Multilingual Row Detection in Tables: Beyond TATR with YOLO, Faster R-CNN, and TEDS-S

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Abstract
Multilingual table extraction presents significant challenges due to structural variability, noisy datasets, and script-specific complexities. Traditional heuristic-based approaches, such as the Table Analysis and Recognition Tool (TATR), struggle to generalize across diverse scripts and irregular layouts. This paper investigates deep learning–based alternatives for row detection using the multilingual MUSTARD dataset. YOLO and Faster R-CNN models are evaluated in terms of accuracy, inference speed, and robustness. To enable holistic assessment, TEDS-S is employed to jointly evaluate structural alignment and content fidelity. Experimental results indicate that YOLO provides superior real-time performance, while Faster R-CNN achieves higher precision. Hybrid YOLO–FRCNN cascades further enhance performance, demonstrating the effectiveness of combining object detection with structured evaluation metrics.

Keywords: Table Extraction, Multilingual Tables, Row Detection, YOLO, Faster R-CNN, TEDS-S, MUSTARD Dataset

1. Introduction

Accurate table extraction is a critical component of document image analysis, enabling structured data retrieval from financial reports, government documents, and academic publications. Multilingual tables introduce additional complexity due to script variations such as Devanagari, Arabic, and Latin, along with irregular layouts and noisy scans. Heuristic-based systems such as TATR perform adequately on simple Latin-script tables but fail to generalize across multilingual contexts. Recent advances in object detection offer promising alternatives for robust row detection.

2. Problem Statement

Existing heuristic-based table row detection methods fail to generalize across multilingual and noisy table structures, leading to inaccurate segmentation and reduced extraction performance.

Objectives

The objectives of this study are to quantify the limitations of TATR in multilingual contexts, evaluate YOLO and Faster R-CNN models for row detection across diverse scripts, and employ TEDS-S as a unified evaluation metric for optimizing structural and content accuracy.

Methodologies for Row Detection

TATR (Table Transformer)

TATR relies on heuristic rules such as whitespace distribution, line separators, and geometric alignment to segment table rows. While computationally efficient and training-free, it lacks robustness when handling merged cells, skewed layouts, and non-Latin scripts.

YOLO (You Only Look Once)

YOLO formulates row detection as a single-stage object detection task. Using a CSPDarknet backbone and PANet neck, it predicts bounding boxes for table rows in a single pass. YOLO achieves high inference speed and competitive accuracy but is sensitive to overlapping rows in dense layouts.

Faster R-CNN (FRCNN)

Faster R-CNN employs a two-stage detection pipeline consisting of a Region Proposal Network and a ResNet-101 backbone with Feature Pyramid Network. It provides high precision and robustness across multilingual tables at the cost of higher computational requirements.

Evaluation Framework: TEDS-S

TEDS-S (Tree Edit Distance Similarity—Structure and Content) evaluates both structural alignment and textual accuracy. It combines tree edit distance for table structure comparison with content similarity, enabling holistic performance evaluation and feedback-driven refinement.

Table 1: TEDS-S Scores and Inference Time on MUSTARD Dataset

Model	TEDS-S Score	Inference Time (ms)
TATR	0.68	36
YOLOv8	0.85	22
Faster R-CNN	0.91	83

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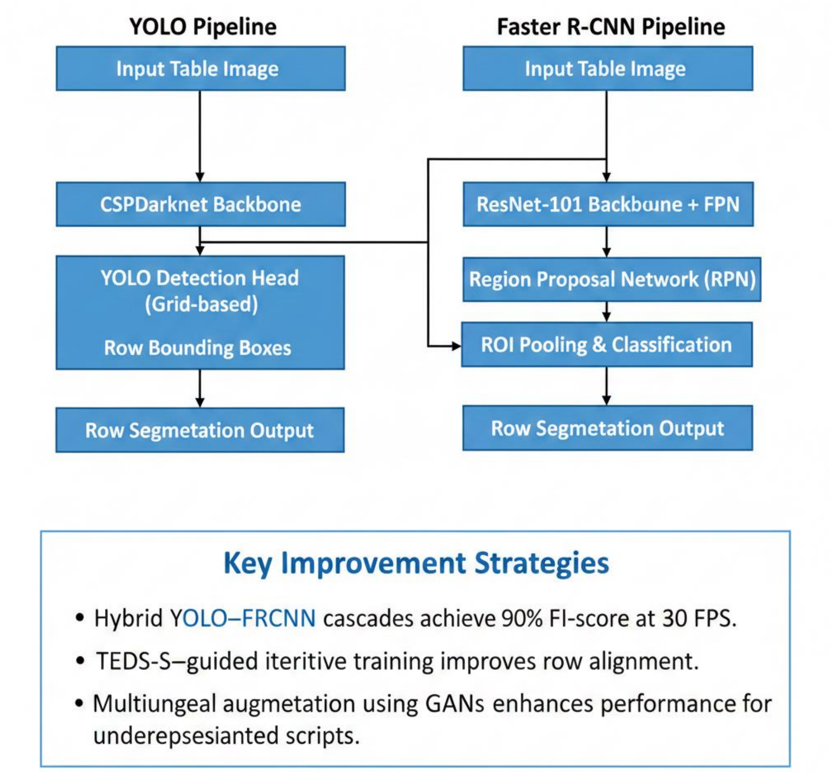
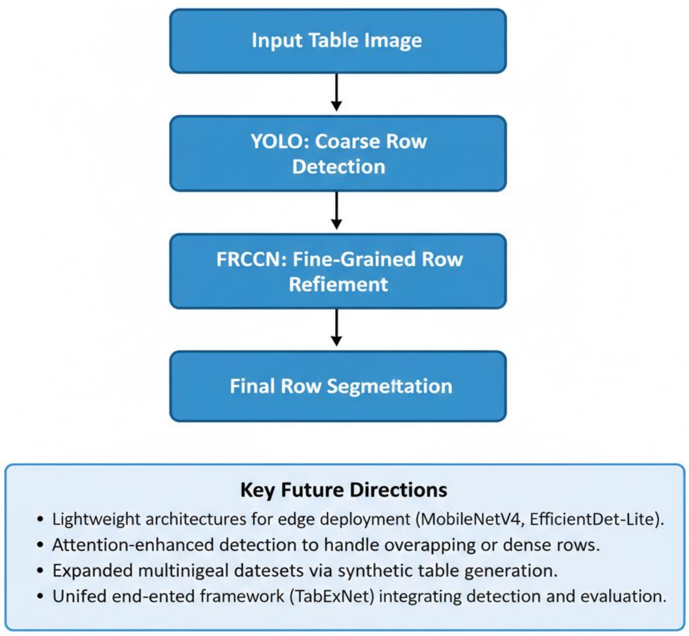
Figures

Figure 1: YOLO-Based Row Detection Pipeline



Input table images are processed through a CSPDarknet backbone followed by a detection head to generate bounding boxes representing table rows.

Figure 2: Hybrid YOLO–FRCNN Cascade Architecture



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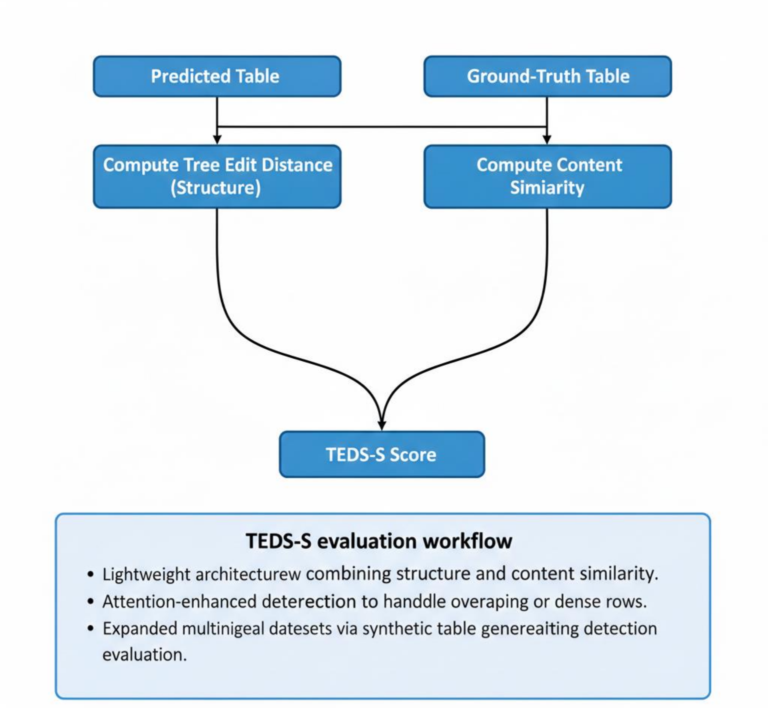
YOLO performs coarse row detection followed by Faster R-CNN for fine-grained refinement, balancing real-time performance and accuracy.

Figure 3: TEDS-S Evaluation Workflow



Structural similarity is computed using tree edit distance and combined with content similarity to generate the final TEDS-S score.

3. Discussion

Comparative analysis shows that TATR is lightweight but unsuitable for multilingual and noisy tables. YOLO provides real-time performance but struggles with overlapping rows. Faster R-CNN achieves superior accuracy and robustness, though with increased computational cost.

4. Future Directions

Future work includes exploring lightweight architectures for edge deployment, incorporating attention mechanisms for dense row handling, expanding multilingual datasets through synthetic generation, and developing unified end-to-end frameworks integrating detection and evaluation.

5. Conclusion

YOLO and Faster R-CNN significantly outperform heuristic-based approaches for multilingual table extraction. Hybrid detection strategies combined with TEDS-S evaluation enable scalable, accurate, and real-time table understanding.

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