RESEARCH ARTICLE

tbiExtractor: A framework for extracting traumatic brain injury common data elements from radiology reports

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Abstract

Background

The manual extraction of valuable data from electronic medical records is cumbersome, error-prone, and inconsistent. By automating extraction in conjunction with standardized terminology, the quality and consistency of data utilized for research and clinical purposes would be substantially improved. Here, we set out to develop and validate a framework to extract pertinent clinical conditions for traumatic brain injury (TBI) from computed tomography (CT) reports.

Methods

We developed tbiExtractor, which extends pyConTextNLP, a regular expression algorithm using negation detection and contextual features, to create a framework for extracting TBI common data elements from radiology reports. The algorithm inputs radiology reports and outputs a structured summary containing 27 clinical findings with their respective annotations. Development and validation of the algorithm was completed using two physician annotators as the gold standard.

Results

tbiExtractor displayed high sensitivity (0.92–0.94) and specificity (0.99) when compared to the gold standard. The algorithm also demonstrated a high equivalence (94.6%) with the annotators. A majority of clinical findings (85%) had minimal errors (F1 Score ≥ 0.80). When compared to annotators, tbiExtractor extracted information in significantly less time (0.3 sec vs 1.7 min per report).

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Conclusion

tbiExtractor is a validated algorithm for extraction of TBI common data elements from radiology reports. This automation reduces the time spent to extract structured data and improves the consistency of data extracted. Lastly, tbiExtractor can be used to stratify subjects into groups based on visible damage by partitioning the annotations of the pertinent clinical conditions on a radiology report.

Introduction

Radiology reports from electronic medical records (EMR) are formatted as unstructured narrative text meant for human consumption and contain vast amounts of detailed information that is underutilized. For example, one of the most valuable sources of information for assessing traumatic brain injury (TBI) is the initial head computed tomography (CT) scan. Notably, CT findings have been shown to be one of the most powerful prognosticators in assessing six-month outcomes in TBI [1]. However, extracting structured information from radiology reports is time consuming, error-prone, requires trained professionals for accuracy, and is inconsistent across clinical trial sites and research studies [2].

To address these inconsistencies, many fields have adopted common data elements [3], which are predefined units of information to be used in a collaborative fashion; in other words, a set of uniform terminology [4]. By enabling this interoperability of data via common data elements, the design of clinical trials and research studies based on standard stratification of subject groups is possible [2]. It should be noted that two standardized classifications of TBI based on CT findings have been widely used, namely Marshall and Rotterdam scores [5,6]. However, these classifications focus on subjects with severe injuries and forgo granularity in variables describing the underlying pathology. Therefore, the focus on common data elements remains important for detailing TBI injuries.

Even with the adoption of common data elements, extracting structured information from radiology reports is limited by manual annotation, which takes time and is error-prone. Bypassing this human bottleneck through automation has the potential to expedite research findings, aid in large-scale clinical trials, and ultimately improve clinical care for TBI patients [7]. To facilitate this automation, natural language processing methods can be utilized to parse free-text clinical narratives from EMRs by analyzing linguistic concepts and categorizing them appropriately [8,9].

The field of natural language processing is extensive with a diverse set of subproblems [10] that have been implemented in a variety of medical contexts [11–21]. Four subproblems of interest are problem-specific segmentation, named entity recognition, negation and uncertainty identification, and information extraction. Problem-specific segmentation aims to separate text into groups; for example, segmenting sections of a radiology report into "History" and "Findings" sections. Named entity recognition aims to identify and categorize specific words or phrases; for example, categorizing a set of radiology reports based on type of scan (e.g., head CT vs lumbar spine CT). Negation and uncertainty identification aim to identify specific words or phrases as present or absent; for example, "no evidence of intracranial pathology" would indicate absence of pathology. Information extraction aims to identify and translate problem-specific information into structured data; for example, identifying mass lesions on a radiology report requiring surgical evacuation.

The purpose of our study was to develop and validate an algorithm, termed tbiExtractor, which incorporates natural language processing methods to extract twenty-seven common data elements from radiology reports in an automated fashion. The output provides a structured summary of pertinent clinical conditions for a TBI subject. Successful implementation of this algorithm has the potential to reduce the time spent to extract structured data, improve the quality of data extracted, and provide a mechanism for systematic placement of subjects into research groups.

Materials and methods

Development and analysis were performed using Python 3.6.6 [22] with the following libraries: Pandas (0.23.4) [23], NumPy (1.15.0) [24], SciPy (1.1.0) [25], spaCy (2.0.12) [26], scikit-learn (0.19.2) [27], pyConTextNLP (0.6.2.0) [28], NetworkX (1.11) [29], Matplotlib (2.2.3) [30], and Seaborn (0.9.0) [31]. A methods flowchart is shown in Fig 1.

Ethics statement

Data were acquired from subjects participating in the CLASSIFY-TBI study (details in S1 Appendix). Written informed consent was obtained from the patient or legal proxy, except in the rare case of permanently waived consent, justified in accordance with 45 Code of Federal Regulations 46.116(d). Permanently waived consent was only applicable to expired patients whose family members, or legal representatives, did not present to the hospital or who could not be contacted by any other means during the patient's hospitalization. This study was reviewed and approved by the Hennepin Healthcare Research Institute's Institutional Review Board.

Data capture and cleaning

Hospital admission radiology reports from non-contrast head CT scans were extracted from EMRs. The text for a given radiology report was written by neuroradiologists at Hennepin County Medical Center as part of the standard-of-care. Each radiology report was converted to a spaCy [26] container for assessing linguistic annotations and partitioned into sentences. Sentences before "Findings" and after "Impressions" sections were removed. Then, the sentences were concatenated with newline characters replaced with a space, symbols removed, and whitespace stripped. Radiology reports that did not contain "Findings" or "Impressions" sections were removed along with radiology reports containing multiple scan types.

Calculate TF-IDF and cosine similarities

Using scikit-learn [27] TfidfVectorizer, the corpus was converted into a matrix of TF-IDF (term-frequency times inverse document-frequency) features using *n*-grams with *n*-range from one to ten. Cosine similarities were calculated between each pair of radiology reports by multiplying the TF-IDF matrix by its transpose. Using the cosine similarity for each pair of radiology reports, one radiology report was randomly selected and all radiology reports with at least 0.70 cosine similarity to that radiology report were collected in a set. From this set, one radiology report was randomly selected to keep for further analysis and the remainder were removed. This was applied recursively for each set until each radiology report was retained for further analysis or marked for removal. The purpose of this removal was to reduce the data requiring human annotation. Details in S2 Appendix.

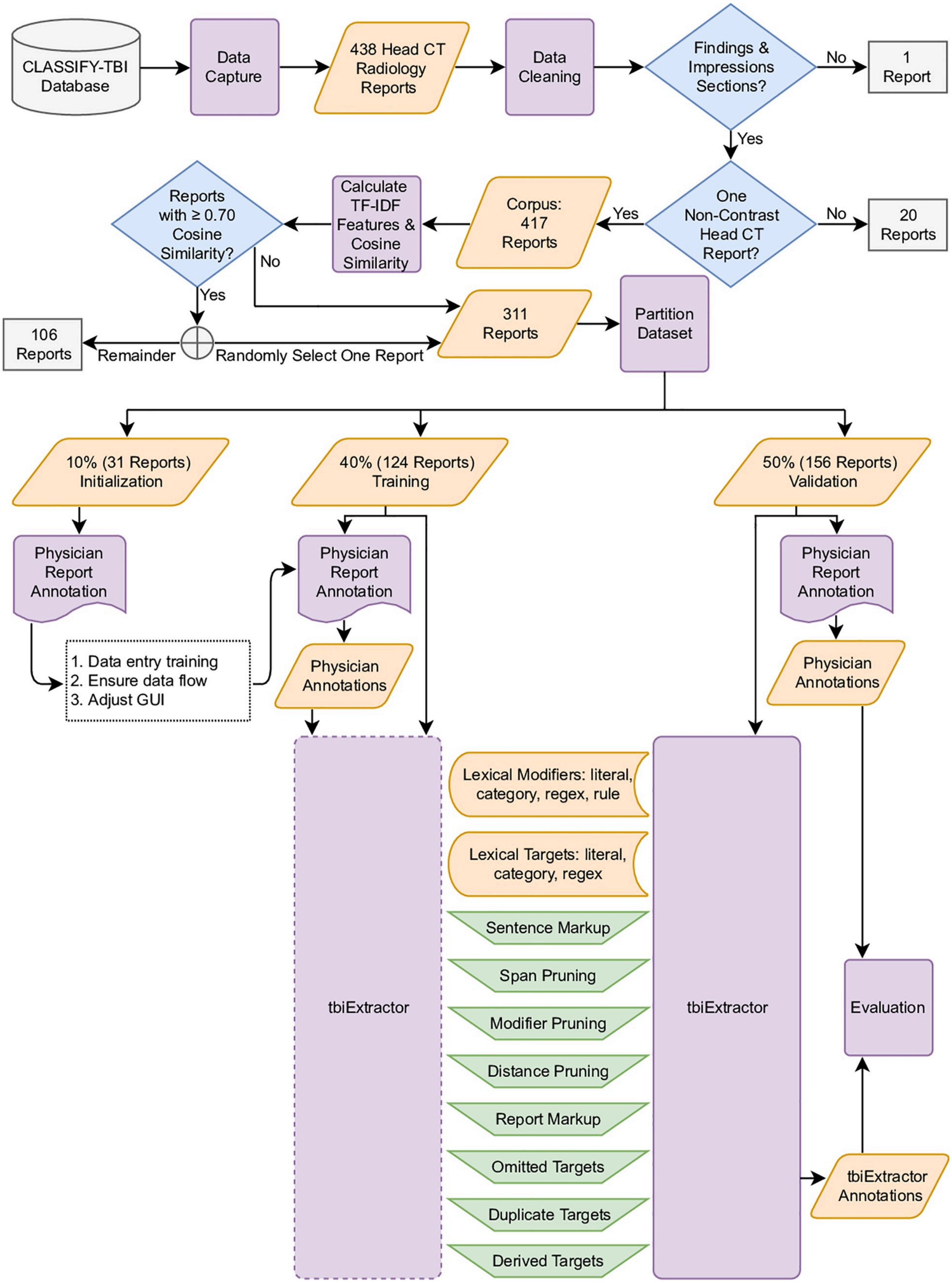
CLASSIFY-TBI Database
Data Capture
438 Head CT Radiology Reports
Data Cleaning
Findings & Impressions Sections?
No
1 Report
Yes
One Non-Contrast Head CT Report?
No
20 Reports
Yes
Corpus: 417 Reports
Calculate TF-IDF Features & Cosine Similarity
Reports with ≥ 0.70 Cosine Similarity?
No
Yes
106 Reports
Remainder
Randomly Select One Report
311 Reports
Partition Dataset
10% (31 Reports) Initialization
40% (124 Reports) Training
50% (156 Reports) Validation
Physician Report Annotation
1. Data entry training
2. Ensure data flow
3. Adjust GUI
Physician Report Annotation
Physician Annotations
Physician Report Annotation
Physician Annotations
tbiExtractor
Lexical Modifiers: literal, category, regex, rule
Lexical Targets: literal, category, regex
Sentence Markup
Span Pruning
Modifier Pruning
Distance Pruning
Report Markup
Omitted Targets
Duplicate Targets
Derived Targets
tbiExtractor
tbiExtractor Annotations
Evaluation

Fig 1. Graphical outline of the methods. Purple rectangle shapes correspond to methods subsections, meaning they represent steps in the processing workflow, orange parallelogram shapes represent data, blue diamond shapes represent binary decisions on data, gray rectangle shapes represent excluded data, and green isosceles trapezoid shapes correspond to subcomponents of the algorithm.

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Dataset partitioning

A random deck of three numbers the same size as the number of radiology reports retained for analysis was created. The three numbers represented the proportion of radiology reports to be assigned to each of the datasets: 10% initialization, 40% training, and 50% validation. From the set of radiology reports retained for analysis, one radiology report was randomly selected along with up to three most similar radiology reports, based on cosine similarity. From this subset, each radiology report was assigned the next number in the shuffled deck. This was applied recursively until each radiology report was assigned to one dataset.

The initialization dataset was solely used for training annotators and was not used by the algorithm, the training dataset was used to enhance the development of the algorithm by incorporating input from annotators, and the validation dataset was used to compare the annotators to the developed algorithm to determine the algorithm's viability.

Radiology report annotation

The annotators are TBI researchers with professional medical training/education (authors: DR & ME) supervised by both a board-certified neurosurgeon (author: US) and two board-certified neuroradiologists (authors: CT & MO). The annotators underwent training by reading and discussing [3].

A custom-built Graphical User Interface (GUI) was developed using Python's TkInter library [22]. The GUI presented two physician annotators with one de-identified radiology report and drop-down menus, one for each lexical target with the respective annotation options (a screenshot of the GUI is provided in S3 Appendix). Annotators viewed one radiology report at a time and were not allowed to edit their annotations after submission. Additionally, annotators were not given access to the corresponding DICOM images for the non-contrast head CT scan for interpretation and exclusively relied on the radiology report for annotations. The annotation options were: PRESENT: radiology report explicitly denotes lexical target. SUSPECTED: radiology report indicates potential lexical target. INDETERMINATE: radiology report mentions lexical target as one of multiple etiologies. NOT SPECIFIED: radiology report does not explicitly mention lexical target but has potential for being present given the clinical context. ABSENT: radiology report explicitly denies lexical targets presence or is not mentioned or inferred from the clinical context. NORMAL: radiology report explicitly states lexical target is normal or is not mentioned but given the clinical context, is assumed to be normal. ABNORMAL: radiology report explicitly states lexical target is abnormal or is inferred based on clinical context.

Each dataset was presented to annotators separately. The initialization dataset was used to train annotators on the data entry process and scope of the project, ensure the data processing flow was valid, and make adjustments to the GUI. The training and validation datasets were presented to the annotators and their annotations were retained for development and validation of the algorithm, respectively.

tbiExtractor development

We developed tbiExtractor, which extends pyConTextNLP [28] to create a framework for extracting TBI common data elements from radiology reports [3]. tbiExtractor inputs a non-contrast head CT radiology report and outputs a structured summary containing 27 common data elements with their respective annotations. For example, subdural hemorrhage (common data element) is PRESENT (annotation). Code and data files to implement tbiExtractor, along with a Jupyter notebook tutorial, are available at https://github.com/margaretmahan/tbiExtractor.

pyConTextNLP background. Based on a regular expression algorithm called NegEx [32], which uses negation detection (e.g., no evidence of intracranial pathology), the ConText [33,34] algorithm captures the contextual features surrounding the clinical condition by relying on trigger terms and termination clues. A more extensible version of the ConText algorithm was implemented in Python, pyConTextNLP [28], and offers added flexibility for user-defined contextual features and indexed events (e.g., specific clinical conditions) [35].

As a lexicon-based method, pyConTextNLP inputs tab-separated files for lexical targets (indexed events) and lexical modifiers (contextual features). It then converts these into item-Data, which contains a literal, category, regular expression, and rule (the latter two are optional). The literal, belonging to a category (e.g., ABSENT), is the lexical phrase (e.g., is negative) in the text. The regular expression allows for variant text phrases (e.g., was negative) giving rise to the same literal and is generated from the literal if not provided. Further, the rule provides context to the span of the literal (e.g., backward).

For text data, pyConTextNLP marks the text with lexical modifiers and lexical targets according to their representative itemData. The pyConTextNLP algorithm outputs a directional graph via NetworkX [29] which represents these markups. Nodes in the graph represent the concepts (i.e., lexical modifiers and lexical targets) in the text and edges in the graph represent the relationship between the concepts.

The following three subsections will describe the details used for extending pyConTextNLP.

Lexical modifiers and lexical targets. Lexical modifiers were adapted from a pyConTextNLP application to CT pulmonary angiography reports [35]. Modifications in deriving the final lexical modifiers are as follows:

1. The literal is a lexical phrase (e.g., was not excluded). Literals were added and removed during the training stage.
2. The category is what the literal refers to (e.g., INDETERMINATE). Each literal was assigned a category before the initialization stage and updated during the training stage. The categories used for this study are PRESENT, SUSPECTED, INDETERMINATE, NOT SPECIFIED, ABSENT, NORMAL, and ABNORMAL. Henceforth, the term "annotation" will be used when referencing the category to maintain consistency between annotators and algorithm vocabulary.
3. The regular expression is used to find variant text phrases (or patterns) for the same literal (e.g., the regular expression: `(was|were)\snot\sexcluded`, would find sentences with "was not excluded" and "were not excluded"). Regular expressions were added and updated during the training stage.
4. The rule dictates the span of the literal (e.g., backward). Each literal was assigned a rule before the initialization stage and updated during the training stage. The rules used for this study are forward, backward, and bidirectional.

Lexical targets were adapted from the common data elements in radiologic imaging of TBI [3]. These included pertinent clinical findings in the acute phase of TBI across all severities. By utilizing an array of specific pathologic features (e.g., subarachnoid hemorrhage, subdural hemorrhage, epidural hemorrhage, and intraparenchymal hemorrhage) our framework allows TBI researchers to dynamically categorize subjects and evaluate the significance of pathological patterns and their impact on cerebral tissues. In deriving the lexical targets, the literal represents a clinical condition relevant to TBI on a non-contrast head CT scan (e.g., microhemorrhage) and the category, in this study, is the same (e.g., MICROHEMORRHAGE). The regular expression for each literal (e.g., `microhemorrhage(s)?`) was added and updated during the training stage.

Two examples (Figs 2 and 3) are provided for detailed explanation of the application of lexical modifiers and lexical targets during the algorithm process.

Sentence markup followed by span, modifier, and distance pruning. To implement tbiExtractor, each cleaned radiology report was converted to a spaCy [26] container and subsequently partitioned into sentences. Using pyConTextNLP [28], each sentence was marked with lexical modifiers and lexical targets according to their representative itemData. Following the markup, concepts that are a subset of another concept, within the same concept type, are pruned (span pruning). For example, if the text contained the phrase "findings do not appear significantly changed", the lexical modifier not would be pruned and the lexical modifier do not appear significantly changed would be retained. Then, for the marked lexical targets, the lexical modifiers are applied. Lexical modifiers that are not linked to a lexical target are dropped (modifier pruning). For multiple lexical modifiers for the same lexical target in the same sentence, the nearest lexical modifier by character length is chosen (distance pruning). For example, if the text contained the phrase "multifocal subarachnoid hemorrhage as described above most notably in the right sylvian fissure", the lexical modifier multifocal would be selected via distance pruning over the lexical modifier in the since it is closer in character length to the lexical target, *subarachnoid hemorrhage*. Span and modifier pruning are part of the pyConTextNLP implementation. Distance pruning was added as part of tbiExtractor.

At this stage of processing, each sentence in the radiology report will be marked with lexical targets and linked lexical modifiers. There will be one lexical modifier assigned to one lexical target.

Report markup with revisions for omitted, duplicate, and derived targets. A radiology report may have duplicate lexical targets if identified in multiple sentences within the radiology report or a radiology report may not have any lexical targets indicated. To mitigate this, tbiExtractor employs decision rules. First, for each radiology report, omitted lexical targets are added with the default annotation of NORMAL for *gray-white matter differentiation* and *cistern* lexical targets and annotation of ABSENT for the remaining 25 lexical targets (omitted targets). Second, if duplicate lexical targets are identified, the majority vote is selected (duplicate targets). For example, if a lexical target appears in the radiology report three times and the lexical modifiers for two occurrences have an annotation of ABSENT and the other has an annotation of PRESENT, tbiExtractor will choose ABSENT. Similarly, if there are two lexical modifiers with an annotation of PRESENT, two with ABSENT, and one with SUSPECTED, tbiExtractor removes SUSPECTED based on the majority vote. However, the annotations PRESENT and ABSENT require further decision rules because no majority exists.

In the case where no majority exists, the first lexical modifier in the ordered annotation list is selected. If the lexical target is *extraaxial fluid collection*, *hemorrhage not otherwise specified (NOS)*, or *intracranial pathology*, the ordered annotation list is: ABSENT, INDETERMINATE, SUSPECTED, PRESENT, NORMAL, ABNORMAL. For all other lexical targets, the ordered annotation list is: PRESENT, SUSPECTED, INDETERMINATE, ABSENT, ABNORMAL, NORMAL. Following this, annotations that are not in the set of annotations for that lexical target are replaced with their predetermined counterpart (e.g., if the lexical target *cisterns* has an

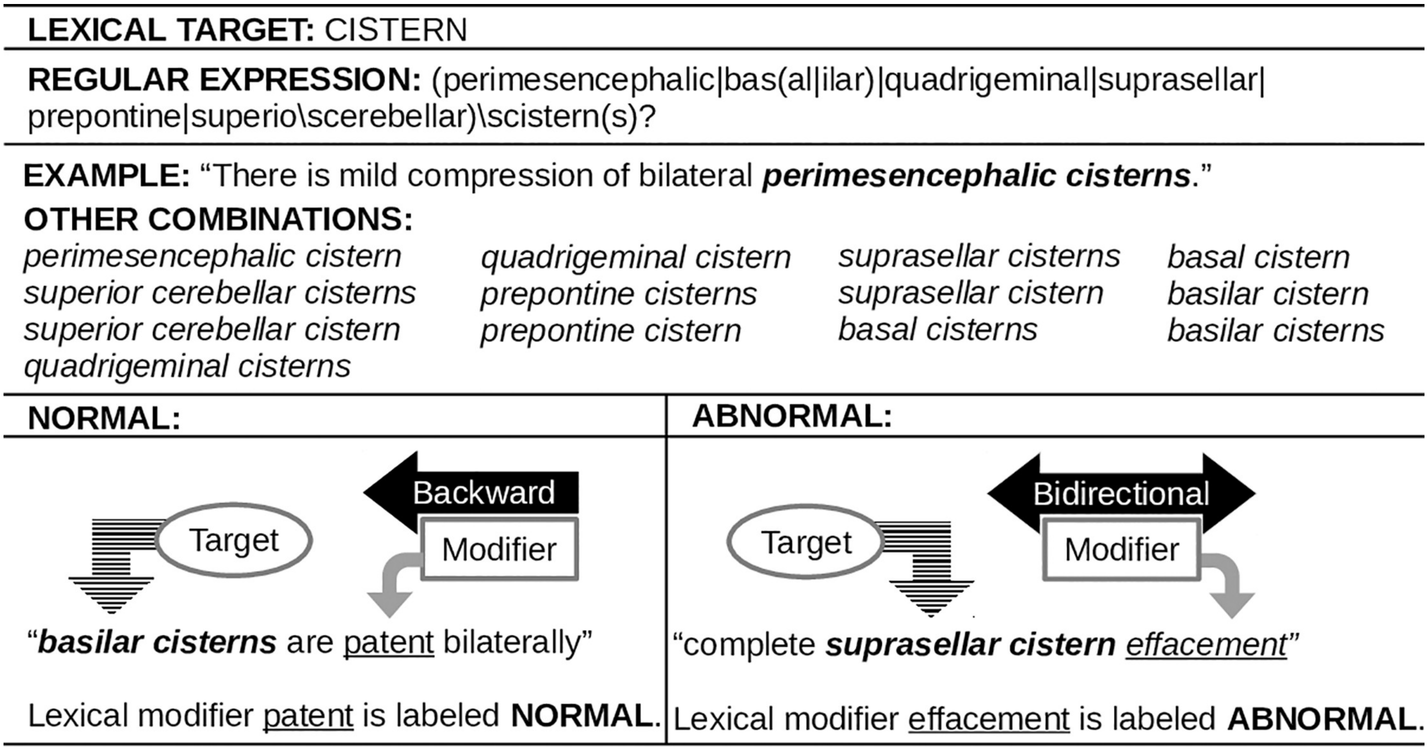
LEXICAL TARGET: CISTERN
REGULAR EXPRESSION: (perimesencephalic|bas(al|ilar)|quadrigeminal|suprasellar|prepontine|superio\scerebellar)\scistern(s)?
EXAMPLE: “There is mild compression of bilateral perimesencephalic cisterns.”
OTHER COMBINATIONS:
perimesencephalic cistern
superior cerebellar cisterns
superior cerebellar cistern
quadrigeminal cisterns
quadrigeminal cistern
prepontine cisterns
prepontine cistern
suprasellar cisterns
suprasellar cistern
basal cisterns
basal cistern
basilar cistern
basilar cisterns
NORMAL:
Backward
Target
Modifier
“basilar cisterns are patent bilaterally”
Lexical modifier patent is labeled NORMAL.
ABNORMAL:
Bidirectional
Target
Modifier
“complete suprasellar cistern effacement”
Lexical modifier effacement is labeled ABNORMAL.

Fig 2. First example of the application of lexical targets and lexical modifiers.

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annotation of ABSENT, the annotation is replaced with NORMAL). At this stage of processing, each lexical target has one annotation for the entire radiology report.

The annotations for three lexical targets can be altered based on the annotations of other lexical targets in the same radiology report. Thus, a second set of derived decision rules are applied by tbiExtractor (derived targets). First, if *epidural hemorrhage*, *subdural hemorrhage*, or *subarachnoid hemorrhage*, are PRESENT or SUSPECTED, *hemorrhage (NOS)* is annotated ABSENT. Second, if *epidural hemorrhage*, *subdural hemorrhage*, or *subarachnoid hemorrhage*, are PRESENT, *extraaxial fluid collection* is annotated PRESENT. If these lexical targets were annotated SUSPECTED, and *extraaxial fluid collection* was annotated ABSENT by default, then *extraaxial fluid collection* is annotated SUSPECTED. If *gray-white differentiation*, *cistern*, *hydrocephalus*, *pneumocephalus*, *extraaxial fluid collection*, *midline shift*, *mass effect*, *diffuse axonal injury*, *anoxic*, *herniation*, *aneurysm*, *contusion*, *brain swelling*, *ischemia*, *hemorrhage (NOS)*, *intraventricular hemorrhage*, or *intraventricular hemorrhage* are annotated PRESENT, SUSPECTED, or ABNORMAL, then *intracranial pathology* is annotated PRESENT.

Omitted, duplicate, and derived targets were implemented as part of the tbiExtractor. At the end of the above processing steps, each radiology report will have a list of 27 lexical targets each with one annotation, which constitutes the structured summary output.

Evaluation

Radiology reports were assessed using standard descriptive measures (minimum, maximum, mean, and standard deviation). The assessment included descriptive measures for sentences, words, and cosine similarities summarized for each datasets (initialization, training, validation, and remainder).

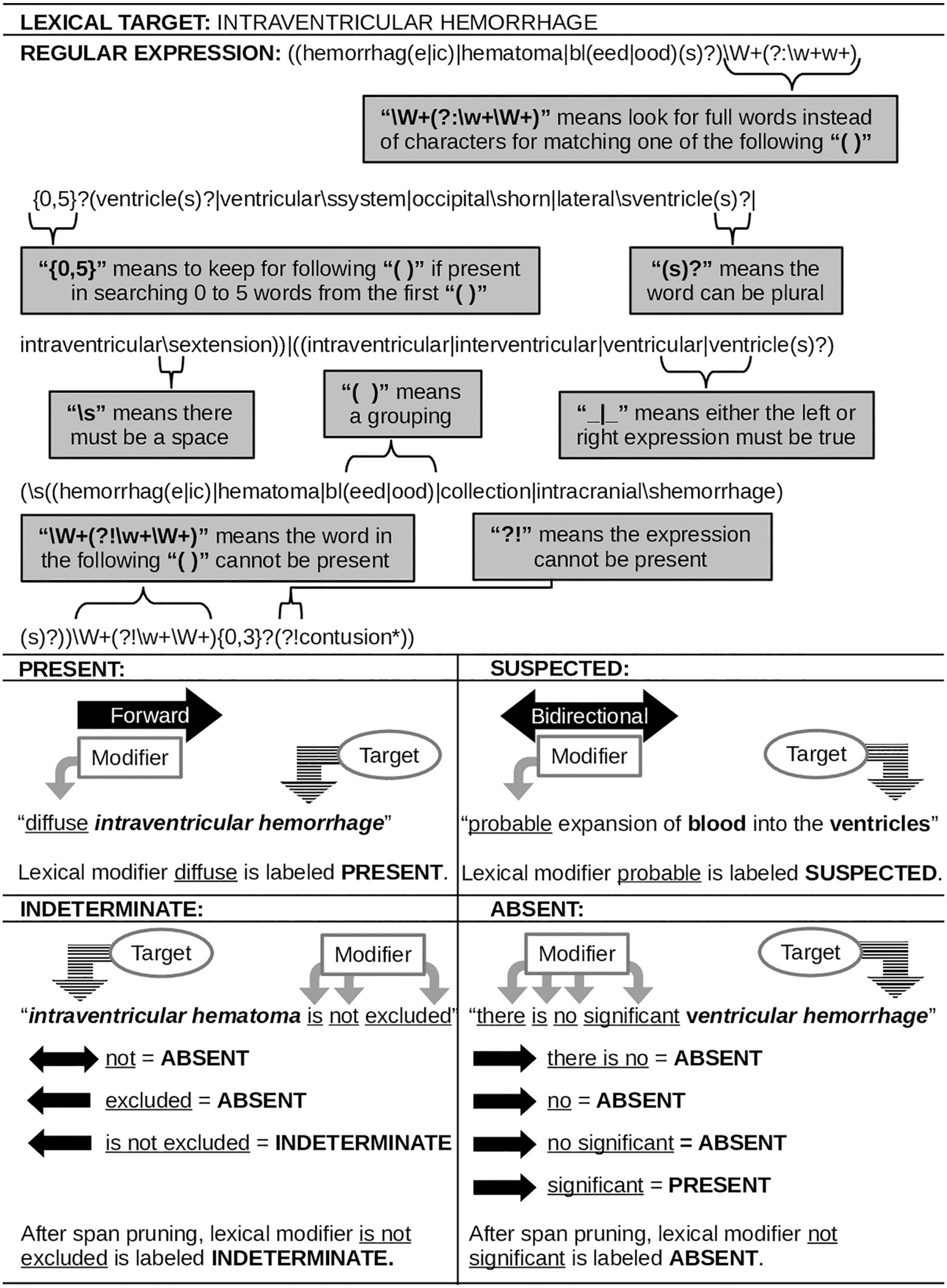
LEXICAL TARGET: INTRAVENTRICULAR HEMORRHAGE
REGULAR EXPRESSION: ((hemorrhag(e|ic)|hematoma|bl(eed|ood)(s)?)\W+(?:\w+w+)
"\W+(?:\w+\W+)" means look for full words instead of characters for matching one of the following **"( )"**
{0,5}?(ventricle(s)?|ventricular\ssystem|occipital\shorn|lateral\sventricle(s)?|
"{0,5}" means to keep for following **"( )"** if present in searching 0 to 5 words from the first **"( )"**
"(s)?" means the word can be plural
intraventricular\sextension))|((intraventricular|interventricular|ventricular|ventricle(s)?)
"\s" means there must be a space
"( )" means a grouping
"_|_" means either the left or right expression must be true
(\s((hemorrhag(e|ic)|hematoma|bl(eed|ood)|collection|intracranial\shemorrhage)
"\W+(?!\w+\W+)" means the word in the following **"( )"** cannot be present
"?!" means the expression cannot be present
(s)?))\W+(?!\w+\W+){0,3}?(?!contusion*))
PRESENT:
Forward
Modifier
Target
"diffuse ***intraventricular hemorrhage***"
Lexical modifier diffuse is labeled **PRESENT**.
SUSPECTED:
Bidirectional
Modifier
Target
"probable expansion of **blood** into the **ventricles**"
Lexical modifier probable is labeled **SUSPECTED**.
INDETERMINATE:
Target
Modifier
"***intraventricular hematoma*** is not excluded"
not = **ABSENT**
excluded = **ABSENT**
is not excluded = **INDETERMINATE**
After span pruning, lexical modifier is not excluded is labeled **INDETERMINATE.**
ABSENT:
Modifier
Target
"there is no significant ***ventricular hemorrhage***"
there is no = **ABSENT**
no = **ABSENT**
no significant **= ABSENT**
significant = **PRESENT**
After span pruning, lexical modifier not significant is labeled **ABSENT**.

Fig 3. Second example of the application of lexical targets and lexical modifiers.

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The annotations from physician annotators for the training and validation datasets were compared. These annotations were compared in the training and validation datasets by summing each annotation option for each dataset. Annotations were deemed equivalent if they were the same, similar if one annotation was PRESENT and the other was SUSPECTED, or divergent if one annotation was ABSENT or NORMAL and the other was PRESENT or ABNORMAL. Next, annotator reliability was measured using Cohen's kappa (κ) [36,37], which measures the inter-rater reliability with $\kappa = 0$ when annotators are in divergence and $\kappa = 1$ when annotators are equivalent.

tbiExtractor was evaluated using standard classification performance metrics (equations listed below). A gold-standard was determined to be when annotators were equivalent and those annotations were used to evaluated tbiExtractor. True positives (TP) were defined as the number of times a lexical target was annotated as PRESENT or ABNORMAL by tbiExtractor and annotators, in the first case. In the second case, SUSPECTED was also assigned to the positive group. True negatives (TN) were defined as the number of times a lexical target was annotated as ABSENT or NORMAL by tbiExtractor and annotators. False positives (FP) and false negatives (FN) were defined for all other cases. In addition, false positives and false negatives were examined to explore why tbiExtractor errors occurred.

Classification performance metrics equations

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

$$\text{Positive Predictive Value} = \frac{TP}{TP + FP}$$

$$\text{Negative Predictive Value} = \frac{TN}{TN + FN}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

$$\text{F1 Score} = \frac{2 * PPV * Sensitivity}{PPV + Sensitivity}$$

Results

Radiology report characteristics

There were 438 radiology reports extracted: 1 was removed because it did not have both "Findings" and "Impressions" sections, 20 were removed because they contained more than one scan type, and 106 were removed for high cosine similarity. The remaining 311 reports were split into initialization, training, and validation datasets (Table 1).

Radiology report characteristics for each of the four subsets of data. Values displayed as minimum, maximum, mean ± standard deviation.

Table 1. Radiology report characteristics.

Dataset	Initialization	Training	Validation	Remainder
Reports	31	124	156	106
Sentences	8, 22	4, 72	6, 32	6, 28
	14.5 ± 4.1	14.9 ± 7.6	14.3 ± 5.1	8.9 ± 3.4
Words	58, 268	22, 656	35, 284	43, 315
	123.5 ± 54.1	122.5 ± 75.9	121.1 ± 53.6	69.7 ± 35.9
Cosine Similarity	0.34, 0.70	0.14, 0.70	0.26, 0.69	0.35, 1.00
	0.47 ± 0.05	0.44 ± 0.08	0.46 ± 0.06	0.69 ± 0.13

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Analysis of annotators

In the training dataset, annotators took an average of 2.84 minutes per radiology report. Between 15% and 16% of annotations across radiology reports were selected from default (Table 2). There was high equivalence in annotations between the annotators (N = 3175). Further, there were an additional 424 similar annotations (i.e., one annotation PRESENT and the other SUSPECTED). In contrast, there were only 88 divergent annotations (i.e., one annotation ABSENT or NORMAL and the other PRESENT or ABNORMAL). Overall, the two annotators were in high agreement (κ = 0.861). After training, NOT SPECIFIED was removed as an annotation option secondary to the overlap with ABSENT and INDETERMINATE.

In the validation dataset, annotators took an average of 1.67 minutes per radiology report. Similar to the training dataset, 16% of annotations across radiology reports were selected from default (Table 2). For the validation dataset, there was high equivalence in annotations between the annotators (N = 4072), with an additional 598 similar annotations, and only 87 divergent annotations. Overall, the two annotators were in high agreement (κ = 0.913).

Number and type of annotation selected for each annotator along with comparisons between them for training and validation sets. There were 3348 possible annotations for training and 4212 for validation.

Table 2. Physician annotator comparison.

		Training	Validation
Annotator 1	Absent	2623	3244
	Present	405	569
	Suspected	50	74
	Indeterminate	22	13
	Abnormal	21	23
	Normal	227	289
	Not Specified	0	0
Annotator 2	Absent	2593	3249
	Present	440	598
	Suspected	56	48
	Indeterminate	9	5
	Abnormal	17	25
	Normal	231	287
	Not Specified	2	0
Comparing Annotators	Equivalent	94.8%	96.7%
	Similar	12.7%	14.2%
	Divergent	2.6%	2.1%
	Cohen's kappa	0.861	0.913

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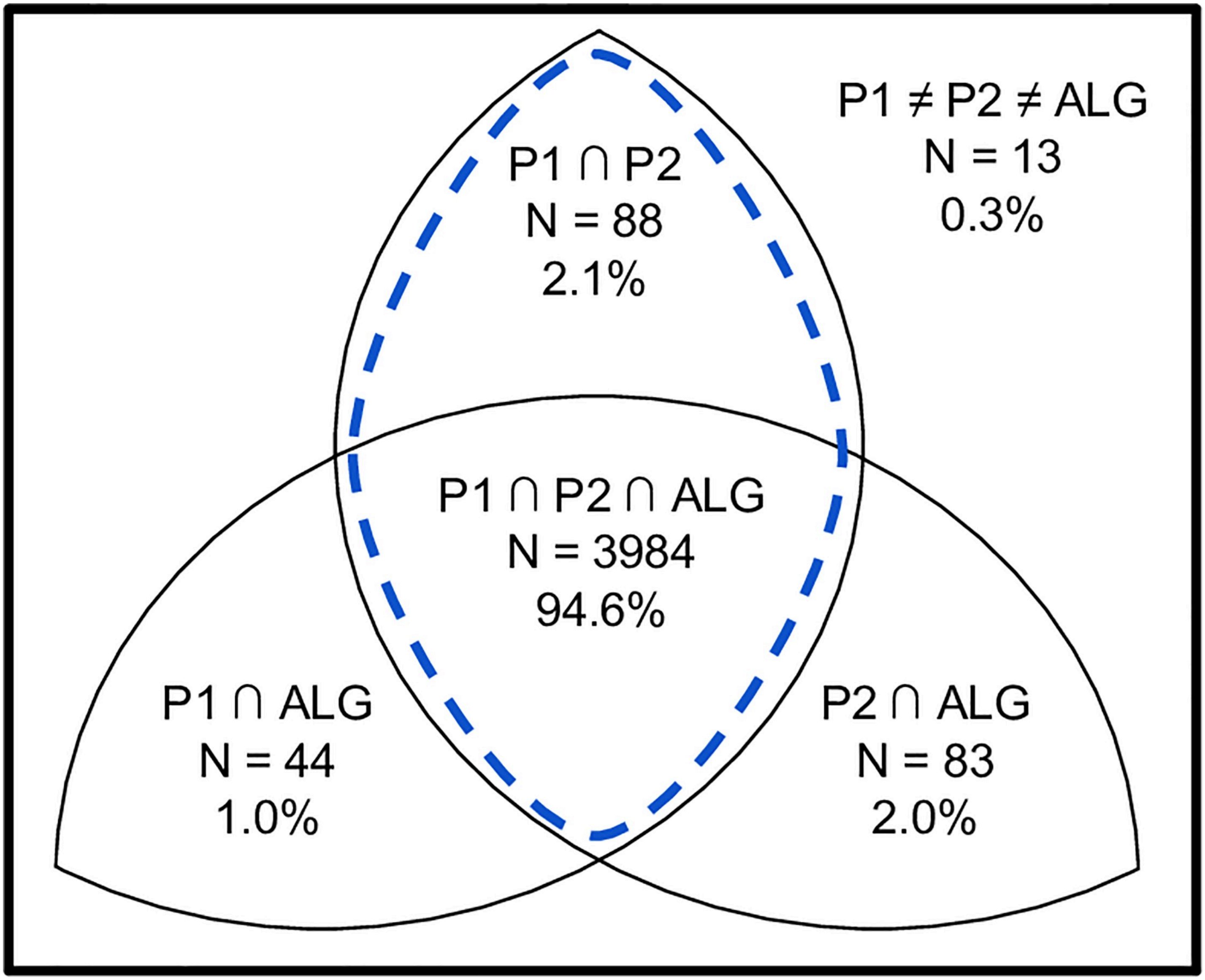

Fig 4. Annotation overlap. Diagram depicting the overlap in annotations for two annotators (P1, P2) and tbiExtractor (ALG) in validation dataset. Dashed line indicates gold standard (i.e., where two annotators are in agreement).

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tbiExtractor performance

tbiExtractor took an average of 0.294 seconds per radiology report. A diagram showing the set of annotations across tbiExtractor and annotators for the validation dataset is shown in Fig 4. When comparing tbiExtractor to annotators, there was high equivalence (N = 3984) and low disagreement (N = 13). For the purposes of evaluating the performance of tbiExtractor, cases where annotators were equivalent was considered the gold standard (Fig 4 dashed line). The evaluation revealed high performance across all metrics (Table 3).

From the validation dataset (N = 156), the number of lexical targets with equivalence ranged from 20 to 27 (25.5 ± 1.7, mean ± standard deviation), indicating most radiology reports had few errors. Approximately 77% (N = 120) of radiology reports exhibited partial equivalence with at least 25 lexical targets accurately annotated and 93% (N = 145) with at least 23

Table 3. tbiExtractor performance metrics.

Metrics	Case 1: where positive if {present, abnormal}	Case 2: where positive if {present, suspected, abnormal}
Sensitivity	0.938	0.924
Specificity	0.993	0.993
Positive Predictive Value	0.957	0.960
Negative Predictive Value	0.990	0.987
Accuracy	0.986	0.983
F1 Score	0.948	0.941

tbiExtractor performance metrics for two cases of positive selection. In both cases, negative if {absent, normal}.

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lexical targets. To show the final lexical targets and their annotations, tbiExtractor was run on the corpus and results for each lexical target are shown in Fig 5.

Error analysis

tbiExtractor was evaluated for accuracy on the 27 lexical targets (Table 4). Two lexical targets, *intraparenchymal hemorrhage* and *facial fracture*, produced the most false negatives, meaning tbiExtractor missed these lexical targets outright. This is likely due to the complexity of these lexical targets and the restriction in the regular expressions to term distance (i.e., the distance between fracture and a term indicating facial is more than the allocated {0, 5} from the regular expression). The remaining lexical targets produced minimal false negatives.

For each of the 27 lexical targets, the occurrences in the validation dataset of each lexical target are displayed with the number of false negatives (FN), false positives (FP), and F1 score performance metric.

Six false positives were produced for *intracranial pathology* and four for *hemorrhage (NOS)*, meaning tbiExtractor identified these lexical targets as PRESENT, while the annotators marked these as ABSENT. This is due to the derivation of these lexical targets in relation to other lexical targets (i.e., if *extraaxial fluid collection* is PRESENT, then by decision rules, so is *intracranial pathology*). The remaining lexical targets produced less minimal false positives. Overall, the errors are minimal as measured by the high F1 scores for the majority of lexical targets.

Further examination of divergent cases (i.e., annotators annotated ABSENT and tbiExtractor annotated PRESENT, or vice versa) revealed the most common diverged lexical targets to be *intracranial pathology*, *facial fracture*, *intraparenchymal hemorrhage*, *hemorrhage (NOS)*, and *herniation*. The remaining lexical targets exhibited less than four diverged responses. The most common lexical modifiers in the divergent cases were the default selection and the derived-from-decision-rules *intracranial pathology*, indicating that most errors were from tbiExtractor missing the lexical targets outright. In most divergent cases where this was not the reason, there were more complex structures to the sentences. In a few other instances, there were sentences that only displayed the lexical target with no available lexical modifier (e.g., *hemorrhagic* extension into the *lateral ventricles*). Two divergent examples are shown in Fig 6.

Discussion

Assessing the corpus revealed noteworthy characteristics of radiology reports from TBI subjects. First, cosine similarities across the four subsets of data were not different and indicated a normal, albeit slender, distribution of radiology report similarity. Second, the average number

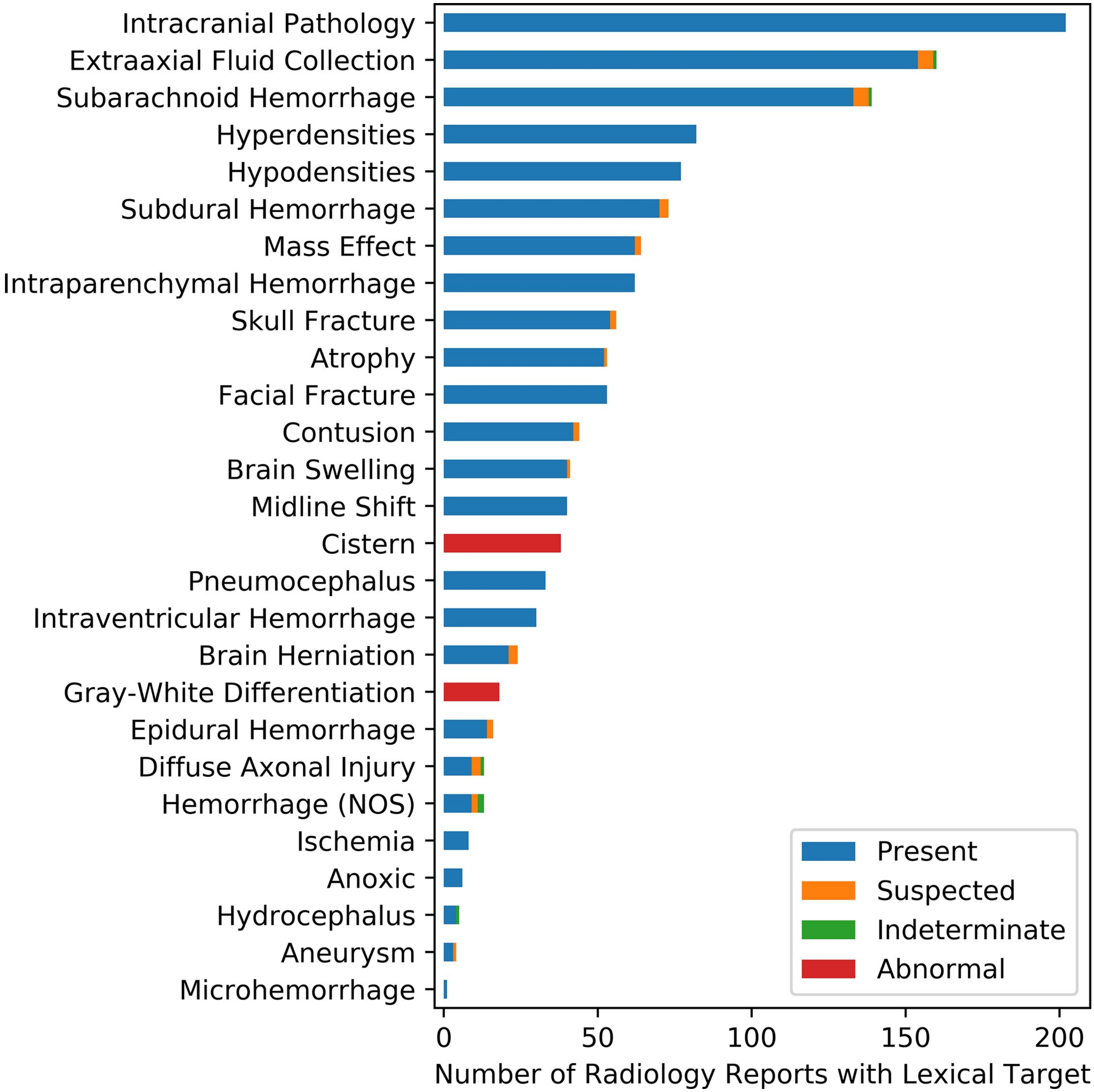

Fig 5. tbiExtractor output annotations. tbiExtractor output annotations for the 27 selected lexical targets over the entire corpus (N = 417 radiology reports).

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of sentences in each radiology reports approached the minimum, indicating a skewed right distribution where the majority of radiology reports will have low numbers of sentences. The same holds true for the number of words. Taken together, this could be reflective of the findings generally found in CT reports on TBI subjects, where the prevalence of CT findings is less

Table 4. tbiExtractor lexical target errors.

Lexical Target	Occurrences	FN	FP	F1 score
Intraparenchymal Hemorrhage	29	7	1	0.85
Facial Fracture	30	6	1	0.87
Extraaxial Fluid Collection	75	3	0	0.98
Hypodensities	36	3	0	0.96
Skull Fracture	27	3	0	0.94
Intraventricular Hemorrhage	17	3	0	0.90
Herniation	11	2	3	0.78
Mass Effect	26	2	2	0.92
Subarachnoid Hemorrhage	69	2	0	0.99
Subdural Hemorrhage	40	2	0	0.97
Hyperdensities	33	2	0	0.97
Atrophy	22	2	0	0.95
Contusion	17	2	0	0.94
Hemorrhage	2	1	4	0.29
Swelling	20	1	2	0.93
Pneumocephalus	17	1	1	0.94
Ischemia	2	1	1	0.50
Epidural Hemorrhage	8	1	0	0.93
Anoxic	4	1	0	0.86
Aneurysm	3	1	0	0.80
Hydrocephalus	2	1	0	0.67
Intracranial Pathology	84	0	6	0.97
Gray-White Differentiation	7	0	2	0.88
Cistern	11	0	1	0.96
Midline Shift	20	0	0	1.00
Diffuse Axonal Injury	3	0	0	1.00
Microhemorrhage	1	0	0	1.00

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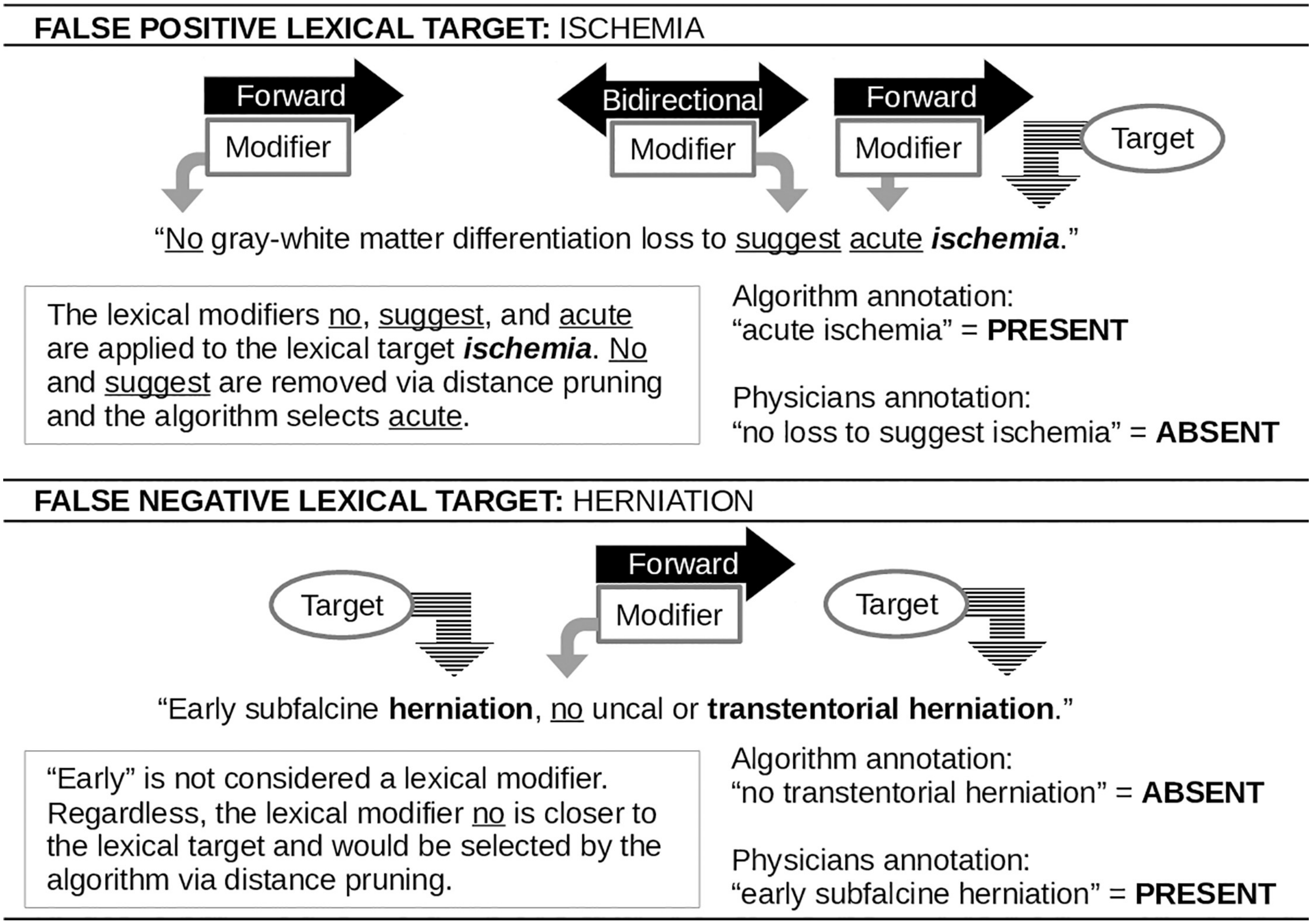
than 10% in mild TBI cases [38–42], which constitute approximately 80% of TBI subjects [43,44].

Annotators displayed high equivalent and low divergent annotations. This provided a solid foundation for developing and validating tbiExtractor. In cases where annotators were not equivalent, data entry issues tended to be the culprit. Mostly, this was a result of overlooking the lexical target and not selecting an annotation different from default. The overlooking could be a result of annotator fatigue, which may be attributed to length and/or complexity of the radiology report. Another data entry issue appears with derived lexical targets, which may be attributed to differences in how the lexical targets are interrelated, and hence, their derivation is differently inferred. In other cases, differences in interpretation of the radiology report were the basis for annotator disagreement. For example, “mixed density lesion” was attributed to *hypodensity* in one case and *hyperdensity* in another. There was also a difference in whether “parenchymal contusion” was considered an *intraparenchymal hemorrhage*. However, the differences between the annotators was minimal and therefore provided a valid gold standard to develop and validate tbiExtractor.

Standard assessment metrics for evaluating tbiExtractor were exceptionally high, demonstrating the utility of the algorithm for extracting accurate clinical conditions relevant to TBI research. Additionally, 93% of radiology reports in the validation dataset were accurate for over 85% of the lexical targets. While the errors from tbiExtractor on the validation dataset



"No gray-white matter differentiation loss to suggest acute ***ischemia***."

The lexical modifiers no, suggest, and acute are applied to the lexical target ***ischemia***. No and suggest are removed via distance pruning and the algorithm selects acute.

Algorithm annotation:
"acute ischemia" = **PRESENT**

Physicians annotation:
"no loss to suggest ischemia" = **ABSENT**

"Early subfalcine **herniation**, no uncal or **transtentorial herniation**."

"Early" is not considered a lexical modifier. Regardless, the lexical modifier no is closer to the lexical target and would be selected by the algorithm via distance pruning.

Algorithm annotation:
"no transtentorial herniation" = **ABSENT**

Physicians annotation:
"early subfalcine herniation" = **PRESENT**

Fig 6. Divergent annotation examples. Two examples of divergent annotations between annotators and tbiExtractor.

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were minimal, there are a few cases worth exploring. First, regular expressions are unable to handle complex syntax and semantics to select the lexical target. One particularly error-prone case was *facial fracture*. Often, radiology reports with *facial fractures* are lengthy and involve compound sentence structures, which are missed by the regular expressions and span pruning. Second, there were several cases where the lexical modifier was absent or at a distance further away than another lexical modifier. For example, "cerebellar volume loss" would indicate *atrophy* is PRESENT, but with this sentence, there is no lexical modifier available and therefore would result in a default lexical modifier of ABSENT. Third, there were cases where derived lexical targets were not accurately annotated by tbiExtractor. After reviewing these errors, many of them were the result of ambiguous reports where "smart-phrases" had not been updated by the radiologist. These "smart-phrases" are made available in EMR systems to provide structured text statements that can easily be programmed for rapid reporting of results. For example, the sentence "there is no evidence of intracranial hemorrhage, mass effect, midline shift or abnormal extraaxial fluid collection" was frequently the first sentence in the radiology reports. This "smart-phrase" provides valuable information, however, if it is not updated, say if later in the radiology report a *subdural hemorrhage* is reported, then tbiExtractor is unable to distinguish this and annotates *extraaxial fluid collection* to be ABSENT. Further examination of these errors is an avenue for future research that may aid in optimizing tbiExtractor.

While tbiExtractor is a valuable algorithm with high performance metrics, there are limitations to its design. The dataset used for this study was from a single institution which limits the style of radiology reports and decreases heterogeneity in the sample. Furthermore, the dataset was limited in size as there were only two annotators available for annotation. In addition, there were data entry issues from extracting the radiology report from the EMRs. For example, a subsequent radiology report was used instead of the admission. Lastly, the only scan considered in this dataset is the admission non-contrast head CT. With the nature of TBIs, some visible pathologies are only seen on follow-up CTs and would be missed on initial imaging.

Conclusion

tbiExtractor was developed to automate the extraction of TBI common data elements from radiology reports. Using two annotators as the gold standard, tbiExtractor displayed high sensitivity and specificity. Findings also showed high equivalence in annotations between annotators and tbiExtractor. Additionally, the time it took tbiExtractor to extract information from the radiology reports was significantly less than the time it took annotators to complete the same task. In conclusion, tbiExtractor is a highly sensitive algorithm for extracting clinical conditions of interest in TBI by providing a structured summary of their status from the radiology report. This algorithm can be used to stratify subjects into severity-groups based on visible damage by partitioning the annotations of the pertinent clinical conditions on a non-contrast head CT report.

Supporting information

S1 Appendix. CLASSIFY-TBI study design.
(DOCX)

S2 Appendix. Calculate TF-IDF and cosine similarities.
(DOCX)

S3 Appendix. Radiology report annotation GUI screenshot.
(DOCX)

S4 Appendix. Classification performance metrics equations.
(PDF)

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Validation: Margaret Mahan.

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Writing – original draft: Margaret Mahan.

Writing – review & editing: Margaret Mahan, Daniel Rafter, Hannah Casey, Marta Engelking, Tessneem Abdallah, Charles Truwit, Mark Oswood, Uzma Samadani.

References

1. Murray G, Butcher I, McHugh G, et al. Multivariable prognostic analysis in traumatic brain injury: Results from the IMPACT study. Journal of Neurotrauma 2006; 24: 329–337.
2. Weng C. Optimizing clinical research participant selection with informatics. Trends in Pharmacological Sciences 2015; 36: 706–709. https://doi.org/10.1016/j.tips.2015.08.007 PMID: 26549161
3. Haacke E, Duhaime A, Gean A, et al. Common data elements in radiologic imaging of traumatic brain injury. Journal of Magnetic Resonance Imaging 2010; 32: 516–543. https://doi.org/10.1002/jmri.22259 PMID: 20815050
4. Rubin D, Khan C. Common data elements in radiology. Radiology 2017; 283: 837–844. https://doi.org/10.1148/radiol.2016161553 PMID: 27831831
5. Marshall L, Marshall S, Kaluber M, et al. The diagnosis of head injury requires a classification based on computed axial tomography. Journal of Neurotrauma 1992; 9: S287–S292. PMID: 1588618
6. Mass A, Hukkelhoven C, Marshall L, et al. Prediction of outcome in traumatic brain injury with computed tomographic characteristics: A comparison between the computed tomographic classification and combinations of computed tomographic predictors. Neurosurgery 2005: 57:1173–1181. https://doi.org/10.1227/01.neu.0000186013.63046.6b PMID: 16331165
7. Demner-Fushman D, Chapman W, McDonald C. What can natural language processing do for clinical decision support? Journal of Biomedical Informatics 2009; 42: 760–772. https://doi.org/10.1016/j.jbi.2009.08.007 PMID: 19683066
8. Pons E, Braun M, Hunink M, et al. Natural language processing in pathology: A systematic review. Radiology 2016; 279: 329–343. https://doi.org/10.1148/radiol.16142770 PMID: 27089187
9. Cai T, Giannopoulus A, Yu S, et al. Natural language processing technologies in radiology research and clinical applications. RadioGraphics 2016; 36: 176–191. https://doi.org/10.1148/rg.2016150080 PMID: 26761536
10. Nadkarni P, Ohno-Machado L, Chapman W. Natural language processing: An introduction. Journal of the American Medical Informatics Association 2011; 18: 544–551, 2011.
11. Friedman C, Shagina L, Lussier Y, et al. Automated encoding of clinical documents based on natural language processing. Journal of the American Medical Informatics Association 2004; 11: 392–402. https://doi.org/10.1197/jamia.M1552 PMID: 15187068
12. Zheng C, Rashid N, Koblick R, et al. Medication extraction from electronic clinical notes in an integrated health system: A study on aspirin use in patients with nonvalvular atrial fibrillation. Clinical Therapeutics 2015; 37: 2048–2058. https://doi.org/10.1016/j.clinthera.2015.07.002 PMID: 26233471
13. Zeng Q, Goryachey S, Weiss S, et al. Extracting principal diagnosis, co-morbidity and smoking status for asthma research: Evaluation of a natural language processing system", BMC Medical Informatics and Decision Making, vol. 6, no. 30, pp. 1–9, 2006. https://doi.org/10.1186/1472-6947-6-30 PMID: 16872495
14. Strauss J, Chao C, Kwan M, et al. Identifying primary and recurrent cancers using a SAS-based natural language processing algorithm. Journal of the American Medical Informatics Association 2013; 20: 349–355. https://doi.org/10.1136/amiajnl-2012-000928 PMID: 22822041
15. Yadav K, Sarioglu E, Smith M, et al. Automated outcome classification of emergency department computed tomography imaging reports. Academic Emergency Medicine 2013; 20: 848–854. https://doi.org/10.1111/acem.12174 PMID: 24033628

16. Yadav K, Sarioglu E, Choi H, et al. Automated outcome classification of computed tomography imaging reports for pediatric traumatic brain injury. Academic Emergency Medicine 2016; 23: 171–178. https://doi.org/10.1111/acem.12859 PMID: 26766600

17. Hassanpour S, Langlotz C. Information extraction from multi-institutional radiology reports. Artificial Intelligence in Medicine 2016; 66: 29–39. https://doi.org/10.1016/j.artmed.2015.09.007 PMID: 26481140

18. Sevenster M, Buurman J, Liu P, et al. Natural language processing techniques for extracting and categorizing finding measurements in narrative radiology reports. Applied Clinical Informatics 2015; 6: 600–610. https://doi.org/10.4338/ACI-2014-11-RA-0110 PMID: 26448801

19. Sevenster M, Bozeman J, Cowhy A, et al. A natural language processing pipeline for pairing measurements uniquely across free-text CT reports. Journal of Biomedical Informatics 2015; 53: 36–48. https://doi.org/10.1016/j.jbi.2014.08.015 PMID: 25200472

20. Chapman B, Mowery D, Narasimhan E, et al. Assessing the feasibility of an automated suggestion system for communicating critical findings from chest radiology reports to referring physicians. Proceedings of the 15th Workshop on Biomedical Natural Language Processing 2016; 181–185.

21. Hassanpour S, Bay G, Langlotz C. Characterization of change and significance for clinical findings in radiology reports through natural language processing. Journal of Digital Imaging 2017; 30: 314–322. https://doi.org/10.1007/s10278-016-9931-8 PMID: 28050714

22. Python Software Foundation. https://www.python.org. Accessed February 2019.

23. McKinney W. Data structures for statistical computing in python. Proceedings of the 9th Python in Science Conference 2010; 51–56.

24. Oliphant T. A guide to NumPy. Trelgol Publishing 2006. http://web.mit.edu/dvp/Public/numpybook.pdf. Accessed February 2019.

25. Jones E, Oliphant T, Peterson P. SciPy: Open source scientific tools for Python. http://www.scipy.org/. Accessed February 2019.

26. SpaCy. https://spacy.io/. Accessed February 2019.

27. Pedregosa F, Varoquaux G, Gramfort A, et al. Scikit-learn: Machine learning in python. Journal of Machine Learning Research 2011; 12:2825–2830.

28. pyConTextNLP. https://pypi.org/project/pyConTextNLP/. Accessed February 2019.

29. Hagberg A, Schult D, Swart P. Exploring network structure, dynamics, and function using NetworkX. Proceedings of the 7th Python in Science Conference 2008; 11–15.

30. Hunter J. Matplotlib: A 2D graphics environment. Computing in Science and Engineering 2007; 9:21–29.

31. Seaborn. https://seaborn.pydata.org/. Accessed February 2019.

32. Chapman W, Bridewell W, Hanbury P, et al. A simple algorithm for identifying negated findings and diseases in discharge summaries. Journal of Biomedical Informatics 2001; 34:301–310. https://doi.org/10.1006/jbin.2001.1029 PMID: 12123149

33. Chapman W, Chu D, Dowling J. ConText: An algorithm for identifying contextual features from clinical text. BioNLP 2007: Biological, translational, and clinical language processing; 81–88.

34. Harkema H, Dowling J, Thornblade T, et al. Context: An algorithm for determining negation, experiencer, and temporal status from clinical reports. Journal of Biomedical Informatics 2009; 42:839–851. https://doi.org/10.1016/j.jbi.2009.05.002 PMID: 19435614

35. Chapman B, Lee S, Kang H, et al. Document-level classification of CT pulmonary angiography reports based on an extension of the ConText algorithm. Journal of Biomedical Informatics 2011; 44:728–737. https://doi.org/10.1016/j.jbi.2011.03.011 PMID: 21459155

36. Artstein R, Poesio M. Inter-Coder agreement for computational linguistics. Computational Linguistics 2008; 34:555–596.

37. Cohen J. A coefficient of agreement for nominal scales. Educational and Psychological Measurement 1960; 20:37–46.

38. Wintermark M, Sanelli P, Anzai Y, et al. Imaging evidence and recommendations for traumatic brain injury: Conventional neuroimaging techniques. Journal of the American College of Radiology 2015; 12: e1–e14. https://doi.org/10.1016/j.jacr.2014.10.014 PMID: 25456317

39. Fabbri A, Servadei F, Marchesini G, et al. Prospective validation of a proposal for diagnosis and management of patients attending the emergency department for mild head injury. Journal of Neurology Neurosurgery and Psychiatry 2004; 75:410–416.

40. Borg J, Holm L, Cassidy J, et al. Diagnostic procedures in mild traumatic brain injury: results of the WHO collaborating centre task force on mild traumatic brain injury. Journal of Rehabilitation Medicine 2004; 43:61–75.

41. Af Geijerstem J, Britton M. Mild head injury—mortality and complication rate: Meta-analysis of findings in a systematic literature review. Acta Neurochirurgica 2003; 145:843–850. https://doi.org/10.1007/s00701-003-0115-1 PMID: 14577005

42. Haydel M, Preston C, Mills T, et al. Indications for computed tomography in patients with minor head injuries. The New England Journal of Medicine 2000; 343:100–105. https://doi.org/10.1056/NEJM200007133430204 PMID: 10891517

43. Faul M, Coronado V. Epidemiology of traumatic brain injury, Grafman J. and Salazar A. Eds. Elsevier 2015; 127:25–29.

44. Brown A, Elovic E, Kothari S, et al. Congenital and acquired brain injury. 1. Epidemiology, pathophysiology, prognostication, innovative treatments, and prevention. Archives of Physical Medicine and Rehabilitation 2008; 89:3–8.