**ABSTRACT**

The contribution of this paper is two fold. First, it presents a novel approach called DeepBiRD which is inspired from human visual perception and exploits layout features to identify individual references in a scientific publication. Second, we present a new dataset for image-based reference detection with 2401 scans containing 12244 references, all manually annotated for individual reference. Our proposed approach consists of two stages, firstly it identifies whether given document image is single column or multi-column. Using this information, document image is then splitted into individual columns. Secondly it performs layout driven reference detection using Mask R-CNN in a given scientific publication. DeepBiRD was evaluated on two different datasets to demonstrate the generalization of this approach. The proposed system achieved an F-measure of 0.96 on our dataset. DeepBiRD detected 2.5 times more references than current state-of-the-art approach on their own dataset. Therefore, suggesting that DeepBiRD is significantly superior in performance, generalizable and independent of any domain or referencing style.

**Keywords** Reference Extraction · Layout Detection · Image-based Reference Detection

1 Introduction

There has been a rapid increase in every field of research since the start of 21st century, subsequently increasing the volume of scientific literature exponentially. Each scientific publication consists of several components i.e. header, abstract, sections and references. Bibliographic references play a vital role in every publication as they provide information, discuss and give credit to scientific contributions by other researchers in the field. With the growth in scientific literature, there has been surge in demand for an automatic solution for reference extraction.

Bibliographic references are of a particular interest for library communities. They play a key role in compiling library catalogs. These catalogs contain information regarding all bibliographic items like books, journals, conference proceedings, magazines and other media present in a library. For such purpose it is not feasible to manually find and
index such huge volume of references. In order to develop automatic systems for ingesting bibliographic data, it is crucial to have a reliable solution to detect references.

Resource Discovery Systems seems to be a viable solution for the libraries to further expanding their horizon by providing the indexed data available from external resources. Some resources are commercial and are thus paid to use their collected data i.e. Web of Science, Scopus. According to a scientometric study [19], both Scopus and Web of Science have mostly coverage of English journal articles from Biomedical and Social Science domains and therefore have low overall coverage for journals and articles from other languages. Thus ruling out Resource Discovery Systems as an optimal solution for bibliographic cataloging.

With the introduction of this automatic reference detection approach, there will be a substantial improvement in the bibliographic reference extraction pipeline. Majority of the related work on this problem are text-based and therefore makes use of textual features like Author names, publication titles etc in a document to detect references. Text-based approaches use a set of carefully crafted heuristics and regular expressions based on the position of constituents of a reference string i.e. author names, affiliations, publisher, journal / book / conference name, year of publishing etc. With the introduction of new referencing styles, such carefully crafted heuristics become deprecated right away thus making text-based approaches less robust and eventually not generalizable. For instance, most common referencing styles like MLA and APA have author name and publication title as the starting features of a reference string. On the other hand there also exist some rare bibliography styles in social sciences such as Alpha or hybrid Chicago in which reference strings either start with a reference identifier or publication year respectively. Such cases are problematic for text-based approaches because they do not comply with the other common traditional referencing styles and are rarely used. Comparison of results from text-based and layout-based approaches on such cases are shown in Fig 1. It can be observed that text-based approach was unable to detect an unusual reference string as it entirely rely on textual features while overlooking other important facet i.e. layout features.

This paper introduces an automatic, reliable and generalized approach for reference detection from document images. It works equally good for digital-born PDFs by treating them as scanned document. Our approach uses Convolutional Neural Networks (CNN) to learn visual layout features from a given document to identify bibliographic references. CNNs thus abolishing our dependency on textual features which were the major hindrance in realizing generalization for this task. Our approach is generalized and is thus applicable to any bibliographic publication independent of its domain or referencing style.

The contribution of this publication are as follows:

- We present a novel two staged layout driven approach for automatic reference detection from scientific publications, which effectively exploits the visual cues to firstly identify and segment the document layout followed by reference detection.
- In this paper we release a new & larger dataset for image based reference detection which will be publicly available for the community.
- We also demonstrate the superiority of proposed approach by carrying out a series of comparative performance evaluations against existing approaches.

The rest of the paper is structured as follows: Section 2 discusses the relevant work done so far on the problem of reference detection. Section 3 discusses the details of the datasets used in this work. Section 4 presents the architecture and pipeline of our proposed approach. Section 5 discusses different experimental setups used for this publication. Section 6 discusses and analyses the results obtained from different experiments to demonstrate the effectiveness of our approach. And lastly, Section 7 makes the concluding remarks of this paper.
2 Related Work

A lot of work has been done in the field of reference detection. Bibliographic reference detection is generally performed by two methods like text-based and layout-based. Most of the approaches are based on analysis of textual content to identify references. There are several techniques employed by each text-based approach to identify references. Here we will discuss such techniques used for bibliographic reference detection, starting from simplest and moving towards more sophisticated ones.

2.1 Text-based Approaches

The simplest of the text-based reference detection techniques employ regular expressions and carefully crafted heuristics [6] for this task. Such approaches are mostly not considered as optimal solution because of their limited coverage. For example, MLA and APA are the most common referencing styles in which a reference string starts with author names.

In order to detect such references, adopted heuristics will look for coma separated author names at the start of the reference string. The drawback of such approach is that it will be unable to detect a reference if it does not comply with the defined heuristics i.e. reference string with Alpha style where reference string starts with a custom ID. Every domain has its own referencing style and sometime there are multiple referencing styles within one domain. Such challenges makes simple approaches unsuitable for this complex task.

Citation-Parser [6] is a typical example of heuristics based tool. To identify components of bibliographic reference string i.e. authors, title, conference/journal etc. it employs a set of carefully designed heuristics. Sautter et al. [22] proposed a tool named RefParse which exploits similarities between individual reference strings to identify different referencing style for parsing a reference string. Perl also provided an extension named Biblio [4] for parsing and extracting reference string metadata. Chen et al. [5] proposed BibPro, an approach which identifies citation style by matching it with referencing styles available in its database and then uses gene sequence alignment technique to identify components of reference strings. AnyStyle-Parser [1] is another example of a tool which identifies bibliographic references using heuristics. PDFSSA4MET [12] proposed a slightly different approach to identify references in a Born-digital PDF. In this approach, textual PDF is firstly converted into an XML file. Then by employing pattern matching mechanisms, syntactic and structural analysis of XML is performed to identify reference section.

Lafferty et al. [13] proposed an advanced approach known as Conditional Random Fields (CRF). CRF is a probabilistic approach for labeling sequence data like reference strings. This labeling includes identifying different parts of a reference string i.e. authors, publication title, year, conference/journal name etc. Such labeling assists in recognizing a reference string based on its labeled components.

Tkaczyk et al. [26] proposed "Content ExtRactor and MINEr (CERMINE)" a CRF based system for extracting and mining bibliographic metadata from references in born-digital PDF scientific articles. Free-cite [9] computes features from tokenized citation string and then classify that token sequence using trained CRF. Science Parse [23] is a tool based on CRF to identify and extract metadata of references from a document. Matsuoka et al. [18] proposed an approach which demonstrated the use of lexical features by CRF results in increase in accuracy. Councill et al. [7] presented a CRF based package called "ParsCit" for reference metadata tagging problem. In which the reference strings were identified from plain text, based on fine grained heuristics. [7] claims ParsCit to be one of the best known and widely used open-source system based on Heuristics and CRF for reference detection, string parsing and metadata tagging. Tkaczyk et al. [25] also proposed a reference metadata recommender system which provided 10 most popular opens-source citation parser tools in one system. Selected tools were a mixture of simple heuristics based and machine learning based solutions.

Now a days, artificial neural networks are most popular choice as a solution to most of the scientific problems. Similarly some literature also explored the potential of neural networks for the task of bibliographic reference detection and parsing.

Zou et al. [27] proposed a two steps approach to locate and parse bibliographic references in HTML medical articles. In the first step individual references are located using machine learning approaches whereas in second step by employing CRFs, metadata is extracted from each reference.

Contrary to the traditional approaches for reference tagging, Parsad et al. [20] proposed a bibliographic reference string parser named "Neural-ParsCit" based on deep neural networks. The authors tried to capture long range dependencies in reference strings using Long Short Term Memory (LSTM) [11] based architecture. Lopez et al. [17] proposed a tool named "Grobid" based on state-of-the-art machine learning techniques for reliable extraction of bibliographic references and their metadata.
Table 1: Distribution of image samples in BibX[2] dataset

| Layout Type       | Single Column | Double Column |
|-------------------|---------------|---------------|
| Number of Images  | 429           | 25            |

Table 2: Overall distribution of BibX[2] dataset

| Dataset Type     | Train Set | Validation Set | Test Set |
|------------------|-----------|----------------|----------|
| Number of Images | 287       | 25             | 143      |
| Number of References | 5741 | 478            | 2547     |
| Single Column    | 270       | 24             | 136      |
| Double Column    | 17        | 1              | 7        |

Text-based approaches are not directly applicable to document images. In order to identify reference from scanned documents, text must be extracted from given document by performing Optical Character Recognition (OCR) and then applying the selected approach to extracted text. The disadvantage of this approach is the potential introduction of OCR error which will eventually contribute in detection error thus making the task unnecessarily complicated.

2.2 Layout-based Approaches

Literature discussed so far rely only on textual features to identify references. Text-based approaches do not take advantage of layout features thus abandoning an important aspect. There are very few approaches which explored the potential of exploiting layout information for detecting bibliographic references.

Bhardwaj et al. [3] used layout information to detect references from a scanned document. For that purpose, Fully Convolutional Neural Network (FCN) [16] was used to segment the references and later post-processed to identify individual references. To our best knowledge, it is currently the state-of-the-art for image based reference detection task. The authors also released a small dataset [2] for image-based reference detection. In this paper this dataset will be referred as BibX dataset. Lauscher et al. [14] used this layout based reference detection in their system [15] to build an open database of citations for libraries indexing use case. Recently, Rizvi et al. [24] gauged the performance of four state-of-the-art object detection models using layout information to detect bibliographic references in a scientific publication.

3 datasets

3.1 BibX dataset

This section provides insights about the dataset used for training and baseline performance comparison of DeepBIBX [3] and our proposed approach DeepBiRD for the task of layout-based reference detection. To the best of authors knowledge, it is the only image based dataset which contain annotations of references. BibX dataset consists of 455 document images from several social sciences books and journals, containing 429 and 25 document image samples from single and double column layouts respectively. The dataset is divided into train, validation and test set with 287, 25 and 143 samples respectively. Distribution details of BibX dataset are mentioned in Table 1 & 2. Furthermore, considering the limited size of the dataset, we propose a new dataset called BibDecDB dataset. Details of this new dataset are discussed in the following section.

3.2 BibDecDB dataset

In this paper, we are releasing a dataset named BibDecDB [8] for imaged-based reference detection. This dataset has been curated from the reference section of various Journals, Monographs, Articles and Books from social sciences domain. Resolution of images vary from 1500 to 4500 for larger side of the image. Image quality is maintained on at least 300 dpi. All images were manually annotated where a box was drawn around each single reference.

There are 2,401 scanned document images in BibDecDB dataset containing 38,863 references in total. Document scans were initially divided into three groups based on the number of columns i.e. single, double and triple columns. Table 3 shows distribution of samples in layout groups. These groups were further distributed into train, val and test set with balanced representation from each group. Fig 2 shows sample scans with different layouts. The distribution of train test...
and validation set along with their respective number of references are shown in Table 4. Dataset is shared on the following link: https://madata.bib.uni-mannheim.de/283/.

4 Proposed Approach

In our proposed approach we exploited layout information to detect references from a document image. Our pipeline consists of two stages. In the first stage, document image is processed using deep neural networks to identify document layout. If this stage detects multiple columns then the document image is split into individual columns. In the second stage, references are detected from each split column image. Details for both of these stages of our pipeline are discussed as follows.

4.1 Stage 1: Layout Detection & Page Segmentation

The first stage in our pipeline is layout detection followed by page segmentation. The way to read a document highly depends on the layout of that specific document. For example, in case of two or more columns layout, we must start from the left most column and finish it from top to bottom before proceeding to the next column on its right. In order to references from multi-column document image, we must first detect layout before moving on to the reference detection task. Once layout is known, the document image is then cropped into individual columns using that layout information.

4.1.1 Architecture

For layout detection task and page segmentation, we used deep neural network based architecture known as Faster R-CNN [21]. As it also provides respective coordinates along with detected columns. In case of multi-column document image, the classification model is trained to detect columns and also returns the coordinates of the columns.

Figure 2: Samples of different layouts from input files

| Table 3: Distribution of image samples in BibDecDB dataset |
|-----------------------------------------------------------|
| Single Column | Double Column | Triple Column |
| 2240          | 145           | 16            |

| Table 4: Overall distribution of BibDecDB dataset |
|--------------------------------------------------|
| No. of Images | Train Set | Validation Set | Test Set |
|---------------|-----------|----------------|----------|
| No. of Images | 1513      | 132            | 756      |
| No. of References | 24606 | 2013           | 12244    |
| Single Column | 1411      | 124            | 705      |
| Double Column | 92        | 7              | 46       |
| Triple Column | 10        | 1              | 5        |
Figure 3: Overview of proposed two-stage pipeline for layout-based reference detection
layout, the detection box coordinates are used to split columns present in the given document image. Layout detection pipeline is shown in Fig 3.

To train the network, we used a set of 50 scanned documents from all representative classes and manually annotated each sample with bounding box around every column. We have document images with single, double and triple column layout in our dataset. First of all the network was initialized with ResNet-50 model. Then employing transfer learning, it was fine-tuned on our dataset for the task of column detection.

4.1.2 Parameters

The network was trained for 100 epochs with the base learning rate of 0.001. Learning rate was decreased in steps by a factor of 0.0001 at 50 and 75 epochs respectively. In all experiments the number of images per batch was set to 1.

4.1.3 Inference

Inference performed on each input image outputs box’s coordinates and a confidence score representing the extent to which the network is sure about that specific detection. The confidence score ranges from 0 to 1, where 0 being least confident and 1 being certain about a detection. All detections below confidence score of 0.9 are discarded. In pruned detections each detection refers to a column detected in that specific scan. Results from Layout Detection are then used to split images into columns such that each image contains only one column. For instance if there were two columns detected in a scan document, then each column is cropped into a separate image thus producing two images containing one column each.

4.2 Stage 2: Reference Detection

All images processed through Stage 1 are in fact converted into single column crops, thus making all images uniform for the further processing. Next step is to process each of splitted document image through stage 2 to detect bibliographic references.

4.2.1 Architecture

For reference detection task, due to close proximity a network was needed which can also separate references from each other in addition to detect those references. For that purpose we employed deep neural network based architecture known as Mask R-CNN [10]. It is one of the most popular networks for object detection and instance segmentation. Fig 3 depicts complete pipeline of our two staged proposed system.

The baseline model used for this task is ResNet-50. Then it was fine-tuned on trainset of BibX dataset with 287 images containing 5741 references, using transfer learning.

4.2.2 Parameters

The network was trained for 100 epochs with the base learning rate of 0.001. Learning rate was decreased in steps by a factor of 0.0001 at 50 and 75 epochs respectively. In all experiments the number of images per batch was set to 1.

4.2.3 Inference

By performing inference on the input image we get coordinates of the detected reference’s box along with a confidence score. The confidence score ranges from 0 to 1, where 0 being lowest and 1 being highest. It represents the extent to which the network is sure about that specific detection. Each detection in the results represents a reference. Once

| Models          | Trained on | Tested on | Precision | Recall | F-Measure |
|-----------------|------------|-----------|-----------|--------|-----------|
| DeepBiRD        | BibX       | BibX      | 0.94      | 0.96   | 0.95      |
|                 | BibX       | BibDecDB  | 0.82      | 0.89   | 0.85      |
|                 | BibX + BibDecDB | BibX | 0.82 | 0.92 | 0.86 |
|                 | BibX + BibDecDB | BibDecDB | 0.97 | 0.94 | 0.96 |
| DeepBIBX[3]    | BibX       | BibX      | 0.49      | 0.40   | 0.44      |
|                 | BibX + BibDecDB | BibDecDB | 0.53 | 0.39 | 0.45 |

Table 5: Detection results from all variations of DeepBiRD and DeepBIBX [3] on both datasets
detection results are ready, OCR can be performed on each detected reference separately, thus extracting all references from an input image.

5 Experiments & Results

To evaluate our system, we performed various experiments using DeepBIBX [3] model and multiple settings of DeepBiRD on two datasets. These datasets include our own BibDecDB [8] dataset and the one proposed by DeepBIBX [3], BibX dataset [2]. In the later dataset, due to limited set of samples, the authors augmented the whole dataset by cropping and resizing every image in train, validation and test set. We carefully re-implemented DeepBIBX [3] with every detail provided by original authors. The only difference being that in our experiments we only used non-augmented images from the dataset to enable results to be directly comparable with our approach.

Further we will elaborate the results of the experiments performed for evaluation. The evaluation results are divided into two groups Quantitative and Qualitative evaluations. Firstly we will discuss the results from all experiments performing quantitative analysis and later we will discuss the qualitative part.

5.1 Quantitative Evaluation

Experiments 1 through 4 were carried out to perform quantitative evaluation of our system. We will discuss results from each experiment as follows:

5.1.1 Baseline comparison of our approach with DeepBIBX [3]

The purpose of this experiment was to validate the effectiveness of our approach on BibX dataset and compare its performance with DeepBIBX [3]. In this experiment, we trained DeepBiRD on BibX dataset with aforementioned parameters. we also trained a Fully Convolutional Network (FCN) [16] on BibX dataset with exactly same settings as mentioned in DeepBIBX original paper [3]. Once the training finished, both models were evaluated on Non-Augmented test set of BibX dataset. By doing so it enabled us to directly compare the performance of our approach with DeepBIBX [3] approach on BibX dataset.

Table 5 shows comparison of DeepBiRD results with DeepBIBX [3]. It can be seen that DeepBIBX [3] was able to achieve precision, recall and F-measure of 0.49, 0.40 and 0.44 respectively. On the other hand, DeepBiRD was able to achieve precision, recall and F-measure of 0.94, 0.96 and 0.95 respectively. It indicates that DeepBiRD is significantly more effective than the DeepBIBX [3] by factor of two. It is to be noted here that each detection was validated using Intersection over Union (IoU) with ground truth annotations. If a detection had IoU more than a certain threshold, then it was termed as correct detection. Fig 4 compares the detection results from both DeepBiRD and DeepBIBX [3] at different IoU thresholds i.e. 0.5, 0.75 and 0.9. Where blue line represents DeepBiRD and orange line represents DeepBIBX [3]. It can be clearly observed that detection rate of DeepBiRD is much more than that of DeepBIBX [3].
5.1.2 Robustness

The purpose of this experiment was to validate the extent of robustness for both DeepBiRD and DeepBIBX [3]. In order to do so, we evaluated both systems on more unseen data i.e. test set from another dataset. In this experiment, we trained a Fully Convolutional Network (FCN) [16] on BibX dataset with exactly same settings as mentioned in DeepBIBX original paper [3]. We also trained DeepBiRD on Non-Augmented BibX dataset along with aforementioned parameters. Once the training was finished, both models were evaluated on test set of BibDecDB dataset. The results from this experiment will show the extent of effectiveness of DeepBIBX [3] & DeepBiRD on unseen data. Table 5 shows the results of DeepBIBX [3] model on BibDecDB dataset. It can be seen that DeepBIBX [3] was able to detect only 4794 references out of 12244. So the overall detection accuracy is 39.15% which is quite low. More than half of the references were not detected by DeepBIBX [3] from unseen data which indicates that DeepBIBX [3] lacks robustness. Comparison of DeepBiRD with DeepBIBX [3] on BibDecDB dataset is also shown in Fig 5.

On the other hand, DeepBiRD detected 10886 references out of 12244 references which is 85.39%. It can be inferred from these results that DeepBiRD is significantly more robust than DeepBIBX [3] as it worked very well on an unseen dataset.

5.1.3 Generalization

The purpose of this experiment was to verify DeepBiRD for generalization by employing transfer learning to adapt network on BibDecDB dataset. In this experiment the pre-trained model on BibX dataset was used as a baseline and was then fine-tuned on train set of BibDecDB dataset to learn more reference examples. Once the training was finished, final model was evaluated on test set of BibDecDB dataset.

Fine tuned model was able to detect 11615 references out of 12244. So the overall detection accuracy is 94.86%, which is 5.95% better than the results before fine-tuning of the model. Results of this experiment are shown in Table 5. It can be observed that fine tuning increased the F-measure of the system by nearly 10%. From these results we can infer that

| Dataset | Quality               | DeepBiRD | DeepBIBX [3] |
|---------|-----------------------|----------|--------------|
| BibX    | One-to-One Detections | 2463     | 972          |
|         | Over Segmentation     | 5        | 1            |
|         | Under Segmentation    | 0        | 0            |
|         | Undetected            | 84       | 1575         |
| BibDecDB| One-to-One Detections | 11615    | 4794         |
|         | Over Segmentation     | 2        | 1            |
|         | Under Segmentation    | 0        | 0            |
|         | Undetected            | 629      | 7450         |

Table 6: Qualitative results from DeepBiRD (proposed approach) and DeepBIBX [3] on BibX dataset
DeepBiRD can be generalized as it can work very well on new data. Fig 8 shows the effect on accuracy by variation in IOU.

5.1.4 Analyzing Effects of Column Splitting

The purpose of this experiment was to analyze the effect of splitting columns before performing reference detection task. In this experiment The fine-tuned model on BibDecDB was evaluated on BibX dataset by disabling our pre-processing step, the layout analysis component, in our main pipeline. Then results obtained from both pipelines i.e. with enabled and disabled layout detection component, were compared to see whether cropping multi-column scans into individual columns improves the system results. The results of this experiment are shown in Table 7.

In case of disabled column splitting DeepBiRD was able to detect 2461 references out of 2547 which is 96.62% of the total references. On the other hand, with column splitting DeepBiRD was able to detect 2463 references out of 2547 which is 96.70% of the total references. In this case, the accuracy was also increased but only by a marginal 0.08%. Here the boost was not significant because BibX dataset has a very limited number of samples for multi-columns scans. From these results we can infer that splitting multi-column documents into respective columns relatively simplifies the problem by converting multi-column documents into single column documents. These results urged us to use column-splitting as a pre-processing step.

5.2 Qualitative Evaluation

The purpose of this analysis was to evaluate output of our system from quality perspective. For an optimal reference detection system, merely number of detected references are not important but also the quality of detection too. Quality of a detection can be defined as the extent to which the reference was accurately identified. It can be estimated by co-relating the area of reference in ground truth with area in detection. It could be the case that the detection result includes only subset of original reference. It might also be possible that sometimes, detector detects more than one references as one reference.

Qualitative evaluation also plays an important role in validating the quality of the detected references. There are several cases which can define the quality of the detection process. Ideally one reference should be detected as one reference. On the other hand, there are sometimes cases where either two references are detected as one reference or single reference is detected as two separate references, called under-segmentation and over-segmentation respectively.

In order to discuss the qualitative analysis of our approach we refer to Table 6. Which contain the qualitative results on BibDecDB and BibX dataset. It can be observed that in BibX dataset, DeepBIBX [3] accurately predicted 972 references out of 2547 total references; while it performed over segmentation for just 1 reference and 1338 references were undetected. On the other hand, in BibDecDB dataset, it correctly detected 4794 references out of 12244 references. while there was only 1 case of over segmentation and 7450 references were not detected.

For DeepBiRD on BibX dataset, it was able to correctly detect 2463 references out of 2547. while it performed over segmentation on only 5 references and 84 references were undetected. On the other hand, in BibDecDB dataset it correctly detected 11615 references out of 12244, while 40 references were over segmented and 629 references were undetected. It is quite evident that DeepBiRD was able to correctly detect significantly more references as compared to DeepBIBX [3].

5.3 Overall discussion

The overall results of evaluations i.e. Precision, Recall and F-Measure, on BibDecDB and BibX datasets are presented in Fig 6 and 7 respectively. It can be observed that DeepBIBX [3] performed worse on both datasets. On the other hand, DeepBiRD outperformed DeepBIBX [3] with significant margins. Fig 9, 10 & 11 show visual examples of best, average and worst results from our system. Results from DeepBIBX [3] and ParsCit for each example are also shown for comparison. All these results demonstrate the dominance of DeepBiRD over all other text-based or layout-based approaches.

| Table 7: Effects of column-splitting on BibX dataset |
|-----------------------------------------------------|
| Non-Split | Split |
| Total Detections | 2461 | 2463 |
| Detection Accuracy | 0.96 | 0.97 |
6 Conclusion

In this paper, we presented a novel two stage layout driven reference detection approach called "DeepBiRD" which exploits human intuition and visual cues to effectively detect references without taking textual features into account. By meticulous experimentation we pushed the boundaries of automatic reference detection and set a new state-of-the-art. To conclude the DeepBiRD is an effective, generalizeable and robust approach for the problem of automatic reference detection from document images. In spite of outperforming other approaches and achieving promising results, DeepBiRD can still be further improvised by merging it with text-based approach, so that both approaches can benefit from the expertise of each other.

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Figure 8: IoU vs Confidence vs Accuracy on BibDecDB dataset

Figure 9: Best case output sample in comparison with state-of-the-art approaches

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Figure 10: Average case output sample in comparison with state-of-the-art approaches

Figure 11: Worst case output sample in comparison with state-of-the-art approaches

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