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PhD Forum: Multimodal IoT and EMR based Smart Health Application for Asthma Management in Children

Utkarshani Jaimini
Ohio Center of Excellence in Knowledge-enabled Computing (Kno.e.sis), Wright State University, Dayton OH, USA

Abstract

According to a study done in 2014 by National Health Interview Survey around 6.3 million children in United States suffer from asthma [1]. Asthma remains one of the leading reasons for pediatric admissions to children's hospitals, and has a prevalence rate of approximately 10% in children and it leads to missed days from school and other societal costs. This occurs despite improved medications to control asthma symptoms. Asthma management is challenging as it involves understanding asthma causes and avoiding asthma triggers that are both multi-factorial and individualistic in nature. It is almost impossible for doctors to constantly monitor each patient's health and environmental triggers. According to a recent article, the IoT device market in health-care will increase to a worth of $117 billion by the year 2020 [2]. The monitoring segment of IoT devices have predicted to increase $15 billion in 2017 [5]. The sales of smart watches, fitness and health trackers, are expected to account for more than 70% of all wearables sale worldwide in 2016 [6]. According to IBM, the volume of health-care data has reached to 150 exabytes in 2017 [7]. The data generated from these consumer graded devices is increasing day by day. This data collection has exacerbated the problem of understanding the data and making sense of it.

We can use these low-cost sensors and consumer graded devices for continuous monitoring and management of asthma patients. We developed kHealth[1], a framework for continuous monitoring of the patient's personal, public and population-based health signals and send alerts to the patient when a condition deserves patient's or clinician's attention. This can assist the clinician in determining the triggers and deciding the future course of action for prevention and treatment of the disease. More importantly, it can also help a patient to better take control of his/her health management by taking more timely actions(e.g., in case of asthma, using an inhaler in a more timely manner to ward off an attack). Our kHealth framework goes well beyond the efforts of data collection and focuses on contextual and personalized processing of multi-modal data to help understand asthma control level and vulnerability score (change in conditions that increases the chances of an adverse event, thus requiring proactive action). Another unique aspect of our research is close collaboration with clinician combined with on-going evaluation of clinician's at the Dayton Children's hospital which involves an ongoing trial of our novel technical approach with a cohort of 200 patients.

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[1]http://bit.ly/kAsthma

As shown in the Fig 1., we capture the broadest variety of personal, population and public level signals relevant to asthma management. The key research challenge of this project is the development of AI algorithms that can take multi-modal data and translate them to practical and actionable information for asthma patients and their health-care providers. Specifically, provide information on asthma control level based on symptoms and their severity, asthma triggers and early alerts for increasing asthma symptoms. In the preliminary study [9] for a single patient, we collected over 250,000 observations/day using the kHealth framework. In the study of three patients, we collected over 9 million data points. We observed examples of correlations in the data which can be useful in asthma management: (1) The medication (Albuterol) taken by a patient possibly decreased the exhaled nitric oxide. (2) Patient's activity limitation is possibly related to high exhaled nitric oxide. (3) Low exhaled nitric oxide of the patient is possibly related to the absence of coughing on the same day. (4) Patient's activity limitation is possibly related to high pollen activity on the same day. Such correlations illustrates the need of actionable information such as varying medication dosage or change in medication, hypothesize triggers (e.g., low/high indoor humidity, indoor smoking etc) to determine corrective actions (e.g., physician recommends humidifier), and alert the patient/parent to take predefined actions including contacting the doctor.

As part of the study, we investigated the indoor environment using the indoor air quality sensor named Foobot for events like cooking, smoking etc [8]. The indoor air quality and environment varies significantly with the indoor events such as cooking, smoking, vacuum cleaning the room etc. In the studies [3] [4] the variation in these activities have shown to severely affect the asthma in children. We proposed a continuous monitoring-activity detection system for understanding the indoor air quality of asthma patients. We collected the data from seven different environment over a period of 15 days. We were successfully able to detect a high concentration of particulate matter, carbon dioxide and volatile organic compounds during cooking and smoking events. We detected 1) cooking with an error rate of 11%; 2) smoking with an error rate of 1%; and 3) obtained an overall 95.7% percent accuracy classification across all events (control- when no event was taking place), cooking and smoking).

Our next step is to develop and evaluate a patient's personalized vulnerability score by combining current patient health score with dynamic environment conditions. This score will act as a warning to the patient to avoid or minimize the risk of asthma attacks. We will also formulate finding features of asthma and their impact on asthma as Bayesian Networks and Markov Networks learning problem. We propose to determine statistical, correlation-based knowledge from data collected from sensors and electronic medical records (EMRs), collaborate with domain experts to verify its soundness, and then refine and integrate it with complementary declarative knowledge from domain experts.

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Fig. 1.

The personal level data includes exhaled nitric oxide level, forced exhaled volume in 1 second (FEV1) using the spirometry, activity measurement using fitness trackers, and contextually relevant health questions. IoTs measure in-home environmental measurements of the carbon dioxide level, volatile organic compounds, indoor temperature and humidity, communicates with the mobile application. The population level real time IoT data includes pollen level, air quality index, outdoor temperature and humidity. Finally, public level data includes asthma related social media tweets. We utilize the tweets from nearby locations with reference to the patient location to explain anomalous dynamics between personal level, population level and public level signals. We use multi-modal data from multiple sources including social media (Twitter), environmental data (humidity, air quality index, pollen level, temperature), as well as personal health signals (activity, heart rate, etc)