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Abstract

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Estimating the Corneal Thickness for post-operative Laser Eye Surgery using Deep Neural Network

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ABSTRACT

The Deep Neural Network helps to understand the interaction between the human brain and the simulated computational studies. Making best decision and gives an explicit result with an algorithm solves the limitation of input data, the hidden layers, and the overlapping problem between the connection layers. On the other side, estimating the central corneal thickness post-operatively during the laser eye surgery are mostly important parameter that may play the main roles in clinical decisions. Decisions like fully, under or over correction of refractive error of human eye. This decision is related to a number of clinical measurements (19 sets of inputs) that may be interconnected in complex form.

In the present work the Deep Belief Neural Network have been modeled, capable of estimating the weight of the input clinical parameters relative to the final central depth for the laser eye surgery. Estimating these interconnection weights will help to correct amount of dose of laser to return the eye to its normal state. A gradient descent and back propagation technique algorithm through the training test will also help to correct the overlapping problem and how much the data and the hidden layers rise the machine will still stable. Result shows how much this model is stable in compare with the standard practical and theories and it gives the best and accurate decision which can depend on it within the medical diagnosis and treatment.

Keywords: ***Deep neural Network; Central corneal thickness ; LASIK; corneal pachymetry***.

1. INTRODUCTION

Corneal thickness draws more attention nowadays after many retrospective evaluation studies, concerning the clinical and surgical interrelations with different pre and post findings. Investigation of keratoconus, corneal hypertension and refractive error correction with their safety consideration are more related to the central corneal thickness (CCT) estimation [1, 2].

Furthermore, treatment of keratoconus using collagen cross linking, candidate need to have a CCT of at least 400 μm [3].

Many measurement techniques have been adopted to check and evaluate the CCT. The widely spread method used is the ultrasound pachymetry, which represent the benchmark standard to the optical devices [4, 5]. However, ultrasound pachymetry has more and less restrictions, associated with the operational experience, histologically measurement position and the acoustic impedance properties of the non-standardized tissue (abnormal pathological changes or post reshaped corneas due to LASIK (laser-assisted in situ keratomileusis)or PRK(Photorefractive keratectomy) [6].

These restrictions have led to modify new techniques that offer more corneal area coverage (expanding number of measured points), rapid non-contact scan and more patient suitability [7]. Topographic pachymetry map generated either by the rotating Scheimpflug camera (pentacam for example) or by the ocular coherance tomography (OCT), become common request for clinical pre and post evaluation of ocular anterior segment [8].

A number of prior studies direcly compared the central and para–central corneal thickess results of these instruments [4–5, 7–11] suggested the differences between them in the measured values. Huang et. al. [4] compared beteen three types of topographers with the OCT and found that the topographers are interchangable in measuring the CCT, while the OCT is underestimated. Chen et. al. [7], found that the pentacam and the OCT could be interchangable with each other but not with the pachymetry. Nassiri et. al. [9] found that preoperatively CCT measurement were higher in pentacam with respect to the pachymetry, while postoperatively the pentacam became lower than it.

Thinner or thicker, virgin or treated, normal or biomechanically unstable and measured with topography or any other optical devices are variables reported by different research studies talking about estimating the corneal thickness.

Deep neural network

Deep Neural Network (DNN) (also known as deep learning or deep machine learning) is a new trend of scientific study in the machine learning subject, constructed upon a set of procedures that model the data in high level [12]. In DNN there are several layers among the input and output permitting the procedures to use several processing layers, composed of many linear and nonlinear alterations [13].

Deep Belief Networks (DBNs) are possibly the most well-known and basic kind of DNN procedures. This is a probabilistic kind with one visible layer at the bottom and many hidden layers up to the output. Each hidden layer unit learns the statistical representation via the links to the lower layers. The more higher the layers, the more complex are the representations. DBN is categorized by probabilistic multiplicative model, deep architecture – multiple layers and unsupervised pre-learning delivers a good initialization of the network [14],This The main Characteristics of DBN used for build an algorithem to estimate the central corneal thickness (CCT).

2.1 MATERIAL AND METHODS

The process of construction and expending the DBN were usually discussed by many research studies [15]. This is done at this point by modifying regular procedure to the present case study and as follows:

1. As a case study, sets of data collected from laser eye surgery patients (data are collected from ALAMAL LASIK center in AL Karada – Baghdad), this input sets of data are(1.Gender,2.treatment,type,3.sphare,4.Cylinder,5.TZ,6.OZ,7.AZ,8.AXIS,9. Asphericity ,10.cornal thickness, 11.Eye ,12. K1 ,13.Axis of K1 ,14.K2,15.Axis of K2, ,16.PD,17.R FIT ,18.RSP , 19.flap thickness),they used to decide the critical central depth of the cornea during the laser treatment, and this is very important to decide the desire refractive error correction.
2. Using of MATLAB program, the input sets of data here, used in the analysis, is a matrix of 110 patients and 19 measured values per each, (110×19) and targeted central depth (110×1) as an output.
3. The dominant parameters effect the laser eye surgery have been specified through the clinical experiences.
4. Check the final dominated parameters validity using the practical and theoretical NN studies.
5. At this stage changing the hidden layers with the range of (5, 10, 15, 20, and 25) to check the stability and the modification in results.
6. Lastly, by doubling our inputted matrix (input data) to become (220×19) and iterate step 5, another result that approves the variance of the neural network machine behavior, and its sensitive to any increments of the data use or the number of hidden layers.

2.2 Deep belief network model :

The DBN model generated by Hinton et al. [14], obtained by training and stacking several layers of Restricted Boltzmann Machines (RBM) in a greedy manner. Once this stack of RBMs is trained, it can be used to initialize a multi-layer neural network for classification. An RBM with n hidden units is a Markov Random Field (MRF) for the joint distribution between hidden variables h_i and observed variables x_j, which gives rise to the following joint distribution:

$$P(x,h) \propto e^{h'Wx+b'x+c'h} \quad (1)$$

with corresponding parameters $\theta = (W,b,c)$. If h_i and x_j are restrict to be binary units, it is straightforward to show that:

$$P(x|h) = \prod_j P(x_j|h) \text{ with } P(x_j = 1|h) = \text{sigmoid}(b_j + \textstyle\sum_i W_{ij}h_i) \quad (2)$$

Where: $sigmoid(a) = \frac{1}{1+\exp(-a)}$, and $P(h|x)$ also has a similar form:

$$P(h|x) = \prod_i P(h_i|x) \text{ with } P(h_i = 1|x) = \text{sigmoid}(c_i + \textstyle\sum_j W_{ij}x_j) \quad (3)$$

The RBM form can be generalized to other conditional distributions besides the binomial, including continuous variables. RBM models can be trained by approximate stochastic gradient descent. Although P(x) is not tractable in an RBM, the Contrastive Divergence estimator [16] is a good stochastic approximation of $\frac{\partial logP(x)}{\partial\theta}$, in that it very often has the same sign [17].

A DBN is a multi-layer generative model with layer variables h_0 (the input or visible layer), h_1, h_2, etc. The top two layers have a joint distribution which is an RBM, and $P(h_k|h_{k+1})$ are parametrized in the same way as for an RBM. Hence a 2-layer DBN is an RBM, and a stack of RBMs share parametrization with a corresponding DBN. The contrastive divergence update direction can be used to initialize each layer of a DBN as an RBM, as follows. Consider the first layer of the DBN trained as an RBM P_1 with hidden layer h_1 and visible layer v_1. We can train a second RBM P_2 that models (in its visible layer) the samples h_1 from $P_1(h_1|v_1)$ when v_1 is sampled from the training data set. It can be shown that this maximizes a lower bound on the log-likelihood of the DBN. The number of layers can be increased greedily, with the newly added top layer trained as an RBM to model the samples produced by chaining the posteriors $P(h_k|h_{k-1})$ of the lower layers (starting from h_0 from the training data set). The parameters of a DBN or of a stack of RBMs also correspond to the parameters of a deterministic feed-forward multi-layer neural network. The i^{th} unit of the k^{th} layer of the neural network outputs as:

$$h_{ki} = \mathrm{sigmoid}(c_{ki} + \textstyle\sum_j W_{kij}\, h_{k-1,j}) \tag{4}$$

Using the parameters c_k and W_k of the k^{th} layer of the DBN. Hence, once the stack of RBMs or the DBN is trained, one can use those parameters to initialize the first layers of a corresponding multi-layer neural network. One or more additional layers can be added to map the top-level features h_k to the predictions associated with a target variable (here the probabilities associated with each class in a classification task).

3.RESULT AND DISCUSTION

3.1 Neural network results.

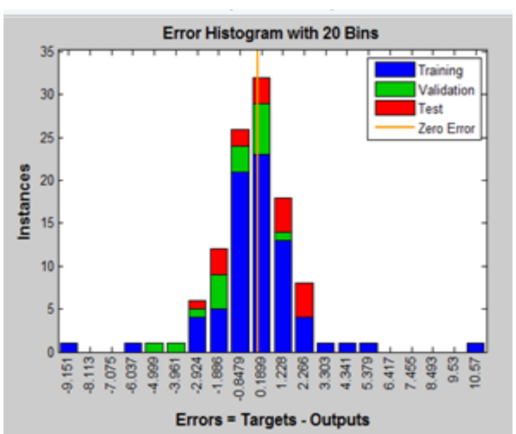
1. By checking the final dominated parameters validity using the practical and theoretical NN studies, it gave the result shown in Figure (1).

0	epoch	time	performance	gradient	mu	validation	
1	3	0	2.26 e+03	676@1.26e-11	0.001@1.0e-6	3	gender
2	4	0	1.25e+03	900@5.12e-12	0.001@1.0e-7	4	treatment type
3	3	0	1.24e+3	812@5.33e-10	0.001@1.0e-6	3	eye
4	6	0	151	140@10.9	0.001@0.1	6	sphere
5	6	0	1.66e+03@1.62	481@4.85	0.001@1.0	6	asphericity
6	3	0	1.15e+3@1.15e	110@2.02e-5	0.001@1.0e+11	2	oz
7	6	0	1.06e+3@931	558@10.1	0.001@1.00	6	axis
8	6	0	816@785	1.35e+3@10.1	0.001@1.00e-9	6	tz
9	6	0	1.20e+03@1.16	612@126	0.001@0.1	6	k1
10	6	0	1.19e+3@1.11e	1.16e+3@22.6	0.001@1.00	6	axis of k1
11	6	0	1.09e+3@1.05e	900@37.3	0.001@1.00	6	k2
12	6	0	1.03e+3@926	1.07e+3@149	0.001@0.1	6	axis of k2
13	6	0	783@646	1.59e+3@377	0.001@0.1	6	cylinder
14	6	0	1.03e+3@959	1.28e+3@33.8	0.001@1.0	6	RSB
15	6	0	1.12e+3@1.05e	448@5.11e-11	0.001@0.0001	6	pd
16	6	0	1.03e+3@850	2.32e+3@33.5	0.001@10.0	6	corneal thickne
17	3	0	3.52e+3@3.51e	860@2.05e-9	0.001@1.0e-6	3	flap thickness
18	6	0	1.25e+3@1.23e	1.01e+3@15.1	0.001@0.1	6	R fit
19	6	0	1.09e+3@1.08e	761@6.41e-9	0.001@1.9e-8	6	AZ

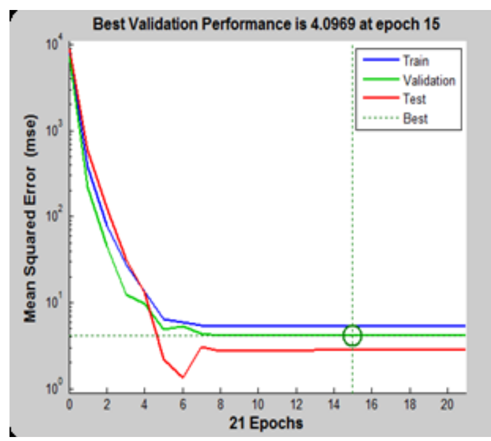
Figure (1) Dominant parameters to specify the central depth of the laser.

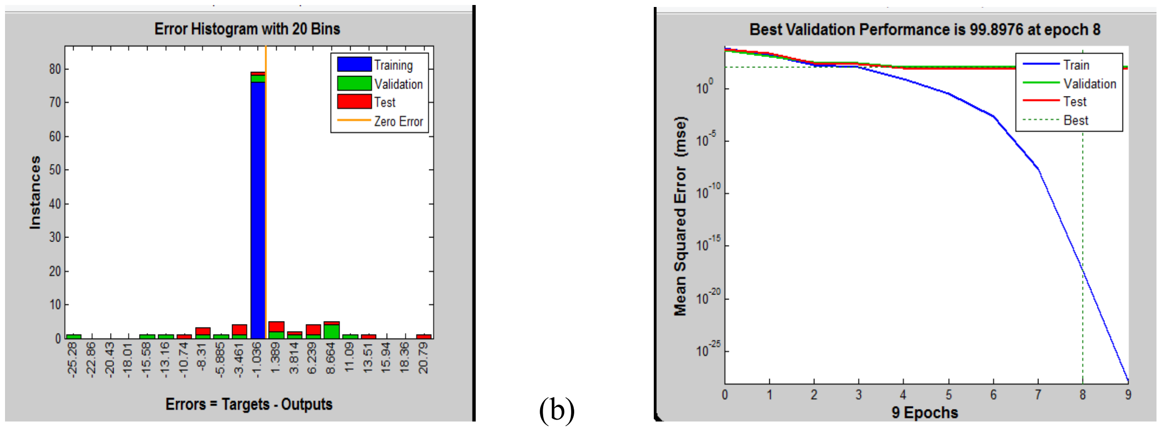
This result approve that the optical zone (oz) as shown in fig(1) is the most dominant parameter to specify the central depth of the laser and by comparing this result theoretically with the theory (munnerlyn theory) that built for the machine that use to specify the central depth for correcting amount of laser ,we get that they are the same.Q3

2. Throughout changing the hidden layers with the range of (5, 10, 15, 20, 25 and 30), it have been found that for each hidden layer, the train of the neural network machine variant as the hidden layer increase. This explained throughout the histogram error and the mean square error values as explained in Figure (2),as the complexity inside the machine rise and since the neural network doesn't have aback propagation technique to correct any mistake in each weight of each hidden layer then it gives a sense for this changes and make the neural network machine an stable one then the difference of mean value for each histogram in each run produce in fig (3).Q4



(a)





(b)

Figure (2) Neural Network result (a) Histogram error deviation of the values and the mean square error values for number of hidden layers=5,(b) Histogram error deviation of the values and the mean square error values for number of hidden layers=15.

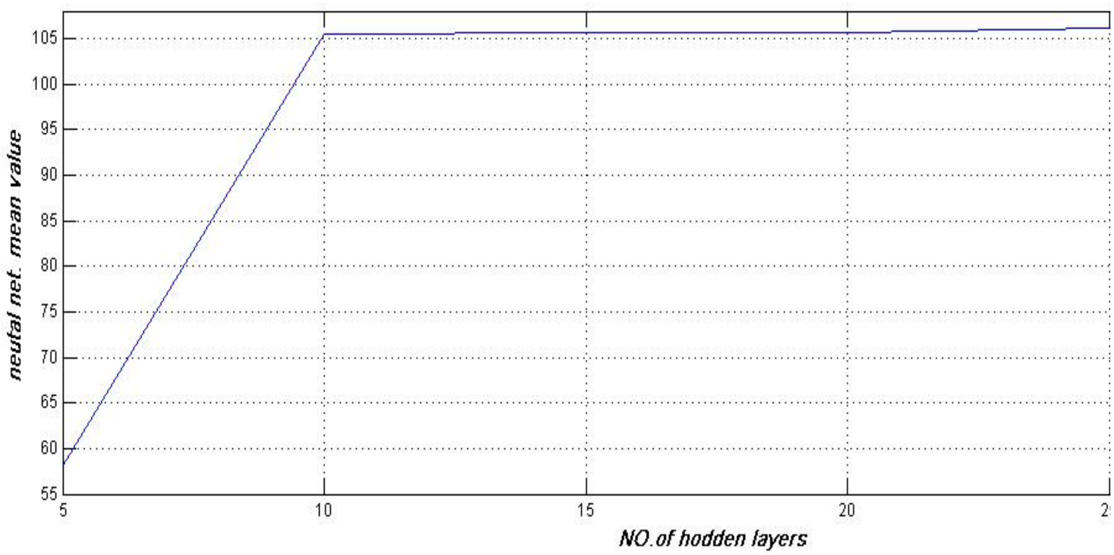


Figure (3) the fluctuated variance of means values with increments of number of hidden layers.

After doubling input data to become (220×19) and changing the number of hidden layers (5,10,15,20,25 and 30), another result the machine will give which approve that the variety of the neural network machine behavior makes over lapping when the input data are increase , and this lead to say that the neural network machine sensitive to any increment in the data use or the number of hidden layers. Some of this results is present in fig(4) and the mean histogram error for each run shown in fig(5).

The mean histogram error for each run shown in fig(5) is approve that the variety of the neural network machine behavior makes over lapping when the input data are increase happiened through the hidden layer increases,this seen at hidden layer25 .Q5,Q7

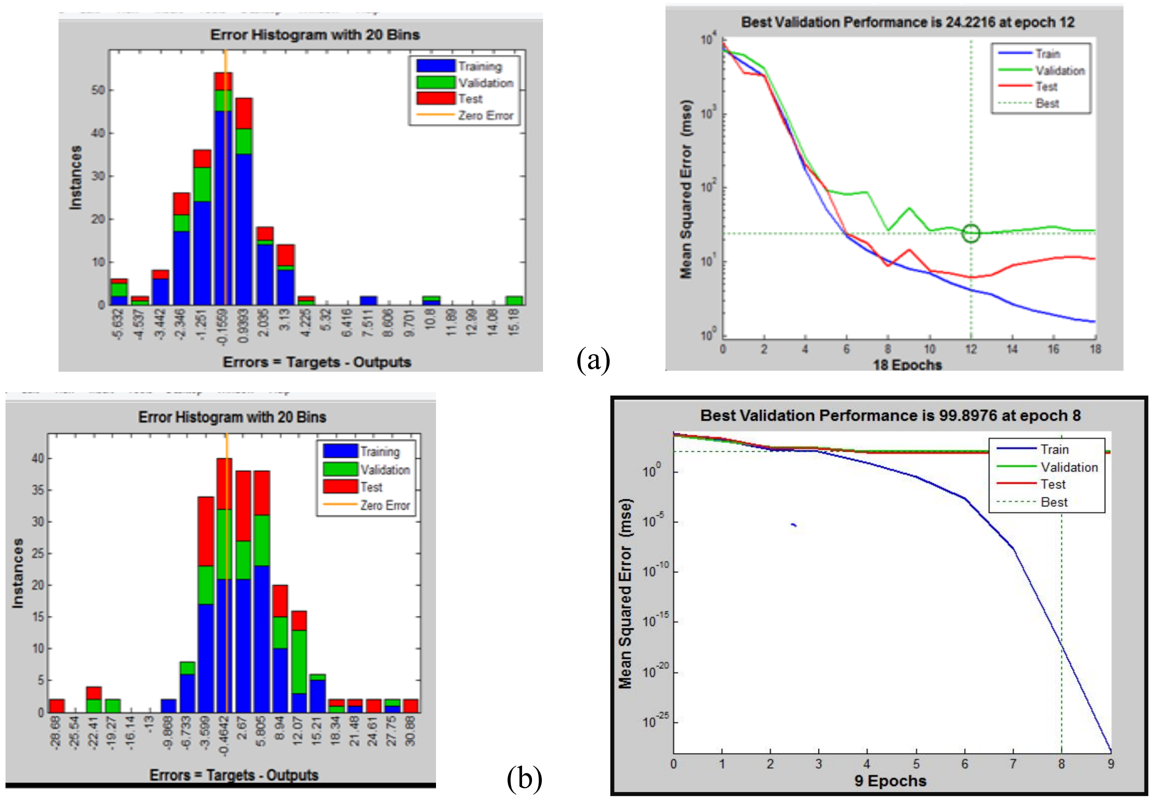


Figure (4). Neural Network result (a) Histogram error deviation of the values and the mean square error values for number of hidden layers=5, (b) Histogram error deviation of the values and the mean squared error values for number of hidden layers=15.

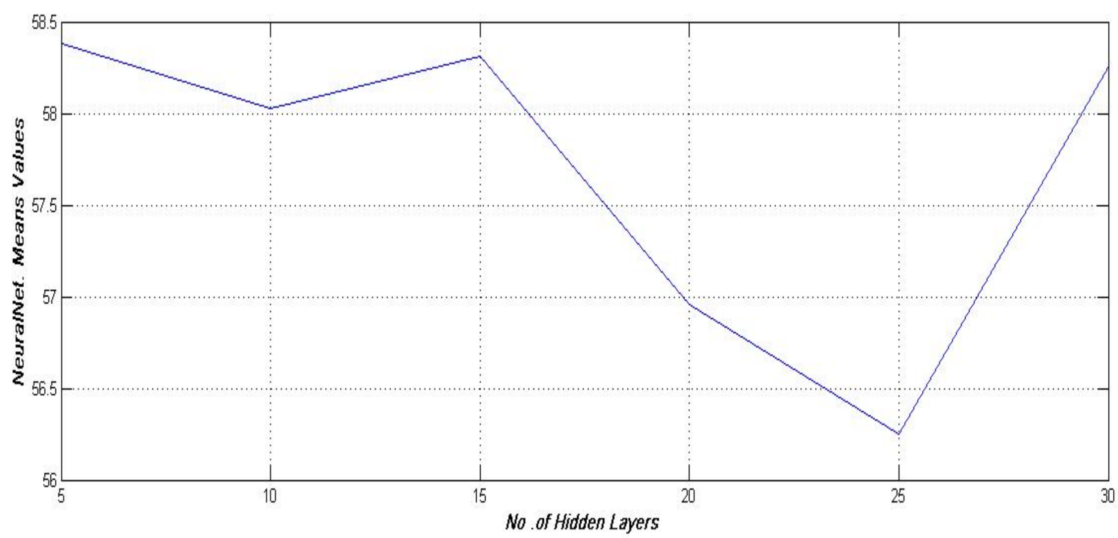
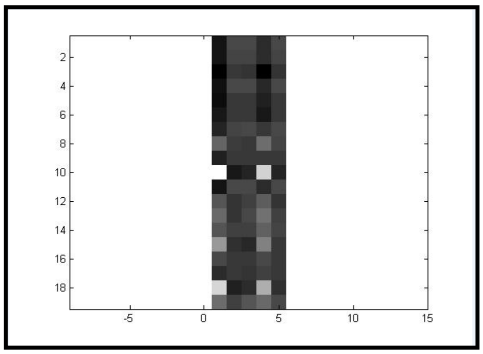


Figure (5). The fluctuated variance of means values with increments of number of hidden layers.

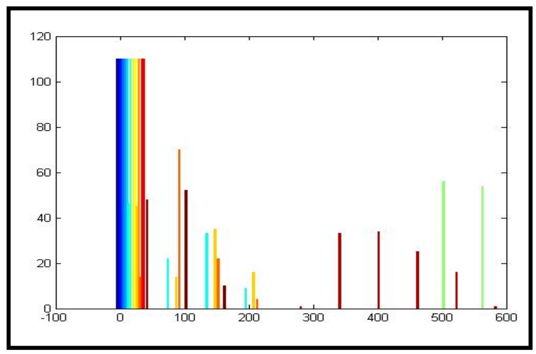
3.2. Deep belief network results .

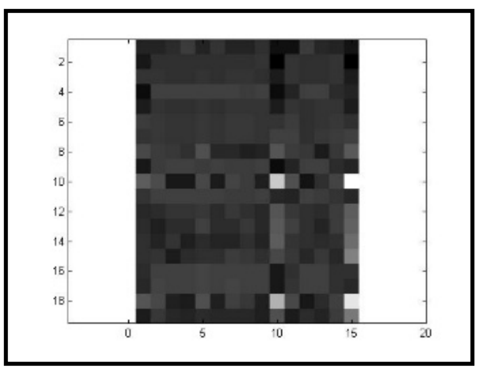
1. Through the use the MATLAB toolbox, for deep learning, and by using the deep belief network technique, making many adjustments to satisfy the present case study the result get is in the form

of images and by changing the number of hidden layers (5, 10, 15, 20, 25 and 30). It gave us the images shown in Figure (6) and also by making specific formula on it to get the residual image and a histogram for each residual image , and means values for some of the residual images that produce will shows in Figure (7) . this will show the linear behavior of the new machine of neural network(DBN) and how much the back propagation theory makes the require enhancement on the neuron weights for use the brain machine to detect and give a desire result .Q6Q8



(a)





(b)

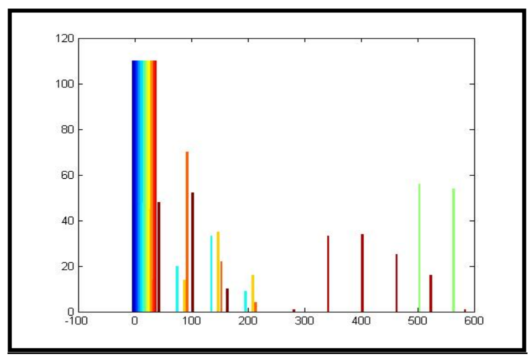


Figure (6) Deep Neural (DBN) results (a) Residual image and histogram error deviation of the values for number of hidden layers=5,(b) Residual image and histogram error deviation of the values for number of hidden layers=15.

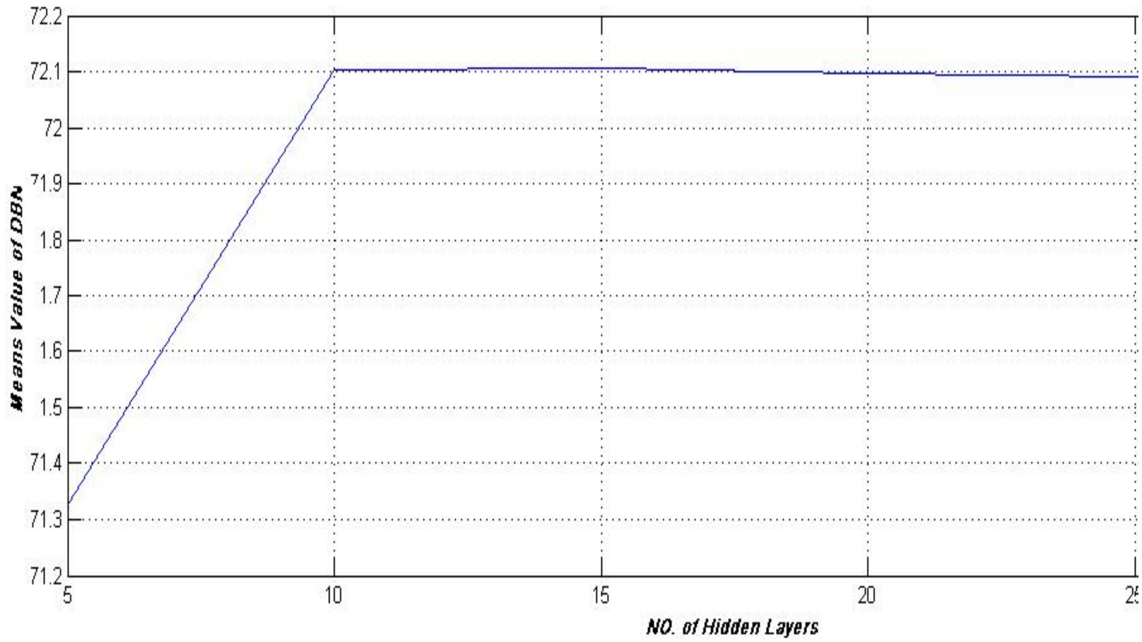
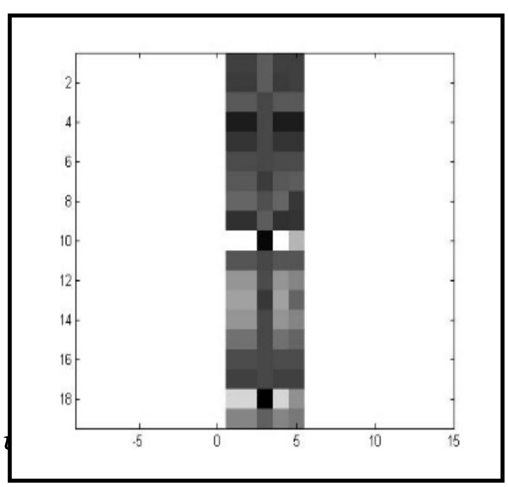
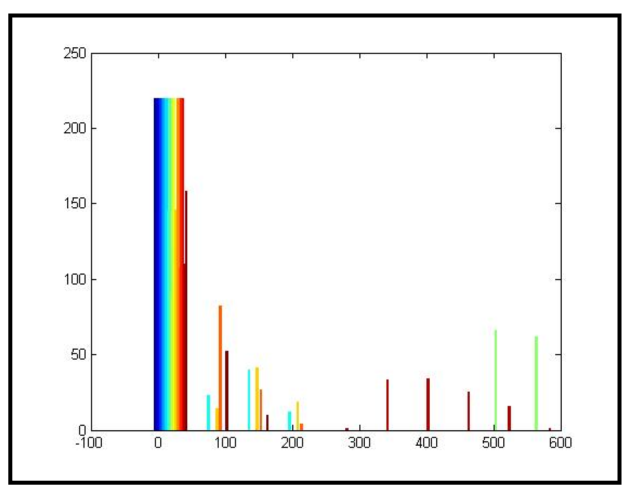


Figure (7) Smooth variance for the mean error value with the number of hidden layers.

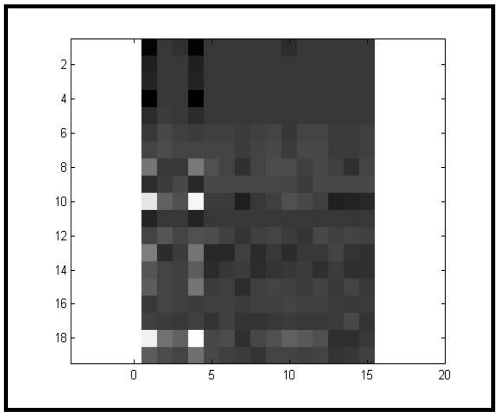
Doubling input data to become (220×19) and changing the number of hidden layers (5,10,15,20,25 and 30),some of the new results shown in Figure (8), and the variance of mean values with rises of hidden layers for each run shown in Figure (9). This approve that the machine is very stable and provide a linear variety of behavior as the data are increase ,the new model of neural network machine performance makes a perfect corrections of the over lapping since it use the gradient descent theory throw out the training test on the inputs data and how much the data increase it will also be a linear ,and the back propagation technique is enhance the lost or mistakes on the weights as the neurons number are rises , and this lead to say that the deep neural network machine (deep belief network) is a very stable machine and give specific and accurate decision.

2.





(a)



(b)

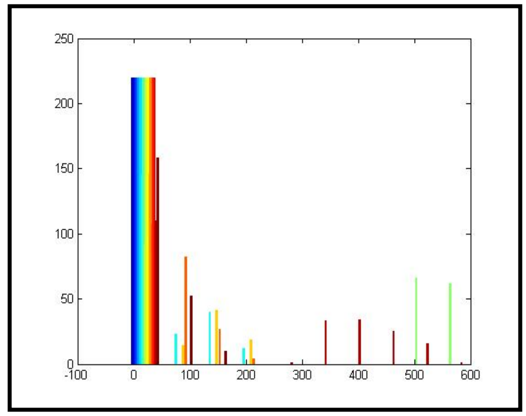


figure (8) Deep Neural results for double data. (a) Residual image and histogram error deviation of the values for number of hidden layers=5 (b) Residual image and histogram error deviation for number of hidden layers=15.

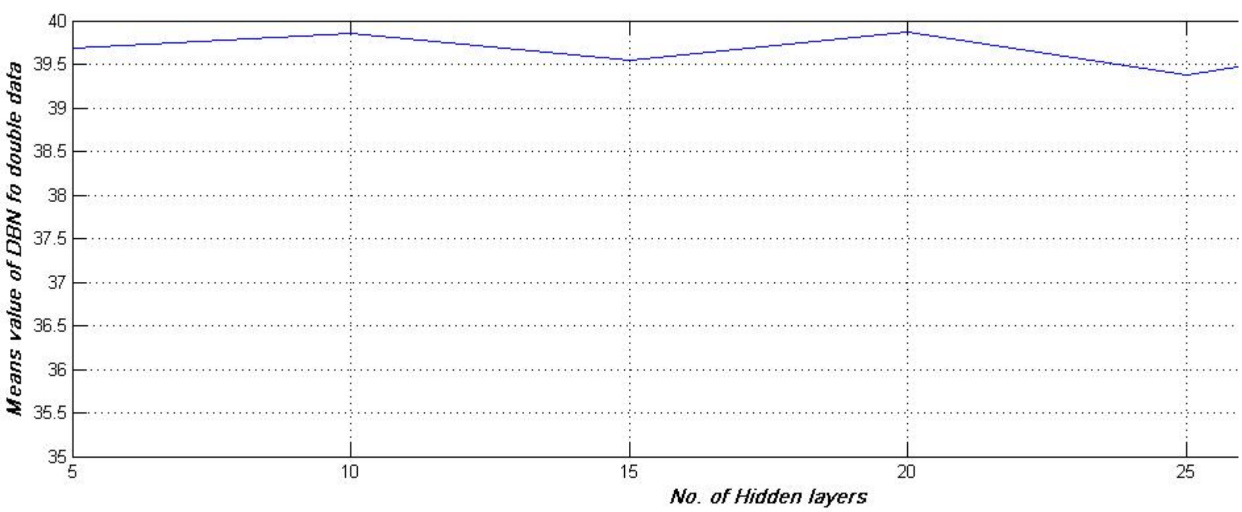


Figure (9) Variance of the means values with number of hidden layers.

4. CONCLUSION

Through the tested cases and results, it is good to conclude that the use of the DBN as a new tool for the medical application is powerful. Specially sensitivity and fast reach results. This is true when reviewing Figure (1), that shows that the optical zone (OZ) is the most dominant paramter that effect the central depth calculating during the laser eye surgery. For sure this is come concident with the theortical and exoerimental experience for such surgical procedure.

The NN produce unstability train as the input data increased and as the hidden layers increased also, and this is shown in Figures (2), (3) and compared to (4), (5). This unstability of the behaviour are related to:

1- The absence of the back propagation theorem that enable the machine for make the desire correction hidden layers.
2- This machine provide a very an acceptable overlapping in the input data spatially for huge data input.

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