Review Of Research
Vol. 3 | Issue. 11 | Aug. 2014
Impact Factor : 2.1002 (UIF)
ISSN:-2249-894X Available online at www.lbp.world

ORIGINAL ARTICLE

ARTIFICIAL NEURAL NETWORKS USE IN MEDICAL FIELD FOR TREATMENT OF DIFFERENT DISEASES

Md. Atheeq Sultan Ghori
Assistant Professor , Department of CSE ,
Telangana University , NIZAMABAD.

ABSTRACT:

An extensive amount of information is currently available to clinical specialists, extending from points of interest of clinical side effects to different sorts of biochemical information and yields of imaging gadgets. Each sort of information gives data that must be assessed and assigned to a specific pathology amid the symptomatic procedure. To streamline the indicative procedure in day by day routine and evade misdiagnosis, manmade brainpower strategies (particularly PC supported determination and manufactured neural systems) can be utilized. These versatile learning calculations can deal with various sorts of restorative information and incorporate them into classified yields. In this paper, we quickly survey and examine the theory, capacities, and limitations of artificial neural networks in medical diagnosis through selected examples.

Key words: medical diagnosis; artificial intelligence; artificial neural networks; cancer; cardiovascular diseases; diabetes

INTRODUCTION

Artificial neural networks (ANNs) are broadly utilized as a part of science and innovation with applications in different branches of science, material science, and science. For instance, ANNs are utilized as a part of concoction energy (Amato et al. 2012), forecast of the conduct of modern reactors (Molga et al. 2000), demonstrating energy of medication discharge (Li et al. 2005), improvement of electrophoretic strategies (Havel et al. 1998), order of horticultural items, for example, onion assortments (Rodríguez Galdón et al. 2010), and even species assurance (Fedor et al. 2008, Michalkova et al. 2009, Murarikova et al. 2010). When all is said in done, exceptionally differing information, for example, characterization of organic s, substance dynamic information, or even clinical parameters can be dealt with in basically a similar way. Progressed computational techniques, including ANNs, use differing sorts of information that are handled with regards to past preparing history on a characterized test database to create a clinically significant yield, for instance the likelihood of a specific pathology or characterization of biomedical s. Because of the considerable pliancy of information, ANNs have demonstrated helpful in the examination of blood and pee tests of diabetic patients (Catalogna et al. 2012, Fernandez de Canete et al. 2012), finding of tuberculosis (Er et al. 2008, Elveren and Yumuşak 2011), leukemia arrangement (Dey et al. 2012), investigation of confounded emanation tests (Barwad et al. 2012), and picture investigation of radiographs or notwithstanding living tissue (Barbosa et al. 2012, Saghiri et al. 2012). The point of this paper is to introduce the general logic for the utilization of ANNs in symptomatic methodologies through chose illustrations, archiving the huge fluctuation of information that can fill in as contributions for ANNs. Consideration won't just be given to the energy of ANNs applications, yet in addition to assessment of their points of confinement, conceivable patterns, and future advancements and associations with different branches of human drug (Fig. 1).

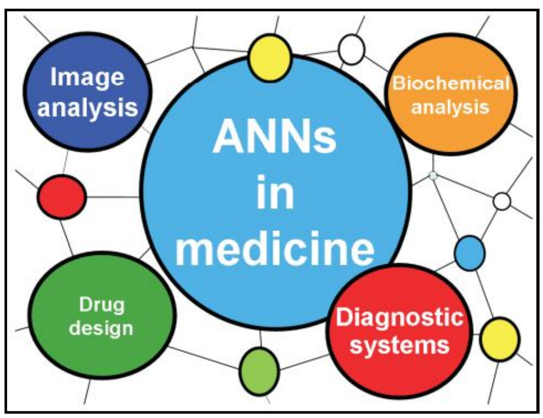

Fig. 1. Overview of the main applications of artificial neural networks in medicine.

ARTIFICIAL NEURAL NETWORKS

An ANN is a mathematical representation of the human neural design, reflecting its "learning" and "speculation" capacities. Consequently, ANNs have a place with the field of computerized reasoning. ANNs are generally connected in look into on the grounds that they can display exceedingly non-direct frameworks in which the relationship among the factors is obscure or extremely intricate. An audit of different classes of neural systems can be found in (Aleksander and Morton 1995, Zupan and Gasteiger 1999).

MATHEMATICAL BACKGROUND

A neural system is shaped by a progression of "neurons" (or "hubs") that are sorted out in layers. Every neuron in a layer is associated with every neuron in the following layer through a weighted association. The estimation of the weight w_{ij} shows the quality of the association between the i^{th} neuron in a layer and the j^{th} neuron in the following one.

The structure of a neural system is framed by an "info" layer, at least one "concealed" layers, and the "yield" layer. The quantity of neurons in a layer and the quantity of layers depends emphatically on the multifaceted nature of the framework examined. In this manner, the ideal system design must be resolved. The general plan of a run of the mill three-layered ANN design is given in Fig. 2.

The neurons in the information layer get the information and exchange them to neurons in the principal shrouded layer through the weighted connections. Here, the information are scientifically prepared and the outcome is exchanged to the neurons in the following layer. At last, the neurons in the last layer give the system's yield. The j^{th} neuron in a shrouded layer forms the approaching information (x_i) by: (I) figuring the weighted entirety and including an "inclination" term (θ_j) as indicated by Eq. 1:

$$net_j = \sum_{i=1}^{m} x_i \times w_{ij} + \theta_j \quad (j = 1, 2, \ldots, n) \quad (1)$$

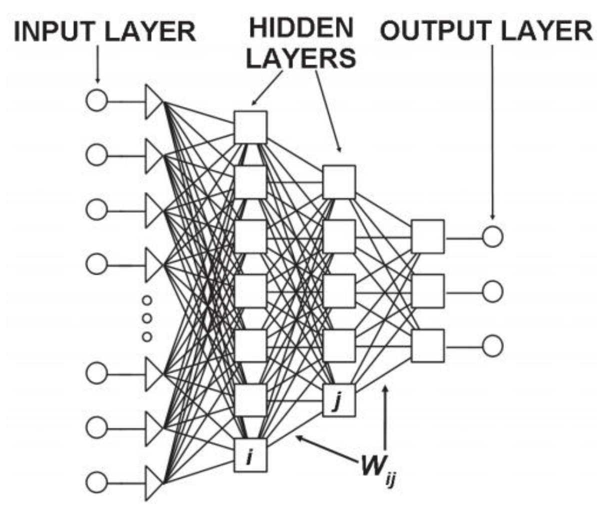

Fig. 2. General structure of a neural network with two hidden layers. The w_{ij} is the weight of the connection between the $i-^{th}$ and the $j-^{th}$ node.

(ii) transforming the net j through a reasonable scientific "exchange capacity", and (iii) exchanging the outcome to neurons in the following layer. Different exchange capacities are accessible (Zupan and Gasteiger 1999); notwithstanding, the most ordinarily utilized is the sigmoid one.

$$f(x)=\frac{1}{1+e^{-x}} \qquad (2)$$

Network learning The mathematical process through which the system accomplishes "learning" can be primarily disregarded by the last client. Along these lines, the system can be seen as a "black box" that gets a vector with m inputs and furnishes a vector with n yields (Fig. 3). Here we will give just a short portrayal of the learning procedure; more subtle elements are given to case in the survey by (Basheer and Hajmeer 2000). The system "learns" from a progression of "illustrations" that frame the "preparation database" (Fig. 4). An “example” is formed by a vector $X_{im} = (x_{i1}, x_{i2}, \ldots., x_{im})$ of inputs and a vector $Y_{in} = (y_{i1}, y_{i2}, \ldots.., y_{in})$ of outputs. The objective of the training process is to approximate the function f between the vectors X_{im} and the Y_{in}

$$Y_{i,n} = f(X_{i,m}) \qquad (3)$$

This is accomplished by changing iteratively the estimations of the association weights (w_ij) as indicated by an appropriate scientific run called the preparation calculation.

The values of the weights are changed by utilizing the steepest plummet technique to limit a reasonable capacity utilized as the preparation halting criteria. One of the capacities most normally utilized is the whole of squared residuals given by Eq. 4:

$$E=\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(y_{ij}-y_{ij}^{*}\right)^{2} \qquad (4)$$

where y_{ij} and y_{ij}^{*} are the actual and network’s $j-^{th}$ output corresponding to the ith input vector, respectively. The current weight change on a given layer is given by Eq. (5):

$$\Delta w_{ij} = -\eta\frac{dE}{dw_{ij}} \qquad (5)$$

where η is a positive constant called the learning rate. To achieve faster learning and avoid local minima, an additional term is used and Eq. 5 becomes:

$$\Delta w_{ij}^{k} = -\eta \frac{dE}{dw_{ij}} + \mu \Delta w_{ij}^{k-1} \qquad (6)$$

where μ is the "momentum" term and Δw_{ij}^{k-1} is the change of the weight w_{ij} from the $(k-1)-^{th}$ learning cycle. The learning rate controls the weight update rate according to the new weight change and the momentum acts as a stabilizer, being aware of the previous weight change.

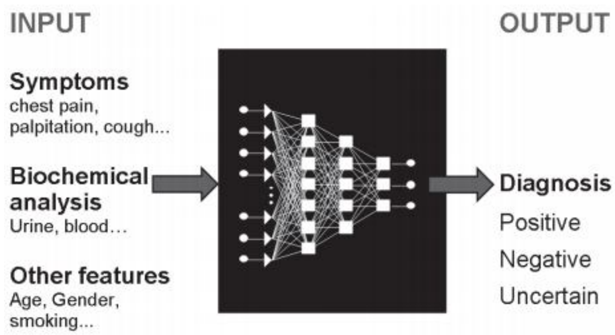

Fig. 3. Details of input and output items concerning ANNs-based diagnosis (ANN architecture is often hidden and it is indicated here as a black box).

Patient code	MEDICAL DATA					DIAGNOSIS
1	$data_{1,1}$	...	$data_{1,i}$	...	$data_{1,m}$	POSITIVE
2	$data_{2,1}$	...	$data_{2,i}$	...	$data_{2,m}$	POSITIVE
3	$data_{3,1}$	...	$data_{3,i}$	...	$data_{3,m}$	POSITIVE
...	...	...	...	...	...	...
k	$data_{k,1}$	...	$data_{k,i}$	...	$data_{k,m}$	NEGATIVE
k+1	$data_{k+1,1}$	...	$data_{k+1,i}$	...	$data_{k+1,m}$	NEGATIVE
...	...	...	...	...	...	...
n	$data_{n,1}$	...	$data_{n,i}$	...	$data_{n,m}$	NEGATIVE

Fig. 4. Example of training database structure. Each row refers to a different patient labeled with a numerical code. The element datak, i refers to the $i-^{th}$ medical data (symptom, laboratory data, etc.) of the $k-^{th}$ patient.

The capacity given by Eq. 4 is likewise utilized as the basis to upgrade the system design since it relies upon the quantity of shrouded layers and the quantity of neurons in that. To locate the ideal design, the most widely recognized approach is to plot the estimation of E (Eq. 4) as a component of the quantity of hubs in the concealed layer (q). A case of such a plot is given in Fig. 5. As q builds, E diminishes.

Be that as it may, after an ideal estimation of q the change is fairly poor. More often than not, the ideal estimation of q is found from the convergence purpose of the two branches of the plot. After the ideal neural system engineering is discovered, the preparation procedure is performed until the point that a legitimate least estimation of E is come to. A short time later, the system is checked with illustrations not already utilized as a part of the preparation step. This procedure is called check. At last, the system can be utilized to foresee yields for new info vectors.

STRUCTURE OF THE TRAINING DATABASE

As stated above, the network must be prepared utilizing a reasonable database. The database is a table (or grid) of information concerning patients for whom the conclusion (positive or negative) about a specific sickness is as of now known. Each column of the network alludes to one patient. The principal m components of the line are therapeutic information and the keep going n components speak to the yield (determination). The expression "medicinal information" shows biochemical, atomic attractive reverberation (NMR), research center information, and side effects and other data gave by the therapeutic expert (Table 1). A case of such preparing framework with one yield variable (n = 1) that may expect two conceivable esteems (positive or negative) is given in Fig. 4.

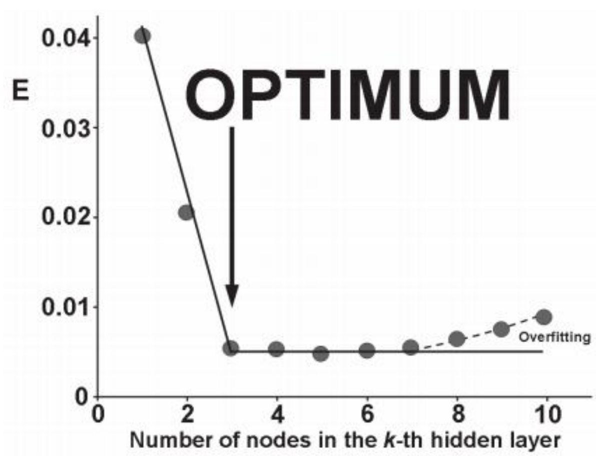

Fig. 5. Example of the plot used to select the optimal number of nodes in a given hidden layer. It is indicated that too high number of nodes might lead to over fitting.

Table 1. Brief overview of data in clinical context used as inputs for ANN.

Input data or method	Clinical context	Output information	Reference
Age, cholesterol concentration, arterial hypertension	Coronary artery disease	Diagnosis	(Atkov et al. 2012)
Heart sound	Valve stenosis	Diagnosis	(Uğuz 2012)
Hematologic profile	Chronic myeloid leukemia	Classification of leukemia	(Dey et al. 2012)
Visual information of wireless capsule endoscopy	Small bowel tumors	Diagnosis, classification of tumor	(Barbosa et al. 2012)
Glucose concentration – Near-infrared spectroscopy	Diabetes	Diagnosis	(Arnold 1996)
Demographic and clinicopathologic data, surgical outcome	Hepatocellular carcinoma	Prediction of disease free survival	(Ho et al. 2012)
Cytology of effusion fluid	Carcinoma	Presence of malignant cells	(Barwad et al. 2012)
Speech record	Oral/Oropharyngeal cancer	Detection of nasalence (hypernasality)	(de Bruijn et al. 2011)
Electroencephalographic (EEG) recordings	Epilepsy	Prediction of seizures	(Fernandez-Blanco et al. 2012)

OVERVIEW OF ANNs IN MEDICAL DIAGNOSIS

There are several reviews concerning the utilization of ANNs in restorative determination. The idea was first laid out in 1988 in the spearheading work of (Szolovits et al. 1988) and from that point forward many papers have been distributed. The general utilization of ANNs in therapeutic determination has beforehand been depicted (Alkim et al. 2012). For example, ANNs have been related in the finding of: (I) colorectal peril (Spelt et al. 2012), (ii) different sclerosis wounds (Mortazavi et al. 2012a, b), (iii) colon tumor (Ahmed 2005), (iv) pancreatic disorder (Bartosch-Härlid et al. 2008), (v) gynecological sicknesses (Siristatidis et al. 2010), and (vi) early diabetes (Shankaracharya et al. 2010). Besides, ANNs have also been associated in the examination of data and decisive gathering of patients with uninvestigated dyspepsia in gastroenterology (Pace and Savarino 2007) and in the search for biomarkers (Bradley 2012). A novel, general, smart, and versatile sickness conclusion framework has been made in context of learning vector quantization ANNs. This calculation is the primary proposed versatile calculation and can be connected to totally extraordinary sicknesses, as exhibited by the 99.5% characterization precision accomplished for both bosom and thyroid malignancies. Tumor, diabetes, and cardiovascular illnesses are among the most genuine and differing infections. The measure of information originating from instrumental and clinical examination of these infections is very substantial and in this manner the advancement of devices to encourage determination is of incredible importance. Therefore, we will give a short diagram of the advances in the utilization of ANNs to the field of diagnosis for each of these diseases.

CARDIOVASCULAR DISEASES

Cardiovascular diseases (CVDs) are characterized as all illnesses that influence the heart or veins, the two supply routes and veins. They are a standout amongst the most vital reasons for death in a few nations. CVD has hence turned into a critical field of concentrate amid the most recent 20 years.

As indicated by the NCHS, coronary vein malady (CAD) is right now the main source of death around the world, subsequently early analysis is imperative. With this point, Karabulut and Ibrikçi connected ANNs with the Levenberg-Marquardt back spread calculation as base classifiers of the revolution woods troupe strategy (Karabulut and Ibrikçi 2012). Finding of CAD with 91.2% precision was accomplished from information gathered non-obtrusively, inexpensively, and effectively from the patient. Other information, for example, age, various types of cholesterol, or blood vessel hypertension have been utilized to analyze CAD (Atkov et al. 2012). The model that performed with the best exactness (93%) was the one that included both hereditary and non-hereditary elements identified with the illness.

CANCER

A fast and right conclusion is fundamental for the clinical administration of tumor, including determination of the most appropriate helpful approach. The utilization of ANNs in recognizing specific malignancy writes or the expectation of growth advancement rose in the late 1990s as a promising computational-based indicative device utilizing different information sources. Utilization of novel sub-atomic methodologies, for example, small scale RNA screens, expands the potential outcomes for the use of ANNs in the scan for designs particular for a specific sickness, for instance rectal malignancy and its reaction to cytoreductive treatment (Kheirelseid et al. 2012). Later on, sensible forecast of the deliberate in vitro chemotherapeutic reaction in light of 1 H NMR of glioma biopsy separates was accomplished utilizing ANNs to acquire programmed differential finding of glioma (El-Deredy et al. 1997)

The utilizations of ANNs in radiology mean to create computerized choice emotionally supportive networks, helping, for instance, in the order of cerebrum tumors by attractive reverberation (Tate et al. 2006). The idea and configuration raised by Tate was likewise connected by Brougham and associates on lung carcinoma (Brougham et al. 2011). In this procedure, the same trial convention was done by two distinct groups of analysts looking at two arrangements of entire cell 1 H NMR spectra at various circumstances.

DIABETES

Diabetes speaks to a genuine medical issue in created nations, with assessed numbers accomplishing 366 million diabetes cases comprehensive in 2030 (Leon et al. 2012). The most broadly perceived sort of diabetes is type II, in which the cell response to insulin is debilitated inciting aggravation of tissue homeostasis and hyperglycemia. The standard in diabetes investigation or checking is quick estimation of glucose obsession in blood tests. The ANNs extrapolate glucose centers from ghost twist, thus engaging supportive seeing of diabetes in the midst of step by step works out.

FUNDAMENTAL STEPS IN ANNs-BASED MEDICAL DIAGNOSIS

The work process of ANN examination emerging from the portrayed out clinical conditions is showed up in Fig. 6 which gives a short review of the essential advances that ought to be taken after to apply ANNs for the reasons for restorative finding with adequate certainty.

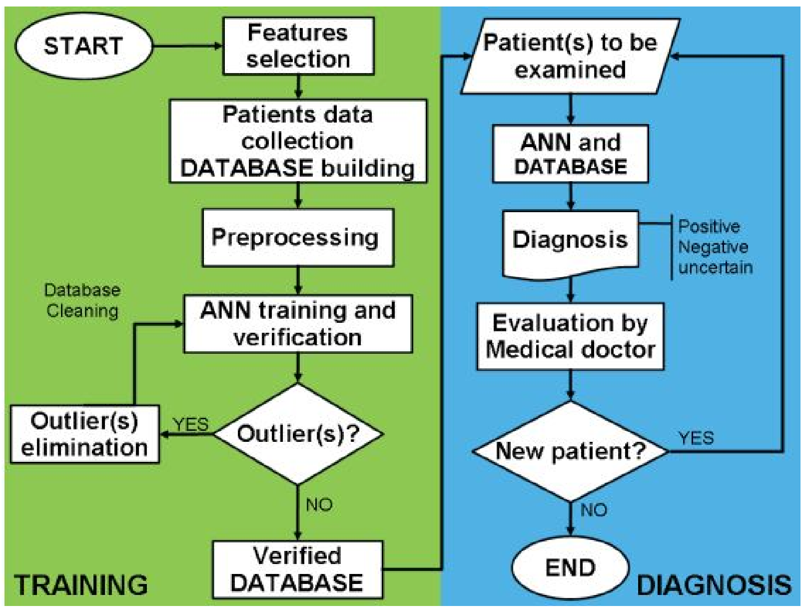

Fig. 6. Diagram of fundamental steps in ANNs-based medical diagnosis. Building of the database and "learning" represents the left half (green) and its application for the diagnosis is the right part (blue).

For the reasons discussed above, the network receives patient's information to anticipate the conclusion of a specific illness. After the objective malady is set up, the following stage is to appropriately choose the highlights (e.g., side effects, lab, and instrumental information) that give the data expected to segregate the distinctive wellbeing states of the patient. This should be possible in different ways. Instruments utilized as a part of chemometrics permit the disposal of variables that give just excess data or those that contribute just to the clamor. In this manner, cautious determination of appropriate highlights must be completed in the principal arrange. In the subsequent stage, the database is constructed, approved and "cleaned" of exceptions. Subsequent to preparing and check, the system can be utilized as a part of training to foresee the finding. At long last, the anticipated determination is assessed by a clinical master. The major steps can be summarized as:

FEATURES SELECTION

Building the database

- Data cleaning and preprocessing
- Data homoscedasticity

  Training and verification of database using ANN
- Network type and architecture
- Training algorithm
- Verification
- Robustness of ANN-based approaches

TESTING IN MEDICAL PRACTICE

The individual steps listed above will be shortly commented and some details given.

FEATURES SELECTION

Correct diagnosis of any disease is based on various, and typically incongruous, information (highlights): for instance, clinicopathologic assessment, research center and instrumental information, subjective anamnesis of the patient, and contemplations of the clinician. Clinicians are prepared to remove the applicable data from each sort of information to distinguish conceivable conclusions. In fake neural system application such information are called "highlights". Highlights can be manifestations, biochemical investigation information as well as whichever other pertinent data helping in conclusion. In this manner, the experience of the expert is firmly identified with the last determination. The capacity of ANNs to gain from cases makes them extremely adaptable and effective instruments to quicken restorative conclusion. A few sorts of neural systems are reasonable for taking care of perceptual issues while others are more adjusted for information demonstrating and utilitarian guess (Dayhoff and Deleo 2001). Despite the highlights chose, those decided for preparing the neural system ought to be "powerful" pointers for a given clinical circumstance or pathology. When all is said in done, highlight choice depends upon past clinical experience. Highlights that bring lacking, repetitive, non-particular, or uproarious data about the examined issue ought to be evaded. The determination/extraction of appropriate highlights among every single accessible one is generally completed utilizing different methodologies.

BUILDING THE DATABASE

The neural system is prepared utilizing an appropriate database of "illustration" cases. A "case" is given by one patient whose esteems for the chose highlights have been gathered and assessed. The nature of preparing and the resultant speculation, and in this way the expectation capacity of the system, unequivocally rely upon the database utilized for the preparation. The database ought to contain an adequate number of dependable "cases" (for which the conclusion is known) to enable the system to learn by separating the structure covered up in the dataset and afterward utilize this "information" to "sum up" the control to new cases. Likewise, clinical research center information ought to be in a shape that is promptly transferable to programs for PC helped conclusion (Strike et al. 1986).

DATA CLEANING AND PREPROCESSING

Information in the preparation database must be preprocessed before assessment by the neural system. A few methodologies are accessible for this reason. Information are typically scaled to exist in the interim [0, 1] on the grounds that the most usually utilized transference work is the socalled strategic one. Also, it has been shown that cases for which a few information are missing ought to be expelled from the database to enhance the arrangement execution of the system (Gannous and Elhaddad 2011).

DATA HOMOSCEDASTICITY

Once the appropriate highlights, database, information preprocessing strategy, preparing calculation, and system design have been distinguished, information concerning "new" patients who are excluded in the preparation database can be assessed by the prepared system. The inquiry is whether the new information have a place with an indistinguishable populace from those in the database (homoscedasticity). Disappointment at this progression may lead the system to misclassify the new information. This issue can be settled by the utilization of an extra parameter that demonstrates the populace to which a specific example has a place.

TRAINING AND VERIFICATION OF DATABASE USING ANN

Network type and architecture

In spite of the fact that multilayer sustain forward neural systems are frequently utilized, there are a vast assortment of different systems including bayesian, stochastic, repetitive, or fluffy. The ideal neural system design must be chosen in the main stage. This is typically done testing systems with various number of shrouded layers and hubs in that. The ideal engineering is that for which the base estimation of E (Eq. 4) for both preparing and check is acquired.

Training algorithm

Various training algorithms are available. As talked about in "System learning" area, backpropagation calculation requires the utilization of two preparing parameters: (I) learning rate and (ii) force. Typically, high estimations of such parameters prompt shaky learning, and in this manner poor speculation capacity of the system. The ideal estimations of the preparation parameters rely on the multifaceted nature of the considered framework. When all is said in done, the estimation of force is lower than that of learning rate. Moreover, the entirety of their esteems ought to be around equivalent to one.

Verification

ANNs-based medical diagnosis should be verified by means of a dataset different from that one used for training

Robustness of ANN-based approaches

It is outstanding that ANNs can endure a specific level of commotion in the information and therefore they commonly give adequate expectation precision. Be that as it may, this commotion may now and then reason deluding comes about, particularly when demonstrating exceptionally complex frameworks, for example, the wellbeing state of a human body. Such commotion would not just effect the ordinary vulnerability of the deliberate information yet may likewise affect optional elements, for instance the conjunction of more than one sickness. Crossed impacts can't be anticipated unless they have been considered amid working of the preparation database. Any factor that impacts the side effects of the malady under investigation must be considered by incorporating such cases in the database. Just along these lines can the system accurately order the patient. Obviously, one approach to stay away from this is to join the experience of the clinical expert with the discriminative energy of ANN-based methodologies.

Testing in medical practice

As the final step in ANN-aided diagnosis should be testing in medical practice. For each new patient the system's result is to be precisely analyzed by a clinician. Restorative information of patients for which the anticipated finding is right can be inevitably incorporated into the preparation database.

In any case, wide and broad evaluation of ANN helped analysis applications in clinical setting is fundamental even all through various establishments. Checked ANN-helped restorative conclusion bolster applications in clinical setting are fundamental condition for assist extension in prescription.

CONCLUSIONS

ANNs represent a powerful tool to help physicians perform finding and different authorizations. In such manner, ANNs have a few points of interest including:

(I) The capacity to process substantial measure of information
(ii) Reduced probability of ignoring pertinent data
(iii) Reduction of finding time

ANNs have proven suitable for satisfactory diagnosis of various diseases. Moreover, their utilization makes the finding more dependable and thusly expands tolerant fulfillment. In any case, in spite of their wide application in present day analysis, they should be viewed as just as a device to encourage an official conclusion of a clinician, who is at last in charge of basic assessment of the ANN yield. Techniques for abridging and explaining on instructive and insightful information are constantly enhancing and can contribute extraordinarily to viable, exact, and quick therapeutic determination.

REFERENCES

1. Brougham D, Ivanova G, Gottschalk M, Collins D, Eustace A, O'Connor R, Havel J. Artificial neural networks for classification in metabolomic studies of whole cells using 1H nuclear magnetic resonance. J Biomed Biotechnol. 2011: 158094, 2011.
2. Ahmed F. Artificial neural networks for diagnosis and survival prediction in colon cancer. Mol Cancer. 4: 29, 2005.
3. Elveren E, Yumuşak N. Tuberculosis disease diagnosis using artificial neural network trained with genetic algorithm. J Med Syst. 35: 329–332, 2011.
4. Pace F, Savarino V. The use of artificial neural network in gastroenterology: the experience of the first 10 years. Eur J Gastroenterol Hepatol. 19: 1043–1045, 2007.
5. Dey P, Lamba A, Kumari S, Marwaha N. Application of an artificial neural network in the prognosis of chronic myeloid leukemia. Anal Quant Cytol Histol. 33: 335–339, 2012.
6. Bartosch-Härlid A, Andersson B, Aho U, Nilsson J, Andersson R. Artificial neural networks in pancreatic disease. Br J Surg. 95: 817–826, 2008.
7. Uğuz H. A biomedical system based on artificial neural network and principal component analysis for diagnosis of the heart valve diseases. J Med Syst. 36: 61–72, 2012.
8. Elveren E, Yumuşak N. Tuberculosis disease diagnosis using artificial neural network trained with genetic algorithm. J Med Syst. 35: 329–332, 2011.
9. Szolovits P, Patil RS, Schwartz W. Artificial Intelligence in Medical Diagnosis. Ann Intern Med. 108: 80–87, 1988.
10. Qeethara Kadhim Al-Shayea, "Artificial neural network in medical diagnosis", International journal of computer science Vol.8, Issue 2, March 2011.
11. Qeethara Kadhim Al-Shayea and Itedal S.H. Bahia, "Urinary system Dieseases Diagnosis Using Artificial neural networks", IJCSNS, Vol.10, No.7, July 2010.
12. Ahmed F. Artificial neural networks for diagnosis and survival prediction in colon cancer. Mol Cancer. 4: 29, 2005.
13. Abdel- Badeeh M. Salem, "Case Base Reasoning Technology for Medical Diagnosis", World Academic of Science, Engineering and Technology 7, 2007.

14. Hongmin Zhang, Xuefueng Dia, "The Application of Fuzzy Neural Network in Medicine", International Conference on Biological and Biomedical Sciences Advances in Biomedical engineering Vol.9, 2012.
15. Kaushal Kumar & Abhishek, "Artificial Neural Networks for Diagnosis of Kidney stone Disease", I.J. Information technology and computer science July-2012.
16. J.B.Siddharth Jonathan and K.N. Shruthi, "A two tier neural inter- Network Based Approach to Medical Diagnosis Using K- Nearest Neighbor classification for Diagnosis pruning.