ViBERTgrid BiLSTM-CRF: Multimodal Key Information Extraction from Unstructured Financial Documents

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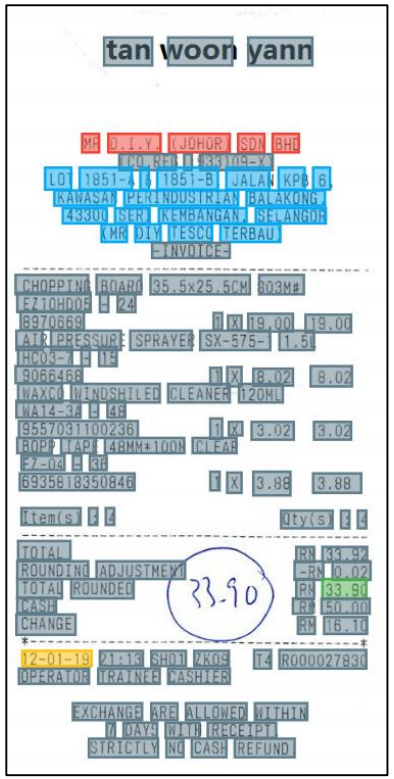
YapıKredi Teknoloji

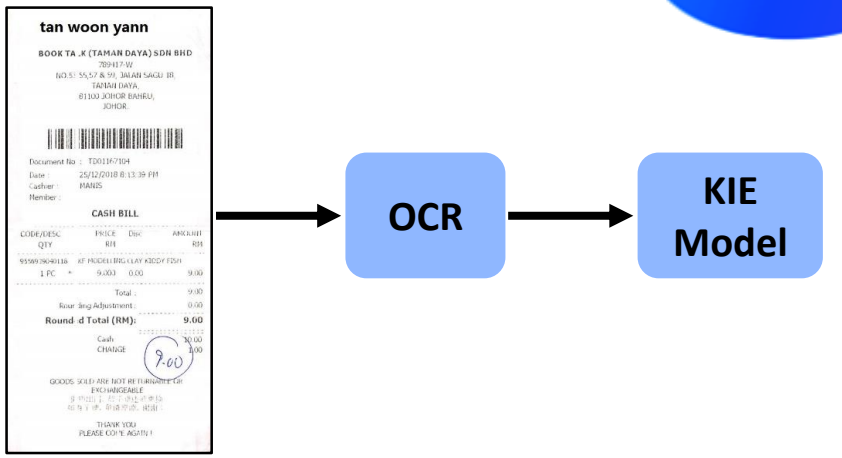
Problem Statement

- **Key Information Extraction (KIE)** from document images is the automated process of retrieving relevant data presented visually in the document.
- **Optical Character Recognition (OCR)** tools are used to extract the text in the document.

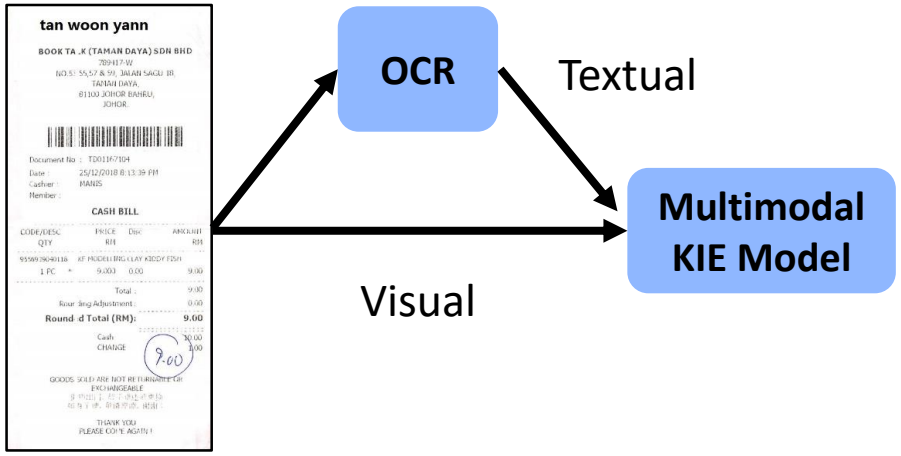


Problem Statement

- Using the OCR text, many studies model the KIE task as a **sequence tagging** problem and **solve using NER** (Yu et. al, 2021).



- **Multimodal** approaches combine the OCR output with visual information of the document image and position information of the tokens.

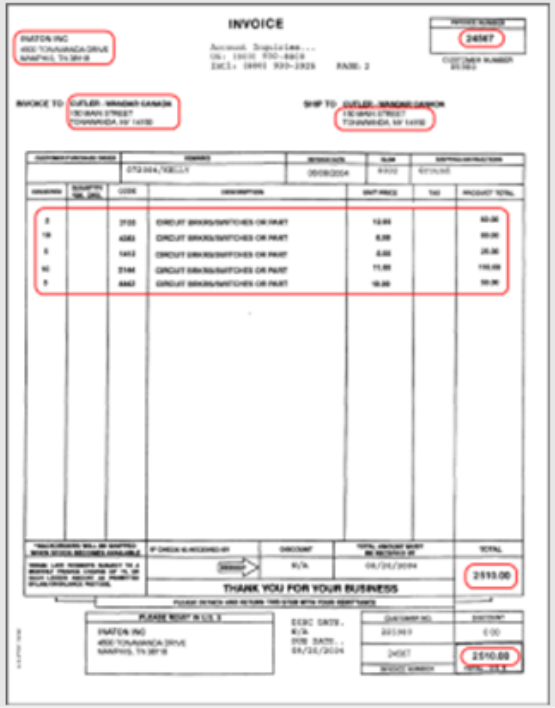


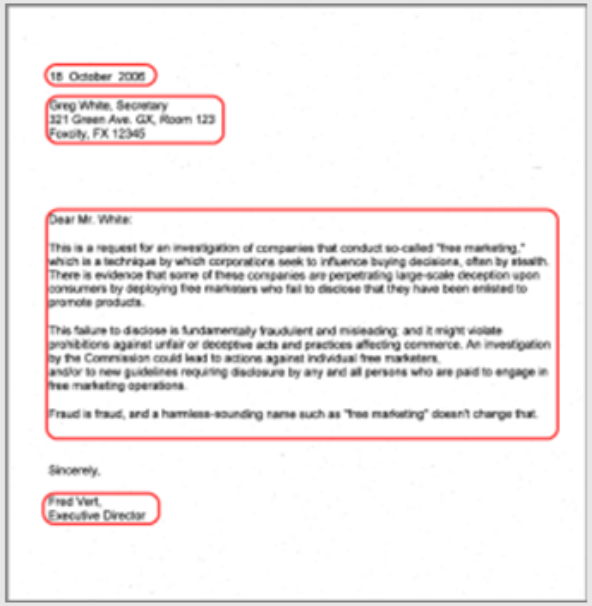
Yu, W., Lu, N., Qi, X., Gong, P., Xiao, R.: Pick: processing key information extraction from documents using improved graph learning-convolutional networks. In: 2020 25th International Conference on Pattern Recognition (ICPR). pp. 4363– 4370. IEEE (2021)

Document Types

YapıKredi Teknoloji

Fixed-form / structured documents	Semi-structured documents	Unstructured documents
• Surveys • Questionnaires • Tests • Claim forms	• Invoices • Purchase orders • Bills of lading • EOBs	• Contracts • Letters • Articles • Notes





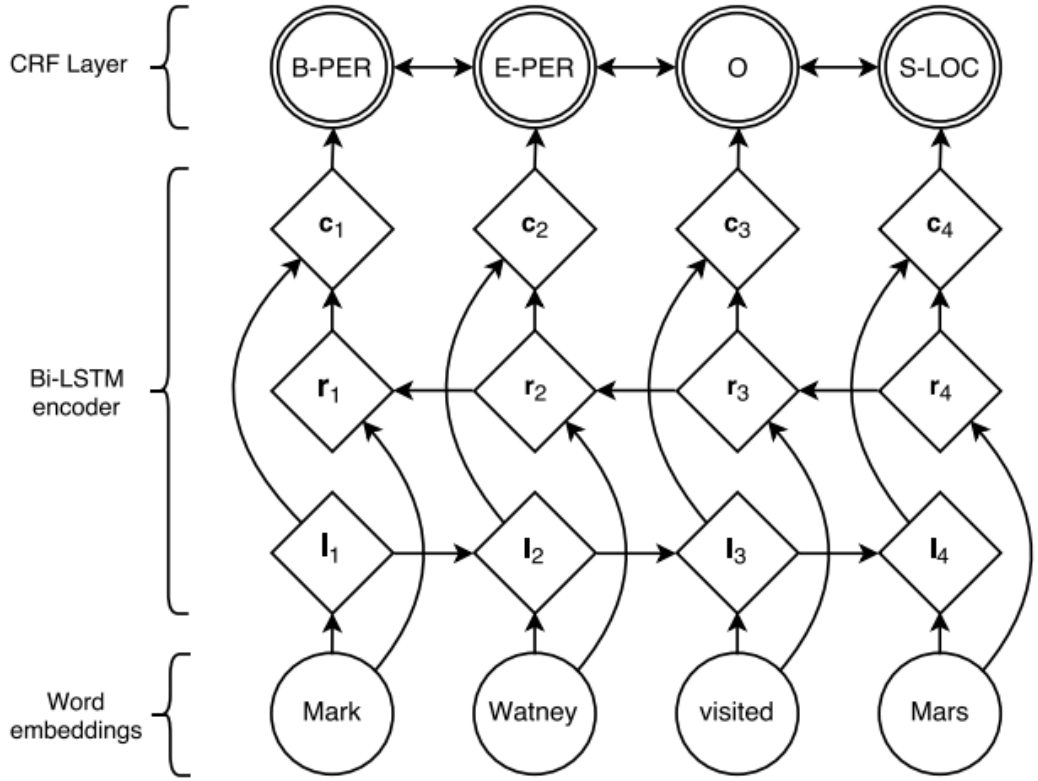
Previous Methods and Limitations

BiLSTM-CRF (Huang et. al, 2015)

- Pros:
  - Effective in sequence tagging and NER tasks.
  - Uses both past and future tokens.
  - Capture sentence level meaning.

- Cons:
  - Uses only textual information.
  - Unable to utilize layout or visual information directly.

Works best on unstructured documents.



Huang, Z., Xu, W., Yu, K.: Bidirectional lstm-crf models for sequence tagging. arXiv preprint arXiv:1508.01991 (2015)

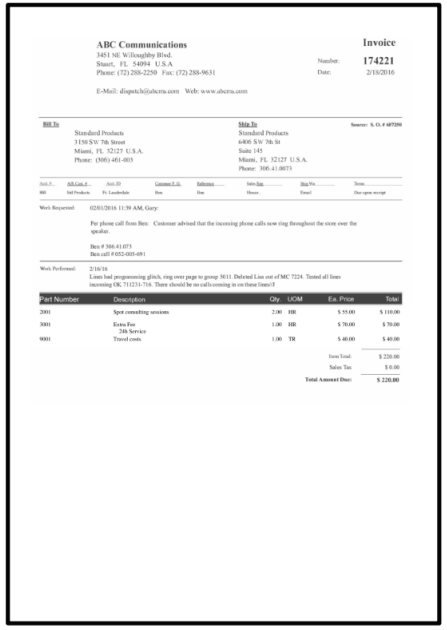
Previous Methods and Limitations

Chargrid (Katti et. al, 2018)

- Pros:
  - Converts a page into 2D grid of chars.
  - Encodes spatial features.
  - Better in structured documents.

- Cons:
  - Using only char level information is not sufficient for understanding the semantics.
  - Thus, not as effective in unstructured documents as in structured ones.

Raw data



Chargrid

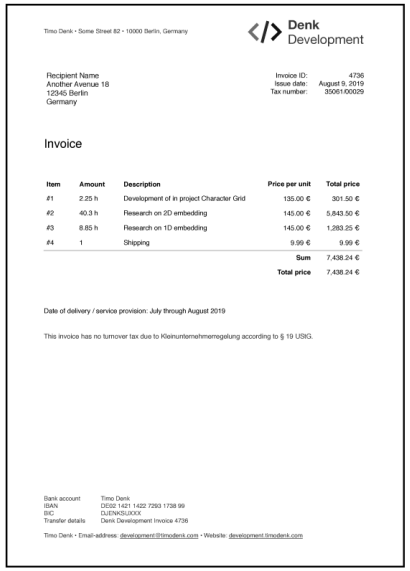
Katti, A.R., Reisswig, C., Guder, C., Brarda, S., Bickel, S., H¨ohne, J., Faddoul, J.B.: Chargrid: Towards understanding 2d documents. arXiv preprint arXiv:1809.08799 (2018)

Previous Methods and Limitations

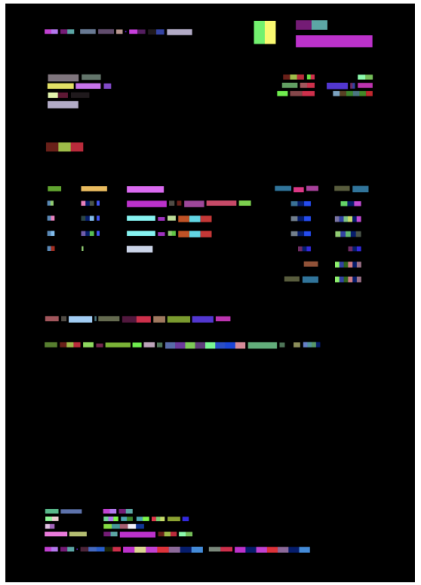
BERTgrid (Denk et. al, 2019)

- Pros:
  - Converts a page into 2D grid of contextualized word embeddings obtained from BERT.
  - Possible to understand the semantics of document.

- Cons:
  - BERT language model is frozen during training.
  - Image of the document page is not directly utilized.



Raw image



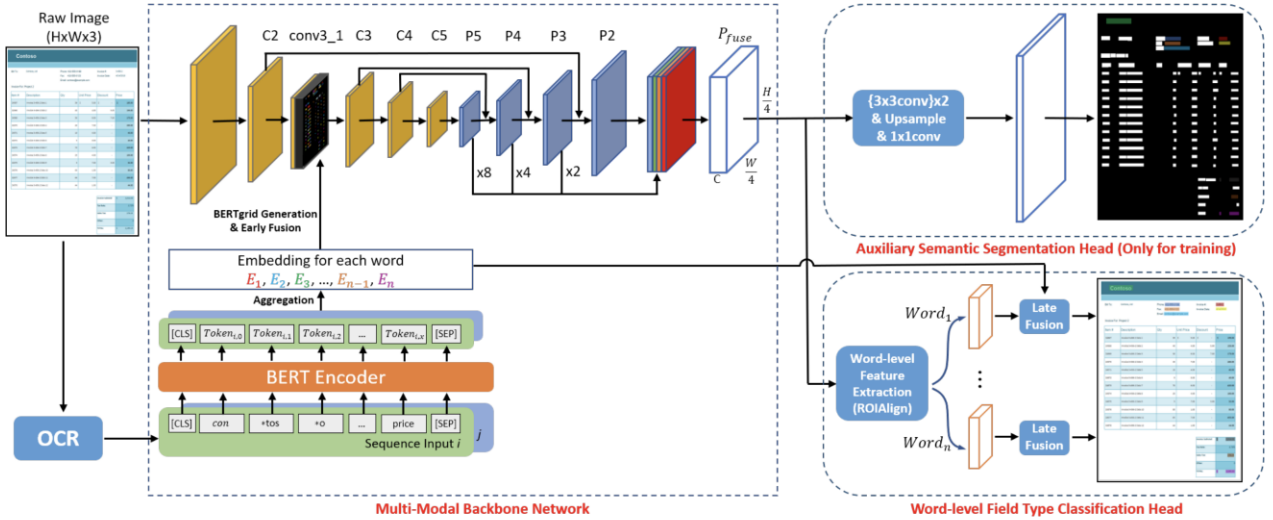
BERTgrid representation

Denk, T.I., Reisswig, C.: Bertgrid: Contextualized embedding for 2d document representation and understanding. arXiv preprint arXiv:1909.04948 (2019)

Previous Methods and Limitations

ViBERTgrid (Lin et. al, 2021)

- Pros:
  - Incorporates BERTgrid with a CNN to process the raw image directly.
  - Jointly trains BERT and CNN.



- Cons from our observations:
  - Could not outperform a pure textual model (BiLSTM-CRF on BERT emb.) on unstructured money transfer order documents.

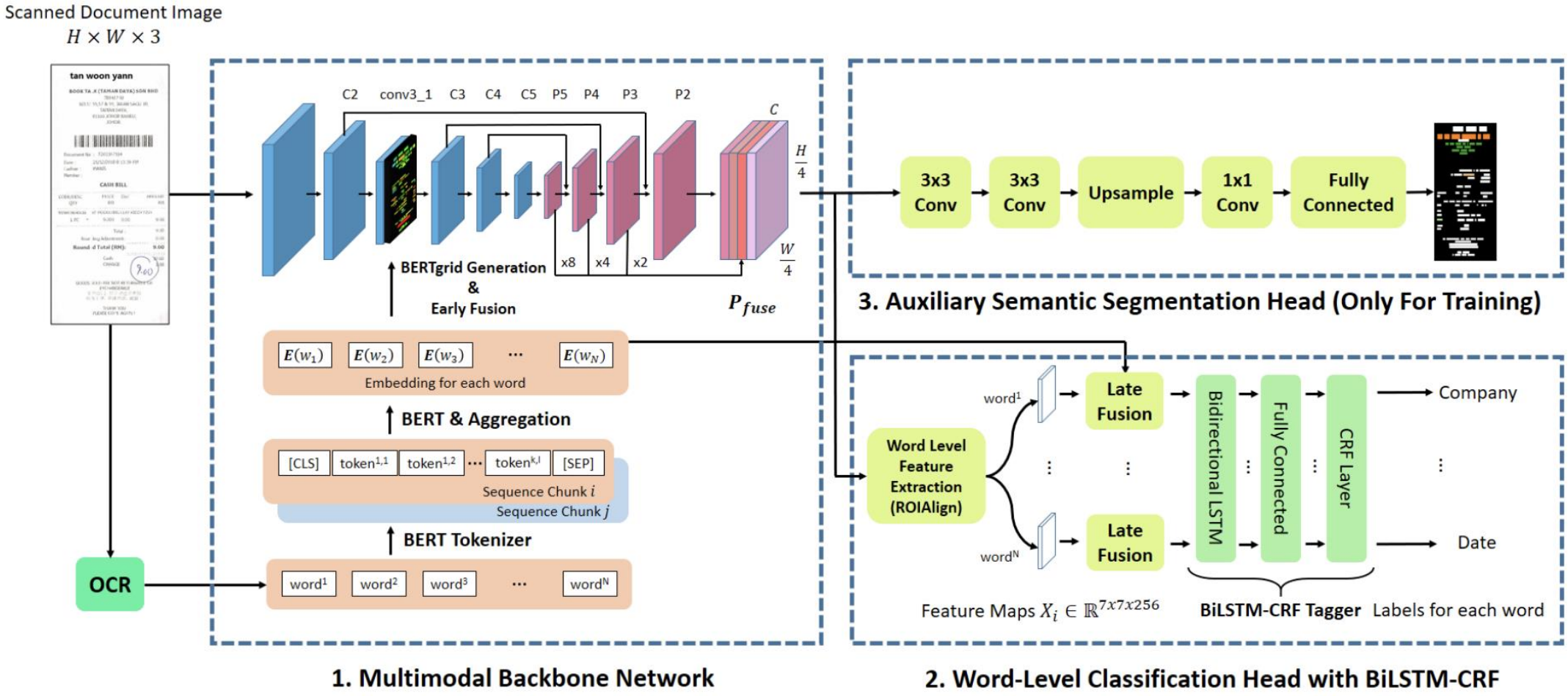
Works best on structured documents.

Lin, W., Gao, Q., Sun, L., Zhong, Z., Hu, K., Ren, Q., Huo, Q.: Vibertgrid: a jointly trained multi-modal 2d document representation for key information extraction from documents. In: International Conference on Document Analysis and Recognition. pp. 548–563. Springer (2021)

Idea

What if we combine the best performing models?

Proposed Approach: ViBERTgrid BiLSTM-CRF



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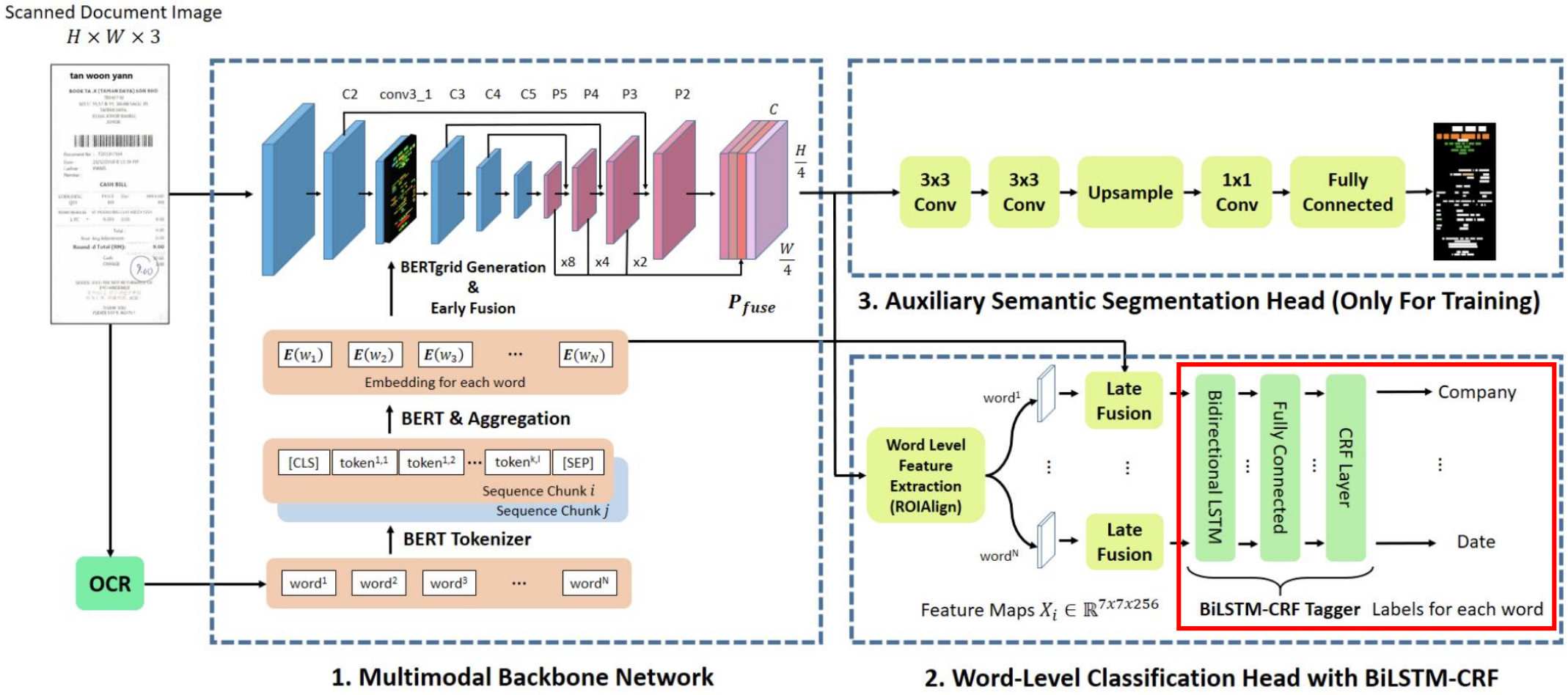

Datasets

SROIE

- ICDAR SROIE dataset[1]: 973 receipts (626 training, 347 testing samples).
- Semi-structured documents.
- Four entity types: company, date, address, total.
- Dataset presents key information fields and OCR output separately.
- Previous studies[2,3] used text-based matching but results in poor matching.
- We manually annotated the entire dataset on the word-level.
- We publicly release the word-level annotations of SROIE dataset for use in multimodal transformers. (https://github.com/YKT-NLP/ICDAR-2019-SROIE-Token-Level-Annotations)
- Evaluation on test set is still problematic due to discrepancies between OCR output and key information fields, e.g., mismatched punctuation, extra or missing white spaces, typos etc.
- Some of these errors have been documented and manually fixed.

[1]Huang, Z., Chen, K., He, J., Bai, X., Karatzas, D., Lu, S., Jawahar, C.V.: Icdar2019 competition on scanned receipt ocr and information extraction. In: 2019 International Conference on Document Analysis and Recognition (ICDAR). pp. 1516–1520 (2019). https://doi.org/10.1109/ICDAR.2019.00244

[2]Lin, Z.: Vibertgrid pytorch (2021), https://github.com/ZeningLin/ ViBERTgrid-PyTorch

[3]Delplace, A.: Chargrid model : Extraction of meaningful instances from document images (2020), https://github.com/antoinedelplace/Chargrid

Datasets

Transactional Documents

- In-house dataset consists of unstructured Turkish money transfer order documents, introduced by Oral et. al (2022).
- Has two sets: **U**nstructured **T**ransactional **D**ocuments (**UTD**) and **U**nstructured **M**ulti-**T**ransaction **D**ocuments (**UMTD**).
- UTD has 3500 documents (2500 for training, 400 validation, 600 testing).
- UMTD has 1154 documents (954 for training, 200 testing).
- Within the UMTD test set, 54 out of 200 documents have tabular-like layouts (**TLL**), the rest has non-tabular-like (**noTLL**) documents.
- We used the same splits as in Oral et. al (2022) for consistency.

Oral, B., Eryiğit, G.: Fusion of visual representations for multimodal information extraction from unstructured transactional documents. International Journal on Document Analysis and Recognition (IJDAR) pp. 1–19 (2022)

Experiments & Results

SROIE

Table 1. Performance comparison on SROIE.

Model	Macro F1 Score (%)
ViBERTgrid	$93.56_{\pm 0.005}$
ViBERTgrid BiLSTM-CRF	$\mathbf{93.85}_{\pm \mathbf{0.003}}$

Experiments & Results

Transactional Documents

Train Set	Test Set					
	UTD_{test}		UMTD_{test}			
	All		All		noTLL (73%)		TLL (27%)	
	w/o	w/	w/o	w/	w/o	w/	w/o	w/
UTD_{train}	$90.95_{\pm 0.57}$	$\mathbf{92.19}_{\pm 0.18}$	$91.04_{\pm 0.33}$	$\mathbf{92.42}_{\pm 0.14}$	$91.73_{\pm 0.40}$	$\mathbf{93.03}_{\pm 0.19}$	$89.61_{\pm 0.38}$	$\mathbf{91.12}_{\pm 0.30}$
	$87.76_{\pm 0.53}$	$\mathbf{89.57}_{\pm 0.39}$	$86.71_{\pm 0.82}$	$\mathbf{89.29}_{\pm 1.03}$	$85.83_{\pm 1.15}$	$\mathbf{88.26}_{\pm 0.75}$	$85.53_{\pm 0.72}$	$\mathbf{87.97}_{\pm 0.70}$
$\text{UTD}_{train} + \text{UMTD}_{train}$	$91.05_{\pm 0.30}$	$\mathbf{92.04}_{\pm 0.50}$	$93.28_{\pm 0.34}$	$\mathbf{93.98}_{\pm 0.29}$	$93.41_{\pm 0.31}$	$\mathbf{94.13}_{\pm 0.33}$	$93.11_{\pm 0.52}$	$\mathbf{93.70}_{\pm 0.70}$
	$87.61_{\pm 0.33}$	$\mathbf{89.09}_{\pm 0.53}$	$90.15_{\pm 0.71}$	$\mathbf{91.78}_{\pm 0.26}$	$88.54_{\pm 0.66}$	$\mathbf{89.69}_{\pm 0.74}$	$90.66_{\pm 0.65}$	$\mathbf{91.77}_{\pm 0.57}$

vanilla ViBERTgrid

micro F1

macro F1

ViBERTgrid with BiLSTM-CRF (ours)

Experiments & Results

Transactional Documents

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Oral et. al (2022) obtained a micro and macro F1 score of **91.48** and **88.45** on UTD dataset using a textual only BiLSTM-CRF model pretrained on BERT embeddings.

Experiments & Results

Transactional Documents

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Experiments & Results

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Conclusion

- We focused on the impact of using a multimodal transformer (i.e., ViBERTgrid previously explored on semistructured documents) on the NER task from **unstructured financial documents**.
- The initial results showed that the original ViBERTgrid has a **negative impact on unstructured** documents compared to a pure textual baseline.
- We presented an approach to enhance the performance of ViBERTgrid on unstructured documents by **extending it with a BiLSTM-CRF layer.**
- As a result, our proposed **ViBERTgrid BiLSTM-CRF** model demonstrated a significant improvement in performance (**up to 2 percentage points**) on unstructured documents, while maintaining its performance on semi-structured documents, in the **domain of financial and banking documents**.
- As an additional contribution, we publicly released token-level annotations for the SROIE dataset to pave the way for its use in multimodal sequence labelling models.

Q & A ?

YapıKredi Teknoloji