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APPLICATION OF MACHINE LEARNING TO SUPPORT SELF-MANAGEMENT OF ASTHMA WITH M-HEALTH

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Abstract: Several initiatives have been made to employ mHealth technology to aid in the treatment of asthma, but none of them give personalized algorithms that can deliver real-time feedback and individualized counsel to patients based on monitoring. In this study, the Asthma Mobile Health Study (AMHS) dataset was used with machine learning approaches to create early warning algorithms for improved asthma self-management. There were 13,614 weekly surveys and 75,795 daily surveys in the AMHS, all from the same group of 5,875 patients. Both logistic regression and nave Bayes-based classifiers had great accuracy (AUC > 0.87) when we used them to distinguish between stable and unstable periods using a variety of well-known supervised learning techniques (classification). In order of decreasing relevance, we identified characteristics associated with the use of quick-relief puffs, night symptoms, data input frequency, and day symptoms as the best indicators of impending loss of control. No improvement in early warning algorithms at the population level was seen when peak flow measurements were included.

Key Words: Application of Machine learning to support self-management of Asthma with mhealth

INTRODUCTION

Asthma is a disease that can be different for each person and affects about 5.4 million people in the UK [1]. In the UK alone, someone has an asthma attack every 10 seconds, and a few of them are life-threatening [1]. Patients with asthma are treated in two ways: by controlling their symptoms and by preventing asthma attacks. Most people with asthma wheeze, cough, feel tight in the chest, and have trouble getting enough air.Most of the time, the situation is steady and easy to deal with, and these signs are either not present or weak. But if a person is exposed to a trigger, which is different for each person, these symptoms can get worse and lead to an attack, which is a long-lasting worsening of symptoms that needs emergency treatment like oral steroids or hospitalization if it isn't treated right away.There is no fix for asthma right now. But the condition can be kept under control with methods already in use, such as "preventer" inhalers. Supported self-management, which includes making an action plan, lowers the chance of an asthma attack by a lot [2]. An important part Monitoring is a part of self-management. Monitoring can be silent, meaning the patient doesn't have to do much, which is best, or active, meaning the patient has to do something, which may be difficult or boring and cause less commitment. Mobile health (mHealth) is a potential tool for mixing passive and active methods to create an interesting and successful system for self-management of asthma. Severalattempts have been made to use mHealth technologies to help people control their own asthma [3]. myAsthma is a mobile app made by My mHealth and approved by the National Health Service (NHS). It has movies showing how to use an inhaler, tracks symptoms and peak flow, gives area weather forecasts, and saves action plans. AsthmaMD has similar features. It keeps track of the user's asthma activity, peak flow, medicines, and triggers, stores action plans without paper, and can send custom alerts[5]. But as of now, there isn't a widely used, successful digital self-management option for asthma. This means that such data can't be added to general care records to improve care. This is because current solutions aren't often interesting enough to make people more likely to keep up with tracking, and they don't have personalized systems to give real-time feedback based on symptoms and other factors. So, our long-term goal is to create an effective and interesting mHealth system that makes self-monitoring easy and uses personalized algorithms to give patients fast and useful feedback (early warning).To get closer to our goal, we used a freely available mHealth dataset to apply and measure machine learning methods to create early-warning algorithms.

Objective

The goal of this meta-analysis was to summarise evidence on the impact of mHealth apps on a range of self-reported outcomes in asthma patients and to evaluate the capabilities of this type of intervention.

Literature survey:

Guidelines for the treatment of asthma have advocated for supported self-management for the last three decades, but the present implementation is far from ideal. For this reason, researchers commissioned a meta-analysis called the Practical Systematic study of Self-Management Support (PRISMS) and a health economics study called Reducing Care Utilization via Self-Management Interventions (RECURSIVE). We aimed to learn whether, for which groups, and what variables contribute to its success, assisted asthma self-management minimizes the use of healthcare resources and improves asthma control. Finally, we looked at how much offering assisted self-management would add to the price tag for healthcare services.

Self-management of asthma has shown to reduce the burden of asthma on individuals and healthcare systems. In theory, mobile health (mHealth) applications should provide efficient asthma self-management treatments, bettering patients' quality of life while decreasing healthcare systems' financial burden. Clinical assessment of asthma mHealth applications is lacking, and many of these apps are not based on medical criteria, according to previous evaluations in this area. However, little is known about the potential apps may have for enhancing asthma self-management beyond the absence of evidence for clinical benefit.

There is a chance to collect an unparalleled depth of data on people thanks to the widespread use of smart mobile platforms, a rising network of sensors including passive location monitoring, and the capacity to access other data sources. The use of mobile health technology has the potential to improve our knowledge of common illnesses like asthma and aid in their treatment. To evaluate the viability of such an approach, the clinical features of cohorts recruited through a mobile platform, the quality of the data acquired, user retention trends, and user data sharing choices, we performed a prospective observational study of asthma. We provide descriptive statistics and data from the Asthma Mobile Health Study, in which participants used an iPhone app developed using Apple's ResearchKit framework to track their asthma symptoms. Six thousand three hundred and forty-six American participants, who choose to make their data publicly accessible, have already done so. Using these tools, researchers may be able to pool their efforts to further our knowledge of asthma and mobile health research methods as a whole.

When it comes to chronic respiratory disorders, asthma is among the most prevalent. Asthma exacerbations (AEs) may occur for several reasons, even with frequent usage of maintenance medicines. Adverse events (AEs) may be fatal, therefore people in many nations end up using healthcare services they hadn't planned on.12 Thus, predicting and preventing AEs is crucial for better asthma care.34
Reduced baseline lung function,5 poor adherence to prescriptions, termination of frequent use of inhaled corticosteroids (ICSs),678 viral infections,39 and concomitant diseases, such as allergic rhinitis, have all been linked to acute AEs in previous research.10 Several measures of asthma activity have been proposed to indicate whether or not an individual has recovered from AEs. Symptom scores5, peripheral eosinophil count11, exhaled nitric oxide (FeNO) fraction12,13, and vascular endothelial growth factor14 and soluble CD93 serum levels are all examples of such measures.15 To far, however, no indicators have been validated to the point where they might be routinely used to forecast and monitor AEs and the time it takes for patients to recover from them.

METHODS:

First, we talk about the data set from the Asthma Mobile Health Study (AMHS) that we used in our study. Then, we talk about the way we came up with to look at the data. "Data pre-processing and labeling," "feature extraction," "feature selection," "classification," and "model evaluation" are the most important steps in the method. The diagram in Figure 1 shows the big picture.

SYSTEM ANALYSIS:

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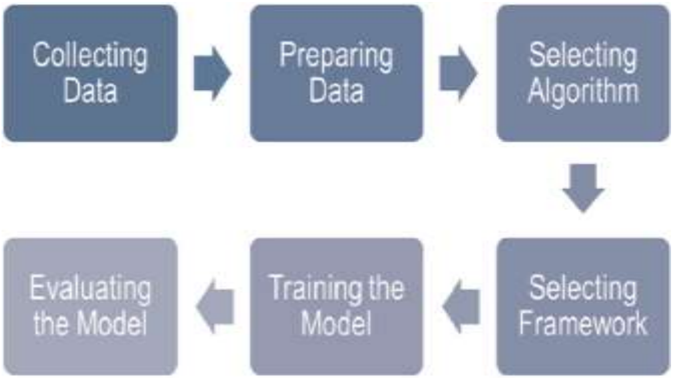
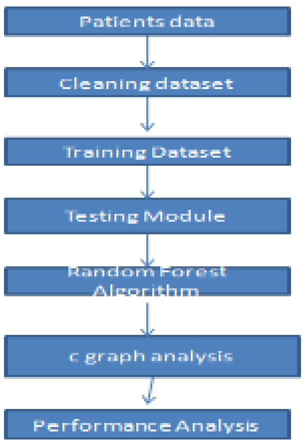
Proposed System

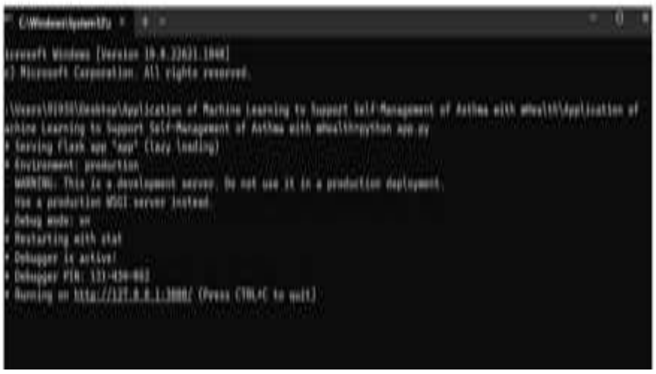
A subgroup of patients who completed at least one weekly survey entry and three daily survey entries with peak flow data were analyzed for this investigation. The weekly survey provided information on the patient's state (stable or unstable) while the daily survey provided information about the patient's symptoms.
See Table I for a breakdown of the survey questions used to compile data on day and nighttime symptoms, inhaler use, asthma triggers, and peak flow that was used to inform the model. These align with the Global Initiative for Asthma definitions and the Royal College of Physicians' "3 Questions" for clinical assessment of asthma control [8][9].

ARCHITECTURE





Results and Analysis:



After pre-processing and labeling, the sample used for further analysis had 2,309 times, of which 2,145 (92.9%) were in the stable class and 164 (7.1%) were in the unstable class. The 2,309 periods added up to 25,412 daily surveys (24,079 in the stable class and 1,333 in the unstable class), which were done over 55,509 days of patient tracking. This suggests that, on average, a patient did a daily survey every 2.2 days. The different steps of processing data are shown in Fig. 1.

A. Ranking of Features

Table II shows the rank that comes with using all 25 features. From the 150 ranks, the median size of the best model was six, and all of them used the same traits.

But the order of the top three changed between the 150 ranks. In decreasing order of value, the top six traits are: quick-relief puffs (mean), quick-relief puffs (absolute gradient), night symptoms (absolute gradient), night symptoms (mean), regularity, and day symptoms (mean). The "one-standard-error" rule [15] says that the best model had six traits. Notably, nighttime symptoms were rated higher than daytime symptoms, which makes sense from a clinical point of view

TABLE II

LASSO RANKING AND WEIGHT IN OPTIMAL MODEL

Rank	Feature	Weight
=1	quick-relief puffs (mean)	0.18
=1	quick-relief puffs (absolute gradient)	0.14
=1	night symptoms (absolute gradient)	0.17
4	night symptoms (mean)	0.14
5	frequency	-0.22
6	day symptoms (mean)	0.20
7	day symptoms (absolute gradient)	0
8	number of triggers (gradient)	0
=9	peak flow (absolute gradient)	0
=9	peak flow (gradient)	0

Conclusion:

Using the AMHS dataset, we showed that machine learning methods can help people control their own asthma, since the results of the data-driven methods matched what doctors knew. More specifically, we found that both a probabilistic (naive Bayes) and a discriminant (logistic regression) predictor could provide high accuracy (AUC > 0.87) for early warning. Our work has shown that the method, which collects randomly sampled data to make summary variables and lets you compare data from different times, has a lot of promise. This work also showed that the accuracy of prediction models could be improved by adding traits that show how things change over time. Also, this work found that features based on peak flow readings did not add more value than other self-reported features used in the study, such as those based on the use of quickrelief puffs and symptoms during the day and night.

One problem with the data was that it was hard to figure out what an unsteady event was because it was only measured once a week. Also, the app could only be used on Apple devices, which aren't used by everyone in the US. This could make the data less accurate.

Before patients can trust the predictions made by the models used in this study, more research with a wider range of data needs to be done. Our study used self-reported data, and we think that if objective measures were available as feature inputs for forecast, the stated results would be even better. Our future work will focus on expanding the study of this dataset by using 3-digit ZIP code prefixes to link past weather data, building demographic, regional, and seasonal sub-models, looking for links between feelings and symptoms, and trying more complex models. Also, the data from the time between unstable and stable phases and data from the edges of time were not used in this study. These data points could be added to future models using multi-scale models.

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