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Solving Medical Problems through Computational Intelligence Methodologies: A Review

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Abstract. The primary objective of studies related to medical diagnoses, predictions, and classifications is to help health care clinicians with support in the context of more precise, economical and trouble-free systems. This investigation focuses on the review of newly developed computational intelligence algorithms in the context of computer-generated neural networks, fuzzy logic and neuro-fuzzy systems. Relevant literature in this area offers concise explanations on the concept of computational intelligence algorithms and how they are employed to analyse, forecast and solve predicaments in the medical domain. This work includes a portrayal of the benefits that come with the various methods employed for arriving at solutions to medical problems.

Keywords: medical diagnoses, health care, neural networks, fuzzy logic, computational intelligence.

INTRODUCTION

Healthcare establishments are constantly striving to provide good quality services at acceptable rates. Good quality services entail accurate diagnoses and the provision of effective remedies. Inaccurate clinical decisions need to be avoided as they can result in devastating outcomes. More often than not, clinical decisions derive from the instinct and knowledge of doctors and not from informative data stashed away in a database. This situation opens the door to unwelcome partialities, inaccuracies and elevated medical expenses. These issues compromise the provision of high-quality treatment to recipients of health care services.

AI, a wide-ranging domain, emphasizes the employment of computer schemes that demonstrate the capacity for intelligence [1]. The primary goal of AI is to produce intelligent machines that are not only able to function in difficult and volatile situations but are also more proficient when it comes to human reasoning, decision making and adaptation. Among the instruments of AI is (CI). This instrument relies on observations and experience to facilitate the crafting of a computer's model [2-6] forwarded papers on the use of CI for overcoming medical predicaments. CI systems can be fashioned from several separate technologies. These include ANN, fuzzy logic and neuro-fuzzy systems.

ANN is described as a formidable CI process that comes with the capacity to consider an array of data for the structuring of weight matrices that correspond to learning patterns. It is a mathematical model that imitates the human brain's biological neural network activity. Research related to the employment of ANN in the medical domain was conducted by [7-9].

The application of fuzzy logic, an offshoot of AI, has proven to be effective in several areas [10]. Among them are categorization, diagnosis, medical applications and computer vision. In line with fuzzy logic's capacity to manage indistinct and formless problems, [11-16] delved into its utilization as an instrument for decision making.

For the most part, issues in the medical field can be classified as (a) diagnosis i.e. the management of input values to analyse several outputs, (b) classification i.e. the management of input values to ascertain the category of

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the input, and (c) prediction i.e. the management of input values to forecast several outputs. After an explanation of the fundamental facets of ANN, fuzzy logic and neuro-fuzzy systems, we scrutinized several previous investigations conducted on issues related to prediction, classification and diagnosis. This was followed by a discussion on the benefits to be gained from the application of CI technologies in the medical domain.

COMPUTATIONAL INTELLIGENCE: A SUMMARIZATION

A description of three contemporary CI procedures (artificial neural network, fuzzy logic and neuro-fuzzy system) is provided in the sub-sections below.

Artificial Neural Network (ANN)

This is a CI algorithm that comes with an information processing capacity. Defined as a mathematical model, an ANN imitates the biological neural network's activity. The majority of ANNs are also capable of altering their configuration during the learning stage according to the passage of external or internal information through the network. Primed exclusively for the management of non-linear or non-stationary problems, an ANN can be employed for modeling the complicated linkages between the system's input and output data [17].

On the whole, a neural network comprises a collection of neurons, a connectivity pattern, a propagation rule, an activation rule, a transfer function, and a learning rule [18]. The design of an ANN comes in a wide variety of configurations. The most commonly utilized ANN structure is the uncomplicated multi-layered perception (MLP) model [19]. As illustrated in Figure 1, this model is a feed-forward network made up of an input layer, one or more than one hidden layer(s), and an output layer. The neurons in the layers may differ in quantity from one layer to another. The input layer neurons are utilized for conveying the input signals x_i to neurons in the hidden layer. Every neuron present in the hidden layers or output layer collects a weighted sum from every neuron in the preceding layer [20]. Outputs of the hidden layer neurons are computed with distinct transfer functions (f) alongside the output layer neurons. The computation for neuron outputs is as follows:

$$y_j = f(\sum w_{ji} x_i) \tag{1}$$

In this equation, f can represent either a sigmoidal or a hyperbolic tangent function, while w_{ji} denotes weight. Several learning algorithms can be harnessed for the setting of ANN weights. The training of MLP neural networks can be achieved by way of the backpropagation (BP) learning algorithm. Error (E) in the BP algorithm is computed as the sum of squared differences between the output neurons sought after and real values. The updating of the weights is realized through the propagation of the output neurons through the neuron layers. The definition of E is achieved through Equation 2 below.

$$E = \frac{1}{2}\sum_j (y_{dj} - y_j)^2 \tag{2}$$

Here, y_j represents the real value of an output neuron, while y_{dj} denotes that output neuron's sought after value [20, 21].

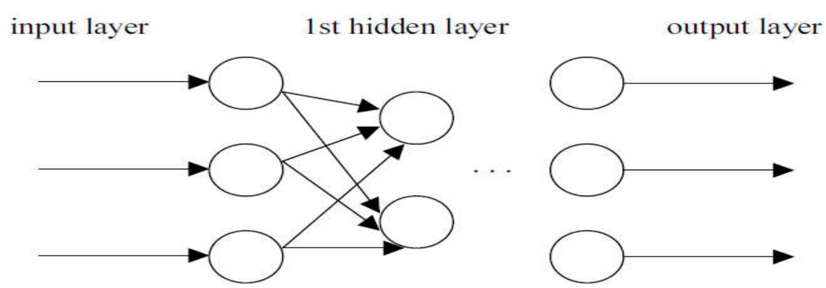

FIGURE 1. Multi-layered perception (MLP) model

Fuzzy Logic

As stated earlier, the AI derivative fuzzy logic has been observed to be effective in several areas [22]. These include pattern identification, medical applications and computer vision. It is a mathematical system deriving from a fuzzy cluster and secondary clusters. In an orthodox fuzzy logic methodology, an existence can either be deemed an element of a cluster or not an element of a cluster. From a mathematical perspective, in a situation where an existence is deemed an element of a cluster, it receives a value of '1'. On the other hand, an existence not considered an element of a cluster receives a value of '0'. In this approach, which is an extension of the conventional cluster indication process, every existence in a fuzzy existence cluster is tagged with a grade of membership. The grade of membership in the context of existence is gauged on a scale ranging between '0' and '1'.

The utilization of fuzzy logic was initiated by [23] to manage the lack of clarity in linguistics, as well as naturally convey human knowledge and inference. The fuzzy logic process commences with the creation of a fuzzy set (FS). This set, which is devoid of a decisive and distinct border, holds elements whose grade of membership is merely fractional. The curve describing how each point in the input area is plotted to a membership grade is termed the membership function (MF). As mentioned earlier, the degree of membership is rated on a scale ranging between '0' and '1'. The input area is also known as the universe of discourse. In equation 3, X represents the universe of discourse and x denotes a generic element of X. A conventional Set A is described as a compilation of elements or objects $x \in X$ in such a manner that x can either fit into or not fit into the set A, A-X. The definition of a characteristic (or membership) function for each element x in X facilitates the representation of a conventional Set A by a compilation of organized pairings (x, 0) or (x, 1). Membership is denoted as 1, while non-membership is denoted as 0. In contrast to a conventional set, the fuzzy set portrays the degree to which an element fits into a set. This permits the characteristic function of a fuzzy set to have a value ranging between 0 and 1. This value represents an element's membership degree in a specified set. If X is a compilation of objects generally symbolized by x, it follows that a fuzzy set A in X is recognized as a set of organized pairings:

$$A = \{ (x, \mu_A(x)) | x \in X\} \tag{3}$$

The membership function of linguistic variable x in A is represented as $\mu A(x)$. It plots X to the membership area M, M = [0, 1]. Here, only two points (0 and 1) are held by M. A is crisp, while $\mu A(x)$ matches the characteristic function of a decisive set.

The most uncomplicated triangular and trapezoidal membership functions are those shaped with the utilization of straight lines. Gaussian, generalized bell, sigmoidal and polynomial based curves are examples of other formations.

The shapes of two frequently employed MFs are featured in Figure 2. Notably, fuzzy logical reasoning is a superset of conventional Boolean logic.

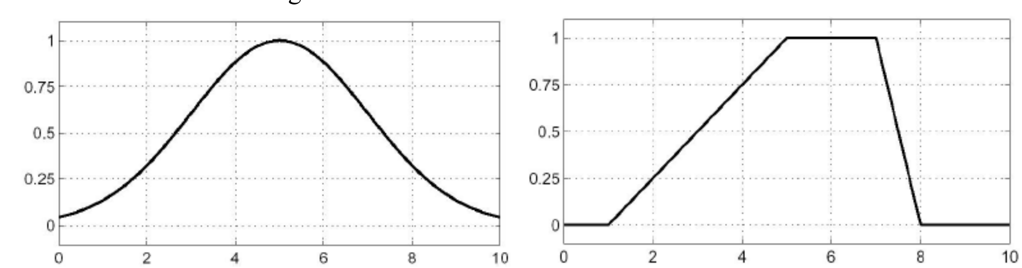

FIGURE 2. Shapes of two frequently employed MFs

Neuro-Fuzzy System

Described as an amalgamation of the fuzzy inference system and the neural network theory, the neuro-fuzzy process serves to ascertain the fuzzy sets as well as fuzzy rules. The effectiveness of the fuzzy inference system is attributed to its suitability for depicting the nature of human comprehension and reasoning methods. The neural network employs a variety of approaches for dealing with the same issues. Furnished with an outstanding capacity to learn by example, it successfully uncovers input and output patterns.

The neuro-fuzzy process exploits the qualities of the fuzzy inference and neural network systems. It harnesses the mathematical features of the neural network to fine-tune the human information processing procedure depicted by the rule-based fuzzy system [24]. Developments in the area of fuzzy neural networks progressed from the fine-tuning of the fuzzy system to the automated formation of fuzzy systems from data. Evidence of functional equivalence linked to several fuzzy models and neural networks served to propel research in this domain to a more advanced level [25].

Neural networks and fuzzy logic are non-linear models which are highly regarded for the analysis of medical data. These models complement the computational and logical aspects of statistical procedures. While the performance of perceptron is exceptional for the management of hefty datasets, the merging of neural learning and fuzzy logical network interpretation makes available a reduced network that is appropriate for the management of slighter datasets [26].

CI IN THE AREA OF MEDICAL DIAGNOSIS

Medical diagnosis is described as a vital procedure for characterizing a patient and categorizing his/her ailment to determine the most suitable remedy at hand [27]. A substantial number of ground-breaking schemes relevant to this subject matter have been recorded in literature. For instance, [28] recommended a detection scheme involving endoscopic image processing for the diagnosis and identification of lacerations that appear to be out of the ordinary. This scheme involves the implementation of a sophisticated fuzzy inference neural network that merges fuzzy systems and artificial neural networks. Also introduced was the concept of multiple classifier fusion directed at particular feature parameters. Innovative schemes have made their presence felt in the chromatic and achromatic fields. These schemes extract new texture features from the texture spectra for a specific region. The extraction of these texture features involves every colour component histogram of endoscopic images. The 100% degree of accuracy credited to such intelligence schemes suggests that they can be employed as a complementary diagnostic instrument for endoscopy procedures. A procedure for the early detection of Alzheimer disease (AD) was forwarded by [29]. In this process, fifteen distinct models of feed-forward and complex-recurrent ANNs (acquired from the Semeion Research Centre) were weighed against the linear discriminant analysis (LDA). These comparisons were based on a variety of learning laws (backpropagation, sinnet, and bi-modal). The superior ANN model accurately recognized mild AD patients in 94% of instances and 92% of instances with regards to the control subjects. This is an indication that in comparison to traditional statistical methods, the processing of biochemical tests associated with beta-amyloid cascade with ANNs offers a better discernment of early-stage AD. An early warning system for dengue fever that utilizes a fuzzy logic approach was recommended by [30]. In this system, the involvement of fuzzy logic as an inference engine that is applied to the rules of a knowledge base within a fuzzy (or a crisp rule-based) classification, reliably ascertains if a patient is afflicted with dengue fever. An innovative and speedy neural model for examining hefty volumes of medical data was proposed by [31]. This process entails the employment of neural networks to quicken the procedure for perceiving and categorizing pediatric respiratory ailments. This is realized through the application of cross-correlation between the input patterns and the input weights of neural networks in the frequency domain instead of the time domain. The fact that 98% of the tested cases were accurately categorized bears out the effectiveness of this model.

THE UTILIZATION OF CI FOR MEDICAL CLASSIFICATION

Among the major problems in the medical field is the issue of classification. Classification involves the utilization of input values to ascertain the category of the input [32]. a novel classification approach, presented by [33] uses artificial neural network ensembles to analyse gene expression microarray data. This process begins with the employment of the Wilcoxon test to single out significant genes for classification. This is followed by the generation of learning data sets for all members of the neural network ensemble by way of convex pseudo-data (CPD) procedures. A straightforward averaging process was used to amalgamate the predictions of individual networks. The test results disclosed that the efficiency of classification operations was enhanced by this process. It was also revealed that the employment of neural network groupings and microarray data is reliable for the classification of cancer. A system for the detection and classification of the region of interest (ROI) for tumours in positron emission tomography (PET) images was forwarded by [34]. This system involves the employment of a multilayer feed-forward neural network and a backpropagation training algorithm. Thresholding and multi-resolution analysis (MRA) procedures were utilized for delivering the generated features to the network. Two ANNs, each holding an input layer, two hidden layers and an output layer, were developed. The results from evaluations and investigations conducted on this system with regards to phantom and real PET images have been observed to be encouraging. The dynamic and competent PET volume classification technique crafted by [35] is known as the adaptive neuro-fuzzy inference system (ANFIS). The formation and learning process of this system derives from the implementation of a fuzzy inference scheme into the structure of an adaptive network. The ANFIS harnesses a hybrid learning method to learn a human knowledge-based plot which can be structured by ‘if-then’ fuzzy rules. This system is effective for the classification of lesions. Utilizing a deep convolutional neural network (CNN), [36] developed a system for the classification of lung CT image patches into seven categories. These categories embrace six distinct interstitial lung disease (ILD) designs. Comprising five convolutional layers with 2x2 kernels, this system employs LeakyRelu activations followed by average pooling with a size equivalent to sizes of the ultimate feature maps and three closely packed layers. In terms of training, the Adam optimizer was utilized to reduce the categorical cross-entropy. This procedure was observed to be superior to contemporary approaches when put to the test on a demanding dataset comprising 120 CT scans originating from a range of medical establishments and scanners.

THE UTILIZATION OF CI FOR MEDICAL PREDICTIONS

Medical predictions entail the utilization of input values to forecast various outputs. [37] came up with a system for forecasting the behavior of tumours' that proved to be more precise than conventional statistical procedures. An ANN and the neuro-fuzzy modelling (NFM) method were involved in this endeavor. In the ANN, the function layers are hidden and the uninterpretable weights are affixed to separate variables. This lack of clarity represents a stumbling block to the extensive use of ANNs in this area. NFM overcomes this dilemma by harnessing the modelling capabilities of fuzzy-logic to realize a full profile for every variable. This serves to generate an array of corresponding rules which are summed up in series and deciphered to achieve a quantitative output. This comparison between the ANN and NFM revealed that NFM is either equal to, or superior to ANN in terms of prediction accuracy. Furthermore, NFM is exceptionally efficient when it comes to the management of small-sized datasets. [38] conceived a scheme to facilitate the prediction of a dependable brain death index (BDI). This scheme separates the distinct patterns of brain-dead patients into three separate levels of coma. After the training of 100 networks, the 10 networks with the smallest amount of training inaccuracies were picked for the construction of the BDI model. The input data for the network was represented by 10 individual signals. This process employs a three-layer and a four-layer network structure. The effectiveness of each network holding a dissimilar quantity of neurons in the hidden layers was put to the test. The test results revealed that the performance of the network with four layers is superior to that with three layers. A procedure which entails the training of a multi-layer perceptron (MLP) was presented by [39]. This procedure utilizes a backpropagation learning algorithm to forecast asthma that perseveres throughout infancy. As the coding of output is binary and is based on the presence or absence of asthma, the network's output comes in the form of a single neuron. The trial and error format was introduced to identify the optimum transfer functions for the input and hidden layers. The network with a sigmoid transfer function in the hidden layer and a saturating linear function in the output layer provided the most outstanding results. This investigation employed correlation analysis to assess the diagnostic precision of 98 clinical factors and identified the 10 most significant factors for chronic asthma.

BENEFITS OF CI METHODS IN MEDICAL DOMAIN

Wide-ranging studies in the domain of CI have given rise to a variety of exceedingly helpful computing instruments. Such instruments have not only provided better solutions to problems in this area but also facilitated the solution of problems that were previously deemed unsolvable [2]. The dire need for precise medical analyses has highlighted the significance of CI expertise. Other than recognizing interrelationships contained in bulky datasets, the ANN is also adept at managing non-linear or non-static predicaments. Additionally, it can be employed for modelling the intricate associations between a system's input and output data [17]. Fuzzy logic is exceptionally competent at managing ambiguity and partial information, as well as the lack of clarity associated with certain medical problems. The categorization of symptoms, indications and laboratory experiments under one label is proving to be easier said than done. The contributory factors to this dilemma include the immense volume of medical data available, and more importantly, the indistinctness of diagnostic procedures. This situation makes urgent the need for procedures aimed at generating efficient diagnostic schemes. And currently, fuzzy logic appears to be at the forefront to fill this void. The neuro-fuzzy procedure gets its strength from the exploitation of two schemes: the fuzzy inference system and the neural network. It utilizes the mathematical features of the neural network to fine-tune the rule-based fuzzy system. The benefits that come with the utilization of CI methods to overcome problems related to the areas of diagnosis, prediction, and classification are displayed in Table 1.

TABLE 1. Benefits that come with the utilization of CI methods

Medical Problem	CI Method(s)	Benefits

Prediction	Neuro-fuzzy modelling (NFM) [37]	-NFM exploits the modelling capabilities of fuzzy-logic to achieve a comprehensive profile for each variable. This generates a set of corresponding rules which are summed up in series and interpreted to realize a quantitative output. -NFM can hypothetically alter a single variable while maintaining the constancy of others to generate fresh exploratory predictions. This facilitates the conducting of hypothesis testing and individual risk evaluation.
Diagnosis	Neuro-fuzzy system [28]	-The merging of fuzzy schemes and ANN enhances the effectiveness of this system, while the adoption of the multiple classifier fusion concepts facilitates the management of specific feature parameters.
Diagnosis	ANN [32]	-ANN achieves superior predictive values. This is attributed to its taking into account the parameters that may not be significant for the whole population, but are substantially significant within certain secondary groupings.
Classification	Ensembled ANN[33]	-This neural network ensemble can considerably enhance the effectiveness of a system that employs a single neural network. -The utilization of the bagging and boosting process significantly raises the level of precision during problem management. This is particularly helpful for overcoming problems in higher dimensions. Bagging is frequently applied as the convergence pace of neural network training tends to be slow.
Prediction	Ensembled ANN [38]	-This system reduces the influence of errors deriving from the output and enhances the predicting precision. This renders the system appropriate for the development of intricate models.
Classification	ANN [34]	-The mean squared error (MSE) of the ANN at 2.39e − 16 is minor, and this system comes with the capacity for precise tumour quantification.

Medical problem	**CI method(s)**	**Benefits**

Prediction	Multi-Layer Perceptron (MLP) network [39]	-The MLP network system evaluates 98 clinical factors to recognize the 10 most significant factors for an ailment. The classifier resulting from this process elevates the classification precision and reduces the dimension of the feature set. - The application of a trial and error format resulted in the identification of the best transfer functions for the input and hidden layers.
Classification	Adaptive neuro-fuzzy inference system (ANFIS) [35]	-This system successfully depicts the nature of human comprehension and reasoning processes. -The implementation of a fuzzy system into the framework of an adaptive network facilitates the utilization of a variety of strategies to realize a solution to an individual problem.
Diagnosis	Fuzzy logic [30]	-This system generates results that appear to be more accurate than those resulting from the diagnostic procedures of doctors. -This system reduces the workload of medical personnel and offers extensive information on the diagnostic process. It is also a public source of updated information on dengue fever.
Diagnosis	Neural networks[31]	-The extent of the feature input vector is decreased through the utilization of rough sets, and the training of the neural networks involves the most significant feature elements.
Classification	Convolutional neural network (CNN) [36]	-The design of this unique network depicts the low-level textural aspects of lung tissue. -This network significantly decreases the parameter count to enhance effectiveness and avert overfitting.

CONCLUSIONS

This study delves into the use of (CI) algorithms for the solution of problems in the medical field. CI technologies can be developed from fuzzy logic, ANN and neuro-fuzzy schemes. Neural networks come in a variety of structures. These include multi-layer perceptron's, ensemble ANN and convolutional neural networks. These systems, which are applied to solve medical problems related to prediction, diagnosis and classification, have proven to be a cut above the rest in the context of precision. Fuzzy logic is particularly adept at managing vague and incomplete information. It also appears to be the best option for facilitating the classification of the various symptoms, indications and laboratory experiments under a single label. The neuro-fuzzy procedure was devised through the merging of the fuzzy inference system and neural network. This blend paved the way to an elevation inefficiency as it exploits the outstanding qualities of both systems.

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