TabProIS: A Transfer Learning-Based Model for Detecting Tables in Product Information Sheets

Michael Sildatke[1], Jan Delember[2], Bodo Kraft[1] and Albert Zündorf[3]
[1]*FH Aachen, University of Applied Sciences, Germany*
[2]*Maastricht University, The Netherlands*
[3]*University of Kassel, Germany*

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Abstract: Product Information Sheets (PIS) are human-readable documents containing relevant product specifications. In these documents, tables often present the most important information. Hence, table detection is a crucial task for automating the process of Information Extraction (IE) from PIS. Modern table detection algorithms are Machine Learning (ML)-based and popular object detection networks like Faster R-CNN or Cascade Mask R-CNN form their foundation. State-of-the-art models like TableBank or CDeCNet are trained on publicly available table detection datasets. However, the documents in these datasets do not cover particular characteristics of PIS, e.g., background design elements like provider logos or watermarks. Consequently, these state-of-the-art models do not perform well enough on PIS. Transfer Learning (TL) and Ensembling describe two methods of reusing existing models to improve their performance on a specific problem. We use these techniques to build an optimized model for detecting tables in PIS, named TabProIS. This paper presents three main contributions: First, we provide a new table detection dataset containing 5,600 document images generated from PIS of the German energy industry. Second, we offer three TL-based models with different underlying network architectures, namely TableBank, CDeC-Net, and You Only Look Once (YOLO). Third, we present a pipeline to automatically optimize available models based on different Ensembling and post-processing strategies. A selection of our models and the dataset will be publicly released to enable the reproducibility of the results.

1 INTRODUCTION

Table analysis is a well-recognized research area with an increasing trend in the number of publications for the last five years (Hashmi et al., 2021). Table understanding includes three steps: *Table Detection* focuses on detecting boundaries as bounding boxes in documents, *Table Segmentation* aims to determine the structure of a table regarding rows and columns, and *Table Recognition* combines segmentation and information parsing (Zhong et al., 2020). Therefore, table detection is an essential requirement and a crucial task in automated Information Extraction (IE) from tables (Sildatke et al., 2022b).

A vast number of Machine Learning (ML) table detection models based on different object detection networks like *Faster R-CNN* (Ren et al., 2016) or *Cascade R-CNN* (Cai and Vasconcelos, 2017) emerged. *TableBank* is a popular example using Faster R-CNN as a basis and a custom dataset with over 417,000 document images for training (Li et al., 2019). *CDeC-Net* uses Cascade R-CNN (Agarwal et al., 2020) and is trained on publicly available datasets like *ICDAR-2013* or *ICDAR-2019* (Gobel et al., 2013; Gao et al., 2019). Both models achieve excellent results with F1 scores over 95% and therefore represent the latest state-of-the-art. Hence, they are promising candidates for detecting tables in Product Information Sheets (PIS).

PIS are human-readable documents presenting product information to customers. Among tables, these sheets often contain elements to attract the attention of potential customers, like product pictures or company logos. Modern companies often provide services based on information originating from PIS, e.g., price comparison portals. Since employees often have to extract relevant information by hand, IE processes are time-consuming and expensive. Hence,

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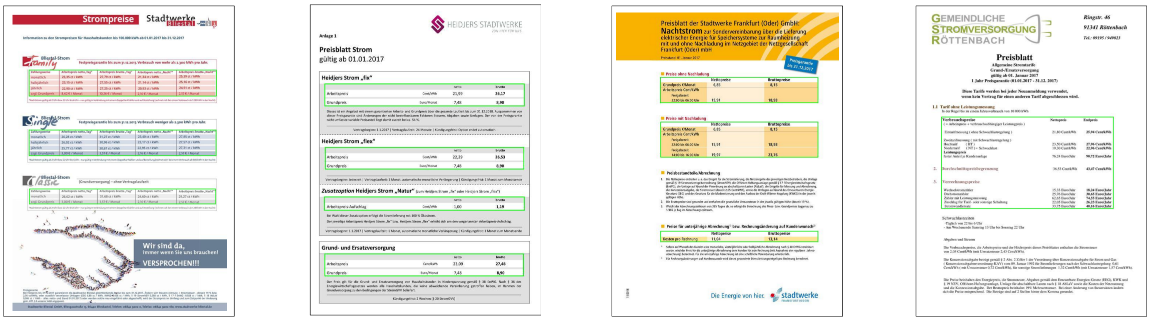


(a) Example with Logos and Background Images

(b) Example with Surrounding Boxes

(c) Example with Colored Tables

(d) Example with a Table as Part of an Enumeration

Figure 1: TableBank and CDeC-Net not Detecting Expected Tables (Marked Green) in Product Information Sheets (PIS).

service providers try to automate these processes using the newest findings from research. However, publicly available datasets mainly originate from scientific papers and do not cover particular characteristics of PIS. Consequently, state-of-the-art models such as TableBank or CDeC-Net cannot detect tables in PIS well enough. Figure 1 shows four examples of PIS in which TableBank and CDeC-Net do not detect any of the expected tables.

This circumstance indicates the need for a custom dataset that covers all relevant characteristics of PIS to evaluate existing models appropriately and train new specialized models for detecting tables in PIS. Transfer Learning (TL) describes a technique to adapt existing models and specialize them for different but related use cases (Torrey and Shavlik, 2009). Based on this method, we specialize the existing state-of-the-art table detection models TableBank and CDeC-Net on PIS. Since *YOLO* is the state-of-the-art algorithm for general object detection (Bochkovskiy et al., 2020), we also use it to train a specialized model for detecting tables in PIS. Furthermore, we combine the TL-based models to generate model results using different Ensembling strategies. *Ensembling* describes methods for combining several model outputs to generate more appropriate results. (Zhang and Ma, 2012). Due to customizable model parameters like the ensemble strategy, thresholds, or confidences, the number of possible resulting models is vast. For this reason, we automate the model optimization process by implementing a pipeline that automatically finds the best available parameter setting.

In order to tackle the challenges mentioned above, this paper presents three main contributions:

1. We provide the *TabProDS*[1] dataset containing 5,600 document images that originate from PIS of the German energy industry.
2. We offer three TL models for detecting tables in PIS, based on different state-of-the-art architectures, namely TableBank, CDeC-Net, and YOLO.
3. We present a pipeline to automatically optimize available models based on different ensemble and post-processing strategies to find the best one, called *TabProIS*[2].

This paper is structured as follows: Section 2 provides background information about the challenges and related works. Section 3 introduces the framework for training *TabProIS*, providing the dataset, TL models, and the model optimization pipeline. Section 4 shows the evaluation of the resulting models, and Section 5 concludes this paper.

2 BACKGROUND

This section provides background information about the challenges in table detection as a subproblem of object detection. Furthermore, it describes related works and builds the foundation for the model evaluation.

2.1 Object & Table Detection Models

As a branch of deep learning, *Object Detection* deals with finding objects in images or videos (Zou et al., 2019). In the context of TL, pre-trained object detection models like *ImageNet* (Krizhevsky et al., 2012), *ZF-Net* (Zeiler and Fergus, 2013), or *COCO* (Lin et al., 2015) often form the basis for specializations. More sophisticated models like *Fast R-CNN* (Girshick, 2015) and *Faster R-CNN* (Ren et al., 2016) use them as a base layer and, in turn, serve as a basis for TL-based table detection models. Popular examples

[1] https://github.com/msildatke/TabProDS

[2] https://github.com/msildatke/TabProIS

are introduced by (Gilani et al., 2017), (Das et al., 2018), (Siddiqui et al., 2018), and (Li et al., 2019). *Mask R-CNN* extends the Faster R-CNN model (He et al., 2018), and some approaches like (Cai and Vasconcelos, 2017), (Agarwal et al., 2020), and (Prasad et al., 2020) use it to provide specialized table detection models. Another approach shows the benefits of close-domain fine-tuning for table detection in document images based on different model architectures (Casado-Garcia et al., 2019). TableBank (Li et al., 2019) and CDeC-Net (Agarwal et al., 2020) are popular examples of TL models that use these object detection networks as a basis and perform excellently on public benchmark datasets. Finally, YOLO is the state-of-the-art algorithm for solving general object detection problems (Bochkovskiy et al., 2020).

2.2 Table Detection Datasets

Various publicly available datasets serve two purposes: a) training table detection models and b) comparing and evaluating the results of different table detection models. In this paper, we focus on the datasets that were used to train and evaluate the selected candidate models. The *ICDAR-2013* dataset is introduced by (Gobel et al., 2013) and has annotations for table detection and recognition. It contains 238 images converted from PDF files, of which 128 incorporate tables. (Gao et al., 2017) provide the *ICDAR-2017-POD* dataset. It is widely used and contains more examples than the ICDAR-2013 dataset, with 2417 images and 1081 table annotations. The *UNLV* dataset is made available by (Taghva et al., 2000) and is composed of approximately 10,000 scanned documents, of which 427 contain tables. The *ICDAR-2019* dataset was published as a foundation for the *Competition on Table Detection and Recognition* and contains 3,600 documents split into two separate datasets. The first contains modern documents, while the second contains historical and handwritten documents (Gao et al., 2019). (Fang et al., 2012) present the *Marmot* dataset that contains 2,000 document images originating from English and Chinese conference papers. Finally, (Li et al., 2019) introduce *TableBank*, a dataset that contains 417,000 images originating from Word and LaTeX documents.

However, Subsection 3.2 shows that existing datasets do not cover essential characteristics of PIS, so that state-of-the-art models fail detecting tables in PIS appropriately.

2.3 Performance Metrics

Intersection over Union (IoU) is the standard evaluation metric in object detection (Rezatofighi et al., 2019), described by the following formula:

$$\frac{Area\ of\ Overlap\ Regions}{Area\ of\ Union\ Area}$$

(Shafait and Smith, 2010) determine the number of true and false positive table predictions based on IoU to calculate precision, recall, and f-measure.

However, when using IoU-based performance measures, there is always the question of the optimal choice of an appropriate threshold. Therefore, we refer to the following threshold-independent and area-based performance measures, also introduced by (Shafait and Smith, 2010):

A. *AreaPrecision*
Indicates the percentage of detected table regions that belong to ground truth regions.

$$\frac{Area\ of\ Ground\ Truth\ Regions\ in\ Detected\ Regions}{Area\ of\ All\ Detected\ Table\ Regions}$$

i.e.,

$$\frac{\sum_i \sum_{j,k} \text{area}(D_{ij} \cap G_{ik})}{\sum_i \sum_j \text{area}(D_{ij})},$$

with each D_{ij} and G_{ik}, representing the k^{th} detection box and j^{th} ground truth box on the i^{th} image, respectively.

B. *AreaRecall*
Indicates the percentage of ground truth regions the model detects correctly.

$$\frac{Area\ of\ Ground\ Truth\ Regions\ in\ Detected\ Regions}{Area\ of\ All\ Ground\ Truth\ Table\ Regions}$$

i.e.,

$$\frac{\sum_i \sum_{j,k} \text{area}(D_{ij} \cap G_{ik})}{\sum_i \sum_k \text{area}(G_{ik})},$$

with the same definitions as above.

C. *F1 Score*
Considers area precision and area recall to compute the threshold-independent performance of a model.

$$2 \cdot \frac{AreaPrecision \cdot AreaRecall}{AreaPrecision + AreaRecall}$$

2.4 Ensembling Strategies & Methods

In object detection, bounding boxes mark relevant image parts as objects of interest (Zou et al., 2019).

Applying Ensembling methods leads to the problem of finding the most accurate bounding box combining several model results. Weighted Boxes Fusion (WBF) and Non-Maximum Suppression (NMS) are algorithms using IoU to determine boxes describing the same object. Based on that, they efficiently reduce a set of detected bounding boxes (Solovyev et al., 2021; Zhou et al., 2017).

(Casado-Garcia and Heras, 2020) have shown that applying Ensembling methods can improve the detection quality of models. Furthermore, they introduce three strategies to improve the Ensembling quality, which we adapt for our use case. To achieve this, we define a list $LD = [D_1, ..., D_n]$ where n is the number of table detection models and each D_i contains the list of respective model predictions. Based on the IoU of the model predictions, we define object groups $O = [O_1, ..., O_m]$ that describe predictions related to m objects. The related predictions of a specific object O_i are described by $OD_i = [OD_1^{O_i}, ..., OD_l^{O_i}]$ with l describing the index of the predicting model with $|OD_i| = n$, if all models generate a prediction related to a specific object. Based on this definitions, we define three Ensembling strategies as follows:

1. *Affirmative*.
   Each object O_i is kept for ensemble if $|OD_i| \geq 1$. This means that at least one model has to make a prediction about a potential object.
2. *Consensus*.
   Each object O_i is kept for ensemble if $|OD_i| \geq \frac{n}{2}$. This strategy is also known as *Majority Voting*.
3. *Unanimous*.
   Each object O_i is kept for ensemble if $|OD_i| = n$. This means that each model has to make a prediction about a potential object.

Applying a specific strategy filters object candidates for the actual Ensembling.

3 TRAINING FRAMEWORK

This section presents our TabProIS framework providing the TabProDS dataset, our TL models, and a pipeline to optimize model performances based on Ensembling and post-processing steps.

3.1 TabProDS Dataset

Since the above-mentioned publicly available datasets do not represent particular characteristics of PIS, we created the *TabProDS* dataset. The dataset contains 5,600 document images, of which 4,496 have table annotations in the COCO format. The source of these documents are PIS which describe electricity products from the German energy industry. Initially, product providers published the documents in PDF format on their websites. Subsection 3.2 shows in detail that some of these characteristics lead to poorly performing model candidates. We randomly picked 15% of the 5,600 annotated images into a fixed validation dataset, which resulted in 840 samples. The validation dataset is a basis for the independent evaluation and comparison of different models. We split the remaining 4,760 documents into 838 randomly picked test and 3,922 training samples for each model training. To guarantee a high annotation quality, we calculated an inter-annotator agreement between all annotators referring to (Fleiss et al., 2003). With a calculated kappa of 0.82, the agreement can be classified as *almost perfect* following (Viera and Garrett, 2005).

3.2 Transfer Learning Models

In our experiments, TableBank, CDeC-Net, and YOLO serve as base models for detecting tables in PIS. Table 1 shows the performance of TableBank and CDeC-Net on our validation dataset. Since YOLO only provides general object detection models, we can not explicitly evaluate the performance of any available base model on our dataset.

Table 1: Performance of the Base Models.

Model	Precision	Recall	F1 Score
TableBank	0.84	0.50	0.63
CDeC-Net	**0.73**	**0.86**	**0.79**

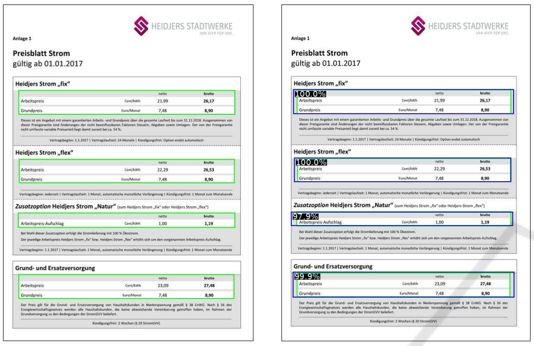
The evaluation of the base models on our validation dataset shows that available state-of-the-art models do not perform well enough as a requirement for the automated IE from PIS. Therefore, we use our TabProDS dataset to specialize these base models for detecting tables in PIS by applying TL. We run all TL experiments on a workstation with three NVIDIA Quadro RTX 8000, providing 48 GB VRAM each.

3.2.1 TableBank Fine-Tuning

(Li et al., 2019) use the open-source object detection framework *detectron2* (Wu et al., 2019), based on PyTorch, to train TableBank. The authors provide models with two different versions of ResNeXt as network baseline, i.e., X101 and X152. They use three datasets for training. The first one contains about 163,500 document images originating from Word documents. The second one contains about 253,800 document images from LaTeX documents. The third one combines the previous ones, resulting in about 417,300 samples.

Our evaluation has shown that the X101(LaTeX) model performs best on the TabProDS dataset. Therefore, we use the pre-trained X101(LaTeX) model to train our fine-tuned TableBank*f* (TB*f*) model.

We experiment with different base learning rates ranging from 0.005 to 0.1 and various levels of backbone freezing (0 to 5 stages). We achieve the best results without freezing any stages, aiming at completely recalculating the model weights. All experiments run 125,000 iterations with a batch size of 4. Figure 2 shows an exemplary prediction comparison of TableBank and TB*f*.



(a) TableBank (b) TableBank*f* (TB*f*)

Figure 2: Exemplary Prediction Comparison of TableBank and TableBank*f* (TB*f*).

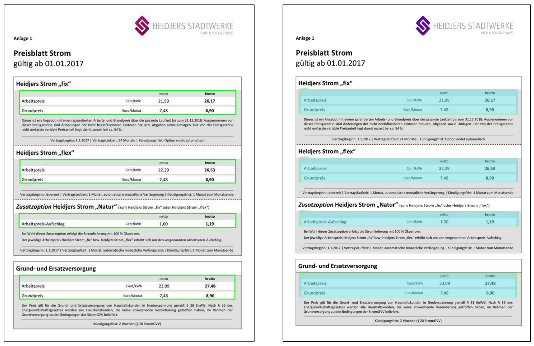
3.2.2 CDeC-Net Fine-Tuning

(Agarwal et al., 2020) use the MMdetection toolbox (Chen et al., 2019) based on PyTorch to train their CDeC-Net table detection model. The backbone of CDeC-Net is a ResNeXt-101 pre-trained on MS-COCO, while a Feature Pyramid Network (FPN) (Lin et al., 2017) forms the network head. The authors provide different models trained on various publicly available datasets. Our experiments show that CDeC-Net trained on the ICDAR-2013 dataset performs best on our TabProDS dataset. Therefore, we use this model's base settings and weights for TL, experimenting with different base learning rates and stage freezes. Our best TL-based CDeC-Net, CDeC-Net*f* (CDeC*f*), trains 50 epochs with an initial learning rate $lr = 0.00125$ and two frozen stages.

Figure 3 shows an exemplary prediction comparison of CDeC-Net and CDeC*f*.

3.2.3 YOLO Fine-Tuning

Since YOLO does not provide a specific model for table detection, we have to train one from scratch. For training, we use the Python implementation YOLOv5[3] which is also based on PyTorch. We test different sizes of the YOLO network, namely YOLOv5s, YOLOv5l, and YOLOv5x. To speed up convergence, we experiment with setting the initial weights from different checkpoints. We achieve the best results using the YOLOv5x network which scales input images to a size of 1280×1546 pixels. Table 2 shows the results of YOLO*f*.



(a) CDeC-Net (b) CDeC-Net*f* (CDeC*f*)

Figure 3: Exemplary Prediction Comparison of CDeC-Net and CDeC-Net*f* (CDeC*f*).

3.2.4 Performance of the Fine-Tuned Models

The evaluation of our fine-tuned models shows that performance heavily depends on the confidence threshold C of predictions (c.f. Table 2). While TB*f* and CDeC*f* reach their best F1 scores with a confidence threshold $C = 0.8$, YOLO*f* performs best with $C = 0.7$.

Table 2: Performance of the Fine-Tuned Models.

Model	C	Precision	Recall	F1 Score
TB*f*	0.7	0.840	0.930	0.883
CDeC*f*	0.7	0.875	0.903	0.889
YOLO*f*	**0.7**	**0.891**	**0.860**	**0.875**
TB*f*	**0.8**	**0.887**	**0.903**	**0.895**
CDeC*f*	**0.8**	**0.899**	**0.881**	**0.890**
YOLO*f*	0.8	0.903	0.797	0.847
TB*f*	0.9	0.921	0.839	0.878
CDeC*f*	0.9	0.922	0.837	0.877
YOLO*f*	0.9	0.923	0.626	0.746

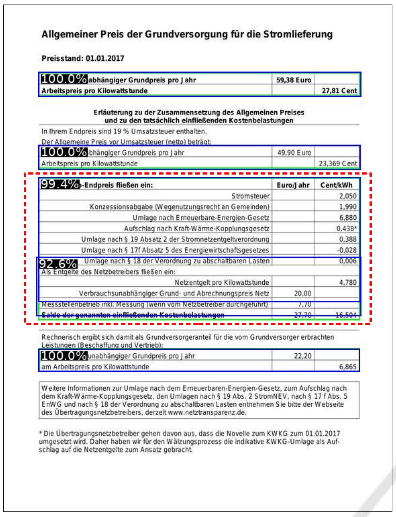
By performing TL, we improve the F1 score for TableBank by +26%- and CDeC-Net by +10%-points.

3.3 Post-Processing

As shown in Figure 4, the models sometimes make so-called Table-in-Table Predictions (TiTPs). In contrast to classic object detection problems, there are no tables in front of each other in our use case. There-

[3]https://github.com/ultralytics/yolov5

fore, we delete the predicted inner tables improving the performance. Since the IoU of the red-bordered predictions (99.4% and 92.6%) is relatively small, Ensembling does not remove the inner box. Hence, we must implement specific post-processing steps to remove TiTPs automatically.


Allgemeiner Preis der Grundversorgung für die Stromlieferung

Preisstand: 01.01.2017

100.0%abhängiger Grundpreis pro Jahr	**59,38 Euro**	
Arbeitspreis pro Kilowattstunde		**27,81 Cent**

Erläuterung zu der Zusammensetzung des Allgemeinen Preises und zu den tatsächlich einfließenden Kostenbelastungen

In Ihrem Endpreis sind 19 % Umsatzsteuer enthalten.

Der Allgemeine Preis vor Umsatzsteuer (netto) beträgt:

100.0%bhängiger Grundpreis pro Jahr	49,90 Euro	
Arbeitspreis pro Kilowattstunde		23,369 Cent

99.4%-Endpreis fließen ein:	**Euro/Jahr**	**Cent/kWh**
Stromsteuer		2,050
Konzessionsabgabe (Wegenutzungsrecht an Gemeinden)		1,990
Umlage nach Erneuerbare-Energien-Gesetz		6,880
Aufschlag nach Kraft-Wärme-Kopplungsgesetz		0,438*
Umlage nach § 19 Absatz 2 der Stromnetzentgeltverordnung		0,388
Umlage nach § 17f Absatz 5 des Energiewirtschaftsgesetzes		-0,028
92.6% Umlage nach § 18 der Verordnung zu abschaltbaren Lasten		0,006
Als Entgelte des Netzbetreibers fließen ein:		
Netzentgelt pro Kilowattstunde		4,780
Verbrauchsunabhängiger Grund- und Abrechnungspreis Netz	20,00	
Messstellenbetrieb inkl. Messung (wenn vom Netzbetreiber durchgeführt)	7,70	
Saldo der genannten einfließenden Kostenbelastungen	27,70	16,504

Rechnerisch ergibt sich damit als Grundversorgeranteil für die vom Grundversorger erbrachten Leistungen (Beschaffung und Vertrieb):

100.0%unabhängiger Grundpreis pro Jahr	22,20	
am Arbeitspreis pro Kilowattstunde		6,865

Weitere Informationen zur Umlage nach dem Erneuerbaren-Energien-Gesetz, zum Aufschlag nach dem Kraft-Wärme-Kopplungsgesetz, den Umlagen nach § 19 Abs. 2 StromNEV, nach § 17 f Abs. 5 EnWG und nach § 18 der Verordnung zu abschaltbaren Lasten entnehmen Sie bitte der Webseite des Übertragungsnetzbetreibers, derzeit www.netztransparenz.de.

* Die Übertragungsnetzbetreiber gehen davon aus, dass die Novelle zum KWKG zum 01.01.2017 umgesetzt wird. Daher haben wir für den Wälzungsprozess die indikative KWKG-Umlage als Aufschlag auf die Netzentgelte zum Ansatz gebracht.

Figure 4: Table-in-Table Prediction (TiTP).

To achieve automatic removal of TiTPs, we iterate over each combination of predicted bounding boxes (B_n, B_m) and calculate the intersection area of these boxes. If the intersection area A_I is equal to the area of one of the bounding boxes A_{B_n} or A_{B_m}, the corresponding box will be removed. Additionally, we introduce a threshold $0 < IoU_{PP} \leq 1$ that supports the post-processing so that each bounding box B_i will be removed if any resulting intersection area $I_{A_i} \leq IoU_{PP} \cdot \text{area}(B_i)$.

3.4 Microservice Implementation

According to (Sildatke et al., 2022a), we implement our resulting model as a FastAPI[4] microservice to easily use it for complex IE pipelines. (Sildatke et al., 2022a) introduce the *ARTIFACT* framework which harmonizes IE processes by splitting them into the tasks of document conversion, decomposition, and extraction. ARTIFACT enables developers to implement components like `Converters`, `Decomposers`, or `Extractors` that each solve a specific task, e.g., the detection of tables in a `PdfDocument`. Each component has to provide an endpoint offering service information (`\info`) and one for the actual operation. Following the convention of (Sildatke et al., 2022a), we implement our table detection as a `Converter` component that provides a `\convert` endpoint. Code Listing 1 shows the `\info` endpoint of our component.

```
@controller.get("/info",
    ↪ response_model=
    ↪ ComponentEndpointInfo)
def get_info():
  return ComponentEndpointInfo(
    name="PISTableDetector",
    consumes="PdfDocument",
    produces="ImageDocument",
    version="1.0.0",
    endpoint="/convert"
  )
```

Code Listing 1: Info Endpoint of `PISTableDetector`.

Internally, the microservice converts each page of the input `PdfDocument` into a single image. For each image, it requests all models to predict tables, i.e. TB*f*, CDeC*f*, and YOLO*f*. Afterwards, it generates ensemble predictions according to the selected strategy and method. Finally, it post-processes the ensemble predictions and returns the corresponding sections of the images as a list of `ImageDocuments` (c.f. Figure 5).

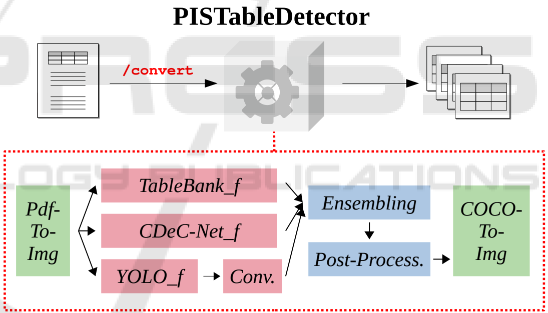


Figure 5: Microservice Implementation.

3.5 Model Optimization Pipeline

There are a large number of possible model variants based on various parameters such as Ensembling strategies and methods as well as IoU thresholds and model confidences. To find the optimal variant, we provide a model optimization pipeline that automatically evaluates a predefined set of different parameter settings. For this, we formalize the following parameter options that serve as input for the optimization pipeline:

- A list of non-filtered model results MR
- A list of model combinations MC
- A list of IoU thresholds for Ensembling IoU_{Ens}
- A list of Ensembling strategies E_S
- A list of Ensembling methods E_M

[4]https://fastapi.tiangolo.com/

- A list of intersection area thresholds for post-processing IoU_{PP}

We implement the pipeline as a CLI application with Python. It processes the relevant input parameters and produces the resulting model metrics as output (c.f. Figure 6).

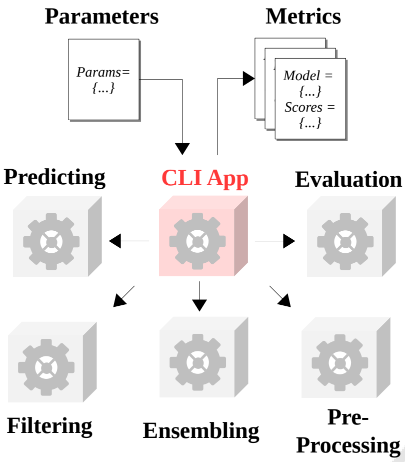


Figure 6: Model Optimization Pipeline.

Based on the input parameters, the model optimization starts with predicting results for each selected model on the validation dataset with a confidence threshold $C = 0$. It produces annotation files for each model in COCO format, while converting the respective YOLO annotations. During the result filtering step, the optimizer filters previously generated results according to the desired confidences. It combines the filtered model results using the given Ensembling strategies and methods. Based on the predefined intersection area thresholds, the optimizer finally post-processes each of the Ensembling results. The evaluation step marks the end of the optimization pipeline, evaluating each output of the previous steps. As a result, this step produces a list of all models and their performance metrics, ordered by F1 score.

4 EVALUATION

Our model optimization pipeline allows the configuration of different parameters influencing the resulting models. As shown in Code Listing 2, we trigger the model optimization pipeline to evaluate the model performances using default parameters. The `EvaluationRunner` generates predictions for each model in the validation step and runs the evaluation to determine the requested performance metrics.

```
if __name__ =="__main__":
  args=ArgumentParser().parse_args()

  if len(args)==1: # Default Params
    model_results =EvaluationRunner.predict(
      models=["tb_f", "cdec_f", "yolo_f"]
    )
    EvaluationRunner.evaluate(
      model_results= model_results,
      model_confidences= [0.7, 0.8, 0.9],
      model_combinations= [
        ("tb_f", "cdec_f", "yolo_f"),
        ("tb_f", "cdec_f"),
        ("tb_f", "yolo_f"),
        ("cdec_f", "yolo_f")
      ],
      ensemble_iou_thresholds= [
        0.1, 0.2, 0.5, 0.8
      ],
      ensemble_strategies= [1, 2, 3],
      ensemble_methods= [1, 2],
      postprocessing_area_thresholds=[
        0.7, 0.8, 0.9
      ]
    )
```

Code Listing 2: Starting an Evaluation Run.

Based on this configuration, the model optimization pipeline automatically calculates the performance for over 3,800 different model variants. Table 3 shows a selection of the resulting model performances. The complete evaluation results will be available in the provided GitHub repository. As shown in Table 3, we gathered several insights during the evaluation:

- Applying Ensembling and post-processing leads to an improvement of +2% for the F1 score (c.f. Table 3a).
- The WBF method is sensitive to the selected IoU threshold, performing better for higher ones (c.f. Table 3b).
- Lower IoU thresholds for Ensembling can compensate for lower model confidence values (c.f. Table 3c).
- Applying Ensembling and post-processing compensates for lower model confidence values most effectively (c.f. Table 3d).

We also gathered other insights that can be gleaned from the published results in the provided GitHub repository, including:

- The best model combination does not necessarily have to be the combination of the best single models; e.g., YOLO*f* solely performs better with a confidence $C = 0.7$, while the best Ensembling model selects a threshold of $C = 0.9$ for YOLO*f*.

Table 3: Selected Results of the Evaluation

TB_f	CDeC*f*	YOLO*f*	IoU_{Ens}	Strategy	Method	IoU_{PP}	Precision	Recall	F1 Score
0.8	-	-	-	-	-	-	0.887	0.903	0.895
-	0.8	-	-	-	-	-	0.899	0.881	0.890
-	-	0.7	-	-	-	-	0.891	0.860	0.875
0.8	0.8	0.7	0.5	Affirm.	NMS	-	0.770	0.942	0.848
0.8	0.8	0.7	0.5	Affirm.	WBF	-	0.767	0.948	0.848
0.8	0.8	0.7	0.5	Consens.	NMS	-	0.907	0.862	0.884
0.8	0.8	0.7	0.5	Consens.	WBF	-	0.903	0.868	0.885
0.8	0.8	0.7	0.5	Unani.	NMS	-	0.907	0.862	0.884
0.8	0.8	0.7	0.5	Unani.	WBF	-	0.945	0.690	0.797
0.8	0.9	0.9	0.5	Affirm.	WBF	-	0.825	0.934	0.876
0.8	0.9	0.9	0.5	Affirm.	WBF	0.7	0.897	0.933	0.914

(a) Results Showing Better Overall Performance Applying Ensembling + Post-Processing

TB*f*	CDeC*f*	YOLO*f*	IoU_{Ens}	Strategy	Method	IoU_{PP}	Precision	Recall	F1 Score
0.8	0.9	0.9	0.1	Affirm.	WBF	0.7	0.908	0.892	0.900
0.8	0.9	0.9	0.1	Affirm.	WBF	0.8	0.908	0.892	0.900
0.8	0.9	0.9	0.1	Affirm.	WBF	0.9	0.907	0.892	0.900
0.8	0.9	0.9	0.8	Affirm.	WBF	0.7	0.900	0.877	0.888
0.8	0.9	0.9	0.8	Affirm.	WBF	0.8	0.900	0.934	0.916
0.8	**0.9**	**0.9**	**0.8**	**Affirm.**	**WBF**	**0.9**	**0.895**	**0.942**	**0.918**

(b) Results Showing That WBF is Better For Greater IoU-Thresholds

TB*f*	CDeC*f*	YOLO*f*	IoU_{Ens}	Strategy	Method	IoU_{PP}	Precision	Recall	F1 Score
0.7	0.7	0.7	0.1	Affirm.	WBF	-	0.874	0.901	0.888
0.7	0.7	0.7	0.2	Affirm.	WBF	-	0.848	0.922	0.883
0.7	0.7	0.7	0.5	Affirm.	WBF	-	0.742	0.953	0.835
0.7	0.7	0.7	0.8	Affirm.	WBF	-	0.645	0.960	0.772

(c) Results Showing Lower IoU-Thresholds for Ensembling Compensate Lower Model Confidences

TB*f*	CDeC*f*	YOLO*f*	IoU_{Ens}	Strategy	Method	IoU_{PP}	Precision	Recall	F1 Score
0.7	0.7	0.7	0.1	Affirm.	WBF	0.9	0.880	0.901	0.890
0.7	0.7	0.7	0.2	Affirm.	WBF	0.9	0.865	0.922	0.893
0.7	0.7	0.7	0.5	Affirm.	WBF	0.9	0.855	0.952	0.901
0.7	0.7	0.7	0.8	Affirm.	WBF	0.9	0.859	0.959	0.906

(d) Results Showing Post-Processing + Ensembling Compensate Lower Model Confidences Best

Note: **TB*f***, **CDeC*f*** *and* **YOLO*f*** *are the confidence thresholds of the respective models.*

- TB*f* and CDeC*f* are always part of the excellently performing Ensembling models, while the impact of YOLO*f* is less significant.
- The NMS method is also sensitive to IoU thresholds, performing better for lower ones.
- The Affirmative strategy creates models with the highest F1 score (91.18%) because it improves precision, while Unanimous and Consensus produce models with the highest recall (95.8%).

The evaluation shows that combining Ensembling with specific post-processing can improve the performance of TL models. However, the prediction time of the resulting models increases, since not only one, but each model has to make its prediction. Nevertheless, since the targeted IE processes do not require real-time responses, such as object detection problems in videos, a longer processing time is quite acceptable.

5 CONCLUSION

Product Information Sheets (PIS) contain essential product specifications and are often the starting point for complex Information Extraction (IE) processes. They form the basis for digital services of modern companies, like price comparison portals. Since PIS are human-readable, employees of these companies usually have to extract relevant information by hand. The companies concerned try to automate these processes in order to reduce costs and minimize their duration.

Since tables frequently present relevant information in PIS, table detection is crucial in automating the processes. For this reason, a vast number of Machine Learning (ML)-based models emerged in recent years, based on popular object detection networks such as Faster R-CNN or Cascade R-CNN. State-of-the-art models, such as TableBank or CDeC-Net, are trained on publicly available table detection datasets like ICDAR-2013 or ICDAR-2019, and achieve excellent performance results with F1 scores over 95%. However, since PIS have particular characteristics that these public datasets do not cover, the performance of TableBank and CDeC-Net on PIS is insufficient.

In this paper, we provided a new table detection dataset, named TabProDS, containing 5,600 document images from PIS of the German energy industry to harmonically evaluate the performance of table detection models on PIS. Applying Transfer Learning (TL)-methods on TableBank , CDeC-Net, and YOLO, we used this dataset to train optimized models for detecting tables in PIS appropriately. We experimented with different Ensembling strategies (i.e., Affirmative, Consensus, and Unanimous) and methods (i.e., Weighted Boxes Fusion (WBF) and Non-Maximum Suppression (NMS)) to further improve the quality of the TL models. Additionally, we implemented post-processing steps to remove so-called Table-in-Table Predictions (TiTP). A specific model variant depends on many parameters, e.g., the selected Ensembling strategy and method, as well as different thresholds. Consequently, the number of possible model variants is very large. Therefore, we implemented a model optimization pipeline that automatically evaluates the quality of the resulting models based on a predefined set of parameters.

We evaluated over 3,800 different model variants and gathered several insights. The evaluation has shown that combining Ensembling with specific post-processing steps can compensate for lower model confidences. Also it has shown that applying TL improves the F1 score of TableBank by 26%- (from 63% to 89%) and CDeC-Net by 10%-points (from 79% to 89%). Furthermore, it shows that combining TL with Ensembling and post-processing improves the quality by another 2%-points. Finally, our TabProIS model achieves an F1 score of 91.18% on the validation dataset of TabProDS, containing 840 samples. Since detecting tables in PIS does not require real-time processing, the overhead of Ensembling and post-processing is quite acceptable.

We will publish a selection of our models and the dataset on GitHub so that our results can be reproduced.

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