DavarOCR: A Toolbox for OCR and Multi-Modal Document Understanding

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ABSTRACT
This paper presents DavarOCR, an open-source toolbox for OCR and document understanding tasks. DavarOCR currently implements 19 advanced algorithms, covering 9 different task forms. DavarOCR provides detailed usage instructions and the trained models for each algorithm. Compared with the previous open-source OCR toolbox, DavarOCR has relatively more complete support for the sub-tasks of the cutting-edge technology of document understanding. In order to promote the development and application of OCR technology in academia and industry, we pay more attention to the use of modules that different sub-domains of technology can share. DavarOCR is publicly released at https://github.com/hikopensource/Davar-Lab-OCR.

CCS CONCEPTS
• Computing methodologies → Computer vision problems.

KEYWORDS
Open-source, OCR, Document Understanding

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1 INTRODUCTION
OCR (Optical Character Recognition) is an essential technique in deep learning and has been applied in many fields like finance, transportation, and health care. With the continuous development of technology, people’s demand for OCR ability has changed from simple text content extraction to more diversified and intelligent tasks that can directly solve the problems in actual production. Based on this, we divide the OCR tasks into two types, the basic OCR tasks and document understanding tasks.

The basic OCR tasks are the perception tasks that aim to obtain the content of the text in the images/videos and convert it into the electronic format, usually including text detection [1, 18, 37] and text recognition [2, 5, 26]. To be more efficient and robust, people also propose end-to-end architectures [15, 17, 22]. However, solely capturing text content sometimes cannot directly address the actual needs. In actual OCR production, intelligent systems need to perform a variety of downstream tasks based on the results of OCR. We call these tasks document understanding. These tasks can be regarded as cognitive tasks that require people to further understand the information (semantic information or relational information) conveyed by the text of the document. For example, Key Information Extraction (KIE) [13, 27, 35] is one of the common tasks in the financial instrument identification system, where the model needs to identify the values of the specific items like ‘invoice code’ and ‘amount’. Other common forms of document understanding tasks include layout analysis [32, 34], Reading Order Detection (ROD) [16, 30], table recognition [14, 21] and understanding [12, 29], document Question-Answering (QA) [19], Named Entity Recognition (NER) [7, 10, 24, 31], etc.

Nowadays, many advanced open-source OCR toolboxes aim to provide more efficient and unified OCR services. Tesseract1, ChineseOCR2, chineseOCR_lite3, EasyOCR4 are some earlier OCR...

1https://github.com/tesseract-ocr/tesseract
2https://github.com/chineseocr/chineseocr
3https://github.com/DayBreak-u/chineseocr_lite
4https://github.com/JaidedAI/EasyOCR
Table 1: Comparison of support algorithms between different open-source OCR toolboxes. All methods in Basic OCR Tasks only use visual information. In Document Understanding tasks, methods labelled with ♦ means using visual features, with ♣ means using textual features, with ♦♣ means using positional features.

| Toolbox | Basic OCR Tasks | Document Understanding Tasks |
|---------|-----------------|-----------------------------|
|         | Text Detection  | Text Recognition | End-to-End Text Spotting | Video Text | KIE | NER | Layout Analysis | ROD | Table Recognition |
| tesseract | convention | LSTM | - | - | - | - | - | - | - |
| chinesocr | Yolo[23] | CRNN[25] | - | - | - | - | - | - | - |
| chinesocr lite | DB[18] | CRNN[25] | - | - | - | - | - | - | - |
| EasyOCR | CRAFT[1] | CRNN[25] | - | - | - | - | - | - | - |
| PaddleOCR | DB[18], EAST[37], M-RCNN[8], etc. (4) | CRNN[25], Rosetta[2], etc. (7) | PGNet[28] | - | SDMGR[27] ♦♣ | - | Yolo[23]♦ | - | RARE[26]♦ |
| mmocr | DB[18], M-RCNN[8], etc. (6) | CRNN[25], ABINet[6], etc. (8) | - | - | SDMGR[27] ♦♣ | BERT-Softmax[5]♣ | - | - | - |
| davarocr | EAST[37], CRNN[25], M-RCNN[8], TP[22], SPN[33], TP-det[22], M-RCNN-e2e, etc. (5) | TP[22], MANGO[20], YOLO[4] | Chargrid[13]♣ | - | BERT-Softmax♣ | /Span/CRF[5]♣ | VSR[34]♣ | GCN-PN[16]♣ | LGPMA[21]♣ |

To further support the vast majority of current basic OCR and document understanding tasks, we do not implement many methods for well support the vast majority of current basic OCR and document understanding tasks. In some of its latest versions (up to v2.2), PaddleOCR starts to provide the support of some document understanding tasks, including KIE, Layout Analysis, Table Recognition and Document VQA. In each task at this stage, they provide some fairly basic and simple implementations, e.g., a basic object detection solution (Yolo[23]) for layout analysis. Mmocr is a recent Pytorch-based OCR toolbox that collects many implementations of advanced OCR algorithms. It provides a rich and flexible component configuration to build an OCR model, including different backbones, necks, heads, losses, etc. Currently, mmocr has little support for document understanding tasks, i.e., an KIE (SDMGR[27]) model and NER (BERT-Softmax[5]) model.

In this paper, we present DavarOCR, a new OCR toolbox that can well support the vast majority of current basic OCR and document understanding tasks. Similar to mmocr, DavarOCR is also built based on the training engine mmcv and the architecture design of mmdetection. This means the whole framework can be compatible with mmocr. Therefore, we do not implement many methods for text detection and recognition algorithms but focus on expanding the tasks that MMOCR cannot support. For the basic OCR tasks, besides other text detection and recognition algorithms, we extend the framework to well support end-to-end text spotting and video text tasks. Notably, DavarOCR contains complete modules for end-to-end text spotting tasks, including both two-staged (TP[22], Mask-RCNN-based) and one-staged (MANGO[20]) text spotting architectures. For the document understanding tasks, we extend the framework’s support for some new tasks, including Layout Analysis, ROD, and Table Recognition. Shortly, we will continue to expand the implementation of new tasks, including Document VQA and Table Understanding. At the present stage, DavarOCR contains the implementations of 19 advanced algorithms, including 10 algorithms that any other previous framework has not implemented. An algorithm-level comparison between the open-source toolboxes is shown in Table 1.

DavarOCR is released under the Apache-2.0 License. The code repository contains the one-click setup script, accompanied by the complete demo and detailed instruments to make researchers understanding easier.

2 HIGHLIGHT FEATURES OF DAVAROCR

2.1 Across Tasks Module Sharing

DavarOCR inherits the idea of modular design from mmdetection [3] and extends it to support more tasks. In mmdetection, a model can be divided into 4 parts: BACKBONE, NECK, ROI_EXTRACTOR and HEAD. We can modify the configuration to make the model be integrated with an arbitrary combination of modules, such as different backbones. Although text detection models can mostly follow the same module divisions, other tasks will inevitably introduce new modules. In DavarOCR, some of the extended model-related modules include:

- TRANSFORMATION: In text recognition, some algorithms will integrate a learnable deformation correction module to rectify the text with irregular shapes, such as Affine[11], TPS[26]. These modules can also be used in text spotting, video text tasks.

- EMBEDDING: In some tasks that require textual or positional information, the model needs to utilize the features encoded by an embedding layer. For example, word/sentence embedding is used in representing the textual feature, and 2D positional embedding is used to establish spatial location connections. The related tasks include KIE, NER, Layout Analysis, ROD, etc.

https://github.com/PaddlePaddle/PaddleOCR
https://github.com/open-mmlab/mmocr
https://github.com/open-mmlab/mmcv
https://github.com/open-mmlab/mmdetection
Figure 1: The modular design for the end-to-end KIE model TRIE.

CONNECT. Some intermediate connection modules are used frequently in a model like feature enhancement, feature deformation, and feature fusion. For example, Bi-LSTM[9] is a typical module used to enhance sequence features, which can be used in any text-recognition-related (text spotting, KIE, etc.) and NER tasks.

In addition to the above mentioned model-related components, many commonly used modules/operators/tools can be found in DavarOCR. All of the above modular design in DavarOCR allows for maximum component sharing between different tasks, enabling researchers to build a cross-task model quickly. Figure 1 demonstrates an example architecture of the modal TRIE[35], which is an end-to-end model contains three sub-tasks: text detection, recognition and information extraction.

2.2 Uniform Data Label Format

Because of the different types of tasks, we often need to use different supervision to train models, which leads to varying forms of task-dependent data annotation. In fact, there are many similarities between basic OCR and document understanding tasks. To further unify the data processing logic in DavarOCR, We try to integrate all possible tasks and propose some unified basic formats for the data label.

Figure 2: Illustration of the basic data label

Figure 2 shows an illustration of the basic image-based data label format. In the basic format, annotation information for all images is arranged in a JSON file, and the keys are the images’ paths. The detailed annotation is stored in the item of “content_ann”. All the items in “content_ann” are array types and have the same length on the outermost level. This indicates that all the labeling information corresponds to each bounding box. If someone needs to store full-image-level annotations, all the lists are of length 1, and “boxes” default to contain a single box to represent the entire image range. Item of “labels” saves the category information for an object or the whole image, which is used in the tasks related to object classification like KIE and Layout Analysis. It is stored in a two-dimensional list to support the classification of multitasking. Notably, we add keywords (“content_ann2”) to save multilevel labels for supporting the multilevel task. For example, in the multi-modal layout analysis task, the model needs to simultaneously learn the page-level (block-level) and text-line-level tasks.

The basic data label format supports most image-based tasks, including text detection, text recognition, end-to-end text spotting, KIE, and Layout Analysis. When we use the data to train a model, we can freely select any combination of the keywords to form the required information for the task. We can define the task-specific data form for new tasks that inherit the basic format to supplement the required items. For example, in table recognition tasks, the model relies on the item to represent cell indexes. DavarOCR also provides the data format for the video-based (Video Text) of plain-text-based (NER) tasks.

Table 2: Multi-modal ablation results of the Key Information Extraction task on WildReceipt[27].

| Algorithm | Modalities     | Backbone   | Testing Scale | F1-Score |
|-----------|----------------|------------|---------------|----------|
| Chargrid[13] | Visual+Textual | ChargridNet | (512,512) | 67.10 |
| TRIE[35]    | Visual         | ResNet-50  | (512,512) | 78.25 |
|            | Visual+Textual | ResNet-50  | (512,512) | 84.67 |
|            | Visual+Positional | ResNet-50 | (512,512) | 86.57 |
|            | Visual+Textual+Positional | ResNet-50 | (512,512) | 87.08 |

Through the uniform data format, most of the tasks from different domains can share the same data processing functions like data loading, data augmentation and data formatting.
Table 3: Multi-modal ablation results of the Layout Analysis task on PubLayNet[36]. (C) means Character-level textual feature, and (S) means Sentence-level textual feature.

| Algorithm | Modalities | Backbone | Testing Scale | mAP |
|-----------|------------|----------|---------------|-----|
| VSR[34]   | Visual     | ResNeXt-101 | (1300,800) | 92.6 |
|           | Visual+Textual (C) | ResNeXt-101 | (1300,800) | 94.5 |
|           | Visual+Textual (S) | ResNeXt-101 | (1300,800) | 94.7 |
|           | Visual-Textual (C+S)-Positional | ResNeXt-101 | (1300,800) | 95.8 |

3 CASE STUDY: MULTI-MODAL DOCUMENT UNDERSTANDING

Different modal information may play different roles in document understanding tasks. This section demonstrates some of the modality ablation results in DavarOCR.

Table 2 and Table 3 separately show some models' ablation results on the KIE and Layout Analysis tasks. In the KIE experiments, the task can be simply implemented by a single visual-based model, which equals an object detection task. The Chargrid model uses a char-level segmentation map to introduce textual features, and TRIE will extract the positional and textual features to compromise the box-level multi-modal features. From the results, we can see that involving additional modalities can greatly improve the model’s performance.

4 CONCLUSION

This paper presents an open-source toolbox, DavarOCR, for comprehensive OCR and document understanding tasks. DavarOCR currently implements 19 state-of-the-art algorithms, covering 9 different task areas. In DavarOCR, researchers can freely combine the reusable modules and adopt multi-modal information to implement more complex algorithms involving perception and cognition. We hope that this framework can further promote the implementation of new technologies in actual production.

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