Redefining the Practice of Peer Review Through Intelligent Automation—Part 3: Automated Report Analysis and Data Reconciliation

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Published online: 25 July 2017
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Abstract One method for addressing existing peer review limitations is the assignment of peer review cases on a completely blinded basis, in which the peer reviewer would create an independent report which can then be cross-referenced with the primary reader report of record. By leveraging existing computerized data mining techniques, one could in theory automate and objectify the process of report data extraction, classification, and analysis, while reducing time and resource requirements intrinsic to manual peer review report analysis. Once inter-report analysis has been performed, resulting inter-report discrepancies can be presented to the radiologist of record for review, along with the option to directly communicate with the peer reviewer through an electronic data reconciliation tool aimed at collaboratively resolving inter-report discrepancies and improving report accuracy. All associated report and reconciled data could in turn be recorded in a referenceable peer review database, which provides opportunity for context and user-specific education and decision support.

Keywords Peer review · Data mining · Report analysis

Introduction

In conventional radiology peer review practice, the reviewer serves as the principle determinant of ground truth, effectively

judging the accuracy of the radiologist of record and corresponding report. In addition to a number of well-documented biases (e.g., contextual, hindsight, outcome), this approach to peer review may be negatively impacted by the degree of relative authority it assigns to the peer reviewer [1]. Regardless of their intended desire to be fair and accurate, reviewers are human and as a result, they are subject to the same interpretive errors and oversights as the colleagues which they evaluate. While hindsight is often said to be 20/20, this is far from the reality when it comes to medical analysis. Two well-trained professionals given the same data may arrive at different interpretations and conclusions, which should require further in-depth and impartial analysis for determination of truth.

An alternative and arguably superior peer review strategy would blind the reviewer, require both the parties to create independent reports, and analyze the resulting reports in a neutral and standardize fashion through computerized technology which would objectify the peer review process while simultaneously reducing the need for time, expense, and productivity requirements of human report analysis [1]. Upon completion of such a computer-derived report analysis, inter-report discrepancies can be addressed and potentially resolved through computer-assisted data reconciliation. All associated data can in turn be recorded in a referenceable finding-specific peer review database which offers the potential for context-specific education, decision support, and technology development.

Report Components Subject to Peer Review

The various components contained within a diagnostic radiology report are listed in Table 1; many of which are mandated by a combination of professional, societal, legislative, and

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Table 1 Report metrics for peer review analysis

A. Demographics
1. Provider (facility identification, location, ordering physician name, date and time of exam, radiologist name)
2. Patient (patient identification, age, gender)
B. Clinical data (reason for exam, pertinent clinical data, patient allergies)
C. Technical data (exam type, acquisition parameters, image processing, number of views, imaging device, exam start and stop times, dose data [radiation, contrast, pharmaceutical])
D. Exam limitations (image quality deficiencies, technical malfunction, patient complications)
E. Historical imaging data (exam type, date, institution, images, report)
F. Report Content
1. Individual findings (positive and negative)
2. Finding support data (measurements, morphology, enhancement)
3. Diagnosis or differential diagnosis
4. Finding clinical significance
5. Degree of confidence (uncertainty, ambiguity)
6. Follow-up recommendations
7. Interval change
8. Anatomic specificity
9. Errors (typographical, anatomy)
10. Completeness
11. Impression
G. Communication (critical results, healthcare professional consultations, patient communication, prior report discrepancies)

legal standards. While traditional peer review analysis focuses on pathology, a wide array of other data elements play an important role in peer review analysis. As an example, if one was interested in identifying potential causative or contributing factors related to a missed lung nodule on chest CT, a number of report data may be of interest. Demographic data (e.g., patient age), clinical data (e.g., smoking, occupational history), technical data (e.g., acquisition parameters, image processing), exam limitations (e.g., patient compliance, motion artifact), and historical imaging data (e.g., comparison CT data) all have the potential to affect not only diagnostic accuracy but also follow-up recommendations.

In addition to the identification of individual findings, an optimal radiology report should also include finding-specific descriptive data, differential diagnosis, clinical significance, follow-up recommendations, detailed anatomic localization, temporal change, communication, and any mitigating factors which may influence diagnosis. In the absence of this information, the radiology report may be considered to be incomplete and limited in its diagnostic value to the ordering clinician in establishing diagnosis, treatment planning, and clinical management decisions.

While peer review routinely focuses on the finding/s of the greatest clinical significance, a number of other findings are frequently contained within the radiology report which may or may not ultimately affect clinical outcomes. In order to optimize the peer review process, all report findings should be subjected to analysis, which ideally should be extended over

the lifetime of the individual patient. A 3-mm nodular breast lesion may appear to be inconsequential in analyzing current peer review in the mammogram of a patient with suspicious microcalcifications, but its significance may be magnified over time with the benefit of sequential follow-up mammograms demonstrating significant interval growth. This illustrates the fact that optimal peer review should be inclusive of all report findings and have the ability to be longitudinal in nature.

Automated Report Analysis

A number of technologies currently exist (and are rapidly expanding) which provide the means for automated data mining and analysis of text-based radiology reports. These include (but are not limited to) natural language processing, machine learning, support vector machine, neural networks, Bayesian networks, decision trees, regression analysis, clustering, taxonomy generation, and predictive modeling [2–7]. These technologies provide one with the ability to automatically extract, classify, and analyze report data in real time, creating an opportunity to analyze report data and intervene at the point of care. If applied to the described peer review strategy, these technologies could theoretically analyze both reports created by the radiologist of record and peer reviewer and identify inter-report discrepancies.

While conventional peer review focuses almost exclusively on report findings, the proposed use of automated report data mining technologies provides an important tool for comprehensive report analysis, which can include all of the report components listed in Table 1. While several of these report components (e.g., radiation exposure, contrast dose) are currently mandated, they are often under-analyzed in current peer review practice.

Using the proposed peer review model where reports would be independently created by both the radiologist of record (i.e. primary reader) and peer reviewer/s, all derived reports would be subjected to the same automated report analysis. This provides an objective, consistent, and unbiased method for analyzing report data while simultaneously identifying inter-report discrepancies. The derived report analyses can in turn provide immediate feedback to the report authors, which would be particularly beneficial when the report data is determined to be incomplete (e.g., missing data) and of questionable accuracy (e.g., contradicted by other report data), or warrants additional action (e.g., critical results communication). When multiple reports are incorporated into the analysis, inter-report differences or discrepancies can be identified and categorized, and presented to the report authors for data reconciliation.

Report Data Reconciliation

Following the completion of individual report analysis, a combined multi-report comparative analysis would be performed to identify specific differences in report content related to imaging findings, diagnosis, follow-up recommendations, and communication (Table 2). Computerized artificial intelligence techniques (e.g., neural networks, rules-based analysis, machine learning) could be used to categorize and prioritize these inter-report differences based upon potential clinical impact. When a discrepant finding is identified which exceeds a predefined clinical threshold, an automated trigger would alert the participants as to the potential for a “high clinical significance report discrepancy” requiring further action. Since the clinical and legal responsibility of the primary report rests in the hands of the primary radiologist (i.e., radiologist of record), he or she would need to determine whether any contradictory data contained in the peer reviewer report/s is valid and what if any appropriate action is required for optimizing patient care. In order to standardize this process of data reconciliation and ensure referenceable data is collected in a peer review database, a standardized schema can be created as listed in Table 3. The goal is to provide the primary radiologist with a standardized list of data reconciliation options and resources, without undermining their final decision making. In the event that a radiologist was to select the option for consultation, an electronic consultation tool could be invoked which provides for direct interaction between the peer review participants through electronic and/or audio communication. Alternatively, if the option for additional data is requested, a number of options may be selected for providing computerized decision support for the primary radiologist who can utilize established professional guidelines, computer-aided diagnosis (CAD) software, extraction of data from historical reports in the patient medical record, and/or data mining of the peer review database. If for example, there is disagreement as to the characterization of a carotid artery stenosis, the request for additional data may provide the radiologist with NASCET index criteria, arterial CAD analysis, extraction of

Table 2 Comparative peer review report analysis

1. Individual findings (positive and negative)
2. Finding support data (measurements, morphology, enhancement)
3. Diagnosis or differential diagnosis
4. Finding-specific clinical significance
5. Degree of confidence (uncertainty, ambiguity)
6. Follow-up recommendations
7. Interval change
8. Anatomic specificity
9. Errors (typographical, anatomy)
10. Communication (critical results, consultations)

Table 3 Data reconciliation: radiologist response

1: Agree with opposing data, will revise report accordingly and communicate with ordering physician (Agree, Action required)
2: Agree with opposing data but do not believe it impacts clinical care, therefore no formal report modification or communication is required (Agree, No action required)
3: Uncertain as to validity of opposing data, request radiologist consultation for data reconciliation (Uncertain, Consultation required)
4: Uncertain as to validity of opposing data, request additional data (e.g., professional guidelines, computer-aided diagnosis, data mining of historical reports and/or peer review database) (Uncertain, Additional data required)
5: Disagree with opposing data, no report modification or communication is required (Disagree, No action required)

related clinical and/or imaging results from the patient EMR, or comparable carotid artery stenosis data contained within the peer review database. In addition, the radiologist may be provided with ACR critical results communication guidelines in the event that a high-grade carotid artery stenosis is determined.

In the event that the data reconciliation process is unsuccessful at resolving inter-report discrepancies, three options are available. In the first option, the radiologist of record may choose to issue the report “as is,” with the report flagged in the peer review database as an unresolved peer review discrepancy. In the second option, an additional peer review request would be instituted, with the designated peer reviewer selected based upon their high peer review performance records for the exam/findings in question. In the third option, a designated expert third party would be consulted to resolve the report discrepancy. All data involved in the data reconciliation process would be recorded in the peer review database (including the identities of the involved parties), for the purpose of longitudinal data analysis and internal quality assurance.

Education and Decision Support

The ability to analyze peer review data on the basis of both individual report findings and end-users (i.e., radiologists) provides a unique educational opportunity since interpretive errors may often be repetitive in nature. Periodic analysis of each radiologist’s peer review records can provide individual radiologists with an itemized list of peer review discrepancies relating to exam type, individual report finding, classification of the discrepancy (e.g., missed finding, communication failure, incomplete differential diagnosis), and clinical significance. These customized peer review discrepancy analytics can in turn be used for targeted continuing medical education and the identification of decision support resources. The

ongoing collection of decision support resources can be accumulated through day to day operation of the peer review data reconciliation process. In the prior example, the peer reviewing radiologist may have referenced NASCET index criteria to support his/her claim that the carotid artery stenosis in the primary radiologist initial report was incorrect. If accepted and agreed upon by the primary radiologist, this index data would then be incorporated into the individual radiologist's peer review database as a valid decision support resource. In future interpretations of carotid artery ultrasound exams, the primary radiologist could be presented with this "flagged" resource to assist them in prospective exam interpretation and even request this be automatically presented during exam workflow for all future carotid artery exam interpretations. The ultimate goal of such an application is to utilize the peer review database for customizable education based upon the individual needs and practice patterns for each individual end-user based upon longitudinal and dynamic peer review data analysis.

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