Deep Structured Feature Networks
for Table Detection and Tabular Data Extraction
from Scanned Financial Document Images

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Abstract—Automatic table detection in PDF documents has achieved a great success but tabular data extraction is still challenging due to the integrity and noise issues in detected table areas. The accurate data extraction is extremely crucial in finance area. Inspired by this, the aim of this research is proposing an automated table detection and tabular data extraction from financial PDF documents. We proposed a method that consists of three main processes, which are detecting table areas with a Faster R-CNN (Region-based Convolutional Neural Network) model with Feature Pyramid Network (FPN) on each page image, extracting contents and structures by a compounded layout segmentation technique based on optical character recognition (OCR) and formulating regular expression rules for table header separation. The tabular data extraction feature is embedded with rule-based filtering and restructuring functions that are highly scalable. We annotate a new Financial Documents dataset with table regions for the experiment. The excellent table detection performance of the detection model is obtained from our customized dataset. The main contributions of this paper are proposing the Financial Documents dataset with table-area annotations, the superior detection model and the rule-based layout segmentation technique for the tabular data extraction from PDF files.

Index Terms—Applications of document analysis, Applications of deep learning to document analysis, Document image processing

I. INTRODUCTION

Tables in PDF documents usually contain the essence of information, however, locating and extracting tables in files manually can be time-consuming and human-errors are common. As the descendent from PostScript Page Description Programming Language, PDFs files create complexity in machine readability, which is why the efficiency of algorithms for text and structural information recognition is the main limitation for table extraction [1]. As a classical topic of pattern recognition, table detection goes through diverse experiments starting from different perspectives like tag detection on a text-based document, region detection on page images, and so forth. And the tabular data extraction from table image is also challenging since we want to discard noise and remain table’s original structure.

Most researches concentrate on table detection and tabular extraction separately while less would consider them as a united process. There are difficulties in each field. First, not all PDF files are text-based as PDF pages can be stable images and scanned graphs without tags on the whole page. Thus, the tag classifier is not suitable or useful on document images. label classification based on text-based documents [2] has an erroneous detection performance on unstructured tabular. Second, there are different types of table formats, framed or unframed, line-based or irregular and single or combined. End-to-end deep learning model [3] prefers extract structured tables for cell recognition. Furthermore, it is a hard task to maintain the original layout and complete the contents of the tables. Text noise would impact the detection result by using current popular Nurminen algorithms. And lack of header is another common issue on contents extraction by using related tools [4]. There are few datasets with a large volume of text-based tables for table detection and extraction. Thus, automatic and smart extraction for tables is a complex and difficult task.

To overcome the difficulties mentioned above, in this paper, we propose a method that extracting tabular data from table images detected by an object recognition model. Cutting-edge object detection algorithms for our table detection model are embedded into feature pyramid networks. Our table detection algorithms are tested on the Financial Document dataset and the performance of our table detection is competitive. Detected table images are processed by layout segmentation techniques based on OCR to output data-frames that contain intact table contents and original structures. Generally, table extraction only contains information obtaining and structure rebuilding while the separation of header and body is usually another single topic. To achieve separating table schema and records, we adopt seq2seq model combined with beam research architecture and regular expression rules to extract headers. In this paper, we take account of the practical utility of tables and exploit the semantic separation to support header division. These data-frames are automatically stored into the database along with detection results summary sheets. The workflow is demonstrated in Figure [1] We annotate our own dataset which contains 3238 page images where there are diverse embedded tables. All page images are from 108 Financial Documents where 78 files are training data and 30 files are
testing data. A new annotated dataset for table detection, the optimal table detection performance of our Faster-RCNN FPN model, effective table segmentation techniques and a functional program that can automate the whole tabular data extraction process is the main contributions of this paper. We jointly consider the table detection and layout extraction as one whole topic and improve the practical utilization of tables after detection and extraction.

The rest of this paper is organized as follows. Section 2 reviews related works. Section 3 elaborates on the proposed methodology. Section 4 provides details on our Faster-RCNN with FPN model for detection and hybrid segmentation and restructuration based on OCR techniques for tabular data extracting. Section 5 presents experimental results and evaluation metrics and section 6 draws the conclusion.

II. RELATED WORK

A. PDF Page Object detection

Table detection is one specialization from object detection for PDF document images. Li et al. [5] used a conditional random field (CRF) classification model as line region type and link classifier on the page object detection. The deep structured predictor performed well on detecting formulas, tables and figures within PDF document images and it mainly achieves to classify regions for different classes. Das et al. [6] performed a Deep Convolutional Neural Network model - VGG16 for document structure learning, and constructed levels of transfer learning for model training for image segments. The approach is more suitable for region-based classification for scanned PDF images. Loc et al. [7] used a fully convolutional network (FCN) to do watermarking regions detection, and FCN-based approach is powerful for region segmentation on stable contents such as tables, headers and so on.

B. Table and structure recognition

There are remarkable works on extracting all table data from PDF files, which contain table detection and structure recognition. Paliwal et al. [3] demonstrated a novel end-to-end deep learning model - TableNet which was based on pre-trained VGG-19, so as to detect tabular regions and column masks. They mentioned that the model was built for detection and extraction from scanned images and needs strictly vertical table layouts as the input for column detection, so the extraction was limited by the table formats. Prasad et al. [8] proposed CascadeTabNet which is a Cascade mask Region-based CNN High-Resolution Network model combining the transfer learning, image transformation and data augmentation technique to improve the process. They used the approach for end-to-end tabular region detection and recognized the structural table cells from document images. Li et al. [5] presented a new image-based dataset - TableBank for table detection and recognition from PDF documents. In order to test the quality of the dataset, they used the Faster R-CNN with Region Proposal Network (RPN) architecture to detect table areas and adopted the image-to-markup model [9] to extract the tabular structure.

Faster RCNN system is a typical deep learning model for object detection. Ren et al. [10] introduced RPN on the Fast RCNN model to share feature maps and the Faster RCNN model performed effectively on real-time object detection. For text and structure extraction, OCR is a powerful technique, ”reading” all word positions within documents. Paliwal et al. [3] used Tesseract OCR to formulate rules for row segmentation covering different problems from line demarcations.

C. Table Region Detection

III. METHODOLOGY

A. System Overview

In this paper, we aim to detect tabular regions from page images through deep learning architecture and extract embedded texts from table images in order to rebuild the layout. Thus, we used the Hybrid Faster-RCNN modelling with FPN framework to locate tabular regions in page images. To achieve the target of texts and structure extraction, we integrate row and column segmentation rules based on the OCR technique and design a deep learning language modelling, Sequence-to-Sequence (seq2seq), to separate headers and instances.

Our main procedures contain the conversion from PDF files to page images, detection of table region images on page images, extraction of cell information embedded in table region image, reconstruction of table layout, separation of table schema and instances. After the process of detection and extraction, the system outputs structured tables and saves in...
We used the Faster-RCNN model as the baseline to support object recognition and introduced the FPN backbone to build the feature pyramids so as to improve the speed and accuracy of the model. As the original input of our proposed deep learning model, PDF files have various types, including text-based or image-based pages which cannot be used directly as input to predict bounding boxes of tables. Therefore, we converted all PDF files into page images with stable size and dropped all dot per inch (dpi) down to 200 for keeping acceptable image quality. All unified page images can improve the learning capability of our proposed model.

Faster RCNN [10] is one of classical deep learning detectors that uses a single Convolutional Neural Network (CNN) to make regional proposals and bounding box regressors, rather than using Selective Search to generate a pile of potential regions. In our detection model, the page image is provided as the input for the convolutional neural network, providing a convolutional tabular map. The original Region Proposal Network (RPN) works by passing a sliding window over the CNN feature map and outputs four potential bounding boxes for table regions in each window, as well as the corresponding and expected quality score. The related Region of Interest (RoI) pooling layers are adopted to reshape the table region proposals from feature maps and extract $7 \times 7$ tabular areas. And then all pooled table regions go through the hidden fully-connected (FC) layers to output 1024 dimension table images, and the ///bounding box regressor/// predicts the final table regions in the last output layers. Figure 2 shows the process of the detection model. It is consistent with the R-CNN model, using information such as classifying the content within the border or discarding it, marking the border content with the background, and adjusting the coordinates of the border to better contain the target [10].

To improve the performance of Faster RCNN detector, we defined four feature pyramid levels of FPN [11] on the model to further advance the accuracy of the segment proposal. Figure 3 shows the approach of how a table block in a page image is determined by conjointly using bottom-up pathway and up-down pathway. After undergoing $1 \times 1$ convolution, we obtain low-resolution but semantically strong table maps on four convolution layers, and then we capture high-resolution but semantically weak table blocks which are upsampled by a factor of 2. After the lateral connection, we merged tabular maps with the same size on each stage and predict the final feature maps for tabular regions in page images. FPN replaces the single-scale feature map in Region Proposal Network (RPN) by multi-level feature pyramid architecture and generates strong semantic tabular maps at four anchors with the area of $256^2$, $512^2$, $1024^2$, $2048^2$ pixels on P2, P3, P4, P5, P6 respectively in figure 3. In this way, we input images from a single scale and quickly build a feature pyramid with strong semantic information on all scales without any obvious cost [12].

### B. Text and Structure Extraction

All table regions in page images are located and generated through the detection model based on the deep learning architecture. In page images, table areas are displayed with diverse formats where the segmentation between each cell could be done by lines or white spaces. In most of the previous experiments, table extraction would be considered as the structure recognition which needs a large and complex annotated dataset to conduct the cell classification. However, it is hard for object detection to capture the completed and detailed layout as it relies on diverse and complex region annotations on the huge datasets. Therefore, we put forward an integrated layout segmentation architecture combined with OCR technique to simplify the extraction process and reconstruct tabular structure only depending on the original layout. Py-tesseract, a typical OCR tool, can “read out” spatial positions of word patches embedded in images. The approach is capable to deal with most structured and numerical tables with strictly horizontal and vertical distributions, based on which the foreground texts can be segmented cleanly from the background image. We designed a sequential procedure from word extraction to row and column segmentation for efficient layout reconstruction.

1) **Spatial Character Extraction of Text:** Our segmentation rule was built on the horizontal and vertical level of texts in the table, which is different from typical cell region recognition by detection models. Region recognition needs a manual annotation dataset and deep learning architecture, which as
a result, depends on vast amount of pre-work and external tools compared with our approach. OCR technique provides a strong power to support the extraction of all word positions. According to the features of the input image, we set a flexible OCR engine mode which is either single mode or a merged mode based on Legacy and Neural net Long Short-Term Memory (LSTM) engine, and additionally, we assumed the entire table as a single uniform block of texts. Therefore, each word embedded in the tabular image is obtained with its verbose spatial data, line number, word sequence, horizontal and vertical coordinates, etc. All characters are captured from the spatial distribution of texts and used as row and column demarcations for table rebuilding.

2) Reconstruction of Tabular Layout: In most table structure recognition models, the performance would be impacted by the diversity of table formats and complexity of manual annotations on cells. However, spatial segmentation rule is formulated by the original distribution of word patches, and the reconstruction complies with the table formation and is not limited by the complex table layout. Same line numbers and ascending word numbers extracted by OCR technique can generally segment table rows where words are sorted by horizontal and vertical levels successively. Spaces between adjacent words identify words in one cell, and the largest number of cells in each row is equal to the number of table columns. Furthermore, horizontal centers of cells in this longest and unique row list act as standard column demarcations. We mapped column demarcations to horizontal levels of cells in each row to segment table columns. In tables, wherever a row lacks of row title, that non-blank cell needs to be merged into cells in the upper layer. The procedure of row and column segmentation is the table layout reconstruction as well, and it maintains the original structure as accurate as possible.

3) Separation of Table Header: Although table structure is extracted by segmentation rule, contents cannot be divided by position demarcation. After the row segmentation process, headers may be the super contents which can spread out over multiple cells. Seq2seq model in conjunction with beam-search optimization schema [13] inherits and extends the estimation for global, next-word sequence. The model predicts the occurrence possibility of the followed word when being provided a header content if the first word of the next cell falls into the candidate words, and then it is marked as a header. This technique utilizes deep learning modelling and can be continually improved with the growing size of candidate words. Considering the size of the word library, we design another alternative method, regular expression to classify header and instances. The premise is that tables keep consistent structures and headings. Since all instances have unified data types which is quite different from headers, we determine the boundary of the table schema when comparing the similarity for row values. Using a rule-based program to specify what content we are expecting as a header row works.
effectively in our program.

IV. EXPERIMENT RESULT

A. Dataset

We conducted experiments on the Financial Documents dataset, which is a customized dataset. There are 78 PDF files used as training data and 30 PDF files used as the testing data for the performance evaluation. This testing data contains 438 tables within pages images from Financial Documents. We convert all PDF files into page images and use them to test the performance of our detection model. Furthermore, we perform our table extraction approach on the testing dataset for evaluation.

B. Data Annotation

There are few text-based datasets containing large volume of page images for table detection and extraction. To improve the training effect, we annotate 108 Financial Documents collected from the Business School of the University of Sydney. All PDF files are the text-based format so all table areas are stable and structured. After converting each page in PDF documents into files of images, we labelled each qualified table with the category, Table, and use rectangles to outline the tabular region. in every image and there might be several tables on a single page image. In the dataset, we draw bounding boxes on 3238 page images where the training data is 2800 images and testing data is 438 images. There are totally more than 4000 tables in the training dataset to support the training process so as to improve the effectiveness of the learning procedure.

![Fig. 5: Samples from annotated Financial Documents Dataset](image)

C. Implementation Details

We built and implemented the Faster R-CNN model with the adjusted configurations, the model has pre-trained backbones on financial document dataset with training schedules of 450 iterations. The learning rate is modified as 0.0015, the batch size is set as 128, momentum is defined as 0.9, and other configurations are kept as default. All models and baselines are obtained based on Big Basin servers with 8 NVIDIA V100 GPUs & NVLink and software such as PyTorch 1.3, CUDA 9.2, cuDNN 7.4.2 or 7.6.3. The experiments were conducted on Google Colaboratory platform, with P100 PCIE GPU of 15.90 GB GPU memory, Intel(R) Xeon(R) CPU @ 2.20GHz and 12.72 GB of RAM.

D. Evaluation

To evaluate the performance of our own detection model, we adopt average precision (AP), average recall (AR), F1 score based on diverse Intersection Over Union (IOU) threshold. The experimental results for table detection are measured by these standard metrics.

The precision rate is computed by the equation: precision = True positive / (True Positive + False Positive) and recall rate is computed by the equation: recall = True positive / (True positive + False negative). In addition, F-score is computed as the harmonic average of recall and precision value, which is equation 2 * (Precision * Recall) / (Precision + Recall).

We uniformly define the True Positive type of detection result and use them to compute the precision and recall. All regions recognized should include the table header and all instances, which ensure that the whole table in the ground truth is captured. The area within the bounding box must be without any noise that impacts the purity of the tabular region. In our model, other elements in a confusion matrix are represented as False Positive which means not being a table with bounding boxes and False Negative which means actual tables with incorrect bounding boxes or without bounding boxes. We use confusion metrics to calculate the precision, recall and F1 metric.

In our model, elements in a confusion matrix are represented as the result and the ground truth to compute the evaluation metrics. IoU is calculated to tell if a table region is correctly detected, and it’s used to measure the overlapping of the detected polygons. GTP defines the Ground Truth Polygon of the table region and DTP defines the Detected Table Polygon. IoU has a range from 0 to 1, where 1 suggests the best possible segmentation. When evaluating, different threshold values of IoU will be used to determine if a region is considered as being detected correctly. For example, the threshold value of 0.5 indicates that once the detected region is greater than 0.5, it will be considered as correctly detected.

E. Result and Analysis

TABLE I: Evaluation Result for Detection Model

| Model                | AP (IOU) 0.5 | AP (IOU) 0.75 | AP (IOU) 0.90 | AR    | F1    |
|----------------------|--------------|---------------|---------------|-------|-------|
| FRRCNN-R50-FPN-1×    | 0.940        | 0.864         | 0.662         | 0.729 | 0.693 |
| FRRCNN-R50-FPN-3×    | 0.940        | 0.766         | 0.655         | 0.739 | 0.694 |
| FRRCNN-R101-DC5-3×   | 0.958        | 0.815         | 0.661         | 0.757 | 0.706 |
| Our model            | 0.958        | 0.888         | 0.784         | 0.833 | 0.808 |

1) Table Detection: Table I shows the comparison of the proposed method and other baselines. We use the following table detection models to implement fine-tuning above our Financial Documents dataset. FR-RCNN-R50-FPN is the Faster RCNN model based on ResNet-50 model and FPN as the backbone, FR-RCNN-R101-DC5 is the Faster RCNN model
Fig. 6: Three samples represent the procedure of table detection and extraction. Each row shows the stages from original page images (a),(d),(g), to detection results (b),(e),(h) and to extraction results (c),(f),(i)

based on ResNet-101 model with dilations in conv5 and FR-RCNN-R101-C4 is the Faster RCNN model using ResNet conv4 backbone with conv5 head. As we can see, our proposed method achieves better results on all the metrics. This is mostly because we implemented FPN Faster R-CNN in conjunction with FPN on our model of ResNeXt101. ResNeXt101 requires minimal extra effort designing each path, and the total number of neural network is 101 which is double of the number layer of ResNet model implemented by FR-RCNN-R50-FPN-1x and FR-RCNN-R50-FPN-3x models. Thus, AP under IOU 50 of these models are similar, however, AP among IOU 50 to 95 of our model is obviously higher than others. Moreover, unlike ResNet model, the neurons in ResNeXt at path will not be connected to the neurons at other paths. In addition, compared to other models based on Faster R-CNN in conjunction with DC5 and C4 backbones, such as FR-RCNN-R101-DC5-3x and FR-RCNN-R101-C4-3x models respectively, combinations that involve the FPN and 101 layers of neural network use standard Conv and FC heads for mask and box prediction, therefore, it can obtain the best accuracy. Model experimental results are shown in Table I.

2) Table Extraction: In the experiment for table extraction, we present tables in the database (like figure 5) after using our segmentation and restructure rules for table regions since our approach relies on the real spatial positions of sub-cell not the object recognition architecture. The table schema is the
table headers separated from table instances, which shows the table structure and data types as well. All values in the table body are specific attributes of records. We extract tables from the original PDF page image and save them into the database for practical using. The accuracy of text extraction depends on the OCR technique and the language of original PDF documents. In this paper, our approach can extract all texts within tables from the Financial Documents dataset apart from special characters. There are diverse tabular formats in PDF files increasing the difficulty of structure reconstruction. Each instance can be restructured completely, however, it exists minor error in deciding values of attributions.

V. Conclusion

In this paper, we propose a PDF table detector for tabular regions in PDF documents by using Faster R-CNN model with FPN backbone, and a hybrid layout segmentation and reconstruction approach based on OCR technique. We convert original PDF documents into page images, detect table areas by the deep learning model and extract all texts and structure by spatial locations. We annotate a new dataset manually for table detection and extraction and our proposed method achieves outstanding performance on detecting table areas. Table schema and instances are separated effectively and saved in the database for practical utilizing. In the future, we tend to add object classes, such as figure, formula, text, etc. in the annotated dataset to improve the accuracy for table detection. There are some limits in special character extraction from table regions so another focusing point is optimizing the text extraction method.

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