Natural Language Processing in Radiology Reports

Chapter 15: Natural Language Processing in Radiology Reports

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Introduction

In the clinical domain, we have so much data, of which a lot of textual entries are unstructured free text. Nevertheless, it is of no use in its existing form. The majority of free-text clinical data in the electronic medical records remain unusable. The problem with this data is captured by the 5V's- Volume (quantity), Variety (format), Velocity(increasing), Value(richness), Veracity (quality & integrity). The radiology reports form a significant part of the unstructured free text content in the Hospital Information System (HIS). Radiology reports are stored in the EMR in the form of free text. [(1-4)] These reports contain rich content about the tumor, stage of the disease, response to treatment, and suggestions for additional investigations stored in an unstructured format. Interpretation of these reports requires an expert to read the text and infer the report. For the last few years, researchers are trying to mine these reports to extract meaningful information. Natural Language Processing (NLP) can help reduce significant time and efforts in extracting such information. NLP is a sub-domain of linguistics, computer science, and artificial intelligence (AI) that deals with programming or training machines to handle and comprehend human language.[(5)]

"Natural" refers to a form of speech/text that follows human communication norms. NLP deals with how machines can correctly extract information and meaning from humans' unstructured text to communicate information. In order to train algorithms to understand natural language the way humans do, algorithms may be provided with sufficient vocabulary that might allow the machines to perform basic translation and classification tasks. [(6)] However, to map the complexity of words and meanings in sentences, it is essential to capture the context. NLP helps model all these complexities of human language into mathematical form for it to be machine-readable. [(7)]

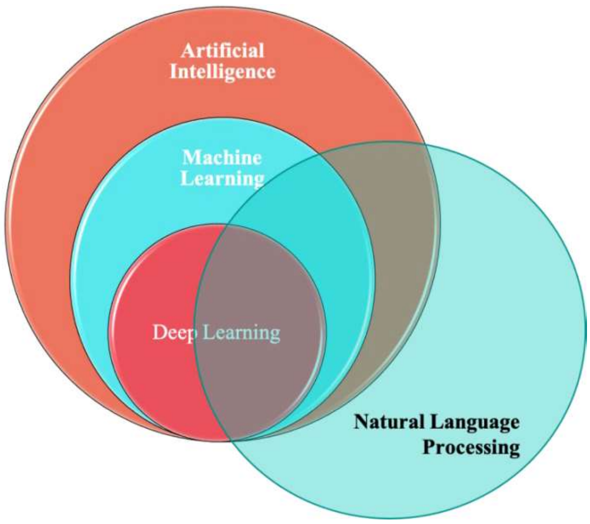

Figure 1: Natural language processing as a sub-domain of artificial intelligence

This may be performed by rule-based approach, statistical approach, or hybrid (a combination of both). A statistical approach is employed by machine learning, which helps extract the right information or make the right correlation. Another sub-branch of machine learning that is frequently utilized is deep learning which uses artificial neural networks to correct correlations and extract information. Neural networks are various types depending on the task at hand [8, 9](Figure 1). The process followed for extraction of structured information from the free text medical reports is shown in Fig 2. [10-30]

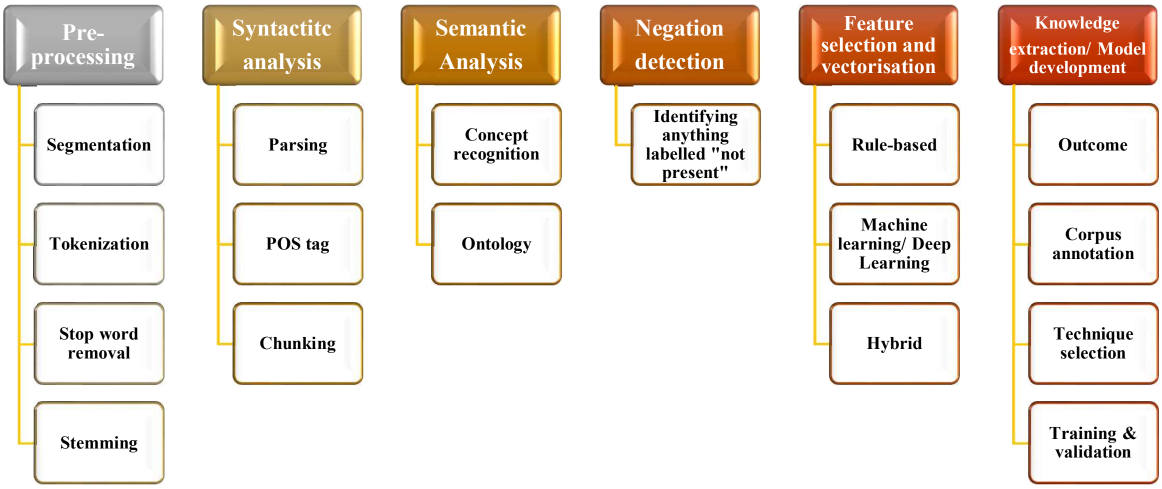

Figure 2: Processes involved in NLP

Application of Natural Language Processing in Radiology Reports

Application of NLP tools can be found in research as well as in the clinic. In research, NLP is useful for creating a clean, structured corpus for future use, filtering data using case identification, query-based retrieval of data, report classification, Development of decision support systems& prediction modeling. In the clinic, we can use NLP for diagnostic surveillance and auto-generation of emergency alerts, report standardization, assistive reporting, error correction, improving radiology reporting by quality assessment, uncertainty detection in reports, data modeling for clinical support to improve the accuracy of diagnosis or provide a better idea of disease prognosis or the efficacy of a treatment. NLP applications in imaging can help oncology with faster report summarization, case identification, staging, and treatment outcome detection.[30-106]

NLP applications have been developed using programming languages like Java, Python, Julia, R.The Development of these tools is, however, data-driven. Limited clinical data sharing is a significant limitation for the Development of NLP applications. Ontology-driven concept recognition and mapping can help develop such applications without data leaving the institution by distributed learning.[66-68] Several ontologies from UMLS vocabulary have been used for semantic mapping concepts from radiology reports like RadLexLexicon, Radiation Oncology Ontology (ROO), NCIT (National Cancer Institute Thesaurus), SNOMED CT(Systematized Nomenclature of Medicine -- Clinical Terms). Severaltools and datasets are available for NLP created for specific tasks, some of which are open source [24-29]. (Table 1-2)

Sharp NLP	LEXIMER	CGMIM	Concept Mapper	Iscout
Metamap	ONYX	MeInfoText	I2b2	LifeCode
QuExT	Ctakes	MedTag	Clear Forest	LINNAEUS
GATE	YTEX	CaTIES	MedTAS/P	Aleph
I2E	MOSES	ClinRead	MEDTEX	ABNER

Table 1: Tools available for NLP

Datasets	Availability
Render- radiology study repository	Not publicly available
mtsamples	Public dataset
i2b2challenge sets	Available on request

Table 2: Radiology datasets available for NLP

NLP has been used for cohort building for epidemiology studies by automatically selecting studies for various conditions like renal cysts, pneumonia, pulmonary nodules.[(38-42).]Zhou et al. used NLP for automatic classification of radiology reports for retrospective studies.[(43)]Similar work was done by Schuemie et al. using electronic health records.[(44)] NLP has been used to extract radiology reports based on specific concepts related to congestive heart failure or strokes or peripheral arterial diseases or aortic aneurysms.[(45-55)]
Query-based case retrieval has been developed,which helps case retrieval employ a query with the user's fields. Applications with web-based systems linked to reports in PACS using ontologies have been used for case retrieval. Customizing ontologies has been found to improve such algorithms' performance from 42% sensitivity to 95%. Similar tools have been used for data filtering and report classification.[(33,35,42,57,61,62,69,75,76)]NLP was also used for query-based image retrieval using concepts from radiology reports.[(58)] A commercial application LifeCode designed for billing purposes, was used to extract findings from radiology reports by employing a Radlex lexicon and reported 85% sensitivity & 96% precision.[(57)] Some similar applications were used for image retrieval for educational purposes.[(107)]

Several applications have explored features extracted from free-text reports to develop decision support systems and prediction modeling using EMR free text. However, there is still work going on to use radiology report information extraction to develop decision support systems.[(98, 100)]
Some critical observations are not explicitly mentioned in reports. An NLP system can help detect an implicit diagnosis like disease status, staging, infections, or suggestions for additional investigation. Systems thatautomatically detect such observations help minimize communication delays between the radiologist and the referring clinician by generating automatic alerts. SeveralML-based algorithms have reported sensitivity and specificity >90% for critical observation for surveillance and generation of alerts. Some algorithms have

obtained comparable results with a hybrid approach using a customized lexicon.[31-37,73-75,78,79]Li et al. used a commercially available NLP tool Health Care Analytics Solution (HACAS), for automated data extraction for identifying from a group of Computed Tomography reports, reports that contained patients positive for ureteric stones with a sensitivity of 66%, a specificity of 95% and accuracy 85%.[90] Similar work was done to identify incidental lung nodules (ILNs) and assess management recommendations in radiology reports with 91% sensitivity & 82% specificity for identifying ILNs[91].These may also be useful if employed with an alert generation system.Sinha et al.found 90%accuracy and high user satisfaction using a graphic interface tool to implement prospective structuring of radiology reports using a predefined but customizable vocabulary.[101]

Several NLP tools have been used for quality assessment of radiological practice and checking adherence to reporting guidelines.[60,61,69,102-106]These applications were used for assessing recommendation behavior, report quality assessment. The collection of disease-specific phrases & detection of recommendations for actions or investigations were extracted for this. [60-61]

Another critical aspect of radiology reports has understood the certainty of findings and observations in the reports.[93-96] Callen et al. used NLP for characterizing and comparing uncertainty terms used in radiology reports. The algorithm created by them was used to detect published uncertainty terms and compared against the gold standard of two radiologists' identification of these terms. The authors reported an accuracy between 0.84-0.91 for the algorithm.[97]

Several NLP-basedclinical support servicetools like SymText have been developed with nearly 100% sensitivity and 99% specificity for concept extraction[64-65]. Sevenster et al. described an NLP algorithm for pairing measurements across consecutive radiology reports with a measurement extraction engine with a precision of 0.994 and a recall of 0.991.[77]Hassanpour et al. used a machine learning-based NLP system to build an information extraction model. They compared dictionary-based annotation (using cTAKES and RadLex lexicon), conditional Markov model (CMM) based annotation, and conditional random field(CRF) based annotation and found that the CMM and CRF based annotations gave better results for Named Entity Recognition.[18-19] Recently applications like MedTagger (a rule-based NLP algorithm) have been used for extracting information related to skeletal site-specific fractures with very high sensitivity specificity & precision 0.930, 1.0, 1.0. [78] Brown et al. have used an open-source NLP tool and ML software like logistic regression, support vector machine (SVM), and random forest and compared them. They used bag-of-words model and TF-IDF representations for word representation and found that TF-IDF with the SVM model outperformed all other models(79). Goff et al.also automated report summarisation system extracts asserted and negated disease entities from radiology reports with sensitivity &precision of 0.86&0.66, respectively (80). Senders et al. compared bag-of-words approach algorithms (logistic regression, least absolute shrinkage, selection operator [LASSO] regression, and multilayer perceptron)with sequence-based approach algorithms (1D–convolutional neural networks, long short-term memory, and gated recurrent unit) to classify MRI brain reports into single metastasis mentions versus multiple metastases mentions. They found that LASSO performed best among the compared algorithms.[92] Nobel et al. developed and validated a rule-based algorithm to classify lung cancer radiology reports for T-staging. The algorithm also used regular expressions and reported an accuracy of 0.87.[98]Bozkurt et al. used a hybrid NLP algorithm for automated extraction of measurements and their descriptors in radiology reports. The pipeline employed by them used a rule-based algorithm with a CRF model to extract measurements andRadLex lexicon for descriptors in CT & MRI reports (96% accuracy).[99] Word embeddings like Sent2Vec and GloVe have been used for featuring unstructured text from radiology reports along with machine learning and deep learning algorithms (with recurrent neural networks and convolutional neural networks) to detect outcome mentions in radiology reports with promising results[81-89].

Conclusion

NLP will be useful in furthering and improving research in cancer and aiding in personalized medicine approaches. The recent NLP research suggests the increasing role of NLP in radiology report interpretation, radiology report generation, emergency alert generation, uncertainty detection, data extraction for clinical decision support systems, predictive modeling, and cohort generation for research.

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