Review of Neural Network Techniques in the Verge of Image Processing

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Abstract Image processing is a vast area in the research field nowadays. This paper is a fleeting review on various technologies implemented to satisfy different image processing tasks like image segmentation, enhancement, restoration, acquisition, compression, classification, and many more. Neural network is one of the major techniques which is emphasized here. Different types of techniques using neural networks and hybridizations of neural network are discussed here briefly which are used for many image processing applications.

Keywords Image processing · Artificial neural network

1 Introduction

With the keen expansion and development of this computer era, a huge amount of data have been assembled and stored in databases of various fields like biology, medicine, industry, security, engineering, management sciences, humanities, and it is increasing day by day. For expressing, sharing, and interpreting of information, the use of digital images has been expanded a lot during this period of digital communication. These images need to be analyzed properly to understand in a better way so as to make it easy to use and to manage the upcoming new data accordingly. Working with digital images looks easy when there are less images but it becomes extremely complex when the number of images are more like millions. Here data mining, image mining comes to place which extracts required knowledge from a large database. A number of computational and mathematical approaches have been discovered to precisely analyze the complexities of data, but those models have a strict boundary which could not be applied to solve problems those

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M.S. Reddy et al. (eds.), *International Proceedings on Advances in Soft Computing, Intelligent Systems and Applications*, Advances in Intelligent Systems and Computing 628, https://doi.org/10.1007/978-981-10-5272-9_33

are uncertain, unpredictable, or lies between 0 and 1. But soft computing can and also it works fine on the problems having uncertainty and partial truth. The principal component of soft computing techniques includes artificial neural network, fuzzy logic, and genetic algorithms. Amid of these, artificial neural networks (ANNs) have been used for the development of image processing algorithms for a long time in different fields. Here, this neural network is considered for the study, thus highlighting different techniques of it for different purposes of image processing.

Artificial neural network (ANN) is a mathematical or computational model developed by the basic concepts of biological nervous systems and is capable of machine learning as well as pattern recognition. These are built by interconnection of artificial neurons called as nodes or processing elements or units. These networks are represented as systems of interconnected neurons that compute outputs from inputs. The neuron in it is an abstraction of biological neurons and the basic unit in an ANN. These neurons known as the processing units of the networks are taken to form many layers and the interconnected layers to form a complete neural network. It mainly has an input layer to take input, one or more hidden layers and an output layer to produce the output. The inputs are fed simultaneously into the input units of the input layer which pass through the input layer and then weighted and fed simultaneously to the second layer known as hidden layer. The outputs calculated from the hidden layer units are taken as input to other hidden layer and so on up to the output layer. The number of hidden layer is inconsistent, usually only one is used. The weighted outputs of the last hidden layer are the input to the output layer, which finally produces the computational output. This is the basic computational procedure followed for the network.

2 Literature Survey

Neural network has been used in varieties of image processing techniques for last decades. Many hybridization techniques are also designed for the development in performance and accuracy. A concise elucidation of few technical implementations of neural network is done here.

A combinational approach of neural networks has been proposed to provide image classification system with high performance. There is an approach proposed by G. Giorgio and F. Roli in their work to design the ensemble of neural networks automatically. From the study of previous works, it is concluded that to make an effective ensemble of neural networks the networks should make different errors which is considered as the principal factor for effectiveness of the neural network ensemble. The error diversity must exist between the neural nets, i.e., the errors are different for each network. So different approaches are available for the design of ensemble of error-independent networks for the classification of multisensory remote sensing images out of which the ‘overproduce and choose’ strategy proved to be systematic and effective. It is difficult to create an error-independent network directly but by choosing this strategy the methods for the creation ensemble members can be exploited effectively. A set of available methods is used in the overproduction phase for the creation of a large set of candidate members and then the choice phase selects the most error-independent networks as ensemble members for the final combination. The system provides the optimal solution for the design [1].

Graphical image representation needs a huge storage space and more transmission time. Here comes the requirement of image compression and decompression. Fractal image compression/decompression gives high compression ratio and low loss ratio, but due to more computations it has a limited application. The parallel processing property of neural network can be considered as a helpful strategy for this purpose. K.T. Sun et al. has taken two separate models of neural network in their work for the fractal image compression and decompression having same architecture but different transformation functions. The neural network approach is applied in partitioned iterated function system (PIFS) for image compression/decompression. This PFIS is functionally used in many fields to determine the fractal code automatically [2, 3], which improves iterated function system (IFS) used previously for this intention. The image pixels are represented as a neuron, and the weights and thresholds are taken as fractal code to be generated. The required fractal code (i.e. the weights and thresholds in the NN) is obtained through training or compression, and the original image can be regained by retrieving or decompression. This proposed technical system gives high-quality decompressed images along with a good compression ratio compared to traditional PIFS method. The image compression and decompression is faster due to the parallel computing system. Here it shows that the better quality and smaller compressed images are obtained with the learning rate of the neural network was 0.1 for linear model and between 0.2 and 0.3 for nonlinear model of neural network [4].

To automatically locate or detect frontal view of human faces in scattered scenes, image decomposition and neural network techniques are applied in a work by Hazem M. Ei-Bakry. Comparing to other techniques [5], neural networks are proved as efficient face detectors [6–8]. Image decomposition is done by applying divide and conquer method, i.e., smaller sub-images are generated from the single image. Each of these sub-images is tested using the fast neural network to identify the availability/non-availability of human faces. Applying parallel processing of the NN to simultaneously test the sub-images gives a faster result by decreasing the running time and increasing the speed-up ratio. Compared to conventional neural networks, the fast neural network gives reduced detection time. Further the grouping of sub-images and testing them reduces the computational steps in order to speed up the execution time [9].

Image processing task like image segmentation is one of the oldest techniques. The segmentation generally depends upon the quality of image, contrast of region of interest (ROI) in the image [10]. Dokur et al. [11] has taken hybrid network structure called intersecting spheres (InS) neural network for the segmentation of ultrasound images in their work. This is a dynamic structured network having incremental learning whose synaptic weights and network arrangement are automatically determined during the training procedure. The feature vectors are produced by using the discrete cosine transform of image pixel intensities in the ROI. The dimension and the elements of the feature vectors are determined in view of two parameters, i.e., the amount of ignored coefficients and the dimension of the ROI. The proposed network is having three hidden layers, and the first hidden layer is formed by using genetic algorithms (GA) and back propagation is used to train all the layers. The nodes of the first layer network represent hyperspheres (HSs) in the feature space whose location and radius are found by GA. The difference in the proposed neural network and the previous studies is different in the sense of partitioning the feature space. Here the feature space is partitioned by intersecting HSs to represent the distribution of classes. This network is compared to three other networks out of which the Modified Restricted Coulomb energy (MoRCE) network is one where intersection of the HS is not allowed. Restricted Coulomb energy (RCE) network, modified RCE network, multilayer perceptron (MLP), and the proposed hybrid neural network are comparatively experimented for the segmentation of ultrasound images. The classification performances of the four neural networks for the segmented images are analyzed, and the proposed InS neural network is outstanding among them.

In another exertion by Coppini et al. [12] an architecture is proposed and tested for lung nodule detection that narrates a neural network-based system which detects lung nodules in chest radiograms with the help of computer. It is based on multiscale processing and artificial neural networks (ANNs). The computational scheme is related to multiscale processing which is principally implemented by a feed-forward artificial neural network (FFANN). For the development and testing phases, various aspects are analyzed on the public JSRT database along with additional cross validation with the images from UNIFI database. Different points of view on image processing techniques like conventional pattern recognition methods and artificial neural networks (ANNs) are archived. Here the first one locates possible nodular patterns while the second, implemented by a convolutional neural network, differentiates nodules from non-nodules [12]. The feed-forward neural networks are also used in the system proposed by Penedo et al. There, dubious regions are first detected in a low-resolution image, and at the same time local image curvature is analyzed to locate nodules. Here the problem of nodule detection is solved by using two-layer architecture. At first to locate possible nodular regions securing high sensitivity, an attention-focusing subsystem that processes whole radiography is applied and then at second a validation is done, i.e., a sub-system is followed which reduces false alarms and increase detection specificity by evaluating the prospect of the presence of a nodule by processing regions of interest. For the enhancement of image features, biologically inspired filters are used. The FFANN allows an efficient use of the previous knowledge about the shape of nodules and the background structure. Experimental results are narrated by ROC/FROC analysis. The noted system performances support the undertaking of system validation in clinical settings. The intense changeability of chest radio graphs and the variation in nodular patterns are a prime concern in designing CAD (computer-aided diagnostic scheme) systems. Though the extended representation of data sets is still a vital issue, the winning approach is to use machine learning methods [13].

One more image processing technique using artificial neural network has been developed by Kenji Suzuki et al. for the detection of lung nodules. Here by repressing the contrast of ribs and clavicles in chest radio graphs, a technique is developed for the lung nodule detection. The lung nodules and lung vessels are made prominent or clear by suppressing the rib components to a large extent by virtue of multiresolution massive training artificial neural network (MTANN). Three MTANNs for three different resolution images are developed, each having decomposition/composition techniques for the effective suppression of ribs having different spatial frequencies. MTANN is a highly nonlinear filter and is trained by using input chest radio graphs and the corresponding "teaching" images. The "bone" images obtained by use of a dual-energy subtraction technique are employed as the teaching images. After training with input chest radio graphs and its corresponding dual-energy bone images, the multiresolution MTANN provides "bone-image-like" images which were similar to the teaching bone images. By subtracting the bone-image-like images from the corresponding chest radio graphs, "soft-tissue-image-like" images are produced where ribs and clavicles were substantially suppressed. Thus this image processing technique for rib suppression with the help of a multiresolution MTANN can be potentially useful for radiologists and CAD schemes to detect the lung nodules on chest radio graphs [14].

Soo Beom Park et al. initiated a content-based image classification method using artificial neural network in 2004. At first, a region segmentation technique is used. Feature information is extracted from images by using the wavelet transform and the sliding window-based feature extraction. A neural network classifier using back-propagation learning algorithm is created using the texture features to reflect shape of an object. The feature vectors are used as input values in the training process to construct a classifier of the object unit. A higher classification rate is achieved by this. It is applicable for raising the performance of content-based image indexing or retrieval systems, and it can be used to classify various object images, also it can automatically perform all processing for object image classification. It shows the capacity to retrieve images more efficiently by an automatic classification system and is suitable for many practical applications. A test with 300 training data and 300 test data formulated of 10 images from each of 30 classes exhibits classification rates of 81.7 and 76.7% correct, respectively [15].

In image processing techniques like handwriting recognition, text recognition, fingerprint classification, data compression, etc. binary image thinning is a primary part. It represents the structural shape of original images by using less data. A good thinning method produces skeletons including the shape information of original object so that it can be suitably used. Gu et al. proposed a new approach for binary image thinning by using the pulse-coupled neural network (PCNN). Pulse-coupled neural network (PCNN) models are bio-inspired networks based on the experimental analysis of synchronous pulse bursts in the cat visual cortex which is not similar as traditional artificial neural networks. PCNN can be applied in many fields, such as image processing, image recognition, and optimization. Here the pulse parallel transmission characteristic of PCNN is used for binary image thinning. By using this algorithm, including PCNN noise-reducing process, thin binary image can be generated and skeletons are produced with accuracy. The proposed procedure is said to be faster compared to other methods [16]. Another approach using PCNN is proposed by Xiaodong Gu et al. for the purpose of image shadow removal. Image shadow is taken as the reduction of image intensity. Two steps are followed to remove the image shadow. At first the shadowed image is segmented using PCNN that results in a multivalued segmented image. In the second step, the original shadowed image is divided by the multivalued segmented image where the quotient image comes as a result. In the quotient image, the object is more obvious and easy to find as it keeps the information of the original image. The results shows that shadows are removed completely, and the shadow-removed images are almost as the same as the original non-shadowed images. So this approach can be efficiently used for removing shadows which does not have random noise [17].

Among different image compression methods applied for medical image compression, Meyer-Bäse [18] has suggested a new method using topology-preserving neural networks. It is quite advantageous in a way that it can be applied to larger image blocks in order to obtain a low bit rate digital representation of the image with reduced image data without any impelling loss of the image quality. A combination of transformation-based linear neural network for PCA analysis and a vector-quantization neural network or neural-gas network as data compressor is applied. The linear neural network performs three types of PCA analysis by three algorithms such as Generalized Hebbian Algorithm (GHA), Oja's symmetric algorithm (OJA), and nonlinear PCA (NLPCA). The image blocks are taken as data vectors on which the PCA transformations are applied and projected on a low-dim space. The compression ratio comparisons shows an improvement in the image quality, and OJA algorithms turns out the best for it while nonlinear PCA turns out as fastest among all. PCA combined with neural vector quantizer can be taken as primary technique for image compression after studying the efficiency by blending mathematical phantom features into clinically proved cancer free mammograms [18]. Another hybrid neural model called direct classification model is proposed for image compression by Soliman and Omari [19]. Here the model is developed as a hybridization of two technique, i.e., Self-Organizing Kohonen (SOK) model and Adaptive Resonance Theory (ART) model. The features like accuracy and fastness of SOK model and ART model, respectively, generates an effective and efficient hybrid neural model for the purpose of image compression so as to achieve high image quality at high compression ratio. It provides better result than the traditional peer techniques like JPEG2000 and DjVu wavelet technology specifically for the colored images and immobile satellite images [19].

Artificial neural network is extensively applied in pattern recognition. Fadzilah Siraj et al. have taken this technique for the emotion classification. For the purpose of communication, emotion has become a prime interface between human and machine to play a primary role in rational decision-making, perception, learning along with various cognitive tasks. For emotion detection, the application of pattern recognition technology has raised a lot. Based on the physiological mensuration, facial expression, and vocal recognition, emotions are detected in human being. A human being shows the similar facial muscles while expressing a particular emotion, from which the emotion can be quantified. There are six primary emotions like anger, happiness, surprise, disgust, fear, and sadness, which were classified using neural network. For neural network training and testing real dataset of facial expression, images were captured and processed. By using multilayer perceptron network with back-propagation learning algorithm and regression analysis, the data are tested. The experimental result shows that neural network has a misclassification rate of 2.5%, while regression analysis gains a misclassification rate of 33.33%. The emotion classification model developed in by Fadzilah Siraj et al. can support the development of intelligent tutoring system in particular, and E-learning system in general [20].

To estimate the total suspended matter (TSM) concentration from remotely sensed multispectral data in a particular area of the Portuguese coast, different methodologies are applied by Ana C. Teodoro et al. in their work. These techniques based on single-band models, multiple regressions, and artificial neural networks (ANN) were evaluated by error estimation to find out the more accurate methodology. The root-mean-square errors by both the linear and nonlinear models are analyzed and found out that they support the hypothesis that the relationship between the seawater reflectance and TSM concentration is clearly nonlinear. For estimating the TSM concentration estimation, the ANNs are found to be more useful from reflectance of visible and bands of different sensors used. The ANN which is implemented here is with ten units in the hidden layer and is able to model the transfer function better than multiple regressions [21].

A large review says that artificial neural networks hold a huge role to amplify the performance of classification or segmentation. Mehmet Nadir Kurnaz et al. has proposed an unsupervised incremental neural network for segmentation of tissues in ultrasound images and compared its performances with another unsupervised neural network known as Kohonen neural network. Kohonen neural network is a non-incremental unsupervised neural network for which the topology is defined before while for incremental neural network is not essentially predefined. Trial and error method is used to determine the number of output nodes in the KNN while in incremental NN they are selected by analyzing histograms and the image to be processed. To extract the feature from the images, 2D-DFT (Discrete Fourier Transform) and 2D-DCT (Discrete Cosine Transform) are used. The incremental neural network gives better result compared to Kohonen network in terms of both result and time. Some works also describes that incremental neural network gives enhanced performance in terms of quality of the reconstructed images along with the compression rates. The proposed network takes less number of nodes so that less time to perform and giver better performance. The neural network is a two-layer incremental neural network which can be used further without any modifications easily only by forming the training sets to resolve the topology of the network accordingly [22, 23].

In the medical science and orthopedic community, the identification of the spinal deformity classification is an important topic. The artificial neural network

(ANN) can also be used to identify the classification patterns of the scoliosis spinal deformity. Lin Hong in his paper has used a multilayer feed-forward neural network with back propagation (MLFF/BP) for the classification. At first based on the coronal and sagittal X-ray images, the simplified 3-D spine model was constructed and the features of the central axis curve of the spinal deformity patterns were extracted by the total curvature analysis. The discrete form of the total curvature, including the curvature and the torsion of the central axis of the simplified 3-D spine model, was derived from the difference quotients. The total curvature values are taken as input to the MLFF/BP ANN and five neurons are at output layer representing five King classification types. About 67% of the data is taken for training and the rest for testing. Two types of network architecture are taken into consideration: one with only one hidden layer and the other network having two hidden layers. The result was found that the two-layer hidden neural network performs better, which can be further improved by increasing the number of training datasets or by participation of more experienced observers [24].

A fusion of neural network is taken as a classifier for image classification problems here by Sanggil Kang et al. The input features such as color layout (CL), edge histogram (EH), and region-based shape (RS) are extracted from different MPEG-7 descriptors. The fusion of input features which are extracted from multiple descriptors gives better performance than the features extracted from single descriptor. The networking system has two parts: a feature extraction module and a classification module. The conclusive result of the experiment says that this method provides robust training performance compared to conventional neural network classifier. It is useful in cases where fusion of different dimension features is used for neural network classifier. The disadvantage of using this method is complexity, i.e., the proposed classifier is more complicated than the conventional neural network for its functionality [25].

In the field of remote sensing for complex retrieval tasks, artificial neural networks (ANNs) are proved to be very effective technique. For solving the unmixing problem in hyperspectral data, Licciardi and Frate have used artificial neural network. The neural network have two stages of processing: the first stage is used to reduce the dimension of the input vector, and the second stage maps the reduced input vector to the abundance percentages. For the dimensionality reduction, auto-associative N's is used. Both the dimensionality reduction procedure and the final unfixing are performed by the developed neural network model. The final scheme of the model is a single architecture of NN sequencing the two operations in an automatic mode. Different sets of experimental data are taken for the performance estimation. The unmixing results show that the reduced vector helps to yield accurate pixel abundance estimation. The result shows that it is effective in terms of dimensionality reduction as well as accuracy in the final estimation. The impact of the applied technique is quite advantageous and could be more significant for future use as the satellite multiconfiguration data is continuously increasing day by day [26].

In recognition of handwritten digits or traffic signs, machine learning methods do not perform well all times while the wide deep artificial neural network

(DNN) gives satisfactory results many times. A large depth network is obtained by minimal receptive fields of convolutional winner-take-all neurons, which results in many sparsely connected neural layers and only winner neurons are need to be trained. Dan Ciresan et al. have taken a DNN having two-dimensional layers of winner-take-all neurons with overlapping receptive fields whose weights are shared. DNN columns are combined to make multicolumn DNN (MCDNN) inspired by microcolumns of neurons in the cerebral cortex and give a far better performance compared to single DNN. The method is fully supervised and does not use any additional unlabeled data source. This proposed method improves the state of the art by 30–80% over many image classification datasets. Drastically improvement is recognized on MNIST, NIST SD 19, Chinese characters, traffic signs, CIFAR10, and NORB datasets [27].

Along with different usage, neural networks also show their applicability in the agricultural field. A classification technique has been developed in Malaysia by Z. Husin et al. to recognize and to classify the herbal plants. They developed a device capable of recognizing herbs species by classification technique based on structural characteristics of the leaves. Generally, these are done by human directly which is time-consuming so turned to be ineffective and inefficient. So to identify the herbs and agricultural plants, different image processing methods are used successfully. The picture samples of leaves were collected from the Agricultural Department of Malaysia Perlis University on which the image processing techniques are applied and tested. The RGB image is converted to a gray scale image which is again converted to a binary image from which features are extracted. These features are gone through processing using morphological technique and SVD function to get the input for the neural network. The neural network used here is back-propagation neural network (BPNN). The inputs for the neural network are the individual pixels of a leaf image developed through appropriate image processing steps. A two-layer BPNN is used which has 20 hidden neurons, 4800 input neurons and 20 output neurons and threshold value is set to be 0.5. Here each output neuron is a type of plant species to be identified. Most outstandingly, the system is capable of identifying the herbs leaves species even though they are dried, wet, torn, or deformed. The average correct recognition rate is found to be 98.9% which is quite appreciable [28].

Dan Ciresan et al. from Switzerland have developed a system using multicolumn deep neural network (MCDNN) for the traffic signal recognition. This is essential for the automotive industry and for many traffic associated applications. The MCDNN is developed by combining several deep neural networks (DNN), which are training by several pre-processed data. The DNN contains a sequence of convolutional and max-pooling layers and is of feed forward type. This creates feature vectors from the pixel intensities and the adaptable parameters are optimized through minimization of the misclassification error over the training set. Eventually, the MCDNN is formed by averaging the output activations of several DNN columns. Compared to single DNN, the combination of DNNs gives a better improved result robust to noise. This particular proposition has won the final phase of the German traffic sign recognition benchmark and achieved a recognition rate of 99.46% which is far better than human recognition rate [29] (Table 1).

Table 1 Comparison of neural network-based image processing techniques

Year/author/publisher	Type of image data and data source	Applied method/technique	Findings
2001, G. Giacinto, F. Roli, Image and vision computing (Elsevier)	Multisensor remote sensing image (related to agricultural area)	An ensemble of neural network model is applied. For choosing the networks, ‘overproduce and choose’ strategy is used	Provides better results as compared to other models and methods
2001, K.T. Sun, S. J. Lee, and P.Y. Wu, Neurocomputing (Elsevier)	Lena or Lenna images Source: http://sipi.usc.edu	Neural network in partitioned iterated function system (PIFS) is used	Gives good compression ratio compared to traditional PIFS method
2002, Hazem M. El-Bakry, Neurocomputing (Elsevier)	–	Image decomposition and fast neural networks	Better result is obtained with decreasing running time, thus increasing speed-up ratio compared to conventional neural network
2002, Zumray Dokur, Tamer Olmez, Pattern recognition Letter (Elsevier)	Ultrasound images of bladder and kidney cyst are taken	Intersecting spheres (InS) neural network	Classification performance is better than RCE, MoRCE, and MLP
2003, G. Coppini et al., IEEE Transactions on Information Technology in Biomedical	Chest radiograph images (medical image data) Source: Japanese Society of Radiological Technology (JSRT) and Department of Physiopathology of University of Florence	Feed-forward ANN system is used based on multiscale processing, and a convolutional NN is used for discrimination	Performs better than other models
2004, Soo Beom Park et al., Pattern recognition Letter (Elsevier)	Different object images are taken from Internet	Back-propagation neural network	A higher classification rate is achieved

(continued)

Table 1 (continued)

Year/author/publisher	Type of image data and data source	Applied method/technique	Findings
2004, X.D. Gu, D.H. Yu, L.M. Zang, Pattern recognition Letter (Elsevier)	Binary images including English words, Chinese words, and other images	Pulse-coupled neural network (PCNN)	Performs better compared to traditional parallel algorithm
2005, X.D. Gu, D.H. Yu, L.M.Zang, IEEE Transactions on neural network	Gray images and a color image are taken with shadow	Pulse-coupled neural network (PCNN)	PCNN can be used for the shadow removal technique
2005, A.M. Base et al., Engineering applications on artificial intelligence (Elsevier)	Mammogram images Source: MIAS database at http://skye.icrac.uk/misdb/miasdb.html	Topology-preserving neural network	This neural network approach provides better probability distribution estimation method
2006, H.S. Soliman, M. Omari, Applied soft computing (Elsevier)	Several satellite images and Lena images are used Source: http://sipi.usc.edu	A hybrid neural network called direct classification neural network	DC model performed well for image compression compared to the peer state-of-the-art models
2006, S. Kenji, H. Abe, H. Mecmohan, IEEE transactions on medical imaging	Chest Radio graph Images Source: Digital Image database developed by Japanese Society of Radiological Technology (JSRT) and FCR 9501ES; Fujifilm medical Systems, Stanford, CT	Nonlinear filter MTANN is used for suppressing the contrast of ribs and clavicles in chest radio graphs	Proved to be a useful technique for radiologists and CAD schemes in detection of lung nodules
2006, F. Siraj, N. Yusoff, L.C. Kee, Computing and informatics (IEEE conference)	Image data Captured by digital camera	Multilayer perceptron with back-propagation learning algorithm and regression analysis is used	Neural network gives less error, i.e., NN performs better than regression analysis
2007, Ana. C. Teodoro, F.V. Gomes, H. Goncalves, IEEE Transactions on Geo-science and Remote sensing	Remote-sensed multispectral data	Multiple regression and artificial neural network are used	ANN performs better than multiple regression

(continued)

Table 1 (continued)

Year/author/publisher	Type of image data and data source	Applied method/technique	Findings
2007, Mehmet Nadir Kurnaz, Zu mray Dokur, Tamer Olmez, Computer methods and programs in biomedicine (Elsevier)	Phantom ultrasound bladder image and an original bladder image are taken Source: www.fantom.suite.dk http://drgdiaz.com	An incremental neural network is used	Incremental neural network performs better than Kohonen neural network
2008, Hong Lin, IEEE Transactions on biomedical engineering	3-D spine models are constructed based on coronal and sagittal spinal images	Total curvature analysis is used for feature extraction, and multilayer feed-forward neural network with single and double hidden layers are used	Neural network with two hidden layers performs better
2009, S. Kang, S. Park, Pattern recognition Letter (Elsevier)	Sports image data collected from Internet	Feature extraction using two MPEG-7 descriptors EH and RS. Neural network and a fusion of neural network is used	Proposed fusion neural network is better than conventional neural network
2011, G.A. Licciardi, F.D. Frate, IEEE Transactions on Geo-science and remote sensing	Airborne and space-borne hyperspectral scanning images Source: INTA-AHS instrument dataset from European Space aging (ESA), CHRIS-PROBA images and AVIRIS images from http://avairis.jpe.nasa.gov	Auto-associative neural network is used	Though auto-associative NN is used for airborne images before, it can also be used for space-borne images
2012, C. Dan et al. Computer vision and pattern recognition (IEEE conferences)	MNIST, NIST SD 19, Chinese characters, Traffic Signs, CIFARIO NORB databases are used	Multicolumn deep neural network (MCDNN)	Improved classification is observed
2012, Z. Husin et al., Computers and electronics in agriculture (Elsevier)	Leaf of different species are taken Source: Agricultural Department of Malaysia Perlis University	Back-propagation neural network	Recognition rate of 98.9% is achieved
2012, Dan Cireşan et al., Neural networks (Elsevier)	Traffic sign imagers are taken	Multicolumn deep neural network (MCDNN)	Recognition rate of 99.46% is achieved

3 Different Type of Neural Networks

Neural networks have been applied for solving a large variety of tasks that are generally not easy to resolve using ordinary rule-based or traditional programming. Many types of neural network models are developed which has been used in many fields for solving different problems, and some of the types are briefly discussed below.

3.1 Feed-Forward Artificial Neural Network (FFANN)

The feed forward neural network is the simple artificial neural network. It is said to be feed-forward type or acyclic in nature as they do not have any feedback loop or self-feedback links between the layers, i.e., here the processing units, the neurons are only connected forward. In this network, the information moves in a single (forward) direction, i.e., from input units, through the hidden units to the output units. It can be of single layered or multilayered called as multilayer feed-forward neural network. Such a network is fully connected if each node in layer I is connected to all nodes in layer $i + 1$ for all I.

When a training tuple is fed to the input layer of the network, the inputs pass through the input units, unchanged in the input layer first. That is, for an input unit, j, its output, O_j is equal to its input value, I_j. Then the net input and output of each unit in the hidden and output layers are computed. The net input to a unit in the hidden or output layers is computed as a linear combination of its inputs. Each connection has a weight. To compute the net input to the unit, each input connected to the unit is multiplied by its corresponding weight, and the summation is calculated.

Given a unit j in a hidden or output layer, the net input, I_j, to unit j is

$$I_j = \sum w_{ij} O_j + \theta_j \tag{1}$$

where w_{ij} is the weight of the connection from unit i in the previous layer to unit j, O_j is the output of unit i from the previous layer, and θ_j is the bias of the unit.

Each unit in the hidden and output layers takes its net input and then applies an activation function to it. The function symbolizes the activation of the neuron represented by the unit. Given the net input I_j to unit j, then O_j, the output of unit j, is computed as

$$O_j = 1/1 + \mathrm{e}^{-I_j} \tag{2}$$

Thus, the output of the network is calculated and compared with the target output for the training purpose.

3.2 Multilayer Perceptron (MLP)

A multilayer perceptron is a feed-forward artificial neural network which maps the sets of input data to a set of appropriate outputs. It has multiple layers of nodes in a directed graph, where every layer is fully connected to the next layer. The calculations are similar to feed-forward neural networks as described above.

3.3 Massive Training Artificial Neural Network (MTANN)

The massive training artificial neural network (MTANN) is a modified multilayer ANN, which can directly handle input gray levels and output gray levels. Here for each layer, a different activation function is selected. The activation functions of the input, hidden, and output layers are a linear, a sigmoid, and a linear function, respectively. In this network, image processing or pattern recognition is performed by scanning an image with the modified ANN. The MTANN consists of a linear-output multilayer ANN model for which it is capable of operating on image data directly. The MTANN uses a linear function as the activation function in the output layer that significantly improves the characteristics of an ANN.

3.4 Deep Artificial Neural Network and Multicolumn Deep Artificial Neural Network

A deep neural network (DNN) is an artificial neural network that contains many hidden layers of units between the input and output layers. Generally, DNNs are designed as feed-forward networks, but can be designed as recurrent neural network recently for the applications such as language modeling. A DNN can be trained with the standard back-propagation algorithm. Here the weight updating can be done using the following equation:

$$w_{ij}(t+1) = w_{ij}(t) + \eta \frac{\partial C}{\partial w_{ij}} \tag{3}$$

Here η is the learning rate and C is the cost function. The choice function depends on the type of learning and activation function chosen.

3.5 Pulse-Coupled Neural Network (PCNN)

PCNN is a single-layered, two-dimensional artificial neural network developed by Johnson et al. In this network, each neuron corresponds to one pixel of the input image. It has three parts mainly, i.e., input, linking, and the pulse generator. PCNN receives the input stimulus through both feeding and linking connections that are combined in an internal activation system and accumulates the stimuli until it exceeds a dynamic threshold, resulting in a pulse output. It does not need any pre-training. Through iterative computation, PCNN neurons produce temporal series of pulse outputs that contain information of input images to be employed for miscellaneous applications of image processing.

4 Conclusion and Future Direction

Here many applications of artificial neural network have been elaborately discussed. The discussion shows a wide usability of the network in various image processing techniques. Its role in image processing can be primary or secondary, or can be used as a part of different combination of techniques. Also it can be used in supervised/unsupervised or parametric/nonparametric or linear/nonlinear regression functions or feature extractions and many more. Every applications of neural network are unique and no technique is better than another, each has its own strength and weaknesses. Though it has been applied and proved to be very usable for a wide range of applications, it has also been seen that the combination of different models/techniques works more effectively. Therefore, it can lead to the development of many hybrid models in future. The neural network performance depends on different parameters of the models which need to be properly decided and optimized so as to design some new helpful models.

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