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Review Article

Artificial neural networks for medical diagnosis: A review of recent trends

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Abstract

Artificial Intelligence systems (especially computer aided diagnosis and artificial neural network)are increasingly finding many uses in the medical diagnosis application in recent times. These methods are known to be adaptive learning algorithms that are capable of handling diverse types of medical data and integrate them into categorized outputs. In this study, we briefly review and discuss the concept, capabilities and applications of artificial neural network techniques to medical diagnosis, through consideration of some selected physical and mental diseases. The study focuses on scholarly researches within the years, 2010 to 2019.Findings show that no electronic online clinical database exist in Nigeria and the Sub-Saharan countries, most review researches in this area focused mainly on physical diseases without considering mental illnesses, the application of ANN in mental and comorbid disorders have not be thoroughly studies, ANN models and algorithms consider mainly homogeneous input data sources and not heterogeneous input data sources, and ANN models on multi-objective output systems are few as compared to single output ANN models.
Keywords: Medical diagnosis, Artificial intelligence, Artificial neural networks, Feed-forward back propagation, Convolutional Neural Network, diabetes, cardiovascular, cancer, malaria and Mental Disorder .

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1. Introduction

The Diagnosis is one of the major tasks of all physicians and its importance to man cannot be over emphasized. In diagnosing, physicians are challenged with the task of deducing certain diseases or formulating a treatment based on specified signs and symptoms or observations and knowledge. Zagorechi *et al* [1] also define diagnosis as "the process of assigning a label to an illness or other problems by examining observations and symptoms". Simple as stated, diagnosis has been observed by scholars as a rigorous, complex and multifaceted task that is bedeviled with multiple challenges. Some of such challenges include, having symptoms of disease(s) that are not specific to only one disease and sometimes overlapping with the symptoms of other diseases[2]; having unclear or inadequate description of how and what a patient feels in the body as a result of loss of memory or voice; having severe mental conditions that distorts cognitive abilities; frequency of the occurrence of diseases; and risk factors such as age, sex and body mass index (BMI) that influences both the structure of dependencies between symptoms and illnesses. Others include, wrong and untimely interpretation of information provided by patients, and unnecessary delay and errors in analysis of laboratory results [3], lack of facilities, poor technical know-how and imbalanced ratio of patients to doctors in healthcare especially in the developing countries, etc. No wonder, Brause *et al* [4] asserts that 50% of diagnoses are wrong.

Over the years, a number of positive advancements has been recorded in the field of medical diagnosis from antiquity to modern times. In all, however, traditionally, the wealth of experience of physicians over years in service play significant roles in effective medical diagnosis. This experience depends largely on the intuitive statistical analysis of situations by the physician to arrive at diagnostic solutions. For instance, reports show that the disease AIDS which manifested by a myriad of infections and cancer states was not discovered directly by physicians but by statistical experts who were observing the improbable density of rare cancer cases at the US west coast [5]. This supports the assertion that "informing clinical decision making through insights from past data is the essence of evidence –based medicine"[6]. However, there are many inadequacies of statistical estimation techniques, one of which is that quality cannot be guaranteed when dealing with incomplete, noisy and non-linear data [7]. In addition to the statistical techniques, two classification methods, namely: International Classification of Diseases – 10th Revision (ICD – 10) and the Diagnostic and Statistical Manual of Mental Disorders –IV edition (DSM –IV) which are standard disease classifiers are used [8].

In recent times, artificial intelligence (AI) has increased the possibilities of statistically inexperienced physicians to apply the benefits of intelligent diagnostic approaches to enhance improved services [6], by providing techniques that uncover complex associations which cannot be reduced to an equation. Artificial Intelligence (AI) approaches, provides reasoning capability, which consists of inferences from facts and rules using heuristics, pattern matching or other search approaches [9] and has contributed significantly in the evolution of biomedicine and medical informatics[10]. Recent areas of development in AI in relationship to medical diagnostics which are the leading methods with which physicians are assisted in this demanding task include - the expert system [11-13], fuzzy logic [14], Artificial Neural Networks [15] and neuro-fuzzy expert system [16,17].

This study is aimed at reviewing scholarly researches on the application of Artificial Neural Network (ANN) techniques to medical diagnosis. Specifically, focus is on relevant literatures that fall within years 2010 to 2019. After a description of the basic elements of ANN and their operations, its application in medicine and potential future trends are examined.

2. Material and methods

A search criterion was designed for the extraction of relevant literature on research works regarding ANN in medical diagnosis from three (3) selected online scientific electronic open-source libraries namely "Science Direct", "Microsoft Academic", and "IEEE Transaction". The search was based on the query strings "Artificial Neural Networks", "Artificial Neural Network in Medical Diagnostics" and "Artificial Neural Networks in Mental Disorder Diagnosis" which produced approximately 2000 articles. The abstracts of the articles were first reviewed to eliminate researches that are not relevant to the topic. Thereafter, the full text of the articles was meticulously reviewed to further eliminate articles that are not relevant to the study. The criteria used were as follows:

i. Only articles published in ANN or medical diagnostic related journals were selected;
ii. Only articles that clearly describe how the mentioned ANN techniques could be applied, and (or) improve medical diagnosis were selected;
iii. Conference papers, textbooks, masters and doctoral dissertations, and unpublished working papers were excluded. This is due to the report by Nord *et al*[18] that journals are the leading source and reference of researchers.

After thorough analysis of the selected articles, the collected notes were organized into two sections as: Concept of Artificial Neural Networks, and a review of artificial neural networks in medical diagnostics.

3. Conceptual framework of artificial neural networks

Artificial Neural Network (ANN) is a computational model and an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information [19]. It is a mathematical representation of the human neural architecture, reflecting its "learning", "generalization" and "abstraction" abilities [20]. Artificial neural network consists of various layers of interconnected "neurons" (or "nodes") called processing elements (PEs). ANNs consist of small number of neurons or processing elements (PEs), say from tens to thousands of PEs. Each neuron or PE in a layer is connected with each neuron or PE in the next layer through a weighted connection. The value of the weight w_{ij} indicates the strength of the connection between the i-th neuron or PE in a layer and the j-th neuron or PE in the next layer. Each layer contains finite nodes with activation functions. Data items are received by the processing elements (PEs) in the input layer and transferred to the processing elements (PEs) in the first hidden layer through the weighted links. The data at this point is mathematically processed and the result is transferred to the next layer and so on until it gets to the output layer which is the last layer. And finally, the output is assembled at the output layer as shown in fig. 1.

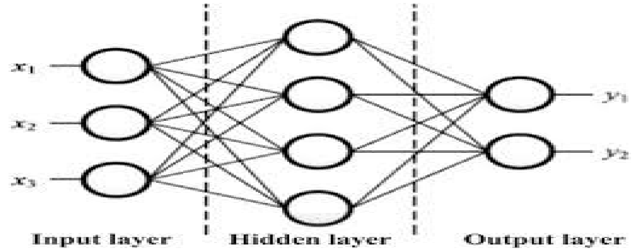

Fig.1. Artificial Neural network structure and layers (Sourced from: [20])

There are different architectural structures of ANN of which the most common is the multilayer perceptron (MLP). The MLP and many other variations of ANN, learn by using an algorithm known as the back propagation. The back propagation allows input data to be repeatedly presented to the neural network. The structure is designed such that the first layer is the input layer and the last layer is the output layer. Between the input and the output is an additional one or more layers of units called hidden layers. The number of neurons or PEs in a layer and the number of layers depends strongly on the complexity of the system studied. Thus, the determination of the optimal network architecture is necessary.

4. Application of Artificial Neural Networks in Medical Diagnosis

The concept of the "application of artificial neural networks in medical diagnostics" was pioneered by Szolovits *et al* [21] in their article titled, "Artificial intelligence in medical diagnosis" and has since attracted much attention. Several research papers spread across diverse fields of medical sciences have been published among which Szolovits *et al* [21], Papik [22] and Perveen [23] so on. In almost all the reviews, emphasis was placed on physical diseases, leaving out mental and social illnesses. Suffice it to say that WHO [24] defines health as "a state of complete physical, mental and social well-being and not merely the absence of diseases and infirmities". Thus, a healthy human must be both physically and mentally and socially sound in health. In this research, we review the application artificial neural network technique to medical diagnosis on some selected physical and mental disorders.

4.1 Diabetes

Diabetes represents a serious health problem in developed countries [25] with estimated numbers reaching 425 million cases globally, 16 million cases in African region and about 1,731,811 cases in Nigeria as at 2015(IDF , 2019). It is on the increase and have been projected by the WHO of becoming the 7th leading cause of death in 2030. Diabetes occurs as a result of increased glucose level in the human body system due to absence of or inadequate amount of insulin in the body. Artificial Neural Networks have been successfully trained to solve the problem of its diagnosis. Notable is the research of Alade *et al* [26], where they developed and trained an ANN model for the diagnosis of diabetes mellitus in pregnant women. They developed a four-layer Artificial Neural Network and trained it using the back-propagation and the Bayesian Regulation (BR) algorithm. Eight (8) neurons were used in the input layer, two hidden layers with ten (10) neurons each, and one neuron in the output layer which is the diagnosis result. The dataset was gathered from a medical database called the Prima Indian Database set. It contained 768 rows of data and the tests on the individuals used were on their blood pressure, Triceps Skin Thickness, Insulin, Body Mass Index, Diabetes Pedigree Function, and age. 500 people tested positive and 268 people tested negative giving an accuracy level of 92% after validation by regression. Sadi *et al* [27] also developed a diagnostic model using three (3) variations of ANN (Bayesian Regulation Algorithm (BRA), J48 & Radial Basis Function – Neural Networks (RBF-NN)) from a sample of data collected from 768 respondents collected from the Pima Indian Database. The diagnostic accuracy rate for BRA proved to be 79.95%, that of J48 yielded 76.52% and RBF-NN yielded 74.34%.

4.2 Cardiovascular Disease

Cardiovascular diseases (CVDs) are"diseases that affect the heart or blood vessels, both arteries and veins" [21], that includes coronary heart disease (disease of the blood vessels supplying the heart muscle); cerebrovascular disease (disease of the blood vessels supplying the brain); peripheral arterial disease (disease of blood vessels supplying the arms and legs); rheumatic heart disease (damage to the heart muscle and heart valves from rheumatic fever, caused by streptococcal bacteria); congenital heart disease(malformations of heart structure existing at birth); and deep vein thrombosis and pulmonary embolism (blood clots in the leg veins, which can dislodge and move to the heart and lungs. It has been found to be one of the leading causes of death in several countries with an estimate of 17.9 million people dying annually representing 31% of global deaths. Artificial Neural Network has been trained for the analysis and diagnosis of this disease with high degree of success. Qeetha *et al* [15] used Feed forward Back Propagation Neural Networks (FFBP-NN) to diagnose Acute Nephritis & Heart disease with and an accuracy rate of 99% and 95% respectively. Myers *et al* [28] used ANN with Firefly (FF), multilayer Perceptron neural networks (MPNN) and Back Propagation(BP) to diagnose CVD and it yielded 72% on testing the model on data collected from Va Palo Alto Healthcare. Atkov *et al* [29], and Miao [30] developed ANN and DNN respectively to diagnose

Coronary heart Disease. The former collected 487 samples of data from the Central Clinical Hospital of Russian Railway and the later collected data samples of 303 from the Cleveland Clinic Foundation, New York, USA. Accuracy results were (64 - 94)% and 83.67% respectively. Acharya *et al* [31,32] also used the CNN to diagnose Myocardial Infarction and Deep Convolutional Neural Networks (DCNN) to diagnose Heartbeat rhymes. The 2017a study yielded accuracy rate of 93.53% for original and 95.22% for noise free electroencephalograms (ECGs) respectively while the Acharya *et al* [32] study yielded accuracy rate 94.03% and 93.47% for original and noise free ECGs respectively.

4.3 Cancer

According to estimates from the International Agency for Research on Cancer (IARC) published in the American Cancer Society (www.cancer.org), in 2018 there were 17 million new cancer cases and 9.5 million cancer deaths worldwide. By 2040, the global burden is expected to grow to 27.5 million new cancer cases and 16.3 million cancer deaths simply due to growth and aging of the population. The future burden will probably be even larger due to increasing prevalence of factors that increase risk, such as smoking, unhealthy diet, physical inactivity, and fewer childbirths, in economically transitioning countries. Artificial neural networks have been successfully applied to solve the problem of diagnosis of Cancer globally. Notable among them is the work of [33-37], etc. In the research of Pergialiotis *et al* [37], the aim was to investigate the diagnostic accuracy of three different methodologies (i.e. logistic regression, ANNs and CARTs) for the prediction of endometrial cancer in postmenopausal women with vaginal bleeding or endometrial thickness 5mm, as determined by ultrasound examination. A retrospective case-control study based on data from analysis of pathology reports of curettage specimens in postmenopausal women was conducted. Classical regression analysis was performed in addition to ANN and CART analysis using the IBM SPSS and MATLAB statistical packages. Overall, 178 women were enrolled. Among them, 106 women were diagnosed with carcinoma, whereas the remaining 72 women had normal histology in the final specimen. ANN analysis seems to perform better with a sensitivity of 86.8%, specificity of 83.3%, and overall accuracy (OA) of 85.4%. CART analysis did not perform well with a sensitivity of 78.3%, specificity of 76.4%, and OA of 77.5%. Regression analysis had a poorer predictive accuracy with a sensitivity of 76.4%, a specificity of 66.7%, and an OA of 72.5%.

4.4 Malaria

In a world malaria report of 2017 that draws on data from 91 countries in the globe and areas with ongoing malaria transmission, the world health organization [24] estimated 216 million cases of malaria occurred worldwide (95% CI: 196 – 263 million), an increase of 5 million cases over 2015. 90% of the malaria cases were in the WHO African regions followed by 7% by the Who South East Asia Region and the WHO Eastern Mediterranean Region with 2%. It is also reported that 80% of the global malaria burden cases and 15 countries out of the 91 countries reporting indigenous malaria cases are from the sub-Saharan Africa. An estimated 445,000 deaths from malaria globally, were recorded and the WHO African Region accounted for 91% of all malaria deaths in 2016; all of these countries are in sub-Saharan African countries. Artificial Neural Networks have been applied to diagnose Malaria, and its likes successfully. Ziynet *et al* [38] and Neha *et al* [39] worked on Anemia using Feed Back Neural Networks (FBNN), Deep Neural Networks (DNN), Probabilistic Neural Networks (PNN), Learning Vector Quantization(LVQ) and CNN with an accuracy result of 99.16% and 97.31% respectively. Parveen *et al* [40] and Pandit & Anand [41] worked on malaria diagnosis using MLP-BP and FFBP-NN with an accuracy yield of 85% and 100% respectively.

4.5 Mental Disorders

Mental Disorders (MD) are diseases characterized by persistently depressed mood, feeling of sadness or lose of interest in activities, causing significant impairment in daily life and have become one of the commonest causes of disabilities in the globe [24]. Artificial neural networks have recorded breakthroughs in the diagnosis of mental health problems such as depression, schizophrenia, bipolar and etc. Acharya *et al* [32] used the DCNN to diagnose seizure using EEG signal data collected from the Boon University Germany which yielded an accuracy rate and sensitivity rate of 88.67% and 95.00% respectively. In another study, Lyu *et al* [42] developed a diagnostic model using the BPNN for suicide attempt prediction with an accuracy rate for positive prediction value as 86.0% and for negative prediction value as 84.1%. Huang *et al* [43] proposed a domain adaptation method based on a hierarchical spectral clustering algorithm to adapt a labeled emotion database into a collected unlabeled mood database for alleviating the data bias problem in an emotion space. A convolutional neural network (CNN) with an attention mechanism was used to generate an emotion profile (EP) of each elicited speech response. The proposed method achieved an overall detection accuracy of 75.56%, outperforming support-vector-machine- (62.22%) and CNN-based (66.67%) methods.[44] developed a model for the diagnosis of Bipolar and Schizophrenia using BPNN approach. This yielded an accuracy rate of 90% when tested with sociodemographic and biochemical data. Basaia *et al* [45] researched on the diagnosis of Alzheimer's disease using the CNN model and Bansal [46] worked on dementia diagnosis, comparing the of performance of 4 machine learning techniques namely J48, NB, RF & MLP-NN. The accuracy rate, obtained after testing the performance on dataset collected from the OASIS-brain Organization was J48 – 99.52%, NB – 99.28%, RF – 92.55% and MLP-NN – 96.88%. Zeng *et al* [47] studied the diagnosis of schizophrenia using the DDAN model and achieved an accuracy rate of 85.0% for multi-site pooling classification and 81.0% for leaving-site-out transfer classification.

4.6 Depression/Comorbid Disease

Chattopadhyay *et al* [48] applied the BPNN and ANFIS models to differentiate depression into grades. Of the two model types, ANFIS yielded a better performance than BPNN on testing the models on datasets collected from various sources in India. Acharya *et al* [32] again studied the diagnosis of depression using the ANN. Using EEG signal data from the rights & left hemisphere, the accuracy rates of 93.5% and 86.0% respectively. It was shown that EEG from the right hemisphere is more distinctive in depression detection than those from the left hemisphere. Ojeme & Mbogho [49] applied BN, BPNN, SOV, KNN and FL to classify depression. Dataset were sourced from the University of Benin Teaching Hospital (UBTH) and accuracy results were, BN = 0.975, BPNN = 0.971, SVM = 0.916, KNN = 0.959 and FL = 0.951.[50] in another study considered depression and comorbid diseases using the MBNC model. Dataset consisted of 1090 patients of which 454 were males and 606 were females, from the University of Benin Teaching Hospital (UBTH). The accuracy rate was not measured but however, it was shown that predictive models have the potential of offering good performances to co-occurring disease in a patient.

5. Findings

The research showed that:

a. There is no electronic online medical / clinical database library in Nigeria and other sub Saharan countries. Medical data is sourced manually from hospitals and research agencies in the developing countries like Nigeria. The few scholars who delved into this study either sourced their data directly from known hospitals using conventional data gathering methods such as interviews, observations, questionnaires as well as organizing workshops [3,9,17,50] while others sourced their data from foreign sources;
b. Emphasis was placed on physical diseases like cancer, cardiovascular diseases, diabetes mellitus, etc. in most of the literature reviews by scholars on Artificial Neural Networks in Medical diagnostics paying little or no attention to mental and social disorders. Reviews involving mental disorders were targeted on a particular disorder and known focused on Africa and the sub-Saharan nations;
c. No scholar has worked on Application of ANN in Mental and comorbidity disorders. The few works in this area applied methodologies and algorithms such as Bayesian Networks [50], where they identified a gap in literature and stated that, “there is a gap in literature on how the same techniques of machine learning could be used to simultaneously identify depression and comorbid physical illnesses”.
d. The input datasets of most of the researches using ANN are from homogeneous sources such as symptoms, signs, images, voices, physiological, text messages and activities on social media. Known has considered multiple input sources, that is, heterogeneous sources of datasets.
e. Most of the works considered diagnosis and prognosis of a particular disease at a time. The cases of multi-objective output, that is, diagnosis of multiple diseases given and input source lacks authoritative study.
f. Combining multiple machine learning algorithms such as genetic algorithm, fuzzy logic and artificial neural networks yields better improved accuracy rate.

6. Conclusion

This paper shows a growing interest in Artificial Neural Networks (ANN) that its models and algorithms are becoming standard tools in Computer science and especially in decision support and expert systems. ANN no doubt represents a powerful tool to help physicians and other medical experts and stakeholders perform diagnosis, prognosis and other enforcements. The advantages of ANN which include:

a. Adaptability and flexibility of the systems;
b. Ability to process large volume of dataset;
c. Reduced likelihood of overlooking relevant information;
d. Timely diagnosis of diseases
e. Ability to process datasets collected from multiple sources like voices, images, symptoms, text messages, etc.

Makes it an important computational model in development of modern clinical decision support and expert systems.

The studies reviewed here suggest that ANNS have proven to be suitable for satisfactory medical diagnosis of both physical and mental illnesses. Their use has improved diagnostic accuracy and reliability thus increased patients’ satisfaction. However, according to Guntuku *et al* [51],” ethical and legal questions about data ownership and protection, as well as clinical and operational questions about integration into systems of care should be addressed with urgency”. Patient’s privacy protection is a major issue all over the world and needs to be addressed. In addition, despite the wide spread use of ANNs and other intelligent computational algorithms, the tool must be considered only as a facilitator of the final decision of a physician who holds the ultimate responsibility for critical evaluation of the ANN output.

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