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August 16, 2024

Clinical Findings Extraction from Lumbar Imaging Reports

Lower back pain is the leading cause of disability worldwide and accounts for annual costs of $102 billion in the United States (Martin et al, 2008). In addition to the economic burden, lower back pain affects the individual’s quality of life, social identity, and mental health (Tagliaferri, 2020). Despite its prevalence and significant costs, diagnosis is difficult and treatments are often ineffective, resulting in poor patient outcomes and ongoing dysfunction (Deyo, 2014). Furthermore, findings on spinal imaging are often found on asymptomatic patients, leading to uncertainty of the significance of imaging findings (Brinjiki et al, 2015). However, certain degenerative findings, such as vertebral end plate changes, seem to be more prevalent in symptomatic populations. Identifying these types of conditions on imaging will help improve treatments and outcomes (Czaplewski et al, 2023). An important aspect of identifying patterns and relationships between findings on imaging and patients’ symptoms is accurate and timely extraction of the clinical findings from the imaging reports (Tan et al, 2018). While performing this extraction manually on a small scale is possible, it is very costly, and cannot not be performed at a large scale. Cotiviti could invest in developing and implementing a system to automate the classification of clinical findings on lumbar spine radiology reports to reduce the costs and save time. A variety of technical solutions could be utilized and should be considered to automate this process.

Technologies that could streamline this process include lumbar spine image processing using artificial intelligence (AI) or natural language processing (NLP) solutions that utilize the radiologist report. Jamaludin et al (2017) reported 95.6% accuracy in vertebral body and disc detection with lumbar spine imaging processing AI. Jamaludin et al (2017) did not evaluate other clinical findings, such as end plate changes or central canal stenosis; some of the diagnoses which are often clinically significant for patients with lower back pain (Czaplewski et al, 2023). Cui et al (2022) indicate that there have been promising results in using AI to identify additional structures in the spine, but not classify different types of conditions. At this time there does not appear to be studies that have demonstrated a validated and reliable way to classify lower back pain diagnoses with image processing. While this is an exciting emerging technology, it may not be as clinically useful as an NLP solution that could accurately identify and classify a greater number of imaging findings.

An NLP approach could utilize rules-based NLP and/ or machine learning models. Both strategies have pros and cons that must be considered before designing and implementing a solution. The primary advantage of utilizing a rules-based NLP system would be the low set up costs. However, a significant limitation would be the scalability of the system. While a rules-based approach may work for a small data set, it will not be feasible to implement on a large scale across multiple systems. Scalability is a key factor in designing this solution as it would need to be applied across hospital systems and regions to have the largest impact. A machine learning approach would be more flexible and remain accurate on a large scale and over time. Machine learning does however require a large dataset for its development. Access to large, heterogeneous data sets is limited, but increasingly available through open-source networks. Despite the challenge of obtaining appropriate data, a machine learning NLP approach would be the preferred method due to its scalability for real world application.

Tan et al (2018) designed and tested both rules-based and machine learning NLP on lumbar spine radiology reports in their paper *A Comparison of Natural Language Processing Methods for the Classification of Lumbar Spine Imaging Findings Related to Lower Back Pain*. Their model could be used as a starting point in building an NLP system to identify findings on lumbar imaging. As in their solution, I suggest utilizing a supervised learning approach due to the nature of radiology reports. These reports consist of unstructured data so medical experts would be required to annotate a test group of the data. The NLP pipeline also must consist of preprocessing tasks such as segmentation and normalization. Tan et al (2018) then used featurization including Regex, Negex, N-grams, and document embeddings. These types of features have been shown to be as accurate as more complex features (Zech et al, 2018). The final step in the pipeline is to either implement the rules-based model or machine learning model using logistic regression. Their results indicate that machine learned models had significantly higher sensitivities and slightly lower specificities vs rules-based models. This was especially true where there was more than one mention of lumbar pathology in the text (Tan et al, 2018). With improved scalability, high sensitivity, and relatively simple machine learning algorithms, a machine-learning NLP solution for classifying patients with lower back pain would be a feasible and useful tool (Zech et al, 2018).

The development of a machine learning NLP tool to classify lumbar pathology could have multiple applications. On the clinical side it could be used as part of a pipeline to develop a clinical decision support tool for appropriate referrals or to assist in implementing a care process model to help clinicians manage low back pain in the most effective way. On the payer side, a classification tool such as this could help streamline authorizations for insurers. It could also be used in concert with other tools to identify referral patterns, minimize waste, and reduce costs to the consumer and health plan. By developing and implementing a tool to automate the extraction of clinical findings from lumbar radiology reports Cotiviti stands to improve efficiency and reduce capital outlays for expensive personnel.

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