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Automatic Detection of Vital Signs in Clinical Notes of the Outpatient Settings

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Abstract. The determination of vital signs is a fundamental aspect of patient care. Electronic health records have a structured format for their registration. It is known that the frequency with which this data is recollected is not representative of reality. To complement the missing data we have created a tool that extract the information regarding blood pressure, heart rate, respiratory rate, height, weight and pain level recorded in free text in the clinical notes of outpatients.

Keywords. Natural Language Processing, Vital Signs, Electronic Health Records

1. Introduction

The determination of vital signs is a fundamental part of patient care in order to control, maintain or modify the therapeutic measures carried out. Most electronic health records have a structured format for the registration of this information, however, the frequency with which this data is recorded is not representative of reality [1]. Electronic health records capture data in two ways: in a structured format and in free text format. For the use of clinical data for secondary purposes the data must be structured. However, the exclusive approach of structured data for the entry of clinical data can result in the loss of significant information that is usually entered in free text format. [2,3] To complement the data of vital signs missing from the clinical notes we have created a tool that extracts this information regarding blood pressure, heart rate, respiratory rate, body temperature, height, weight and pain level recorded in free text of the clinical notes of outpatients.

2. Methods

The system extracts mentioned vital signs from the text of the clinical notes. These texts typically include ad hoc abbreviations, common words and spelling errors. In order to create the extraction system, a set of clinical notes was manually annotated by experts and analyzed to infer patterns. Such patterns were coded as regular expressions, each with a degree of specificity. The system attempts to detect vital signs by first applying more specific rules and then testing more generic rules along with additional validity checks to exclude false positives. The application of more sophisticated machine learning techniques was evaluated but rejected due to the requirement of both high precision and false positive detection in this specific problem. The results of these patterns and rules

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in the clinical notes were evaluated by experts, who tried to find opposite examples and then refine them in an iterative way to increase accuracy and recall. The system was implemented within the UIMA (Unstructured Information Management Architecture)[4]. The analysis of each clinical note is comprised by several phases: first a phase where grammatical sentences are divided, followed by a tokenization phase which aims to detect running words and, finally, a vital signs detection phase. The detectors of each vital sign are implements as independent components that the tool calls during the start of the process, so the tool is scalable and should be able to access new future components when available.

3. Results

For the phase of manual registration of vital signs in the clinical records, 3960 representative clinical notes of the different specialties that record information in search of the vital signs were evaluated. We identified in the free text: 2 records of pain level (PL), 101 heart rate (HR), 22 respiratory rate (RR), 35 body weight (BW), 225 blood pressure (BP), 7 of height (HT) and 53 of body temperature (BT).
Different configurations of the extraction tool were tested until obtaining a specificity and sensitivity of 100% against the training set.
The tool was implemented in such a way that it would be executed after 5 seconds of inactivity of the medical user in the outpatient electronic health record. The registration rate of structured vital signs data was measured one year prior to implementation and measured again after implementing the tool. The results were as follows: HR 448 occurrences, RR 122, BW 6935, BP 4156, HT 2610, BT 82, PL 15 and HR 4444, RR 1084, BW 8289, BP 9820, HT 3786, BT 1472, PL 1230 respectively. Increases were registered in the PL record 82 times more, BT 18 times more, HR 10 times more, RR 9 times more, BP 2.5 times more, HT 1.5 times more and BW 1.2 times more.

4. Conclusions

Vital signs registration in clinical notes is presented in patterns which can be determined and, therefore, rules can be developed to achieve their extraction by using tools that help achieve greater completeness of the records. The use of these tools increases the structured registration of these data, enabling their subsequent secondary use in clinical decision making.

5. References

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