

Classification of brain tumors using the multilayer perceptron artificial neural network

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Abstract

Information from 54 Magnetic Resonance Imaging (MRI) brain tumor images (27 benign and 27 malignant) were collected and subjected to multilayer perceptron artificial neural network available on the well know software of IBM SPSS 17 (Statistical Package for the Social Sciences). After many attempts, automatic architecture was decided to be adopted in this research work. Thirteen shape and statistical characteristics of images were considered. The neural network revealed an 89.1 % of correct classification for the training sample and 100 % of correct classification for the test sample. The normalized importance of the considered characteristics showed that kurtosis accounted for 100 % which means that this variable has a substantial effect on how the network perform when predicting cases of brain tumor, contrast accounted for 64.3 %, correlation accounted for 56.7 %, and entropy accounted for 54.8 %. All remaining characteristics accounted for 21.3-46.8 % of normalized importance. The output of the neural networks showed that sensitivity and specificity were scored remarkably high level of probability as it approached % 96.

Key words

Brain Tumor, IBM SPSS Ver. 17 & 20, Artificial Neural Networks (ANN).

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تصنيف أورام الدماغ باستخدام الشبكة العصبية الاصطناعية لمستقبلات متعددة الطبقات

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الخلاصة

جمعت معلومات من 54 صورة لورم الدماغ من صور جهاز الرنين المغناطيسي (27 صورة لورم الدماغ الحميد و 27 صورة لورم الدماغ الخبيث) و عرضت هذه المعلومات لشبكة اعصاب افتراضية متعددة الطبقات متوفرة على البرنامج الاحصائي IBM SPSS 17. بعد محاولات عديدة تم اختيار معمارية شبكة الاعصاب الافتراضية الذاتية لمعلومات هذا البحث. ثلاثة عشر معلومة عن الجوانب الاحصائية و الشكلية للصورة تم اعتمادها في هذا البحث. لقد اظهرت شبكة الاعصاب المستخدمة نسب تصنيف صحيح في مجموعة التدريب بلغت 89.1 % بينما بلغت 100 % في مجموعة الاختبار. لقد اظهرت الاهمية المعدلة طبيعياً ان التفرطح (kurtosis) كان المعلومة الاكثر اهمية (100 %) في التمييز بين نوعي ورم الدماغ، و هذا يؤشر الاهمية الجوهرية لهذه المعلومة في التنبؤ بنوع الورم للحالات الجديدة من خلال معلومات صورة الورم. لقد كان لتباين لمعان الصورة (contrast) اهمية طبيعية 64.3 %، و للارتباط 56.7 % و 54.8 % للانتروبي (Entropy) و الذي هو عبارة عن مقياس احصائي للعشوائية التي تستخدم لتمييز نسيج الصورة. لقد تراوحت الاهمية المعدلة طبيعياً لكل المعلومات الباقية بين 21.3-46.8 %. لقد اظهرت النتائج التي افرزتها شبكة الاعصاب الافتراضية ان احتمال تنبؤ نوع الورم الحميد تصل الى 96 % (sensitivity) و حالة الورم الخبيث (specificity) تصل الى نفس المستوى .

Introduction

Brain tumor is a medical issue that harvest according to the American brain tumor association [1] thousands of lives every year. In the United States of America the number of new cases with brain tumor is expected to be 27110 in this 2017. It is also expected that 17000 will lose their lives during this year. In this context one can expect how significant is this issue when bearing in mind that thousands of people all over the world will be the victims of this disease. Two main types of brain tumors can be identified, these are; benign and malignant [2]. Benign tumor can be defined as a mass that is very slowly growing with well-defined borders and rarely spread or invade neighbor cells [2]. Malignant tumor can be defined as a mass that is invading neighbor cells and growing fast and is life threatening [2]. Epidemiological studies in different parts of the world showed that brain and central nervous system tumors are relatively low compared to other cancer types [3]. In Austria [4] the country that has developed many studies on brain tumors, the incidence rate of brain tumors is 18.1 per 100000 person/year. Brain tumors issue was and still the main concern of many researchers as well as many health organizations. The field of image processing witnesses many development in both segmentation and classification of brain tumors. Rajesh and Bhalchanda [5], used MATLAB to extract brain tumors from MRI images. Suhag and Mohan [6], used Support Vector Machines (SVM) classifier to detect and classify brain tumors from MRI images. Hassan and Aboshgifa [7], designed MATLAB GUI for the detection of brain tumors from MRI images. Saini and Singh [8] Singh used MATLAB image processing for the detection of brain tumors.

Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) was widely used in the process of detecting and classification of brain tumors. Monica Subashini and Sarat Kumar used ANN in the detection of brain tumors from MRI images [9]. Pulse coupled neural network was used to enhance MRI images before segmentation. The classification was to detect either normal or abnormal images depending on the performance of the network. The abnormal images are not classified to what this abnormal mass refers to, rather the issue left to further investigation under the aid of special medical support. In addition to the investigation of the MRI images, shape and texture characteristics of the images were also subjected to different statistical techniques in order to provide valuable information about characteristics that best describe the type of tumor. In this context Neelam Marshkole et al. [10], used texture and shape features of MRI images to classify brain tumors to either malignant or benign using linear vector quantization technique. They found these features very effective in the process of classification. In this paper the features that previously used by Zhang et al. [11] in an image processing program to classify two states of brain tumors (benign and malignant) were used here in order to see how good is the performance of ANN to enhance classification.

Preparing methods

The stage of introducing MRI brain images into the algorithm of the work of Zhang et al. [11] build it in MATLAB Ver. 2014a program which used the principal component analysis method (PCA) to reduce the output dimensions and using (KSVM) kernel and used the GRB kernel achieves to do classification, then the matrix output units produced by this

algorithm, which including Mean, Standard Deviation, Entropy, Root Means Square (RMS), Variance, Smoothness, Kurtosis, Skewness,

Inverse Difference Movement (IDM), Contrast, Correlation, Energy and Homogeneity, as shown in Table 1.

Table 1: Statistical characteristics of images [11].

Name	Mean	Standard.D	Entropy	RMS	Variance	Smoothnes	Kurtosis	Skewness	IDM	Cotrast	Correlation	Energy	Homogenei	RBF	Ac	Linear	Polygc	Quadr	Type	Tumer	Diagnose	name
x1	0.0027162	0.0897736	2.59825	0.0898027	0.0080661	0.909945	11.3508	0.877318	0.833787	0.26891	0.182297	0.80448	0.945194	90%	90%	80%	90%	BENIGN	Benign	ABD_MADHLOOM_FAADH		
x2	0.0055469	0.0896432	2.8213	0.0898027	0.0080538	0.953777	11.3826	1.11445	-0.211103	0.307286	0.132056	0.77244	0.935183	70%	90%	80%	80%	MALIGNANT	Benign	AHMED_MOHY		
x3	0.0051506	0.0896669	2.70277	0.0898027	0.0080535	0.950397	10.5718	1.00063	1.74481	0.299221	0.113543	0.778203	0.935734	80%	90%	90%	70%	MALIGNANT	Benign	AMERA_ABD_ALAMEER		
x4	0.0035741	0.0897436	2.47097	0.0898027	0.0080535	0.930049	17.7999	1.59296	1.19348	0.324249	0.0688363	0.770555	0.934151	80%	90%	80%	80%	BENIGN	Benign	ASMAA_FOAD		
x5	0.0044023	0.0897067	2.51315	0.0898027	0.0080585	0.942451	21.7897	1.94067	0.816539	0.348165	0.112744	0.798832	0.942189	70%	90%	90%	80%	BENIGN	Benign	FAESI_GHAZY		
x6	0.0024331	0.0897818	2.5489	0.0898027	0.0080627	0.900509	17.7999	1.47139	0.921672	0.312291	0.0926402	0.794718	0.941453	70%	90%	70%	80%	BENIGN	Benign	FAKHRYA_JASEM		
x7	0.0046489	0.0896943	2.62812	0.0898027	0.0080468	0.945337	16.7239	1.68756	0.169128	0.295884	0.20434	0.794457	0.941654	70%	90%	80%	80%	BENIGN	Benign	FALAH_HASN_ZEDAN		
x8	0.0065769	0.0895735	2.20827	0.0898027	0.0080555	0.960732	35.2515	3.41193	1.67907	0.445217	0.123389	0.846732	0.954046	70%	90%	80%	80%	BENIGN	Benign	FATEMA_HAMED		
x9	0.0033595	0.0897519	2.50503	0.0898027	0.0080472	0.92591	15.621	1.30532	-0.644037	0.33287	0.100551	0.804955	0.943718	80%	90%	70%	70%	BENIGN	Benign	GHALEA_HADMOOL		
x10	0.0065126	0.0895782	2.69422	0.0898027	0.0080478	0.96036	12.2608	1.37432	0.40913	0.322581	0.132216	0.777045	0.93731	90%	90%	90%	80%	MALIGNANT	Benign	HASAN_HANON		
x11	0.0046317	0.0896952	1.57961	0.0898027	0.0080721	0.945146	41.0959	3.6879	3.40516	0.460512	0.117664	0.87618	0.961736	70%	100%	70%	80%	BENIGN	Benign	KALTHOM_KADHEM		
x12	0.0039416	0.0897282	2.50011	0.0898027	0.00805	0.936154	19.5789	1.63904	1.20752	0.356785	0.073653	0.803431	0.941725	80%	80%	80%	70%	BENIGN	Benign	KAREMA_TAHER		
x13	0.002204	0.0897877	2.43871	0.0898027	0.0080584	0.891291	12.7357	0.964955	-0.190051	0.288764	0.160447	0.795166	0.941681	80%	90%	80%	80%	BENIGN	Benign	MAESON_HERAN		
x14	0.0056219	0.0896386	2.63739	0.0898027	0.0080405	0.954366	13.3513	1.062	0.538243	0.30673	0.0871708	0.754496	0.929424	70%	90%	70%	80%	MALIGNANT	Benign	MAHDY_SALEH		
x15	0.0049787	0.0896766	2.72414	0.0898027	0.0080537	0.948772	15.8378	1.54733	0.222582	0.314238	0.18231	0.809305	0.944957	70%	80%	80%	80%	BENIGN	Benign	MEHSEN_MANSOR		
x16	0.0045267	0.0897005	2.3703	0.0898027	0.0080612	0.943944	22.0365	2.18041	1.45825	0.348443	0.144594	0.806359	0.944131	80%	80%	70%	80%	BENIGN	Benign	QESMA_KHALEF		
x17	0.0045784	0.0896979	2.54279	0.0898027	0.0080477	0.944542	13.3974	1.22528	-0.353794	0.275306	0.197909	0.780542	0.938536	80%	80%	80%	80%	BENIGN	Benign	RAFAH_RASHED		
x18	0.0067934	0.0895574	2.49915	0.0898027	0.0080573	0.961936	25.669	2.3506	0.875253	0.392102	0.0681033	0.789116	0.93785	80%	90%	80%	80%	MALIGNANT	Benign	REKON_NAFEL		
x19	0.0059426	0.0896179	0.798655	0.0898027	0.0080576	0.956722	75.2468	6.57795	14.1441	0.584538	0.0711565	0.928061	0.97504	80%	80%	70%	70%	BENIGN	Benign	SALEH_MAHDI		
x20	0.0031898	0.089758	2.5175	0.0898027	0.0080682	0.922277	10.2616	0.868306	-0.0636282	0.288376	0.10209	0.775965	0.936601	70%	90%	80%	70%	BENIGN	Benign	SANAA_SATAR		
x21	0.0049795	0.0896765	2.60674	0.0898027	0.0080549	0.94878	14.8265	1.34049	-0.230111	0.303393	0.183184	0.792062	0.940122	80%	90%	80%	70%	BENIGN	Benign	SHAEMAA_HSEEN		
x22	0.0044996	0.0897019	2.52579	0.0898027	0.0080491	0.943626	19.0434	1.71048	0.251215	0.336207	0.119962	0.785885	0.938237	70%	80%	80%	70%	BENIGN	Benign	SONDS_LATEF		
x23	0.0013624	0.0898044	2.66567	0.0898027	0.0080567	0.835206	10.4985	0.871408	-0.111988	0.271135	0.162296	0.799682	0.94207	80%	80%	80%	80%	BENIGN	Benign	SUHELA_EBRAHEM		
x24	0.0045096	0.0897014	2.5165	0.0898027	0.0080598	0.943744	19.4968	1.69139	0.244408	0.308954	0.134809	0.795837	0.943239	80%	90%	70%	70%	BENIGN	Benign	SUHELA_SHAMEL		
x25	0.0023888	0.0897829	2.59625	0.0898027	0.0080657	0.89885	11.9589	0.990308	-0.0732406	0.281424	0.104401	0.768494	0.934823	70%	90%	80%	80%	BENIGN	Benign	YOUSIF_KHALID_JASEM		
x26	0.0058961	0.0896209	1.80899	0.0898027	0.008065	0.956396	42.7597	3.97558	6.26757	0.451613	0.0911928	0.855272	0.956339	80%	80%	80%	80%	BENIGN	Benign	ZAENAB_ALI		
x27	0.0045862	0.0896975	2.59571	0.0898027	0.0080489	0.944631	18.4215	1.71685	-0.0761922	0.345662	0.0938048	0.802143	0.942869	70%	80%	70%	70%	BENIGN	Benign	ZAHRA_ABAS		
x28	0.0033663	0.0897516	2.62972	0.0898027	0.0080524	0.926051	16.1067	1.42888	0.822684	0.323693	0.124584	0.808233	0.943099	90%	90%	80%	80%	BENIGN	Benign	ZUHER_ABD_ALGHANY		

Patients and methods

MRI images from 54 patients attending Baghdad medical city, Baghdad-Iraq, for brain tumor investigations were collected during the period March to June 2016. The

most common cancer tumors in Iraq that have taken samples of MRI images from hospitals in the Baghdad medical city are Meningioma for benign and Glioblastoma for malignant diseases as shown in Fig. 1.

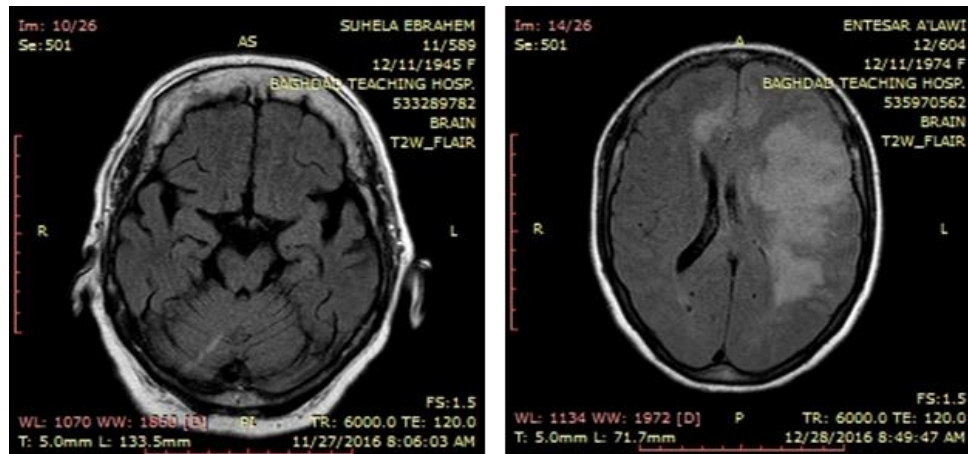


Fig. 1: The brain images of the MRI of two types of diseases from Baghdad medical city.

All images were subjected to the program of Zhang et al. [11] in order to collect information about the statistical and shape features considered in the program. These features are listed in Table 2. The ability of this program to detect benign tumors from the 54 images was not as good as expected and the best performance was no more than 78% of correct classification. As a matter of fact such a percentage cannot be considered well enough and many alterations were made to the program in an attempts to increase the percentage of correct classification, but unfortunately the results were always disappointed. For this reason the information of the thirteen features listed in Table 2 were subjected to a multilayer perceptron artificial neural network. The output of the image processing software designed by Zhang et al. [11] were used as an input to the ANN multilayer perceptron discriminant function. It is worthwhile mentioning that formulas and detailed explanation of the meaning of all functions listed in Table 2 are available in MATLAB13 and later versions.

ANN have been developed as generalizations of mathematical models of biological nervous systems [12]. The basic processing elements of neural networks are called artificial neurons, or simply neurons or nodes. In a simplified mathematical model of the neuron, the effects of the synapses are represented by connection weights that modulate the effect of the associated input signals, and the nonlinear characteristic exhibited by neurons is represented by a transfer function. The neuron impulse is then computed as the weighted sum of the input signals, transformed by the transfer function. The learning capability of an artificial neuron is achieved by adjusting the weights in accordance to the chosen learning algorithm.

Table 2: Variables adopted in this study as described in the paper mentioned previously in this paper.

Variable name	Symbol
Mean	x1
Standard deviation	x2
Entropy	x3
RMS	x4
Variance	x5
Smoothness	x6
Kurtosis	x7
Skewness	x8
IDM	x9
Contrast	x10
Correlation	x11
Energy	x12
Homogeneity	x13

Artificial neural networks are characterized by their architecture, activation function and learn paradigm. Multilayer Perceptron (MLP) is one of the mostly used ANNs and about 80 % of ANNs researches focused on [13]. It consists of a series of fully interconnected layers of nodes where there are only connections between adjacent layers. General structure is showed in Fig. 2.

If there is several inputs such as x_1, x_2, \dots, x_n , then these inputs will represent the first layer in the design of the MLP NN, the other layer which will be serve as a hidden layer is the weights (also called synapses) that corresponds to each input w_1, w_2, \dots, w_n . In addition there is a bias parameter which refers to w_0 , and can be interpreted as synapse that is associated with artificial input $x_0 = -1$. The output neuron y will be the sum of the products of the input vector $x_0, x_1, x_2, \dots, x_n$ by the vector $w_0, w_1, w_2, \dots, w_n$, that is:

$$\underline{x} \cdot \underline{w} = \sum_{i=0}^n x_i w_i \quad (1)$$

The output neuron can then be calculated by the means of activation function

$$y = f_{net}(x \cdot y) \tag{2}$$

where a hyperbolic tangent function is usually adopted defined for a generic value a; however it is common to use other activation function in certain situations:

$$f(a) = \frac{1 - e^{-a}}{1 + e^{+a}} \tag{3}$$

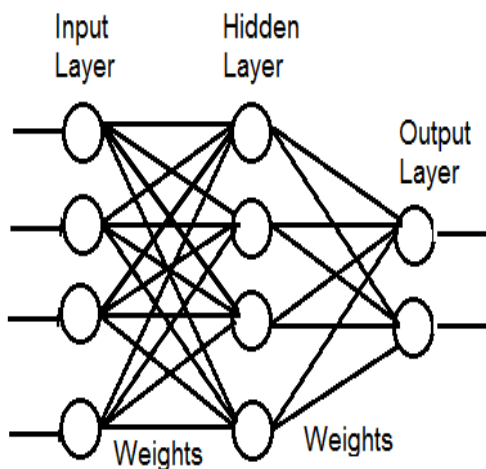


Fig. 2: Multilayer perceptron neural network [9].

One can easily realize that the architect of the multilayer perceptron involves:

- Input layer
- Hidden layer(s)
- Output layer

The software was used with an updated version IBM SPSS ver. 20 which is provides a neural network tools that have two main options; radial base and multilayer perceptron. In this paper

multilayer perceptron was used with automatic architect option.

Results

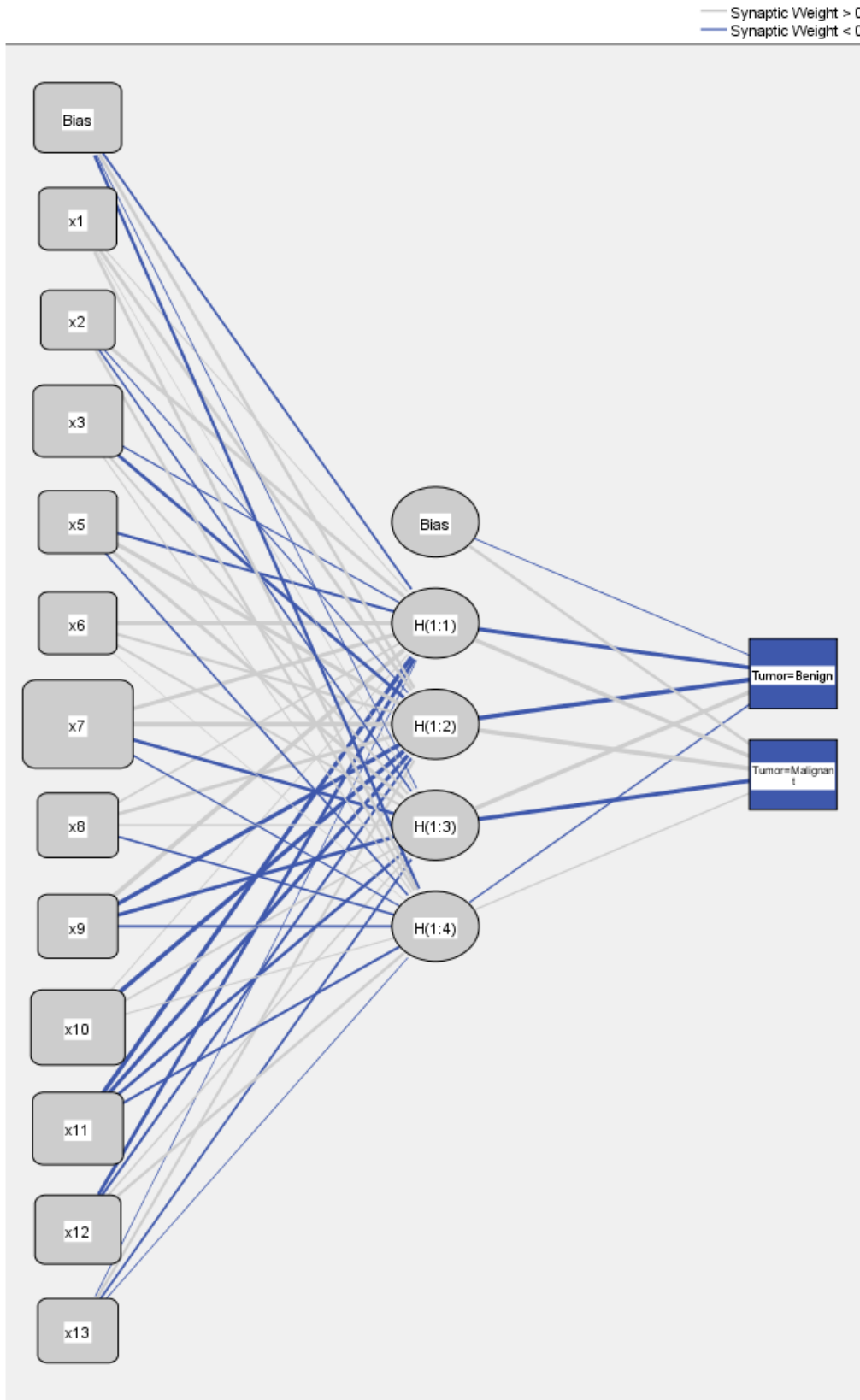
Table 3 shows the summary of the number of cases used in the procedure of the MLP ANN. In this table we can see the total number of cases used (valid cases) was 54 and that partitioned as 46 cases for the training group and 8 cases for the test group.

Table 3: Summary table.

Case Processing Summary		
Sample	N	Percent
Training	46	85.2%
Testing	8	14.8%
Valid	54	100.0%
Excluded	0	
Total	54	

Fig. 3 shows the structure of the MLP ANN as produced by the SPSS ver. 20. It is clear from this figure the addition of the bias parameter which mentioned previously. There is no need to add it, rather it will be added automatically. It is also clear that the output layer contained two neurons namely Tumor Benign and Tumor Malignant. And these are connected to the input layer through a hidden layer and synapses. The classification process is then to retain the image to an output category that is closest to it.

Percentages of correct classification will calculated with respect to the classification rule derived by MLP ANN. The sensitivity and specificity are directly affected by the classification rule.



Hidden layer activation function: Hyperbolic tangent

Output layer activation function: Softmax

Fig. 3: Structure of the MLP ANN.

Table 4 shows the cross classification according to performance of the MLP ANN.

The percent of correct classification for the training set is found to be 89.1 whereas for the testing group it found to be 100 %. This result is actually promising and is much better obtained by the image processing program mentioned previously.

Fig. 4 shows the boxplot of the predicted pseudo probabilities with respect to the benign and malignant

categories of the dependent variable tumor. The blue box in the category of benign represent the predicted probability of having benign tumor for the cases with benign tumor. The portion above 0.5 on the y-axis showing the correct classification listed in Table 3. The portion below 0.5 represents incorrect prediction. It is clear that malignant tumor cases have more chance to correctly classify according to the distribution of the pseudo probabilities of Fig. 4.

Table 4: Cross classification of used cases with respect to categories of tumor.

Sample	Observed	Predicted		
		Benign	Malignant	Percent Correct
Training	Benign	19	3	86.4%
	Malignant	2	22	91.7%
	Overall Percent	45.7%	54.3%	89.1%
Testing	Benign	5	0	100.0%
	Malignant	0	3	100.0%
	Overall Percent	62.5%	37.5%	100.0%

Fig. 5 shows the Receiver Operating Characteristic (ROC) curve which gives a visual display of the sensitivity and specificity. Two curves one for each category of the dependent variable tumor were showed in the figure. The two curves are about to be similar to each other which indicates the performance of the MLP ANN is very good in detecting cases from the two categories of tumor. Fig. 6 shows

the normalized importance of the input variables sorted in an ascending manner. It is clear that x7 (kurtosis) accounted for the highest normalized importance which indicates its role in the judgment of the cases to either category of the dependent variable tumor. The variables contrast, correlation, entropy and energy have a remarkable normalized importance but less than that of the kurtosis.

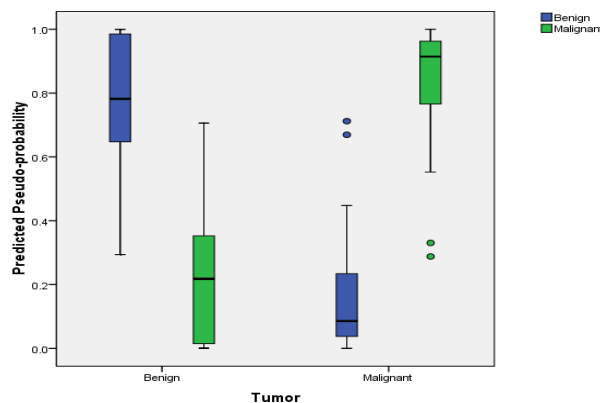


Fig. 4: Boxplot of the predicted pseudo probabilities of tumor categories.

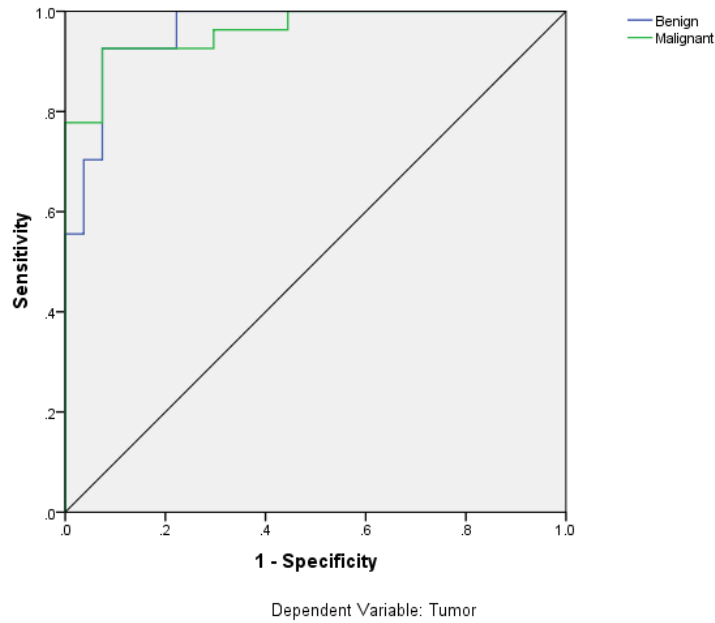


Fig. 5: ROC curve for the categories of the tumor.

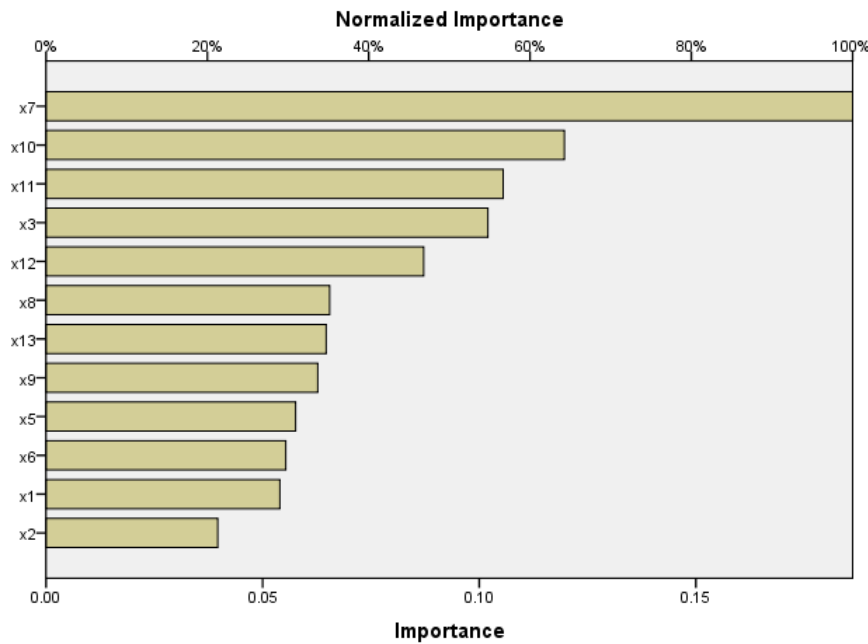


Fig.6: The normalized importance for the input variables used to produce the MLP ANN.

Discussion

The performance of the ANN depends on the available data and how the set of independent variables prescribe the variation of the dependent variable. Sometimes, the independent variables are not well selected and have no significant effect in explaining any amount of the total variability of the dependent variable.

In such situations neither the ANN nor the classic statistical models can help predicting the dependent variable. The size of the data has also an effect on the performance of the ANN, in the case of this research work the number of brain tumor images collected from the Baghdad medical city was not really enough to accomplish more reliable results. It is strongly

recommended that the number of these images should be increased by adding new cases in order to repeat the analysis at every time to observe potential changes.

With respect to the variables with high normalized importance such as kurtosis, contrast, entropy, energy, correlation and all other variables are not really reflecting a threshold of classification to categories of brain tumor categories by their own. This is because another factors needs to be involved and added to the set of independent variables. Laboratorial information may add substantial information about the type of brain tumor. Observation of the brain tumor images suggests that tumors can be characterized by three factors; these are: site, size and shape. Information about these factors may also helped producing more reliable criteria of classification.

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