ARTIFICIAL INTELLIGENCE AND APPLICATIONS

Artificial Neural Networks for Estimation of Dementias Types

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Abstract:
In the last decades, there is a vivid interest of many researchers about algorithms with natural procedure similarities. Artificial Neural Networks (ANNs) are wide known algorithms, which have been developed in order to solve complex combinational problems and can be proven as a powerful tool in medical research. This paper implements computational algorithms, which were based on artificial neural networks for the dementia's types distinguish. Diversity of ANN architectures are implemented and assessed for correct prediction of types of dementia, based on available cases. The obtained results prove that ANNs have the ability to be incorporated in the field of Neurology.

Keywords:
Artificial neural networks; Cognitive impairment; Computational intelligence; Dementia

1. INTRODUCTION

The increasing power of computers and the desire of resolving problems without prior knowledge and symbolic representation of their rules have contributed to the development of non - symbolic learning methods. One of the approaches is the Artificial Neural Networks (ANNs). The number of applications and [1–3], which ANNs can be used, is an important element for their large development. ANNs simulate the function of human biological neurons and are used in many fields, such as robotics, medicine [4–6], financial and banking science [7–9], applied mathematics [10], development of environmental prediction models [11] and other fields [12].

Physicians use medical protocols in order to diagnose diseases. Medical diagnosis is the accurate decision of upon the nature of a patient's disease, the prediction of its likely evolution and the chances of recovery by a physician, based on a set of clinical and laboratorial criteria, applicable to a particular case. The diagnosis estimation for medical diseases is a complicated problem due to the non-linear interaction of the diagnostic factors [13].

ANNs are suitable for the prognosisof the diseaseas they use a set of examples that represent variants of the disease, instant of diagnostic rules. The neural networks have proven to be a powerful tool in the diagnosis of diseasesin different medical areas [4, 6, 14–17], such as oncology [18–21], endocrinology [22–24], urology [25, 26], pediatric [27], cardiology [28, 29], radiology [30], ophthalmology [31], neurology [32–34] and others [35, 36].

The implementation of appropriate neural network architecture is a critical point in many applications. Aneural network with few neurons involves insufficient knowledge representation, where as neural network architecture with many neurons leads to poor generalization ability. Aconventional technique for determining the appropriate architecture of the neural networks by trialand errormethod [37].

By utilization of available attributes in dementia diagnosis, as they proposed by physicians, combining with the engineers' knowledge in ANNs technologies, leads to the development of a neural network for prediction / prognosis of dementias. The determination of dementias' types using ANNs assists the physician in the selection of the appropriate medication. The specified ANN and the obtained results are presented in this paper.

2. DIAGNOTIC FACTORS OF DEMENTIA – DATA COLLECTION

Dementia is a clinical syndrome of widespread progressive deterioration of cognitive abilities and normal daily functioning. These cognitive and behavioral impairments pose considerable challenges to individuals with dementia, along with their family members and caregivers [38].

The clinical syndrome of dementia generally follows three primary expressions [39–42]. First, a neuropsychological component consisting of a range of cognitive impairments, often includes: memory impairments, aphasias, apraxias, agnosias, attentional difficulties and executive functioning impairments. The second primary expression of this syndrome is a neuro psychiatric element with associated symptoms and behavioral disturbances.These psychiatric features are present in a substantial proportionof affected individuals, and are commonly referredto as Behavioral and Psychological Symptoms of Dementia (BPSD). Common BPSD disturbances include depression,paranoid ideation, delusions, hallucinations, aggression, andwandering [43]. The third primary clinical expression includes deficits in activities of daily living [40]. In the early stages of dementia, impaired instrumental activities of daily livingmay be manifest including self-neglect of diet, personal hygiene, and common household tasks. Towards the later stages of dementia, basic activities of daily living are often impaired, presenting with obvious problems in dressing, eating, and bathing [44, 45].

The diagnosis of dementias' type, in this study, based on the following 30 parameters, nominally: i. memory impairment, ii. normal overall cognition, iii. normal daily life activities, iv. clinical significant memory impairment, v. clinical significant executive functions, vi. clinical significant visuospatial abilities disorder, vii. Verbal fluency and comprehension disorder, viii. change of clinical behavior, ix. progression disorders, x. decline of tactile sensations, xi.initiation of early memory disorder, xii. initiation of visuospatial abilities impairments, xiii. initiation of speech disorders, xiv. initiation of executive functions disorders,xv. early decline in social interpersonal conduct,xvi. early impairment in regulation of personal conduct, xvii. early emotional blunting, xviii. early loss of insight, xix. behavioural disorders, xx. speech – language disorders, xxi. cerebral-vasculardisease with focal findings on neurological examination, xxii. correlation between dementia and cerebral - vascular disease, with one or more of the following: a.sudden onset dementia, or within 3 months from a clinical stroke, b. sudden deterioration of cognitive function, c. ranging gradual deterioration of cognitive deficits, xxiii. cerebral - vascular disease indications by brain imaging, xxiv. neuropsychological tests: deficits in recall, episodic memory, short-term memory, executive function, orientation, concentration, abstract thinking, naming, xxv. neuropsychological tests: impaired non-verbal semantic memory, affective disorders, deficits in long-term memory / recall, impaired expression / definitions, xxvi. decline in personal hygiene and grooming, xxvii. hyperoralityand dietary changes, xxviii. primitive reflexes, xxix. Incontinence and xxx.absence of clinical or radiological evidence of systemic or other neurological disease (secondary dementia).

The coding of parameters i-iv is based on the existence or the absence of each symptom. On the other hand, the patient could not answer the parameters v-xxx. Consequently, the aforementioned parameters could have three values, which are the existence, the absence and the non-answered (NA) choice. In case of an aforementioned symptom exists, the corresponding value in ANN input layer will be set to one (1), otherwise to zero (0). The non-answered (NA) value of the v-xxx parameters is coding as -1, and this value is used by the ANN. The encoding of the diagnostic factors based on the principal that critical values have to be enforced in contrast to non-critical values of the used attributes.

The estimation of dementias' type is the main purpose of the assessment of the diagnostic factors, so that the timely administration of appropriate medication to act retarded for the disease progression. Depending on the values of diagnostic parameters, the dementia types may be one of the following: i. mild cognitive disorder (1), ii. Alzheimer's disease (2), iii. frontotemporal dementia (3), iv. vascular cognitive impairment (4), v. Alzheimer's disease with vascular cognitive impairment (5) and vi. frontotemporal dementia and vascular cognitive disorder (6). The dementia types have to be encoded in order to be used during the implementation and testing phase of neural networks. The number in parenthesis, next to each dementia description, corresponds to coding for the ANNs development.

This study employs a data set consisting of 90 cases, where all the patients had a dementia type disease. This data set was divided into two subsets, the first used for training of the neural networks and the second one for testing of the implemented ANNs. The patients' records were obtained from the Neurological Clinical Information System (CIS) of the University Hospital of Alexandroupolis, Greece.

3. ANN ARCHITECTURES FOR DEMENTIA TYPES ESTIMATION

In this study, two dementia types prediction models based on a non-symbolic learning approach are presented. The proposed models use Multi-Layer Perceptron (MLP) networks and Probabilistic Neural Networks (PNNs).

Multi-Layer Perceptron (MLP) networks with error back-propagation learning algorithm as well as Probabilistic Neural Networks (PNNs) can be used in order to face classification issues. The aim of this study is the correct identification of dementia's type, falling in classification problem, using computational intelligence. Consequently, the prognostic and diagnostic procedures in clinical medicine can be approached by a MLP neural network or a PNN [37, 46, 47].

Multi-layer feed-forward networks transmit the provided data from input layer towards their output layer. The architecture of a multi-layer feed-forward network is not completely constrained by the problem to be solved. The number of neurons in the input and output layer is constrained by the given number of inputs and the desired number of outputs, respectively, required by the problem [48]. However, the number and the size of layers between input and output layers are up to the design method.

During the MLP training process, the gradient descent with adaptive learning rate back-propagation algorithms was selected for ANNs' training [37]. This learning algorithm based on back-propagation rule was used in order to speed up the convergence.

PNNs are a variant of Radial Basis Function Networks and approximate Bayesian statistical techniques. The modus operandi of PNNs is familiar to the human decision making approach [8]. The patterns' classification by PNNs is based on Parzen's Probabilistic Density Function (PDF) estimator [8]. A PNN is a feed-forward neural network, consisting of two layers. The first layer, which consists of radial basis function units, computes the distances between each input vector and the training input vectors [15]. The obtained vector's values indicate the propinquity of the input vector to a training input. The second layer, which is a competitive layer, sums these contributions for each class of inputs to produce a vector of probabilities as output. These probabilities indicate the likelihood of the input vector to be classified in each of the available classes. The transfer function of the second layer detects the maximum probability and classifies the input vector to the corresponding class.

More details about the specific implementation of the used PNNs can be found in [37]. The PNN learns with exposure to training patterns with a single pass without the necessity of extended training. This feature implies that the PNN may manage large quantities of data much faster that other ANN architectures. The maximum accuracy requires the determination of a “smoothing factor”, which represents the width of the calculated Gaussian curve for each probability density function.

4. EXPERIMENTAL RESULTS

The development and performance assessment of ANN models were based on MATLAB Neural Network Toolbox, due to its effectiveness and user-friendly interface [49].

As it was explained in Section 2, there are various types of dementia. The development of neural networks based on the data set described in the Section 2. MLPs and PNNs used in order to estimate the dementia type, as these architectures are suitable for classification problems. Therefore, MLPs and PNNs can approach procedures prognosis and diagnosis in medicine [37, 46]. Specifically, four artificial neural network architectures implemented for the determination of dementia type and its treatment.

In this study, the MLP architecture included a hidden layer. The determination of the hidden layer neurons was performed by a technique based on the construct algorithms. The specific technique starts with a minimum MLP neural network 30-2-1 structure and neurons in hidden layer are added step-by-step. The stopping criterion of the process is the Mean Square Error (MSE) of the MLP on the available data set. The method subtracts the MSE of an ANN structure with the MSE of ANN architecture abated with a node in hidden layer. If the subtraction is negative, the algorithm adds a neuron in the hidden layer, otherwise, the algorithm removes the last neuron in the hidden layer and the procedure terminates [50]. It is mentioned that the algorithm starts with two neurons in the hidden layer so that the MLP has the ability to classify the cases and consequently, the determination of dementia type and its appropriate medication.

Additionally, PNNs implemented for the assessmentof dementia. Although PNNs have few applications in medicine, how ever they have satisfactory results [50].

The number of neuronsin the input layer is equal to the number of attributes required for diagnosis of dementia; thus there are 30 neurons in the first level of PNN. In PNN, each possible outcome of an application corresponds to aneuron in the output layer. Consequently, the output layer of the implemented PNN has 6 neurons, as there are 6 possible types of dementia.

The structure of PNN depends on the number of neurons in the hidden layer and the spread of radial basis function, representing the width of the Gaussian curve. The number of neurons in the hidden layer is determined by the number of input / output cases used during the constructive phase. An algorithm implemented for the determination of spread. This algorithm increases the spread value from 0.1 to 50, by step 0.2, keeping all other parameters constant.

The 90 cases in the data set, divided into a setconsisting of 50 cases for the training phase of the MLPs and the constructive phase of the PNNs, and another one with 40 cases for the simulation and testing phase of the MLP and PNN. Then, the two sets were modified to consist of 65 and 25 cases, respectively.

The implemented ANN structures are presented in **Table 1** . The first column is the neural network architecture. The epochs are recorded in the second column of the Table. It is mentioned that the epochs are available for the MLP networks. In the other hand, the PNNs learn with a single pass of the training cases, so it is not an aspect for PNN architecture. The cases for training or constructive set and the training

Table 1. **Implemented ANNs For Dementia's type Estimation**

Neural Network Architecture	epochs	Number of Training Cases	Number of Testing Cases	Number of Input Neurons	Hidden Layer		Output Layer	
					Transfer function	Number of Neurons	Transfer function	Number of Neurons
MLP_1	80	50	40	30	Hyperbolic tangent sigmoid (tansig)	2	Linear	1
PNN_1	-	50	40	30	Radial Basis Function (spread=9.5)	50	Competitive	6
MLP_2	100	65	25	30	Hyperbolic tangent sigmoid (tansig)	4	Linear	1
PNN_2	-	65	25	30	Radial Basis Function (spread=8.2)	65	Competitive	6

set are presented in the third and fourth column of the Table. The numbers of neurons in input, hidden and output layer as well as the transfer functions of hidden and output layers for each of architecture are summarized from the $5^{th}$to 9^{th}columns in the **Table 1** . The spread of the radial basis function, representing the width of the Gaussian curve, varied during the experimental design phase of the PNNs.

The optimal ANN structures for 50 cases of training or constructive set are a three level PNN with 30-50-6 neurons, whereas the spread value offering the best performance is equal to 9.5 and a MLP neural network with 30-2-1 architecture. The corresponding neural networks for 65 cases of the training or the constructive phase are a PNN 30-65-6 architecture with spread value equals to 8.2 and a MLP network with 30-4-1 structure.

The obtained results from the optimal PNNs and MLP neural networks for the estimation of dementias' type are summarized in **Table 2** . In this study, the classification ability of MLP and PNN neural networks based on the percentage of correctly classified cases for the testing set, training set and the overall dataset. The performance of the proposed neural networks is recorded from the 2^{nd} to the 4^{th} column of the Table.

The PNN_1 and PNN_2 neural networks perform well over the testing data set as well as the training data set, in contrast to MLP_1 and MLP_2 networks, respectively. This performance of PNNs indicates that this neural network architecture has ability to identify the dementia's type based on a set of diagnostic factors.

It is obvious that the PNN_2 outperforms other neural networks, as the rates of successful prediction of testing, training and overall data is much better than the other ANN implemented. Therefore, PNN_2 can be used in assessing the form of dementia patient.

It is shown clearly that PNN_2 outperforms other implemented neural networks, as the percentages of successful prognosis for overall and pathological cases for testing, training and for the entire data set are higher. Therefore, the PNN_2 has the ability to distinguish the dementia's type by diagnostic factors. It is clear the satisfactory performance of PNN_2 in terms of dementia's type estimation. Consequently, the PNN_2 has been characterized as the optimal choice of ANN for being potentially used towards dementia prediction.

The results presented above were considered quite satisfactory and the proposed method has incorporated in the Neurological CIS. The advantage of this CIS against other information systems is the acquired knowledge of the system. This knowledge is obtained by the embedded ANN architecture, in combination with stored data of the Neurological CIS, so in the occurrence of a new case record toCIS, the physician can be informed about dementia's type.

Table 2. **Performances of Optimal Neural Networks**

Neural Network	Testing Set	Training Set	Overall Data Set
MLP_1	89.92	89.11	89.42
PNN_1	94.08	93.08	93.80
MLP_2	96.19	95.45	95.90
PNN_2	98.91	98.62	97.25

5. CONCLUSIONS

ANNs, as a subfield of computational intelligence, are used widely in industrial and medical applications. Despite of the ANN's architectures, learning algorithms and transfer functions variety, the basic function of ANNs is the presence of an input data set, and the generation of corresponding outputs based on vector mapping.

In this paper, the possibility of applying artificial neural models in the dementia's type estimation has been examined, because it is an important medical problem for public health. Its frequency and the serious consequences for patients are the reasons for the vivid interesting for development of accurate techniques.

The development of artificial neural techniques was based on MLPs with back-propagation algorithm, as well as PNNs, which are both feed-forward neural networks. The MLPs has been characterized as black boxes, because the internal connections are highly non-linear and not subject to the usual statistics. On the other hand, PNNs approximate Bayesian function; however, their output is clearly not a probability, as several steps are required to dementia's types prediction.

As it was found, the PNNs outperformed the MLPs, in terms of the successful prognosis of cases. Therefore the proposed methodology unveiled the PNN artificial models' behavior contrary to MLPs artificial networks' behavior is much better, or in other words, the prognostic ability of PNNs is enhanced compared to MLPs categorization performance.

In the future studies, the implemented ANN architecture will be tested on a dataset with more cases compared to the available testing sets. Furthermore, it will be applied artificial intelligent techniques, to insulate the major parameters for determination of dementia's types. This will be done in order to searchfor possible elimination of some of the input parameters of the ANN, thus achieving to simpler,pruned and more efficient ANN network architectures that give high performance in terms of dementia's classification.

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