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Prediction Models for the Diagnosis of Asthma

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Abstract: ***Asthma is popular with substantial patient morbidity and costs for healthcare. We performed a systematic literature review to identify different algorithms used in asthma diagnostic systems. In this paper we reviewed the 35 papers based on asthma diagonosis system and we identified that the algorithms used in these papers gives how much accuracy. We read different prediction models designed to help diagnostics determine clinicians to evaluate patients with asthma-suggesting symptoms in primary care or similar settings***

I. INTRODUCTION

Asthma nowadays is a commonly occurring disorder at any age that is a concern for public health worldwide. It is a chronic respiratory inflammatory condition which can be particularly responsive to a number of stimuli. The asthma patient is affected by attacks including coughing, dyspnea and wheezing. Sounds created during respiration can be a good source of lung health information. Any characteristic changes in normal lung sounds may involve an infection that is likely to enter the lung. Each disease type is different and its sound signature, pitch, amplitude, frequency, length and so on will detect this variation. To improve asthma treatment and performance, having an correct diagnosis of asthma is fundamental. However, in children and adults, asthma is commonly misdiagnosed and over- and under-diagnosed. Over-diagnosis leads to insufficient treatment and avoidable morbidity and mortality while under-diagnosis leads to expensive, potentially dangerous treatment and needless health care.
It is difficult to reliably diagnose asthma. Asthma is a disorder that involves multiple genotypes, endotypes and phenotypes. There is no gold standard to affirm or deny diagnosis categorically. Therefore, Asthma is the clinical diagnosis, but the particular sensitivities / specificity of individual symptoms , signs and tests are low. In comparing guidance between national and international guidelines and in commentary aimed at minimising confusion for clinicians, ambiguity about the correct combination of clinical properties and tests for asthma diagnosis are expressed.

A clinical prediction model can be used to estimate the likelihood of outcomes using an algorithm based on datadriven, which incorporates at least two predictors, such as clinic history components, physical tests, test results and/or treatment response. Models for clinical forecasts will help health practitioners evaluate the chance of a diagnosis, improve collaborative decision making and help patients Subtypes stratification. Because most diagnosis of asthma occur in specialist settings where health conditions generally arise undifferentially and the evaluation frequently relies on probabilities, it may be important to enhance the precision of the diagnisation of asthma by reviewing available clinical evidence and directing further measures. We aimed to define, compare and synthesise current models of clinical prediction aiming at promoting asthma diagnoses in children and adults with symptoms of primary care asthma or similar conditions.

II. LITERATURE REVIEW

1) William Checkley, Maria P. Deza, Jost Klawitter,Karina M. Romero, Jelena Klawitter, Suzanne L. Pollard, Robert A. Wise, Uwe Christians, Nadia N. Hansel :- Through using a metabolomics approach applied to serum, we were able to differentiate through revealing specific metabolic trends between children with and without asthma. Such findings show that serum metabolomics can be a diagnostic method for asthma, and can be useful in recognizing asthma phenotypes.

2) JULIA E. HECK, AND JUDITH S. JACOBSON, Dr P.H. :- They found that asthma was more prevalent among individuals living in SSRs in the United States than among those residing in households of the opposite sex. Although a number of risk factors for asthma include smoking, elevated stress and obesity. They found that living in SSR was correlated with asthma even after controlling for the above-mentioned factors (among lesbians) more prevalent in SSR than in OSR subjects. Additional studies can help identify risk factors that increase the prevalence of asthma in this population and may be important to others. The sexual orientation relation to stress and depression is poorly known, and its effects on asthma require further research.

3) Richard D. O'Connor, Eugene R. Bleecker, Aidan Long, Donald Tashkin, Stephen Peters, David Klingman and Benjamin Gutierrez:- For this study, the risk of subsequent exacerbation for patients with both SALAC and acute asthma exacerbations was highest, followed only by those with exacerbations and then those with SALAC. SO reported an additional 26 per cent of patients with asthma at elevated risk for follow-up To exacerbate.

4) M. Bonini, G. Lapucci, G. Petrelli, A. Torado, T. Pamich, G. Rasi, S. Bonini:- Ninety-eight national pre-Olympic athletes underwent an comprehensive medical evaluation including a validated asthma and rhinitis questionnaire, spirometric records and skin prick testing with a panel of the most common inhalant allergens. In asthmatic subjects both bronchodilator and/or exercise test was performed. Owing to the high incidence of allergy, rhinitis, and asthma in this group, allergy testing and spirometry should be conducted regularly in athletes. But the predictive value of these and the bronchial measures Provoking tests carried out in this study tend to be too poor to record mild or On athletes subclinical asthma.

5) Naveed Ahmad, Swati Biswas, Sejong Bae, Karen E. S. Meador, Rong Huang, Karan P. Singh:- In this paperthe overall prevalence was 24.5 percent of obesity and 12.5 percent of asthma. For children in the 7–12 and 13–17 age classes, the modified risk ratio of asthma to obesity remains substantially greater than 1. Sex and race in all age groups were substantially linked with asthma. In the 0–6 year age range, the two parent family structure demonstrated important asthma protectiveness with infants. Poverty in the 7–12 age group was positively related to asthma. In the 0–6 and 13–17 age groups, having a smoker in the household raised the chances of asthma by 29 per cent and 23.5 percent , respectively. Sex and race have been related significantly to asthma. Asthma has been positively correlated with obesity, household education level, health care coverage, and household smoking in the age groups 13–17. Further research may describe how the family structure and the degree of household education affect childhood asthma in age groups of 0–6 and 13–17, respectively.

6) L. L. Magnusson, A. B. Olesen, H. Wennborg and J. Olsen:- The relationship dose-response between maternal prenatal smoking and wheezing is in line with previous publications. No correlation was found between asthma and exposure to in utero smoke, while slightly decreased effect measurements were obtained for hayfever and atopic eczema. But the findings may have been influenced by the lack of control methods for hereditary causes.

7) S. Thavagnanam, J. Fleming, A. Bromley, M.D. Shields and C. R. Cardwell:- This paper reviews published literature and meta-analysis for performa which summarises the evidence for the association of children born to caesarea and asthma. The related studies were conducted by Medline, Web Science, the Google Scholar, and the PubMed team. For every study of the asthma prevalence reported in children born to the Caesarean setion and the control children, the Odds Ratio (OR) and the 95 % Confidence Interval (CI) were determined. A combination OR- and research test was then used Heterogeneity of studies results.

8) Judith W Dexheimer, Thomas J Abramo, Donald H Arnold, Kevin Johnson, Yu Shyr, Fei Ye, Kang Hsein Fan, Neal Patel, Dominik Aronsky:- In an urban, tertiary paediatric ED, they have conducted a prospective, randomised controlled examination. The disease detection system has been tested for inclusion by all patients aged 2 to 18 years who were presented to ED between October 2010 and February 2011. Randomized monitoring or supervision was used for patients classified as having an asthma exacerbation. For intervention patients, asthma treatment was computer-driven and workflow-integrate, with computer-based asthma scoring in triage, and time-based asthma-related alert showing in tandem with a guideline-compliant order set on the electronic patient status board. The Bayesian network reported 1339 asthma exacerbation patientes, 788 of whom were diagnosed with asthma decided by an ED doctor (positive predictive value 69.9%).

9) Jorge L. M. Amaral, Agnaldo J. Lopes, Juliana Veiga, Alvaro C.D. Faria, Pedro L. Melo:- This study aimed to develop automatic classification systems to simplify Medical use and accuracy in diagnosis of airway obstruction in patients with asthma of forced oscillation techniques (FOT). The data consisted of 75 volunteers' FOT parameters (39 with obstructions and 36 without obstruction). Various supervised machine learning (ML) techniques including K-nearest neighbours (KNN), RF, AdaBoost (ADAb) and Function Dependent Dissimilarity Space Classifier (FDSC) were investigated. ADAB was also examined for this study. Experiments involving cross-products of the FOT parameters showed that the diagnostic accuracy of all classifiers was enhanced and that KNN was able to achieve a high degree of precision (AUC = 0.91).

10) Young Moon Chae and Seung Hee Ho, Chein Soo Hong and Cheol Woo Kim:- They contrasted three information models for asthma diagnosis (namely, the network of neurons, case-based reasoning and differential analysis). Data were obtained from 294 asthmatic symptom patients attending the Bronchial Asthma Clinics, Yonsei University Severance Hospital's Department of Internal Medicine, from June 1992 to May 1995. Diagnostic diagnosis The three awareness models differed in their capabilities. The most successful prediction rates for asthma were the neural network (92%) and the highest predictor for asthma (96%), the highest predictor for non-asthma (80%) for discriminant analysis, and the lowest prediction rates in all categories.

11) Aman Tyagi and Preetvanti Singh:- Asthma is a persistent respiratory condition due to the patient's short airway. In designing a symptom-based decision-making aid method, this paper focuses on the successful diagnosis. In this first step, asthma is diagnosed by data mining instruments and the second phase, by using a fluorescent inferencing device, is assessed at asthma control level. The diagnosis is based on symptoms such as sneezing, shrubbery and so on. Control asthma is based on the signs

of shortness of breath, movement restriction, signs of the day and so on. The quality and reliability of the device Calculated and posted on here is kappa coefficient.

12) David G. Tinkleman, David B. Price, Robert J. Nordyke, R. J. Halbert:- They registered individuals 40 years or older with pre-diagnosis or with obstructive pulmonary disease medicines. In Aberdeen, Scotland and Denver, Colorado, patients were recruited by random mailing. Subjects have been reported on previous diagnoses of chronic bronchitis or emphysema (CBE) and asthma. Pre- and after-bronchodilator spirometry was performed by participants. An COPD study diagnosis was defined in 1 second / forcible vital capacity (FEV1 / FVC) < 0.70 using postbronchodilators forced expiratory volume. In 597 patients, a study of 235 (39.4 percent) had a diagnosis of COPD was completed. Of individuals who have a COPD diagnosed spirometry (51.5%) before their asthma diagnosis, 89 (37.9%) reported prior diagnosed CBE, and 25 (10.6%) reported that their obstructive lung disease hasn't been identified prior to the diagnosis. Despite the availability of guidance for diagnosis in the Consensus Guidelines, asthma and COPD diagnostic uncertainty appears common. To facilitate effective patient care and treatment, a greater understanding of the discrepancies between the two conditions is important.

13) Chao-Hui Lee, Jessie Chia-Yu Chen, Vincent S. Tseng:- They suggested two methods of data mining, namely the Model Base Decision Tree (PBDT) and the Model Class Association Law (PBCAR). Both methods combine sequential model mining concepts to extract the characteristics of the asthme attacks and then construct classifiers with decisions tree mining concepts and laws. The experimental results indicate PBCAR 's accuracy at 86.89%, 84.12%, and PBDT 's accuracy at 87.52% and 85.59% .. These findings also demonstrate that their methods can be extremely reliable and remember projections of attacks with chronic diseases.

14) Md. Ariful Islama, Irin Bandyopadhyaya, Parthasarathi Bhattacharyya, Goutam Saha:- They obtained the pulmonologist 's suggested lung sounds from 60 subjects (30 regular and 30 asthma) using a new, four-channel data collection method from four positions over the back of the thorax. A spectral extraction scheme based on subbands that works with the artificial neural network is proposed. (ANN) and multichannel signal support (SVM) classifiers. The performance for each single channel and four channels together is calculated in the first part of this analysis when the cumulative channel performance is higher than that of the individual channels. The performance of all possible combinations of channels will then be tested. For 2-channel and 3-channel composites in ANN and SVM classificers, a best classification accuracy is achieved of 89.2(±3.87) percent and 93.3(±3.10) percent.

15) Priyanka Sharma, Sonal Saxena, Dr.Yatendra Mohan Sharma:- This paper aimed at a suitable model for multi-region decision support. The proposed model will animately choose the most suitable classification group and range from a variety of expertise. The procedure for the data set provided and the method feature chosen was pooled in layer format to enhance the accuracy level. The act of the proposed model analysed three different types of data set, Diabetes, Labor and Australian credit risk, using five most common classification algorithms. Could test result shows that The solution suggested increases predictability.

16) Matthew R. Gingo, Sally E. Wenzel, Chad Steele, Cathy J. Kessinger, Lorrie Lucht, Tammi Lawther, Michelle Busch, Maria E. Hillenberd, Rennee Weinman, William A. Silvka, Deborah K. McMohan, Yingze Zhang, Frank C. Sciurba, Alison Morris:- We tried to identify and identify potential mechanisms for the prevalence of diagnosed asthma and related pulmonary malnormalities in the HIV-infected cohort. Cross-sectional analysis was carried out on 223 HIV-infected individuals, including data on respiratory symptoms, diagnoses, pulmonary function, sputum cell counts and serum / sputum asthma-connected cytokines and chemokines.

17) Tove Fall, Cecilia Lundholm, Anne K Ortqvist, Katja Fall, Fang Fang, Ake Hedhammar, Olle Kampe, Erik Ingelsson, Catarina Almqvist:- The analysis included 376 638 pre-school children (53 460 [14,2%] exposed to dogs and 1729 [0.5%] exposed to farm animals) and 276 298 school children (22 529 [8,2%] exposed to dog and 9 58 [0,3%] exposed to farm animals). Of these, 18 799 (5.0 percent) children in the pre-school children's cohort had an asthmatic event before baseline, while 28 511 and 906 071 years at risk of asthma (incidence rate, 3.1 cases per 1000 years at risk) were reported during follow-up. 11 585 children (4.2 percent) in the school age group The seventh year of life was asthmatic event. The risk of asthma in school age children (OR 0.97; 95 percent CI 0.81-0.93) and in pre-school children aged between 3 years or older was associated with decreased exposure during the first year of life (HR 0.90; 95 percent CI 0.83-0.99), but not among children under 3 (HR, 1.03; 95 percent CI, 1.00-1.07). When only firstborn children were analysed, results were comparable. The exposure of farm animals in the pre-school age children (OR, 0,48; 95 % CI, 0,31%-0,76; and HR, 0,69%; 95 % CI, 0,56-0,84%) was associated to a reduced risk of asthma.

18) P Montemery, L Hansson, J. Lanke, L-H Lindholm, P Nyberg, C-G Lofdahl, E. Adelroth:- The aim of the study was to examine whether the low prevalence of asthma in primary health was a result of under diagnosed asthma and whether an initial asthma

diagnosis by GPs in primary health care was validated. In the entire group of 3025 patients for the first time during the study period, 99 were diagnosed with ashthma. In 52 of the 68 patients who were examined by a respiratory physician after the test, the diagnosis was checked. 221 patients were randomly selected to form the control group among the remaining 2926 patients. There were 3 patients with asthma in this gorup.

19) Laura Rooney, Chaloner Chute, William J Buchanan, Adrian Smales, Legh Anne Hepburn:- The history of respiratory symptoms including wheeze, shortness of breath, tightness of the throat and cough is described, varying with time and intensity, along with a variable expiratory restriction of airflow. We know that to date Many different factors are causing asthma or inducing attacks – such as viruses, allergens, and noise –, but why or how they do. This article explains how the data collection of the open source can be used to estimate the asthma rates of hospitalisation and how this rate can be estimated by machinery between 7.5% and 86.67%.

20) Dinh-Van Phan, Nan-Ping Yang, Ching-Yen Kuo & Chien-Lung Chan:- Asthma patients' disease history has been translated into sequences The sleep disorder prediction matrices are based on machine learning (ML) and deep learning (ML) models including the Neural Network (NNN), Long Shorter Term Memory (LST) as well as Random Forest Manuscript Approved Services (RF) and the Convolution Neural Network (CNN). There were 4469 subjects with sleeping condition between 2002 and 2010, out of 14,818 new asthma subjects in 2002. Models of sleeping disorder prediction for KNN, SVM and RF have been shown to be successful, Accuracies are respectively 0.798, 0.793 and 0.813 (AUC: 0.737, 0.690 and 0.719). DL results showed accuracy of 0.744, 0.815, 0.782 and 0.951, respectively, for the RNN, LSTM, GRU, and CNN, respectively (AUC: 0.658, 0.750 and 0.732 and 0.934). The findings showed that the model of the CNN had the highest performance in the asthma cohort for sleep disorder.

21) Quan Do, Tran Cao Son, Jamil Chaudri:- This article presents the findings of a study to assess the future usage at the national and hospital level of TensorFlow and Inpatient Databases to predict the asthma intensity. Deep Neural Network Approaches (DNN), as well as treatment strategies, have been applied for classification of disease conditions. The results show that a DNN can be trained to predict the severity of asthma or an imminent asthma attack.

22) Hillary A. Cuesta, Donna L. Coffman, Charles Branas, Heather M. Murphy:- The secondary information on the health and perception of neighbourhood characteristics of individuals (N=450) and Philadelphia LandCare Program (N=676) has been obtained from May 2011 to November 2014. The software was used to perform decision tree analyses for RapidMiner open access data mining. The prevalence of asthma and diabetes in this urban population has repeatedly been shown to be correlated with better community conditions associated with social and physical disorders.

23) B.N. Zamora-Mendoza, R. Espinosa-Tanguma, M.G. Ramírez-Elías, R. Cabrera-Alonso, G. Montero-Moran, D. Portales-Pérez, J.A. Rosales-Romo, J.F. Gonzalez, C. Gonzalez:- This research aimed to detect biomarkers of bronchial inflammation through immunoassay and surface in the saliva of children with asthma Spectroscopy of strengthened Raman (SERS). A cross-sectional research was performed in 44 children aged 6-12 and an asthma diagnosis was conducted according to the GINA (Global Asthma Initiative) guidelines. Children's saliva have been examined in a confocal Raman microscope at 785 nm by immunoassay for the measurement of 37 cytokines and by SERS study. We have found an important connexion between bronchial obstruction and SCD163 (p=0,003) and IL-8 (p=0,004), IL-10 (p=0,008). In the region of 760 to 1750 cm−1, the Raman spectrum showed substantial amplification. A 85% sensitivity, a specificity of 82% and a precision of 84% for diagnosis of asthma have been shown in the principal component analysis and a linear differential analysis (PCA-LDA) process.

24) E. Chatzimichail, E. Paraskakis, M. Sitzimi and A. Rigas:- This study provides a new method for asthma outcome prediction, based on main component analysis and the VectorMachine Classifier Last Squeeze Support. Most cases of asthma appear during early lifetime. The early identification of young children at high risk of persistent disease symptoms in childhood is therefore a method for predicting asthma results. Significant concern for public health. As shown in the experimental data , the proposed prediction system can be used with a 95.54% success in asthma prediction. This study demonstrates that the proposed method is a potentially useful tool for promoting asthma prediction. Certain risk factors boost their ability to predict asthma.

25) L-P Boulet, H. Turcotte, C. Laprise, C. Lavertu, P-M Bedard, A. Lavoie and J Hebert:- There is yet to be documented the variability determinants in clinical atopic expression. The aim of the study was to identify the potential for symptomatic asthma or rhinitis in subjects with clinical diagnoses. Contribution of various indoor and outdoor types of allergens to their disease development by looking at the prevalence and sensitivity level of these allergens by age and sex. In 3371 consecutive patients, grouped according to diagnoses of allergy asthma, rhinitis, or both, we analysed allergy skin prick tests on common airborne indoor and outdoor allergens. The prevalence of sensitization to indoor or outdoor allergens, the atopic index was calculated for

each of these three groups. (Al), the number of positive reactions and the mean diameter of these reactions to the skin allergy prick test. (MWD).

26) Mario Milicevic, Igor Mazic and Mirjana Bonkovic:- This study compares the efficiency of classification algorithms used in real life clinical environments, both in on-line signals and in children. With a suitable signal processing technique which results in MFCC features, it is possible for signals recorded under ineffective conditions to achieve high classification accuracy.

27) Utkarshani Jaimini, Tanvi Banerjee, William Romine, Krishnaprasad Thirunarayan, Amit Sheth and Maninder Kalra:- They suggest a data-driven approach to establish a continuous monitoring-activity detection system aimed at understanding and enhancing indoor air quality in asthma management. In this study they were successfully able to detect a high concentration of Particulate Matter (PM), Volatile Organic Compounds (VOC), and Carbon Dioxide (CO2) during cooking and smoking activities. They observed (a) the error rate of 1% smoking, (b) the error rate of 11% cooking, and (c) the overall accuracy rate for all events (control, cooking and smoke) was 95.7%.

28) Edward P. Sarafino, Mara Gates, Daniel DePaulo:- This study examined the age connexion in asthma diagnosis in connexion to the subsequent impacts of twelve common asthma causes which are either physically or psycho-socially highly mediated. The causes were physically focused on air pollution, tobacco smoke, high humidity, temperature / low environmental, allergy issues, respiratory infection, physical activity and evening hours; Stress or anxiety , frustration, rush, laughing. In a broader analysis of biological and psychosocial causes in asthma and other asthma, the data were obtained with questionnaires from family members of asthmatic children (n = 115), ages 2 to 20 years. For later diagnosed children, the results of all four psychosocially induced asthma attacks were far greater than the results of early diagnosed children

29) Almin Badnjevic, Lejla Gurbeta, Eddie Custovic:- In this analysis, several broad data sources are linked in order to establish an epidemiological model to predict the prevalence of asthma in geographic regions. You use (1) Twitter social media tracking (N = 500 million tweets / day), (2) the BRFSS (N = 464 664) and (3) the American Group 2014. The following are: U.S. (ACS) sample Survey Office of Census (N = 3.5 million annually). In the typical survey (BRFSS), they predict asthma prevalence using social Media and socioeconomic variables collected from Twitter collected by ACS. The proof indicates that asthma tracking tweets might be possible Provide details to forecast results from conventional surveys in real time

30) Noreen M Clark, Julia A. Dodge, M.S. Smita Shah, Lara J. Thomas, Rebecca R. Andridge and daniel Awad:- Describe a large population of low-income African American children during this period of developmentally significant, the degree of asthma severity and control, and the clinical regimes. Parents of 1,292 children of asthma were enrolled in a study of low-income neighbourhoods in Detril, Michigan among 6,827 students at 19 middle schools in predominantly African-American schools. Data were gathered by means of autonomous surveys and telephone interviews and were used by 936 participants. Demographic, asthma symptom and medical use research queries. Study questions. A random intercept for school was used in mixed effect models Destination and control determination and association of medical regimens to these.

31) M. Mozaffarinya, A.Reza Shahriyari, M. Karim Bahadori, A. Ghazvini, S. Shamsadin Athari, G. Vahedi:- The goal of this study was to examine important factors in the onset / growth of asthma that are central to an accurate disease diagnosis. The results were analysed using MATLAB and RapidMiner and were evaluated using a decision algorithm. The results were evaluated. A major factor in childhood asthma was also found in family history. The results of the study are consistent with expert doctors, supporting their ability to produce information from test data and creating an accepted diagnosis.

32) Khaled M. Gharaibeh and Orabah Al-Momani:- The conclusion of the presence of asthma attacks in asthma patients is based upon fuzzy logical data fusion of the heart rate (HR), respiration rate (RR) and oxygen saturation (SpO2). The results show that the fusion of these vital signs by fuzzy data eliminates the strict threshold values used in the rule-based data fusion of these vital signs and thus better decisions about the intensity of asthma episodes can be reached especially in remote health monitoring settings.

33) Mahmood Al-Khassawench, Suzan Bani Mustafa and Faisal Abu Ekteish:- The approach suggested is based on cough sound for the elimination of functions that assist in the diagnosis of asthma. We also sell an asthma attack surveillance hardware framework. A self-designed computer programme written in MATLAB using several asthmatic and non-asthmatic cough sonority samples, was used. The framework was developed and implemented.

34) Gadge PB and Rode SV:- A time-frequency and spectral power estimation algorithm to classify wheats with a high sensitivity that have been built and validated by doctors by listening to every individual RS section. Wheeze include ample information about the obstruction of airways in individual asthmatic patients in RS signal as the frequency of obstruction components of RS are higher than the power spectrum can easily identify. The findings show very large changes between a typical healthy person's RS signal and an asthma patient. Differences were also important with regard to frequency and other examined elements, which

are significantly higher than 1300 Hz in the usual subject range below 600 Hz and those peak frequencies are considerably higher among asthmatic patients.

35) Almir Badnjevic, Lejla Gurbeta, Mario cifrek, Damir Marjanovic, Verlab d.o.o., Sarajevo, Bosnia and Herzegovina:- A method for asthma classifying based on fluid rules is described in this paper. The Guidelines of the Global Asthma Initiative (GINA) and consultations with long-term pulmologists are described as "fuzzy laws." A mixture of Spirometry (SPIR) and Impulse Oscillometry Method (IOS), which are inputs into fuzzy framework, is used to evaluate the intensity of asthma. 1250 medical reports by pulmologists were retroactively checked, 728 were of them Safe people were diagnosed with asthma and 522. On that data collection, 91.89 percent and 95.01 percent respectively were calculated for sensitivity and specificity.

Conclusion table to identify different algorithms used in asthma diagnostic systems

Sr. No.	Year	Algorithm	Tools	Parameters	Accuracy
1	2016	Metabolomics Approach	-	15	-
2	2016	-	-	-	-
3	-	-	SAS Statistical Tool	-	-
4	2007	-	SPSS 13 Software	-	-
5	2009	Logistic Regression Model	SPSS 15.0-complex sampling design model	9	-
6	2005	Multivariate logistic regression	Stata Statistical Software	6	-
7	2007	-	Stata 9.0	-	-
8	2014	Bayesian Network	R	30	69.90%
9	2019	Precision Tree Resolution Algorithm	Rattle R, Weka	-	50
10	2002	Chi-Square	-	-	76.5%
11	2015	Logistic Regresion	-	-	-
12	2011	Multivariate Regression	Stata version 10 software	16	-
13	2019	Decision Tree	Rapid Minor	36	79%
14	2017	Deep Neural Networks	Tensorflow and Multivariate Databases	6	75%
15	2015	LogisticRegression	-	-	-
9	2017	Machine Learning Algorithm	MedCalc 8.2	7	88%
10	1996	Neural Network, Case Based Reasoning, Discriminant analysis	Microsoft Visual Basic, R	3	96%(Neural Network for asthma), 80%(Discriminant analysis
11	2014	Data mining and fuzzy inference system	Weka, Matlab, tanagra	9	90%
12	2006	-	STATA	¤ 3	-

13	2010	Pattern based decision tree, pattern based class association rules	-	11	86.89%(PBCAR), 87.52(PBDT)
14	2018	Artificial Neural Network, SVM Classification	R	4	89.2%-93.3%
15	2018	Anticipated Hybrid Algorithm, Data mining methods	DSS	9,17,15	-
16	2011	Multivariate Refression	Stata version 10 software	16	-
17	2015	Logistic Regression Analysis	-	-	-
18	2002	Chi Square test	-	-	76.50%
19	2018	Auto Associative Memory Neural Network Model, A Backpropagation Model, C4.5 Algorithm, A Bayesian Network, Particle Swarn Optimization	Python	-	86.67%
20	2020	Recurrent Neural Network, Convolutional Neural Network	-	-	>92.3%
21	2017	Deep Neural Network	Tensorflow and Multivariate Databases	6	86%
22	2019	Decision tree	Rapid Minor	36	82-84%
23	2019	Pearson Correlation Coefficient analysis, Linear Regression analysis, Vancouver Raman Algorithm, PCA, LDA	R	8	84%
24	2013	Least Square Support Vector Machine Classifier	-	11	95.54%
25	1997	-	-	8	-
26	-	Neural Networks, Classification, MFCC, SVM, k-NN,	-	-	93.62%
27	2015	Logistic Regression Classifier	R	8	95.70%
28	2001	-	-	-	-
29	2018	Marquardt Algorithm, Neural Network	R	7	98.70%
30	2010	-	SAS	18	-

31	2019	Decision tree	MATLAB	40	97.63%
32	2014	Fuzzy Logic	MATLAB	-	-
33	2011	Correlation Coefficient and the normalized root mean squared error	MATLAB	2	85-90%
34	2016	-	MATLAB	-	-
35	2016	Classification	-	4	95.01 %

III. CONCLUSION

This review provides an insight on asthma diagnosis systems developed by previous researchers and its potential in both clinical and research setting. The literature review was carried out on the 35 articles that satisfy the selection criteria. The table clearly discussed about the algorithms, software used in these papers and their accuracy. The research on the developed systems has been carried out for the past three decades. Research on the treatment of asthmatic patients using biomedical information technology is growing, but further research is needed. Patient electronic technologies such as computerised systems and electronic decision support. We foresee more opportunities to improve the treatment of asthmatic patients with IT solutions to create more mature and widely embraced medical records. Future system developers will implement and evaluate more advanced asthma systems.

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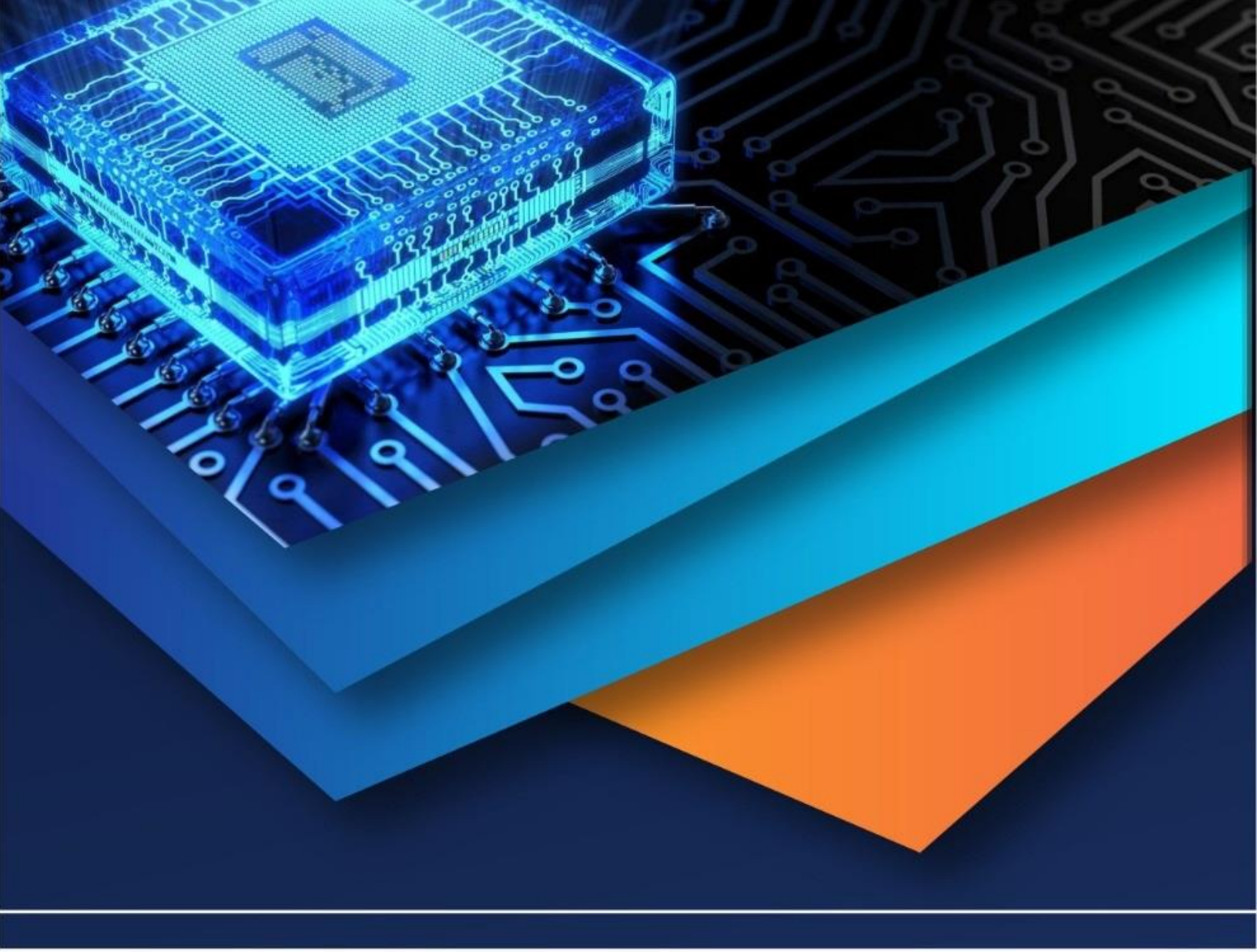

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