# Donut I Document Understanding Transformer without OCR

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#### Abstract

Understanding document images (e.g., invoices) has been an important research topic and has many applications in document processing automation. Through the latest advances in deep learning-based Optical Character Recognition (OCR), current Visual Document Understanding (VDU) systems have come to be designed based on OCR. Although such OCR-based approach promise reasonable performance, they suffer from critical problems induced by the OCR, e.g., (1) expensive computational costs and (2) performance degradation due to the OCR error propagation. In this paper, we propose a novel VDU model that is end-to-end trainable without underpinning OCR framework. To this end, we propose a new task and a synthetic document image generator to pre-train the model to mitigate the dependencies on largescale real document images. Our approach achieves state-of-the-art performance on various document understanding tasks in public benchmark datasets and private industrial service datasets. Through extensive experiments and analysis, we demonstrate the effectiveness of the proposed model especially with consideration for a real-world application.

### 1 Introduction

Semi-structured documents, such as invoices, receipts and business cards, are commonly handled in modern working environments. Some of them exist as digital-born electronic files, while some are in a form of scanned images or even photographs. Visual Document Understanding (VDU) is a task that aims to understand document

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Figure 1: The performance comparison of conventional visual document understanding architectures and the proposed method (**Donut**). The lower the metric score is, the better performance it is. Note that **Donut** does not depend on OCR but operates in an end-to-end manner.

images despite its diverse formats, layouts and contents. VDU is the important step to be preceded for automated document processing. Its various following applications include document classification (Kang et al., 2014; Afzal et al., 2015), parsing (Hwang et al., 2019; Majumder et al., 2020a), and visual question answering (Mathew et al., 2021; Tito et al., 2021).

Through the remarkable advances in deep learning based Optical Character Recognition (OCR) (Baek et al., 2019b,a), most existing VDU systems share a similar architecture that depends on a separated OCR module to extract text information from target document images. The systems are designed to consider OCR-extracted

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Figure 2: The schema of the conventional visual document parsing pipeline. (a) The target problem is to extract the structured information from a given semi-structured document image. In a traditional pipeline, (b) text detection is conducted to obtain text box locations and (c) each text box is passed to the text recognizer to comprehend characters in the box. (d) Finally, the recognized texts and their locations are passed to the following module to be processed for the desired structured form of the information.

text information as input and perform their own objectives with the OCR-extracted texts. (Katti et al., 2018; Hwang et al., 2019, 2020, 2021a; Sage et al., 2020; Majumder et al., 2020a; Xu et al., 2019, 2021). For example, (Hwang et al., 2019), a currently-deployed document parsing system for business card and receipt images, consists of three separate modules for text detection, text recognition, and parsing (See Figure 2).

However, in practice, this kind of approach has several problems. First, OCR is expensive and is not always available. Training an own OCR model requires extensive supervision and largescale datasets (Baek et al., 2019b,a). Moreover, most recent state-of-the-art models require GPUs, which is expensive and increase maintenance cost. To reduce the cost, using a commercial OCR engine can be another option, but it is not always available and the performance of the engine may be poor on the target domain. Second, OCR errors negatively influence subsequent processes (Taghva et al., 2006; Hwang et al., 2021a). This problem becomes more severe in languages with complex and large character sets, such as Korean and Japanese, where OCR is relatively difficult (Rijhwani et al., 2020). Deploying a separate post-OCR correction module (Schaefer and Neudecker, 2020; Rijhwani et al., 2020; Duong et al., 2021) can be an option, but it is not a practical solution for real application environments since it increases the entire system size and maintenance cost.

We go beyond the traditional framework by

modeling a direct mapping from a raw input image to the desired output. The proposed model **Donut** is *end-to-end* trainable and does not dependent on any other modules (e.g., OCR), that is, the model is *complete* (self-contained). In addition to this, in order to alleviate the dependencies on large-scale real document images, we also present a synthetic document generator **SynthDoG** and its application to a pre-training of our model. Although the idea is simple, our experiments on various datasets including real industrial benchmarks show the efficacy of our proposal. The contributions of this work are summarized as follows:

- 1 We propose a novel approach for visual document understanding. To the best of our knowledge, this is the first method based on a simple OCR-free transformer architecture trained in an end-to-end manner.
- 2 We present a synthetic document image generator and a simple pre-training task for the proposed model. The datasets, pre-trained model weights, and our code will be publicly available at GitHub<sup>1</sup>.
- 3 We conduct extensive experiments and analysis on both public benchmarks and private industrial service datasets, showing that the proposed method not only achieve state-of-the-art performances but also

<sup>&</sup>lt;sup>1</sup>https://github.com/clovaai



Figure 3: The overview of **Donut**. The encoder maps a given document image into embeddings. With the encoded embeddings, the decoder generates a sequence of tokens that can be converted into a target type of information in a structured form.

has many practical advantages (e.g., *cost-effective*) in real-world applications.

#### 2 Method

#### 2.1 Preliminary: background

There have been various visual document understanding (VDU) methods to understand and extract essential information from the semistructured documents such as receipts (Huang et al., 2019; Hwang et al., 2021b; Hong et al., 2021), invoices (Riba et al., 2015; Hong et al., 2019; Majumder et al., 2020b).

Earlier attempts in VDU have been done with vision-based approaches (Kang et al., 2014; Afzal et al., 2015; Harley et al., 2015a), showing the importance of textual understanding in VDU (Xu et al., 2019). With the emergence of BERT (Devlin et al., 2018), most state-of-the-arts (Xu et al., 2019, 2021; Hong et al., 2021) combined the computer vision (CV) and natural language processing (NLP) techniques and showed remarkable advances in recent years.

Most recent methods share a common approach that uses large-scale real document image datasets (e.g., IIT-CDIP (Lewis et al., 2006)), and relies on a separate OCR engine, where the model is pretrained on the huge set of real document images. At the test phase, the OCR engine performs on unseen images to extract text information, which is then fed to the following modules to achieve its own objectives. Therefore, extra effort is required to ensure the performance of an entire VDU model by using a heavy OCR engine.

#### 2.2 Document Understanding Transformer

We propose a simple transformer-based encoderdecoder model, which is named *Document understanding transformer* (Donut), an end-toend model that does not depend on any other module such as OCR. We aim to design a simple architecture based on the transformer (Vaswani et al., 2017).Dount consists of a visual encoder and textural decoder modules. The model directly maps the input document image into a sequence of tokens converted one-to-one into a desired structured format. The overview of the proposed model is shown in Figure 3.

Encoder. The visual encoder converts the input document image  $\mathbf{x} \in \mathbb{R}^{H \times W \times C}$  into a set of embeddings  $\{\mathbf{z}_i | \mathbf{z}_i \in \mathbb{R}^d, 1 \le i \le n\}$ , where *n* is feature map size or the number of image patches and d is the dimension of the latent vectors of the encoder. CNN-based models (such as ResNet (He et al., 2015)) or Transformer-based models (Dosovitskiy et al., 2021; Liu et al., 2021)) can be used as the encoder network. In this study, if not mentioned otherwise, we use Swin Transformer (Liu et al., 2021) because it shows the best performance in our preliminary study in document parsing. Swin Transformer first splits the input image x into non-overlapping patches. Then, the following Swin Transformer blocks where the local self-attentions with the shifted window are inside and patch merging layers are applied on the patch tokens. The output of the final Swin Transformer block  $\{z\}$  is used in the decoder.

**Decoder.** Given the representations  $\{z\}$ , the textual decoder generates a token sequence  $(y_i)_1^m$ ,



Figure 4: The components of SynthDoG.

where  $\mathbf{y}_i \in \mathbb{R}^v$  is an one-hot vector for the token i, v is the size of token vocabulary, and m is a hyperparameter, respectively. We use BART (Lewis et al., 2020) the decoder architecture; specifically, we use the multilingual BART (Liu et al., 2020) model. To meet the applicable speed and memory requirements for diverse real-world applications, we used the first 4 layers of BART.

**Model Input.** Model training is done in a teacher-forcing manner (Williams and Zipser, 1989). In the test phase, inspired by GPT-3 (Brown et al., 2020), the model generates a token sequence given a prompt. We simply introduce some new special tokens for the prompt for each downstream task in our experiments. The prompts that we use for our applications are shown with the desired output sequences in Figure 3.

**Output Conversion.** The output token sequence is converted to a desired structured format. We adopt a JSON format due to its high representation capacity. As shown in Figure 3 a token sequence is one-to-one invertible to a JSON data. We simply add two special tokens [START\_\*] and [END\_\*] per a field \*. If the output token sequence is wrongly structured (e.g., there is only [START\_name] exists but no [END\_name]), we simply treat the field "name" is lost. This algorithm can easily be implemented with some regular expressions. Our code will be publicly available.

# 2.3 Pre-training

As aforementioned, current state-of-the-arts in VDU are heavily relying on large-scale real document images to train the model (Lewis et al., 2006; Xu et al., 2019, 2021; Li et al., 2021). However, this approach is not always available in real-world production environments, in particular handling diverse languages other than English.

Synthetic Document Generator. To remove the dependencies on large-scale real document images, we propose a scalable Synthetic Document Generator, referred to as SynthDoG. The pipeline of rendering images basically follows Yim et al. (2021). As shown in Figure 4, the generated image consists of several components; background, document, text and layout. Background images are sampled from ImageNet (Deng et al., 2009), and a texture of document is sampled from the collected photos. Words and phrases are sampled from Wikipedia. A rule based random patterns are applied to mimic the complex layouts in the real documents. In addition, some major techniques in image rendering (Gupta et al., 2016; Long and Yao, 2020; Yim et al., 2021) are applied to imitate real photographs. The example images generated by SynthDoG are shown in Figure 5. The implementation of our method will be publicly available.

**Task.** We generated 1.2M synthetic document images with SynthDoG. We used corpus extracted from the English, Korean, and Japanese Wikipedia and generated 400K images per language. The task is simple. The model is trained to read all the texts in the images in the reading order from top left to bottom right. The example is shown in Figure 3.

### 2.4 Application

After the model learns *how to read*, in the application stage (i.e., fine-tuning), we teach model *how to understand* given the document image. As shown in Figure 3, we interpret all downstream tasks as a JSON prediction problem.

The decoder is trained to generate the JSON which represents the desired output information. For example, in the document classification task, the decoder is trained to generate a token sequence [START\_class][memo][END\_class] which is 1-to-1 invertible to a JSON {"class": "memo"}. We introduce some special tokens (e.g., [memo] is used for representing the class "memo"), if such replacement is available in the target downstream task. The code will be publicly available at GitHub.

## **3** Experiments and Analysis

## 3.1 Downstream Tasks and Datasets

We provide the downstream tasks we run our experiments on with the datasets in the following. The samples of the datasets are shown in Figure 5.



Figure 5: Our datasets. Left: example images from **SynthDoG**. Right: document images of the downstream applications (from top right clockwise: (a) document classification, (b) visual question answering, (c) receipts and business cards parsing).

### 3.1.1 Document Classification

To see whether the model understands document types, we test a document classification task.

**RVL-CDIP** (Harley et al., 2015b). The RVL-CDIP dataset consists of 400K grayscale images in 16 classes, with 25K images per class. The 16 classes include letter, memo, email, and so on. There are 320K training, 40K validation, and 40K test images. Unlike other models which predict the class label via a softmax on the encoded token embedding, we make the decoder generate a JSON that contains class label information to maintain the uniformity of the task-solving method. We report overall classification accuracy on the test set.

#### 3.1.2 Document Parsing

To see the model fully understands the complex layouts, formats, and contents in given document images, we conduct *document parsing*, which is a task of extracting the desired structured information from the input document image (See Figure 2).

**Indonesian Receipts (Park et al., 2019).** This is a public benchmark dataset that consists of 1K Indonesian receipt images. The dataset also provides OCR annotations (i.e., texts and their 2D location information), and the desired structured information (i.e., ground truth) in JSON format.

Japanese Business Cards (In-Service Data). This dataset is also from one of our products. The dataset consists of 20K Japanese business cards images with corresponding ground truths in JSON format.

Korean Receipts (In-Service Data). This dataset is from one of our real products that are currently deployed. The dataset consists of 55K Korean receipt images with corresponding ground truths in JSON format. The complexity of ground truth JSONs is high compared to the other two parsing tasks.

#### 3.1.3 Document VQA

To validate the further capacity of the model, we conduct a document visual question answering task (DocVQA). In this task, a document image and a natural language question are given and the model predicts the proper answer for the question by understanding both visual and textual information within the image. We make the decoder generate the JSON that contains both the question (given) and answer (predicted) to keep the uniformity of the method.

**DocVQA** (Mathew et al., 2021). The dataset consists of 50K questions defined on more than 12K document images. There are 39,463 training, 5,349 validation, and 5,188 test questions. The evaluation metric for this task is ANLS (Average

	use OCR	#Params	Time(ms)	Accuracy (%)
BERT <sub>BASE</sub>	$\checkmark$	$110M + n/a^{\dagger}$	1392	89.81
RoBERTa <sub>BASE</sub>	$\checkmark$	$125M + n/a^{\dagger}$	1392	90.06
UniLMv2 <sub>BASE</sub>	$\checkmark$	$125M + n/a^{\dagger}$	n/a	90.06
LayoutLM <sub>BASE</sub> (w/ image)	$\checkmark$	$160M + n/a^{\dagger}$	n/a	94.42
LayoutLMv2 <sub>BASE</sub>	$\checkmark$	$200M + n/a^{\dagger}$	1489	95.25
Donut (Proposed)		156M	791	<u>94.50</u>

<sup>†</sup> Parameters for OCR should be considered for the non-E2E models.

Table 1: Classification accuracies on the RVL-CDIP dataset. The proposed **Donut** achieves a comparable accuracy to the state-of-the-art model and the fastest inference speed. Note that the **Donut** does not rely on OCR while other baseline models do.

Normalized Levenshtein Similarity), which is an edit distance-based metric. We reported the ANLS for the test set measured on the official evaluation site.

### **3.2** Common Setting

We pre-trained the multi-lingual **Donut** on the 1.2M synthetic document images as explained in Section 2.3 for an epoch. We fine-tune the model while monitoring normalized edit distance on token sequences of the validation set. We train the model with 8 NVIDIA V100 GPUs and a mini-batch size of 8. We use Adam (Kingma and Ba, 2015) optimizer, the learning rate is scheduled and the initial rate is selected from 2e-5 to 8e-5. For an estimation of the number of parameters and speeds,  $\sim$  represents approximate estimation.

For the OCR-dependent baselines, provided OCR results in the datasets are used if not explained otherwise. In some tasks, states-of-theart commercial OCR products are used. At the estimation of OCR speeds, we utilize Microsoft OCR API used in Xu et al. (2021). In document parsing tasks, we use CLOVA OCR<sup>2</sup> specialized in the OCR on receipts and business cards images.

#### 3.3 Results

#### 3.3.1 Document Classification

The classification accuracies are shown in Table 1. The proposed Donut shows a comparable performance to state-of-the-arts *without* relying on OCR or large-scale real document images. It is surprising that our model shows a higher score than one of the start-of-the-arts LayoutLM (Xu et al., 2019) which has a dependency on large-scale scanned document images IIT-CDIP (Lewis et al., 2006) consists of 11M images. Note that, unlike the other transformer-based models, the

token embeddings of our model can be dropped in this task as the inference is done in an *end-toend* fashion.

#### 3.3.2 Document Parsing

The normalized Tree Edit Distance (nTED) scores (Hwang et al., 2021a) are shown in Table 2. We compare the proposed model with the baseline that has been in our real products for years. For all domains including public and private inservice datasets, our proposal shows the best nTED scores among the comparing models. Moreover, the inference time is significantly reduced especially for a domain that has high complexity, i.e., Korean receipt parsing task. This demonstrate the effectiveness of our proposal for a real-world application.

As a real product, localizing the extracted value is sometimes demanded by customers. We show the cross attention maps of the decoder given an unseen Indonesian receipt in Figure 6. It shows interesting results that the model attends to a desired location in the given image. With simple heuristics, we converted the attention maps into a bounding box and the sample is shown in the figure. Although it is not as accurate as commercial OCR products, the model shows meaningful results that can be used as an auxiliary indicator.

#### 3.3.3 Document VQA

The results are shown in Table 3. Our approach shows a promising result *without* depending on OCR and large-scale real document images, e.g., IIT-CDIP (Lewis et al., 2006).

The first group of Table 3 utilizes the OCR results provided in the dataset and the scores are from Mathew et al. (2021). The second group is from (Tito et al., 2021), where CLOVA OCR is utilized to extract text information. The third group utilizes Microsoft OCR API and both LayoutLM

<sup>&</sup>lt;sup>2</sup>https://clova.ai/ocr

			Indonesian l	Indonesian Receipt		Korean Receipt		Japanese Business Card	
	use OCR	Params	Time (s)	nTED	Time (s)	nTED	Time (s)	nTED	
BERT-based Extractor*	$\checkmark$	$86M^{\dagger} + n/a^{\ddagger}$	0.89 + 0.54	11.3	1.14 + 1.74	21.67	0.83 + 0.50	9.56	
SPADE (Hwang et al., 2021b)	$\checkmark$	$93M^{\dagger} + n/a^{\ddagger}$	3.32 + 0.54	10.0	6.56 + 1.74	21.65	3.34 + 0.50	9.77	
Donut (Proposed)		$156 M^{\dagger}$	1.07	8.45	1.99	5.87	1.39	3.70	

\* Our currently-deployed model for parsing business cards and receipts in our real products. The pipeline is based on Hwang et al. (2019). † Parameters for token (vocabulary) embeddings are omitted for a fair comparison.

<sup>‡</sup> Parameters for OCR should be considered for non-E2E models.

Table 2: The normalized tree edit distance (nTED) scores on the three different document parsing tasks. The lower nTED score denotes the better performance. Our **Donut** achieves the best nTED scores for all the tasks with significantly faster inference speed. The gain is huge especially for the Korean Receipt parsing task, which is the most complex.

	OCR	Params <sup>‡</sup>	Time (ms)	ANLS
LoRRA	$\checkmark$	~223M	n/a	11.2
M4C	$\checkmark$	$\sim 91M$	n/a	39.1
BERTBASE	$\checkmark$	110M	n/a	57.4
CLOVA OCR	$\checkmark$	n/a	$\gtrsim 3226$	32.96
UGLIFT v0.1	$\checkmark$	n/a	$\gtrsim 3226$	44.17
BERTBASE	$\checkmark$	$110M + n/a^{\dagger}$	1517	63.54
LayoutLM <sub>BASE</sub>	$\checkmark$	113M + n/a	1519	69.79
LayoutLMv2 <sub>BASE</sub>	$\checkmark$	200M + n/a	1610	78.08
Donut		$\sim 207 M$	809	47.14
+ 10K imgs of trainset				53.14

<sup>†</sup> Parameters for OCR should be considered for non-E2E models.

 $^{\ddagger}$  Token embeddings for English is counted for a fair comparison.

Table 3: Average Normalized Levenshtein Similarity (ANLS) score on the DocVQA dataset. The higher ANLS score denotes the better performance. Our **Donut** shows a promising result without using OCR and pre-training with a large number of real images. In contrast, the LayoutLM and LayoutLMv2 were pre-trained with the IIT-CDIP dataset consisting of 11M images.

and LayoutLMv2 are pre-trained with large-scale scanned English document dataset (Lewis et al., 2006) (11M images). Their scores are from Xu et al. (2021). The gap between their scores and ours implies the impact of pre-training on large-scale real documents, which will be one of our future works to tackle.

Donut shows reasonable performance with faster inference speed than the comparison methods. To show the potential ability of Donut, we also show the performance of Donut by extra pre-training with 10K real images of DocVQA trainset. Although the additional pre-training images are noisy and the number of images is small (10K), it leads to a significant performance improvement (47.14  $\rightarrow$  53.14), which demonstrates the importance of real document images.



Figure 6: Visualization of cross-attention map and its application to bounding box localization. Left: tokens and their corresponding regions in the image are plotted. Right: detected bounding boxes are shown.

### 4 Related Work

### 4.1 Optical Character Recognition

Current trends in OCR are to utilize deep learning models in its two sub-steps: 1) text areas are predicted by a detector; 2) a text recognizer then recognizes all characters in the cropped image instances. Both are trained with a large-scale datasets including the synthetic images (Jaderberg et al., 2014; Gupta et al., 2016) and real images (Lucas et al., 2003; Mishra et al., 2012; Wang et al., 2011; Karatzas et al., 2015; Phan et al., 2013).

Early text detection methods were based on convolutional neural networks (CNNs) to predict local segments and then applied heuristics to merge the segments into detection lines (Huang et al., 2014; Zhang et al., 2016). Later, following the general object detection methods (Liu et al., 2016a; He et al., 2017), region proposal and bounding box regression based methods were proposed (Liao et al., 2017; Minghui Liao and Bai, 2018; Zhang et al., 2018). More recently, by focusing on the homogeneity and locality of texts, componentlevel approaches were proposed to predict subtext components and assemble them into a text instance (Tian et al., 2016, 2019; Baek et al., 2019b). By its nature, these can better adapt to curved, long, and oriented texts.

Many modern text recognizer share a similar approach (Borisyuk et al., 2018; Lee and Osindero, 2016; Liu et al., 2016b; Shi et al., 2016; Wang and Hu, 2017; Shi et al., 2017) that can be interpreted into a combination of several common deep modules (Baek et al., 2019a). Given the cropped text instance image, most recent text recognition models apply CNNs to encode the image into a feature space. A decoder is then applied to extract characters from the features.

### 4.2 Visual Document Understanding

Classification of the document type is a fundamental task but is a core step towards automated document processing. Early methods treated the problem as a general image classification, so various CNNs were tested (Kang et al., 2014; Afzal et al., 2015; Harley et al., 2015a). Recently, with BERT (Devlin et al., 2018), the methods based on a combination of CV and NLP were widely proposed (Xu et al., 2019; Li et al., 2021). As a common approach, most methods rely on an OCR engine to extract texts; then the OCR-ed texts are serialized into a token sequence; finally they are fed into a language model (e.g., BERT) with some visual features if available. Although the idea is simple, the methods showed remarkable performance improvements and became a main trend in recent years (Xu et al., 2021; Appalaraju et al., 2021).

Document parsing performs mapping each document to a structured form consistent with the target ontology or database schema. This covers a wide range of real applications, for example, given a bunch of raw receipt images, a document parser can automate a major part of receipt digitization, which has been required numerous human-labors in the traditional pipeline. Most recent models (Hwang et al., 2019; Majumder et al., 2020a; Hwang et al., 2021b,a) take the output of OCR as their input. The OCR results are then converted to the final parse through several processes, which are often complex. Despite the needs in the industry, only a few works have been attempted on end-to-end parsing. Recently, some works are proposed to simplify the complex parsing processes (Hwang et al., 2021b,a). But they still rely on a separate OCR to extract text information.

Question Answering (VQA) Visual on documents seeks to answer questions asked on document images. This task requires reasoning over visual elements of the image and general knowledge to infer the correct answer (Mathew et al., 2021). Currently, most state-of-the-arts follow a simple pipeline consisting of applying OCR followed by BERT-like transformers (Xu et al., 2019, 2021). However, the methods work in an extractive manner by their nature. Hence, there are some concerns for the question whose answer does not appear in the given image (Tito et al., 2021). To tackle the concerns, generation-based methods have also been proposed (Powalski et al., 2021).

# 5 Concluding Remarks

In this work, we propose a novel end-to-end method for visual document understanding. The proposed method, Donut, directly maps an input document image into a desired structured output. Unlike traditional methodologies, our method does not depend on OCR and large-scale real document images. We also propose a synthetic document image generator, SynthDoG, which plays an important role in pre-training of the model in a curriculum learning manner. We gradually trained the model from how to read to how to understand through the proposed training pipeline. Our extensive experiments and analysis on both external public benchmarks and private internal service datasets show higher performance and better cost-effectiveness of the proposed method. This is a significant impact as the target tasks are already practically used in industries. Our future work is to expand the proposed method to other domains/tasks regarding document understanding.

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