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Redaction detection in publicly published government papers

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1 **ABSTRACT**

Not all documents are made up entirely of language-based information. Non-linguistic features in a document, such as redacted regions that are usually present in documents as geometrical shapes, may contain useful information but are difficult to decipher by OCR or other state of the art techniques. As a result, a specific solution to recognize and comprehend such aspects is required, and that is the why behind this research paper. This research will investigate the use of state of the art techniques (such deep learning and machine learning) in order to detect redacted regions in PDF documents. To be more clear, an attempt will be made to detect the regions in PDF documents that hide/whitewash text or information. Deeplearning and machine learning models will be used to address this problem. The expected output from this research will be presented by showing the accuracy of the segmentation metrics.

KEYWORDS

Image segmentation, Deep-Learning, Redaction, Machine Learning, Image processing.

INTRODUCTION

In literature, several approaches have been used to detect or extract features and information from PDFs such as region detection, image segmentation, colors detection and shape detection. For example, [14] presents a representative local region detector based on color-contrastpixel ranking and [13] proposes extracting more information and features from PDFs by converting PDFs to HTML form. Furthermore, different research papers proposed different ways to extract information from PDFs after turning them into images. Such as using a Convolutional Neural Network model to extract image features. What most of the research papers have in common is that they used the extracted image features such as shape or color to detect certain objects or to classify types of documents. What was insufficient from the literature is conducting features extraction and / or segmentation on textual documents to

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detect and classify redaction. In this paper, an attempt was made to successfully detect whitewashed text in pdfs documents by applying deeplearning and machine learningtechniques. In other words, different approaches will be applied to detect the deleted or hidden text (whitewashed text) in PDF documents and the best approach will be chosen. The models performance will be checked by comparing the scores of segmentation metrics. The running time will be considered since the models must go through large PDF documents.

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The research question that this research is trying to answer is: **RQ**: To What extent can state-of-the-art algorithms in image segmentation and classification improve the segmentation metrics (such as Panoptic Quality) [7] when detecting and calculating the percentage of redacted regions in FoIA pages? **SO1**: How do baseline models based on [12] preform on FoIA pages when detecting redacted regions while using a single source data (such PDFs from a specific municipality/ministry)? SQ 2: How can this performance be improved by enriching the data by using an annotation tool [11] and Convolutional filters with machine learning? SQ 3:How do these models perform when applied to FoIA pages from different sources?

RELATED WORK

This section will discuss the related work. Firs the redaction (whitewashing) will be discussed and after that, the related literature that relates to object, edge and shape detection will be discussed, since the discussed methods can help detect redaction.

4.1 What is Redaction and how it is done?

Several papers discussed redaction when it comes to sensitive information. Redaction is the process of removing visible information from a document [3]. This research investigate redaction in government documents that were made public. The information that was redaction was about private data. Private data is any personally identifying information that could be used to determine the producer's identity, the identity or personal information of individuals known to the producer (e.g., friends, relatives, and clients), or is linked to a private record (e.g., medical, employment, and education). Social security numbers, credit card numbers, bank records, medical records, employment information, education records, passwords and cryptographic keys, and local and online account records are examples of this. The reason why redaction in this case is important is because there are three primary hazards to digital heritage if collecting institutions do not improve their methods for discovering, identifying, and redacting sensitive content. First, collecting institutions may be viewed as untrustworthy actors incapable of properly caring for digital collections. As a result, digital content creators may be hesitant to hand over their works to institutions for long-term storage. Second, if processing costs are unreasonably high, institutions are likely to acquire fewer collections than they would otherwise [1]. Now more on the redaction process. When the information that needs to be redacted is identified. There are two

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approaches mentioned by [4]. The first one is called conventional 101 redaction: The naive approach is to decompress the image, redact a region encompassing the offending pixels (e.g., replace with black or background values), and possibly recompress the image if the pixels in the image contain identifying information in the form of burned-in text that needs to be removed to protect privacy. The second one is called Block selective redaction: Because only a tiny number of pixel regions must be redacted to remove the identifying information, and the JPEG process divides the image into MCUs of small numbers of 8 x 8 blocks, it is clear that only those blocks that are affected must be edited, while the rest can be left alone. This method entirely eliminates any loss in areas that do not intersect the redacted areas. Every original block that is completely contained in a redacted zone can then be replaced with a new block. After the redaction process was over, [11] suggested a metric to calculate the accuracy of the process. Mean Intersection Over Union (mIoU) was suggested which is an evaluation metric used to measure the accuracy of an object detector on a particular dataset, the mIoU can be calculated using the following formula. $\sum (tp/(tp+fp+fn))$.

It is worth mentioning that the authors of this paper [11] labeled the ground truth image dataset by hand to ensure accuracy.

4.2 Contour and Edge Detection

First, let's give a definition to edge detection. The method of edge detection seeks to capture the important properties of objects in an image. Discontinuities in the photometrical, geometrical, and physical qualities of objects are examples of these properties. Variants in the grey level image result from this information; the most common variations are discontinuities (step edges), local extrema (lines edges), and 2D features generated when at least two edges meet (jounctions) [8].

Since that several redacted regions in documents are presented 119 in geometrical like shapes. Several papers that aimed to detect certain shapes or edges are discussed. In [5] a method for accurately detecting two-dimensional (2-D) forms has been suggested. The shape boundary's cross section is described as a step function. First, a one-dimensional (1-D) optimal step edge operator was developed that reduces both noise power and mean squared error between the input and filter output. This approach of detecting a form is a natural extension of the problem of pixel-level edge detection to the problem of global contour identification. This simple filtering approach also serves as a tool for analyzing edge-based shape identification in a systematic manner. For detecting a certain shape, contour detection techniques should be investigated. It is pointed out in [2] that contour detection is fundamental in image segmentation and object detection and classification. Instead of old-fashioned simple filtering, the authors chose to build a detector by comprising parallel k-means, convolution, and skeletonization routines in addition to the local cues and eigensolver routines. Combining these contributions helped reduce the run-time.

Improving the accuracy for contour detection by using deep learning instead of old fashioned simple filtering also worked in [12] where a CNN model was trained on a multi-class classification task, namely to classify an image patch to which shape class or the negative class. The goal of training a standard CNN is to maximize 2022-05-24 12:24. Page 3 of 1-5.

the probability of the correct class, which is achieved by minimizing the softmax loss.

5 METHODOLOGY

This chapter is about methodology and discusses research strategies, data collection methods and data analysis methods.

5.1 Dataset

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The dataset consists of 365 PDF files which contain a total of 32 thousand textual pages. The documents can be found and downloaded from the dutch government website webcovid19 (https://wobcovid19.rijksqyerheid The pdf documents contain information such as decisions from Dutch ministries concerning corona regulations. The pdf documents mostly contain textual data but due to the privacy laws such

as article 10 [10] that protects people personal data, non-linguistic elements are also present in the documents. Non-linguistic elements such as redacted regions that cover personal information.

5.2 Dataset preparation

To prepare the dataset, a few steps needed to be done. The first step was to write a script that would download the pdf documents from the government website. The next step would be to write a script that converts the downloaded pdf documents to images. Considering the relatively huge number of pdf documents, a common laptop would take up to two days to download the pdf documents and turn them into images.

Since not all pages pages contain redacted regions, an approach that only extracts pages that contain redaction was needed. The first approach that was tried to extract pages that only contained redaction was to write a script (in python) that detected certain shapes such as geometrical shapes since geometrical shapes were used in several of the downloaded PDF documents. This approach helped extract pages that contained redacted regions with sharp edges and geometrical shapes(such as quadrilateral shapes). As an example figure 1 is shown. However, there was an issue with this approach. This approach could not extract pages with different redaction styles from different sources (As an example check figure 2). As a result, the dataset missed several pages that contained different redaction styles. To solve this problem, another approach was chosen. For this approach, the PDF pages were reviewed by hand to look for all kinds of redaction styles and then label them using an annotation tool which was Label Studio. Label Studio is one of the most used tools for image segmentation, classification and detection purposes. This tool is used by well known companies such as Facebook and IBM [6].





Figure 1: Example of redaction using quadrilateral shapes

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Figure 2: Example of redaction that was done by hand.

Redaction detection model implementation

The first model was a 3-layer CNN model will be used on the images dataset, with the current image dataset a CNN model would have a high accuracy [9]. To optimize the output of the model, some regularization and an Adam are needed such as relu or sigmoid functions. For higher accuracy, the network should be trained independently on each type of image sample. If a new image shape is introduced, a new network can be established.

5.4 Experimental setup

Before building and training a CNN model that detects redaction in a dataset that consists of documents. The documents must be converted into images because models such as CNN work better on image features. After having the dataset ready. The dataset should be randomly split into a training, validation, and test set. To reduce the over-fitting, the hyper-parameter epochs can be set to 100 and the training will be stopped if the validation loss does not improve after 10 epochs. While building the CNN model, 3 layers must be added after that regularization functions and Adam must be added to optimize the output. The model was implemented using Python, TensorFlow, and Keras software.

5.5 Evaluation

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182 495 ₁₈₃ To measure the performance of the mode that handles segmentation problems, the panoptic quality(PQ) is used. The PQ is a combination of the IoU(Intersection over Union) and AP(Average Precision). The PQ consists of two steps. The first step is matching the predicted and the ground truth segment. The second step is mathematically calculating the PQ using the PQ formula. [7]

RESULTS

This section will discuss the results.

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Мо	del 3	94 %	
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RE	EFERENCES		
[1]	Adobe. Why redact or r		
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[3]		Woods Christopher (Cal) Lee. Automated Redaction of Private and Personal	
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	images. 2015.	of burned in text in irre	versibly compressed JPEG medical
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Figure 3: Results of models

DISCUSSION

CONCLUSION

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