Automated Surveillance To Detect An Influenza Epidemic: Which Respiratory Syndrome Should We Monitor?

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BACKGROUND AND OBJECTIVE

Syndromic surveillance systems (SSS) seek early detection of infectious diseases outbreaks by focusing on pre-diagnostic symptoms. We do not yet know which respiratory syndrome should be monitored for a SSS to discover an influenza epidemic as soon as possible. This work compares the delay and workload required to detect an influenza epidemic using a SSS that targets either (1) all cases of acute respiratory infections (ARI) or (2) only those ARI cases that are febrile and satisfy CDC’s definition for an influenza-like illness (ILI).

METHODS

Using an explicit definition of ARI and ILI, we reviewed the electronic medical record (EMR) of 15,377 outpatient encounters at the Veterans Administration (VA) system. Found ARI and ILI cases served as a reference to develop case-detection algorithms (CDAs) that utilized combinations of structured EMR data and text analyses of clinical notes. We recreated historical background casecount time series by applying the most successful CDAs to historical EMR data. We injected factitious influenza cases to CDA-specific backgrounds using an age-structured modeled influenza epidemic and then used a modified CUSUM statistic daily for 50 days to detect the outbreak. This injection/prospective-surveillance cycle was repeated each week of the study year. To distinguish between true- and background-positive alarms, the daily statistics were performed on paired background+injection vs. background-only time series. We compared these benchmarks: 1) the average “Detection Delay”, from the time of each injection to the first true-positive alarm; 2) the “Workload”, defined as the yearly number of cases included in all the background-positive alarms.

RESULTS

Statistical performance of illustrative CDAs targeting either ARI or (febrile) ILI is shown in the Table. For ARI, the CDAs that minimized both Detection Delay and Workload were those that maximized specificity and positive predictive value (PPV) and yet retained a sensitivity of 69-100% (Models 4 and 6). Compared to the “respiratory” ICD-9 codeset used by CDC’s “BioSense” SSS, the best ARI CDA decreased Detection Delay from 38 to 30 days, and Workload from 2397 to 483 cases/year (Figure). The best (febrile) ILI-targeted CDA further reduced Delay to 22 days and Workload to 121 cases/year (Model 7).

CONCLUSIONS

Case detection methods that take advantage of information from the full EMR and that focus only on those ILI cases that are febrile can lower both the delay and the workload required to detect an influenza epidemic in the community.