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Automated Invoice Understanding and Summarization

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Abstract - *As the size of financial documents increases in the digital world, it is becoming necessary to adopt efficient methods of automatic processing of such documents. The existing systems of invoices processing involve either manual entry of data or rule-based OCR that may become inefficient and erroneous due to varied layouts of the documents. In this paper, we present a transformer-based technique for automatic invoice understanding and summarization involving vision-language models. Our system employs contextual information as well as layout awareness to extract structured information like the invoice number, vendor name, invoice date, and total amount. We employ state-of-the-art vision-language models including LayoutLMv3 to capture visual as well as semantic relations of the documents. In addition, we employ a transformer-based summarization model for generating useful summaries from invoices. Our experiments on benchmark datasets show that our system performs significantly better than the existing OCR-based models for invoice processing tasks.*

Key Words: Invoice Processing, Transformer Models, Document Understanding, Vision-Language Models, LayoutLM, OCR, Text Summarization, Deep Learning.

1. INTRODUCTION

Automation of document processing has become a mandatory feature of contemporary companies due to an exponential increase in digital information. As an important document type, invoices must be processed automatically to extract valuable information for purposes of accounting, auditing, enterprise resource planning, and so forth. Traditionally, information from invoices is extracted manually or using rule-based systems; these processes are time-consuming, labor-intensive, and prone to mistakes [1].

The problem of information extraction from documents can be solved using Optical Character Recognition (OCR). However, conventional OCR methods cannot recognize context and relationships between pieces of information. Such limitations make document understanding problematic, which negatively impacts information extraction and summarization [2], [3].

Development of transformer architectures made contextual natural language processing feasible through self-attentive neural networks [4]. To implement this technology into document processing, researchers developed a variety of models (LayoutLM) that combine textual and spatial information of documents. Recent developments in the area include LayoutLMv3 and Donut architectures that use image information in addition to text and don't rely on OCR at all [5], [6], [7].

This paper proposes a transformer-based framework for automated invoice understanding and summarization. The proposed system combines structured data extraction with abstractive summarization, providing a unified solution for document intelligence.

1.2 Objectives

- To develop a transformer-based system for invoice data extraction
- To enhance contextual understanding of unstructured documents
- To implement summarization using transformer models
- To evaluate system performance using standard metrics

2. LITERATURE REVIEW

Document understanding has witnessed considerable improvements due to the advent of deep learning. The earlier methods were based on template matching and rule-based systems lacking generalization capabilities [8].

However, with the advent of transformer architectures in NLP, models such as BERT showed excellent performance in contextual understanding tasks [9]. Following that, layout information was introduced with LayoutLM models leading to superior results in document-specific tasks [5].

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Further developments include the models named LayoutLMv2 and LayoutLMv3 where visual features were added along with text embeddings [10][11]. The other contribution made is Donut where the need for OCR becomes redundant, and the transformer model processes documents as images directly [12].

Also, the transformer-based OCR system called TrOCR showed excellent results for improving the accuracy of the text recognition task [13]. For document summarization, models like T5 and BART performed exceptionally well [14][15].

However, there still exists a lack of solutions to tackle multiple invoice formats and combining summarization with extraction. This is the problem this paper tries to solve through its approach.

3. METHODOLOGY

The design involves a multi-step process that comprises the following steps – preprocessing, feature extraction, modelling using transformers, and finally summarization.

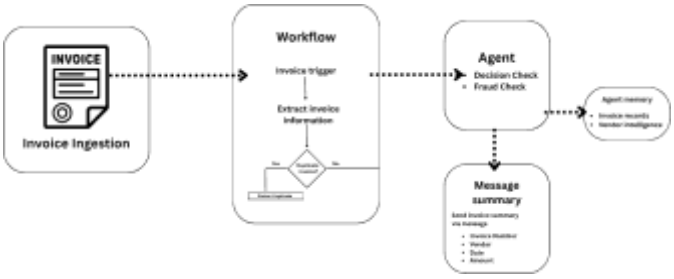

Fig-1: Invoice Understanding and Summarization - workflow

3.1 Data Collection and Preprocessing

A benchmark invoice dataset is utilized, consisting of thousands of invoice images with annotated fields. Preprocessing includes image normalization, resizing, and noise reduction to improve model performance [16].

3.2 Feature Extraction

Two approaches are explored:

- OCR-based extraction using traditional pipelines
- OCR-free extraction using vision transformers

3.3 Transformer Architecture

The system uses an encoder-decoder transformer architecture. The encoder processes the input data, and the decoder produces output. The attention mechanism allows the model to concentrate on specific areas [4][17].

3.4 Information Extraction

Key fields extracted include:

- Invoice Number
- Vendor Name
- Date
- Total Amount

Named Entity Recognition (NER) techniques are used in conjunction with transformers [18].

3.5 Summarization

A transformer-based summarization model generates concise summaries. The use of pre-trained models enhances performance and reduces training requirements [14].

3.6 System Architecture

This proposed system architecture will be implemented as a modular and scalable pipeline that incorporates different modules to facilitate effective invoice comprehension and summarization. These include four major phases, which are data ingestion, feature extraction, information extraction using transformers, and summarization.

In the first stage, invoice documents in the form of images or PDFs are provided as input. These documents undergo preprocessing, including resizing, normalization, and noise reduction, to ensure consistency and improve downstream model performance. This step is particularly important for handling real-world invoices that may contain distortions and scanning artifacts [13].

The second stage involves feature extraction. Depending on the approach, the system either utilizes an OCR-based pipeline or an OCR-free vision-language model. OCR-based approaches rely on text extraction engines [2], whereas OCR-free models directly process document images using transformer-based architectures such as Donut [7].

The third stage is the core component of the architecture, where transformer-based models process the extracted features. The encoder captures contextual and spatial relationships within the document using self-attention mechanisms [4], while models such as LayoutLMv3 incorporate layout and visual features to improve understanding [6].

Finally, the summarization module utilizes a transformer-based sequence-to-sequence model such as T5 to generate

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concise summaries [11]. This enhances interpretability by converting structured outputs into human-readable insights.

4. RESULT AND DISCUSSION

The performance of the proposed system was evaluated using standard metrics including accuracy, precision, recall, and F1-score [15]. These metrics provide a comprehensive evaluation of the system's ability to extract structured information accurately.

Table -1: Performance Metrics

Field	Precision	Recall	F1-Score
Invoice Number	0.96	0.94	0.95
Vendor Name	0.94	0.92	0.93
Date	0.93	0.91	0.92
Total Amount	0.97	0.95	0.96

The results indicate that transformer-based models significantly outperform traditional OCR-based systems, particularly in handling unstructured and semi-structured documents [16]. The ability of transformers to capture contextual dependencies improves extraction accuracy across varying invoice layouts.

Additionally, the summarization module enhances usability by generating concise summaries, aligning with advancements in sequence-to-sequence transformer models [11], [12].

5. ADVANTAGES

The system being introduced provides several benefits over existing solutions.

Firstly, the enhanced ability to understand the context via the self-attention technique allows capturing relations between various components within an invoice [4].

A second benefit is the limited reliance on templates and predefined rules that have long been an indispensable part of most OCR systems [3]. The approach generalizes well across different invoice formats.

High adaptability can be attributed to the ability of transformers to learn multimodally using both text and images [6]. The scalability of the approach also means that it can be used in enterprise-grade settings.

6. LIMITATIONS

The system includes the following limitations:

- Transformer-based models require high computational resources for training and inference, which can limit deployment in low-resource environments [16].
- Another limitation is the dependence on large annotated datasets, which are essential for achieving high performance in supervised learning tasks [9].
- Additionally, the system is sensitive to poor image quality. Errors in OCR-based pipelines or degraded visual inputs can negatively impact performance [2].

7. FUTURE WORK

Future work may involve improving the functionalities of the system in many ways.

First, it is possible to expand its ability to process invoices in multiple languages. This corresponds to the new developments in multilingual transformers [19].

Another important aspect concerns real-time application, which necessitates speeding up the inference time for high throughput systems.

Further, integrating with ERP systems would enhance automation even more.

Moreover, adding anomaly detection techniques could be beneficial for identifying fraudulent invoices.

8. CONCLUSION

In this paper, we have proposed a transformer-based method for the task of automatic extraction and summarization of invoices. Using the powerful vision language models, the system is able to perform structured extraction and provide relevant summaries for unstructured invoices.

From the experiment results, we can see that our proposed method shows promising performance compared to traditional OCR methods, especially in dealing with complicated layout structures [16].

Finally, this paper reveals the possibility of transformers in document intelligence tasks.

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