Fine-Tuning and Aligning Question Answering Models for Complex Information Extraction Tasks

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Abstract: The emergence of Large Language Models (LLMs) has boosted performance and possibilities in various NLP tasks. While the usage of generative AI models like ChatGPT opens up new opportunities for several business use cases, their current tendency to hallucinate fake content strongly limits their applicability to document analysis, such as information retrieval from documents. In contrast, extractive language models like question answering (QA) or passage retrieval models guarantee query results to be found within the boundaries of an according context document, which makes them candidates for more reliable information extraction in productive environments of companies. In this work we propose an approach that uses and integrates extractive QA models for improved feature extraction of German business documents such as insurance reports or medical leaflets into a document analysis solution. We further show that fine-tuning existing German QA models boosts performance for tailored extraction tasks of complex linguistic features like damage cause explanations or descriptions of medication appearance, even with using only a small set of annotated data. Finally, we discuss the relevance of scoring metrics for evaluating information extraction tasks and deduce a combined metric from Levenshtein distance, F1-Score, Exact Match and ROUGE-L to mimic the assessment criteria from human experts.

1 INTRODUCTION

Automated feature extraction from text documents is a necessary first step for the successful application of many business processes. Unstructured text data needs to be analyzed and stored in structured databases in order to be checked and processed by downstream systems. This task is common to many business areas, e.g., customer service centers responding to support requests, insurance companies assessing damage claims or medical authors reviewing scientific literature to prepare documents for drug approval procedures – to name a few examples.

The development of information retrieval systems (IRS's) supporting in these tasks have a long history (Sanderson and Croft, 2012). Typically these kind of systems combine capabilities to support different input formats (to deal with scanned as well as electronic text documents) using rules and models for feature extraction. However, recent progress in the field of Large Language Models (LLM's) has boosted capabilities of possible applications for natural language processing (NLP) (Zhang et al., 2023).

Retrieving some specific information from documents can be arbitrarily complex as text features may appear in form of free wording over several whole sentences (e.g., the cause of a cars damage in a damage report which might be given in form of one or several whole sentences). These kinds of features are difficult to define with rule-based approaches alone in a general way, especially over different context domains and query formulations[1]. This qualifies them as prime candidates for machine learning (ML)-based extractions, specifically language models capable of capturing and interpreting the textual contexts within a written document.

In contrast to the emerging powerful generative

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LLM's like ChatGPT – which suffer from hallucination and produce output that is usually hard to verify (Bang et al., 2023) – the application of extractive question answering (QA) models turned out to be promising for detecting answers in a specific document context (Pearce et al., 2021; Xu et al., 2021). Since these models are usually designed to return text boundaries within the given content as output, they are robust to such failure modes.

For this reason, we investigate the possibilities of applying and fine-tuning extractive QA models integrated in an IRS and applying it to German text documents with different features (from one-word entities to complex phrases) and business domains, focusing on the following research questions:

1. How can Question-Answering (QA) models be used for extraction of complex information from textual documents in specific industrial use cases?
2. To what extent does the fine-tuning of QA models influence performance across different domains and textual features?
3. What metrics are appropriate for (automated) performance evaluations that resemble human expert examination?

The remainder of this is paper is structured as follows: in Section 2, we present similar research and approaches in the field. Section 3 shows our approach for using QA models in complex information extraction tasks. In Section 4, we define evaluation metrics, present our evaluation method and the results. Finally, Section 5 summarizes the main findings and lists improvement ideas we are currently working on.

2 RELATED WORK

Analysis and information extraction from business documents consists of many tasks, starting with image analysis and text region detection, OCR and text classification to actual entity extraction. For example Tang et al. has tackled these issues and propose an extensive solution on the basis of Microsoft Azure Document AI technology (Microsoft, 2022; Tang et al., 2022). However, for many use cases dealing with the analysis of confidential or personal data, entirely relying on third-party cloud infrastructure is not a viable option. Many companies require solutions that can be fine-tuned to their specific needs and deployed on premise.

In (Kintz et al., 2020) we proposed a solution for specific data contexts and tasks in the area of information retrieval from written documents. The approach describes a system for the management of customer claims, that automatically extracts the key entities for handling a claim by utilizing a set of rule-based functions as well as NER models. In (Engelbach et al., 2022) we followed a similar approach, where an automatic address data extraction framework was built. The work compares the various aspects and consequences of implementing either rule-based or deep learning models in IRS's under diverse input feature and boundary conditions. Afterwards, an IRS framework is proposed that combines both approaches in a single detection and evaluation pipeline. Both solutions reported good results in combining human defined rule sets and ML extractors, e.g., for NER, for confident feature retrieval, or for result validation. However, the extraction pipelines described there rely on standard algorithms and ML models and do not profit from (con)text understanding capabilities of modern LLMs.

Previous work on document analysis pipelines with scanned images as input in form of IR products like Transkribus (Kahle et al., 2017) has been published as well. However, the system focuses on digitalizing content of historical documents and lacks capabilities for flexible feature extraction and layout handling in modern business documents.

In the popular and continuously growing Huggingface community (Wolf et al., 2020) a lot of language models have been open sourced. Although many multilingual models have been published there, the number of good performing models for German language is still limited. In the field of question answering (QA), the SQUAD dataset is a popular dataset for training extractive QA models, which aim to find answers to a query within the given boundaries of a context document (Rajpurkar et al., 2016; Cloudera Fast Forward Labs, 2020). The GermanQuAD dataset (Möller et al., 2021) and QA models trained by deepset, the associated company, provides a good starting point for our work. Furthermore, deepset also provides a freely available and locally deployable annotation tool (deepset, 2023) suited for QA related tagging that we utilized for the creation of training and test ground truths for our documents and model trainings.

The choice of evaluation metrics is an important parameter in determining the applicability of a model to a specific task. Using a single or combination of metrics that correlate well with human judgement for the presented domain can be a powerful approach to reduce the required labeling effort. (Han et al., 2021) addressed this issue by defining a customized version of the *hLEPOR* metric (Han et al., 2013) and tuning its hyperparameters to match either the output of pre-trained language models or human evaluation data.

Table 1: Classification of typical features during extraction tasks with three levels of feature complexity: Simple, Dynamic and Complex. Each type of feature recommends a different type of extraction methods like rule based or trained ML model. Based on previous work (Engelbach et al., 2022).

Classification Difficulty	**Features examples**	**Extractor type**
Simple	IBAN, E-mail address, Postal Codes	Rule-based (e.g., regular expressions)
Dynamic	Named Entities (e.g., organization, person name, place)	Trained extraction models (e.g., Named Entity Recognition (NER))
Complex	Cause of an event, name of person with a given role	Question-answering model

The metric is designed for and optimized on a general collection of data for the task of neural machine translation (NMT) and shown to be a good alternative to the commonly used *BLEU* metric (Papineni et al., 2002) for specific language pairs, while our work focuses on the domain of extractive QA.
Instead of using metrics, an alternative approach to capture the implicit judgement rules of humans is the now widely applied alignment technique Reinforcement Learning from Human Feedback (RLHF) for LLM's (Korbak et al., 2023; Ziegler et al., 2019; Glaese et al., 2022; Ouyang et al., 2022; Lambert et al., 2022): By training a reward model on a set of LLM output and human ranking pairs for a given query and using it to optimize the original LLM in a reinforcement learning setting, the language model behavior can be implicitly steered in any desired direction depending on the ranking approach. This, however, requires different label types and significant additional training overhead.

Additionally, (Schaeffer et al., 2023) pointed out that the choice of metrics is important when evaluating the performance of models with respect to sudden performance jumps (also labeled *emergence*) and the associated perception of the model's capabilities by humans. To circumvent the misconception of too expressive individual metrics, this work uses multiple score in conjunction to evaluate the used QA models.

3 INFORMATION EXTRACTION APPROACH

The extraction of features from real documents in different business scenarios can be a challenging task, since the information that needs to be detected within the given contexts can be volatile among different companies, industry domains and document types.

In general, extraction methods face different levels of difficulty, depending on the type of information the system attempts to extract automatically. Based on the former work (Kintz et al., 2020; Engelbach et al., 2022) we classify the difficulty levels in three categories with examples about the kind of information to extract and algorithmic approach usually required to tackle them. The classification is shown in Table 1.

In our previous work (Engelbach et al., 2022), we implemented a document processing pipeline that supports all steps to gain structured data results from scanned documents. Furthermore, we introduced a flexible framework for the implementation of different new extractors based on rules, regular expressions or trained machine learning models. In the following, we describe the application and integration of QA models into our analysis pipeline for providing means of complex feature extraction that may be indexed by a text span of phrases or even whole sentences within a document.

3.1 Information Extraction Pipeline

The implemented pipeline includes multiple preprocessing and data reconstruction steps, the modules for the combined rule- and QA-based information extraction and a final result evaluation. The architecture is shown in Figure 1.

The IRS combines the analysis of layout information (text position on the page, text size, column and tables, etc.) with textual analysis to narrow down and extract the relevant information for a given task. The analysis pipeline works as follows:

1. In a first step, a scanned text document (typically in PDF format) is provided as input to the framework and converted to raw image data.
2. Using adapted region detection algorithms based on components of the German OCR-D project (Neudecker et al., 2019), text blocks are detected and classified (categories can vary depending on the use case, but may include dates, sender or receiver address data, standard text paragraphs, table regions, image regions, etc.). Optical character recognition (OCR) is performed to transform image to text data using optimized workflows based on Tesseract OCR (Smith, 2019).

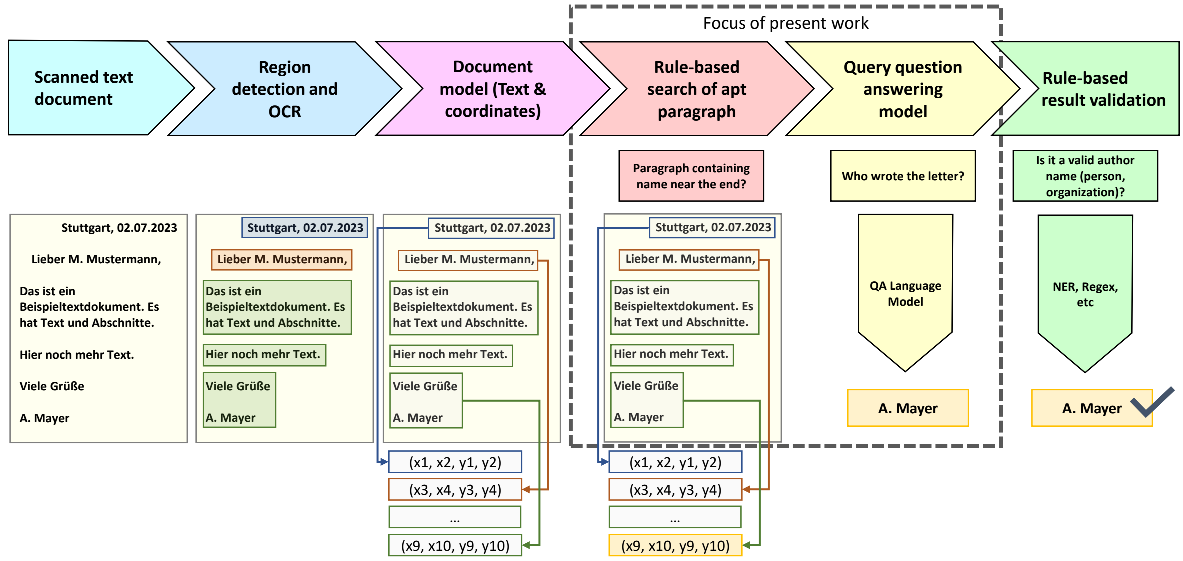


Figure 1: Information Extraction Pipeline starting with visual image processing parts (page segmentation and OCR). Afterwards, the relevant features are extracted using extractive question answering (QA) models (focus of current work).

3. The results are saved as an extended document model, containing the information to region, text content, and respective coordinates (on a region and character basis).
4. Depending on the use case and the usual length of input documents, the search scope may be restricted to the relevant text region or document page that is finally sent to the QA model. This is done using a rule-based approach, for example using keywords or headlines to help identify the proper candidate text regions.
5. With the final search scope, the QA model is then queried by providing the extracted text from the candidate regions and a suitable question targeting the information of interest. As output, the model returns the subsection of the candidate region with the highest probability for containing the answer.
6. Finally, to avoid outputs that are clearly wrong (e.g., numbers when asking for a name or vice-versa), a rule-based validation of the model answer is performed.

The focus of this work lies on the the steps 3 and 4 and evaluating the trained QA models for later integration into the larger IRS framework, as highlighted by the box in Figure 1.

3.2 Fine-Tuning and Evaluation Process

For our task of domain specific QA fine-tuning we used the model *gelectra-large-germanquad* that was pretrained on GermanQuAD (Möller et al., 2021), a German variant of the popular SQuAD data set (Rajpurkar et al., 2016). Both model and data set are provided by deepset and can be accessed via the common Huggingface API for inference and fine-tuning.

To quantify the impact of domain-specific training, we constructed two distinct datasets, one targeting the medical domain and one for the insurance domain, comprising German language data. Each e dataset was enriched with pertinent information features relevant to the respective domain. In this context we chose the features to be different concerning properties like text length and complexity. In detail, we consider the two domains with following features:

Drug Leaflet Data Set: The *leaflet* data set, which consists of 170 medication leaflet documents (which are freely available on many websites) with three QA pairs per document:

- **Ingredient:** the main active ingredient contained in the drug, e.g. *Metoprololtartrat*
- **Look:** The description of the drug appearance and optics, e.g. *White, round pills*
- **Application:** The application scope of the drug, e.g. *moderate pain and fever*

Elemental Damage Report Data Set: The *report* data set, which consists of 47 elemental damage reports documents taken from one of our former projects in the insurance domain and coming with 2 QA pairs per document:

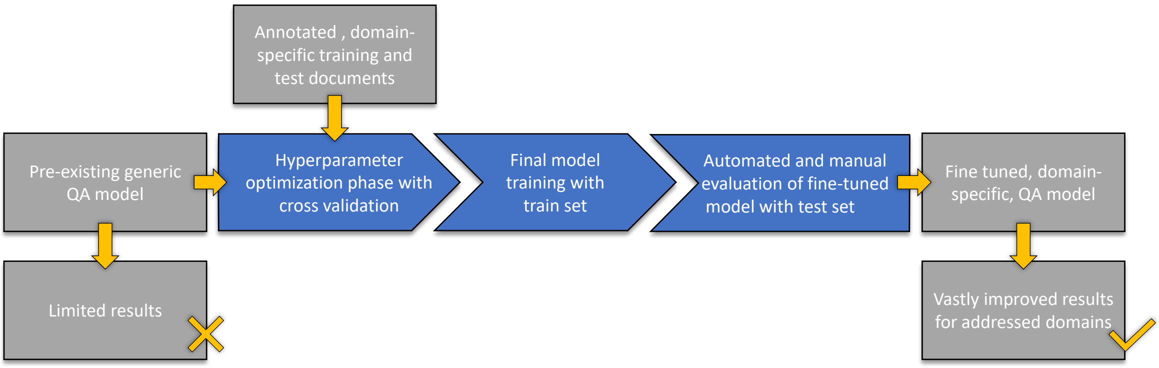


Figure 2: Model Fine-tuning and Evaluation Process starting from a general German base QA model and using hyperparameter optimization with cross validation for before the final (best) model is trained and integrated for productive usage.

- **Damage Cause:** event description of what caused the damage, e.g. *broken pipe due to rotted pipes in the floor*
- **Assessor Name:** The name of the damage assessor who wrote the report, e.g. *Manfred Bauer*

We annotated all documents using the QA annotation tool Haystack(deepset, 2023) with according questions asking for the specific entity of interest, e.g. *What can the drug be applied for?* or *What was the cause of the damage?*.

The further training process is described in Figure 2. In detail, since in this approach we only use data sets with limited amounts of samples, we used 5-fold cross validation splits of 80% / 20% for train and test to train several models in a grid search approach to find the optimal hyperparameter settings for both data sets, namely the values for epoch number, batch size, learning rate and doc stride. The latter one describes the amount of overlapping tokens when splitting up large documents into smaller chunks to comply with the maximum input size of the QA models (usually 512 tokens). Thus our script performs training and inference on smaller portions of the documents and collects merged predictions among the whole document to find the top confidence answer candidates during model queries.

We compare model performance before and after fine-tuning using automatically computable metrics described in Section 4.1 for settling the optimized hyperparameter configuration for training of the final model. For training the final QA model with optimized hyperparameters we again used one single train / test split of 80% train and 20% test data, which was also evaluated with the additional manual expert metric presented in Section 4.1. In the following we present our evaluation results and key findings for domain specific QA fine-tuning.

4 EVALUATION

4.1 Evaluation Metrics

Evaluating models in the context of NLP is a complex task: statistically relevant results require a large number of labeled data points and thus an automated evaluation. At the same time, creating labeled data sets for specific NLP tasks tend to be even more challenging than in other areas of supervised learning since natural language is fuzzy by nature and many different formulations can have the same meaning or represent a smooth transition between a correct and faulty statement.

Another difficulty is the fact that the correct answer to a question can appear multiple times in a document. For example, the name of the writer of an insurance claim assessment may appear on each page, and may be formatted in different ways (”John Doe” in the header, ”J. Doe” in the text itself, ”Mr. Doe” before the signature on the last page.) All these examples are correct answers to the question ”Who wrote the document?” but report bad performance scores when evaluated with metrics that can not account for fuzziness in natural language, like most automatically evaluated scores.

To address these issues, we combined several evaluation metrics - a common practice when evaluating QA models (Su et al., 2019; Drawehn et al., 2020). For that, we formulate the objective in terms of a supervised learning problem. For a specific question k from the set of all evaluated questions $q_k \in Q$, we denote the labeled set of word vectors of correct answers from N_k different annotators as $y^{(k)} = \{y_1, \ldots, y_{N_k}\}$ (without exact duplicates) and the response of a model to that question as $\hat{y}^{(k)}$. The metrics we used to evaluate our models are described below:

Manual Expert Assessment. As a ground-truth

Table 2: Evaluation criteria for manual expert assessment for each data set and feature to extract. For many features, only a subset of the complete information is considered as sufficient regarding usefulness, e.g. if only last name of the assessor is detected.

Data Set	**Feature**	**Criteria for Answers to be rated as correct**
Drug leaflets	Ingredient	All ingredients (there may be one or more) must be included in the answer, each with correct spelling
Drug leaflets	Look	Description of look (e.g. color and shape of pills) must be correct, details (e.g. notches) may be missing
Drug leaflets	Application	Description of application must be essentially correct, details may be missing
Damage reports	Damage cause	Description of cause must be essentially correct, different wording is acceptable; if there are several possible causes, one of these is sufficient
Damage reports	Assessor name	Last name must be exact, first name may be missing or abbreviated, title may be missing

baseline, we evaluate a set of model answers manually, which although cumbersome and by definition not automated, is the only way to know if the answer provided by the QA model indeed helps accomplish the task that the human end-user was interested in - this is the gold standard reference metric.

To get evaluation values for our data sets, we put ourselves in the role of a user with common knowledge in the subject under consideration and rated all answers as correct that were at least partially correct and not misleading for the user. An overview of the rating criteria for the features in our data sets is given in Table 2. Note that the thresholds for considering extracted information as correct resp. useful strongly depend on the type of feature: while short or even one-word entities like ingredient name leave little room for fuzzy extractions, for other features like look or assessor name it may be sufficient to only extract the most meaningful part of the feature (i.e. color and shape of the drug for look and the last name of the assessor. Other features like damage cause or drug application, which might be mentioned multiple times at different locations in the document context, are rated as correct if the found information is regarded as reasonable, complete and meaningful enough to answer to the question. Exact matches are always rated as correct.

Exact Match. $\mathcal{L}_{EM}$ measures the exact agreement of the model output with regard to the labeled answer(s) on a character basis after text normalization (e.g., lower-case conversion, removal of control characters, etc.) for a question k and is defined as

$$\mathcal{L}_{EM}^{(k)} = \min\left\{1, \sum_{i=1}^{N_k} \mathbb{1}\left(\hat{y}^{(k)} = y_i\right)\right\},$$

where $\mathbb{1}$ is the indicator function. If the characters of the model's prediction exactly match the characters of (one of) the true answer(s), Exact Match (EM) returns 1 and 0 otherwise. This is a strict all-or-nothing metric, which means being off by a single character results in a score of 0 for that question. The metric gives a good indication of the model performance when assessing against negative examples, where the answer to the provided question is not in the text. In this case, if the model predicts any text at all, it automatically receives a score of 0 for that example. The metric is easy to check automatically, however, often insufficient for more complex answers.

Levenshtein. To measure the similarity between a true answer of a given question to its corresponding model output, and also account for the possibly very diverse responses to the same query in natural language, we use the *Levenshtein* distance $\mathcal{L}_{Lev}$ (Levenshtein, 1966) as a character-based distance metric. Levenshtein measures the amount of operations (i.e. insertion, deletion and substitution) that separate two strings of characters.

F1-score. Furthermore, we use the definition of (Rajpurkar et al., 2016) to calculate the F1 score $\mathcal{L}_{F1}$ in the NLP setting by computing the equal, *word-wise* contribution between precision and recall, where precision is the ratio of the number of shared words to the total number of words in the prediction and recall is the ratio of the number of shared words to the total number of words in the ground truth (Rajpurkar et al., 2016; Rajpurkar et al., 2018):

$$\mathcal{L}_{F1}^{(k)} = \frac{1}{N_k} \sum_{i=1}^{N_k} \frac{2}{\frac{|\mathcal{S}_{\hat{y}}^{(k)}|}{|\mathcal{S}_{y_i}^{(k)} \cap \mathcal{S}_{\hat{y}}^{(k)}|} + \frac{|\mathcal{S}_{y_i}^{(k)}|}{|\mathcal{S}_{y_i}^{(k)} \cap \mathcal{S}_{\hat{y}}^{(k)}|}}$$

Table 3: Final hyperparameter configuration for fine-tuning experiments for each data set that have been determined during cross validation phase.

Data set	Base Model	Epochs	Batch Size	Learning rate	Doc Stride
Leaflets	deepset-gelectra-large-germanquad	2	12	0.00001	128
Reports	deepset-gelectra-large-germanquad	5	12	0.00001	128

Here $\mathcal{S}_{\hat{y}}^{(k)}$ denotes the set of distinct words in the model prediction $\hat{y}^{(k)}$ for a given question k, $\mathcal{S}_{y_i}^{(k)}$ the word-set of one of the labeled answers i, and $|\mathcal{S}_\star|$ the set size, i.e. number of unique elements (words) in the set.

ROUGE-L. We additionally calculate the Recall-Oriented Understudy for Gisting Evaluation (ROUGE) metric $\mathcal{L}_{RGE}$ (Lin, 2004), a widely used scoring method to evaluate the summarization quality of a model for a given generated and one or more reference summaries. Specifically, we calculate the ROUGE-L variant, denoted here as $\mathcal{L}_{RGE}$, which looks for the longest common subsequence (LCS) in the n-grams of two given sequences. In the extractive QA setting, we can treat the model output and ground truth in the same way, since with the prior of a given question, the response is a de facto summary of the whole context.

Weighted Average. Finally, we compute a weighted average $\mathcal{L}_{WA}$ of the above automated metrics $\mathcal{L}_C$ with $C = \{\text{EM}, \text{Lev}, \text{F1}, \text{RGE}\}$ as a single score, that indicates the quality of the model response with regard to the different aspects of each individual metric:

$$\mathcal{L}_{WA} = \frac{\sum_{l \in C} w_l \, \mathcal{L}_l}{\sum_{l \in C} w_l}$$

The weights w_l are determined by a linear model trained on the $\mathcal{L}_C$'s and the expert assessment score as the label. To verify that the weights determined by this method are transferable to other QA contexts, we train a regression model on the baseline and fine-tuned QA models of each dataset and compare their deviation.

With this method we aim to create an automatically calculable metric that consists of a combination of individual scores and approximates the implicit criteria from human feedback to rate a model answer.

The calculation of the overall score $\mathcal{L}_C$ for each of the described metrics is done by averaging over all queries Q for one specific dataset, model and question type:

$$\mathcal{L}_C = \frac{1}{|Q|} \sum_{k=1}^{|Q|} \mathcal{L}_C^{(k)}$$

4.2 Experimental Setup

Following the fine-tuning approach described in Section 3.2 we ended up with two final models trained with the configuration shown in Table 3: one for the leaflet document use case and one for the damage report use case. We used 80% of the data for training, the other 20% were hold back as test sets for the final model evaluation, namely 35 leaflets and 10 report documents.

To measure the effect of our fine-tuning we compared model performances before and after the training process. Table 4 lists the results for both data sets with according questions posed to the base and the fine tuned QA model using the metrics introduced in the previous Section 4.1.

4.3 Results and Discussion

The outputs of the metric computations introduced in Section 4.1 indicate a notable increase of model performance for the specific tasks, while the degree of improvements varies among the different data sets and questions with respect to the features of interest.

For instance, with a score of 0.77 and an F1 score of about 0.85 the feature *Ingredient* from the leaflet data set was already detected well by the base model (and got best overall scores). This might be due to the fact that the texts indicating this feature usually only consist of single and very specific words (like ”Tamoxifencitrat”) and additionally are announced by prominent keywords (like ”The ingredient is...”), which makes it easy for a QA model to answer this question.

In contrast, the *Damage Cause* feature, which is usually formed by one or several whole sentences with free formulation, seems to be the hardest to extract correctly due to its complexity. Nonetheless, also for this case we observe an increase of performance achieved by the QA fine-tuning process. Note that here also the base model already gave useful insights providing helpful information for finding the cause of the damage - even if this was not the originally labeled passage in the text (see human expert criteria in Table 2) -, which is also reflected in the comparatively higher Human Expert Assessment metric.

Table 4: Automated Evaluation of base and fine tuned models on medical leaflets and damage reports test sets.

Model	**Dataset**	**Question**	**Levenshtein** $\mathcal{L}_{Lev}$	**Exact Match** $\mathcal{L}_{EM}$	**F1** $\mathcal{L}_{F1}$	**ROUGE-L** $\mathcal{L}_{RGE}$	**Human Expert**
Base	Leaflets	Ingredient	0.960	0.771	0.849	0.909	0.971
Fine-tuned	Leaflets	Ingredient	0.985	0.914	0.941	0.959	1.000
Base	Leaflets	Look	0.611	0.147	0.452	0.468	0.529
Fine-tuned	Leaflets	Look	0.710	0.206	0.657	0.678	0.824
Base	Leaflets	Application	0.563	0.030	0.434	0.436	0.758
Fine-tuned	Leaflets	Application	0.761	0.212	0.694	0.713	0.909
Base	Reports	Damage Cause	0.581	0.000	0.368	0.363	0.800
Fine-tuned	Reports	Damage Cause	0.654	0.200	0.469	0.464	0.800
Base	Reports	Assessor Name	0.671	0.400	0.560	0.547	0.600
Fine-tuned	Reports	Assessor Name	0.771	0.700	0.700	0.700	0.700

The biggest improvement effect could be measured for the leaflet feature *Look*: While the base model had difficulties to answer this question correctly (which might be also due to particularities in the way the question was formulated), the fine tuned model seems to have learned this feature very well, even with having little training samples available, which is indicated by a score increment of more than 0.25 for some of the metrics.

In general, the results of F1 and ROUGE-L appear most similar to each other throughout all data sets and questions. Together with the Levenshtein, which plays to most important factor to approach the human metric through the weighted average score, they constitute results similar to those gained during the manual evaluation. In contrast, the EM metric behaves totally different and does not seem to provide any clue about human result usefulness, a fact that is underlined by the outcomes of the weighted average score computation illustrated in Figures 3a and 3b.

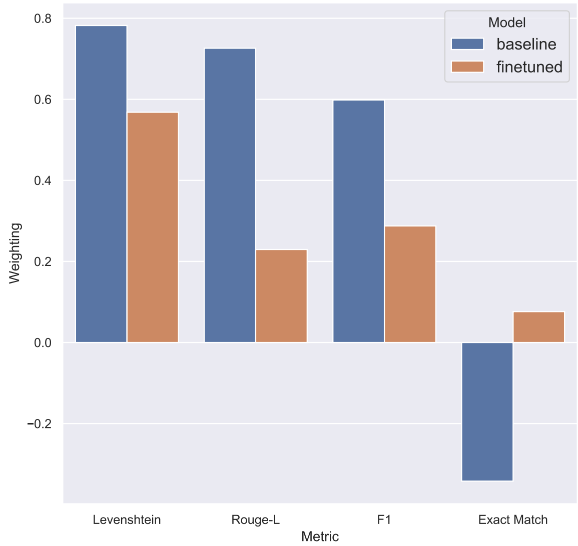
4.4 Human Evaluation Score Approximation

We train the linear model to predict the importance coefficients of the individual, automatically computable metrics from Section 4.1 to resemble the manual expert assessment score, which measures the helpfulness from a human perspective. The experiments show that the model is able to reconstruct the human scoring with a high accuracy of 93.87% using $\mathcal{L}_{Lev}$, $\mathcal{L}_{RGE}$, $\mathcal{L}_{F1}$, and $\mathcal{L}_{EM}$ as features. The coefficient values of the linear model are used as the weights w_l in the $\mathcal{L}_{WA}$ metric and shown in Figure 3. A generalization of this approach over datasets and tasks from different domains could not be observed for our case. While the weighting factors for the *reports* dataset are almost equally distributed between Levenshtein, ROUGE and F1, with EM basically being neglectable, for the *leaflets* dataset a decaying importance of the individual metrics from Levenshtein to F1 can be observed, EM even having a negative influence on the prediction. For both data sets the EM metric is a poor factor in reconstructing the implicit aspects of what humans perceive as a useful answer, which is not very surprising, considering EM as the hardest metric while humans still find an answer useful, even if some characters are missing or added to the model response.

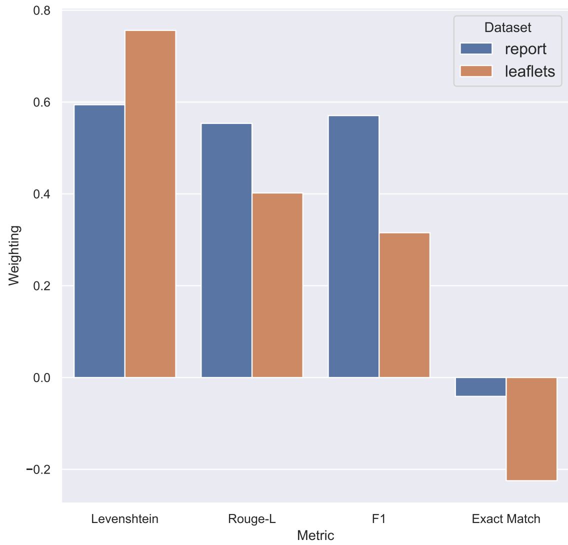
In terms of derivation of the implicit rules for the human definition of helpfulness from a set of simple computable measures, we see metric behaviors that are in line with observations from (Schaeffer et al., 2023): for strict metrics like EM, the baseline and (less severe) the fine-tuned model often produce much lower evaluation results than for the soft ones like F-measure or Levenshtein. This emphasizes that until a model becomes powerful enough to develop emergent abilities, strict metrics are normally less useful to catch the actual performance of the model for its use-case.

5 CONCLUSION AND FUTURE WORK

In this paper, we showed that applying extractive QA models for industrially relevant use cases of complex feature extraction leads to good performance for different kinds of domains, linguistic features and documents. Fine-tuning these QA models makes significant improvement possible and helps to support or automate document analysis. Finally, we show that a weighted average over Levenshtein, ROUGE-L and F1 is a good approximation for manual human expert evaluation, whereas EM is not. For future work, we want to further improve the results by tackling the following aspects:



(a)



(b)

Figure 3: Weighting factors for the individual components $\mathcal{L}_{Lev}$, $\mathcal{L}_{RGE}$, $\mathcal{L}_{F1}$, $\mathcal{L}_{EM}$ of the weighted average metric. The behavior of the weights are compared between the applied models (a) and datasets (b) separately.

- Further fine-tuning of QA models, for example with larger data sets, to get even better accuracy for specific applications areas
- Prompt optimization and answer combination for queries with different wordings for the same question, for example "Who wrote the document?", "Who is the author of the document?" and "Which person wrote the document?" and use majority or another heuristic to decide on the final answer,
- Experimenting with multiple choice questions when applicable, for example "Was the author, John Doe or Max Mustermann?", as done in previous work (Jiang et al., 2021).
- Improvement of page segmentation and region detection to limit the query scope for the QA model by feeding it only the most relevant parts of the text document for better response quality chances.
- Application of rule-based post-validation strategies for assuring quality and reliability of the feature predictions provided by the QA models.
- Investigation of multi-modal QA models that also take into account visual features like regions, boxes and page coordinates.

We further plan to include the best results and models as part of the document analysis pipeline of our industrial platform solution Aikido[2].

[2]https://www.digital.iao.fraunhofer.de/de/leistungen/KI/Aikido.html

REFERENCES

Bang, Y., Cahyawijaya, S., Lee, N., Dai, W., Su, D., Wilie, B., Lovenia, H., Ji, Z., Yu, T., Chung, W., Do, Q. V., Xu, Y., and Fung, P. (2023). A multitask, multilingual, multimodal evaluation of chatgpt on reasoning, hallucination, and interactivity.

Cloudera Fast Forward Labs (2020). Squad2.0: The stanford question answering dataset. https://rajpurkar.github.io/SQuAD-explorer/. Accessed: 2022-12-12.

deepset (2023).

Drawehn, J., Blohm, M., Kintz, M., and Kochanowski, M. (2020). Goal-based evaluation of text mining results in an industrial use case. pages 183–191.

Engelbach, M., Klau, D., Drawehn, J., and Kintz, M. (2022). Combining deep learning and reasoning for address detection in unstructured text documents.

Glaese, A., McAleese, N., Trebacz, M., Aslanides, J., Firoiu, V., Ewalds, T., Rauh, M., Weidinger, L., Chadwick, M., Thacker, P., Campbell-Gillingham, L., Uesato, J., Huang, P.-S., Comanescu, R., Yang, F., See, A., Dathathri, S., Greig, R., Chen, C., Fritz, D., Elias, J. S., Green, R., Mokrá, S., Fernando, N., Wu, B., Foley, R., Young, S., Gabriel, I., Isaac, W., Mellor, J., Hassabis, D., Kavukcuoglu, K., Hendricks, L. A., and Irving, G. (2022). Improving alignment of dialogue agents via targeted human judgements.

Han, L., Sorokina, I., Erofeev, G., and Gladkoff, S. (2021). cushlepor: customising hlepor metric using optuna for higher agreement with human judgments or pretrained language model labse.

Han, L., Wong, D. F., Chao, L. S., He, L., Lu, Y., Xing, J., and Zeng, X. (2013). Language-independent model for machine translation evaluation with reinforced factors. In *Machine Translation Summit*.

Jiang, Z., Araki, J., Ding, H., and Neubig, G. (2021). How can we know when language models know? on the calibration of language models for question answering.

Kahle, P., Colutto, S., Hackl, G., and Mühlberger, G. (2017). Transkribus - a service platform for transcription, recognition and retrieval of historical documents. In *2017 14th IAPR International Conference on Document Analysis and Recognition (ICDAR)*, volume 04, pages 19–24.

Kintz, M., Dukino, C., Blohm, M., and Hanussek, M. (2020). Make your Customers Happy Again. AI and NLP for a Customer Complaint Management Platform.

Korbak, T., Shi, K., Chen, A., Bhalerao, R., Buckley, C. L., Phang, J., Bowman, S. R., and Perez, E. (2023). Pretraining language models with human preferences.

Lambert, N., Castricato, L., von Werra, L., and Havrilla, A. (2022). Illustrating reinforcement learning from human feedback (rlhf). *Hugging Face Blog*. https://huggingface.co/blog/rlhf.

Levenshtein, V. I. (1966). Binary codes capable of correcting deletions, insertions, and reversals. In *Soviet Physics Doklady, vol. 10, no. 8*, pages 707–710.

Lin, C.-Y. (2004). ROUGE: A package for automatic evaluation of summaries. In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

Microsoft (2022). Document ai (intelligent document processing). https://www.microsoft.com/en-us/research/project/document-ai/. Accessed: 2022-12-20.

Möller, T., Risch, J., and Pietsch, M. (2021). GermanQuAD and GermanDPR: Improving non-English question answering and passage retrieval. In *Proceedings of the 3rd Workshop on Machine Reading for Question Answering*, pages 42–50, Punta Cana, Dominican Republic. Association for Computational Linguistics.

Neudecker, C., Baierer, K., Federbusch, M., Boenig, M., Würzner, K.-M., Hartmann, V., and Herrmann, E. (2019). Ocr-d: An end-to-end open source ocr framework for historical printed documents. In *Proceedings of the 3rd International Conference on Digital Access to Textual Cultural Heritage*, DATeCH2019, page 53–58, New York, NY, USA. Association for Computing Machinery.

Ouyang, L., Wu, J., Jiang, X., Almeida, D., Wainwright, C., Mishkin, P., Zhang, C., Agarwal, S., Slama, K., Gray, A., Schulman, J., Hilton, J., Kelton, F., Miller, L., Simens, M., Askell, A., Welinder, P., Christiano, P., Leike, J., and Lowe, R. (2022). Training language models to follow instructions with human feedback. In Oh, A. H., Agarwal, A., Belgrave, D., and Cho, K., editors, *Advances in Neural Information Processing Systems*.

Papineni, K., Roukos, S., Ward, T., and Zhu, W.-J. (2002). Bleu: A method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting on Association for Computational Linguistics*, ACL '02, page 311–318, USA. Association for Computational Linguistics.

Pearce, K., Zhan, T., Komanduri, A., and Zhan, J. (2021). A comparative study of transformer-based language models on extractive question answering. *CoRR*, abs/2110.03142.

Rajpurkar, P., Jia, R., and Liang, P. (2018). Know what you don't know: Unanswerable questions for squad.

Rajpurkar, P., Zhang, J., Lopyrev, K., and Liang, P. (2016). Squad: 100,000+ questions for machine comprehension of text.

Sanderson, M. and Croft, W. B. (2012). The history of information retrieval research. *Proceedings of the IEEE*, 100(Special Centennial Issue):1444–1451.

Schaeffer, R., Miranda, B., and Koyejo, S. (2023). Are emergent abilities of large language models a mirage?

Smith, R. (2019). Tesseract ocr: an optical character recognition engine for various operating systems. https://github.com/tesseract-ocr/tesseract. Accessed: 2021-11-10.

Su, D., Xu, Y., Winata, G. I., Xu, P., Kim, H., Liu, Z., and Fung, P. (2019). Generalizing question answering system with pre-trained language model fine-tuning. In *Proceedings of the 2nd Workshop on Machine Reading for Question Answering*, pages 203–211, Hong Kong, China. Association for Computational Linguistics.

Tang, Z., Yang, Z., Wang, G., Fang, Y., Liu, Y., Zhu, C., Zeng, M., Zhang, C., and Bansal, M. (2022). Unifying vision, text, and layout for universal document processing.

Wolf, T., Debut, L., Sanh, V., Chaumond, J., Delangue, C., Moi, A., Cistac, P., Rault, T., Louf, R., Funtowicz, M., Davison, J., Shleifer, S., von Platen, P., Ma, C., Jernite, Y., Plu, J., Xu, C., Scao, T. L., Gugger, S., Drame, M., Lhoest, Q., and Rush, A. M. (2020). Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, Online. Association for Computational Linguistics.

Xu, P., Liang, D., Huang, Z., and Xiang, B. (2021). Attention-guided generative models for extractive question answering. *CoRR*, abs/2110.06393.

Zhang, J., Chen, Y., Niu, N., and Liu, C. (2023). A preliminary evaluation of chatgpt in requirements information retrieval.

Ziegler, D. M., Stiennon, N., Wu, J., Brown, T. B., Radford, A., Amodei, D., Christiano, P., and Irving, G. (2019). Fine-tuning language models from human preferences. *ArXiv*, abs/1909.08593.