CPA-GNN: Contextual-Based Pattern-Aware Graph Neural Network for Text Spotting

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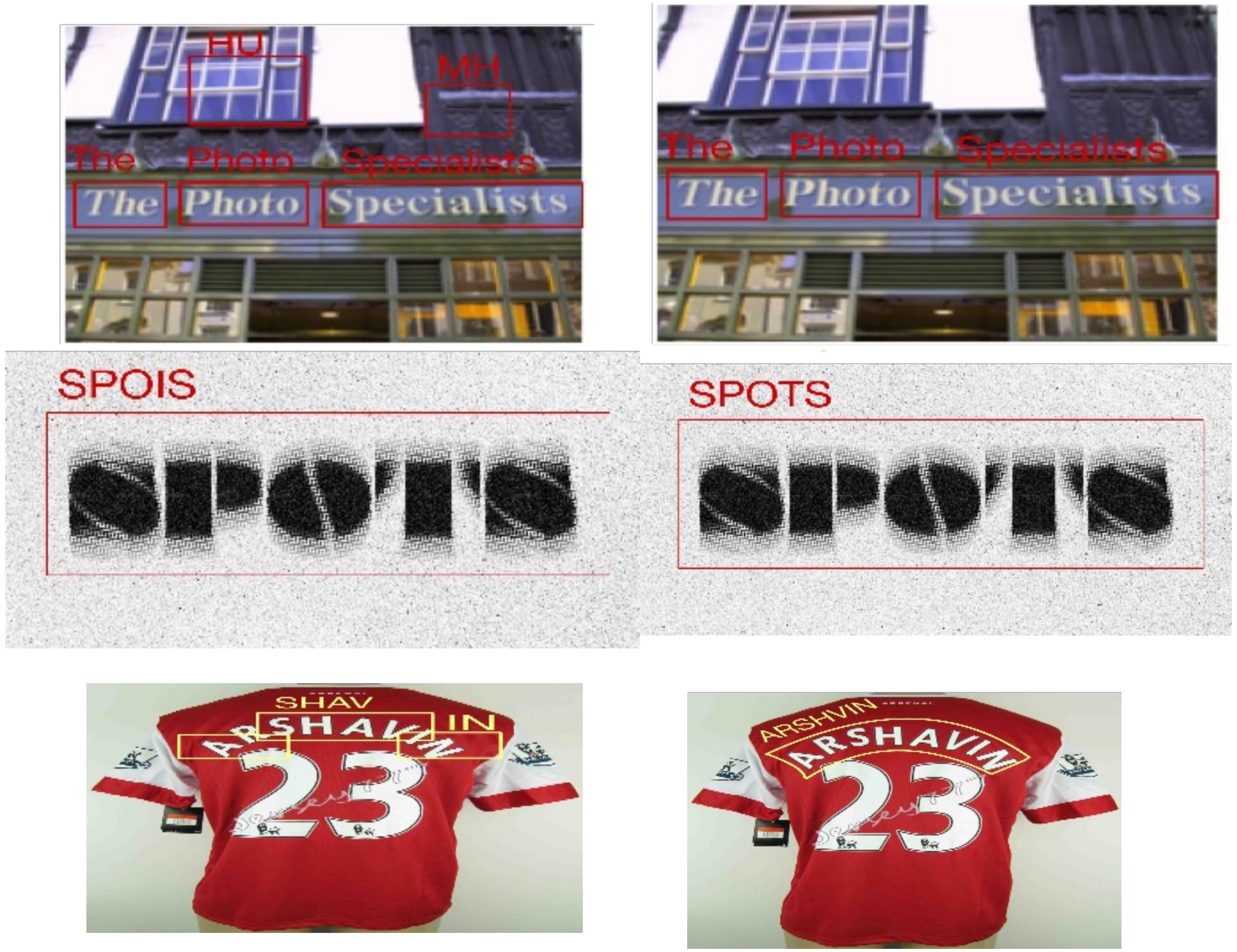
Introduction: The Text Spotting Challenge



Text and non-text in scene images are strongly correlated. Existing models (left) fail on adverse text; CPA-GNN (right) fixes bounding boxes and recognizes text correctly across scene, printed and handwritten domains.

Limitations of Existing Methods

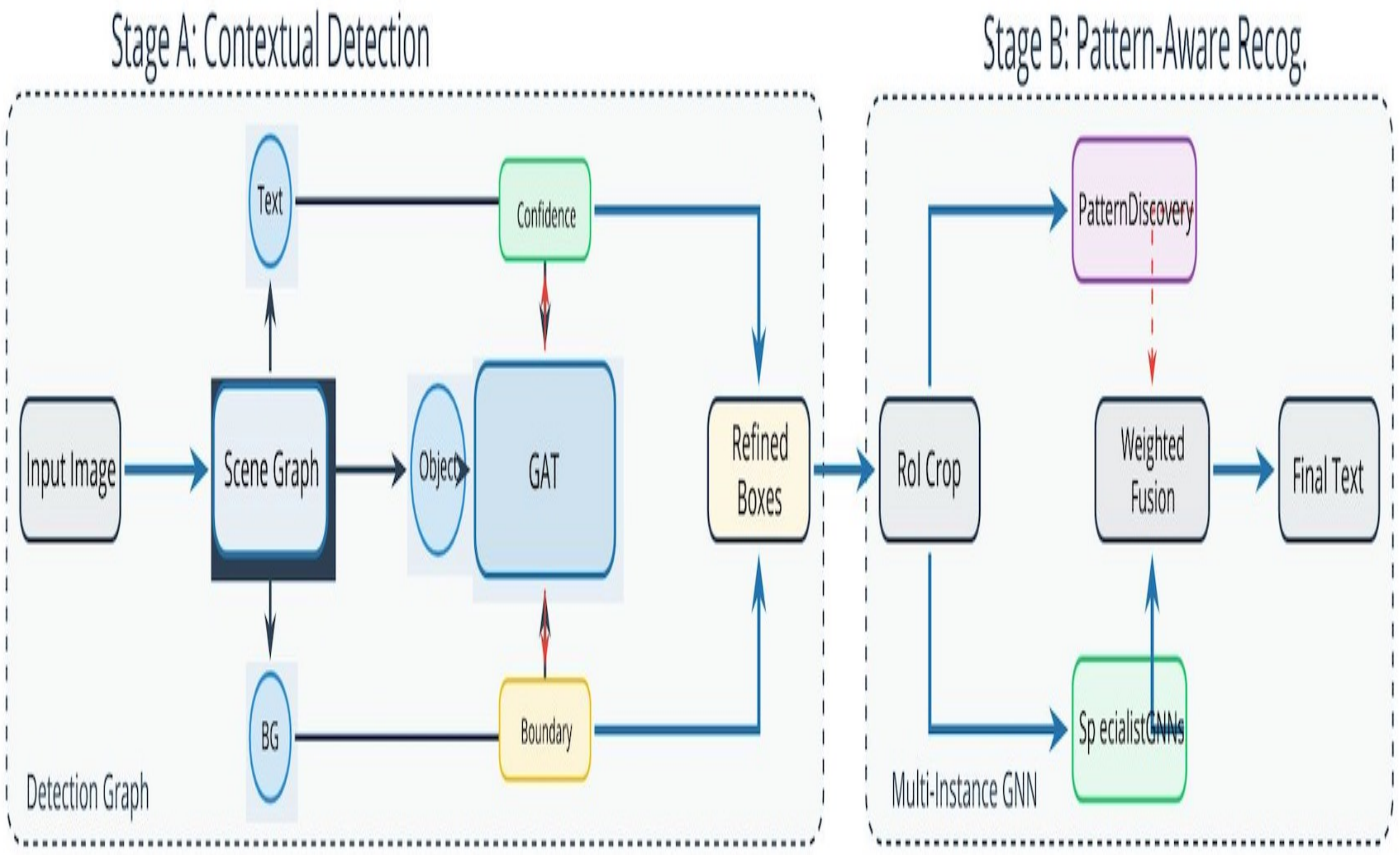
Why Existing Pipelines Fall Short

- **Lack of Context**: Detectors (EAST, CRAFT, DBNet) view text regions in isolation and ignore correlation with surrounding objects and background.
- **Style Variance**: Recognizers (CRNN, ASTER, TrOCR) use one shared encoder, failing on long-tail styles like handwriting or curved text.
- **False Positives**: Local pixel-level features alone cannot distinguish real text from text-like textures in cluttered scenes.
- **Hallucination in LMMs**: Vision-language spotters (Monkey) invent text and give imprecise, loose bounding boxes.
- **Domain Gap**: Jointly trained spotters let the recognition head overfit to the detector's output format, hurting cross-domain generalization.

Contributions

- Implementing a **graph neural network** for extracting **contextual information** between text and non-text in the images.
- Introducing multiple branches to a graph neural network for identifying the pattern of different text styles, called a **"team of specialists."**
- Achieves the **best accuracy** on challenging benchmarks — Total-Text, CDW and ICDAR 2015 — outperforming the state of the art.

Proposed Method Architecture



- Two novel modules: the Contextual Detection Refinement GNN and the Pattern-Aware Recognition GNN.
- Stage A refines text proposals using graph attention over text, object and background nodes.
- Stage B routes recognition features to specialist GNN branches based on the discovered text style.

Contextual Detection Refinement GNN

- Builds a heterogeneous scene graph linking Text, Object and Background nodes.
- L layers of Graph Attention Networks (GAT) propagate context between nodes.
- High attention validates weak text near supportive objects; low attention suppresses background noise.

Pattern-Aware Recognition GNN

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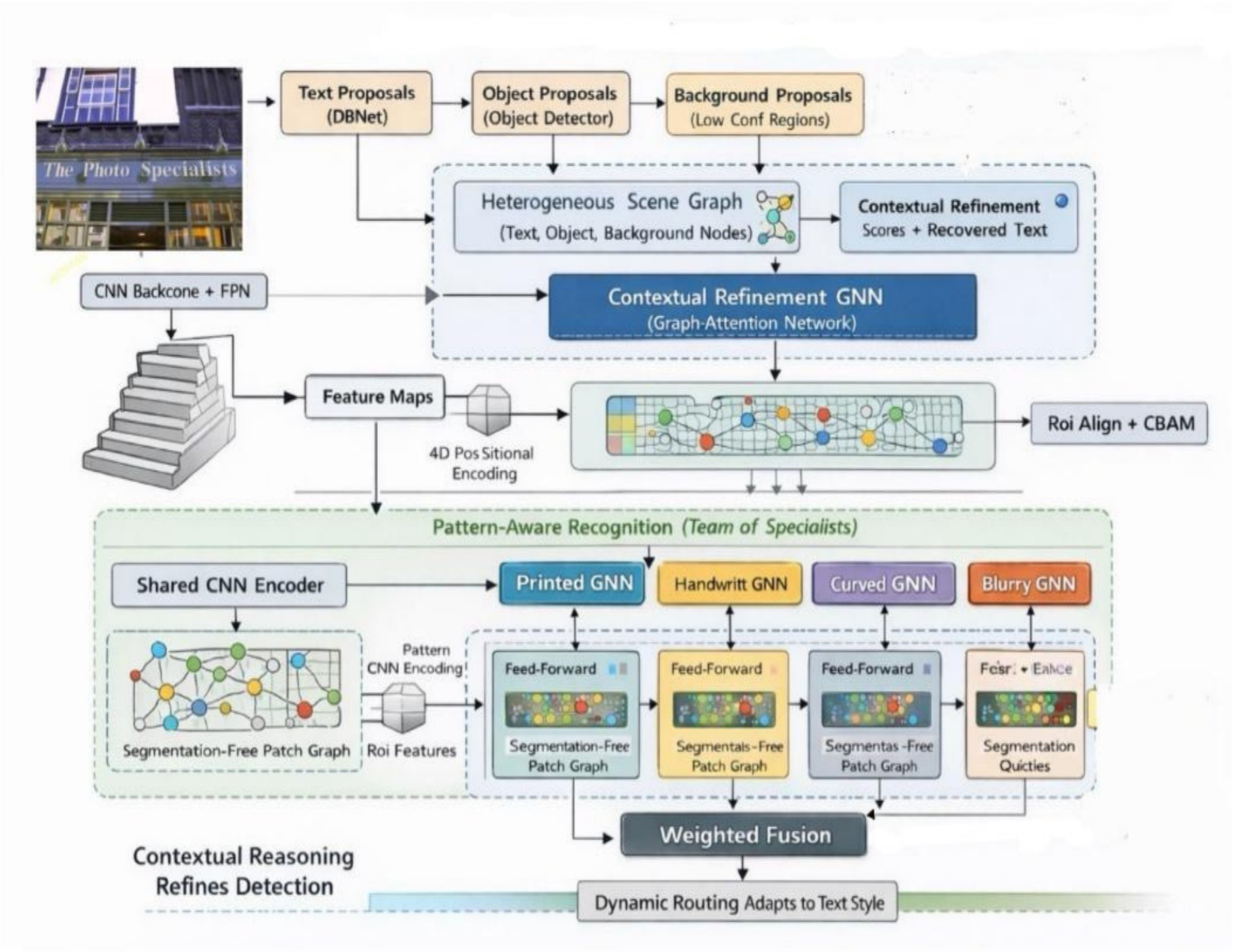
- A Pattern Discovery router assigns each text instance to $K = 4$ latent style specialists.
- A segmentation-free patch graph activates only on text structure, filtering out the background.
- Weighted Fusion combines all specialist outputs via a Log-Sum-Exp for the final prediction.

End-to-End Text Spotting Pipeline



- Proposal Generation: a shared ResNet-50 + FPN backbone extracts multi-scale features.
- Contextual Refinement plus RoIAlign and CBAM sharpen character strokes before recognition.
- Pattern-Aware Recognition then routes each proposal to its style-specific specialist branch.

Dataset Summary

Dataset	Scope
ICDAR 2015	Scene text
Total-Text	Curved text
CDW	Irregular/curved
FUNSD	Document forms

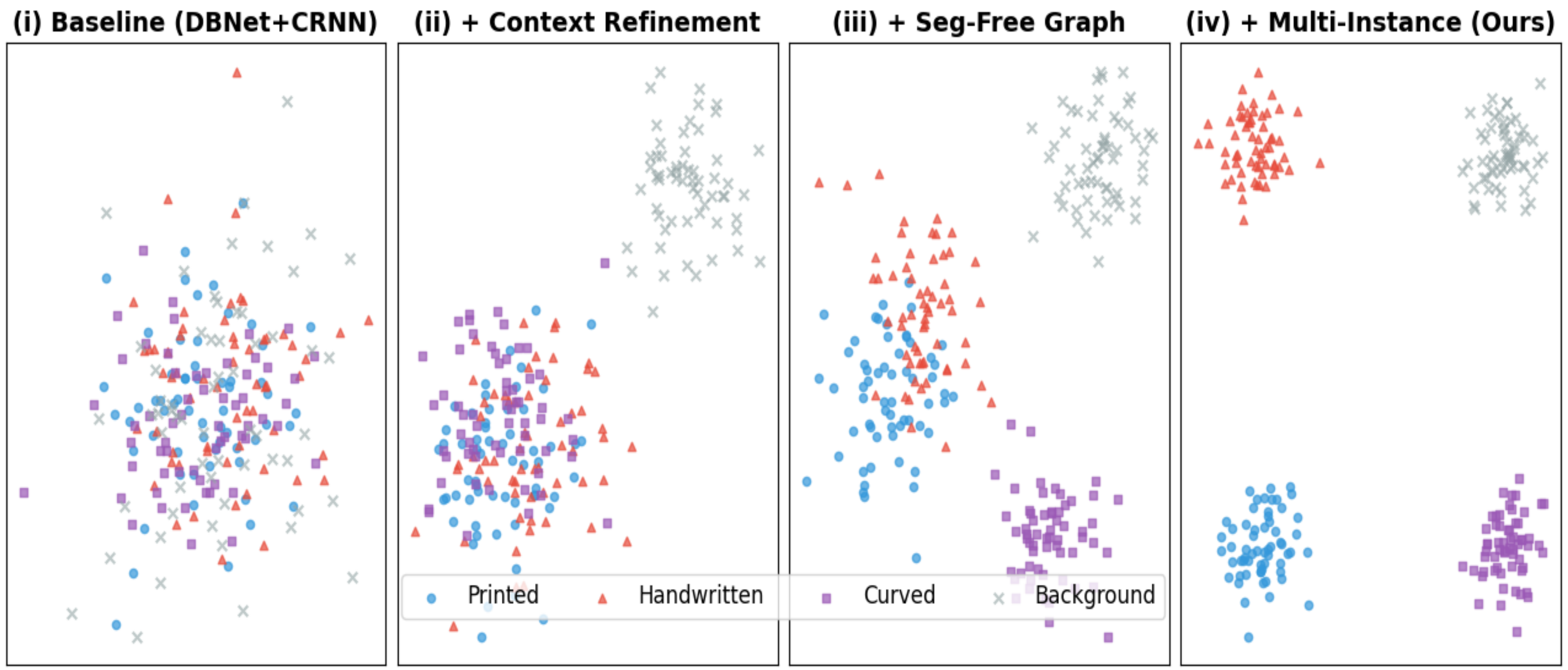
Text Detection Results (F-score)

Method	Detection Datasets (F-score)		
	IC15 (Standard)	Total-Text (Curved)	CDW (Irregular)
EAST (CVPR'17)	80.7	78.4	71.2
CRAFT (CVPR'19)	86.9	82.4	78.5
DBNet (AAAI'20)	87.3	84.7	81.0
DBNet++ (TPAMI'22)	89.1	86.0	83.4
DeepSolo (CVPR'23)	89.6	86.8	85.1
TextDiffuser-2 (ECCV'24)	90.0	87.1	**86.5**
Ours (CPA-GNN)	**90.3**	**87.8**	88.2

Text Spotting Results (H-Mean)

Method	Spotting Datasets (H-Mean)		
	IC15 (Standard)	Total-Text (Curved)	CDW (Irregular)
Mask TextSpotter v3 (ECCV'20)	83.3	71.2	70.5
ABCNet v2 (TPAMI'21)	84.2	78.1	76.9
TESTR (CVPR'22)	86.6	83.3	82.1
DeepSolo (CVPR'23)	87.2	82.4	-
GLASS (ECCV'22)	89.5	83.3	**-**
Ours (CPA-GNN)	**88.2**	**88.0**	88.0

Ablation Study

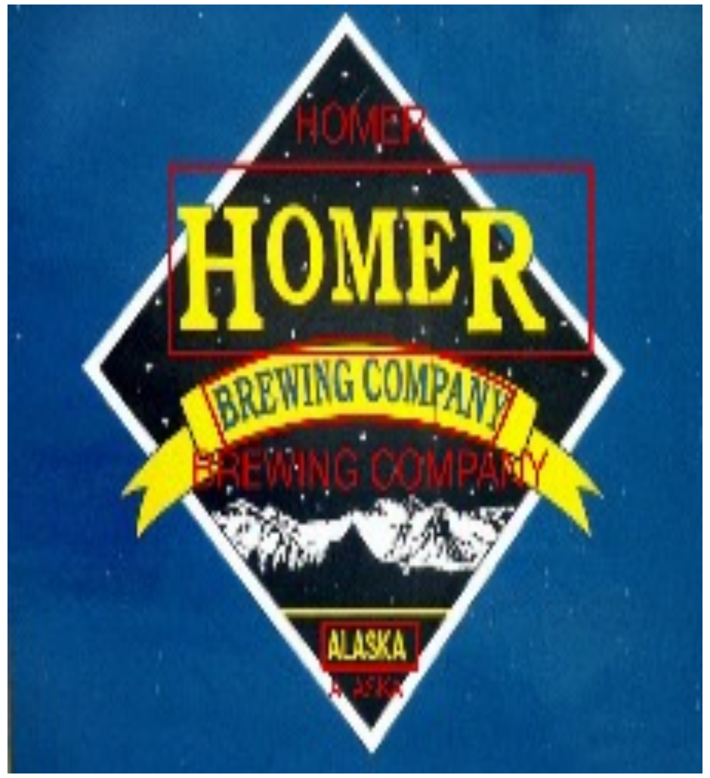


- Baseline (DBNet+CRNN): entangled features with heavy overlap between text styles and background noise.
- +Context Refinement and +Seg-Free Graph progressively separate the curved-text and background clusters.
- +Multi-Instance (full model) yields compact, well-separated style clusters and the best word accuracy across all three datasets.

Cross-Domain Generalisation (Sim-to-Real)

Method	Trained on SynthText, tested on:		
	IC15 (Standard)	Total-Text (Curved)	CDW (Irregular)
CRNN	52.4	43.5	39.1
ASTER	56.8	49.8	44.2
PARSeq	68.4	62.1	59.5
Ours (CPA-GNN)	78.5	74.2	72.0

Qualitative Results



- CPA-GNN accurately detects and recognizes text across Total-Text, CDW and ICDAR 2015.
- Handles printed, stylized and handwritten text within a single unified framework.
- Contextual reasoning recovers text instances that baseline detectors miss entirely.

Limitations

- Dense occlusion severs edges in the patch graph, fragmenting the recognition output.
- Out-of-distribution styles (e.g. graffiti) yield a high-entropy routing vector that confuses specialist fusion.
- Future work: introduce a language model to improve robustness to these failure cases.

Conclusion and Future Works

- To address the computational cost of the multi-branch design, future work will distil CPA-GNN into a smaller, single-branch "Student" network via a Teacher-Student framework.
- Proposed CPA-GNN: a unified graph-based framework combining a Contextual Detection Refinement GNN with a Pattern-Aware "Team of Specialists" Recognition GNN for text spotting.
- Experiments on ICDAR 2015, Total-Text and CDW yield state-of-the-art word accuracy; we plan to integrate a language model to further improve robustness to occlusion and out-of-distribution styles.

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Thank You

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