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Artificial Intelligence in Paediatric Emergencies: A Narrative Review

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Abstract: Background: The functionality of Artificial intelligence (AI) in paediatric practices has been gaining more attention for last five years. Since then, researchers have started observing that the techniques are helpful in dealing multiple facets of childhood diseases including emergency like situations. This article has been aimed to discuss the current status of usefulness of AI in paediatric emergencies. Methods: Total 22 research articles have been reviewed. Articles were searched from electronic database like Pubmed, Medline, Google scholar. Artificial intelligence, machine learning, paediatric emergencies, childhood diseases were the key words used to ease the search. Results: Out of 22, 15 were chosen as relatable to paediatric emergency situations per se. After reviewing the available literature, the utility of AI in paediatric emergencies had been discussed under four sub headings: i) Diagnosis; ii) Predictive modelling iii) Assistance in Antimicrobial stewardship iv) Management of emergency department resources. Conclusion: AI and different machine learning techniques have been proven as reliable accompaniment of paediatricians. They can provide their support in terms of early diagnosis for example the septic shock in children, prediction of disease severity like in the cases of traumatic brain injury, drug doses and emergency resource management. Lack of research on extensive data on far reaching population, legal and trust issues and unfriendly software's are the challenges those need to be resolved for utilizing AI at its higher potential in paediatric healthcare.

Keywords: Artificial Intelligence, Paediatric Emergencies, Childhood Disease, Machine Learning, Algorithms

1. Introduction

The commencement of applications of Artificial Intelligence (AI) in healthcare happened in 1980s when for the first time the speech recognition software was commercialized based on statistical predictive models [1]. Presently, a huge development can be seen in the implications of various AI technologies in sectors of clinical settings and medical research. The term artificial intelligence had been coined by John Mccarthy in 1956. AI is described as the use of computer and technology to simulate intelligent behavior and critical thinking comparable with human brain.

The use of AI techniques in medicine can be bifurcated in terms of their areas of implications: i) virtual ii) physical. The virtual part deals with all types of electronic health record systems and develops algorithms. These algorithms provide additional computational powers to evidence-based medicine and clinician's decision-making abilities in the fields of diagnosis and disease management. The physical part is related to robotics assistance needed during various surgical procedures and smart devices utilized for specific patient care. The computational intelligence in medicine can be developed by various methods, based on two approaches: i) the flow chart approach ii) The database approach. The flow chart-based approach translates the process of history taking into probable diagnosis whereas the database approach utilizes the deep learning techniques to generate patterns and recognize the particular graphical or image-based representation [2]. After the explosion of electronic medical records in last 20 years, it is need of the time to manage and utilize the database in the development and maintenance of modern medical information system. AI solutions enrich the knowledge based medical systems by handling data of medical records, medical imaging technology, preparing the intelligent drug design, optimizing clinical decision making and treatment plans [3]. As in other branches of medicine, in paediatrics also, AI applications are being implemented and recommended by researchers to utilize these techniques in routine clinical practices.

Clinically, treating paediatric population is way more different and strenuous as compared to adult population in terms of symptoms identification, disease diagnosis and chaotic situations in emergencies. So, the usefulness of AI solutions becomes more significant in wholesome clinical management in paediatrics. Thus, the present review article is aimed to discuss and describe the current status of AI applications in Paediatrics with main focus on emergency situations.

2. Methods

The article has been prepared after reviewing 22 original research articles collected from electronic database e.g. Pubmed, Medline and Google Scholar. The data search was done with help of following key words: Childhood diseases, Machine learning, Artificial intelligence and Paediatric emergencies. The obtained information had been arranged and discussed under various headings and subheadings.

3. Results

Total 22 original research articles have been reviewed and utilized for writing this narrative review article. All were related to the applications of AI into paediatrics. Out of 22, 15 were found considerable for discussing further as they were directly or indirectly matching to our search of applicability of AI into paediatric emergencies. It had been first documented and published in 1984 where the computer assisted medical decision-making system called SHELP was introduced. It was aimed to diagnose inborn rare metabolic disorders. Thirty years later this system has been successfully implemented by clinicians in Boston's children hospital to diagnose rare paediatric diseases [4]. Since last 15 years, in paediatric population many researchers studied to establish the usefulness of AI as diagnostic tool of diseases like pulmonary hypertension, Childhood asthma, community acquired pneumonia, screening tool for autism and analytic tool for genetic studies. Machine learning, one of the subsets of AI, has been proven itself in developing diagnostic models of various diseased conditions. Machine learning recognizes the specific pattern of data and take actions to reach the pre-set goals in self-running mode [5]. Gomber-Maitland et al. has developed deep machine learning model for diagnosis of rare disorder, pulmonary hypertension in paediatric population. In this study, the authors first time have put the data in dual analytical system i) the usual statistical comparative analysis and ii) the Bayesian co morbidity network. The Bayesian co morbidity network provides additional information of 186 co morbidities found in children with pulmonary hypertension and helps in development of understanding towards the disease [6]. Similarly, the deep machine learning algorithm has been developed to predict autism related behaviour in infants according to data obtained from MRIs of brain [7]. Neonatal daily care is an important task that can make clinicians landed up in emergency medical scenario once ignored. AI has been proven effective tool in daily neonatal monitoring also, especially for neonatal jaundice [8]. Some researchers have implemented AI in genetic studies in patients of cleft lip and palate and reached to some promising results [9]. As AI provides operational efficiency, in addition to effective disease management, it works positively in maintenance of good paediatrician-patient relationship [10]. As per the available literature, the utility of AI in paediatric emergencies can be discussed under these subheadings in the discussion: i) Diagnosis ii) Predictive modelling iii) Antimicrobial stewardship iv) management of emergency department resources.

4. Discussion

4.1. Diagnosis

Acute appendicitis is one of the major causes of emergency surgery in children and adolescents. Reismann J et al developed a model that helps in diagnosis of appendicitis along with the severity of inflammation present. Their model was found useful to prevent unnecessary surgeries in 66% of cases and 33% sensitive for uncomplicated cases [11]. A small yet helpful study has been done by Michael Schmucker et al. In which they observed the efficacy of machine learning based assistance system in determining the dosage according to weight during paediatric emergencies. They found out that newly developed AI methods are not technically inferior to conventionally developed methods [12]. Sepsis is one of the antecedents of infant's morbidity and mortality worldwide especially in preterm babies. One third of preterm neonates develop sepsis during their NICU stay. Delayed antimicrobial therapy has been observed as an independent risk factor for multiple organ failure and mortality. To inscribe the challenges associated with early sepsis recognition and care management, machine learning and statistical modelling methods have been applied in some studies. Some are done to evaluate the risk of septic shock hours before its onset and some are focused on confirmation of clinical suspicion before the blood culture reports are delivered [13-15]. Masino AJ et al aimed their study to develop a machine learning based model which can predict sepsis developed in NICU even earlier that is at least four hours prior to clinical detection. They developed and trained eight machine learning models to differentiate input data from control and case windows as either sepsis negative or sepsis positive. The results of their study show that machine learning models can be used to detect infant sepsis prior to clinical recognition help in clinical decision making by screening out false cases. Out of those eight models' logistic regression model has shown extra-ordinary performance while being most resilient to over fitting [16].

4.2. Predictive Modelling

Traumatic brain injuries (TBI) in childhood population are putting a great burden on paediatric emergency services. In a study, researchers have developed machine learning tool to predict the severity of traumatic brain injuries in the population aged < 16 years. Their study was aimed to produce a machine learning model that can support the prediction of moderate to severe TBI cases especially in the places where the rate of CT scanning is traditionally low. To predict the severity of TBI cases, two models were developed and compared: 1. Multivariable Logistic regression model 2. Machine learning model. The first model showed that the following four variables were significantly different in cases of TBI (N=39) over controls of non-TBI (N= 156): Involvement in road traffic accident, a history of loss of consciousness, vomiting and signs of base of skull fracture. The machine learning model has been developed by using three extra variables: presence of seizure, confusion and clinical signs of skull fracture. The second model has been proved as better predictive tool over the statistical model with respect to the area under the ROC curve (0.98 vs 0.93), sensitivity (94.9% vs 82.1%), and specificity (97.4% vs 92.3%). It has been recommended that machine learning models, if validated on larger sample size, have the potential for guiding the clinicians to use of CT scanning optionally as well as to select the cases of head injuries who need the continuous monitoring in EDs [17]. Similarly, another group of researchers has formed a machine learning model to predict the risk of development of intra-abdominal injury after blunt abdominal trauma. They have divided the paediatric cases of blunt abdominal trauma (BAT) into two models: i) low risk model ii) high risk model. Six algorithms have been tested for having the potential to identify the BAT cases which can transform into high-risk intra-abdominal injuries requiring intervention (IAI-I). For high-risk models, all six algorithms have been observed having greater predictive power compared with the baseline rate with highest reportable risk as 39%. On the other hand, for low-risk models, four algorithms have been found with better prediction rates over the baseline rates. This study recommends that by using such type of modelling in a web-based application, child specific risk of IAI-I can be estimated ranging from 0.28% to 39% [18].

4.3. Assistance in Antimicrobial Stewardship

Antimicrobial resistance (AMR) is a newly found challenge in public health sector and considered as a global public health emergency. Being highly susceptible to infectious diseases, antibiotics are most widely prescribed in paediatric population. Sometimes these prescriptions are inappropriate, unnecessarily lengthy and loaded with broad spectrum antibiotics when targeted therapy is needed. All of these practices will promote the emergence of multi drug resistant pathogens that results in longer hospital stay, increased healthcare costs and increased mortality. Antimicrobial stewardship is the implementation of strategy to address this fast-growing issue of community health. Application of artificial intelligence is being explored in this field and has been proven potentially helpful in many aspects of prediction and management of infectious diseases with appropriately prescribed antimicrobial therapy in children [19].

In 2014, Beaudoin M. et al. developed and deployed the Antimicrobial Prescription Surveillance System (APSS) to identify inappropriate prescriptions. Their study featured a specific design of self-improved knowledge system based on the user feedback and prescription surveillance. It is a deep machine learning model that keeps itself on learning mode unlike the Neural Networking (NN) model which can't be changed after the onset training. In the later stages APSS is reported helpful during the transition of intravenous to oral antibiotics too [20]. However, in later studies this system was not found sufficiently working by antibiotic stewardship experts.

Researchers have observed the pharmacokinetic variability is an important factor in therapeutic failure and morbidity in children suffering from Tuberculosis by applying the AI algorithms. They also found the threshold of drug concentration that can predict the poor outcomes. 143 Indian children were included in the study and followed up till the completion of their therapy. Out of 143, 110 completed the therapy, 24 failed to complete and 9 were died. Incorporating AI algorithms, including random forests have been used to identify isoniazid and rifampicin, at particular concentrations, as predictors of poor clinical outcomes in children < 3 years old [21].

4.4. Management of Emergency Department Resources

Appropriate judgement regarding the need of hospitalization plays a key role in efficient management of the emergency department resources. In casualty admissions, AI can provide better insights in order to determine the need of hospitalization as compared to conventional triage approaches. Machine learning based triage approach enables the clinicians to predict clinical outcomes and dispositions in a better way [22].

In order to predict the requirement of hospital admission in case of paediatric asthma during EDs, researchers have developed machine learning models by collecting the triage data. Shilpa JP et al. have applied four models: classification decision trees, logistic regressions with L1 (LASSO) regularization, random forests, and gradient boosting machines. Three of them have been proven as effective models for determining the requirement of hospitalization in EDs. Decision trees has been proven worst performing model. They reported that after patient's vital signs and acuity, age, weight, socio-economic status (SES) and weather conditions play the important role in predicting the need of hospitalization [23]. Whereas, in another study, Marion RS et al. analyzed 9,069 ED visit data and constructed two machine learning models: one was based on data available at ED triage and second on the data available within one hour of ED visit. They found the Auto ML models can improve the clinician's ability to predict the need of hospitalization. An outcome at the prior visit, Emergency Severity Index (ESI) score, time to first medication and time to triage are the most important predictive features among all [24].

Some researchers in Taiwan worked on predicting the return visits in EDs by applying Decision tree model. They observed that out of 125, 940 visits, 6,282 (5%) were followed by return visit within 3 days. Age, complete blood count, need of putting on IV fluids and level of hospital care were few predicting factors for estimating the probability of return visit. Once it is predicted, the paediatric emergency care qualities can be improved [25].

Thus, the applications of artificial intelligence and its algorithm-based processes in paediatric emergency care have been demonstrated as high yielding incorporation by many medical researchers. However, AI is not still in use with its whole potential because of not so paediatrician friendly software, some legal and trust issues and lack of research on extensive and far-reaching population [26].

5. Conclusion

In medical research, after using clinical database, AI applications have been emerged as promising tool to deal with various healthcare situations. As far as paediatric emergencies are concerned, these techniques are going to be established in the niche of diagnostics, predictive markings, treatment strategies and effective management of hospital resources. This discussion has shown that implications of AI methods are expanding among paediatric population. It has a huge potential to provide valuable healthcare with high accessibility and good affordability even during emergency conditions. Despite of delivering such optimistic results by the researchers, it has a long way to reach to the ultimate users. Requirement of standardized and larger data sets, privacy policies, regulatory affairs and ethical issues are still acting as the challenges for transforming researches into paediatric bedside disease management.

Abbreviations

ED: Emergency department
ML: Machine learning
NN: Neural networking
AMR: Anti-microbial resistance
APSS: Antimicrobial Prescription Surveillance System
ESI: Emergency severity index
IAI-I: Intra-abdominal injuries requiring intervention (IAI-I)
AI: Artificial Intelligence
TBI: Traumatic brain injuries
BAT: Blunt abdominal trauma

Conflict of Interests

The authors declare that they have no competing interests.

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