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A Comprehensive Survey on Role of Learning Approaches in Respiratory Disease Management with Special Focus on Asthma

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Abstract

Asthma is a heterogeneous disorder with many phenotypes. We discuss the phenotypic characterization of asthma by which disease causality and ultimately management approaches can be developed to improve asthma control while avoiding adverse effects and decreasing the risk of serious outcomes. Thus the discussions would aim at phenotyping asthma based on clinical as well as physiological characteristics as Asthma is defined and diagnosed by a combination of clinical symptoms and physiologic abnormalities by deploying different learning techniques for devising novel approaches, while performing evaluation of the same, which would better define asthma phenotypes that may improve the understanding of the underlying pathobiology of the phenotypes and lead to targeted therapies for individual phenotypes. The approaches developed would serve to cluster, classify and further perform analysis and predict the severity of the disease in future effectively.

Keywords: Phenotypes; Longitudinal; Cluster Analysis

Abbreviations: SOB: Shortness of Breath; PBDT: Pattern Based Decision Tree; PBCAR; Pattern Based Class-Association Rule.

Introduction

Asthma is a complex, multidimensional disease with marked heterogeneity. A number of approaches are now aiming at phototyping individual asthma subtypes to characterize the various patterns of triggers that induce symptoms, different clinical presentations of the disease and different inflammatory markers. Asthma registries form a strong foundation to provide a better understanding of public health need and to define phenotypic heterogeneity which can help in effective management of Asthma.

Asthma is a heterogeneous disease that means not all asthmatics respond to the same treatment. Recent approaches to characterize asthma phenotypes have been based on symptomatology (shortness of breath (SOB), cough, and wheezy phenotypes) in correlation with airway inflammatory biomarkers and FEV1.

A phenotype may be considered as a cluster of either or both clinical and pathological features that tend to be associated. Phenotypes may be constructed as a result of data collection and subjective analysis. Phenotyping recently has been proposed by epidemiological pattern, the presence or absence of atopy, and symptom pattern [1,2]. The existing phenotypes have been identified by performing univariate analysis of core risk factors that contribute to respective asthma phenotype. The presence of comorbidities and the

degree of correlation between asthma and its comorbidities is rarely considered while phenotyping.

Phenotyping in asthma eases the understanding of disease mechanism and helps in optimizing management. Phenotypes show age related variations. Longitudinal data are needed to determine the stability of phenotypes and their prognoses. Retrospective studies of childhood events alone is of limited value as it does not give a good understanding of disease complications in later stages of life [3-5]. In conclusion, a full understanding the multifaceted phenotypes of asthma requires a thorough knowledge of early life events and their consequences over subsequent years.

A phenotype may be considered as a cluster of either or both clinical and pathological features that tend to be associated. Phenotypes may be constructed as a result of data collection and subjective analysis, and thus in a sense are forced on the data by the prejudices of the investigator [6,7].

"Phenotype" is classically defined as the observable structural and functional characteristics of an organism that are determined by the combined influence of genotype and environment. Hence a phenotypic characterization will result in modelling all the data to identify a single multinomial latent variable that best describes the structure of the data [8].

Most of the studies on asthma phenotypes have been related to age and atopy. Results on phenotypic characterization of asthma based on atopy have revealed that not all atopic classes help in predicting asthma.

Although univariate analysis have demonstrated statistical significance between risk factors and resulting severity levels in asthma, multivariate approaches are rarely deployed to explore the hidden significance of the collective variable features characterizing individual asthma phenotypes to the severity of the disease [9,10].

Phenotypes show variation with respect to age. Factors that characterize phenotypes in paediatric and adult populations differ In paediatric asthma further classifications are done with respect to patterns in age such as infant wheeze, preschool years and school age children. Further sub phenotyping within these phenotypes has been done with respect to atopic status and symptom patterns [11-15]. In adult asthma populations the most commonly recognised phenotypes have been identified as exacerbating phenotype, phenotypes resulting from impaired airway development and progressive loss of lung function, brittle asthma, drug sensitive asthma [16]. Risk factors contributing to the development or progression of the disease also are quite different in the paediatric and adult asthma population. Further longitudinal studies play an important role in understanding the mechanisms of progression of disease.

Survey of Learning Approaches Supplied for knowledge Discovery in Asthma Disease

Classification algorithms have been used to categorize asthma in children and suggest the best possible treatment. The type of treatment is based on the severity of the disease. Based on the age group the disease was classified as extrinsic or intrinsic. Further classification was done to group asthmatic having children as sever/general subjects.

Mining was performed on Multiyear asthma drug utilization data. K-means clustering was used to identify groups of patients having similar utilization patterns of asthma drugs. The utilization pattern was characterized by the number of prescription issued per month. Supervised learning technique such ad decision tree classification algorithms was used to identify features that could predict the drug utilization of each patient. Features included sex, age, drug utilization of 4 drugs namely Xanthine, Anticholinergic, Coticosteroids and Beta2_agonists.The results showed that the use of corticosteroids and age of patient can be considered as the main factors in the induced models.

A clinical decision model was used to identify patients having mild/moderate /severe attack. The decision model was basically a rule based system that combined rough sets and expert driven manual feature selection on retrospective data that described asthmatic patients visiting the Emergency department. Four different decision models were built which differed by the subset of clinical attributes that were considered. Model A using all the attributes collected in retrospective study. Model B using only attributes that described patients history, Model C using attributes triage and Model D using attributes from Model C and some attributes from Model B.(Triage attributes like body type, Respiratory rate, heart rate, expiratory /inspiratory wheeze). Consideration given to algoritms based on the symptoms and clinical data to study factors such as validity, reliability, effectiveness and accuracy of proper outcomes that can be mapped with Experts knowledge. The following machine learning algorithms were used for the performance study CSAMM, BP, C 4.5 and PSO. Context dependent associative memory model has been identified as a promising approach in the development of accurate diagnostic tools [11-13]. Based on the data available the Expert system determined whether the disease is particularly Asthma or a variation of te same that occurs in respiratory asthma.

Using Cluster Analysis five basic distinct phenotypes of asthma have been identified. But the phenotypes

incorporate in them ATS definition of asthma severity only and a classification for varying disease severity levels is not identified. Factors like FEV, day time and nocturnal symptoms and frequency of rescue bronchodilator were used to classify different severity levels in asthma in line with the guidelines from NAEPP.

Data mining methods, namely Pattern Based Decision Tree (*PBDT*) and *Pattern Based* Class-Association Rule (*PBCAR*) based on sequential pattern mining were used to extract features of asthma attacks, and then build classifiers with the help of decision trees a**n**d rule-based methods. Apart from the clinical data of patients, environmental factors, which are related to many chronic diseases, were also considered. For experimental evaluations, the children asthma allergic dataset collected from a hospital in Taiwan was used along with the environmental factors like weather and air pollutant data.

Supervised learning techniques such as Bayesian approach applied to a longitudinal dataset has resulted in classes that were identified to be predominantly correct having good face validity and significant relationships with asthma, lung function, and airway reactivity which illustrated satisfactory content validity.

An improved understanding of underlying causes of Asthma will aid in development of new strategies with an aim to control and therefore prevent severe Asthma. Further research into the role of comorbidities and cofactors will help better management of the disease. For the welfare of the public health, a uniform definition of severity asthma levels is needed to identify those patients who require particular attention, to ensure appropriate treatment and regular monitoring and to improve adherence to treatment to reduce the use of emergency departments and hospitalizations. One of the major reason to characterize asthma severity is to guide management and to identify people with asthma at risk of severe exacerbations [17,18].

There is a major concern behind the classification of asthma by severity. Severity is not a stable feature of asthma but may change with time, whereas the current classifications by disease severity suggest a static feature. Severity is an outcome based on current symptoms, resistance of symptoms to standard treatment and future risk of death or exacerbations.

References

1. Vaillant AA, Modi P, Jan A (2021) Atopy. StatPearls Publishing.

2. Kuruvilla ME, Lee F, Lee GB (2019) Understanding asthma phenotypes, endotypes, and mechanisms of disease. Clinical reviews in allergy & immunology 56(2): 219-233.

3. Tai A, Tran H, Roberts M, Clarke N, Gibson AM, et al. (2014) Outcomes of childhood asthma to the age of 50 years. Journal of Allergy and Clinical Immunology 133(6): 1572-1578.

4. Pooja MR, Pushpalatha MP (2015) A hybrid decision support system for the identification of asthmatic subjects in a cross-sectional study. IEEE pp: 288-293.

5. Pooja MR, Pushpalatha MP (2020) Cluster Analysis to Characterize the Patterns of Complementary and Alternative Medicines Usage in Asthma Controls. The Open Public Health Journal 13(1): 227-231.

6. Pooja MR, Pushpalatha MP (2019) A predictive framework for the assessment of asthma control level. Int J Eng Adv Technol 8(3): 239-245.

7. Harber P, Redlich CA, Henneberger P (2018) Work-exacerbated asthma. American journal of respiratory and critical care medicine 197(2): P1.

8. Sockrider M, Fussner L (2020) What is asthma?. American journal of respiratory and critical care medicine 202(9): 25-26.

9. Pooja MR, Pushpalatha MP (2017) An Empirical Analysis of Machine Learning Classifiers for Clinical Decision Making in Asthma. Springer pp: 105-117.

10. Barnes PJ (2016) Asthma-COPD overlaps. Chest 149(1): 7-8.

11. Mali B, Dhal S, Das AK (2021) Diagnosis of asthma in children based on symptoms: a machine learning approach. IEEE pp: 782-787.

12. Chatzimichail E, Paraskakis E, Sitzimi M, Rigas A (2013) An intelligent system approach for asthma prediction in symptomatic preschool children. Computational and mathematical methods in medicine 2013: 240182.

13. Farion K, Michalowski W, Wilk S (2006) Developing a Decision Model for Asthma Exacerbations: Combining Rough Sets and Expert-Driven Selection of Clinical Attributes Rough Sets and Current Trends in Computing. Springer Berlin Heidelberg 4259: 428-437.

14. Mukherjee M, Svenningsen S, Nair P (2017) Glucocortiosteroid subsensitivity and asthma severity. Current opinion in pulmonary medicine 23(1): 78-88.

15. Bus A, Menzies-Gow A (2009) Phenotypic Differences

between Pediatric and Adult Asthma. Proceedings of the American Thoracic Society 6: 712-719.

16. Bousquet (2010) Uniform definition of asthma severity, control, and exacerbations: Document presented for the World Health Organization Consultation on Severe Asthma. Journal of Allergy and Clinical Immunology 126(5): 926-938.

17. Lee CH, Chen JC, Tseng VS (2011) A novel data mining mechanism considering bio-signal and environmental data with applications on asthma monitoring. Computer methods and programs in biomedicine 101(1): 44-61.

18. Alexandropoulos T, Haidich AB, Pilalas D, Dardavessis T, Daniilidis M, et al. (2013) Characteristics of patients with allergic rhinitis in an outpatient clinic: A retrospective study. Allergen Immunopathol 41: 194-200.