Using AI and Natural Language Processing To Identify Imaging Follow-up Recommendations

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November 28-December 2, 2021

Chicago, IL, USA

Introduction: This study investigates the effectiveness of AI for tracking follow-up recommendations – Why?

>50%

of (non-urgent) follow-up recommendations **are delayed or completed missed**

Bad for Patients ☹

100M
missed follow-up recommendations per year

80k
Unnecessary deaths per year

Bad for Providers ☹

$150B+
missed revenue opportunity

1 in 5
malpractice cases

Hypothesis: AI, NLP and automation can accurately classify reports in less time than manual tagging

Accurately Identify Recommendations

The AI and NLP algorithm will accurately identify dictated follow-ups by extracting key data from radiology report text

We anticipated the algorithm maintaining

>90%

true positive rate when compared with the gold standard of manual tagging

Faster than Manual Tagging

Automation will allow the algorithm to process the same number of reports as a human with significantly less time and effort

We anticipated the algorithm processing reports

>500x

faster than a human

Methods: Rules based NLP Algorithm vs trained human staff tagging radiology reports

1392 randomized radiology reports selected for analysis

Dictated by board certified radiologists at a single academic hospital system

Rules based NLP (Within Health, NY, www.seewithin.co) applied to reports

5 rules were applied to determine if a recommendation was present - Table 1

Manual tagging

3 staff members trained on NLP rules, read and tagged all reports

Accuracy & Time measured

Compared accuracy & processing time of NLP to manual tagging

Table 1: Rules used to determine if a recommendation is present in the radiology report

Table 1: NLP Inclusion and Exclusion criteria for determining if an imaging recommendation is present	
Rule 1	Include cases that specifically recommend follow-up imaging (e.g. “CT”, “MRI”, “imaging”)
Rule 2	Include cases that recommend interventional procedures (e.g. “FNA)
Rule 3	Track each recommendation separately if report includes multiple recommendations
Rule 4	Exclude cases that don’t recommend follow-up imaging (e.g. “per guidelines”, “per protocol”)
Rule 5	Exclude follow-up recommendations for direct visualization, biopsies without imaging, or other specialty visits

Results: NLP accurately identified recommendations in significantly less time than humans

NLP Accurately Identified 98.2% of recommendations

Table 2	NLP Classified Positive	NLP Classified Negative
Manual Positive (738)	725 (98.2%)	13 (1.8%)
Manual Negative (654)	147 (22.5%)	507 (77.5%)

Sensitivity: 98.2%
Specificity: 77.5%

NLP Processing in 55 seconds vs 93 hours for manual tagging

Table 3	Processing Time
NLP Tagging	.015 hours (55 seconds)
Manual Tagging	93 hours

Reports processed > 6000x faster by NLP than humans

Manually tagged reports required 4 minutes per report

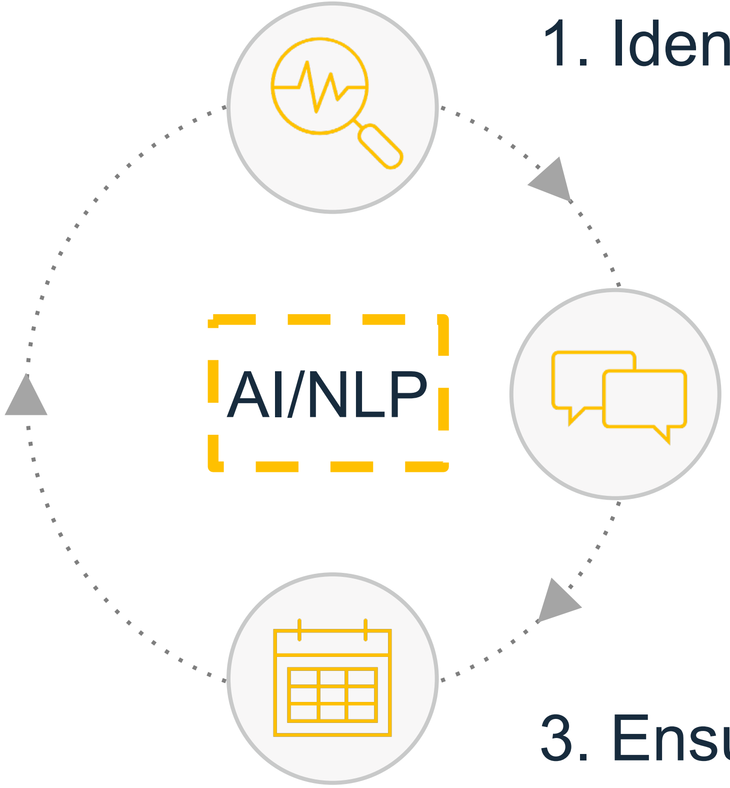
Conclusions: Emerging technologies such as AI and NLP can be accurate and useful in radiology workflows

AI & NLP is accurate for identifying recommendations and associated details (time, modality, anatomy etc.)

AI & NLP can reduce time needed to identify at-risk patients and target them for intervention

Automation can compliment manual workflows and significantly reduce admin time

Real World Applications: AI & NLP can have a major impact on patient care and provider practices



1. Identify at-risk patients
2. Engage patients & care teams
3. Ensure continuity of care

Results

Patients get the care they need on time

Providers grow revenue, reduce risk

Thank You

To learn more, please reach out

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