

MACHINE LEARNING IN HEALTHCARE

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Abstract: *Electronic health records (EHRs) is a digital method of collating patient's medical history, treatment plans and test results. It has proven itself more efficient and advantageous in healthcare delivery system over the traditional use of case notes in many regards such as cost effectiveness, easy accessibility, and portability and so on. However, developing countries like Nigeria have made little effort to adopt the use of this electronic way of keeping health records. This paper reviews the various instances in which machine learning has been used for electronic health records and its many advantages over case notes. The first section presents the introduction of the review, the next section discusses the machine learning in healthcare, the succeeding section contains the various applications in which the technology has been applied for efficient healthcare delivery in recent times and its advantages as well as its prospects and the last section gives the conclusion of the review.*

Keywords: *machine learning, electronic health records, artificial intelligence, healthcare, medical history*

INTRODUCTION

Technology is currently revolutionizing every facet of life in that it is gradually changing perspectives of how different tasks are carried out in recent times presenting more effective solutions to problems and inevitably cutting through several industries. The healthcare sector is however not left in the dark as technology is seeping through to make healthcare delivery very safe, efficient, accessible, cheap and reliable [1] However, despite the numerous successes in healthcare so far in the world, it should be noted that utilizing technology in healthcare is by far one of the most complex tasks compared to other industries. Plsek and Greenhalgh [2] opined that healthcare is a complex adaptive system. This, presumably, may be the reason some developing countries are yet to fully adopt the use of technology in healthcare delivery, especially the electronic way of collecting and keeping health records even though its benefits far more outweigh the many challenges encountered in many regards.

The use and adoption of electronic health records (EHRs) has increased in the past decade around the globe [3]. This increase has been measurable due to strategies and agencies that incentivize their use such as the Health Information for Economic and Clinical Health Act in the United States [4], the National Agency for Health IT in Denmark, and the National eHealth Authority in India [5]. As a result, methods that leverage EHRs to answer questions tackled by epidemiologists [6] and to increase precision in healthcare delivery are now commonplace [7]. It was suggested that EHRs have values in two dimensions: clinical and financial [8]. Even though the full utilization of these dimensions will find great use in the Nigerian healthcare, it's rather a great news to say that the financial dimension is already partly catered for in major hospitals across Nigeria. Primarily, this paper will focus on the clinical dimension of EHRs and how they can be effectively utilized with machine learning. The backbone of the EHRs is the availability of clinical data to use. Machine learning is driven by a data explosion combined with increasing computational power, and classical epidemiology is now incorporating newer data science techniques to harness the power within population data [9].

2. MACHINE LEARNING IN HEALTHCARE

According to Blackford & Ngai [8] Machine learning is a good enough statistical mode which involves the use of observed clinical data to predict outcomes and or categorize observations in future data. Machine learning is an aspect of Artificial Intelligence which utilizes computers to detect unseen perception of healthcare data without using any computer programming [10]. In a recent research by Orion Health, it was stated that there are two essential requirements for machine learning to thrive in healthcare. The first is an intelligent algorithm and the other is rich datasets [11]. These intelligent algorithms are able to interface and investigate clinical the enormous amount of data present and predict recommended treatment plans for each unique patient.

Machine learning algorithm can be grouped into two major categories: supervised and unsupervised learning [12]. The unsupervised learning is well suited for extracting data features, while supervised learning method trains a model used for prediction by using observations on sample clinical data with a known predicted patient datasets through links between the patients traits (as input) and the outcome of interest (as output) [13]. This resulting trained model is then applied to new clinical data to categorize or predict values of outcome for previously unseen clinical data. These predicted values are compared with actual value to determine their performance. The breath of Machine learning is algorithms which are used to train the models [13]. The relevance of supervised learning cannot be overemphasized as it is specifically applied predominantly to healthcare. Out of the numerous algorithms techniques in supervised learning, the crucial ones attributed to healthcare delivery are Naïve Bayes [14], Support vector machine [15], linear regression [16], and logistic regression [17], nearest neighbors [18], random forest, and decision tree [19]. These algorithms can and have been applied in healthcare and have yielded tremendous results, some of which are assessed in the next chapter. Datasets is the compilation of several patients' age, gender, diagnostic imagining, gene expression, physical examination results, clinical symptoms, medications, recovery time etc these compilations are needed to efficiently utilize machine learning in healthcare delivery. The availability of these patient information, usually grouped as datasets are pivotal to the advances in machine learning compared to algorithm. When Garry Kasperov the chess grandmaster was defeated by IBM's Deep blue, the algorithm used was 14 years while the dataset was only 6 years [20].

2.1. Machine Learning For Malaria Diagnosis

In 2016, about \$2.7 billion was invested in malaria control and elimination efforts globally, 74% of this investment was spent in Africa. 37 out of 46 countries in the World Health Organization (WHO) African Region indicated that at least 80% of public health facilities had reported data on malaria through their national health information systems. Among 55 countries where the burden of malaria was estimated, 31 countries have a malaria case reporting rate by surveillance systems of less than 50%. This includes high-burden countries of India and Nigeria [21]. Thus, a diagnostic system for early detection of malaria becomes imperative in these countries.

Ugwu et al [22] developed a malaria diagnostic system using machine learning algorithm (Decision Tree) as the knowledge base. During the diagnosis, symptoms are provided by the patient in the diagnostic system, a comparison was made to find a match for the symptoms provided in the knowledge base. Presence or absence of a match indicates that diagnosis is achieved or not achieved respectively.

Another technique discovered by a different group of researchers involves the use of image analysis software and machine learning to quantify parasitemia in microscopic blood slides i.e. detecting malaria [23]. The technique involved in quantifying parasitemia automatically requires that first, the digital image of the blood slides be preprocessed. Secondly, the blood cells are to be detected after which it will undergo a process called cell segmentation to give accurate cell counts. The third step involves the feature extraction to visually describe which cells are infected or uninfected. Finally, a classifier trained from the available manual annotated training sets distinguishes between the infected and the uninfected. With the classification known, the quantity of parasitemia present can them be determined using mathematical equations.

2.2. Machine Learning in Neurological Predictions.

In many different instances, Machine Learning has been employed in the field of neurosurgery for a variety of applications owing to its capabilities in giving accurate medical cases predictions. Most notably for patients undergoing surgery for [brain tumor](#) [24] [25], [traumatic brain injury](#) [26], epilepsy [27][28], movement disorders[29], neurovascular disease [30], spinal lesions[31] and hydrocephalus[32] to predict and determine survival, recurrence, symptom improvement and possible adverse event outcome of the surgery. After a review of thirty studies that utilized ML algorithms in [33], it was confirmed that the most frequently used algorithm for neurosurgery are artificial neural network (ANN) [34] and support vector machine [35]. The review also gathered that the type of inputs features used depended on the specific prediction task to be done.

The outcome of Machine learning models in neurosurgery prediction is more reliable when compared to other predictive models due to the better accuracy estimated to be with median accuracy of 94.5% interquartile range (IQR) of 87%-95%; 63%-98% and an area under receiver operating curve of 0.84.

2.3. Predicting Suicidal Behavior from Longitudinal Electronic Health Record

Barrack-Corren et al [36] utilized the naïve Bayesian algorithm to mine through the 1.7 million clinical database of over 15 years (1998 -2012) made available by EHRs to predict future suicide attempts and deaths. In this study, the naïve Bayesian algorithm was used to train half of the data so that it could efficiently predict the other half of the data. The predictive ability was measured and found to yield an accuracy of (35%-49% sensitivity at 90%-95% specificity) and, critically, early (3–4 years in advance on average) prediction of patients' future suicidal behavior. This laid down model can serve an early warning system to help clinicians to quickly identify high risk patients so as to give adequate treatments and for further screening. It was however argued that the naïve Bayesian algorithm though was well suited for the job, however, it was a simple approach compared to deep learning [37], neural network [38] and ensemble methods which will achieve notable increase predictions [39].

3. ELECTRONIC HEALTH RECORDS

Electronic health record (EHRs) is a digital method used to collect, organize, analyze and deliver clinical information [40]. The backbone of the EHRs is the availability of clinical data to use. The advent of electronic health record that started in 1950's propelled many hospitals in the United Kingdom (about 80%) to adopt this new advancement [41]. In the United States of America, the adoption of Electronic Health Records (EHR) has increased nine times since 2008 [42]. Despite having warm embrace of technology in a country like Nigeria, the adoption of EHR has received very minimal acceptance hence the collection of health records has been done manually using traditional paper based records methods (case notes). This paper based methods have overtime lost its relevance as it has very limited information management and retrieval capabilities [8]. Doctors and physician may find it difficult utilizing relevant information from paper charts and almost possibly, the paper charts may not be available for use due to loss. The most profound impact of EHRs, is how they efficiently are used for clinical decision support by physician at the point of and time of care [8], [43].

3.1 Application of Machine Learning to Electronic health records.

EHRs provide access to a large number and variety of variables that enable high-quality classification and prediction [44], while machine learning offers the methods to handle the large volumes of high-dimensional data that are typical in a healthcare setting [3]. As a result, the application of machine learning to EHR data analysis is at the forefront of modern clinical informatics [45], fueling advances in both the science and practice of medicine. Machine learning techniques applied to EHR data can generate actionable insights, from improving upon patient risk score systems, to predicting the onset of disease, to streamlining hospital operations [3],[46].

3.2 Advantages of EHRs over Case Notes

In 2005, Walker et al. estimated that fully interoperable EHR systems could save 5% of the US healthcare costs, but that partial interoperability would accrue much lower benefits [47]. The adoption of EHR in healthcare sector will grant an access to the bulk of clinical data lying in case notes dated years back which will enhance the potential for saving lives and cost [48].

EHRs alongside medication decision supports offered can tremendously impact utilization, reducing overuse, underuse, and misuse of medications. For example, brand to generic substitution suggestions, as well as suggestions regarding alternative cost-effective therapies, can reduce medication expenses. Complying with a patient's health plan formulary can provide savings [8].

Adopting EHR also ensures that patient data are transferred with ease to other health care providers under the permission and in accordance to standards. EHR provide up to date information of patients' treatment at one click for continual treatment hence reducing the time in searching for case notes of patients. With little or no coordination in the Nigerian hospital administrative system, the utilization of EHR in hospitals creates an efficient and coordinated environment that is patient centered.

The utilization of Artificial Intelligence and computer applications in healthcare has also made the use of medical data obtained through EHR more beneficial in the practice of medicine. For example, IBM Watson, a cognitive computing platform that has the ability to think and reason like the normal human brain uses data from previous health records of a patient and other libraries to analyse symptoms, to predict disease or medical conditions and suggest the best treatment methods [49], [50], [51]. It is used as a diagnostic support by doctors and has had great successes in cancer diagnosis and treatment even faster than human beings [52], [53], [54].

3.3 Challenges of EHRs

In every coin there are always two sides. Despite the many advantages of EHRs, Utilizing EHRs in Nigerian hospitals will face diverse challenges which include poor usability, time consuming data entry, interference with face to face patient care, degradation of clinical documentation and inefficient work content [41]. Most of these challenges occasionally stem from users not willingly ready to accept the emergence of technology in healthcare as they are already used to the traditional systems [55]. Also, the initial cost of setting up EHRs is very high hence [56]; most hospitals do not wish to spend so much with the availability of cheap traditional means in spite of the flexibility and advantages of EHR over the paper-pencil method. Alongside the cost, there is very few manpower to handle them. Therefore, once faults are discovered, and there is no technical know how to do the repair, the return of the traditional case notes gradually becomes the order of the day.

4. CONCLUSION

The early adoption of Machine learning and EHRs in Nigerian healthcare will set a pedestrian of delivering the greatest value of healthcare than an African country i.e. from surgery to medications predictions. As machine learning, using EHR data, touches a large number of healthcare problems, it will motivate applied research in statistics and computer science. Eventually, machine learning approaches combined with EHR may make it feasible to produce fine-tuned, individualized prognostic models, which will be particularly valuable in patients with conditions or combinations of conditions which would be very difficult for conventional modelling approaches to capture. Future studies should explore the challenges with ethics, social implications of their adoptions.

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