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Optimal Classifier Using Computational Intelligence Techniques For The Diagnosis Of Skin Cancer Using Dermoscopic Images

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Abstract— **classification of dermoscopic images is an essential research topic as it may be advantageous in monitoring skin related problem, and detect the many type of skin cancer disease as soon as they appear. Therefore the need for fast, automatic, less expensive and accurate method to classify skin disease is of great realistic significance. This work aims to provide accurate, robust, reliable and automated dermoscopic image analysis technique, to allow for early detection of malignant melanoma disease.The optimal classifiers in light of using FFT transform with multilayer perceptron (MLP)Neural Network. An alternate Cross-Validation dataset is used for authentic appraisal of the proposed gathering computation with respect to basic execution measures, for instance, MSE and request accuracy. The Average Classification Accuracy of MLP Neural Network containing one covered layers with 9 PE's dealt with in an ordinary topology is seen to be unrivaled (97.22%) for Training and cross-validation. Finally, perfect count has been delivered dependent on the best classifier execution.**

Index Terms— **Neural solution, MatLab, Matlab program, Microsoft excel, ELM images.**

I. INTRODUCTION

Skin cancer is considered one of the most serious public health problems since it increases significantly the mortality rate, especially if it is not detected early. With late diagnosis, melanoma typically does not respond to treatment and can result in death. Thus, successful treatment of melanoma is through performing a simple surgical procedure, is wholly reliant on the early detection of the affected lesion area. One of the most usual types of cancer in different countries is skin cancer, of which the incidence rate has increased during recent years [1]. Among all forms of skin cancers, melanoma is the deadliest one [2]. According to estimation of The American Cancer Society, in Unites States about 76380 new cases of melanoma will be diagnosed (46870 in men and 29510 in women) and about 10130 deaths from melanoma will occur (6750 in men and 3380 in women) in 2016 [3,4] .Early diagnosis of skin disease helps clinicians and dermatologists to find exact signs and prevention approach of it [5]. Chance of curing in early diagnosed people is mostly higher than the others [6]. The present clinical standard for identifying skin lesions is visual examination. India has one of the uppermost skin cancer rates in the world at approximately four epochs the rates in Canada, the US and the UK. it has been assessed 115,000 new cases of cancer spotted and more than 43,000 people are anticipated to die from cancer according to Indian Cancer Society2010 [1], Council prominent that, more than 10,300 people are treated for melanoma, with 1430 people dyingapiece year[1].The skin cancer malignant melanoma is the lethal form of skin cancer. It can be detached by unpretentious surgery if it has not pass in the blood stream. Melanoma can be recovered if diagnosed and treated in premature stages. Early diagnosis is perceptibly dependent upon patient thoughtfulness and precise assessment by a medical consultant. Numerous published classification systems show precision rates ranging from 60%- 92% [2] which concurs with the probable rates attained by general practitioners [3].

These procedures were directing to be able to provide recommendation for nonspecialized users. But the variations of diagnosis are sufficiency large and there are lacks of detail of the test methods. One commercial product, Solar Scan by Polar technics, has an accuracy rate of 92% [4]. Solar Scan is a complex system, taking high quality Epiluminescence Light Microscopy (ELM) images and using unconventional image analysis techniques to excerpt a number of features for classification which it make not apposite for normal person norm[5].

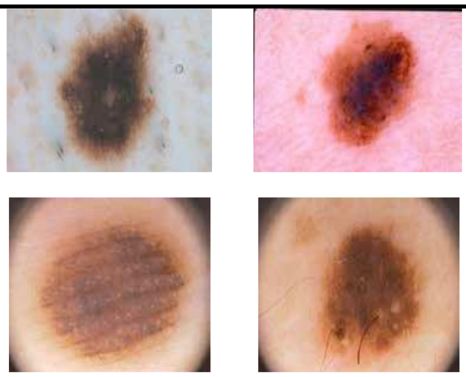

Figure. 1. (a) A dermoscopic image with a common nevi; (b)-(c) Two dermoscopic images with melanoma; (d) A dermoscopic image with an atypical nevi.

The outmoded imaging is just a recording of what the human eye can comprehend by digital camera while the Dermoscopy known as Epiluminescence Light Microscopy (ELM) images prerequisite a professional experience to acquire the required image. Dermoscopy progresses the detection rate of melanomasnoticeably compared to inspection with the naked eyewhose exactitude is only 60% [6, 7, 8]. Nonetheless, it has alsobeen piercing out that the diagnostic accurateness using thismodus operandi largely be contingent on the dermatologist's experience[9, 10].

II. Research Methodology

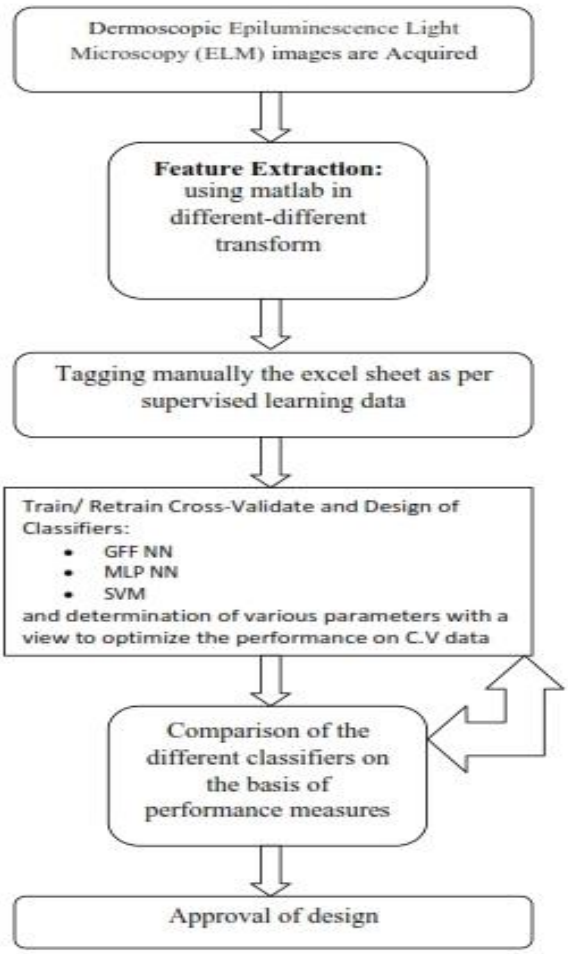

Figure.2 Methodology of work

Data acquisition for the classifier designed for the classification of Three type of dermoscopic images shall be in the form Epiluminescence Light Microscopy (ELM) images. The most important & mutually un correlated features from the images will be extracted .In order to extract features, statistical techniques, MLP NN is used, FFT transformed domain will be used & optimal feature vector will be decided.

2.2Neural Networks

Following Neural Networks are tested:

2.2.1Multilayer perceptron (MLP)

The most common neural network model is the multi layer perceptron (MLP). This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown. A graphical representation of an MLP is shown below:

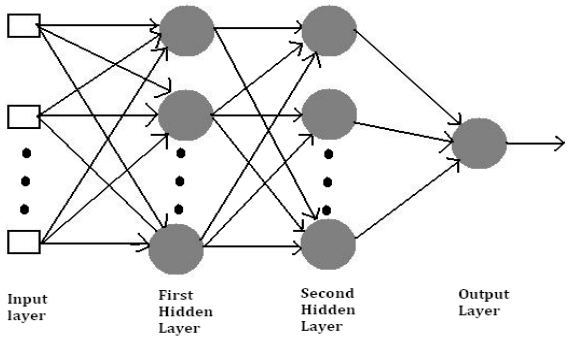

Figure 2. The structure of neural network model MLP.

The MLP and many other neural networks learn using an algorithm called back- propagation. With back-propagation, the input data is repeatedly presented to the neural network. With each presentation the output of the neural network is compared to the desired output and an error is computed. This error is then fed back (back-propagated) to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output. This process is known as "training".

2.3Learning Rules used:

➢ Momentum

Momentum simply adds a fraction m of the previous weight update to the current one. The momentum parameter is used to prevent the system from converging to a local minimum or saddle point. A high momentum parameter can also help to increase the speed of convergence of the system. However, setting the momentum parameter too high can create a risk of overshooting the minimum, which can cause the system to become unstable. A momentum coefficient that is too low cannot reliably avoid local minima, and can also slow down the training of the system.

➢ ***Conjugate Gradient***

CG is the most prevalent iterative technique for unraveling vast frameworks of direct conditions. CG is successful for frameworks of the shape A=xb-A (1) where x _is an obscure vector, b is a known vector, and A _is a known, square, symmetric, positive-unmistakable (or positive-uncertain) lattice. (Try not to stress in the event that you've overlooked what "positive-distinct" implies; we will survey it.) These frameworks emerge in numerous imperative settings, for example, limited contrast and limited component techniques for fathoming incomplete differential conditions, auxiliary examination, circuit investigation, and math homework.

Created by Widrow and Hoff, the delta govern, additionally called the Least Mean Square (LMS) strategy, is a standout amongst the most usually utilized learning rules. For a given information vector, the yield vector is contrasted with the right answer. In the event that the thing that matters is zero, no learning happens; generally, the weights are changed in accordance with lessen this distinction. The adjustment in weight from ui to uj is given by: dwij = r* ai * ej, where r is the learning rate, ai speaks to the initiation of ui and ej is the distinction between the normal yield and the genuine yield of uj. On the off chance that the arrangement of information designs shape a directly autonomous set then subjective affiliations can be gotten the hang of utilizing the delta run the show.

It has been demonstrated that for systems with direct initiation capacities and with no shrouded units (concealed units are found in systems with in excess of two layers), the blunder squared versus the weight chart is a paraboloid in n-space. Since the proportionality steady is negative, the chart of such a capacity is inward upward and has a base esteem. The vertex of this paraboloid speaks to the point where the mistake is limited. The weight vector relating to this point is then the perfect weight vector..

➢ ***Quick propagation***

Quick propagation (Quickprop) [1] is one of the most effective and widely used adaptive learning rules. There is only one global parameter making a significant contribution to the result, the e-parameter. Quick-propagation uses a set of heuristics to optimise Back-propagation, the condition where e is used is when the sign for the current slope and previous slope for the weight is the same.

➢ ***Delta by Delta***

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III. Result

A From the results obtained in FFT domain it concludes that the MLP Neural Network with MOM (MOMENTUM) and hidden layer 1 with processing element 9 gives best results of 94.44% in Cross Validation while in training it gives 100% accuracy so overall accuracy is 97.22%.

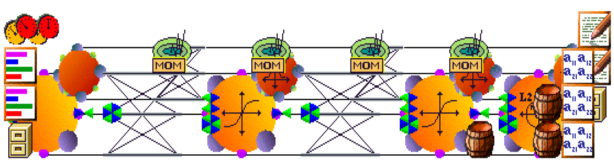

Figure3. The Best Neural network with maximum accuracy (MLP-MOM)

Training Report of the Best Classifier:

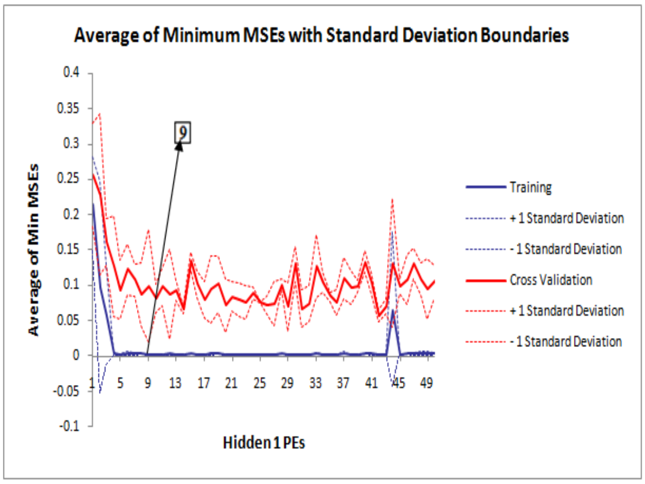

Table 1. Training and cross validation Report of the Best Classifier MLP-MOM.

Best Networks	*Training*	*Cross Validation*
Hidden 1 PEs	20	9
Run #	1	1
Epoch #	1000	398
Minimum MSE	0.000996776	0.037427993
Final MSE	0.000996776	0.037972514

Test on Cross validation (CV):

Table 2. Confusion matrix table of Cross validation (CV)

Output / Desired	*MELANOMA*	*TYPICAL NEVI*	*COMMON NEVI*
MELANOMA	5	0	0
TYPICAL NEVI	1	5	0
COMMON NEVI	0	0	6

Table 3: Performance Measures for cross validation

Performance	*MELANOMA*	*TYPICAL NEVI*	*COMMON NEVI*
MSE	0.02958809	0.0319351	0.00778783
NMSE	0.12955998	0.1538210	0.03410129
MAE	0.09421900	0.1157284	0.05327969
Min Abs Error	0.00701499	0.0106301	0.00875608
Max Abs Error	0.64298065	0.4968121	0.26645780
R	0.93891511	0.9268761	0.98320581
Percent Correct	83.3333333	100	100

Test on Training:

Table 6: Confusion matrix table of Training

Output / Desired	*MELANOMA*	*TYPICAL NEVI*	*COMMON NEVI*
MELANOMA	48	0	0
TYPICAL NEVI	0	46	0
COMMON NEV)	0	0	53

Table 7: Performance Measures for training

Performance	*MELANOMA*	*TYPICAL NEVI*	*COMMON NEVI*
MSE	0.002149492	0.002183052	0.002022258
NMSE	0.009774491	0.010153586	0.008771372
MAE	0.037584582	0.037246723	0.037364649
Min Abs Error	0.001528154	0.000145421	0.000225456
Max Abs Error	0.269592786	0.242453905	0.217522458
r	0.995814939	0.995378054	0.996897827
Percent Correct	100	100	100

IV. Conclusion

A From the results obtained in FFT domain it concludes that the MLP Neural Network with MOM (momentum) and hidden layer 1 with processing element 9 gives best results of 94.44% in Cross Validation while in training it gives 100% accuracy so overall accuracy is 97.22%.

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