# Digitization of Handwritten Ledgers

## An Integrated Approach to Improve Handwritten Text Recognition

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# ABSTRACT

Handwritten text recognition is a crucial step in digitizing historical documents. In this work, we will explore the challenges associated with a handwritten text recognition model using historical ledger pages from the Bank of Amsterdam. We first conduct an error analysis of the model, and based on that make suggestions on where and how the performance of the model could be improved. The main concern is the fact that the model is not able to capture the layout of the pages. We perform post-processing steps to improve the output of the model and we create a layout analysis method, which aims to capture the distinctive tabular layout found in the ledger pages. While earlier research mainly focuses on capturing different elements on documents, such as text, tables and images, our work specifically focuses on capturing table cells and contents from a tabular structure. This is done by isolating the different elements on the page using computer vision tools. We find our layout analysis method to be successful in capturing the different table cells, but not always accurately matching the ground truth bounding boxes. Furthermore, we show that post-processing steps improve the quality of the output of the model.



# KEYWORDS

HTR, Layout analysis, Computer vision, Historical documents, Object detection


# GITHUB REPOSITORY

https://github.com/roderickmajoor/Thesis

# 1 INTRODUCTION

The Bank of Amsterdam was an early bank established in 1609, described by some as the first central bank [20]. The bank played an important role in the financial world of the 17th and 18th century. Transactions made at the bank from 1650 to 1800 were recorded in ledgers and are still preserved to this day. These ledgers contain information about transactions, both debit and credit, of customers of the bank. The ledgers can thus be very important in analyzing the money flow at the time. Digitizing these ledgers may help in preserving them in a much easier to analyze format which would allow for more research into the contents of the ledgers. However, these ledgers are all handwritten making it hard to retrieve the information out of them on large scale. Current efforts to retrieve the information are done by using Handwritten Text Recognition (HTR) tools to extract the text in the ledgers. The problem is that the currently used HTR techniques have too many inaccuracies to be used effectively. Because of this, the handwritten text cannot be recognized correctly and can thus not be digitized properly. To improve digitization efforts, it is crucial to find out why some handwritten text cannot be recognized, what kind of errors are made during the HTR process and how the HTR process can be optimized to improve these inaccuracies. The research question we wish to answer is:

*How can the categorization of errors in handwritten ledger analysis be used to enhance the identification and resolution of text recognition inaccuracies?*

Subquestions belonging to this research question are:

- What factors contribute to text recognition errors in handwritten ledgers?
- What are the different types of errors encountered in handwritten text recognition?
- How can specific processing methods improve text detection and segmentation in handwritten ledgers?
- What strategies can be implemented to mitigate common text recognition errors in handwritten ledgers?

Since we perform a number of different experiments, our report follows the following structure: we start by comparing some related work. Then we will provide a description of the dataset. After that we look at the different experiments, where for each we provide our methodology including evaluation steps as well as results and discussion of that particular experiment. We end with a more general discussion and conclusion.

# 2 RELATED WORK

The research gap being addressed in this project revolves around the challenges associated with the digitization of handwritten ledgers. The proposed research will contribute in closing the research gap within the HTR domain, specifically looking at historical handwritten documents. The digitization of handwritten ledgers contains several steps. In this section, we will look at key research papers that discuss different approaches to the steps of our problem.

## 2.1 Document Layout Analysis

The biggest challenge in our digitization task is being able to find the correct word order from the HTR output. Seuret describes layout analysis and finding the correct word order as one of the main challenges in HTR [21]. Several approaches to solve this problem have been tried. These approaches are typically divided in either deep learning methods or more classical computer vision methods. We will show recent advancements made in both approaches.

Kastanas et al. show the use of different deep learning architectures for layout analysis [8]. Transformer-based, graph-based models, and convolutional neural networks (CNN) are compared. The CNN-based model YOLOv5 and transformed-based model LayoutLMv3 both show promising results for identifying most elements on documents, with YOLOv5 performing slightly better [8].

Multiple other studies describe the use of transformer based methods to perform layout analysis and optical character recognition (OCR) [10, 13, 24]. Furthermore, Smock et al. show that transformer-based object detection models can produce excellent results for the tasks of detection, structure recognition, and functional analysis of tables [22]. While these approaches show promising results, they are not tested for our specific task at hand.

Oliveira et al. propose dhSegment, an open-source implementation of a CNN-based pixel-wise predictor for document segmentation. The approach aims to address various document processing tasks simultaneously, including page extraction, baseline extraction, layout analysis, and illustration and photograph extraction. They show that a single CNN architecture can be used across tasks with competitive results [2].

Droby et al. propose a holistic method that applies Mask R-CNN for text line extraction in historical documents. Their work achieved state-of-the-art results on well known historical datasets [6]. While their work does not directly transfer to our task, it does show the potential for document segmentation and possibly table recognition abilities of Mask R-CNN.

The aforementioned studies show that the use of deep learning methods can be used to perform layout analysis as well as table recognition tasks in historical documents. However, these methods often require massive amounts of training data to be used effectively. To use these methods, we should look whether pre-trained models transfer well to our dataset and are able to detect the layout of our documents. Other approaches use more classical computer vision techniques to segment a document in order to recognize the layout. These methods often require homogeneity of the documents to work effectively.

Lehenmeier et al. show a method that combines various state-of-the-art methods for OCR pro- cessing to detect layout on a document [9]. To perform table recognition, they make use of techniques such as binarization, denoising, and Hough line detection to find relevant parts of the tables. By taking the intersection of relevant horizontal and vertical Hough lines they are able to find table cells and thus determine the layout of the table [9].

Bulacu et al. introduce a method based on contour tracing that generates curvilinear separation paths between text lines in order to preserve the ascenders and descenders of text lines to determine the layout in handwritten historical documents [3]. With this approach they are able to determine seperate elements of tables in historical documents.

Liu et al. describe the use of several key steps, including skew correction, region segmentation, and page layout analysis on historical Tibetan documents [12]. Skew correction is achieved by leveraging baseline features and Hough transform to determine the document's skew angle. Subsequently, region segmentation is accomplished by identifying borders through a series of preprocessing steps, including median filtering, Gaussian smoothing, Sobel edge detection, and removal of small area regions. These processes collectively enable accurate positioning of document borders for further analysis and structure extraction [12].

Liang et al. describe the use of Hessian and Gabor filters in order to find table structures on a document [11]. They show the possiblity for column segmentation for the tables using the found lines.

Prieto et al. address the challenge of document image understanding in documents with complex layouts like tables. They compare two approaches and show promising results [19]. Their approaches take the text lines outputted by HTR systems and use machine learning methods to group these text lines and classify cells based on these grouped text lines in order to find the tabular structure.

It can be seen that depending on the dataset and the homogeneity of the documents, different approaches for layout analysis/table recognition may be suitable. When a similar table structure is clearly drawn on all the documents, approaches using basic image processing techniques could be suitable to determine the structure of the table. When the structure is not easily identifiable on the page, it might be better to look at approaches that use the output of HTR systems such as text lines or words locations to classify table cells. Machine learning based approaches could also be useful in these cases but often require many training data.

### 2.2 HTR Processing Techniques

Typical HTR pipelines consist of pre-processing an image to make it ready for HTR, running the image through the HTR system and post-processing the output of the HTR system [9].

Studies have shown that pre-processing images can lead to better results when using them as input for document layout analysis or OCR. Thus, we want to optimize our image material such that the document layout analysis and HTR can be performed more accurately. There are different methods for doing this such as adjusting the contrast to remove artifacts and noise or fixing the image alignment [1, 5, 9]. It is crucial to find out which pre-processing steps might be useful to our problem at hand. Chen et al. show that the use of several pre-processing steps including character segmentation, tilt correction, offset correction, size normalization and image thinning lead to better HTR output results [4].

Post-processing OCR and HTR output typically consists of trying to correct misidentified words or characters. One strategy to do this is to create a dictionary of candidate characters and use the Levenshtein distance to calculate the distance between predicted and dictionary characters [18]. The use of a dictionary for allowed characters is a shown to be a good strategy to eliminate HTR errors [9]. Other studies show the use of language models to correct word output and spelling in HTR systems [15, 18].

### 2.3 HTR Evaluation Strategies

Typically, HTR systems are evaluated using the word error rate (WER) and character error rate (CER). However, the evaluation of page-level HTR output faces challenges primarily due to the Reading Order (RO) problem [23]. In their study, they define a bag-of-words Word Error Rate (bWER) to accurately measure page-level RO-independent word errors as well as a regularized version of the Hungarian Algorithm (HA) to compute word- and character-level RO-independent recognition accuracy [23]. Another strategy is the use of the intersection over union (IoU) score which matches ground truth and HTR output boxes based on their coordinates on the page [17]. It is then possible to use the WER and CER to calculate the accuracy.

## 3 DATA DESCRIPTION

The dataset used in this study consists of pages from the collection of ledgers from the Bank of Amsterdam. The full collection can be found on the website of The Amsterdam City Archives. In the series of ledgers, the current accounts of the customers were maintained. Each customer had one or more pages, with smaller traders having a portion of a page. An alphabetical list of the traders and the page of their current account can be found in the index. The ledgers kept track of the amounts that were debited and credited from and to a customer. The ledger pages consist of several columns containing information such as the date, account holder name, account number and amount debited/credited. Figure 9 shows an example of what a page looks like. Our dataset is split into multiple subsets that come from different books and that all have slightly varying pages, while still having structural similarity. Figure 1 shows the amount of pages for each subset in the dataset. The total dataset consists of 68 pages. A word count for each page is shown in Figure 2

The ground truth and HTR system output both use a PageXML format to store values on the page. These PageXML store the coordinates for each item (e.g. textregion, tableregion, etc.) on the page. We can plot the values in the PageXML file over our image to better show this. Figure 10 shows the PageXML data of the ground truth and HTR system plotted on the original image for part of one page in our dataset.

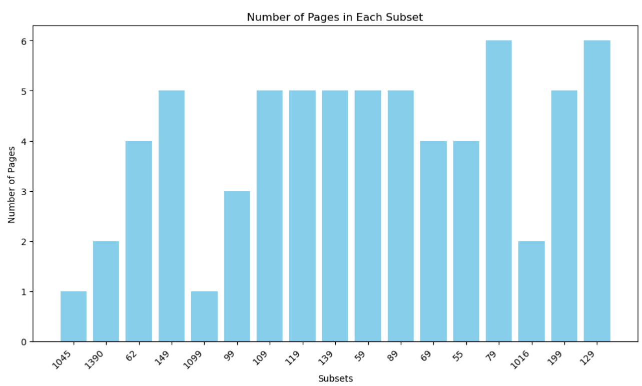



**Figure 1: The amount of pages for each subset in our dataset.**

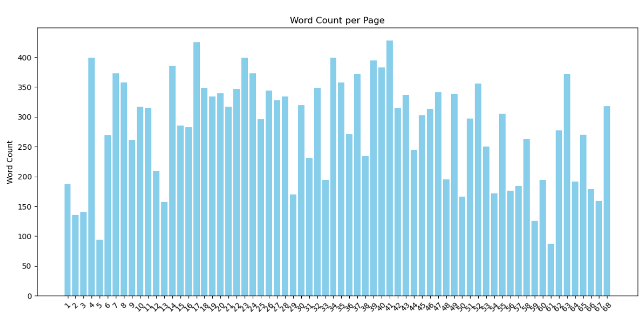



**Figure 2: The word count for each page in our dataset.**

# 4 HTR SYSTEM ERROR ANALYSIS

## 4.1 Method

Before attempting to improve the HTR system, we will first conduct an extensive analysis to identify where the current system fails or has flaws. This will involve creating a categorization scheme that shows for each category the nature of the error and a possible solution. Based on this scheme, we can then try out various steps to improve the HTR system.

To obtain the accuracy of the HTR system, we will need to compare the HTR output to the ground truth values. This in itself is not straightforward, since the ground truth values do not contain all the words in the image while the HTR output does. Furthermore, since the layout of the page is not recognized by the HTR system, the order of the words is completely different in the ground truth and HTR output. To still compare the ground truth values and HTR output, we will use an approach that matches the words based on their bounding box coordinates on the image. To do this we make use of the IoU score. This is a technique that can be used to find how similar two bounding boxes are [17]. By matching each bounding box in the ground truth with a corresponding bounding box in the HTR output based on the highest IoU score, we can compare the groud truth values and HTR output on a word to word basis.

Once we have aligned the words in the ground truth and the HTR output properly, we can start to identify the flaws of the HTR system. We will make use of the Levenshtein distance, which can be used to find the minimum number of single-character edits (insertions, deletions, or substitutions) required to change one string into the other [7]. By applying this on our ground truth values and HTR output on a word to word basis, we can track how many character insertions, deletions and substitutions are done in the HTR output for each word in the ground truth. We will show this for each subset of our data to also see whether some subsets are more difficult for the HTR system. We will also keep track of what characters are inserted, deleted or substituted so we can find what characters seem to be most problematic for the HTR system.

By creating this analysis, we can also better inspect our image by visually showing the words that the HTR system can or cannot match. An example of this visual representation is shown in Figure 11. Using this visual representation, we can inspect the image to see whether there are any characteristics that might cause the HTR system to make errors. This could be noise on parts of the page, words being close together or even overlapping etc.

Upon completing our analysis, we can conduct a list of main errors made by the HTR system and decide on what steps could be taken to mitigate these errors. The approach for these possible solutions is outlined in further sections.

## 4.2 Evaluation

For the evaluation of the HTR system, metrics such as WER, CER, and Levenshtein Distance will be calculated. These metrics measure the minimum number of operations (substitutions, insertions, deletions) needed to transform the HTR output into the ground truth. The formulas for these metrics are:

$$WER = \frac{S_w + D_w + I_w}{N_w} \tag{1}$$

Where $S_w, D_w, I_w$ are the number of word substitutions, deletions and insertions respectively and $N_w$ is the total number of words in the ground truth.

$$CER = \frac{S_c + D_c + I_c}{N_c} \quad (2)$$

Where $S_c, D_c, I_c$ are the number of character substitutions, deletions and insertions respectively and $N_c$ is the total number of characters in the ground truth.

We will also calculate recall and precision scores. To calculate those for HTR output, we first need to define what constitutes true positives (TP), false positives (FP), and false negatives (FN) in our context.

- **TP (True Positive):** Characters correctly recognized by the HTR system.
- **FP (False Positive):** Characters incorrectly recognized by the HTR system (i.e., system identifies text where there is none or incorrectly identifies text).
- **FN (False Negative):** Characters that are present in the ground truth but not recognized by the HTR system.

The recall and precision are then:

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

### 4.3 Results

The accuracy of the current HTR system using the aforementioned metrics is shown in Table 1. As can be seen, the accuracy of the base model is not flawless. The recall is quite high, showing that not a lot of false negatives are found. However, the precision is lower, showing that the models incorrectly captures text. A more in-depth analysis about the amount of character insertions, deletions, substitutions and matches made by the HTR system can be seen in Figure 4 and Figure 3. Here, we can clearly see that substitutions and mainly insertions of characters are the main problem of the HTR model while deletions are relatively low. In order to improve the model, it is thus crucial to find a way to mainly reduce the insertions and substitutions made by the model. Figure 5 shows the frequencies of characters inserted, substituted and deleted. Here we can see that a lot of 'invalid' characters are inserted. These are non-alphanumeric characters that should not be part of our dataset. Furthermore, we see that many numbers and letters that look a like (such as i and 1) are substituted. We use these analyses and the fact that the HTR system is not able to capture the layout of the pages to conduct a list of errors made by the HTR system. A selection of the most common errors and possible solutions is shown in Table 2. In further sections, we will use the results of this section to improve the model.

**Table 1: Baseline scores for the currently used HTR system. We matched the ground truth words with HTR output words based on highest IoU value.**

| Metric | Value |
|---|---|
| WER | 0.4243 |
| CER | 0.3422 |
| Recall | 0.9475 |
| Precision | 0.7403 |
| Total Edit Distance | 18920 |

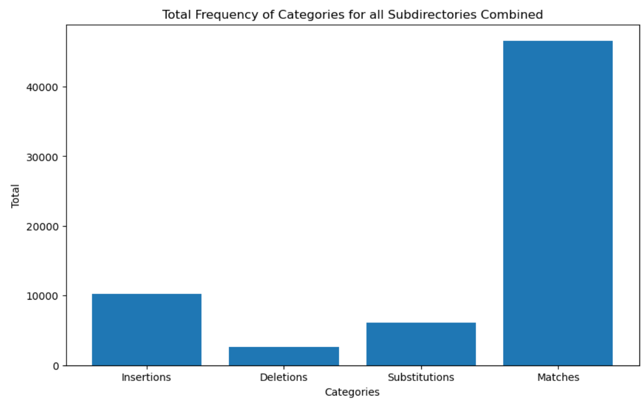
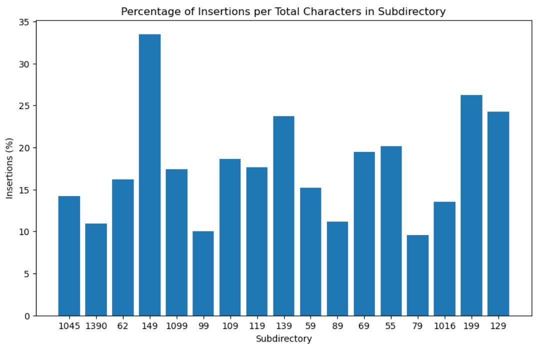
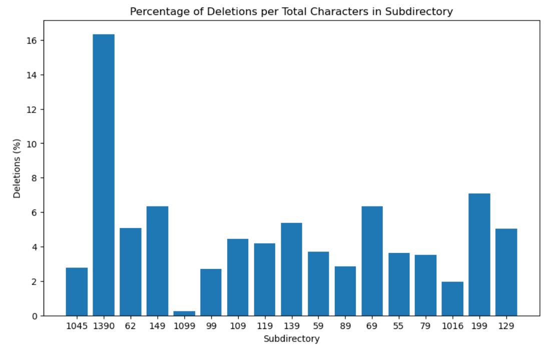


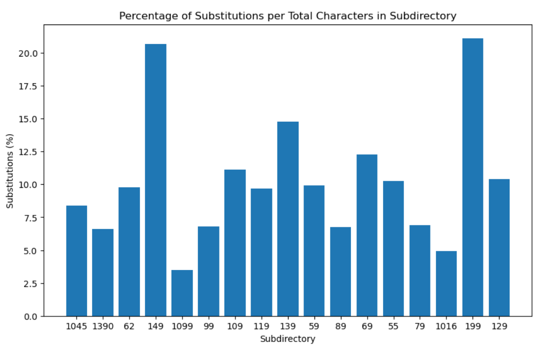

**Figure 3: The total amount of insertions, deletions, substitutions and matches made by the HTR sytsem compared to the ground truth values. The values are on a character level and made word per word.**



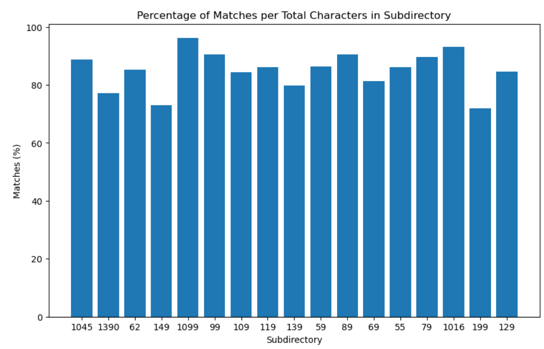

**(a) Amount of insertions made by the HTR system per subdirectory.**




**(b) Amount of deletions made by the HTR system per subdirectory.**




**(c) Amount of substitutions made by the HTR system per subdirectory.**

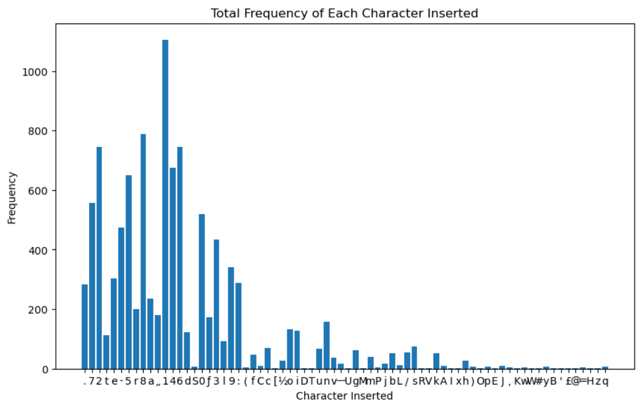



**(d) Amount of matches made by the HTR system per subdirectory.**

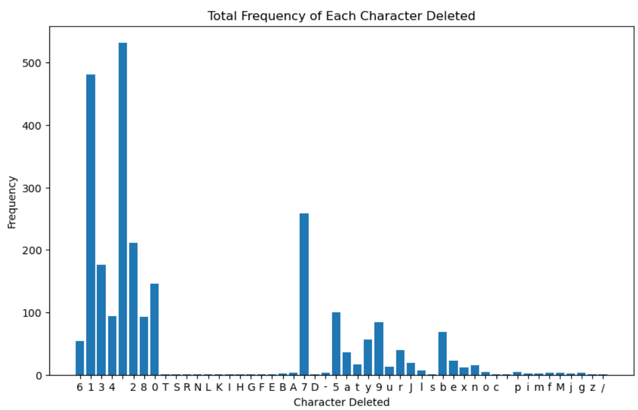
**Figure 4: The amount of insertions, deletions, substitutions and matches made by the HTR system compared to the ground truth values. The values are on a character level and made word per word and as a percentage of total characters in ground truth.**

**Table 2: Categorization of HTR System Errors**

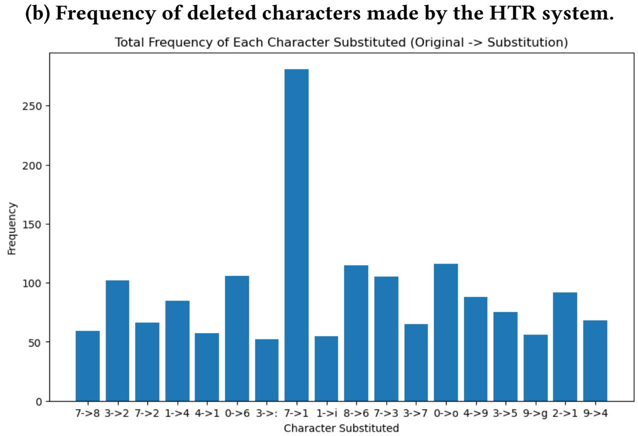
| **Error Type** | **Description** | **Possible Solution** |
|---|---|---|
| Deletions | Characters not recognized at all (false negative) | Improve HTR system, post-processing |
| Insertions | Characters recognized that are not there (false positives) | Improve HTR system, post-processing |
| Substitutions | Characters recognized as another character | Improve HTR system, post-processing |
| Layout - Word Split | Single word is split into separate words | Layout analysis |
| Layout - Word Merge | Multiple words are recognized as one word | Layout analysis |
| Layout - Data Split | Data wrongly split (e.g., 'feb 5' in GT becomes 'feb' and '5' in HTR) | Layout analysis |
| Layout - Word Order | Word order not recognized | Layout analysis |
| HTR - Bounding Box | Wrong location bounding box vs actual location word | Improve HTR system |
| Case Sensitivity | Case sensitivity issues | Post-processing |
| Invalid Characters | Characters that cannot occur | Post-processing |




**(a) Frequency of inserted characters made by the HTR system.**




**(b) Frequency of deleted characters made by the HTR system.**




**(c) Frequency of substituted characters made by the HTR system. The substitutions are shown as (original character -> substituted character). We only show the substitutions with a frequency of 50 or higher.**

**Figure 5: The frequencies of inserted, deleted and substituted characters made by the HTR system.**

# 5 POST-PROCESSING

## 5.1 Method

From our error analysis, we find that using post-processing techniques may lead to improved accuracy. Post-processing in our experimental framework focuses on refining the output generated by the HTR system. One such post-processing step involves the removal of characters from the output strings that do not align with the ground truth dictionary [9, 18]. Analysis of the HTR output (as depicted in Figure 5a) reveals several insertions that are not valid letters or numeric characters. To address this, we employ regular expressions (regex) to filter out invalid characters from the HTR output. We are then left with alphanumeric characters only. Furthermore, the HTR system often substitutes letters for numbers, as can be seen in Figure 5c. We can undo these substitutions in some cases. For instance, when a single character is found to be a letter by the HTR system, we can expect this to be wrong, since single character words are never letters in the ground truth. Also, numbers that contain a letter (such as '11i0') are probably wrong. We use these facts and the most common made substitutions as found in our earlier analysis to recover the right characters. We use the same evaluation metrics as before to compare our method to the baseline scores.

## 5.2 Results

We compare the post-processed HTR output to the original HTR output to see the different accuracy scores. The accuracy scores for both the baseline and post-processed HTR output are shown in Table 3. The comparison of the performances is shown in Figure 6. We see a very slight decrease in recall while all other metrics improve. This shows that our post-processing strategy is successful in eliminating some of the false positives (insertions and substitutions) of the original model while maintaining almost the same rate of false negatives (deletions). However, we can still see that the precision is relatively low compared to the recall, showing that there is still a good amount of false positives that our method did not catch.

**Table 3: WER, CER, precision and recall scores for the HTR system output with and without post-processing techniques applied.**

| Metric | Baseline | Post-Process |
|---|---|---|
| WER | 0.4243 | 0.3916 |
| CER | 0.3422 | 0.3169 |
| Recall | 0.9475 | 0.9418 |
| Precision | 0.7403 | 0.7622 |
| Total Edit Distance | 18920 | 17508 |

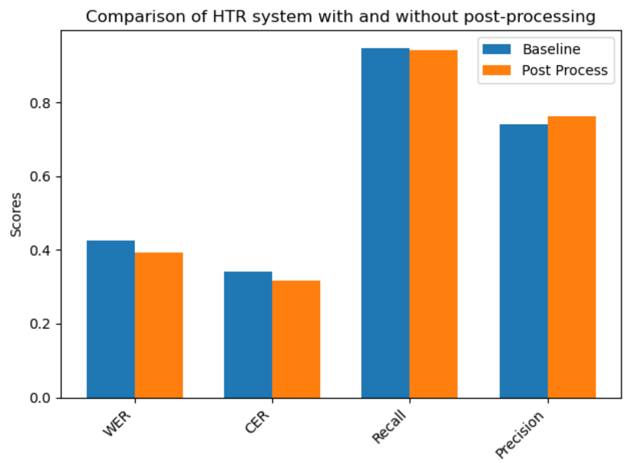



**Figure 6: The WER, CER, precision, and recall scores for the HTR system with and without post-processing applied.**

# 6 LAYOUT ANALYSIS

## 6.1 Method

Up until this point, we have been comparing the HTR output to the ground truth values by matching their bounding boxes based on the highest IoU score. We did this because the HTR system currently is not able to capture the layout of the the tabular structure of the ledger pages and thus we could not just match the output directly, since the word order would be wrong. The final part of the methodology involves analyzing the layout of the documents. Recognizing the layout is a crucial step in digitizing the ledger pages, since without it there is no good way to use the output of the HTR system because the correct word order would not be known. We will perform the layout analysis by using image processing techniques as well as making use of the HTR output. For this, we will use the OpenCV (cv2) library to perform the necessary processing steps.

To detect the tabular structure on the ledger pages, we must find a way to detect the columns and rows of the table to get the table cells. The ledger pages contain physical lines, which separate the different columns. We start by trying to detect these lines.

The first step is to pre-process our image. We do this by converting our image to grayscale and applying a Gaussian blur on the grayscale image. This helps reducing the computational complexity and reduces high frequency noise [14].

Next, we apply two types of thresholding to the blurred image: Otsu's thresholding and Adaptive Gaussian thresholding. Otsu's thresholding only captures the most clear markings on the page, such as the text, while the more thin and faint column lines are not captured [3]. The Adaptive Gaussian threshold captures both the text as well as the column lines. By subtracting the first threshold from the latter, we are left with the column lines and some noise.

Following thresholding, we perform morphological operations, specifically dilation and erosion [16]. We use specific kernels to remove noise while retaining the vertical lines.

We then apply the Hough Line Transform to detect the lines in the image. This can be used to detect (nearly) straight lines in images [9]. We filter the detected lines based on their length and position. For each detected line, we calculate its slope and intercept, and then draw an extended line from the top to the bottom of the foreground area (which contains the ledger page) in the image. This is done using basic principles of line equations in coordinate geometry.

Finally, we perform additional dilation and erosion to merge close lines and remove final noise. We then find contours in the image and draw a line from the top to the bottom of each contour. We are then left with an image containing the contours of each column section, which can then be used to create bounding boxes for the different columns. The whole process is shown in Figure 12.

To detect the rows present in the ledger pages, we have to use a different strategy, since there are no physical markings for row lines on the pages. We will use the word bounding boxes which are outputted by the HTR system in order to find the row bounding boxes.

We start by extracting the bounding boxes of the words outputted by the HTR system. We will only use the word bounding boxes that are kept after performing the post-processing. Since the images in our dataset typically consist of two tables (debit and credit) we have to determine where both tables start and end. We do this by finding the middle column line from the list of column lines we found by our method above. We then separate the bounding boxes into two groups: left boxes and right boxes, based on their x-coordinates relative to the middle column line.

We then take a list of boxes (either left boxes or right boxes) and group them into rows. This is done by sorting the boxes by their x-coordinates (from left to right) and then grouping boxes with similar y-coordinates together. For each box, we find the best row to append the box to, based on the minimum difference in y-coordinates. If no suitable row is found, we create a new row. The result of these steps are shown in Figure 13.

Once we have found the rows, we can extend the bounding boxes from the left side of the ledger page to the middle for the left boxes and from the middle to the right side of the page for the right boxes. We are now left with both the column and row bounding boxes.

Once the row and column bounding boxes are determined, we can use the intersection of these bounding boxes to determine the table cells. Figure 7 shows an example of these found table cells.

## 6.2 Evaluation

For the layout analysis methods, we take the ground truth table cell bounding boxes and compare them to our method's predicted table cell bounding boxes. We do this by matching each ground truth cell to a predicted cell based on the highest IoU score between the two. Only one ground truth cell can be matched to one predicted cell and vice versa. We then determine whether cells are a true positive by setting an IoU threshold. If ground truth and predicted cells are matched with an IoU score higher than this threshold, we consider it a true positive. Ground truth cells that are not matched with an IoU score above the threshold are considered a false negative and

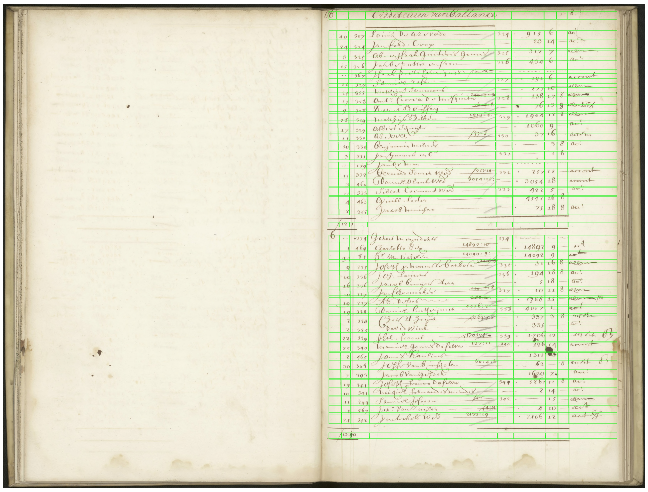


**Figure 7: The bounding boxes of the predicted table cells after taking the intersection of the rows and columns.**

predicted cells that are not matched with an IoU score above the threshold are considered a false positive. We will use a threshold of 0.5, 0.25 and >0. We can then determine the recall and precision scores, using the same formula as before. Additionally, we calculate the F1-score:

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{5}$$

Furthermore, after matching the cells as described above, we further verify the correctness of the match by comparing the text content of the predicted table cells against the text content in the ground truth table cells. This done by taking the words from the HTR output that match location with the predicted cells. The text comparison is done using a normalized Levenshtein distance with various thresholds: 0 (exact match), 0.25, 0.5, and 0.75. We use these thresholds because we cannot be sure that words from the HTR output match exactly with ground truth words because of the imperfections of the HTR system. For each threshold, we calculate the mean accuracy of the word matches. Additionally, we calculate the CER for all the words in the ground truth cells and the words in the predicted cells. If the cells are indeed matched correctly, we would expect to see good mean accuracy of the word matches (especially for the lower thresholds) and we would expect the CER to be close to the value found in Section 4.

### 6.3 Results

The performances using IoU thresholds of 0.5, 0.25 and >0 are shown in Table 6, Table 7 and Table 8 respectively. We show the performance both at the subset level as well as the total mean scores. The 'IoU Score' indicates the mean score for the true positives found at this IoU threshold. The comparison of the total mean scores can be seen in Table 4 and Figure 8. As can be seen, when using a higher IoU threshold, the accuracy scores are low and when using a lower IoU threshold, the accuracy scores are better. This means that when using a lower IoU threshold, a lot of the ground truth table cells are matched with predicted cells while this is not the case when using a higher IoU threshold. One of the main reasons for this behaviour is the fact that the bounding boxes of our predicted cells are much more tight than the ground truth boxes. Furthermore, the bounding boxes for our predicted table cells are often placed slightly lower than the ground truth bounding boxes. This is because we use the word bounding boxes from the HTR model to determine the rows, and these bounding boxes are almost always found to be slightly lower than the actual location of the words on the image. This causes the IoU score of a predicted cell and ground truth cell to be relatively low, even when both capture the same contents of the page. When taking a IoU threshold of 0.25, as shown in Table 7, we see the best ratio of IoU scores and accuracy scores. Here we see that matched cells have a mean IoU score of 0.473, which is quite close to the usual threshold of 0.5. Furthermore, we see a score of 0.804, 0.898 and 0.844 for mean precision, recall, and F1-score respectively. This shows that we have a good rate of false positives and false negatives, as well as having a reasonable area overlap for predicted and ground truth cells.

The accuracy of comparison of text contents for ground truth and predicted cells can be seen in Table 5. Here, 'LT 0' until 'LT 0.75' means how much percent of the text in the ground truth and predicted cells differ. So for the first row, 0.5369 means that 53.69% of texts are matched exactly, 0.5996 means that 59.96% of texts are matched with at most 25% of characters changed etc. If we look at the IoU threshold of 0.25, which seemed to perform well in the previous result, we can see that about 85% of words are matched with at most 75% of the characters differing. Furthermore we see a CER of 0.3859. This is higher than the CER found in Section 4. However, this can partly be explained due to the fact that in the first experiment, we calculated CER by matching one HTR word with a ground truth cell text. That means that we discarded some of the false positives (HTR words that were not matched). In this case, we first append all HTR words into a predicted cell and then compare predicted cell content to ground truth cell content, meaning that in this case we do keep these false positives when comparing the texts. Keeping this in my mind, we can determine that most of the predicted cells and ground truth that are matched by IoU, are also matched based on text contents, showing the success of our method.

**Table 4: Mean table cell performance metrics at different IoU Thresholds. 'IoU Score' indicates the mean score for the true positives found at this IoU threshold.**

| IoU Threshold | IoU Score | Precision | Recall | F1 |
|---|---|---|---|---|
| **>0** | 0.182 | 0.845 | 0.946 | 0.887 |
| **0.25** | 0.473 | 0.804 | 0.898 | 0.844 |
| **0.5** | 0.627 | 0.416 | 0.459 | 0.434 |

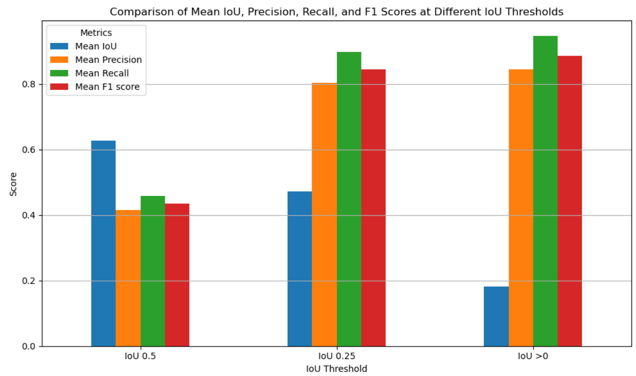



**Figure 8: The mean IoU, precision, recall and F1 scores for ground truth and predicted table cell bounding boxes for different IoU thresholds.**

**Table 5: Mean accuracy and CER for matching ground truth table cells with predicted table cells using different IoU thresholds and comparing their text contents using normalized Levenshtein distance thresholds. Values for LT 0, 0.25, 0.50, and 0.75 indicate the mean accuracy at which the normalized Levenshtein distance between the ground truth and predicted texts is within 0 (total match), 25%, 50%, and 75% respectively. CER indicates the average character error rate for the text content in the matched cells.**

| IoU Thresh. | LT 0 | LT 0.25 | LT 0.50 | LT 0.75 | CER |
|---|---|---|---|---|---|
| >0 | 0.5369 | 0.5996 | 0.7333 | 0.8242 | 0.4290 |
| 0.25 | 0.5555 | 0.6213 | 0.7563 | 0.8469 | 0.3859 |
| 0.50 | 0.5898 | 0.6586 | 0.7984 | 0.8770 | 0.3362 |

# 7 DISCUSSION

Write your discussion here. Do not forget to use sub-sections. Normally, the discussion starts with comparing your results to other studies as precisely as possible. The limitations should be reflected upon in terms such as reproducibility, scalability, generalizability, reliability and validity. It is also important to mention ethical concerns.

# 8 CONCLUSION

Write your conclusion here. Be sure that the relation between the research gap and your contribution is clear. Be honest about how limitations in the study qualify the answer on the research question.

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# Appendix A SUPPLEMENTARY FIGURES

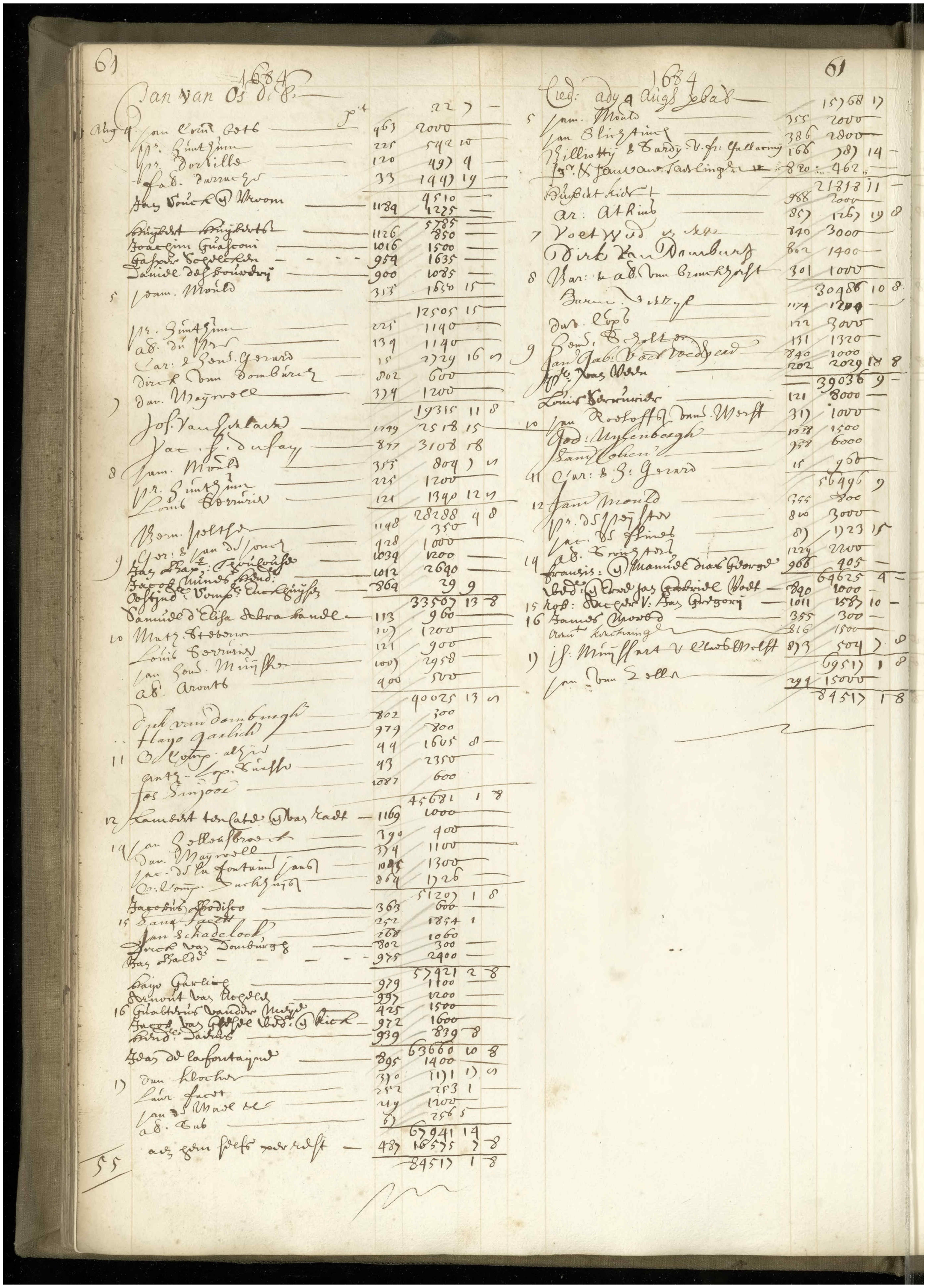
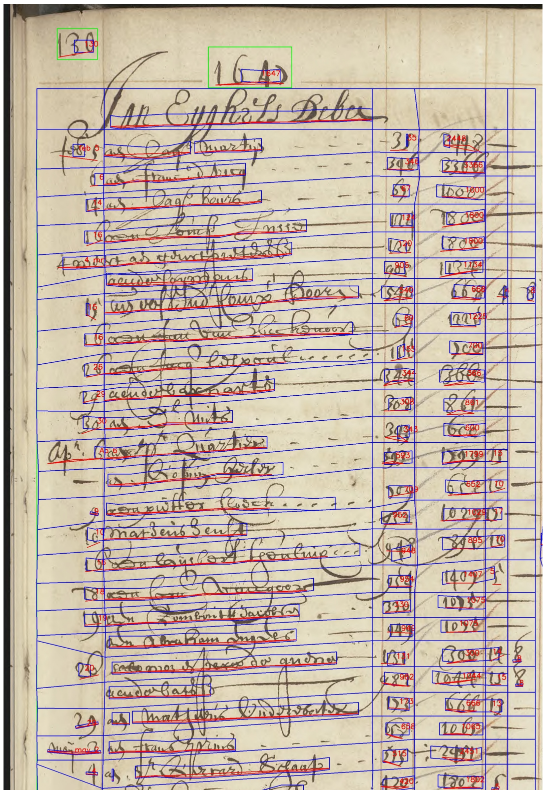
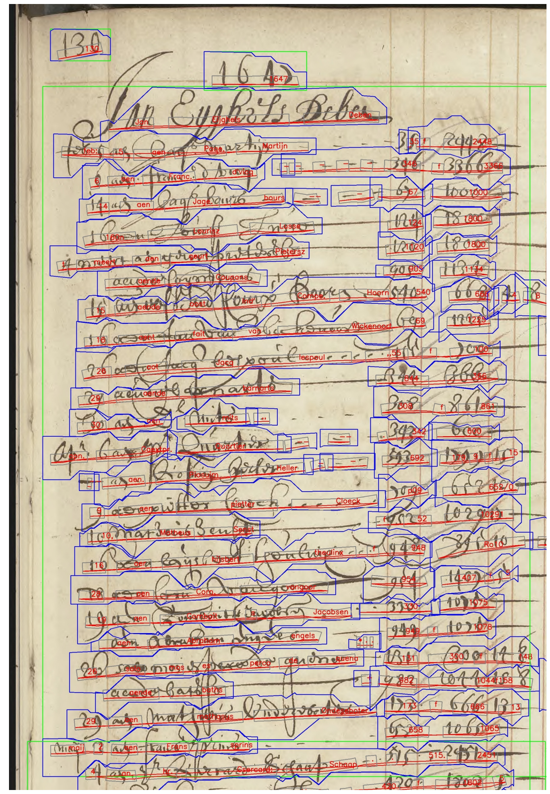


**Figure 9: An example page from the ledger collection.**



(a) The PageXML data of our ground truth plotted on part of the original image.



(b) The PageXML data of the HTR system plotted on part of the original image.

**Figure 10: The PageXML data of the ground truth and HTR system plotted on the orginal image. The tabular structure of the ground truth values can be seen where this is not the case in the HTR output.**

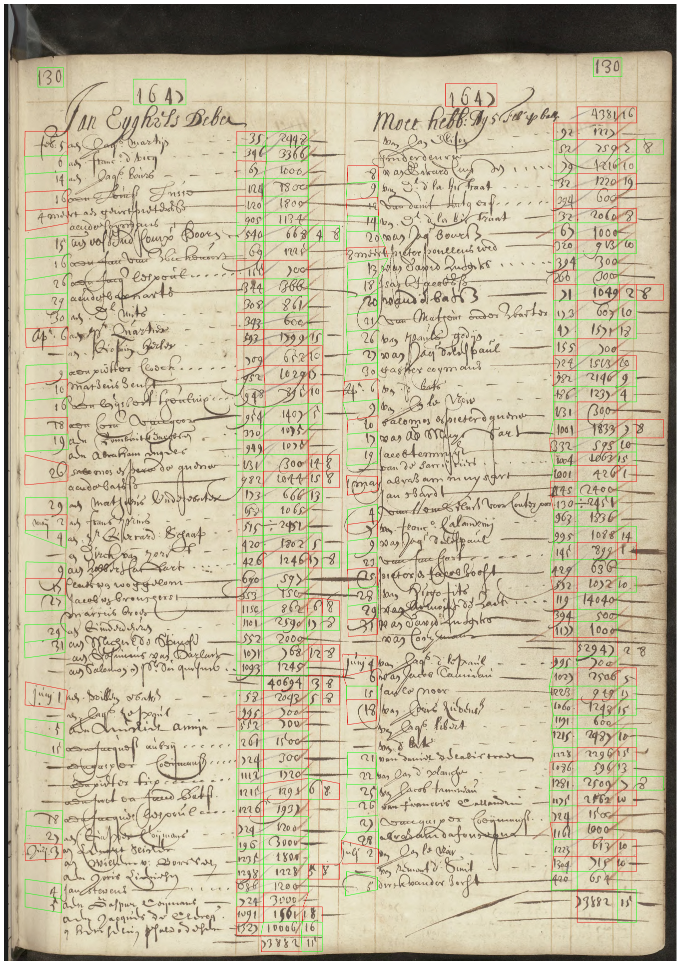


**Figure 11: An example page showing the words correctly matched by the HTR system in green and the words wrongly matched in red. This can be helpful in visually inspecting the page to see whether there are common characteristics on parts of the page that could cause mistakes.**

# Appendix B DETAILED METHODOLOGY

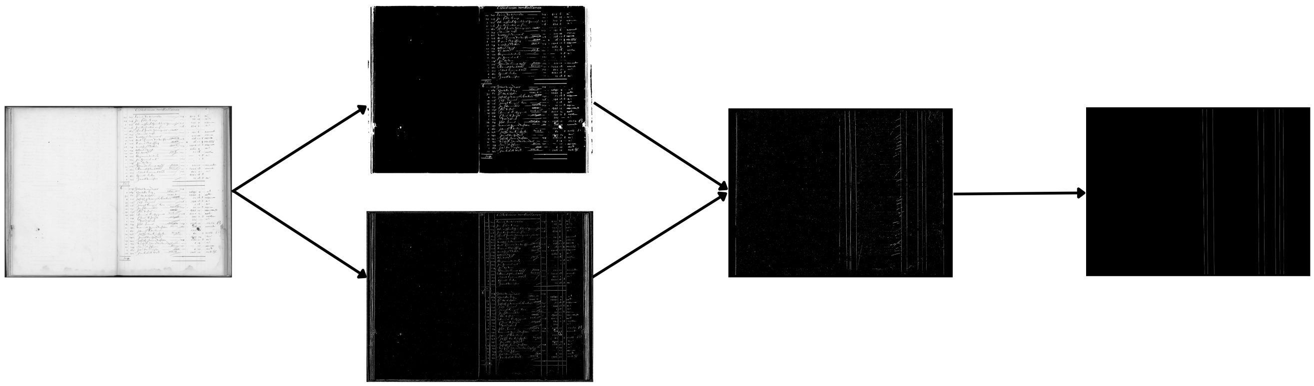


**Figure 12: The process of the extraction of column lines. We start with the blurred grayscale image. From there we create two threshold images, one containing the faint column lines and one that does not contain them. We subtract the images from each other, remove noise and use Hough line detector to find the columns lines.**

**Figure 13: The process of extracting the rows from the ledger page. We use the HTR system to determine bounding boxes of words from the original page. We then determine the row bounding boxes based on the y-coordinates of the word bounding boxes.**

## Appendix C COMPLEMENTARY RESULT TABLES

**Table 6: Table Cell Performance Metrics at IoU Threshold 0.5.**

| Subdir | IoU Score | Precision | Recall | F1 |
|---|---|---|---|---|
| 1045 | 0.638 | 0.674 | 0.674 | 0.674 |
| 1390 | 0.641 | 0.303 | 0.468 | 0.363 |
| 62 | 0.627 | 0.437 | 0.487 | 0.460 |
| 149 | 0.608 | 0.310 | 0.383 | 0.342 |
| 1099 | 0.621 | 0.532 | 0.499 | 0.515 |
| 99 | 0.638 | 0.525 | 0.504 | 0.514 |
| 109 | 0.645 | 0.520 | 0.552 | 0.534 |
| 119 | 0.617 | 0.422 | 0.437 | 0.429 |
| 139 | 0.626 | 0.435 | 0.475 | 0.453 |
| 59 | 0.664 | 0.555 | 0.541 | 0.548 |
| 89 | 0.632 | 0.466 | 0.519 | 0.490 |
| 69 | 0.626 | 0.391 | 0.456 | 0.420 |
| 55 | 0.631 | 0.287 | 0.319 | 0.302 |
| 79 | 0.614 | 0.389 | 0.439 | 0.412 |
| 1016 | 0.661 | 0.637 | 0.635 | 0.636 |
| 199 | 0.594 | 0.243 | 0.339 | 0.278 |
| 129 | 0.617 | 0.342 | 0.404 | 0.369 |
| **Mean** | 0.627 | 0.416 | 0.459 | 0.434 |

**Table 7: Table Cell Performance Metrics at IoU Threshold 0.25.**

| Subdir | IoU Score | Precision | Recall | F1 |
|---|---|---|---|---|
| 1045 | 0.546 | 0.990 | 0.990 | 0.990 |
| 1390 | 0.498 | 0.513 | 0.785 | 0.613 |
| 62 | 0.471 | 0.854 | 0.959 | 0.902 |
| 149 | 0.440 | 0.710 | 0.879 | 0.784 |
| 1099 | 0.473 | 0.939 | 0.881 | 0.909 |
| 99 | 0.504 | 0.916 | 0.878 | 0.896 |
| 109 | 0.508 | 0.848 | 0.894 | 0.867 |
| 119 | 0.460 | 0.869 | 0.901 | 0.885 |
| 139 | 0.474 | 0.819 | 0.894 | 0.853 |
| 59 | 0.525 | 0.910 | 0.888 | 0.899 |
| 89 | 0.475 | 0.862 | 0.961 | 0.907 |
| 69 | 0.464 | 0.821 | 0.963 | 0.884 |
| 55 | 0.451 | 0.726 | 0.811 | 0.765 |
| 79 | 0.452 | 0.829 | 0.929 | 0.875 |
| 1016 | 0.553 | 0.835 | 0.831 | 0.832 |
| 199 | 0.432 | 0.639 | 0.894 | 0.731 |
| 129 | 0.453 | 0.738 | 0.878 | 0.801 |
| **Mean** | 0.473 | 0.804 | 0.898 | 0.844 |

**Table 8: Table Cell Performance Metrics at IoU Threshold >0**

| Subdir | IoU Score | Precision | Recall | F1 |
|---|---|---|---|---|
| 1045 | 0.196 | 1.000 | 1.000 | 1.000 |
| 1390 | 0.152 | 0.603 | 0.952 | 0.729 |
| 62 | 0.190 | 0.876 | 0.984 | 0.925 |
| 149 | 0.169 | 0.762 | 0.943 | 0.841 |
| 1099 | 0.206 | 0.945 | 0.886 | 0.915 |
| 99 | 0.177 | 0.960 | 0.920 | 0.939 |
| 109 | 0.188 | 0.885 | 0.933 | 0.905 |
| 119 | 0.178 | 0.906 | 0.939 | 0.922 |
| 139 | 0.185 | 0.860 | 0.938 | 0.896 |
| 59 | 0.192 | 0.946 | 0.923 | 0.934 |
| 89 | 0.186 | 0.873 | 0.974 | 0.919 |
| 69 | 0.195 | 0.839 | 0.984 | 0.903 |
| 55 | 0.172 | 0.820 | 0.911 | 0.862 |
| 79 | 0.182 | 0.863 | 0.967 | 0.911 |
| 1016 | 0.232 | 0.845 | 0.840 | 0.841 |
| 199 | 0.169 | 0.690 | 0.962 | 0.788 |
| 129 | 0.164 | 0.802 | 0.952 | 0.869 |
| **Mean** | 0.182 | 0.845 | 0.946 | 0.887 |