Join the Virtual Presentation



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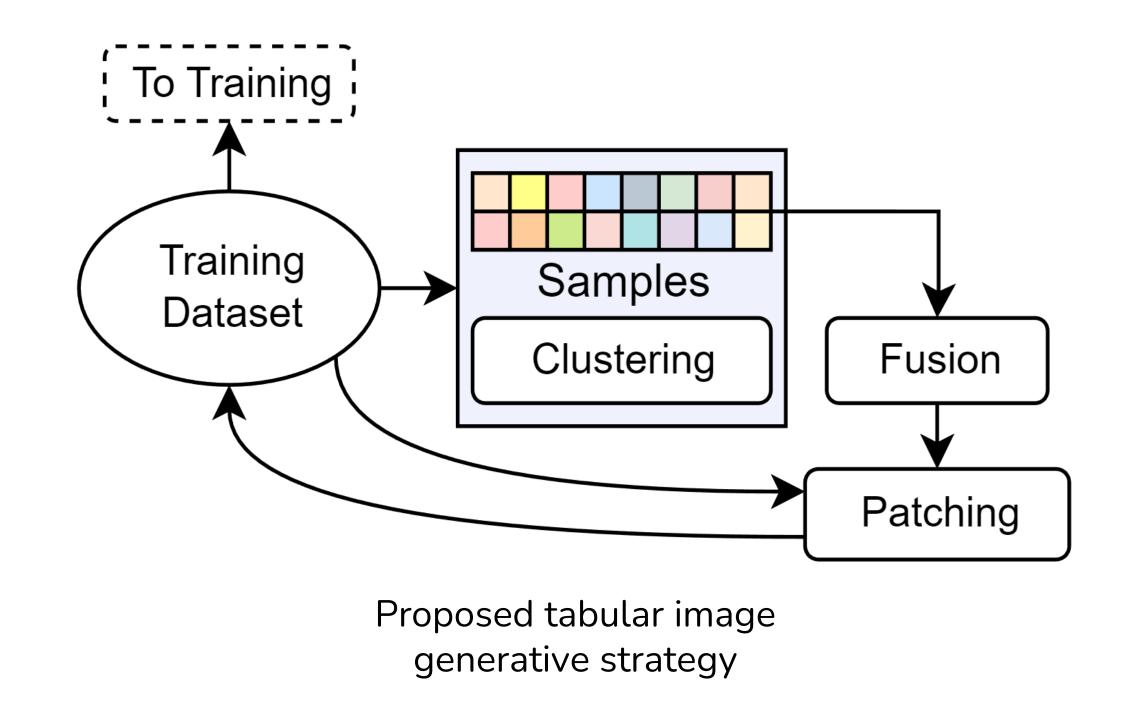
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Introduction

- In this research, we present an architecture leveraging the benefits of Pyramid Vision Transformer backbone paired up with novel augmentation strategies
- We present a novel tabular image generative augmentation technique to effectively train the architecture.

Augmentation Strategy

- Addresses data-hungry nature of transformers.
- Enhances architecture with fine-grained object detection capabilities through:
- Clustering: Groups similar tables using K-means clustering based on visual characteristics
- Fusion: Joins clustered tables horizontally/vertically based on structure after joint masking
- Patching: Patches fused tables onto images from the original dataset



Datasets

Experiments and training were conducted on the open-source and publicly available document analysis datasets

Dataset	# Images	# Tables
ICDAR 2017-POD	1600	731
ICDAR 2019-cTDaR	600	_
Marmot	1967	_
UNLV	10k	427
TableBank	260k	417k
PubLayNet	86k	_

Table 1. Datasets used in the experimentation with their corresponding number of images and tables

Results

Evaluating the augmentation pipeline through in both table detection and structure recognition tasks through the following training pipelines:

- Non-Augmented (NA): No modifications to training images
- Standard (S): Applying standard augmentation techniques combined with strategies from DETR
- Generative (G) (ours): Includes standard and proposed augmentation strategies.

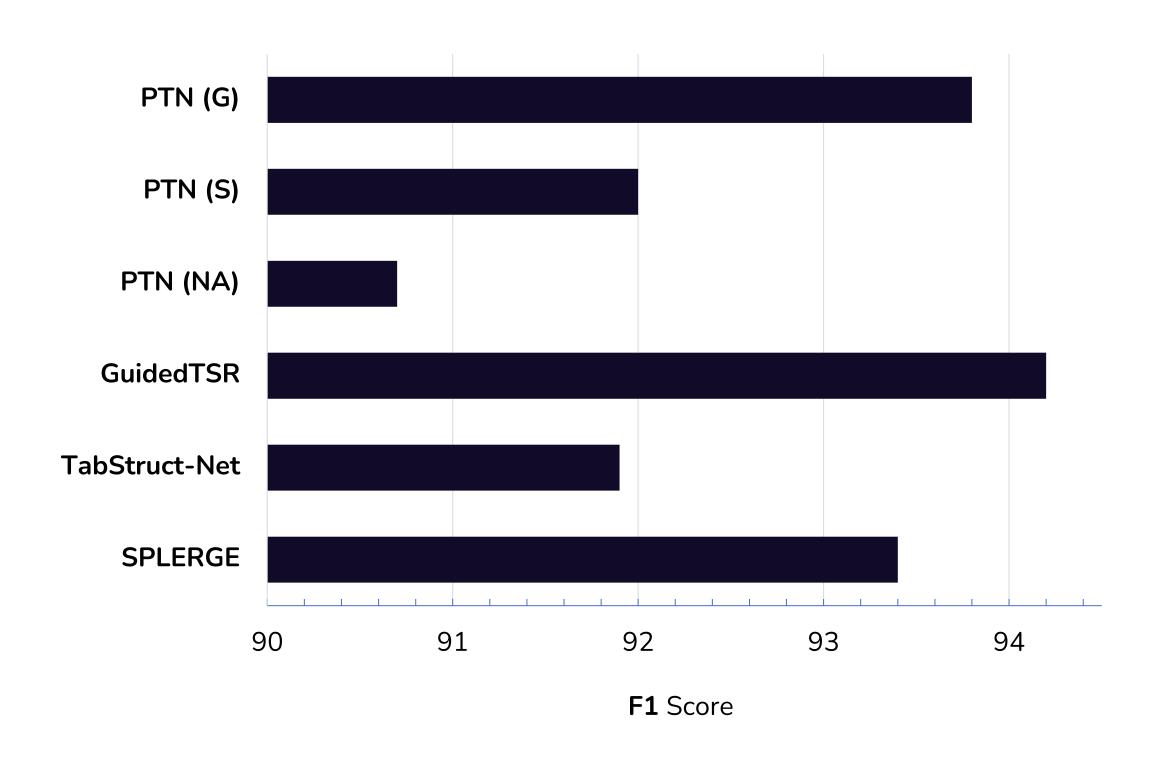
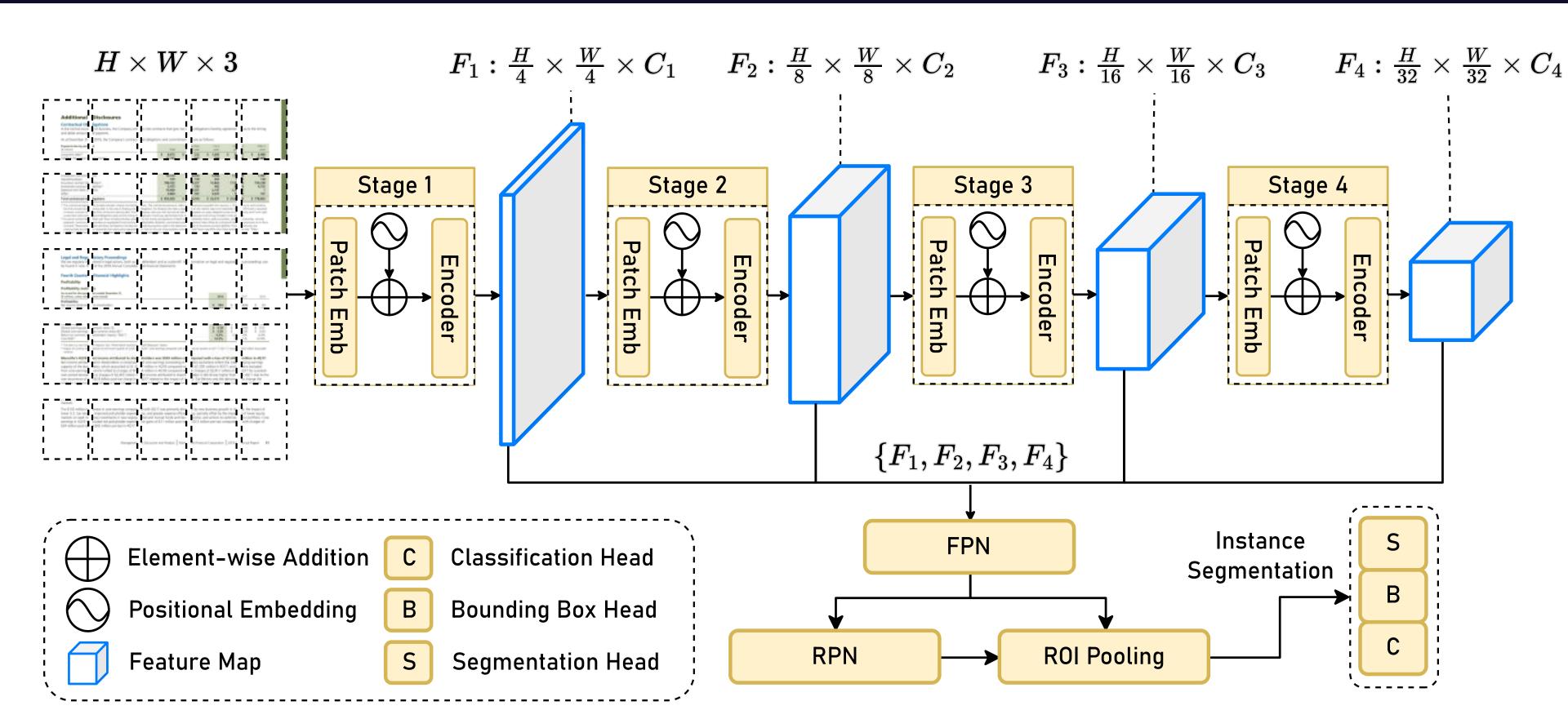


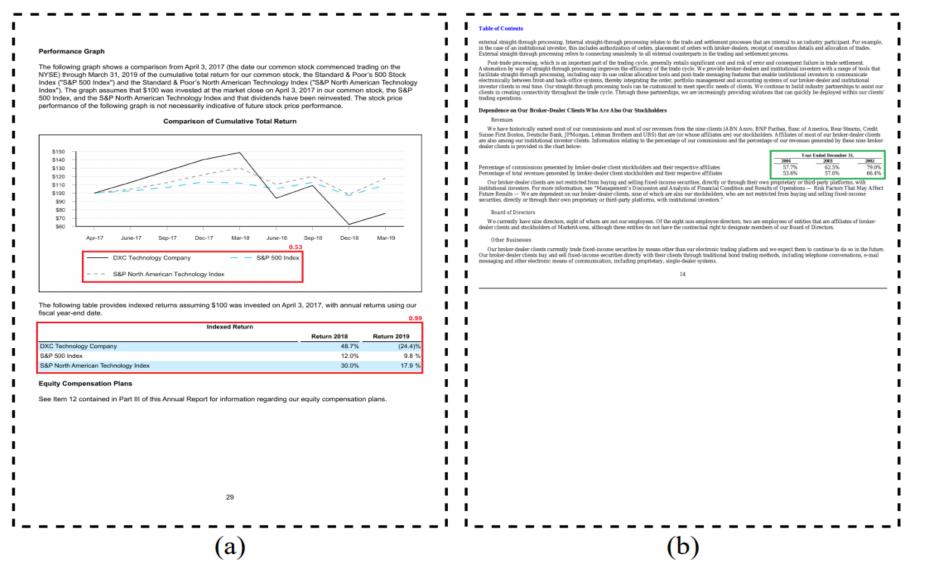
Figure 1. Table structure recognition results on ICDAR 2013, Performance of fine-tuned models is compared without postprocessing techniques as is done in the current state-of-the-art



Proposed architecture of PyramidTabNet

Error Analysis

Inability to make correct predictions due to presence of dual-patching bias in the model (a) and when relative size variation is high (b)





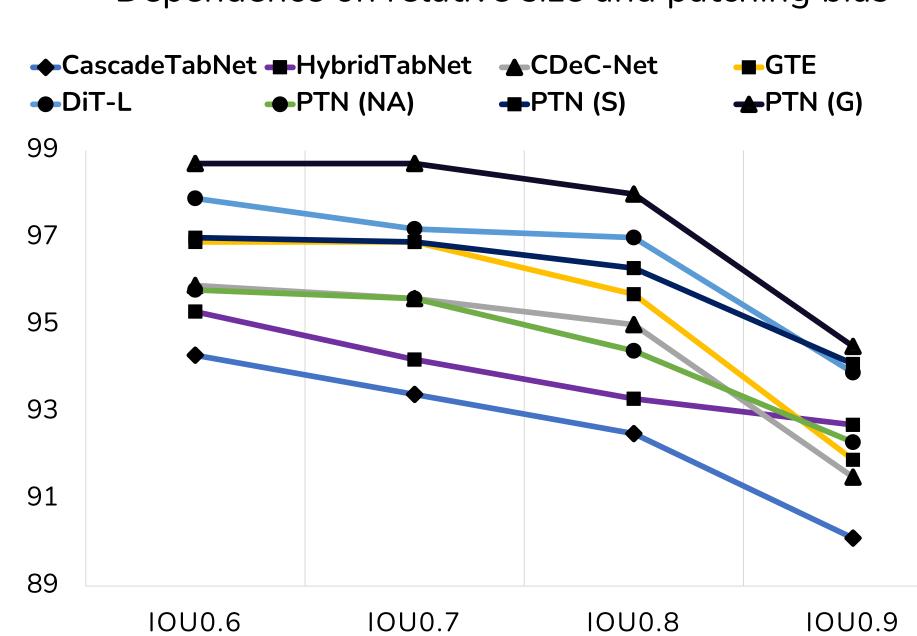


Figure 2. Table detection performance comparison on ICDAR 2019 cTDaR, F1-scores are computed at different IoU thresholds

	Absolute	value of percent	age differenc	e between actual	and projected	values
Projections of Education Statistics to 2017	†	0.7		1.1		1.
Projections of Education Statistics to 2018	0.4	0.7		0.8		1.
Projections of Education Statistics to 2019	#	0.1		0.2		
Projections of Education Statistics to 2020	0.2	С).4	†		
		Me	an absolute p	percentage error		
Example	0.2	0.2		0.7		1.
		(a)				
	Some	(a) e Year 1	No Y	ear 1		
				ear 1 I Start		
Sample Group	Hea	e Year 1	Head		Total	
Sample Group All Randomly Assigned (N=4,667	Hea Parti	e Year 1 nd Start	Head	Start	Total	
	Hea Parti	e Year 1 nd Start	Head	Start	Total	
All Randomly Assigned (N=4,667	Hea Parti	e Year 1 nd Start	Head Partic	Start	Total	

Dependence on header and post-processing

Future Work

4-Year-Old Cohort

Head Start Group

- Extending PTN for complex table layouts
- Applying PTN to document classification and layout analysis
- Improving structure recognition with Al upscaling on low-resolution cropped tables
- Adopting GANs alongside proposed augmentation strategy to further increase input data