



# Automatic Table Detection, Structure Recognition and Data Extraction from Document Images

Borra Vineetha, D. N. D. Harini, Ravi Yelesvarupu

**Abstract:** In the recent advancement, the extensive usage of electronic devices to photograph and upload documents, the requirement for extracting the information present in the unstructured document images is becoming progressively intense. The major obstacle to the objective is, these images often contain information in tabular form and extracting the data from table images presents a series of challenges due to the various layouts and encodings of the tables. It includes the accurate detection of the table present in an image and eventually recognizing the internal structure of the table and extracting the information from it. Although some progress has been made in table detection, obtaining the table contents is still a challenge since this involves more fine-grained table structure (rows and columns) recognition. The digitization of critical information has to be carried out automatically since there are millions of documents. Based on the motivation that AI-based solutions are automating many processors, this work comprises three different stages: First, the table detection using Faster R-CNN algorithm. Second, table internal structure recognition process using morphology operation and refine operation and last the table data extraction using contours algorithm. The dataset used in this work was taken from the UNLV dataset

**Keywords:** Deep Learning, OCR, Scanned documents, Table detection, Structure recognition, Table data extraction

## I. INTRODUCTION

Tables are widely used in many domains to present and communicate structured information to human readers since tables enable readers to search, compare and understand facts and draw conclusions rapidly. Hence, automatically detecting tables from documents and extracting the information contained in tables are of significant importance in the field of document recognition and analysis and have attracted a lot of research efforts in the past few decades. This paper focuses on the table detection, table internal structure recognition and data extraction in scanned documents. Scanned documents

have become more and more popular. However, there is little or no structure information in scanned documents, which makes the information extraction and document understanding a challenging task.

As far as table detection is concerned, many researchers accomplished the task on scanned document images and web pages. Still, no work can handle all the tables well due to the diversity of table layouts and a variety of encodings. The existing methods for table recognition still have some challenging problems. For example, the image-based methods are prone to fail when directly carried out on scanned pages, while most of the rule-based methods are hardly able to recognize the tables without ruling lines or the tables that have complex layouts. More often, intersected vertical and horizontal lines are usually detected as faked tables in prior methods.

Meanwhile, in recent times, Deep learning techniques have improved the results of many computer vision tasks and information processing work to a great extent. In order to improve table detection performance and make up for the limitations of prior methods, this paper proposes a method of table detection based on deep learning techniques. This paper adopts the Faster R-CNN [1] algorithm to detect the tables and proposes the thresholding method to recognize the tabular internal structure. And then uses the adaptive thresholding method through OCR for data extraction from the tables.

In this paper the main focus is on the tabular data present in the images. Section 2 summarizes the relevant work on table detection, internal structure recognition and data extraction. Section 3 describes the framework of the proposed method in detail. Section 4 analyses the experimental results. The conclusion is discussed in Section 5.

## II. RELATED WORK

In 1997, P. Pyreddy and W.B. Croft [2] was the first to propose a method for detecting tables using heuristics. The method was called TINTIN. To recognize table-like structures and their component fields they utilized the structural data present in the document. From the sequence of the words to the gap between them, the heuristics are categorized. Components are detected by visualization but not what they possibly mean. Doo soon Kim and Miao Fan [3] had developed a method for detecting the tabular structure from PDF documents by utilizing three classification algorithms namely Logistic Regression, Support Vector Machine, and Naïve Bayes.

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In 2015, Florence Folake Babatunde et al. [4] presented a work to detect and extract table regions automatically by using Hidden Markov Model (HMM) from heterogeneous documents. The model was tested and trained with 526 self-generated tables. For the testing purpose, they have used the Viterbi algorithm. H.T.Ha et al. [5] introduced the OCR Miner system which is designed to extract the data present in the structured documents from scanned images.

Amir Riad et al. [6] has proposed the classification and information extraction methods for complex tabular structure in images. Their proposed document classification method uses document layout, and OCR'd text information and, based on the combination of relative ROIs and RegEx the information extraction process is performed. Tuan Anh Tran et al. [7] implemented a method for detection of table regions by using a Random Rotation Bounding Box which is used for description and illustration of the table areas. Their system performed three different stages to recognize the table areas: classification of the non-text and text elements present in the input image, recognition of the un-ruling line tables and the ruling-line tables. Their algorithm has been evaluated on three publicly available datasets namely ICDAR2013 table competition, Diotek and UNLV.

Manabu Ohta et al. [8] proposed a cell detection method for table-structure recognition and automatic generation of graphs from the tables. They detected the cells by evaluating indirect rules to identify the table structure. They have used the ICDAR2013 table dataset for implementing their method. Rastan et al. [9] recently developed the TEXUS framework (2019), which identifies the structure of a table in an unconventional layout manner. This work is limited to born-digital PDFs only. In [10], the authors chose to form twenty rules to detect a table. These rules are applied to frames of web pages. The interpretation phase follows locating the tables. They again use visual rules to extract information from the tables. Elvis Koci et al. [11] proposed a framework that will be able to automatically infer the structure and extract the information from the documents in canonical form.

III. PROPOSED METHODOLOGY

The proposed method consists of three major modules: Table Detection, Table Structure Recognition and Table Data Extraction present in the table. This section will discuss each procedure in detail. The system architecture of the proposed work is shown in figure 1.

A. SYSTEM MODEL

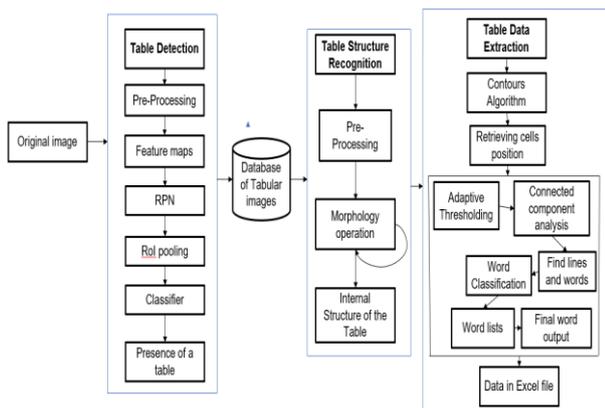


Figure 1. System Architecture

In the above figure 1 there are three stages in the proposed system which are as follows: first, table detection which includes pre-processing and faster R-CNN algorithm; second, the identification of the tabular structure including rows and columns using morphology operations; third, extracting the data present in the table from the document image by applying OCR.

B. Table Detection

In this, we will identify the presence and location of the table present in the image from the scanned document. For this purpose, a deep learning framework called Faster R-CNN is utilized for the detection process. The Faster R-CNN model consists of a detector which is Fast R-CNN and a Region Proposer which is RPN. This is an object detection algorithm. It is the improved version of Fast R-CNN. R-CNN and Fast R-CNN need an external region proposer called selective search whereas Faster R-CNN doesn't need any external Region proposers because it has an RPN model.

The architecture of table detection using Faster R-CNN is shown in the below figure 2. The very first step of the FRCNN algorithm is the Region Proposal Network. The task of RPN is to find out those areas in an image where there is a possibility of an object present. It means the area in the picture where the object can be possibly found. The process of RPN starts with the use of Anchor boxes. These are the set of pre-defined bounding boxes of some height and weight. After generating the anchor boxes the next step is to find out IoU. Under anchor box, with the higher IoU i.e.,  $IoU > 50\%$  will be labelled as foreground labels otherwise labelled as background class. The output from RPN will be a feature map of those with anchor boxes labelled as foreground boxes.

Algorithm: Region Proposal Network Layer

Input:

- Pre-processed scanned document image(S)
- Pre-processed template Document image(T)
- Annotation for template document ( $A_T$ )

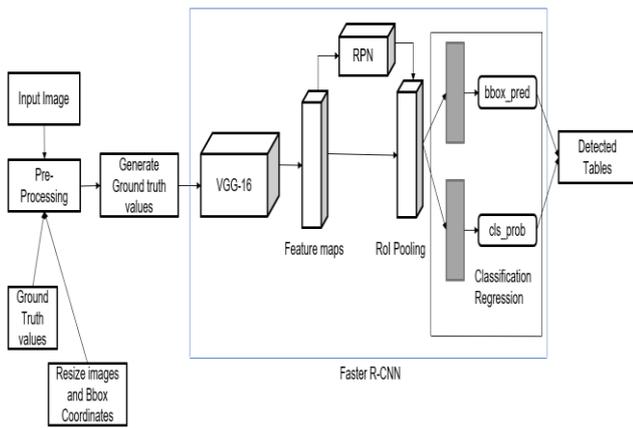
Procedure:

- Image width-  $W_T \leftarrow \text{Width}(T)$
- Image height-  $H_T \leftarrow 1.4 * W_T$
- For each field in  $A_T$  do
  - Obtain rectangular area of the field
  - The area of the rectangle in all the directions should get increased slightly Crop the new area in the document image
  - Find the area of the field in the given image
- End for

Output: region proposals for all the fields in the document images

Figure 2. Architecture of Table detection





Next is the ROI Layer; the data which the ROI layer receives is the output of the RPN layer. The input to this ROI is different sizes of feature maps. The task of ROI is to reduce all the feature maps to the same size. ROI pooling layer will produce fixed size feature maps from the different sized regions using max pool on it. The size of max pool is 7\*7 and number of channels are 512. ROI pooling accepts two inputs. One is ROI which RPN creates and the other is feature maps from VGG. The figure 3 is the output image after performing the table detection process.

Algorithm: Area Selection

Input: Input scanned document Template Document Region proposals in input document Input document and template document dimensions

Procedure:

- for every field in region proposal do
- find the texts which are in common in the proposal area from the input image, and the corresponding area from the template image. ▪
- If same>0 then\*
- Find the text which is nearer to the original value for the field from the template image
- Get a vector from the center of the approx. text and the original value.
- With the help of dimensions of the template image, normalize the vector. Using the dimensions of the input image, de-normalize the vector.
- Predict the center using the vector in the given image for which the value of the field is present.
- Acquire the rectangle in the given image by applying scaling appropriately.
- else acquire the rectangle at the center of the closest area by considering the value of the field in template image
- end if
- end for

Output: Final Bboxes for all the fields in the scanned document given as input.

Undergraduate and Graduate Enrollment: All Bachelor's Degree Recipients

Every five percent of bachelor's degree recipients who enrolled in graduate or first-professional degree programs took out loans to help pay for their education, borrowing an average of \$33,200 by 2003 (table 4). Borrowing a large amount as an undergraduate does not appear to

Table 4. Among 1992-1993 bachelor's degree recipients with graduate degree enrollment, percentage who borrowed for graduate education and, among borrowers, average amount and percentage distribution of amount borrowed for graduate education, by student and institutional characteristics: 2003

Student and institutional characteristics	Percent		Amount borrowed	
	Borrowed	Average	Borrowed	Average
<b>Total</b>	44.8	\$33,200	23.2	\$8.1
<b>Type of degree-granting institution</b>				
Public 4-year	44.4	32,700	23.5	8.0
Private not-for-profit 4-year	45.9	36,000	23.3	8.3
Public 2-year	45.1	32,800	23.7	8.1
Private not-for-profit 2-year	45.7	42,300	15.5	11.8
Other*	42.3	35,900	11.2	10.2
<b>Undergraduate major</b>				
Business and management	34.3	28,700	28.1	7.1
Education	65.1	23,000	17.4	22.8
Engineering, mathematics, or science	47.1	47,400	18.1	8.3
Humanities or social sciences	52.9	24,800	20.6	8.2
Other	47.4	28,100	21.8	14.3
<b>Amount borrowed (undergraduate)</b>				
Less than \$1,000	36.0	36,300	18.1	7.7
\$1,000-\$5,000	45.7	36,300	28.7	9.3
\$5,000-\$10,000	54.5	29,200	23.6	12.8
\$10,000-\$14,999	54.7	28,700	27.7	16.1
\$15,000 or more	58.4	35,100	18.7	9.9
<b>Highly motivated (undergraduate)</b>				
Major's degree	37.9	19,900	38.0	12.1
Second degree	61.1	45,700	18.3	7.8
Post-professional degree	71.8	49,200	4.8	2.8
<b>Highly motivated (graduate)</b>				
Bachelor's degree	32.3	23,800	16.2	11.6
Master's degree	42.4	29,400	21.9	12.8
Doctoral degree	64.3	44,100	21.8	9.8
Post-professional degree	78.0	75,900	7.8	5.2

\*Other includes health care, architecture, law, and other fields. Source: U.S. Department of Education, National Center for Education Statistics, "2003 Undergraduate and Graduate Enrollment: All Bachelor's Degree Recipients" (October 2005).

(which is not confined to food retailing).

Table 4.B: Franchising across the member states

	number of franchises		number of franchisees	
	1993	1994	1993	1994
Austria	80	170	2400	2700
Belgium-Luxembourg	90	130	3000	2400
Denmark	42	42	500	100
Finland	...	...	...	...
France	100	100	3000	3000
Germany	270	420	1500	1800
Greece	20	...	...	...
Ireland	...	...	...	...
Italy	118	361	18100	17700
Netherlands	211	148	12400	13120
Portugal	55	70	...	...
Spain	117	250	14000	20000
Sweden	206	200	900	100
U.K.	273	306	18100	20000
U.S. Total	2096	2084	117000	129115

Source: table 14, p.18, "Retailing in the European Economic Area, 1996", EUBO/ESAF

With the growth of the hypermarket, in particular, new opportunities for scale economies and innovation have emerged. Perhaps most significant of all, is the growing use of electronic scanning at the check out.

The diffusion of scanning has been rapid in recent years. In all member states for which data are available, its usage at least doubled between 1993 and 1994 (Table 4.5). Assuming a faster acceleration post-1994, it may be seen, how become a significant feature in the operations of many of Europe's leading retailers.

Not only does this technology permit a variety of internal economies, but also it provides the retailer with a rich source of detailed information about, for example, the elasticities of demand for specific brands. Undoubtedly, this has sharpened the retailer's capabilities - both in competing with its rivals and in bargaining with its suppliers, the food manufacturers.

appear to use the term consistently.

Figure 3. Detection of Tables

### C. Table Structure Recognition

After the table presence and location is successfully detected from the image, the next step is to recognize the internal structure of the table. For recognizing the tabular structure, a morphology method is utilized. It is one of the most widely used techniques for depicting the shape of the region in the image. The overall process for Table Structure Recognition is shown in Figure 4. Here we apply dual morphological operations i.e., erosion and dilation with dynamic structuring elements the rows and columns of the table. In this work, the horizontal structuring element and vertical structuring element have been selected to detect the horizontal and vertical lines of the table.

Algorithm:

Input: Database of Tabular images

Procedure:

- List all data-lines within the table as  $x_1, x_2, \dots, x_n$ , and traverse possible line pairs.
  - $X_{ij} = \{T_i, T_j\}, 0 < i < j < n$ .
  - If  $T_i$  and  $T_j$  are not vertically aligned, go to step 7
  - If they are vertically aligned, record all their alignment types in  $P_{ij}$ .
  - Check whether  $T_i$  is already included in the existing column and check if intersection of PC and  $P_{ij}$  is not empty.
  - if yes, add  $T_j$  into C. And set the intersection of PC and  $P_{ij}$  as new PC.
  - if no, create a new column candidate  $C_{new} = \{T_i, T_j\}$ . And set  $PC_{new} = P_{ij}$
  - Continue with the next pair.
- Output: Internal Structure of a Table



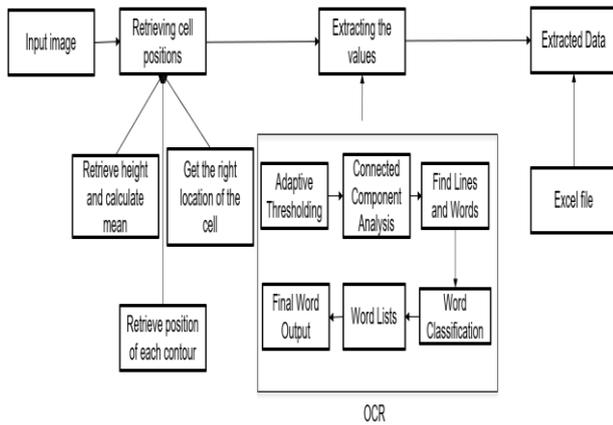


Figure 6: Architecture of Table Data Extraction

Here the box is in the same row if its own (height + mean/2) does not vary more than its original height. But if the height difference is more than the present (height + mean/2), a new row starts. Columns are relevantly arranged from left to right. To know the total number of columns a table contains, the maximum number of columns (meaning cells) should be calculated. After this, the midpoint of each column in a list is to be stored, create an array and sort the values. The proper sequence will be stored in the list final boxes.

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be defined. Do not use abbreviations in

Algorithm:

Input: Database of Tabular images

Procedure:

- assign a confidence weight to every word
  - initialize the confidence for all words to 0
- check the previous word and immediate next word in the correct text using the location to see if it is a match
  - if match
    - increase word confidence and previous word by 25
    - store the location in the database
    - move to next word (again from step 1)
  - if not a match
    - decrease word confidence by 25
    - if current confidence of word=5(match in dict) then
    - decrease confidence of previous word by 25
    - continue to next step
- begin to look for the word in a nearby location
  - search for exact matches after the word for m words (at present m=20)
    - if match
      - increase confidence by 25
      - move to the next word
    - if not match
      - search m words before the previous word
    - if match
      - increase confidence by 1
      - decrease confidence of the previous word by 4
      - move to the next word
      - else

- go to next step
- No match for words immediately after or in the neighbouring x words:
  - Search for matches like in previous step for neighboring words
  - Going to search for words that have an edit distance of Y.

Iterate starting with 1 edit distance until Y  
Limit the size of Y to avoid false positives  
Set a maximum Y of 3  
Edit distance checked is less than Y

- If matching candidate with Y distance is found
  - Increase confidence by 1
  - Move on to the next word
- If not
  - Increase the edit distance (Y++)
  - Continue loop

- If the word is not found, search for the previous X words by allowing an edit distance until Y
- After all these steps if a match is not found
  - Give a confidence of -1
  - Store the location of the previous word plus
  - Apply OCR

Output: Extraction of data from a table

Extracting the values; make use of list final boxes by taking every image-based box and prepare it for Optical Character Recognition by dilating and eroding it. Now let Pytesseract recognize the containing strings. The loop runs over every cell and stores the value in the outer list. The last step is the conversion of the list to a data frame and storing it into an excel-file. The table should now be in an excel-file and can be used for Natural Language Processing, for further analysis via statistics or just for editing it. Figure 7 is the image after data extraction is performed. And that image is in the form of an excel-file.

	A	B	C	D	E	F	G	H
1		0	1	2	3	4	5	6
2		0	Consultant Kaliro Siduco	Project:	XGTR		Customer:	Tech Alive
3		1	Date:	21-May-20	Team:	A	Customer ID	4433228
4		2	Position	service		Factor	Amount	Unit
5		3		Backend			1	10 hours
6		4		Team Meet			1	8 hours
7		5		Milestone P			1	2 hours
8		6		Code Refac			1	4 hours
9		7		Migration			1	4 hours
10		8		Next Steps			1	2 hours
11		9						
12		10				Total		30 hours

Figure 7. Data in excel file



#### IV. RESULTS AND ANALYSIS

The experimental results are shown below. It shows some detected table areas, internal structure of the table and the extracted data present in the table. The table will be in an excel-file and can be used for Natural Language Processing, for further analysis via statistics or just for editing it.

##### A. Evaluation Metrics

Various performance measures have been used for evaluation of table recognition system. These measures include Mean IoU, precision, recall and F1\_score.

- a) Mean IoU: The IoU is the ratio of the area of intersection and area of union of the ground truth bounding box and predicted bounding box.

$$\frac{\text{Area of intersection of predicted and GT bounding box}}{\text{Area of union of predicted and GT bounding box}}$$

- b) Precision: This measure has been used for evaluating the overall performance of table detection method. It finds the percentage of detected tables that belong to table regions of ground truth document image.

$$\frac{\text{Area of GT regions in detected regions}}{\text{Area of all detected table regions}}$$

- c) Recall: It is evaluated by finding the percentage of ground truth table regions that were marked as detected table regions.

$$\frac{\text{Area of GT regions in detected regions}}{\text{Area of all GT table regions}}$$

- d) F1 Score: It is defined as the harmonic mean of the model's precision and recall. It considers both recall and precision to compute the accuracy of the methodology

$$2 \times \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

##### B. Result and Discussions

Performance comparison between Florence Folake Babatunde et al. [4], Ranajit Saha et al. [12], Maik Rhiele et al. [11] and the proposed method is shown in table 1. The results exhibit that the proposed system has better performance by achieving Mean IoU as 88.7, Precision as 97.3, Recall as 92.4 and F1\_score as 90.8. For classification, the mean IoU evaluation metric is used for predicting class labels where the model outputs a single label that is either present or absent. This type of classification makes computing accuracy straightforward. Any algorithm that provides predicting bounding boxes as output can be evaluated using IoU for better results. The work is designed and implemented in the windows operating system having 8GB ram, 2GB Graphic card and 1TB HDD.

Table1: Results Table

Evaluation Metric	Florence Folake Babatunde et al. [4]	Ranajit Saha et al. [12]	Maik Rhiele et al. [11]	Proposed Work
Mean IoU	81.8	-	-	88.7
Precision	96.8	92.8	65.0	97.3
Recall	91.7	92.1	63.0	92.4
F1_Measure	88.8	91.5	61.0	90.8

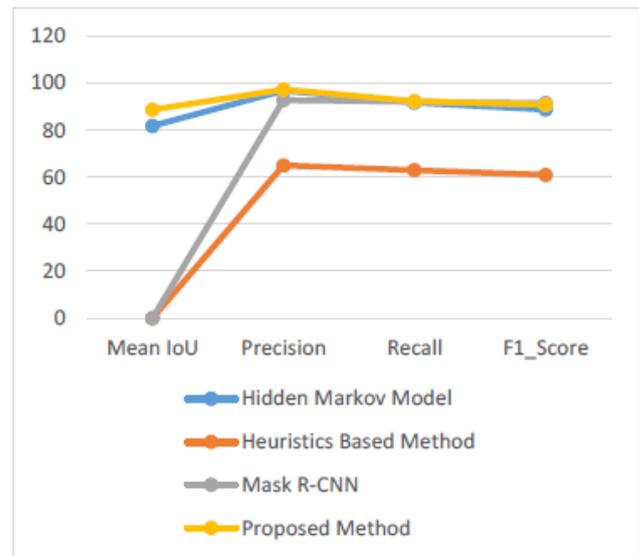


Figure 8: Comparison of Performance Measurements

#### V. CONCLUSION

In this work, a method for extracting data from tables has been developed. In the process of table detection, feature map extraction and classification are done using the Faster R-CNN algorithm. The refine morphological operations erosion and dilation with dynamic structuring elements employed to identify the internal structure of the table. The data from the recognized table is then extracted using the contours algorithm and OCR. In this research, the UNLV dataset is used to extract information from tables. Furthermore, the results of comparative experiments have demonstrated that the proposed method outperforms the existing system and the other approaches with an accuracy of 88%. Further research will focus on improving the system architecture and recognition accuracy for more imbalanced and multiple layout tables.

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**Ravi Yelesvarupu**, completed his Masters in Mathematics from Osmania University, Hyderabad. He had more than 15 years of US experience working for AT&T. Founder of Hallmark solutions, Visakhapatnam. It is an India based startup focusing on cloud, Open source, ML/ AI based solutions in the areas of Data analytics, OCR, Workflow Automation.