Supplementary Online Content

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eMethods.

eFigure 1. Overall Framework of the Deep Learning Model **eFigure 2.** Allergy Keywords **eTable 1.** Expert-Curated Keywords Versus Deep Learning Detected Keywords **eTable 2.** Reasons and Examples Why Keyword Search Failed **eTable 3.** Example False Positive Cases in the Top-k Reviewed Cases that the Deep Learning Model Predicted With a Relative High Probability of Being an Allergy Event **eTable 4.** Key Phrases Automatically Detected by the Deep Learning Model **eTable 5.** Most Common Allergic Reactions (n = 2378)

This supplementary material has been provided by the authors to give readers additional information about their work.

eMethods.

Efficiency and Productivity

We compared our deep learning approach to conventional keyword search in terms of manual review effort (efficiency) and positive case yield (productivity). To compare the efficiency, we determined the number of reports requiring manual review in each approach. For the ADNN model, we used a false negative rate of 0.5% as a cut-off to decide the number of reports, n, requiring manual validation; that is, we manually reviewed top-n reports identified from Datasets II-IV until the last 200 reviewed reports contained only one positive case. For the keyword-search approach, we used the 101 expert-curated keywords to identify all possible cases from Datasets II-IV and calculated the number of cases requiring manual review.

To compare the productivity, we determined the numbers of true cases identified by the two approaches. For the ADNN model, it was the number of cases among the top-*n* reviewed reports manually labeled as allergic reactions. For the keyword search, we estimated the number of true cases as follows: for each dataset of Dataset III and Dataset IV, we split all reports extracted by keyword-search into two subsets, the first containing reports that overlapped with those also identified by ADNN and the second containing reports identified only by keyword search. For the first subset, we used the number of the positive cases manually reviewed when evaluating the model. For the second subset, we estimated the number of positive cases based on the precision of the keyword-search approach on 1000 randomly selected reports, which were manually reviewed. That is, we first manually reviewed 1000 randomly selected cases identified by keywords and calculated the precision. We then estimated the number of positive cases $(n_{\text{nos}} \epsilon N)$ by multiplying the precision by the total of number of cases within each dataset, which is denoted as the following

$$
n_{pos\,\epsilon\,N}\approx\frac{n_{pos\,\in 1000}}{1000}\,\times\,N
$$

where $n_{pos \in 1000}$ is the number of positive cases among the 1000 randomly selected cases and N is the total number of cases within each subset.

Lastly, we summed the numbers of positive cases from the two subsets as the number of positive cases extracted by keyword search. For Dataset II, because these reports did not contain any keywords, so the number of positive cases retrieved by keywords was 0.

In addition, we calculated the precision (i.e., the proportion of true positives among the identified cases) of each approach in identifying allergic reactions for each dataset. Finally, we conducted an error analysis for both approaches and investigated major causes of errors.

Interpretability and Keyword Extension

The ADNN attention layer assigned each input word with a weight that measures how much attention the model gives and to which words when predicting allergic reactions. To identify the words with high attention weight, we selected reports with a greater than 0.8 probability of being allergic reactions. We extracted the words with an attention weight at least two standard deviations above the average weights within that report and generated a list of "high attention keywords" detected by the model. We compared the "high attention keywords" with the 101 expert-curated keywords to identify a list of new keywords extended by the model. We similarly identified a set of key phrases. For each selected report, we extracted the consecutive words with attention weight at least one standard deviation above the average weights within the report and aggregated key phrases from those reports.

Extraction of Common Allergic Reactions

There were 2378 validated allergic events in total in dataset II, III, and IV. We categorized these reactions

into groups (Table 2). Each allergic reaction group includes one or more reaction keywords (Table 2, column "Included Keywords"). We calculated the frequency of each allergic reaction as following: we counted the number of allergic events that included any keyword(s) in the "included keywords" column as the high attention keyword (attention weight was at least two standard deviations above the average weights within the report,), and then divided the above number by all validated true allergic events (i.e. 2378). Then we ranked all the reactions and reported the top 10 most common allergic reactions.

eFigure 1. Overall Framework of the Deep Learning Model

Green, yellow and red circles represent the character-level embeddings, character-sequence representation, and word-level embeddings, respectively. α_t is the attention weight of the t-th word. The character-level representation encodes the character sequence of each word with a one-layer CNN. The output of character CNN is concatenated with the word embedding to build the word representation. The word representation is fed into a bidirectional LSTM to capture the context information of the sentence. An attention layer is applied on top of the word representation layer to calculate the attention weight for each word. The final report-level representation is the weighted sum of all the word vectors within the report, which considers the context of the report. The classifier was trained using the cross-entropy loss function and the Stochastic Gradient Descent (SGD) optimizer. The output of the classifier is a vector representing the probability of whether or not a report contained allergic reactions.

This graph illustrates the importance and frequency of allergic reaction keywords created by clinical experts and detected by the model. The word frequency was calculated by dividing the number of occurrences of a keyword by the total number of words in all reports with greater than 0.8 predicted probability of being an event of allergic reaction. The word importance is the average of a keyword's attention weights in the reports with greater than 0.8 predicted probability in which it appeared. Green squares represent the overlapping keywords identified by both experts and the model. Yellow triangles represent keywords that were only included in the expert-curated list. Blue circles represent extended keywords only identified by the model's attention mechanism. Additional details about these keywords are listed in eTable 1.

eTable 1. Expert-Curated Keywords Versus Deep Learning Detected Keywords**^a**

a "-xxx" represents the matching using "xxx" as the suffix, "xxx-" represents the matching using "xxx" as the prefix.

ª100 failure cases were randomly selected and manually reviewed
^bReports modified slightly to anonymize patient, provider, and institution. Pt: patient. OR: operation room. IV: intravenous injection.

eTable 3. Example False Positive Cases in the Top-k Reviewed Cases that the Deep Learning Model Predicted With a Relative High Probability of Being an Allergy Event^a

ª100 failure cases were randomly selected and manually reviewed
^bReports modified slightly to anonymize patient, provider, and institution. bx: biopsy. PCA: patient care assistant. Pt: patient. Sxs: symptoms. VSS: vital sign stable. **c** The patient likely had shingles, a viral infection that causes a painful rash, and was treated with Neurontin.

eTable 4. Key Phrases Automatically Detected by the Deep Learning Model

eTable 5. Most Common Allergic Reactions (n = 2378)

a Allergic reactions were grouped based on the reaction keywords mentioned in the reports. These keywords included expert-curated keywords as well as those identified by the deep learning model.