“Medical Informatics for Detection of Adverse Events”

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Detection and prevention of adverse events (AEs) in medicine represents a national health care priority. AEs, defined as injuries due to medical management, have important consequences including increased costs, morbidity, and mortality. Large scale initiatives, most prominently through the Institute of Medicine, have focused on the importance of detection and prevention of AEs to improve patient outcomes. AE detection can help improve cognitive processes surrounding possible future events and place potential resources into more *targeted* efforts for AE prevention. Unfortunately, AEs are widely underreported with traditional voluntary methods. Manual chart review for AEs, while effective, remains too costly for routine use. Information technology and informatics tools that use data from electronic health records (EHR) can potentially improve AE detection and have been identified as important tools for creating a “culture of safety”.

Several classes of automated AE detection systems have been described, most of which utilize numeric or coded data from the EHR in the form of diagnostic and procedure coding, medication administration records, laboratory values, and vital signs. Substantial progress has been made in adverse drug event (ADE) detection and prevention, particularly with the introduction of electronic prescribing in both the inpatient and outpatient setting. Natural language processing (NLP), a set of automated techniques that converts narrative text into a format appropriate for computer-based analysis, represents an important set of methods that can be used alone or in combination with other automated techniques to improve AE detection.

Challenges and considerations for automated AE detection systems

With the complexity and lack of standardization of healthcare EHR systems and associated electronic data, AE detection can be challenging, particularly due to issues of data formatting and quality, problems with standardizing AE definitions, variable performance of heuristic rule-based systems, and issues of sparse datasets when the incidence of a certain event is low. While most automated adverse event systems provide feedback in a retrospective manner, the use of "active surveillance" systems which alert providers or administrators of events as they occur have promise for identifying and investigating AEs in a timelier manner.

Sources of coded data with many robust EHR systems include administrative and billing data (International Disease Classification version 9 codes and Current Procedural Terminology codes), demographic data, laboratory data, admission and discharge registration data, medication administration data, and computerized physician order entry (CPOE). With the exception of administrative coding, even structured data can have variable formatting between EHR and hospital systems. While some AEs can be found using coded data, a large number of AEs require supplementary methods and data sources. One reason for this is that administrative and billing data can be incomplete or inaccurate and often does not include AEs explicitly. In addition, more sophisticated concepts of interest in AE detection, which include clinical reasoning, signs and symptoms, clinical summarization, and physical findings are not included as structured data.

In order to accurately measure and analyze AEs, standardized AE definitions are fundamental prerequisites. Currently, centralized nomenclatures or taxonomies have not been settled upon in each health care setting, and national initiatives are needed to expand and bring consensus. Several promising AE classification systems have been proposed according to setting or discipline, including the JCAHO Patient Safety Event Taxonomy and the Clavien-Dindo Classification of Surgical Complications.

Automated systems for AE detection have classically been rule-based heuristic systems utilizing data from a variety of data sources. While heuristic systems may perform well for certain tasks, these systems rely heavily on “triggers” such as an abnormal laboratory value or a low blood pressure indicating a possible AE that are intuitively connected to a potential AE occurrence. Machine learning techniques show promise for detecting events using data that may not always be obvious based upon an intuitive set of rules, particularly for well defined tasks with robust training sets to optimize performance. Classification systems using machine learning can also fail, particularly for datasets with AEs that have a low incidence (i.e. < 1%). In many of these cases, datasets may be sparse and imbalanced. Several techniques have been proposed to provide balance to datasets. Some investigators have now started to focus on issues of imbalance with the use of sampling techniques with variable success.

For AE system design, it is important for developers to understand the relative importance and cost of having false negatives and false positives. This is an important trade-off that must be weighed according to the clinical indication and relative cost of having to screen extra patients to find events versus the cost of missing AE cases. For most AE detection systems, minimizing the false negative rate is particularly important, so as to maximize the overall detection rate followed usually with manual screening as an adjunct.

Adverse drug events: A model example of improved AE detection

Most ADEs occur at the time of ordering (55%), administration (35%), transcription (5%), and dispensing (5%) of medications. Many hospitals now utilize CPOE, where patient orders for medications and other clinical care are entered directly into the EHR system. CPOE has been the most successful example of demonstrating efficacy in helping both to prevent and detect ADEs. Because many CPOE systems now contain alerts and reminders about drug prescribing, these systems can also prevent many ADEs. The use of other "triggers" in coded data from medication administration or abnormal laboratory values (such as a supratherapeutic or subtherapeutic drug level, low hemoglobin, or poor renal function) can improve detection or prevention of many ADEs. This has been demonstrated in several clinical trials in both the inpatient and outpatient settings.

Natural language processing: an important tool to improve detection

Clinical documents from the EHR are particularly promising data sources for AE detection systems because clinical documents often contain concepts such as clinical reasoning, signs and symptoms, clinician summarization, and physical findings which may potentially be helpful for AE detection. While narrative is rich in content, there are significant challenges to its automated use in the medical domain. Several investigators have used "trigger words" for event detection, such as "perforation", "iatrogenic" or "error". This technique is helpful but it does not distinguish whether something potentially occurred, whether it was present or absent, or occurred in the past.

Medical text-mining or NLP has important challenges. Clinical documents are variably formatted with section headers, tabular or other spatial formatting, and transcription errors (i.e. spelling or grammatical problems). Meaning in medical text must also take into account uncertainty, negation, and timing. In addition, medical terms have issues of synonymy, relatedness or similarity of terms, abbreviations (often redundant), and context-specific meanings.

Several automated text-mining tools have been developed for the medical domain, including open source tools available through the National Library of Medicine. One of the more widely used medical NLP applications, MedLEE, uses a vocabulary and grammar to extract data from text. Although initially used to extract information from radiographic reports, MedLEE has been expanded for application to a wide range of medical texts. MedLEE has been applied to discharge summaries and demonstrated to significantly improve AE detection when compared to traditional reporting alone. NLP techniques represent an important potential tool for improving AE detection systems.

CONCLUSION

Automated AE detection systems with automated informatics techniques show promise for improving the detection and ultimately the prevention of AE. National initiatives for universal EHR system adoption and advances in informatics techniques for AE detection will likely increase the penetration of these systems, which currently with the exception of ADE systems in health care remains low. Addressing technical challenges with improved AE nomenclature consensus, machine learning methods, sampling techniques, and NLP applied to

AE will improve system performance as these systems become more widely implemented to improve patient safety.

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