German CheXpert Chest X-ray Radiology Report Labeler

Deutscher CheXpert-Röntgenthorax-Befundlabeler

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ABSTRACT

Purpose The aim of this study was to develop an algorithm to automatically extract annotations from German thoracic radiology reports to train deep learning-based chest X-ray classification models.

Materials and Methods An automatic label extraction model for German thoracic radiology reports was designed based on the CheXpert architecture. The algorithm can extract labels for twelve common chest pathologies, the presence of support devices, and "no finding". For iterative improvements and to generate a ground truth, a web-based multi-reader annotation interface was created. With the proposed annotation interface, a radiologist annotated 1086 retrospectively collected radiology reports from 2020–2021 (data set 1). The effect of automatically extracted labels on chest radiograph classification performance was evaluated on an additional, in-house pneumothorax data set (data set 2), containing 6434 chest radiographs with corresponding reports, by comparing a DenseNet-121 model trained on extracted labels from the associated reports, image-based pneumothorax labels, and publicly available data, respectively.

Results Comparing automated to manual labeling on data set 1: "mention extraction" class-wise F1 scores ranged from 0.8 to 0.995, the "negation detection" F1 scores from 0.624 to 0.981, and F1 scores for "uncertainty detection" from 0.353 to 0.725. Extracted pneumothorax labels on data set 2 had a sensitivity of 0.997 [95 % CI: 0.994, 0.999] and specificity of 0.991 [95 % CI: 0.988, 0.994]. The model trained on publicly available data achieved an area under the receiver operating curve (AUC) for pneumothorax classification of 0.728 [95 % CI: 0.694, 0.760], while the models trained on automatically extracted labels and on manual annotations achieved values of 0.858 [95 % CI: 0.832, 0.882] and 0.934 [95 % CI: 0.918, 0.949], respectively.

Conclusion Automatic label extraction from German thoracic radiology reports is a promising substitute for manual labeling. By reducing the time required for data annotation, larger training data sets can be created, resulting in improved overall modeling performance. Our results demonstrated that a pneumothorax classifier trained on automatically extracted labels strongly outperformed the model trained on publicly available data, without the need for additional annotation time and performed competitively compared to manually labeled data.

Key points:
- An algorithm for automatic German thoracic radiology report annotation was developed.
- Automatic label extraction is a promising substitute for manual labeling.
- The classifier trained on extracted labels outperformed the model trained on publicly available data.

ZUSAMMENFASSUNG

Ziel Das Ziel dieser Studie war die Entwicklung eines Algorithmus zur automatischen Extraktion von Labels aus deutschen

Röntgenthoraxbefunden, um damit tiefe neuronale Netze zur Klassifikation von Röntgenthoraxaufnahmen zu trainieren.

Material und Methoden Basierend auf der CheXpert-Architektur wurde ein Modell zur automatischen Label-Extraktion für deutsche Röntgenthoraxbefunde entworfen. Der Algorithmus kann Labels für zwölf häufige Thoraxpathologien, die Anwesenheit von Fremdmaterial und „Normalbefund" extrahieren. Zur iterativen Verbesserung und Generierung eines Referenzstandards wurde ein webbasiertes Multi-Reader-Annotationsinterface erstellt. Mit dem vorgeschlagenen Programm hat ein Radiologe 1086 retrospektiv gesammelte Befunde aus dem Zeitraum 2020–2021 (Datensatz 1) annotiert. Die Auswirkungen der automatisch extrahierten Labels auf die Leistung der Röntgenbildklassifikation wurden an einem zusätzlichen internen Pneumothorax-Datensatz (Datensatz 2) mit 6434 Thorax-Röntgenaufnahmen und entsprechenden Befunden bewertet, indem ein DenseNet-121-Modell verglichen wurde, das auf extrahierten Labels basierend auf zugehörigen Befunden, bildbasierten Pneumothorax-Labels oder öffentlich verfügbaren Daten trainiert wurde.

Ergebnisse Beim Vergleich automatischer mit manueller Annotation des Datensatzes 1 ergaben sich für die klassenspezifischen F1-Scores der Erwähnungsextraktion Werte zwischen 0,8 und 0,995, für die F1-Scores der Negationserkennung zwischen 0,624 und 0,981 und für die F1-Scores der Unsicherheitserkennung zwischen 0,353 und 0,725. Die extrahierten Pneumothorax-Labels des Datensatzes 2 hatten eine Sensitivität von 0,997 [95 %-KI: 0,994, 0,999] und eine Spezifität von 0,991 [95 %-KI: 0,988, 0,994]. Das auf öffentlich verfügbaren Daten trainierte Modell erreichte eine Fläche unter der Operationscharakteristik-Kurve (AUC) für die Pneumothorax-Klassifikation von 0,728 [95 %-KI: 0,694, 0,760], das Modell, das auf automatisch extrahierten Labels trainiert wurde, erreichte 0,858 [95 %-KI: 0,832, 0,882] und auf manuellen Annotationen 0,934 [95 %-KI: 0,918, 0,949].

Schlussfolgerung Die automatische Annotation von deutschen Röntgenthoraxbefunden ist ein vielversprechender Ersatz für die manuelle Annotation. Durch die schnellere Annotation können größere Trainingsdatensätze erstellt werden, was eine höhere Modellleistung verspricht. Unsere Ergebnisse zeigten, dass ein Pneumothorax-Klassifikator, der auf automatisch extrahierten Labels trainiert wurde, das Modell, das auf öffentlich verfügbaren Daten trainiert wurde, deutlich übertraf, ohne zusätzliche Annotationszeit. Verglichen mit manuell annotierten Daten klassifiziert das Modell vielversprechend.

Kernaussagen:

- Ein Algorithmus für das automatische Labeln von Röntgehnthoraxbefunden wurde entwickelt.
- Das automatische Labeln ist ein vielversprechender Ersatz für das manuelle Labeln.
- Der mit den extrahierten Labels trainierte Klassifikator übertraf das mit öffentlich verfügbaren Daten trainierte Modell.

Zitierweise

- Wollek A, Hyska S, Sedlmeyr T et al. German CheXpert Chest X-ray Radiology Report Labeler. Fortschr Röntgenstr 2024; DOI 10.1055/a-2234-8268

Introduction

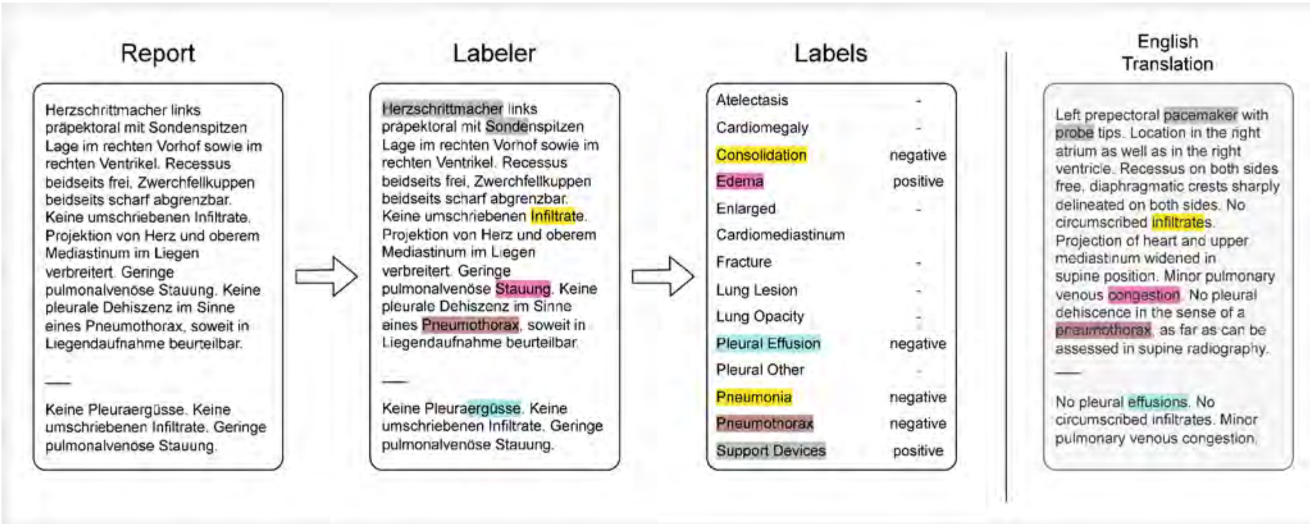
Chest X-rays are a frequently used and essential tool for detecting lung pathologies, like pneumothorax [1, 2]. The accurate interpretation of chest X-rays can be essential for the early detection, timely diagnosis, and effective treatment of these conditions. However, due to the large number of radiological images, radiology departments in many countries and regions are understaffed or overworked, ultimately risking the quality of care [3–5].

Recently, deep learning models used in decision support systems have achieved performance levels in chest X-ray diagnosis of pathologies like pneumonia that are comparable to those of radiologists [6, 7]. The integration of such models into clinical systems could reduce repetitive work, decrease workload, and improve the diagnostic accuracy of radiologists.

One of the reasons for the recent surge of innovation based on deep learning models is the availability of large data sets. For example, the release of the ImageNet data set and the corresponding image classification competition led to huge improvements in the computer vision domain [8–11]. Similarly, the release of the chest X-ray 14 data set [12] sparked the development of chest X-ray classification models like CheXnet [13]. While the number of images used by modern deep learning architectures has increased over the years, large publicly available data sets required for new architectures such as Vision Transformers [14] are missing in radiology, thus limiting the use of advanced models [15] and inhibiting advances in automated chest X-ray diagnosis.

Radiology departments around the world create large amounts of chest X-ray image data with corresponding reports during the clinical routine. Despite the existence of huge numbers of radiological imaging studies and their radiological reports stored in the Picture Archiving and Communication Systems (PACS) of numerous clinics, only a few are used for the development of new deep learning models, due to missing infrastructure, data privacy considerations, and required time, among other things.

Unlike commonly used image data sets, such as ImageNet, chest X-ray data sets obtained from the clinical routine require expert annotation due to the specialized knowledge required to understand the images. This annotation task falls on radiologists, who possess the necessary training and expertise to accurately interpret the X-rays. While decision support systems for chest X-ray diagnosis aim to reduce the workload of radiologists, a significant challenge arises from the need for radiologists to perform the time-consuming task of data annotation. This creates a "chicken-and-egg" problem, where the development of decision sup-



▶ **Fig. 1** Automated labeling of German thoracic radiology reports. A report is passed to the report labeler and converted to 14 labels, based on the CheXpert labels. The labeler detects each class according to class-specific phrases and converts them to positive, negative, or uncertain labels.

port systems depends on large, annotated data sets, yet creating these data sets requires significant time and effort on the part of radiologists.

To reduce the amount of time needed for data annotation, natural language processing systems have been created for extracting structured labels from free-text radiology reports. Such systems can be primarily categorized as rule-based or deep learning-based approaches, each of which has its own benefits and limitations. Rule-based systems, for instance, are easier to implement, require no computationally intensive training, provide higher explainability, and can be easily updated with new rules and classes by anyone. On the other hand, deep learning-based approaches primarily rely on large language models, and thus have the potential to produce more accurate label predictions but require more computational resources and larger (manually) annotated data sets. Furthermore, they can only be developed and maintained by experts. Finally, current state-of-the-art generative language models that do not require fine-tuning, such as GPT-4, cannot be used in a local environment and are potentially not compliant with data protection regulations like the general data protection regulation (GDPR).

Recent public chest X-ray data sets such as chest X-ray 14, CheXpert [16], and MIMIC-CXR [17] were created by converting existing radiological reports to class labels automatically using rule-based systems. For example, the CheXpert labeler converts an existing report to the thirteen classes: atelectasis, cardiomegaly, consolidation, edema, enlarged cardiomediastinum, fracture, lung lesion, lung opacity, pleural effusion, pleural other, pneumonia, pneumothorax, support devices, and an additional "no finding" class. To minimize development time, the CheXpert labeler was used to annotate the MIMIC-CXR data set as well. Moreover, this labeler has been adapted and ported to process reports in other languages, such as Brazilian [18] and Vietnamese [19]. The process of labeling consists of three stages: In the first stage, mention extraction, the labeler scans the report for phrases typical for a class as defined in class-specific lists. For example, the pneumothorax phrase list contains phrases such as "pneumothorax" and "pleural dehiscence". Next, extracted mentions found in the previous phase are classified as positive, negative, or uncertain (mention classification). Finally, all mentions of a specific class found in a single report are aggregated to create the observation label (mention aggregation). If a report happens to mention no observation, except support devices, the report is instead labeled as "no finding".

For German radiology reports, Nowak et al. investigated different approaches for training a deep-learning based labeling model [20]. In contrast to the CheXpert labeler, their model predicted only six observations: pulmonary infiltrates, pleural effusion, pulmonary congestion, pneumothorax, regular position of the central venous catheter (CVC) and misplaced position of the CVC. So far, neither the source code nor the model weights have been released.

In this study, we propose an automatic labeler for German thoracic reports based on the CheXpert algorithm (shown in ▶ **Fig. 1**). Our contributions are:

- We created a rule-based labeling algorithm for converting German thoracic radiology reports to CheXpert labels.
- We propose a web-based annotation tool for radiologists to adapt the labeler to new phrases used in a specific clinic and create a ground truth data set.
- We demonstrated that our proposed labeler performs similarly to radiological report labelers in other languages. In addition, we showed that a pneumothorax classifier trained on weakly labeled data outperforms models trained solely on publicly available data and performs competitively compared to manually labeled data.

Our code is publicly available at https://gitlab.lrz.de/IP/german-radiology-report-labeler.

Materials and Methods

Data Collection

We retrospectively identified thoracic radiology reports from 2020 to 2021 in our institutional PACS and randomly selected 900 reports, prior to the annotation, for the creation of a reference standard and 186 reports for phrase collection and development. We refrained from re-balancing the development and test subsets after data annotation to avoid biases introduced by data selection and from phrases collected during annotation. In the following, we refer to this data set as data set 1 (DS 1). Initially, two radiologists, one board-certified radiologist with more than ten years of experience (BOS), and one first year radiology resident (SA) from Ludwig-Maximilians-University Hospital Munich compiled a list of common phrases for each of the fourteen CheXpert classes. During the following data annotation process, the list of phrases was expanded to include positive, negative, and uncertain phrases.

Data Annotation

To make the labeling of data set 1 as efficient and accurate as possible, we built a multi-user web-based labeling interface. The design and implementation respect patient data privacy by running the process locally in a secure environment.

The annotation tool, shown in ▶ **Fig. 2**, displays the view position and report text on the left side of the screen, with four selectable labeling options available per pathology on the right. These options conform to the original CheXpert architecture and include positive, negative, uncertain, and none, which is used if the specific class was not mentioned. Radiologists can add new class-specific phrases by selecting "add new" and mark and comment on a report for later review. Before saving the annotations, the application highlights the phrases that were recognized by the labeler but were marked as "none" and prompts for a phrase if a class was selected during annotation, but not recognized by the labeler, thereby improving the phrase lists.

To evaluate the labeler's performance and expand the class pattern list, one first year radiology resident (SH) from Ludwig-Maximilians-University Hospital Munich annotated the 1086 randomly selected radiology reports of data set 1 using our proposed annotation interface. The initial annotation process was supervised by a board-certified radiologist with more than 10 years of experience (*). To account for the limitation of a single reader, a second data set was used for testing, see the section Pneumothorax Classification (DS 2). The resulting class distribution is listed in ▶ **Table 1**.

Report Labeler

In German radiology reports, two distinct types of negations were identified: expressions that contain phrases like "nicht" or "kein" ("no", "not") and are observation-independent, which can be resolved by the German NegEx algorithm [21], and medical terms that lack any negations but convey the lack of an observation, for example, "Herz normal groß" ("regular heart size"). As the CheXpert architecture addresses only negated observations, we extended the architecture by using multiple phrase files (positive, negative, uncertain) per observation.

As the original mention classification stage (see ▶ **Fig. 3**) depends on an extensive rule set created for English report texts, our labeler utilizes a modified version of the German NegEx algorithm to classify German mentions instead. In the first step, the labeling algorithm identifies negation phrases such as "kann ausgeschlossen werden" ("can be excluded"), and uncertainty phrases, such as "unwahrscheinlich" ("unlikely"), based on a set of rules and marks them as pre- or post-negation/uncertainty phrases.

To identify whether the classification of a mention is affected by negation/uncertainty terms (see ▶ **Fig. 3**), a cut-off radius determines how many words before and after the mention are taken into consideration, following the German NegEx algorithm. Optimized on the development set of DS 1, a cut-off radius of 15 was used. If the relevant region around the mention contains an uncertainty phrase, the mention is classified as uncertain. If either a pre-negation or post-negation is found near the mention, it is classified as negative. Uncertain phrases overrule negations to account for phrases such as "wahrscheinlich kein [...]" ("probably no [...]"). Finally, if there are no known negation or uncertainty phrases in the surrounding region, the mention is classified as positive.

To form the final label for each observation, the results from mention classification are aggregated as shown in ▶ **Fig. 4**. The following rules are applied to derive the labels:

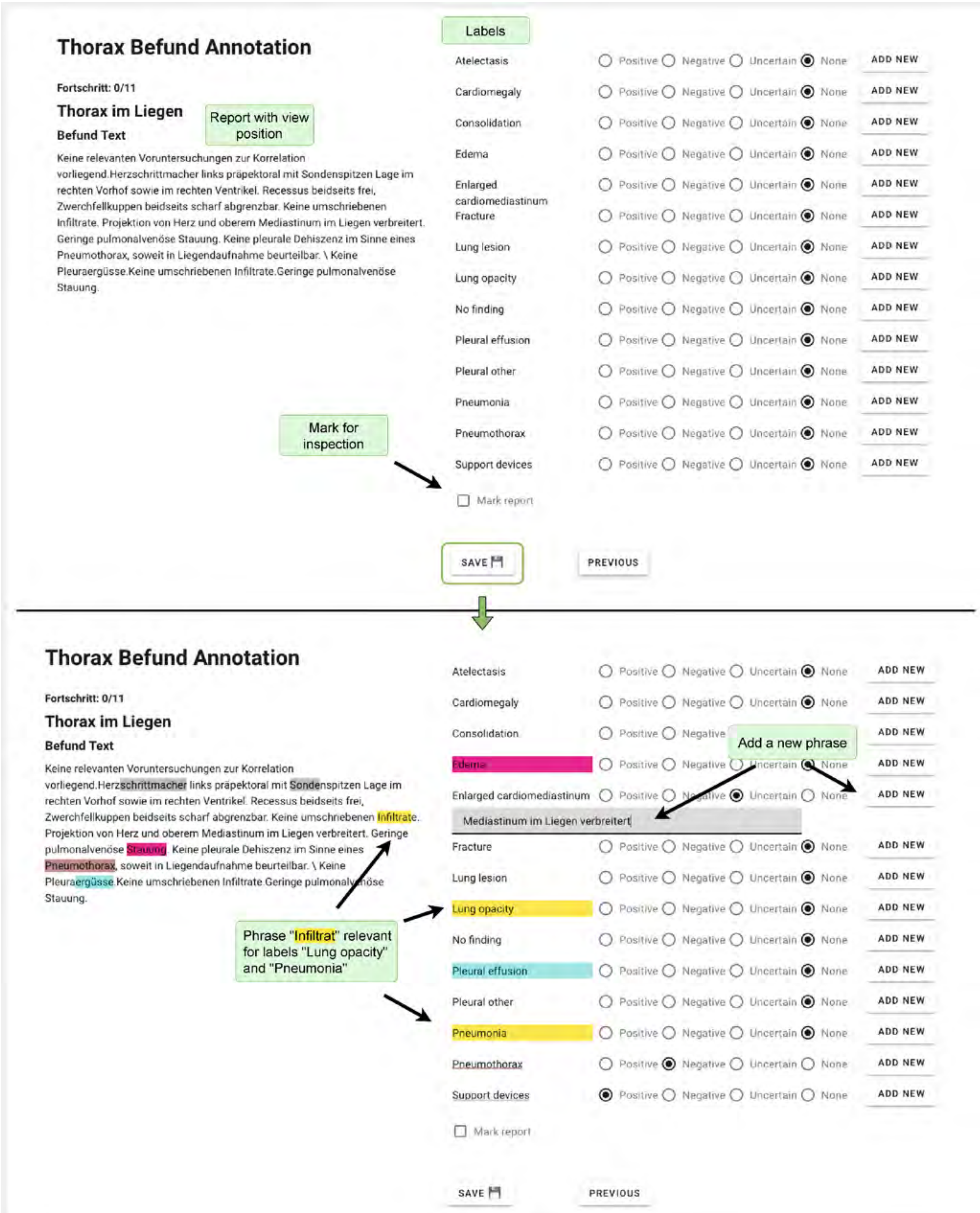
1. Observations with at least one positive mention are assigned a positive label.
2. Observations with no positive mentions and at least one uncertain mention, are labeled as uncertain.
3. Observations with no positive or uncertain mention or at least one negative mention are classified as negative.

The "no finding" label follows a different logic. Initially, a report is labeled as "no finding". The label is changed to negative if any of the other observations (excluding "support devices") are labeled as positive or uncertain.

The main benefit of automated label extraction is time savings. Our proposed algorithm features low memory consumption and enables parallel labeling of multiple reports using multi-threading. Using twelve threads, the algorithm labeled 100 reports on average in 1.84 s ± 27.3 ms on a workstation equipped with an Intel i7–6800K CPU with a clock speed of 3.40GHz.

Label Extraction (DS 1)

Label extraction performance was measured by comparing extracted and annotated labels on DS 1 on three tasks: mention extraction, negation detection, and uncertainty detection. Regarding the mention extraction task, unlabeled findings ("none") were considered negative, and annotated ("positive", "negative", or "uncertain") positive. For negation detection, findings annotated as negative were considered positive, others as negative. For uncertainty detection, annotations were classified analogously. The phrase lists were optimized on the development subset of DS 1. Phrases that were collected during the test subset annotation were discarded to avoid overfitting.



▶ **Fig. 2** Report annotation web interface. Top: On the left side view position and report are displayed, on the right the 14 labels can be selected. Additionally, new phrases can be added by clicking "ADD NEW" and a report can be marked for later inspection. Bottom: After "SAVE" is clicked, the tool highlights the matching phrases with their corresponding labels and asks for a phrase when the selected class was not found by the labeler. Clicking "SAVE" again will save the annotation and load the next report.

▶ **Table 1** Data sets with data splits and annotated classes used in this study. Data set 1 class annotations were acquired using our proposed annotation interface from free text reports. Data set 2 class annotations were acquired from reports and radiographs [23]. Enlarged cardiom. = enlarged cardiomediastinum, P = positive, U = uncertain, N = negative

Data set	Data set 1 (DS 1)						Data set 2 (DS 2)					
Split	Development			Test			Training		Validation		Test	
Reports	186			900			4507		660		1267	
Class	P	U	N	P	U	N	P	N	P	N	P	N
Atelectasis	29	17	1	203	50	2	–	–	–	–	–	–
Cardiomegaly	34	56	41	166	338	248	–	–	–	–	–	–
Consolidation	17	28	115	210	23	552	–	–	–	–	–	–
Edema	61	3	74	259	11	478	–	–	–	–	–	–
Enlarged cardiom.	39	42	52	206	273	277	–	–	–	–	–	–
Fracture	11	1	12	61	4	75	–	–	–	–	–	–
Lung lesion	11	1	1	37	11	12	–	–	–	–	–	–
Lung opacity	31	27	112	275	20	484	–	–	–	–	–	–
No finding	24	–	–	121	–	–	–	–	–	–	–	–
Pleural effusion	72	7	90	411	49	390	–	–	–	–	–	–
Pleural other	11	3	–	53	18	1	–	–	–	–	–	–
Pneumonia	4	48	114	52	142	578	–	–	–	–	–	–
Pneumothorax	27	1	147	62	11	786	1122	3385	204	456	326	941
Support devices	108	–	17	523	2	101	-	-	-	-	-	-

Pneumothorax Classification (DS 2)

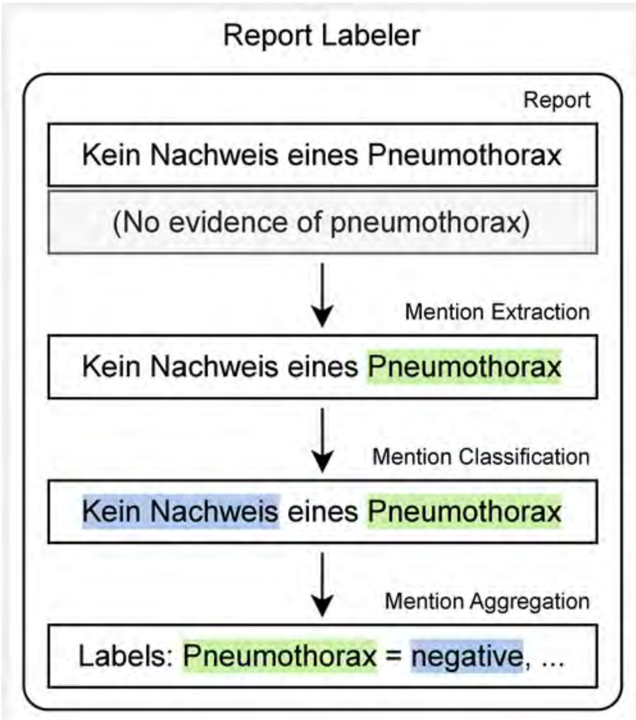
As DS 1 exposes realistic manual data gathering limitations such as limited size and labeling solely based on reports, we tested the label extraction performance on a separate, internal data set (DS 2) [23]. This data set consists of 6434 frontal chest radiographs and their reports, with 1568 being labeled as pneumothorax. Unlike DS 1, the data set was annotated based on the images and patient history rather than solely based on the reports, providing a higher annotation quality. As the pneumothorax label is based on the report and the chest radiograph, "none" labels are not applicable. Because inconclusive cases were excluded, no uncertain cases are available either. Consequently, only binary labels are evaluated.

To measure the effect of automatically extracted labels on downstream model training and classification performance, we extracted pneumothorax labels from the radiology reports of DS 2. We converted the extracted labels to binary labels by considering uncertain cases to be positive, similar to the data collection process. For comparison, we applied the same conversion to DS 1 labels and annotations. Additionally, "none" annotations were considered negative.

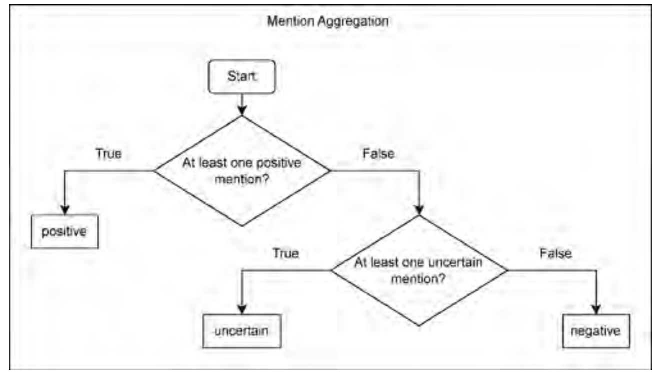
We used a DenseNet-121 pre-trained on ImageNet as the backbone for our network. We replaced the final fully connected layer with a single output when fine-tuned on DS 2. We replaced the final softmax activation with a sigmoid. We used ADAM with a learning rate of 0.003 and a batch size of 32 and trained for 10 epochs. For our experiments, we selected the best checkpoint based on the validation area under the receiver operating characteristic curve (AUC). All images were normalized according to the ImageNet mean and standard deviation and resized to 256 × 256 pixels. For data augmentation we applied ten-crop, i. e., we took 224 × 224 pixel crops from the center and the corners of the regular and horizontally flipped image. For our experiments, we compared a DenseNet-121 fine-tuned on the chest X-ray 14 data set (CheXnet) and fine-tuned on DS 2. When fine-tuning on DS 2, we trained with either radiologists' annotations (annotated) or automatically extracted labels (extracted). All experiments were performed using PyTorch version 1.8.1.

Statistical Evaluation

We evaluated the labeler's performance using F1 score, precision, and recall regarding mention extraction, negation detection, and uncertainty detection by comparing the extracted labels to the annotated labels from DS 1. We evaluated pneumothorax classification performance using receiver operating characteristics (ROC) and AUC. Because our study is exploratory and involves multiple comparisons, we refrained from providing P-values and provide 95 % confidence intervals calculated using the non-parametric bootstrap method with 10,000-fold resampling at the image level. The labeler performance with respect to the binary pneumothorax labels of DS 2 was measured using sensitivity and specificity. For comparison of DS 1 and DS 2, we converted DS 1 labels and annotations to binary labels, measured sensitivity and specificity, and included precision, recall, and F1 score for the binary DS 2 classification task. The statistical analyses in this study were done using NumPy version 1.24.2 and Scikit-Learn version 1.2.2.



▶ **Fig. 3** Labeling flow from our proposed report labeler based on the CheXpert architecture. The report is first matched against a set of class-specific phrases. Afterwards, each match is classified as positive, negative, or uncertain. If the report did not match any phrase, it is labeled as no finding in the final stage. English translation provided below the German report excerpt.



▶ **Fig. 4** Derivation of class labels by aggregating all classified mentions per observation. Since an observation can be mentioned multiple times in a report, they must be aggregated for classification.

Results

Label Extraction (DS 1)

The mention extraction, negation detection, and uncertainty detection results are shown in ▶ **Table 2**. Excluding the special case "no finding", the mention extraction F1 score ranged from 0.8 to 0.995, the negation detection F1 score from 0.624 to 0.981, and the uncertainty detection F1 score from 0.353 to 0.725. The special case "no finding" covers reports that describe a normal chest radiograph and is the default label when the labeler does not find anything. Since blank "none" labels are considered negative for the mention extraction task, the precision reflects the labeler not finding any mention in the report. Results marked as "N/A" have insufficient samples for calculation.

Commonly, chest X-ray classification models are trained on binary labels. Following Irvin et al. [16], we treat uncertain labels as positive and obtain sensitivity and specificity results as reported in ▶ **Table 3**.

Pneumothorax Label Extraction (DS 2)

The labeler extracted pneumothorax labels from DS 2 reports with a sensitivity of 0.997 [95 % CI: 0.994, 0.999] and specificity of 0.991 [95 % CI: 0.988, 0.994], see ▶ **Table 3**. Differences between pneumothorax sensitivity and specificity on DS 1 and DS 2 can be explained by the underlying annotation and data collection procedure. Uncertain DS 1 annotations were considered positive, while missing ("none") annotations were considered negative. In contrast, DS 2 has a higher annotation quality, since, for example, inconclusive pneumothorax cases of DS 2 were discarded during the data collection process of the initial work. The effect of data curation during data collection of DS 2 can also be observed when comparing F1 scores. The model extracted pneumothorax labels with an F1 score of 0.797 [95 % CI: 0.719, 0.864] on DS 1 and 0.987 [95 % CI: 0.982, 0.990] on DS 2.

Pneumothorax Classifier

The ROC curves and corresponding AUC values for the pneumothorax classification models trained on our internal data set with manually annotated labels or extracted labels and trained on the chest X-ray 14 data set are shown in ▶ **Fig. 5**. Training with manually annotated labels from multiple readers performed best with an AUC of 0.934 [95 % CI: 0.918, 0.949], followed by the model trained with labels extracted automatically with our labeler with an AUC of 0.858 [95 % CI: 0.832, 0.882]. The CheXnet model trained on chest X-ray 14 data performed worst with an AUC of 0.728 [95 % CI: 0.694, 0.760].

Discussion

In this study, we proposed an automatic label extraction algorithm for German thoracic radiology reports. Our deep learning model trained on extracted labels demonstrated strong improvements compared to the CheXnet model (0.728 vs. 0.858 AUC) and competitive performance compared to training with manually annotated data (0.858 vs. 0.934 AUC), as shown in ▶ **Fig. 5**. This indicates a promising alternative to manual annotation of the training data, especially as the training data set size can be easily scaled with our proposed method. We expect better performance with larger training data sets, allowing for the use of more advanced model architectures, as larger training data sets generally improve image classification performance [14].

Although the extracted pneumothorax labels from DS 2 had a high label sensitivity and specificity of over 99 % (see ▶ **Table 3**), the larger classification AUC difference by the deep learning mod-

▸ **Table 2** F1 score, precision and recall for the three evaluation tasks of our report labeler: mention extraction, negation detection, and uncertainty detection for each finding. Labels were extracted from DS 1 and compared to manual annotations. F1 = F1 score, R = recall, P = precision.

Data set 1	**Mention extraction**			**Negation**			**Uncertainty**		
Findings	**F1**	**R**	**P**	**F1**	**R**	**P**	**F1**	**R**	**P**
Atelectasis	0.968	0.96	0.976	N/A	N/A	N/A	0.648	0.7	0.603
Cardiomegaly	0.813	0.71	0.952	0.627	0.528	0.771	0.683	0.551	0.898
Consolidation	0.933	0.919	0.947	0.884	0.802	0.984	0.4	0.609	0.298
Edema	0.993	0.996	0.991	0.965	0.941	0.989	0.48	0.545	0.429
Enlarged cardio-mediastinum	0.867	0.807	0.937	0.678	0.569	0.84	0.725	0.607	0.902
Fracture	0.838	0.856	0.821	0.713	0.554	1.0	N/A	N/A	N/A
Lung lesion	0.8	0.833	0.769	0.917	0.917	0.917	0.385	0.455	0.333
Lung opacity	0.92	0.915	0.926	0.851	0.743	0.994	0.364	0.6	0.261
No finding	0.238	1.0	0.135	N/A	N/A	N/A	N/A	N/A	N/A
Pleural effusion	0.99	0.985	0.995	0.948	0.938	0.958	0.5	0.429	0.6
Pleural other	0.864	0.792	0.95	N/A	N/A	N/A	0.8	0.778	0.824
Pneumonia	0.902	0.829	0.988	0.862	0.771	0.976	0.705	0.612	0.833
Pneumothorax	0.995	0.999	0.991	0.981	0.978	0.985	0.353	0.273	0.5
Support devices	0.939	0.92	0.96	0.842	0.762	0.939	N/A	N/A	N/A

el trained on manual and extracted labels could be explained by the effect of noisier labels, making it harder to generalize. Creating class labels from radiological reports will always be inferior to the additional inspection of the image and a manual annotation. While pneumothorax label specificity is similar on both data sets, the sensitivity is considerably lower on data set 1, with a larger confidence interval. We interpret this difference as the effect of converting uncertain predictions to positives, as the uncertainty detection F1 score is comparatively low (see ▸ **Table 2**). Furthermore, inconclusive pneumothorax cases were removed during the original data collection process of DS 2, resulting in a higher data set quality. In contrast, no report was discarded during the data collection process of DS 1 to ensure an unbiased evaluation. While greater annotation quality resulted in better label extraction performance, it must be balanced with the time required to create such annotations. The results of our work show that our proposed labeler is a promising tool for clinical data scientists to create data sets.

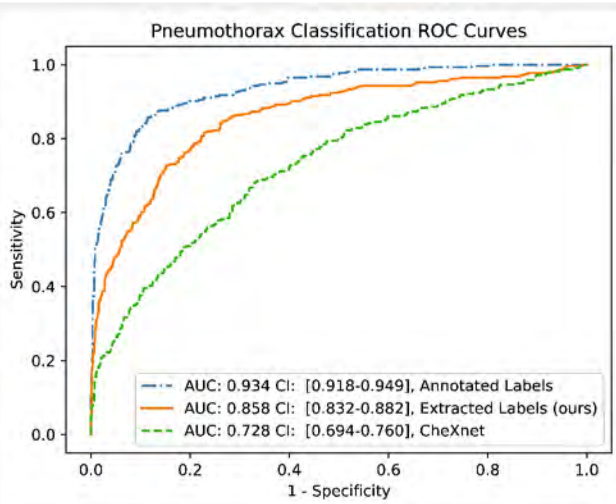
Our label extraction algorithm was successful in identifying corresponding labels in DS 1 across all classes. The results are in line with other methods proposed in the literature [12, 16, 18]. Missed classifications were mostly due to missing phrases. For example, the phrase "unauffällige knöcherne Konfiguration" ("unobtrusive bony configuration") was not considered a negative fracture label because "knöcherne Konfiguration" was not part of the phrase list. Another error pattern was the application of a phrase in the wrong context by the NegEx algorithm. For example, the negation phrase "keine" in "keine pleurale Dehiszenzlinie, verbreitertes Mediastinum" ("no pleural dehiscence line, widened mediastinum") was incorrectly associated with "verbreitertes Mediastinum" leading to an incorrect classification. Extensions to the phrase lists and further improvements to the NegEx algorithm will address these problems. Based on our experience, collecting labeling phrases using the proposed interface and the labeler results, we assume that the method can be easily applied to radiology reports from other clinics. Hence, additional classes can be incorporated quickly. However, the setup requires trained clinical data scientists. Furthermore, the annotation speed can be greatly improved by running the labeler first. Multiple readers could lower the risk of overlooking classes missed by the labeler.

During the process of annotating radiological reports based on the 14 CheXpert class labels, the radiologists commented that not all class labels were equally simple to annotate. In particular, the class "pleural other" was considered too vague for meaningful evaluation. Although the CheXpert labels were chosen based on the glossary of terms for thoracic imaging from the Fleischner Society [22], some of these labels lacked clear definitions, which could lead to inconsistent annotation, particularly when multiple annotators are involved. Especially the "uncertain" classification is arguably too vague to be effectively used for modeling. To address these issues, future work could leverage the proposed annotation tool to refine and expand the CheXpert classes, ensuring that the labels are clearly defined and precise.

Images from a single clinic cannot be representative of the global population. Most chest X-ray data sets that are currently publicly available, such as Chest X-ray 14, CheXpert, or MIMIC-CXR stem from U.S. clinics. By establishing a set of shared class labels and developing chest X-ray report labels for other languages, models built on multi-institutional data sets will be more robust and general. We hope that our work motivates further research in other languages.

▶ **Table 3** Sensitivity and specificity for the extracted labels compared to the reference annotations on DS 1 and DS 2 with corresponding 95 % confidence intervals. To create binary labels, uncertain labels/annotations were considered positive, "none" negative.

	Data set 1	
Findings	**Sensitivity**	**Specificity**
Atelectasis	0.944 [0.915–0.970]	0.988 [0.978–0.995]
Cardiomegaly	0.680 [0.639–0.721]	0.909 [0.880–0.936]
Consolidation	0.952 [0.923–0.978]	0.892 [0.868–0.914]
Edema	0.970 [0.948–0.989]	0.946 [0.928–0.963]
Enlarged cardiomediastinum	0.767 [0.727–0.803]	0.793 [0.754–0.831]
Fracture	0.954 [0.897–1.000]	0.959 [0.945–0.972]
Lung lesion	0.792 [0.667–0.900]	0.986 [0.978–0.993]
Lung opacity	0.979 [0.962–0.993]	0.859 [0.831–0.886]
No finding	0.736 [0.653–0.813]	0.983 [0.974–0.991]
Pleural effusion	0.965 [0.947–0.981]	0.968 [0.951–0.984]
Pleural other	0.789 [0.688–0.881]	0.998 [0.994–1.000]
Pneumonia	0.874 [0.825–0.920]	0.977 [0.966–0.987]
Pneumothorax	0.819 [0.727–0.904]	0.979 [0.969–0.988]
Support devices	0.902 [0.876–0.927]	0.906 [0.876–0.935]
	Data set 2	
Findings	**Sensitivity**	**Specificity**
Pneumothorax	0.997 [0.994, 0.999]	0.991 [0.988, 0.994]



▶ **Fig. 5** Receiver operating characteristic (ROC) curves and areas under the ROC curve (AUC) for pneumothorax classification on chest radiograph on our internal data set (DS 2). The model was trained on public data (CheXnet), on the DS 2 training data with either manual annotation (Annotated Labels), or labels extracted using our report labeler (Extracted Labels).

One limitation of our work is that we evaluated the effect of automatically extracted labels on chest X-ray classification performance only for the pneumothorax case, not for others. As this limited availability of labeled German radiology reports motivated our presented study, future work will evaluate chest X-ray classifiers trained on extracted labels for all fourteen classes. Another limitation is that the proposed labeler cannot handle semantically equivalent words due to its rule-based nature. In a follow-up study, we plan to replace it with a more sophisticated language model. Finally, we observed that few radiology reports described several images. Hence, extracted labels might not refer to the chest radiograph but rather to another image.

In conclusion, we showed that extracting CheXpert labels automatically from German chest X-ray radiology reports is a promising substitute for manual annotation. A pneumothorax model trained on these extracted labels demonstrated competitive performance compared to manually annotated data.

Clinical relevance

The presented automatic label extraction model for German thoracic radiology reports and the annotation interface are promising tools for clinical data scientists collaborating with radiologists. The model can efficiently annotate large data sets for training deep learning-based chest X-ray classification models. Clinical decision support by such models can reduce the workload on radiologists, resulting in improved productivity, and more importantly, accurate and timely diagnosis of chest pathologies.

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Conflict of Interest

The authors declare that they have no conflict of interest.

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