IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
IJARSCT
Impact Factor: 7.53
Volume 4, Issue 1, July 2024

Predicting Chronic Diseases Using Nonlinear Systems

Amarpreet Kaur[1] and Geeta[2]
Department of Mathematics, Geeta University, Panipat[1,2]

Abstract: *Healthcare heavily relies on advanced analytics to predict diseases and risks, with an abundance of health data being gathered through IoT and smart healthcare. Nonlinear systems and synchronization techniques play a crucial role in analyzing this data and predicting chronic diseases, such as cancer, cardiometabolic disease, and Parkinson's disease. Using machine learning and computational intelligence, nonlinear analysis offers valuable insights into the enormous amounts of data collected in smart healthcare settings, enabling more accurate and efficient disease prediction. This chapter explores the various aspects of nonlinear systems and synchronization techniques in predictive analytics, providing a holistic view of their applications in chronic disease prediction*

Keywords: Nonlinear systems, Healthcare, Artificial intel- ligence, Computational intelligence, Machine learning, Predictive analytics, Chronic disease

I. INTRODUCTION

A nonlinear system in healthcare is one where the output doesn't change proportionally with the input. These systems are of special interest to researchers in healthcare because most health systems are inherently nonlinear in nature. Nonlinear dynamical systems describe how variables change over time, but can be chaotic or unpredictable compared to simpler linear systems [1]. Although nonlinear modeling cannot yet explain all the complexity present in human systems, it does provide valuable insights into some system behaviors that linear models cannot. As such, it helps us better understand complex dynamic systems within the human body in both healthy and diseased states. Healthcare delivery is a complex process that involves providing individualized care to patients based on medical history, vital signs, and evidence-based practices. In recent times, there has been a growing emphasis on learning, metrics, and quality improvement to enhance the effectiveness and efficiency of healthcare delivery [2]. With the rise of e-Health, there is a promise of addressing the limited capacity of healthcare systems to manage chronic diseases and promote health behavior change. However, the increasing volume and complexity of patient data generated by electronic health records (EHRs) and other sources necessitates the development of computer-assisted methods to analyze and recognize patterns from the data. Intelligent data analytics is a rapidly emerging field that focuses on analyzing healthcare data to make sense of it. Chronic diseases, which are a major global health concern, are one of the key areas where such analyses are being applied. Intelligent prediction models can help with early detection and prevention of chronic diseases. Nonlinear modeling and predictive models are being developed to analyze data from smart sensors and e-Health devices, powered by the Internet of Things (IoT)[3]. These models can help to compute the risk and other possibilities of chronic diseases, abnormal gait detection, fall detection, and diseases like Parkinson's. The most valuable resource in this context is health data, which is crucial for early detection of chronic diseases using artificial intelligence (AI) [11]. The key challenge lies in detecting these diseases early as they do not exhibit clearly identifiable signs at the initial stage. Therefore, there is a need to develop and refine predictive models that can help healthcare professionals to detect and prevent chronic diseases more efficiently.

The vast potential of health data in detecting and predicting diseases through computational intelligence is a complex process. With healthcare systems being inherently nonlinear, there is a significant opportunity to analyze intricate details of these systems to identify early signs of diseases [1]. Additionally, the importance of superficially obtained health data, such as behavioral, physiological, and metabolic data, cannot be understated [10]. Analyzing this data through computational methods can help predict diseases with greater accuracy. This involves various aspects of data analytics, signal and image processing, and machine learning. This chapter focuses on exploring the potential of machine learning and computational intelligence in analyzing health data and predicting diseases in nonlinear systems.

II. PREDICTIVE ANALYSIS IN HEALTHCARE THROUGH DATA MODELING”

Intelligent healthcare prediction systems rely on data, which is growing at an astonishing rate and needs to be handled as big data [11]. Data preprocessing is critical due to the majority of healthcare data being unstructured, heterogeneous, and lacking interoperability [13]. A well-designed data preprocessing system is essential for comprehensive health data modeling and accurate predictions, especially for nonlinear systems [1]. While traditional data mining techniques have been useful in analyzing patterns in large datasets, recent systems focus on predictive models for more formal and efficient analysis [10].

In the field of disease and risk prediction, identifying the mathematical model of a system is crucial. This task involves determining whether the data model is linear or nonlinear, with the latter being more common in analyzing multidimensional health data. Nonlinear models such as nonlinear regression, clustering, decision trees, nonlinear support vector machines (SVMs), and artificial neural networks (ANNs) are commonly used in predictive medical analytics [4-6].

Nonlinear regression models the observational health data using a function that depends on one or more independent variables. The data is fitted by a method of successive approximations. Supervised learning models like SVMs are used to analyze labeled health data using classification and regression analysis. SVMs use kernels to map nonlinear functions, making it possible to represent very complex functions. However, the drawback is the need for more training and prediction times compared to linear regression [3].

ANNs are nonlinear statistical models that encompass a large class of models and learning methods. They consist of interconnected nodes organized in layers, which contain an activation function. Data is processed in one or more hidden layers using a system of weighted connections, with the last hidden layer linked to the output layer where the result is given. ANNs can model different types of relationships, which otherwise may have been difficult to represent correctly. However, they tend to be slower in training compared to other types of networks because individual artificial neurons are usually processed sequentially [5]. Inclusively, the healthcare domain of intelligent risk prediction is focused on pattern recognition or finding relationships among several health and behavioral parameters and studying their impacts. Nonlinear models, especially ANNs, are commonly used to analyze multidimensional health data and provide insights for disease and risk prediction.

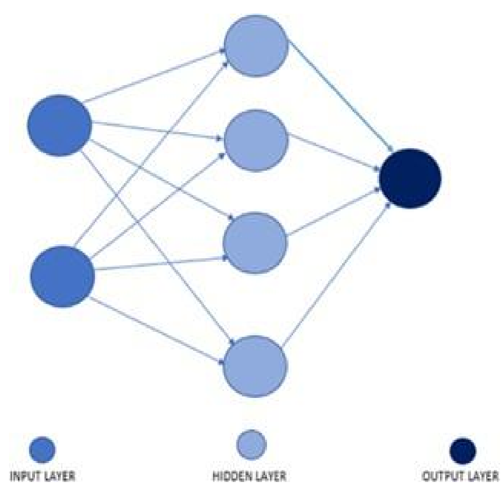

Fig. 1. FORWARD FEED NEURAL NETWORK (FFNN)

Ensemble classifiers have gained importance in predicting health risks among patient populations. Simple probabilistic classifiers, like naive Bayes classifiers, are used in programmed medical analysis. Decision trees, specifically the random forest algorithm, are commonly used in clinical decision support systems. Unsupervised learning techniques, like clustering via k-means, are used to find patterns in unlabeled health data. The choice of algorithm depends on factors like the type of dataset, prior knowledge, computational complexity, and expected results [3]. To determine the degree of bias or variance in a machine learning algorithm, learning curves are used. While the use of machine learning and computational intelligence is crucial in predicting health risks and diseases, it is important to correctly use the model and combine different techniques to create hybrid algorithms [2]

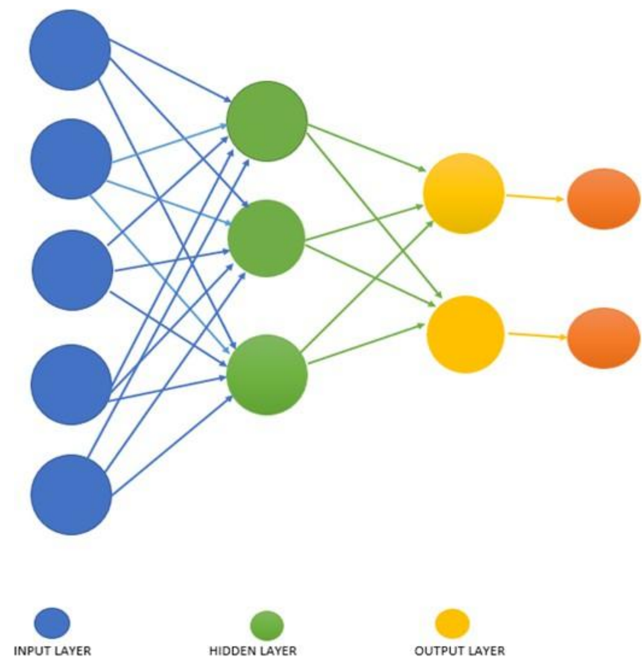

Fig. 2. RECURRENT NEURAL NETWORK (RNN)

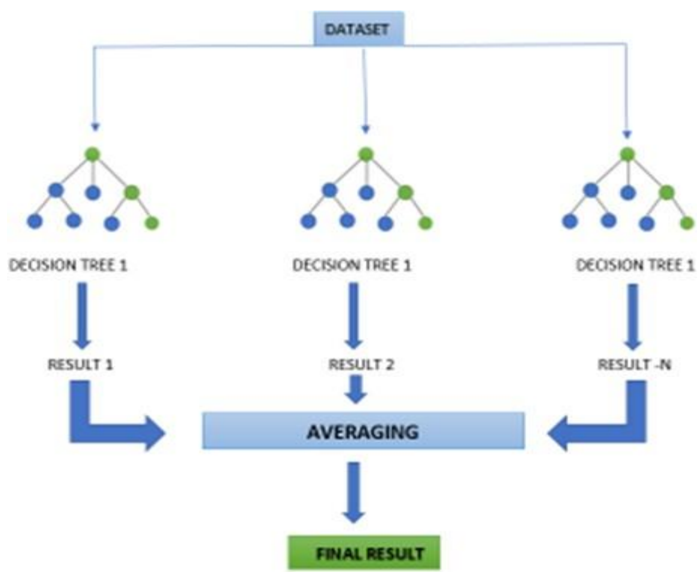

Fig. 3. WORKING PRINCIPLE OF RANDOM FOREST

III. UTILIZING COMPUTATIONAL INTELLIGENCE FOR DISEASE PREDICTION APPLICATIONS

This section discusses various scenarios for predictive analytics aimed at disease and risk prediction, which is an extensive and multi-step process that uses computational intelligence. In the case of cardiometabolic diseases, a detailed physiological and health data including age, gender, blood pressure, cholesterol, diabetes, and smoking habits is considered to calculate the risk scores of patients. This classification helps to categorize the entire population into high and low-risk groups. However, alternative analyses can be performed to identify underlying risk groups for each health parameter in the entire population [10].

For instance, the Framingham Risk Score is used to predict hard-coronary heart diseases based on predictors like age, total cholesterol, high-density lipoproteins (HDL), systolic blood pressure, treatment for hypertension, and smoking status. Although this score can be expressed as a linear equation considering all the parameters, smaller and more specific sample sets of people may have nonlinear relationships of several other parameters pertaining to cardiovascular risks, which are not typically considered in classical risk prediction models.

The traditional approach of identifying and treating risk factors has proven to be insufficient, as it ignores the subclinical stage of the disease, which is valid to define cardiovascular risk strategies. To derive the real individual cardiovascular risk, a morpho-structural and functional analysis of the artery with non-invasive, reliable, and reproducible procedures that are applicable in the youngest population is necessary. Incorporating coronary calcifications along with classic risk factors in a cardiovascular risk model could have significant interest in clinical practice. It has been demonstrated that a significant number of people considered to be at intermediate risk with the traditional approach, in fact, have a high risk of presenting a cardiovascular event.

Therefore, incorporating coronary artery calcium (CAC) into the traditional risk model can improve risk prediction. This was demonstrated by calculating the Framingham model in 618 male patients [11]. The traditional approach has limitations since it does not take into account individual cardiovascular risk and does not detect early atherosclerosis and other arterial wall alterations. Underestimation of individual risk leads to millions of people not receiving adequate medical treatment to reduce their cardiovascular risk, and asymptomatic subjects but vulnerable to having a cardiovascular or cerebrovascular accident in the short term are not offered the benefits of available prophylactic therapies. For instance, hypertension is considered an asymptotic disease, but it has serious and lethal complications if left untreated [12]. The study examined the probability of patients falling into one of four categories of coronary artery calcification (CAC) based on linear and nonlinear regression models, which were adjusted using a relative risk (RR) based on the risk of coronary heart disease (CHD) in individuals. The predictive power of the models was evaluated using receiver operating characteristic (ROC) curves. The CAC model had a remarkable predictive value of atherosclerosis, with an area under the ROC curve of 0.74, and was further improved when combined with conventional risk factors to assess overall risk of CHD. The use of other indices of subclinical atherosclerosis can lead to an integrative risk assessment that can more accurately determine an individual's short- term risk of suffering a cardiovascular or cerebrovascular accident [13]. Machine learning algorithms offer the opportunity to improve accuracy by identifying complex interactions between risk factors. Different regions have developed their own risk scores that incorporate various CVD risk factors and markers of CVDs. While most risk-prediction tools are based on stochastic models using variables from cohort studies, alternative approaches are also being explored [10].

IV. CONCLUSION

Nonlinear systems play a crucial role in predictive analytics for assessing disease and health risks in people. With the increasing importance of data and eHealth, there is a need for specific computational intelligence methods to extract valuable insights from long-term behavioral data, particularly for chronic diseases. Predictive analytics and data modeling can aid in the development of clinical decision support systems, which are fundamental tools for personalized healthcare and enable healthcare providers to make informed decisions based on patients' data. Moreover, computational intelligence and predictive analytics can facilitate the visualization of a comprehensive picture of health across large populations, helping to create more efficient healthcare strategies worldwide. Despite challenges such as the complexity of health data, lack of interoperable systems, and algorithmic biases, machine learning and nonlinear methods using computational intelligence have already shown their potential in predicting health risks and diseases. These technologies are expected to transform the field of health analytics, enabling early detection and prediction of diseases on a global scale.

REFERENCES

[1] P. Chatterjee, LJ. Cymberknop, R. Armentano, W. Legnani, TE. Moschandreou, Nonlinear systems in healthcare towards intelligent disease prediction.In Nonlinear Systems-Theoretical Aspects and Recent Applications.IntechOpen, (2019).

[2] N.A. Noori, A. A., Yassin, Towards for Designing Intelligent Health Care System Based on Machine Learning. Iraqi Journal for Electrical and Electronic Engineering, 17(2), (2021).

[3] N. Donges, The random forest algorithm. Towards data science, 22, (2018).

[4] G. Bebis, M. Georgiopoulos, Feed-forward neural networks. Ieee Potentials, 13(4), 27-31, (1994).

[5] A.K. Jain, J. Mao, K. M. Mohiuddin, Artificial neural networks: A tutorial. Computer, 29(3), 31-44, (1996).

[6] L.R. Medsker, L. C. Jain, Recurrent neural networks. Design and Applications, 5, 64-67, (2001).

[7] S. Madakam, R. Ramaswamy, S. Tripathi, (2015). Internet of Things (IoT): A literature review. Journal of Computer and Communications, 3(5), 164-173, (2015).

[8] I. Volkov, G. Radchenko, A. Tchernykh, Digital twins, internet of things and mobile medicine: a review of current platforms to support smart healthcare. Programming and Computer Software, 47(2021),578-590.

[9] Y. Chang, X. Chen, Estimation of chronic illness severity based on machine learning methods. Wireless Communications and Mobile Computing, 2021, 1-13, (2021).

[10] K. Deepika, S. Seema, Predictive analytics to prevent and control chronic diseases. In 2016 2nd international conference on applied and theoretical computing and communication technology (iCATccT) (pp. 381-386). IEEE, (2016, July).

[11] Y. Kumar, A. Koul, R. Singla, M.F. Ijaz, Artificial intelli- gence in disease diagnosis: a systematic literature review, synthesizing framework and future research agenda. Journal of Ambient Intelligence and Humanized Computing, 1-28, (2022).

[12] A.A. Nancy, D. Ravindran, P. D. Raj Vincent, K. Srinivasan, D. Gutierrez Reina, Iot-cloud-based smart healthcare monitoring system for heart disease prediction via deep learning. Electronics, 11(15), 2292, (2022).

[13] M. Abdul Raheem, I. D. Oladipo, A. Gonza´lez-Briones, J. B., Awotunde, A. R., Tomori, R.G. Jimoh, An efficient lightweight speck technique for edge-IoT-based smart healthcare systems. In 5G IoT and Edge Computing for Smart Healthcare (pp. 139-162)., Academic Press, (2022).

[14] L.K. Ramasamy, F. Khan, M. Shah, B. V. V. S., Prasad, C. Iwendi, C. Biamba, Secure smart wearable computing through artificial intelligence-enabled internet of things and cyber-physical systems for health monitoring. Sensors, 22(3), 1076, (2022).