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Supporting Doctor's Decisions Based on Electronic Medical Documentation in Polish

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Abstract

We describe new functionalities that have been added to an existing and widely used software solution in Polish public healthcare. The system automatically evaluates a number of medical scores. It provides epidemiologic monitoring concerning infectious diseases; classifies a particular patient to a specific risk group; and detects anomalies. Moreover, an analysis of a prescribed drug is performed.

Keywords:

Electronic Health Records, Decision Support Techniques

Introduction

Electronic Health Record (EHR) systems are standard methods for storing and managing health information in clinics at present. They facilitate administrative services, access to treatment histories of patients and supporting doctor's decisions, see [3]. Clinical decision support systems are common for English [6], and available for other languages e.g. Swedish [4], German [5], and Korean [1]. A summary of the use of EHR systems in Poland in 2016 and their perspectives is given in [2]. The use of Polish EHR systems is limited to documentation gathering and administrative activities. The lack of automatic analysis of health records is due to, among other things, poor resources for the processing of medical data in Polish, e.g., there is no Polish version of SNOMED CT.

In the paper, we describe the current status of work on introducing data analysis to drWidget (the EHR system in Polish). The system has been developed for 7 years and is implemented in 16995 outpatient clinics. Recently implemented system improvements aimed at supporting physicians' decisions are based on natural language processing and aggregation of statistical information.

Methods

Medical Scores

As many physicians' decisions are based on scores and scales, both these types of resources should be easily accessible. The formulas that define the values of 42 scales are implemented in such a way that an approximation of the outcome can be made on the basis of incomplete data – the range of the possible values is returned. Data necessary for calculating scale algorithms can be automatically derived from the patients' structured data or entered in any order. There are two types of parameters copied from the patients' data: stable parameters (sex), and those changing in a regular way (age). Variable parameters such as blood pressure should be copied from the structural data of the current visit.

Epidemiologic analysis

Epidemiologic analysis is limited to infectious diseases. It is based on a large set of medical data collected in all clinic centers using the system, in the period directly preceding the time of a visit. After selecting the day and disease the following information is presented in real-time: level of risk, risk for age groups, trends in epidemiologic threats and threats in a particular region. Fig. 1 shows that the most significant rise in the number of visits with diagnosed flu is for children at the beginning of the school year.

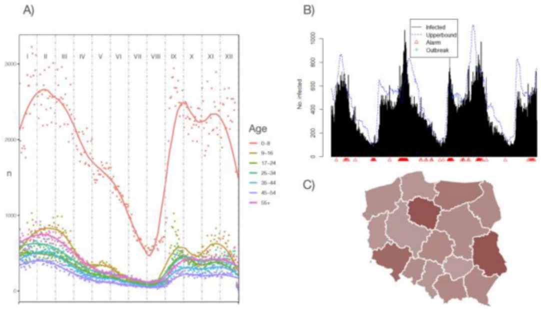

Fig. 1– Epidemiologic analyses of diagnosed flu (I10). Panel A: seasonal variation by age group, panel B: detection of unexpectedly large increases in disease frequency, panel C: geographic analysis of flu risk status.

Patient Segmentation

Patient segmentation makes it possible to classify a patient to a risk group. It also allows statistical information to be displayed about treatment methods specific to a selected group of patients. The analysis of the available data shows that apart from the symptoms, the key distinguishing parameters for segmentation are age, sex and the specialization of the doctor the patient is being examined by. Data for classification parameters is extracted from patient visits, either from structured fields (such as ICD-10) or from the plain text. Information about the therapy is found in two places: in the recommendations and in the prescriptions. As the second source is structured and easier to aggregate, we rely on it, but instead of drugs we use their active components. Among other things, the functional interface allows the following tasks to be performed (see Fig. 2):

- classification of patients into specific risk groups based on ICD-10 codes,
- showing the most commonly used treatments (active components of drugs) for a given disease based on the ICD-10 code,

- showing how often the individual active substances are used for similar cases.

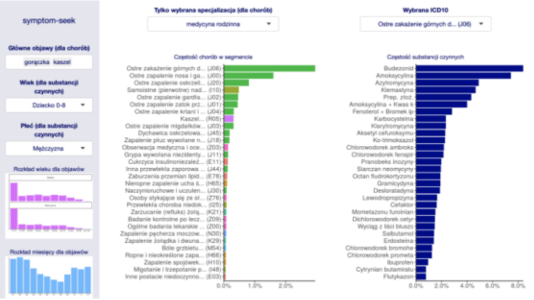

Fig. 2– The distribution of ICD-10 codes and treatments of children with fever and cough. J06 is the most often diagnosed illness and the most often prescribed medication is Budezonid.

Anomaly Detection

The analysis of the patient's historical data contained in the medical records makes it possible to detect anomalies that may indicate a disease process. The tool is designed to detect anomalies for common diseases, e.g., diabetes which early symptoms can be detected by observing changes in systolic blood pressure and patient weight. The anomaly detection task is solved in a hybrid way (by two algorithms). The first one detects if the measurements are outside the range considered as normal, and the other analyzes the change of parameters between measurements.

Drug Prescription

The drug prescription analysis based on the structured knowledge base of drugs (developed in the project) and make it possible to:

- indicate the part of the drug description that applies to a given patient,
- warn if the drug might not be advisable for a given patient,
- verify possible drug-drug interactions,
- suggest that a patient might show symptoms caused by the drug's side-effects or an overdose of the drug,
- verify the dosing regimes.

Results

We performed a preliminary evaluation of the new functionalities of the system which can be tested on simulated data. Evaluation of anomaly detection was postponed to the step for rating the system on real data. Scales were only tested as to whether they properly refer to patients' structured data.

Epidemiologic analysis was tested for selected infectious diseases. A predictive machine learning (ML) model could accurately estimate the upper boundary for the number of visits depending on the day of the year, the age of the patient, the doctor's specialty and the geographical region. The ML models were compared with the Farrington and CUSUM models (Fig. 1, panel B) and were characterized by their greater customizability with similar sensitivity.

To test system functionalities concerning drugs, we created seven types of patients: female senior, adult male, female youngster, women, boy, pregnant women, and breastfeeding woman. They were used for showing relevant excerpts from the dosage descriptions and dosing regimes. A similar method was used for warnings if drugs are not recommended for patients.

Symptoms of possible side effects of the drugs were tested on 50,000 histories of patients' visits. We took into account symptoms, which were described in drug information for medical health professionals. It occurred that warnings would be generated in 1684 cases (3.3%). Warnings about potential overdosing were generated in 236 cases (0.5%). While potential drug-drug interactions were recognized in 60% of questions concerning pairs of drugs.

Conclusions

All the functionalities have been integrated with the system and a preliminary evaluation of the system was performed. We corrected the found differences and prepared the system for tests in the real environment.

In the next step, we will test how often these functionalities are useful in the everyday work of a selected small group of physicians. We plan to monitor each use of a new functionality and analyze the results obtained. This information, together with doctors' comments, will be used to improve the system. We then plan to introduce the functionalities into general use and monitor how often they are used and their ratings.

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