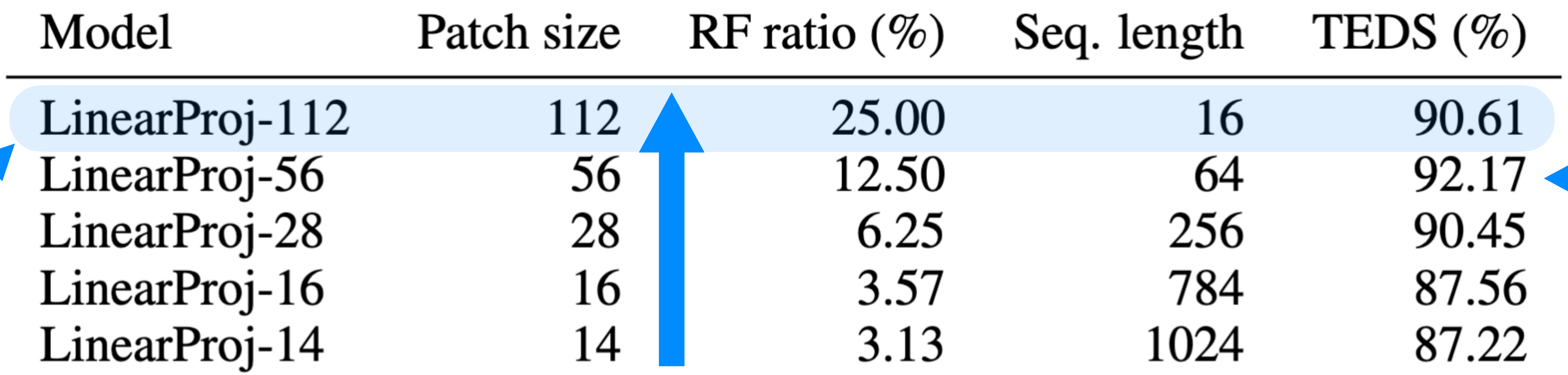
Model	Patch size	RF ratio (%)	Seq. length	TEDS (%)
LinearProj-112	112	25.00	16	90.61
LinearProj-56	56	12.50	64	92.17
LinearProj-28	28	6.25	256	90.45
LinearProj-16	16	3.57	784	87.56
LinearProj-14	14	3.13	1024	87.22

Peak performance

Performance generally improves as patch size increases

Linear Projection

As the patch size increases, performance generally improves, reaching its peak at a patch size of 56



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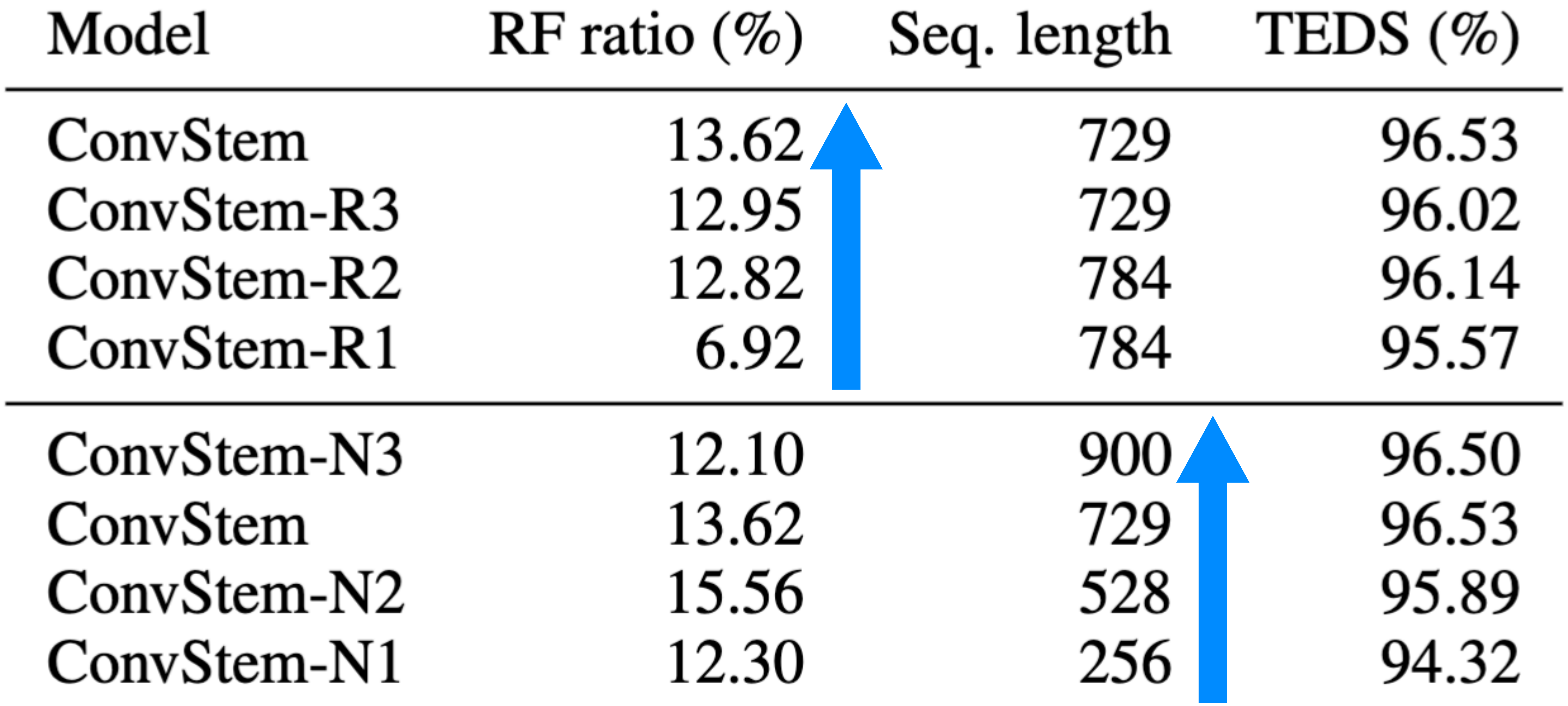
Peak performance

Patch size too large ➡ sequence length too small ➡ worse performance
(Patch size & sequence length inversely correlated)

Convolutional Stem

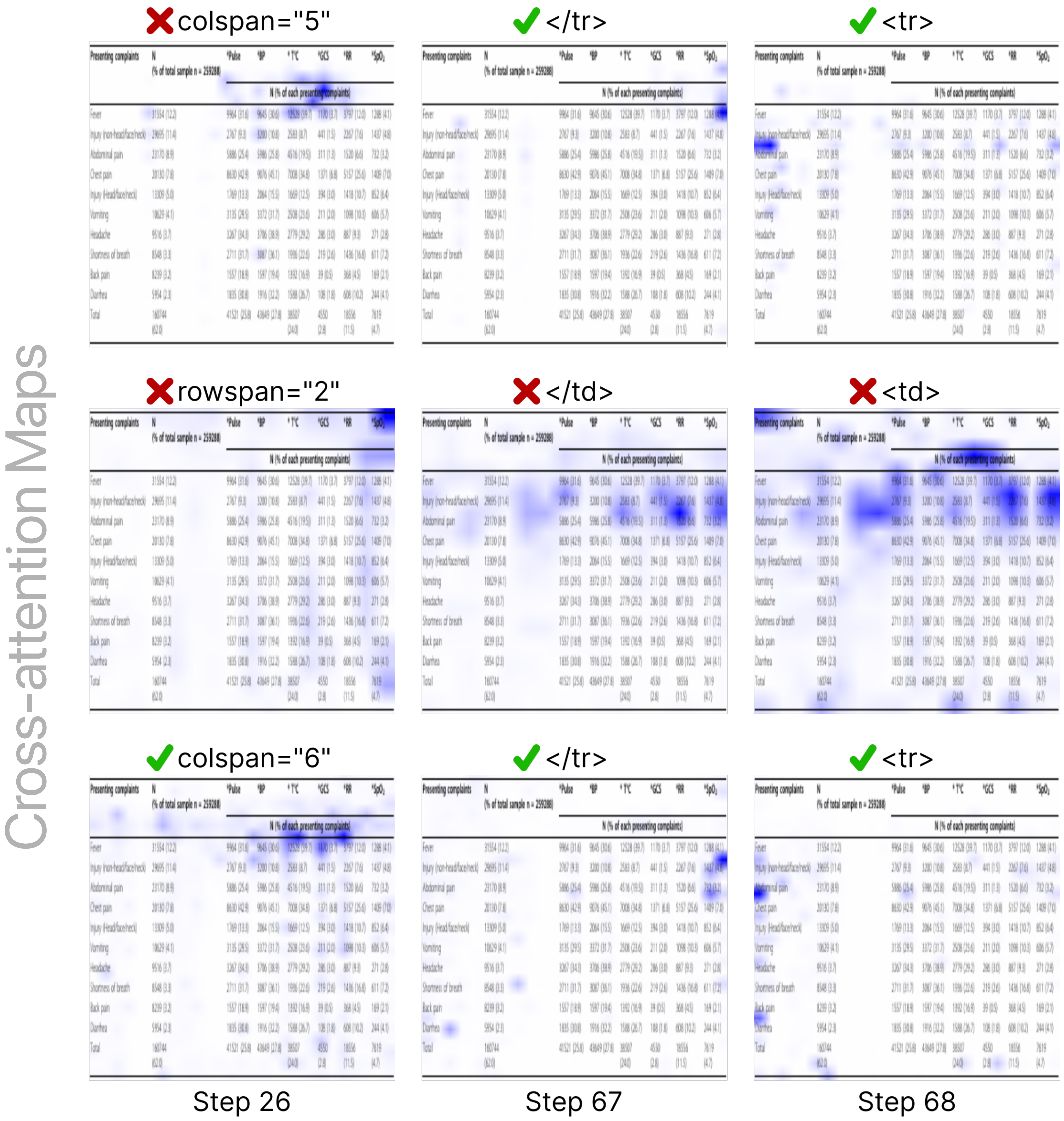
Optimal balance of RF ratio & sequence length



Model	RF ratio (%)	Seq. length	TEDS (%)
ConvStem	13.62	729	96.53
ConvStem-R3	12.95	729	96.02
ConvStem-R2	12.82	784	96.14
ConvStem-R1	6.92	784	95.57
ConvStem-N3	12.10	900	96.50
ConvStem	13.62	729	96.53
ConvStem-N2	15.56	528	95.89
ConvStem-N1	12.30	256	94.32

Higher RF ratio increases TEDS

Longer sequence length increases TEDS



CNN Backbone (ResNet-18)

Miscounts columns in header spanning cell

TEDS: 98.28%

Linear Projection (LinearProj-28)

Mis-predict html tags due to scattered attention

TEDS: 86.07%

ConvStem

Accurately reconstructs table

TEDS: 100.00%

Easy-to-Use Open-Source Research

github.com/poloclub/tsr-convstem

Step 1. Configure experiment

```
EXP_r18_e2_d4_adamw := $(PUBTABNET) $(MODEL_r18_e2_d4) $(OPT_adamw)
```

Step 2. Train & evaluate the model

```
$ make experiments/r18_e2_d4_adamw/.done_teds_structure
```

Thanks!

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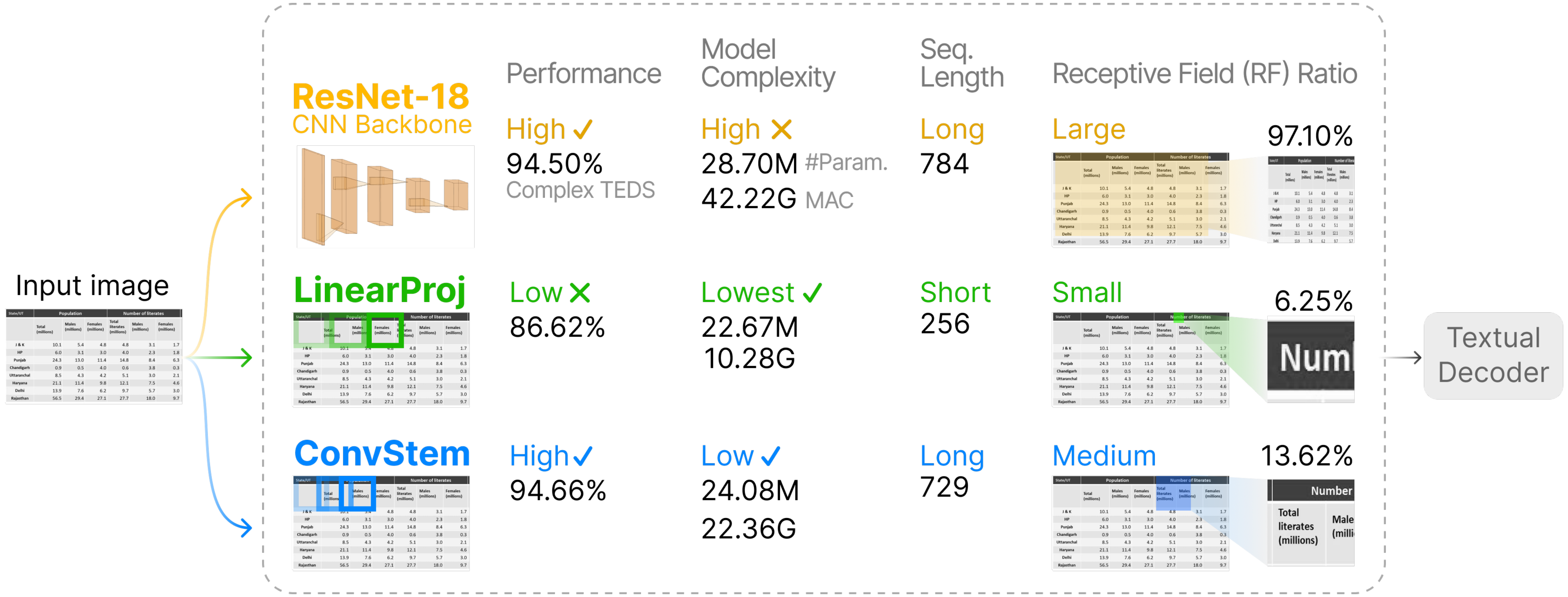
High-Performance Transformers for Table Structure Recognition Need Early Convolutions

ConvStem matches classic CNN backbone performance, with a much simpler model.



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