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STUDY ON AN IDENTIFICATION OF CHRONICAL DISEASE PREDICTION USING ARTIFICIAL INTELLIGENCE AND BIG DATA

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Abstract : Knowledge driven from technology has always benefited the human being to large extent. Few years back during 20th mid-century, what was figment of the imagination of many scientists, Artificial Intelligence has turned into reality. Artificial Intelligence (AI) is the simulation of human intelligence demonstrated by machines This aspect involves learning, reasoning and self-correction. AI has started bringing new revolution in the medical healthcare. The amalgamation of AI in healthcare sector has empowered the human limits. In this review article, various latest development of applications of AI in the field of biomedical including diagnosis and prediction analysis of disease is highlighted. There are certain challenges as well in imbibing the AI framework in medical. The healthcare industry is expanding and rising every year. With this there is huge volume of data generated. As the data grow exponentially, the implementation of machine learning and big data helps in filtering the required data from huge volume of data and turn it into actionable information. Disease always shows the different condition and effects gradually in the diagnosis. But many a time due of lack of correct analysis, disease are not diagnosis prior. This study highlights the different strategies and algorithm used in machine learning, artificial intelligence and big data. This study covered different articles which highlights the various methods and algorithms used to search best optimal way to predict the disease. The data is captured either with Electronic Health Record (EHR) or Medical Health Record (MHR).

IndexTerms - Artificial Intelligence, Big data, Biomedical, Machine learning, Algorithm, Electronic Health Record, Medical Health Record

1. INTRODUCTION

AI is a field of computer science capable of copying human characteristics, learning ability and knowledge storage. It performs human brain tasks in most areas in all aspects of our daily life using big data applications. Supercomputers analyze large amounts of data using the algorithms of advanced deep learning machines, which has enabled improved performance in the field. This area has brought very needy and huge improvements in all aspects of life, especially in healthcare. Big data analysis is introduced to biomedical sciences; The main source of big data has been discussed and explained, especially in the fields of oncology, cardiovascular disease, allergic disease, clinical work, ear disease and so on. Besides this, it also touches on some aspects of the need to combine multiple pathological and clinical sources and quality of life data [1] as well as the unprecedented and quantitative datasets of neuroscience [2]. Medical care and treatment is improving day by day. Researchers collect data to make human care and disease diagnosis efficient and operational. Doctors are skeptical about what artificial intelligence can do for them in their doctor's office. Studies have examined an understandable experience that encompasses all the challenges, risks and comforts since the implementation of AI programmed using healthcare big data in a contagious disease environment. The aim of the program was at designing a set of tools which can support an accurate, objective, and clinical decision-making process efficiently [3]. In biomedicine, there are many ways to collect data from observation and experiments. Scientists are often struggling to collect data about the disease and on how data are being generated for the treatment of disease. This biomedical information is to create thinking, managing, and analyzing and the way they can transform into further scientific perception for enhancing patient care. This is the major challenge for the National Institutes of Healthcare (NIH) to lead the big data to knowledge representation. The agencies are making efforts to collect increasingly data with increasing research productivity. Leading centers are developing to handle this type of cases with large-scale data. They are going to research how much accurate equipment is required for the new generation of biomedical data scientists. In today's world, NIH and Big Data to Knowledge (BD2K) seek the position of data sciences in biomedical research [4].

The term big data has become very popular around the world in recent years. Almost every research area, whether industry or science, generates and analyzes big data for different purposes. The biggest challenge with this huge mountain of data, which can be organized or disorganized, is managing it. Given that big data cannot be handled with traditional software, we need technically advanced applications and software that can leverage high-end, fast and inexpensive computing power for such tasks. The implementation of artificial intelligence (AI) algorithms and novel fusion algorithms would be necessary to make sense of this large amount of data. Indeed, it would be a great achievement to achieve automated decision-making by implementing machine learning (ML) methods such as neural networks and other AI techniques. However, without proper software and hardware support, big data can be quite hazy. We need to develop better techniques to deal with this endless sea of data and intelligent web applications for efficient analysis to gain actionable insights. With appropriate storage and analysis tools, the information and insights gained from Big Data can make the critical components and services of social infrastructure more efficient. In addition, the user-friendly visualization of big data will be a crucial factor in the development of society.

Health information technology (HIT) is designed due to the solution of complex problems such as health disparities. Mix results can be obtained by demonstrating a direct impact on health outcomes. For all these, we must know about collective intelligence, big data, informatics capacities, corresponding terms of smart health, knowledge exchange knowledge, ecosystem, and situational awareness. Standards, guidelines, and objections are established by public health informatics for health equity and health disparities, which will increase health literacy and access to care. HIT [5] bring many benefits to healthcare, such as Improving the quality or effectiveness of health care, increasing the productivity or effectiveness of health care, preventing medical errors and increasing accuracy and procedural correctness in health care, developing administrative efficiency and work processes in health care. Big data in healthcare promotes the realization of the goals of diagnosis, treatment, cure and support of all patients in need of healthcare, pointing directly to the ultimate goals of improved performance or the quality of care that healthcare can provide to the end users (especially patients) in the health and medical sector. HIT has greatly promoted the management of hospital operations and the efficiency of diagnosis and treatment procedures, bringing convenience to patients and saving costs. The benefits of health-related big data have been scrutinized in three aspects, namely preventing disease, identifying modifiable risk factors for disease, and designing interventions to change health behaviors.

Due to the rapid development of AI software and hardware technologies, AI has been applied in various technical fields, such as the IoT [6], machine vision [7], autonomous driving [8, 9], natural language processing [10,11], and robotics [12]. Most interestingly, researchers in the biomedical fields have been actively trying to apply AI to help improve analysis and treatment outcomes and, consequently, increase the efficacy of the overall healthcare industry [13–15]. The growth of interest is obvious, especially in the last five years, and continued growth in future can be forecast. The benefits that AI can offer to biomedicine were envisioned a couple of decades earlier [16]. In fact, reviews have been published on the role of AI in biomedical engineering [14,15]. More recently, new progress has been made in AI and its applications in biomedicine.

Engineering science, in a nutshell, encompasses a variety of applications throughout healthcare. Through leading descriptive, predictive and prescriptive capabilities, AI in medical services in India is ushering in right now to empower the human frontier rather than replace all human labor. There are certain challenges for adopting AI in healthcare in India. There is a need for a sustainable policy framework to manage the protection and trustworthiness of information while addressing issues of social recognition, consent, risk and resolution capacity. AI-enabled specialists can collaborate with physicians to search, discover, introduce and apply the latest clinical and medical knowledge, Companions and analysts that improve overall physician productivity and limit and style of care [17].

This paper reviews recent breakthroughs in the application of AI in biomedicine, covering the main areas in biomedical engineering and healthcare. Major study is to identify the role of AI in disease prediction. The goal for healthcare is to become more personal, predictive, preventative, and participatory, and AI can make major contributions in these directions. From an overview of the progress made, we estimate that AI will continue its momentum to develop and mature as a powerful tool for biomedicine. The remainder of this paper is oriented toward the main AI applications. Section 2 includes the methodology used in this research. Section 3 includes the study of literature review. Section 4 includes a description of information processing and algorithm implementation, while Section 5 focuses on disease diagnostics and prediction. Case studies of the prediction of two medical diseases are reported in Section 6. Finally, conclusions are summarized in Section 7.

2. METHODOLOGY

The study is a based on systematic literature review along with systematic mapping study to identify and analyze research in Artificial Intelligence and big data analytics in healthcare. Fig. 1 shows total 80 articles were reviewed for the last 15 years, from 2001 to 2021. Fig. 2 shows PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) methodology were followed for conducting systematic reviews. The various techniques used in AI like deep learning, machine learning, specific methods of AI like k-Nearest Neighbors (KNN), artificial neural network (ANN), logistic Regression, Reinforcement learning etc.

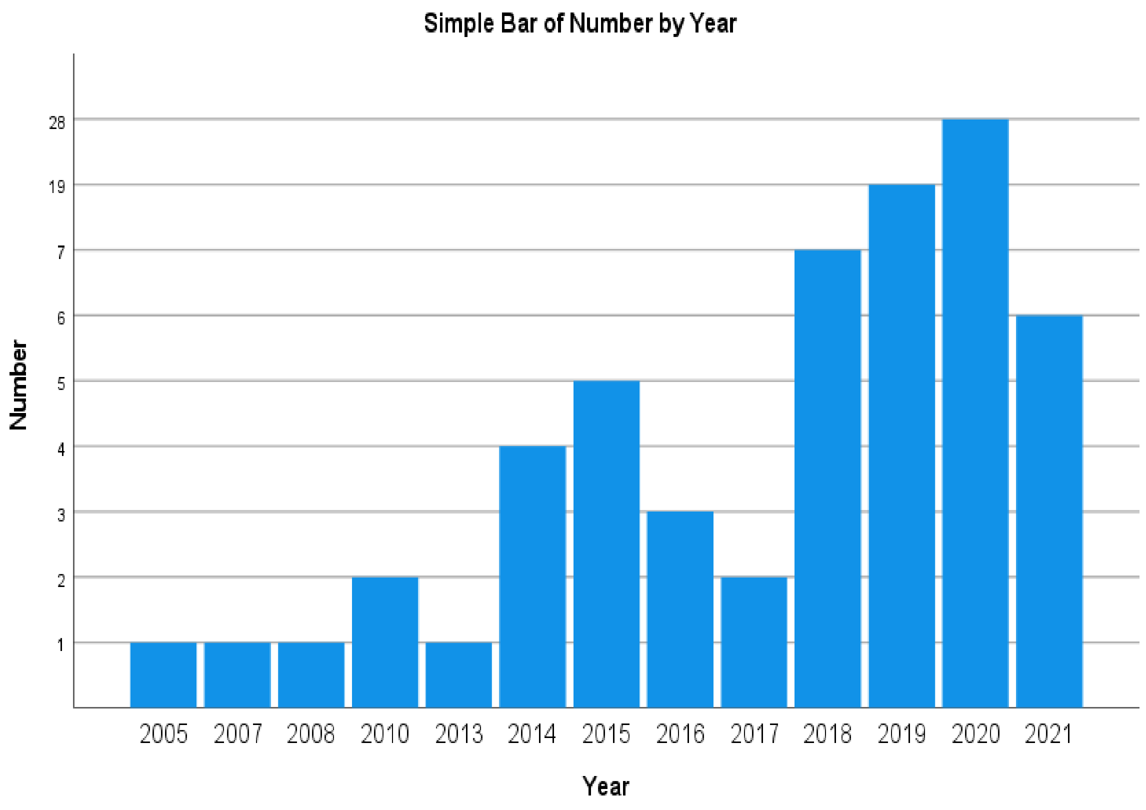

Fig. 1. The literature search was done in using web of science with the topic of "AI", "Big Data" along with the topic of "Healthcare" or "biomedical".

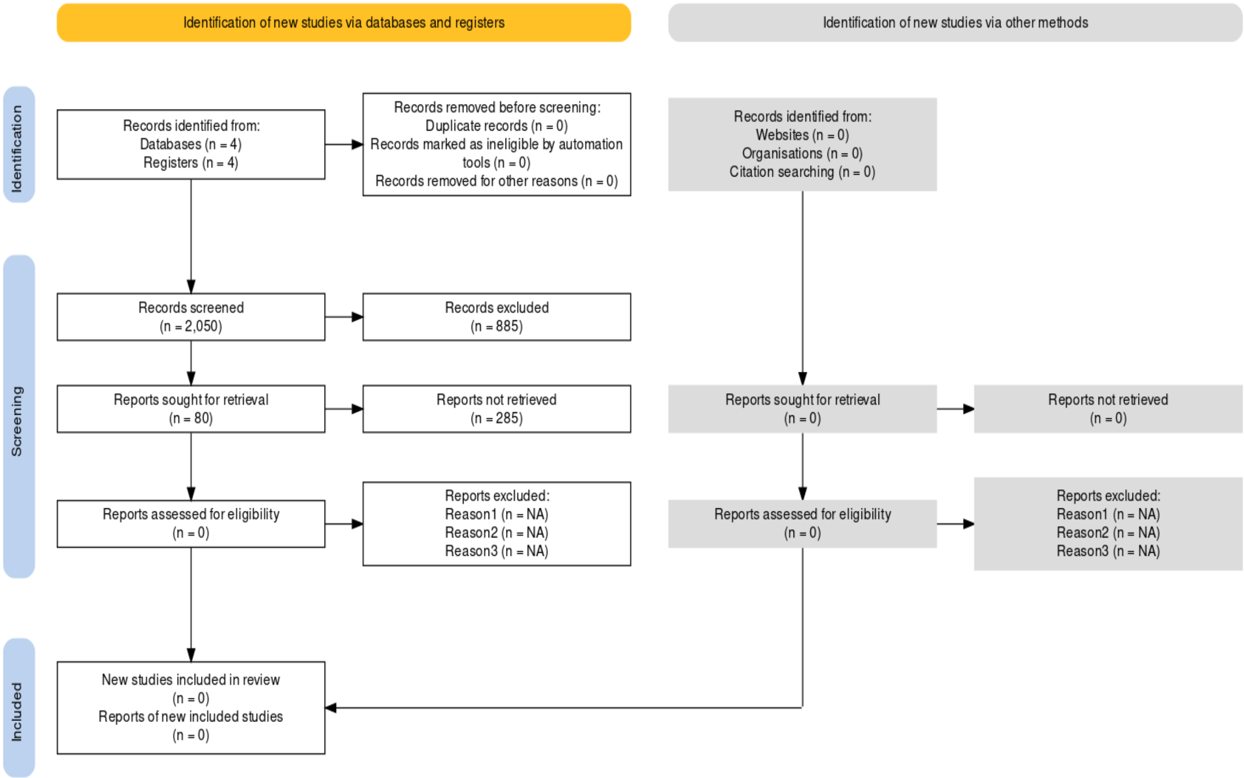

Fig. 2. PRISMA Flow Diagram (Preferred Reporting Items for Systematic Reviews and Meta-Analysis)

3. Literature Review

Heart disease is the leading cause of death in some countries. Hence to have a decision support system is required to help the clinician to take precautionary measures. Author discussed the prediction of cardiac attacks with the Scikit Learn library which is a Python free library for machine learning. It will allow performance optimization [18]. It uses correlation matrix to analyse which attributes have more influence on having a heart disease. AI intervention comprises of computer vision, expert system, natural language processing, chatbots, voice recognition etc in healthcare helps managing the problem of overloaded information associated with diagnostic and treatment. According to the Author, there are major challenges as sustainable framework of guidelines to manage protection over information of data procured. Healthcare program – disease surveillance, image extraction & real time generation of clinical report [19]. In this study, author propose a context aware adaptive framework for monitoring the activities of daily living (ADL) of elderly group. HSH (Health Smart Home) and HIS (Health Information System) provides e-health services in their own home. Three category ideas are studied: Physiological systems (vital sign of illness), movement fall detection (walking, standing etc.), activity monitoring (eating, sleeping etc.) [20]. Disease diagnostics and prediction is carried out as vitro diagnostics using biosensors and biochips which detects microarray data of abnormalities. In this study, author review the categories of AI: Software perspective & hardware perspective. The study revolves around application of AI in biomedicine in four categories: 1st three deals with efficient bigdata access and last deals with the diagnostics and prediction of disease [21]. AI in living assistance, AI in biomedical Information Processing, AI in biomedical Research. F. Gao, K. Deng and C. Hu, the authors of this study showcase the construction of traditional Chinese Medicine (TCM) health management model for COVID-19 patient based on AI [22]. This article will tap the advantages of TCM resources, improve the quality of patient recovery “Rehabilitation”, break the time and space limitations of health management. Various public and private sectors industries generate, store and analyse big data with an aim to improve the services they provide. Biomedical research also generates a significant portion of big data relevant to public health care. This paper highlights the importance of an efficient management, analysis and interpretation of big data in order to derive meaningful information [23]. This research suggests that by implementing eight technology-enabled measures, pharmaceutical companies can expand the data they collect and improve their approach to managing and analyzing these data [24]. Integrate all data, collaborate internally and externally, Employ IT-enabled portfolio-decision support, leverage new discovery technologies, Deploy sensors and devices. Raise clinical-trial efficiency, improve safety and risk management, and Sharpen focus on real-world evidence. One of the solution to control the current havoc can be the diagnosis of disease with the help of various AI tools. Machine learning and natural language processing use big data-based models for pattern recognition, explanation, and prediction. Author listed many models using machine learning approaches such as detected epilepsy, electroencephalogram (EEG) signals are used for detecting, normal and epileptic conditions using artificial neural networks (ANN) [25]. The existing literature mostly examines analytics in clinical and administrative decision-making via conducting a database search between 2005 and 2016 [26]. The methodology used here is Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) and used JBI Critical Appraisal Checklist for quality research and Critical Appraisal Skills Programme (CASP) qualitative research checklist. Analytics is the way of developing insights through the efficient use of data and application of quantitative and qualitative analysis such as planning, management, measurement, and learning. Despite the volume and velocity of Big Data, it is truly about technology connecting humans and assisting them to construct knowledge in new ways. As technology continues to evolve and rise in various industries, such as healthcare, science, education, and gaming, a sophisticated concept known as Big Data is surfacing. This article port Analyses (PRISMA) methodology were followed for conducting systematic reviews. The development of analytical techniques which provides personalized health services to users and supports human decision-making using automated algorithms, challenging the power issues in the doctor-patient relationship and creating new working conditions [28]. This paper presents visual analytics (VA) tools, a nascent category of computational tools that integrate data analytics with interactive visualizations, to facilitate the performance of cognitive activities involving big data [29]. Here it is discussed that the role that VA tools can play in addressing the challenges presented by big data. In doing so, we demonstrate the potential benefit of incorporating VA tools into PH practice, in addition to highlighting the need for further systematic and focused research. PH data can be described by its high volume, great variety, high velocity and low veracity. Several factors for cancer include age, number of sexual partners, age of first sexual intercourse number of pregnancies, smoking habits, hormonal, STD's detected in the patient and any diagnosis performed for cancer and diseases like HPV (Human papillomavirus) and CIN (Cervical intraepithelial neoplasia) are the dataset. This study refers that the Cervical Cancer is one of the main reason of deaths in countries having a low capita income [30]. The best 3 models from each of them is selected and performance is compared that is k-nearest neighbor, decision tree and random forest. The proposed system is designed to enable patients capture surgical wound images of themselves by using a mobile device and upload these images for analysis [31]. Combining image-processing and machine-learning techniques, the proposed method is composed of four phases. First images are segmented in super pixels, secondly these super pixels corresponding to the skin are identified. Thirdly, surgical wounds will be extracted from this area based on the observation of the texture difference between skin and wounds, Lastly, state and symptoms of surgical wound will be assessed. Speedy growth in healthcare and the development of computation in the eld of cardiology enable researchers and practitioners to mine and visualize new insights from patient data. Data-driven approaches emphasize the extraction of meaningful patterns in the data, and they may overlook the physics governing complex biological systems that generate the data. The National Institutes of Health (NIH) supports fundamental research in all medical fields. This paper presents an approach of apt prognostic diagnostics of cardiac health by using Artificial Intelligence (AI) in safety-related based non-invasive bio-medical systems [32]. There are many challenges in identification of abnormalities in cardiac signal such as bio-signal faulted due to high noise signal interference, electronic and software fault, mechanical fault like sensor contacts failures, wear and tear of equipment. This research paper focused different AI techniques in the medical field particularly in heart disease prediction, brain disease, prostate, liver disease, and kidney disease [33]. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) method was used for a systematic review. This survey is about the use of three AI approaches in disease diagnosis.

4. Information processing and algorithm implementation

The main applications of AI in biomedicine can be divided into four categories. The first three categories described in this section are designed to efficiently process big data and provide quick access to data to solve healthcare-related problems. These applications deal with life support for the elderly and disabled, natural language processing techniques and basic research activities. The final category of AI applications relates to disease diagnosis and prediction and is analyzed in Section 5.

4.1. AI for living assistance

In the area of assisted living for elderly and disabled people, AI applications with corresponding intelligent robot systems pave the way for improving the quality of life. Recently, an overview of smart home features and tools for people with loss of autonomy (PLA) and intelligent solution models based on wireless sensor networks, data mining and AI was published [34]. NNs can be trained to recognize human facial expressions as commands using specific image processing steps. Furthermore, human-machine interfaces (HMIs) based on facial expression analysis enable people with disabilities to control wheelchairs and robotic assistance vehicles without joysticks or sensors attached to the body [35]. An environment-intelligent system called RUDO can help blind people live with sighted people and work in specialized fields such as computer science and electronics [36]. Blind people can use multiple features of this smart assistant from a single interface. An intelligent AI-based assistant can help pregnant women with nutritional and other necessary advice at crucial stages of motherhood. It is able to provide advanced level proposals through its own intelligence combined with cloud-based communication media between all stakeholders [37]. A fall detection system based on radar Doppler time-frequency signatures and a sparse Bayesian classifier can reduce fall risks and complications for seniors [38]. In fact, intelligent communication architecture systems for Ambient Assisted Living (AAL) have been developed to make it possible to collect AI-processing information from different communication channels or technologies, thus determining the occurrence of events in the network environment and the need for assistance of elderly people [39] . Smart home environment intelligence can provide activity awareness and subsequent activity support to the elderly, so that AAL environments enable aging-in-place, that is, aging at home. For example, the intelligent agent SALSA (Activity Aware Screening of Activity Limitation and Safety Awareness) can help older people with their daily medication [40]. ML in motion analysis and gait study can raise an alarm in case of dangerous actions and activate preventive measures [41,42]. Fig. 2 [39] shows the model for AAL. In this scenario, sensors collect data about the environment and human behavior, which is then analyzed by cloud computing or edge intelligence. A decision is then made as to what actions are necessary and this decision is used to activate alarms or preventative measures. An AI-based expert system, in conjunction with mobile devices and personal digital assistants (PDAs), can help individuals with permanent memory impairments by improving their memory abilities to achieve independent daily living [43]. This is a significant extension of the Memory Rehabilitation Expert System (ES-MR) for non-expert users.

4.2. AI in biomedical information processing

Breakthroughs have been made in natural language processing for biomedical applications. In the field of biomedical question answering (BioQA), the aim is to find quick and precise answers to user-formulated questions from a reservoir of documents and data sets. Therefore, natural language processing techniques can be expected to search for informative answers [44]. First, the biomedical questions must be classified into different categories in order to extract the appropriate information from the answer. ML can categorize biomedical questions into four basic types with an accuracy of almost 90% [45]. Next, an intelligent biomedical document retrieval system can efficiently retrieve sections of the documents most likely to contain the answers to the biomedical questions [46]. A novel scheme for processing one of the four basic types of BioQA, the yes-or-no answer generator derived from word sentiment analysis, can effectively contribute to information extraction from binary responses [47]. With biomedical information collected from various sources over a long period of time, many important tasks can dominate; these are the merging of clinical information, comparison and conflict resolution [48]. These have long been time-consuming, labor-intensive, and unsatisfactory tasks performed by humans. To improve efficiency and accuracy, AI has been shown to perform these tasks with results as accurate as a professional grader can [49]. Also, natural language processing of medical narratives is required to free humans from the challenging task of tracking events in time while maintaining structure and reason [50]. ML can be used to process highly complex clinical information (e.g. text and various types of linked biomedical data), to integrate logical reasoning into the data set and to use the learned knowledge for a variety of purposes [51].

5. DISEASE DIAGNOSTICS AND PREDICTION

5.1. AI and Disease Identification

The most urgent need for AI in biomedicine is in the diagnosis of diseases. Some interesting breakthroughs have been made in this area. AI enables healthcare professionals to make earlier and more accurate diagnoses for many types of diseases [55]. A major class of diagnostics is based on in vitro diagnostics using biosensors or biochips. For example, gene expression, which is a very important diagnostic tool, can be analysed by ML, where AI interprets microarray data to classify and detect abnormalities [56,57]. A new application is the classification of cancer microarray data for cancer diagnosis [58]. With integrated AI, biosensors and related point-of-care testing (POCT) systems can diagnose cardiovascular disease at an early stage [58]. In addition to diagnosis, AI can help improve survival rates for cancer patients, such as B. colorectal cancer patients [59]. Researchers have also identified some limitations of ML in biomedical diagnosis and suggested steps to minimize the impact of these disadvantages [60]. Therefore, there is still a lot of potential for AI in diagnostics and prognosis. Another important class of disease diagnostics is based on medical imaging (two-dimensional) and signal processing (one-dimensional). Such techniques have been used in the diagnosis, treatment, and prediction of disease. For one-dimensional signal processing, AI has been applied to the extraction of biomedical signal features [61], such as B. electroencephalography (EEG) [62], electromyography (EMG) [63] and electrocardiography (ECG) [64]. An important application of the EEG is the prediction of epileptic seizures. It is very important to predict seizures to minimize their impact on patients [65]. In recent years, AI has been recognized as one of the key elements of an accurate and reliable prediction system [66,67]. It is now possible to make predictions using deep learning [68] and the prediction platform can be deployed in a mobile system [67]. AI can also play an important role in diagnostics based on biomedical image processing [68]. AI has been used in image segmentation [68], multidimensional imaging [69] and thermal imaging [70] to improve image quality and analysis efficiency. AI can also be used in handheld ultrasound devices, allowing untrained personnel to use ultrasound as a powerful tool to diagnose many types of diseases in underdeveloped regions [71]. In addition to the above applications, AI can support standard decision support systems (DSSs) [72,73] to improve diagnostic accuracy and facilitate disease management to reduce the burden on staff. For example, AI has been used in the integrated management of cancer [74], to support the diagnosis and management of tropical diseases [75] and cardiovascular diseases [76], and to support the diagnostic decision-making process [77]. These applications show that AI can be a powerful tool for early and accurate diagnosis, management and even prediction of diseases and patient conditions.

5.2. Big Data and Disease Identification

In daily clinical work, utilizing imaging data can improve cancer treatment by knowing tumor biology and helping to implement precision medicine. For the accession of the tumor and its microenvironment, radiomics helps to monitor and assess tumor characteristics such as temporal and spatial heterogeneity [78]. Asthma is contradictory in terms of clinical associations and poor replication of genetic associations. Asthma is not a single disease but a group of similar diseases with some clinical manifestations. Big data for the disease does not offer a solution, it only provides information about the disease. Bayesian and common approaches let us understand the ethnology of diseases, commonly used in statistical machine learning, and can be applied to both large and small data in health research. We need to know the reality of asthma, not just make predictions. We must draw attention to data science through methodological polemics. The Bayesian and frequent paradigm of contemporary artificial dichotomies is given. Big data is needed to break down asthma into subtypes to find the solution. Use of disaggregated phenotypes and genome research as well as research into lung function as an intermediate phenotype. Coherent inductive and deductive statistical approaches to epidemiological pragmatic bays and unifying graphs are presented [79]. There are techniques and methods that can effectively separate patients into asthmatics and non-asthma patients in long-term remission [80]. VA-PODR (Veterinary Affairs Accurate Oncology Data Collection) is a worldwide large collection of known data on diagnosed cancer patients in the VAs department (Veterans Affairs). This data consists of long-term clinical data from the Veterans Affairs nationwide eHealth dataset, medical photo data, tumor sequencing targets, pathology slides and the Veterans Affairs Central Cancer Registry, and computed tomography (CT) scans. A subset of this data storage is available in GDC (Genomic Data Commune) and TCIA (The Cancer Imaging Archive) [81].

The allergic conjunctivitis population has a frequency of 1520%. However, due to the lack of understanding, the multi-cause of chronic obstructive pulmonary disease is that the environment, location and direct distribution have complex relationships. The benefits of drugs for chronic kidney disease patients and the way of treating dementia and the possibilities for other diseases that patients need to be aware of, which help patients according to the symptoms and risk factors of the social strengthening and rehabilitation interventions of people with chronic obstructive arthritis Lung disease to reduce the body to create lasting solutions and prevent the escalation of social ills [82].

Somatic genomes are increasing in size in biomedical repositories. Thus, the prediction of documents related to cancer sentences using mathematical algorithms is described. Mining models of conventional gene-based somatic cancer are not hampered by somatic gene ranking and trait extraction due to high computational costs and storage of large datasets. A wide range of features, preferences, and feature squeezing techniques are available and they are typically used in many domains. Each of these methods attempts to extract and squeeze some new irrelevant characteristic features from the trained datasets, with the aim of obtaining more and more accurate results for the rearranged documented data. Extracting or compressing data is an activity that provides required and related data from a large collection of datasets according to the information provided. There are criteria for ranking the information which is sorted as the best results have the highest priority so they are at the top of the list provided. Experimental results have different cluster sizes with different gene traits for somatic document clustering. And their generated results prove that the existing model has a high quality of computational clustering [83]. which is sorted as the best results will have the top priority so it will be on the top of the provided list. Experimental results have different cluster sizes with different gene features for clustering of somatic documents. And their generated results prove that the existing model has a high quality of computational clustering [83].

6. HEALTHCARE

AI now covers a wide range of applications in healthcare . In particular, it has been used for signal and image processing and for predicting functional changes such as in bladder control, epileptic seizures [84] and stroke prediction [85]. Below two typical case studies: bladder volume prediction and epileptic seizure prediction are described.

6.1. Bladder Volume Prediction

When the bladder's storage and urination functions fail as a result of spinal cord injury or other neurological disease, medical condition, or aging, various complications arise in the patient's health condition. Today, partial recovery of bladder function in drug-refractory patients can be achieved with implantable neural stimulators. In order to improve the efficiency and safety of neuroprostheses through conditional neurostimulation [86], a bladder sensor is required that recognizes stored urine as a feedback device that applies electrical stimulation only when needed. The sensor can also be used to notify patients with sensory disturbances in good time when the bladder needs to be emptied or when there is an unusually high residual volume after voiding after incomplete voiding. We have proposed new methods [87] and developed a dedicated digital signal processor (DSP) [88] to detect both pressure and its volume in urine by measuring afferent neural activities from the bladder's regular neural roots (i.e., mechanoreceptors). use. showing the changes during filling. Smart neuroprostheses typically consist of two units: an internal unit implanted in the patient and an external unit, usually worn as a wearable device. Both units are typically linked by a wireless connection that transmits data and powers the implant. The internal unit performs several functions: neural signal recording; On-chip processing (to a varying extent depending on the application) of the signals conveying sensory information; neurostimulation of appropriate nerves using functional electrical stimulation (FES) techniques; logical control of implanted device functions; and communication with the external entity. When additional signal processing is required to run more complex algorithms that require additional computing capacities that are not suitable for implantation due to size, power consumption, temperature rise, electromagnetic emission, etc., the internal unit sends the recorded signal to the external unit , which runs more complex algorithms and sends back appropriate neurostimulation commands. The external base station integrates the implant's user interface and the implant's computer interface for greater flexibility. The work presented in this section aims to develop an effective implantable bladder volume and pressure sensor capable of providing the necessary feedback to the neuroprosthesis. Finally, this sensor can be used either for the implementation of a conditional new.

6.2 Epileptic seizure prediction

Epilepsy, a neurodegenerative disease, is one of the most common neurological disorders and is characterized by spontaneous, unpredictable, and recurrent seizures [86,87]. While first lines of treatment consist of long-term drug therapy, more than a third of patients are refractory. On the other hand, the utilization of epilepsy surgical interventions is still relatively low due to very modest success rates and fear of complications. An interesting line of research is to investigate the possibility of seizure prediction, which, if possible, could lead to the development of alternative intervention strategies [88]. Although early research on seizure prediction dates back to the 1970s [89], the limited number of seizure events, the lack of intracranial electroencephalography (iEEG) recordings, and the limited extent of interictal epochs were major hurdles to adequate assessment of seizure prediction performances. Interestingly, iEEG signals from dogs with natural epilepsy implanted with the ambulatory monitor (NeuroVista) were made available via the online portal ieeg.org [89]. However, the seizure onset zone was not disclosed/available. Our group investigated the possibility of predicting seizures using the canine data mentioned above. We then performed a Directed Transfer Function (DTF) based quantitative identification of electrodes located within the epileptic network [90]. A genetic algorithm was used to select the traits that most discriminate the preictal state. We have proposed a new fitness function that is insensitive to skewed data distributions. The retained dataset was reported to have an average sensitivity of 84.82% with a warning time of 10%, improving previous seizure prediction performance [91].

7. CONCLUSION

This article reviews the latest developments in the application of AI in biomedicine, including AI an Big Data in disease diagnostics and prediction, life support, biomedical information processing. AI also has interesting applications in many other biomedical fields. It is becoming apparent that AI is playing an increasingly important role in biomedicine, not only because of the continuous advancement of AI itself, but also because of the inherent complexity of biomedical problems and AI's ability to solve such problems. Big data has made it easy to diagnose diseases through virtual and real-time systems. The contribution of this paper is to review the current research applicable to mHealth and eHealth, where different approaches and models using Big Data for diagnosis and healthcare system are discussed. This paper has summarized the current encouraging applications of AI and big data in medical health and e-health, which have potential added value for disease diagnosis and patient care. New AI capabilities offer novel solutions for biomedicine, and the evolution of biomedicine demands new levels of performance from AI. This matching of supply and demand and coupled developments will significantly advance both areas in the foreseeable future, which will ultimately benefit the quality of life of people in need. The role of AI and big data has brought numerous benefits, from accurately diagnosing disease to providing appropriate methods for patient treatment. It not only improves the monitoring of an individual's personalized data collection in the mobile application, but also initiates the implementation of a cloud-based healthcare framework. Therefore, there is a huge potential of artificial intelligence and big data in human healthcare

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