Natural Language Processing in Radiology Reports

Chapter 15: Natural Language Processing in Radiology Reports

Dr. Sneha Mithun[1,2,3], Dr. Ashish Kumar Jha[1,2,3], Dr. V Rangarajan[1,2], Dr. L. Wee[3], Dr. A. Dekker[3]

[1]Department of Nuclear Medicine and Molecular Imaging, Tata Memorial Hospital, Mumbai, India, [2]HomiBhabha National Institute (HBNI), Deemed University, Mumbai, India,
[3]Department of Radiation Oncology (Maastro), GROW School for Oncology, Maastricht University Medical Centre, 6229 ET Maastricht, The Netherlands.

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]

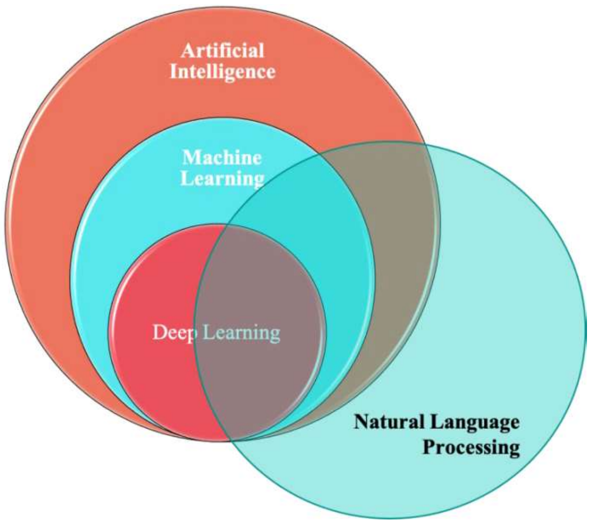

Figure 1: Natural language processing as a sub-domain of artificial intelligence

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]

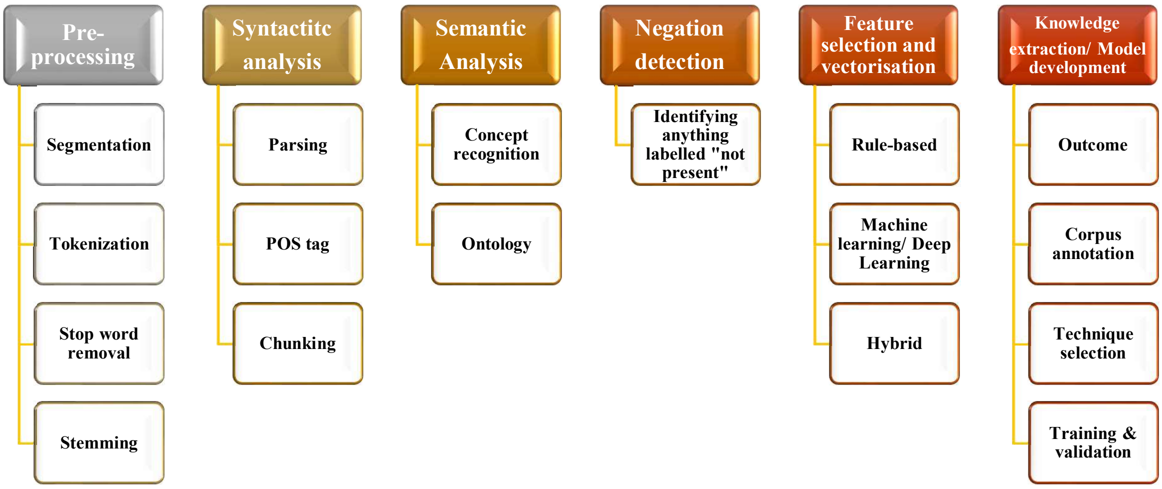

Figure 2: Processes involved in NLP

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.

References:

1. Huhdanpaa HT, Tan WK, Rundell SD, Suri P, Chokshi FH, Comstock BA, Heagerty PJ, James KT, Avins AL, Nedeljkovic SS, Nerenz DR, Kallmes DF, Luetmer PH, Sherman KJ, Organ NL, Griffith B, Langlotz CP, Carrell D, Hassanpour S, Jarvik JG. Using Natural Language Processing of Free-Text Radiology Reports to Identify Type 1 Modic Endplate Changes. J Digit Imaging. 2018 Feb;31(1):84-90. doi: 10.1007/s10278-017-0013-3.
2. Taira RK, Soderland SG, Jakobovits RM. Automatic structuring of radiology free-text reports. Radiographics. 2001 Jan-Feb;21(1):237-45. doi: 10.1148/radiographics.21.1.g01ja18237. PMID: 11158658.
3. Sistrom CL, Honeyman-Buck J. Free text versus structured format: information transfer efficiency of radiology reports. AJR Am J Roentgenol. 2005 Sep;185(3):804-12. doi: 10.2214/ajr.185.3.01850804. PMID: 16120938.
4. Jensen, Kasper et al. "Analysis of free text in electronic health records for identification of cancer patient trajectories." Scientific reports vol. 7 46226. 7 Apr. 2017, doi:10.1038/srep46226
5. https://en.wikipedia.org/wiki/Natural_language_processing
6. https://towardsdatascience.com/natural-language-processing-in-artificial-intelligence-is-almost-human-level-accurate-fbdaffed6392
7. Schank, R. C. (1972). Conceptual dependency: A theory of natural language understanding. Cognitive Psychology, 3 , 552–631.
8. https://towardsdatascience.com/natural-language-processing-from-basics-to-using-rnn-and-lstm-ef6779e4ae66
9. Leijnen S, Veen Fv. The Neural Network Zoo. Proceedings. 2020; 47(1):9. https://doi.org/10.3390/proceedings2020047009.
10. Yim WW, Yetisgen M, Harris WP, Kwan SW. Natural Language Processing in Oncology: A Review. JAMA Oncol. 2016 1 Jun.;2(6):797–804.
11. Martin M. J Semantic Web may be cancer information's next step forward. Natl Cancer Inst. 2011 17 Aug.;103(16):1215-8.
12. Zhu F, Patumcharoenpol P, Zhang C, Yang Y, Chan J, Meechai A, Vongsangnak W, Shen B. Biomedical text mining and its applications in cancer research. J Biomed Inform. 2013 Apr;46(2):200-11.
13. https://towardsdatascience.com/getting-your-text-data-ready-for-your-natural-language-processing-journey-744d52912867
14. Damasceno de Souza A, Barcellos Almeida M. Textual Definitions in the Leukemia Domain: Methodological Guidelines for Biomedical Ontologies. Stud Health Technol Inform. 2015;216:1092.
15. https://pdfs.semanticscholar.org/cb3f/cbd32db5a7d1109a2d7e92c0c534b65e1769.pdf
16. Van Soest J, Lustberg T, Grittner D, Marshall MS, Persoon L, Nijsten B, Feltens P, Dekker A. Towards a semantic PACS: Using Semantic Web technology to represent imaging data. Stud Health Technol Inform. 2014;205:166-70.
17. Spyns, P. (1996). Natural Language Processing in Medicine: An Overview. Methods of Information in Medicine, 35(04/05), 285–301.
18. Hassanpour S, Langlotz CP. Information extraction from multi-institutional radiology reports. ArtifIntell Med. 2016 Jan;66:29–39.
19. Savova GK, et al. Mayo clinical Text Analysis and Knowledge Extraction System (cTAKES): architecture, component evaluation and applications. J. Am. Med. Inf. Assoc. 2010;17:507–513.

20. Matos S, Arrais JP, Maia-Rodrigues J, Oliveira JL. Concept-based query expansion for retrieving gene related publications from MEDLINE. BMCBioinformatics2010;11:212.
21. Kuo CJ, Ling MH, Lin KT, Hsu CN. BIOADI: a machine learning approach to identifying abbreviations and definitions in biological literature. BMCBioinformatics 2009;10(Suppl. 15):S7.
22. Chang JT, Schutze H, Altman RB. Creating an online dictionary of abbreviations from MEDLINE. J Am Med Inform Assoc 2002;9:612–20
23. Liu H, Friedman C. Mining terminological knowledge in large biomedicalcorpora. Pac SympBiocomput 2003:415–26.
24. Bodenreider, O. "The Unified Medical Language System (UMLS): Integrating Biomedical Terminology." Nucleic Acids Research, vol. 32, no. 90001, Jan. 2004, pp. 267D – 270. DOI.org (Crossref), doi:10.1093/nar/gkh061.
25. US National Institutes of Health. National Cancer Institute: NCI Thesaurus. https://ncit.nci.nih.gov/ncitbrowser/. Accessed 5 Dec. 2020.
26. National Cancer Institute Thesaurus | NCBO BioPortal. https://bioportal.bioontology.org/ontologies/NCIT. Accessed 5 Dec. 2020.
27. Radiation Oncology Ontology | NCBO BioPortal. https://bioportal.bioontology.org/ontologies/ROO. Accessed 5 Dec. 2020.
28. Traverso, Alberto, et al. "The Radiation Oncology Ontology (ROO): Publishing Linked Data in Radiation Oncology Using Semantic Web and Ontology Techniques." Medical Physics, vol. 45, no. 10, Oct. 2018, pp. e854–62. DOI.org (Crossref), doi:10.1002/mp.12879.
29. Overview of SNOMED CT. https://www.nlm.nih.gov/healthit/snomedct/snomed_overview.html. Accessed 5 Dec. 2020.
30. Pons E, Braun LM, Hunink MG, Kors JA. Natural Language Processing in Radiology: A Systematic Review. Radiology. 2016 May;279(2):329-43.
31. Rink B, Roberts K, Harabagiu S et al. Extracting actionable findings of appendicitis from radiology reports using natural language processing. AMIA Jt Summits Transl Sci Proc 2013;2013:221.
32. Lakhani P, Kim W, Langlotz CP. Automated detection of critical results in radiology reports. J Digit Imaging 2012;25(1):30-36.
33. Solti I, Cooke CR, Xia F, Wurfel MM. Automated classification of radiology reports for acute lung injury: comparison of keyword and machine learning based natural language processing approaches. Proceedings (IEEE Int Conf Bioinformatics Biomed) 2009;2009:314-319.
34. Zingmond D, Lenert LA. Monitoring free-text data using medical language processing. Comput Biomed Res 1993;26(5):467-481.
35. Garla V, Taylor C, Brandt C. Semi-supervised clinical text classification with Laplacian SVMs: an application to cancer case management. J Biomed Inform 2013;46(5):869-875.
36. Cheng LT, Zheng J, Savova GK, Erickson BJ. Discerning tumor status from unstructured MRI reports: completeness of information in existing reports and utility of automated natural language processing. J Digit Imaging 2010;23(2):119–132.
37. Xu Y, Tsujii J, Chang EI. Named entity recognition of follow-up and time information in 20,000 radiology reports. J Am Med Inform Assoc 2012;19(5):792–799.
38. O'Connor SD, Silverman SG, Ip IK, Maehara CK, Khorasani R. Simple cyst-appearing renal masses at unenhanced CT: can they be presumed to be benign? Radiology 2013;269(3):793–800.
39. Dublin S, Baldwin E, Walker RL et al. Natural Language Processing to identify pneumonia from radiology reports. Pharmacoepidemiol Drug Saf 2013;22(8):834–841.

40. Hripcsak G, Austin JH, Alderson PO, Fried-man C. Use of natural language processing to translate clinical information from a data-base of 889,921 chest radiographic reports. Radiology 2002;224(1):157–163
41. Danforth KN, Early MI, Ngan S, Kosco AE, Zheng C, Gould MK. Automated identification of patients with pulmonary nodules in an integrated health system using administrative health plan data, radiology reports, and natural language processing. J Thorac Oncol2012;7(8):1257–1262.
42. Percha B, Nassif H, Lipson J, Burnside E, Rubin D. Automatic classification of mammography reports by BI-RADS breast tissue composition class. J Am Med Inform Assoc 2012;19(5):913–916.
43. Zhou Y, Amundson PK, Yu F, Kessler MM, Benzinger TL, Wippold FJ. Automated classification of radiology reports to facilitate retrospective study in radiology. J Digit Imaging 2014;27(6):730–736.
44. Schuemie MJ, Sen E, 't Jong GW, van Soest EM, Sturkenboom MC, Kors JA. Automating classification of free-text electronic health records for epidemiological studies. Pharmacoepidemiol Drug Saf 2012;21(6):651–658.
45. Esuli A, Marcheggiani D, Sebastiani F. An enhanced CRFs-based system for information extraction from radiology reports. J Biomed Inform 2013;46(3):425–435
46. Yu S, Kumamaru KK, George E, et al. Classification of CT pulmonary angiography reports by presence, chronicity, and location of pulmonary embolism with natural language processing. J Biomed Inform 2014;52:386–393.
47. Petkov VI, Penberthy LT, Dahman BA, Poklepovic A, Gillam CW, McDermott JH. Automated determination of metastases in unstructured radiology reports for eligibility screening in oncology clinical trials. Exp Biol Med (Maywood) 2013;238(12):1370–1378.
48. Zopf JJ, Langer JM, Boonn WW, Kim W, Zafar HM. Development of automated detection of radiology reports citing adrenal findings. J Digit Imaging 2012;25(1):43–49.
49. Sohn S, Ye Z, Liu H, Chute CG, Kullo IJ. Identifying abdominal aortic aneurysm cases and controls using natural language processing of radiology reports. AMIA Jt Summits Transl Sci Proc 2013;2013:249–253.
50. Savova GK, Fan J, Ye Z, et al. Discovering peripheral arterial disease cases from radiology notes using natural language processing. AMIA AnnuSymp Proc 2010;2010:722–726.
51. Garla V, Lo Re V 3rd, Dorey-Stein Z, et al. The Yale cTAKES extensions for document classification: architecture and application. J Am Med Inform Assoc 2011;18(5):614–620.
52. Rubin D, Wang D, Chambers DA, Chambers JG, South BR, Goldstein MK. Natural language processing for lines and devices in portable chest x-rays. AMIA AnnuSymp Proc 2010;2010:692–696.
53. Trick WE, Chapman WW, Wisniewski MF, Peterson BJ, Solomon SL, Weinstein RA. Electronic interpretation of chest radiograph reports to detect central venous catheters. Infect Control Hosp Epidemiol 2003;24(12):950–954.
54. Flynn RW, Macdonald TM, Schembri N, Murray GD, Doney AS. Automated data capture from free-text radiology reports to enhance accuracy of hospital in-patient stroke codes. Pharmacoepidemiol Drug Saf 2010;19(8):843–847.
55. Friedlin J, McDonald CJ. A natural language processing system to extract and code con-cepts relating to congestive heart failure from chest radiology reports. AMIA AnnuSymp Proc 2006:269–273.
56. Heilbrun ME, Chapman BE, Narasimhan E, Patel N, Mowery D. Feasibility of Natural Language Processing-Assisted Auditing of Critical Findings in Chest Radiology. J Am Coll Radiol. 2019 Sep;16(9 Pt B):1299-1304. Doi: 10.1016/j.jacr.2019.05.038.

57. Mamlin BW, Heinze DT, McDonald CJ. Automated extraction and normalization of findings from cancer-related free-text radiology reports. AMIA AnnuSymp Proc 2003:420-4.
58. Gerstmair A, Daumke P, Simon K, LangerM, Kotter E. Intelligent image retrieval based on radiology reports. Eur Radiol 2012;22(12):2750–2758
59. Warden GI, Lacson R, Khorasani R. Leveraging terminologies for retrieval of radiology reports with critical imaging findings. AMIA AnnuSymp Proc 2011;2011:1481–1488
60. Do BH, Wu AS, Maley J, Biswal S. Automatic retrieval of bone fracture knowledge using natural language processing. J Digit Imaging 2013;26(4):709–713
61. Dreyer KJ, Kalra MK, Maher MM, et al. Application of recently developed computer algorithm for automatic classification of unstructured radiology reports: validation study. Radiology 2005;234(2):323–329
62. Lacson R, Andriole KP, Prevedello LM, Khorasani R. Information from Searching Content with an Ontology-Utilizing Toolkit (iSCOUT). J Digit Imaging 2012;25(4):512–519.
63. Farkas R, Szarvas G. Automatic construction of rule-based ICD-9-CM coding systems. BMC Bioinformatics 2008;9(Suppl 3):S10
64. Fiszman M, Chapman WW, Aronsky D, Evans RS, Haug PJ. Automatic detection of acute bacterial pneumonia from chest x-ray reports. J Am Med Inform Assoc 2000;7(6):593-604. Crossref, Medline, Google Scholar
65. Fiszman M, Chapman WW, Evans SR, Haug PJ. Automatic identification of pneumonia related concepts on chest x-ray reports. Proc AMIA Symp 1999:67-71. Medline, Google Scholar
66. Shi, Z., Zhovannik, I., Traverso, A. et al. Distributed radiomics as a signature validation study using the Personal Health Train infrastructure. Sci Data 6, 218 (2019). https://doi.org/10.1038/s41597-019-0241-0.
67. Jochems A, Deist TM, van Soest J, Eble M, Bulens P, Coucke P, Dries W, Lambin P, Dekker A. Distributed learning: Developing a predictive model based on data from multiple hospitals without data leaving the hospital – A real life proof of concept. Radiother Oncol. 2016 Dec;121(3):459-467. Doi: 10.1016/j.radonc.2016.10.002.
68. Deist TM, Dankers FJWM, Ojha P, Scott Marshall M, Janssen T, Faivre-Finn C, Masciocchi C, Valentini V, Wang J, Chen J, Zhang Z, Spezi E, Button M, Jan Nuyttens J, Vernhout R, van Soest J, Jochems A, Monshouwer R, Bussink J, Price G, Lambin P, Dekker A. Distributed learning on 20 000+ lung cancer patients – The Personal Health Train. Radiother Oncol. 2020 Mar;144:189-200. Doi: 10.1016/j.radonc.2019.11.019.
69. Dang PA, Kalra MK, Blake MA, Schultz TJ, Halpern EF, Dreyer KJ: Extraction of Recommendation Features in Radiology with Natural Language Processing: Exploratory Study. AJR 191:313–320, 2008
70. B. Burnside, H. Strasberg, D. Rubin. Automated indexing of mammography reports using linear least squares fit. 14th International Congress and Exhibition on Computer Assisted Radiology and Surgery (2000), pp. 449-454
71. Cai T, Giannopoulos AA, Yu S, Kelil T, Ripley B, Kumamaru KK, Rybicki FJ, Mitsouras D. Natural Language Processing Technologies in Radiology Research and Clinical Applications. Radiographics. 2016 Jan-Feb;36(1):176-91.
72. Chapman WW, Bridewell W, Hanbury P, Cooper GF,Buchanan BG. A simple algorithm for identifying negated findings and diseases in discharge summaries. J BiomedInform 2001;34(5):301–310.
73. Yetisgen-Yildiz M, Gunn ML, Xia F, Payne TH. A text processing pipeline to extract recommendations from radiology reports. J Biomed Inform 2013;46(2):354–362

74. Chapman WW, Fizman M, Chapman BE, Haug PJ. A comparison of classification algorithms to automatically identify chest x-ray reports that support pneumonia. J Biomed Inform 2001;34(1):4–14.
75. Chapman BE, Lee S, Kang HP, Chapman WW. Document-level classification of CT pulmonary angiography reports based on an extension of the ConText algorithm. J Biomed Inform 2011;44(5):728–737.
76. Yu S, Kumamaru KK, George E, et al. Classification of CT pulmonary angiography reports by presence, chronicity,and location of pulmonary embolism with natural language processing. J Biomed Inform 2014;52:386–393.
77. Sevenster M, Bozeman J, Cowhy A, et al. A natural language processing pipeline for pairing measurements uniquely across free-text CT reports. J Biomed Inform. 2015;53:36–48.
78. Wang, Y., Mehrabi, S., Sohn, S. et al. Natural language processing of radiology reports for identification of skeletal site-specific fractures. BMC Med Inform DecisMak 19, 73 (2019).
79. Brown AD, Kachura JR. Natural Language Processing of Radiology Reports in Patients With Hepatocellular Carcinoma to Predict Radiology Resource Utilization. J Am Coll Radiol. 2019 Jun;16(6):840-844.
80. Goff, D.J., Loehfelm, T.W. Automated Radiology Report Summarization Using an Open-Source Natural Language Processing Pipeline. J Digit Imaging 31, 185–192 (2018).
81. Tshitoyan, V., Dagdelen, J., Weston, L. et al. Unsupervised word embeddings capture latent knowledge from materials science literature. Nature 571, 95–98 (2019). https://doi.org/10.1038/s41586-019-1335-8
82. Naili, M., Chaibi, A. H., & Ben Ghezala, H. H. (2017). Comparative study of word embedding methods in topic segmentation. In Procedia Computer Science (Vol. 112, pp. 340–349).
83. A. Dridi, M. M. Gaber, R. Muhammad Atif Azad and J. Bhogal, "Leap2Trend: A Temporal Word Embedding Approach for Instant Detection of Emerging Scientific Trends," in IEEE Access, vol. 7, pp. 176414-176428, 2019, doi: 10.1109/ACCESS.2019.2957440.
84. Amit Mandelbaum and Adi Shalev. 2016. Word Embeddings and Their Use In Sentence Classification Tasks. arXiv:1610.08229 {cs}. Retrieved from http://arxiv.org/abs/1610.08229
85. Ong CJ, Orfanoudaki A, Zhang R, Caprasse FPM, Hutch M, Ma L, et al. (2020) Machine learning and natural language processing methods to identify ischemic stroke, acuity and location from radiology reports. PloS ONE 15(6): e0234908.
86. Heo TS, Kim YS, Choi JM, Jeong YS, Seo SY, Lee JH, Jeon JP, Kim C. Prediction of Stroke Outcome Using Natural Language Processing-Based Machine Learning of Radiology Report of Brain MRI. J Pers Med. 2020 16 Dec.;10(4):286.
87. Luo JW, Chong JJR. Review of Natural Language Processing in Radiology. Neuroimaging Clin N Am. 2020 Nov;30(4):447-458.
88. Kehl KL, Elmarakeby H, Nishino M, Van Allen EM, Lepisto EM, Hassett MJ, Johnson BE, Schrag D. Assessment of Deep Natural Language Processing in Ascertaining Oncologic Outcomes From Radiology Reports. JAMA Oncol. 2019 25 Jul.;5(10):1421–9.
89. Sorin V, Barash Y, Konen E, Klang E. Deep Learning for Natural Language Processing in Radiology-Fundamentals and a Systematic Review. J Am Coll Radiol. 2020 May;17(5):639-648. Doi: 10.1016/j.jacr.2019.12.026.
90. Li AY, Elliot N. Natural language processing to identify ureteric stones in radiology reports. J Med Imaging Radiat Oncol. 2019 Jun;63(3):307-310. Doi: 10.1111/1754-9485.12861.

91. Kang SK, Garry K, Chung R, Moore WH, Iturrate E, Swartz JL, Kim DC, Horwitz LI, Blecker S. Natural Language Processing for Identification of Incidental Pulmonary Nodules in Radiology Reports. J Am Coll Radiol. 2019 Nov;16(11):1587-1594. Doi: 10.1016/j.jacr.2019.04.026.
92. Senders JT, Karhade AV, Cote DJ, Mehrtash A, Lamba N, DiRisio A, Muskens IS, Gormley WB, Smith TR, Broekman MLD, Arnaout O. Natural Language Processing for Automated Quantification of Brain Metastases Reported in Free-Text Radiology Reports. JCO Clin Cancer Inform. 2019 Apr;3:1-9.
93. Khorasani R, Bates DW, Teeger S, Rothschild JM, Adams DF, Seltzer SE. Is terminology used effectively to convey diagnostic certainty in radiology reports? AcadRadiol 2003; 10:685–688.
94. Hobby JL, Tom BD, Todd C, Bearcroft PW, Dixon AK. Communication of doubt and certainty in radiological reports. Br J Radiol 2000; 73:999–1001.
95. Wibmer A, Vargas HA, Sosa R, Zheng J, Moskowitz C, Hricak H. Value of a standardized lexicon for reporting levels of diagnostic certainty in prostate MRI. AJR 2014; 203:[web]W651–W657.
96. Panicek DM, Hricak H. How Sure Are You, Doctor? A Standardized Lexicon to Describe theRadiologist's Level of Certainty. AJR Am J Roentgenol. 2016 Jul;207(1):2-3. Doi:10.2214/AJR.15.15895. Epub 2016 11 Apr. PMID: 27065212.
97. Callen AL, Dupont SM, Price A, Laguna B, McCoy D, Do B, Talbott J, Kohli M, Narvid J. Between Always and Never: Evaluating Uncertainty in Radiology Reports Using Natural Language Processing. J Digit Imaging. 2020 Oct;33(5):1194-1201.
98. Nobel JM, Puts S, Bakers FCH, Robben SGF, Dekker ALAJ. Natural Language Processing in Dutch Free Text Radiology Reports: Challenges in a Small Language Area Staging Pulmonary Oncology. J Digit Imaging. 2020 Aug;33(4):1002-1008.
99. Bozkurt S, Alkim E, Banerjee I, Rubin DL. Automated Detection of Measurements and Their Descriptors in Radiology Reports Using a Hybrid Natural Language Processing Algorithm. J Digit Imaging. 2019 Aug;32(4):544-553. Doi: 10.1007/s10278-019-00237-9.
100. S. Mithun, A. K. Jha, U. K. Sherkhane, V. Jaiswar, R. V. Prasad, C. M. Ortiz, S. Puts, V. Rangarajan, A. Dekker, L. Wee. Validation of an open source Natural Language Processing (NLP) and an in-house developed python script for named entity recognition from radiology reports of lung carcinoma cases. Presented at: Annual Congress of the European Association of Nuclear Medicine October 12 – 16, 2019 Barcelona, Spain. Eur J Nucl Med Mol Imaging 46, 1–952 (2019). Vol. 46, no. S1, Oct. 2019, pp. 1–952.
101. Sinha U, Dai B, Johnson DB, Taira R, Dionisio J, Tashima G, Golamco M, Kangarloo H. Interactive software for generation and visualization of structured findings in radiology reports. AJR Am J Roentgenol. 2000 Sep;175(3):609-12. Doi: 10.2214/ajr.175.3.1750609. PMID: 10954439.
102. Sistrom CL, Dreyer KJ, Dang PP, et al. Recommendations for additional imaging in radiology reports: multifactorial analysis of 5.9 million examinations. Radiology 2009; 253(2):453–461.
103. Ip IK, Mortele KJ, Prevedello LM, Khorasani R. Focal cystic pancreatic lesions: assessing variation in radiologists' management recommendations. Radiology 2011;259(1):136–141.
104. Gershanik EF, Lacson R, Khorasani R. Critical finding capture in the impression section of radiology reports. AMIA AnnuSymp Proc2011;2011:465–469.
105. Duszak R Jr, Nossal M, Schofield L, Picus D. Physician documentation deficiencies in abdominal ultrasound reports: frequency, characteristics, and financial impact. J Am Coll Radiol 2012;9(6):403–408.
106. Raja AS, Ip IK, Prevedello LM, et al. Effect of computerized clinical decision support on the use and yield of CT pulmonary angiography in the emergency department. Radiology 2012;262(2):468–474.

107. Do BH, Wu A, Biswal S, Kamaya A, Rubin DL. Informatics in radiology: RADTF—a semantic search-enabled, natural language processor-generated radiology teaching file. Radio Graphics 2010;30(7):2039–2048