ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijareeie.com

Vol. 8, Issue 3, March 2019

Melanoma Detection Using RBFN Algorithm

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ABSTRACT: Melanoma is the most dangerous form of skin cancer that develops from the pigment producing cells known as melanocytes. Melanoma skin cancer has been increasingly identified as the major cause of deaths. Melanoma is a condition or a disorder that develops from the melanocytes, which produce a pigment known as melanin. So melanoma regions appear as black or brown in colour. But some of them doesn't produce melanin, they appear is pink, tan or white colour. So an effective melanoma detection technique is needed. RBFN is a class of Artificial Neural Network (ANN) that was used in many classification problems in science and engineering. Back propagation (BP) algorithm is a learning algorithm that was widely used in ANN. However, BP has major disadvantages of slow error rate convergence and always easily stuck at the local minima. A recent MATLAB tool is used for the implementation of the proposed system designed using High Level Synthesis (HLS) design methodology.

KEYWORDS: Melanoma, RBFN, ANN. MATLAB, HLS.

I. INTRODUCTION

Skin cancers are cancers that arise from the skin. They are due to the development of abnormal cells that have the ability to invade or spread to other parts of the body. There are three main types of skin cancers: basal-cell skin cancer (BCC), squamous cell skin cancer (SCC) and melanoma. The first two, along with a number of less common skin cancers, are known as non-melanoma skin cancer (NMSC).Basal-cell cancer grows slowly and can damage the tissue around it but is unlikely to spread to distant areas or result in death. It often appears as a painless raised area of skin, that may be shiny with small blood vessel running over it or may present as a raised area with an ulcer. Squamous-cell skin cancer is more likely to spread. It usually presents as a hard lump with a scaly top but may also form an ulcer. Melanomas are the most aggressive. Signs include a mole that has changed in size, shape, colour, has irregular edges, has more than one colour, is itchy or bleeds.. A skin that has inadequate melanin is exposed to the risk of sunburn as well as harmful ultraviolet rays from the sun .Clinical analysis and biopsy tests are commonly used.

Clinical analysis is done using a dermatoscope by trained dermatologists. A dermatoscope is an optical device used by the dermatologists to get a magnified and enhanced view of skin structure using skin surface reflection. Proper melanoma detection method is needed to detect and diagnose melanoma in the initial stage itself. Concerned scholars have put up into research in order to establish the biology behind early diagnosis melanoma .Research evidences have shown that it is easy to diagnose and control or rather prevent melanoma at its early stages than during its later stages .Researchers have established that there are numerous methods that are used to diagnose melanoma. Some of the remarkable methods include Seven Point Checklist, CASH (colour, architecture, symmetry, and homogeneity) and Melanoma rates have been increasing steadily for 30 years. For white people it is 20 times more common than in African Americans. Overall, during the lifetime, the risk of getting melanoma is approximately 2% (1 in 50) for whites, 0.1% (1 in 1,000) for blacks, and 0.5% (1 in 200) for Hispanics.

Radial Basis Function Networks (RBFN):

We are working in the standard regression framework of function approximation, with a set of N training data points in a D dimensional input space, such that each input vector x p ={x I p:i =1,...,D} has a corresponding K dimensional target output t p ={t k p:k =1,...,K}. The target outputs will generally be generated by some underlying functions g k(x) plus random noise.

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Which have centres {μj} and widths { σ j}. Naturally, the way to proceed is to develop a process for finding the appropriate values for M, {w k j}, {μ I j} and {σ j}.

The RBF Network Architecture

The RBF Mapping can be cast into a form that resembles a neural network:

The hidden to output layer part operates like a standard feed-forward MLP network, with the sum of the weighted hidden unit activations giving the output unit activations. The hidden unit activations are given by the basis functions φ j(x, μ j, σ j), which depend on the "weights" {μ i j, σ j} and input activations {xi} in a non-standard manner.

Computational Power of RBF Networks

Intuitively, it is not difficult to understand why linear super positions of localised basis functions are capable of universal approximation. More formally:

Hartman,Keeler&Kowalski (1990, Neural Computation, vol. 2, pp. 210-215) provided a formal proof of this property for networks with Gaussian basis functions in which the widths {σ j} are treated as adjustable parameters.

Park&Sandberg (1991, Neural Computation, vol. 3, pp. 246-257; and 1993, Neural Computation, vol. 5, pp. 305-316) showed that with only mild restrictions on the basis functions, the universal function approximation property still holds.

As with the corresponding proofs for MLPs, these are existence proofs which rely on the availability of an arbitrarily large number of hidden units (i.e. basis functions). However, they do provide a theoretical foundation on which practical applications can be based with confidence.

Training RBF Networks

The proofs about computational power tell us what an RBF Network can do, but tell us nothing about how to find values for all its parameters/weights{M, w k j, μ j, σ}.

Unlike in MLPs, the hidden and output layers in RBF networks operate in very different ways, and the corresponding "weights" have very different meanings and properties. It is therefore appropriate to use different learning algorithms for them. The input to hidden "weights" (i.e., basis function parameters {μ i j, σ j}) can be trained (or set) using any one of several possible unsupervised learning techniques. Then, after the input to hidden "weights" are found, they are kept fixed while the hidden to output weights are learned. This second stage of training only involves a single layer of weights {w j k} and linear output activation functions, and we have already seen how the necessary weights can be found very quickly and easily using simple matrix pseudo inversion, as in Single Layer Regression Networks or Extreme Learning Machines.

Basis Function Optimization

One major advantage of RBF networks is the possibility of determining suitable hidden unit/basis function parameters without having to perform a full non-linear optimization of the whole network. We shall now look at three ways of doing this:

1. Fixed centres selected at random
2. Clustering based approaches
3. Orthogonal Least Squares

These are all unsupervised techniques, which will be particularly useful in situations where labelled data is in short supply, but there is plenty of unlabelled data (i.e. inputs without output targets). Later we shall look at how one might try to get better results by performing a full supervised non-linear optimization of the network instead.

With all these approaches, determining a good value for M remains a problem. It will generally be appropriate to compare the results for a range of different values, following the same kind of validation/cross validation methodology used for optimizing MLPs.

Fixed Centres Selected At Random

The simplest and quickest approach for setting the RBF parameters is to have their centres fixed at M points selected at random from the N data points, and to set all their widths to be equal and fixed at an appropriate size for the distribution of data pointsand the σ_j are all related in the same way to the maximum or average distance between the chosen centres μ_j. Common choices are

$\sigma_j = d_{max}\ 2M$ or $\sigma_j = 2d_{ave}$

which ensure that the individual RBFs are neither too wide, nor too narrow, for the given training data. For large training sets, this approach gives reasonable results.

II. METHODOLOGY

A. Pre processing

Artefacts such as bubbles and hair represent noise. It is necessary to remove Hair and bubbles before any feature extraction for an accurate diagnosis of disease. Median filter is used to reduce the effect of bubbles, that may appear on the lesion affect the measure of colour and luminosity asymmetry .Hair detection is done with the help of Gabor filters.[10]

B. Segmentation

An important step in the automated system of melanoma detection is the segmentation process which locates the border of skin lesion in order to separate the lesion part from background skin for further feature extraction. This paper gives a study on various segmentation techniques that can be applied for melanoma detection using image processing .Statistical region merging, iterative stochastic region merging, adaptive thresh holding , colour enhancement and iterative segmentation, multilevel thresh holding are discussed in this paper. A comparative study of these segmentation methods is also performed based on the parameters accuracy, sensitivity and specificity. Multilevel thresh holding has the highest accuracy and specificity and maximum sensitivity is obtained for iterative stochastic region merging.

C.Feature Classification

Melanomas have a propensity to grow chaotically and incoherently. The feature extraction is based on the RBFN Algorithm. RBFN is a class of Artificial Neural Network (ANN) that was used in many classification problems in science and engineering. Back propagation (BP) algorithm is a learning algorithm that was widely used in ANN. However, BP has major disadvantages of slow error rate convergence and always easily stuck at the local minima. C programing language was used to develop the program for the proposed method.

III. RESULT

NORMAL IMAGE

Initially non-affected image of skin is given as input. And then various process such as Pre-processing, Feature Extraction, and Feature Classification are get processed. And then its output is displayed below in fig: 1.

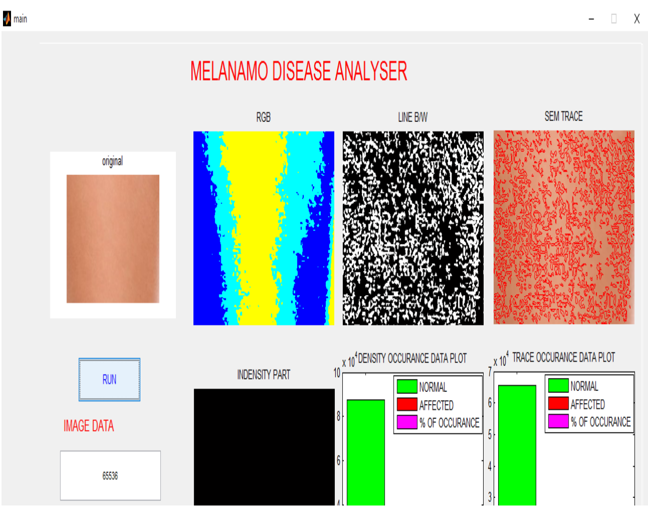

Fig: 1 Non-Affected image output

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COMMAND WINDOW

In this command window it display the pixel value, trace value, and also display the stage of the disease occurred. In this window it also displays the occurrence percentage of the disease fig-2.

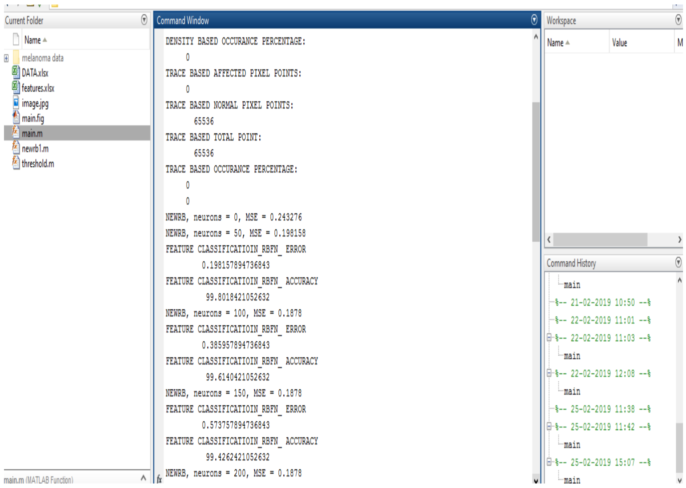

Fig: 2 Command Window for non-affected image

GRAPH

In this graph it shows the stage of the disease. This graph represents the non-affected image performance fig-3.

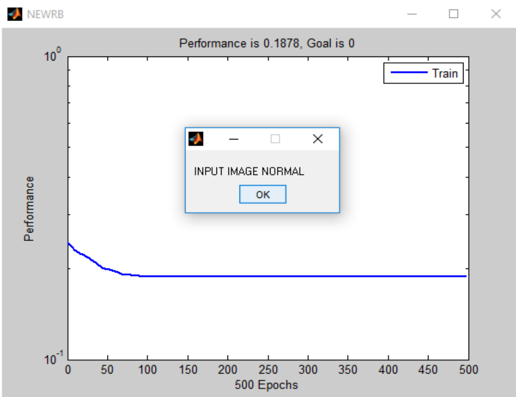

Fig-3 Non-Affected image Graph

AFFECTED IMAGE

Initially Affected image of skin is given as input. And then various process such as Pre-processing, Feature Extraction, and Feature Classification are get processed. And then its output is displayed below in fig: 4.

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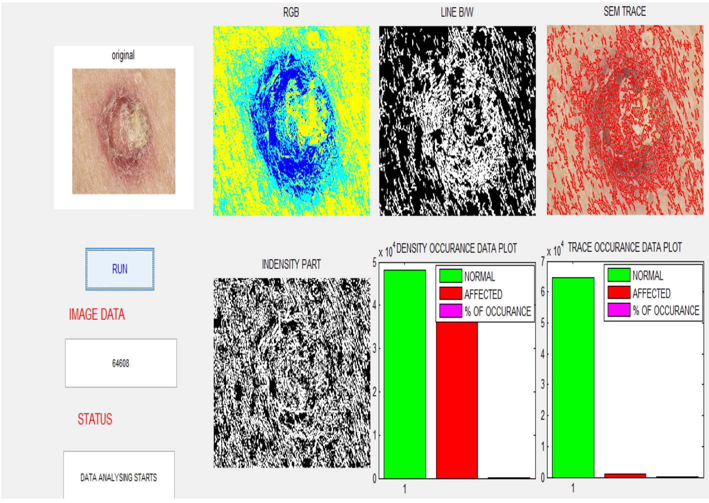

Fig-4 Affected image output

COMMAND WINDOW

In this command window it display affected image pixel value, trace value, and also display the stage of the disease occurred. In this window it also displays the occurrence percentage of the disease fig-5.

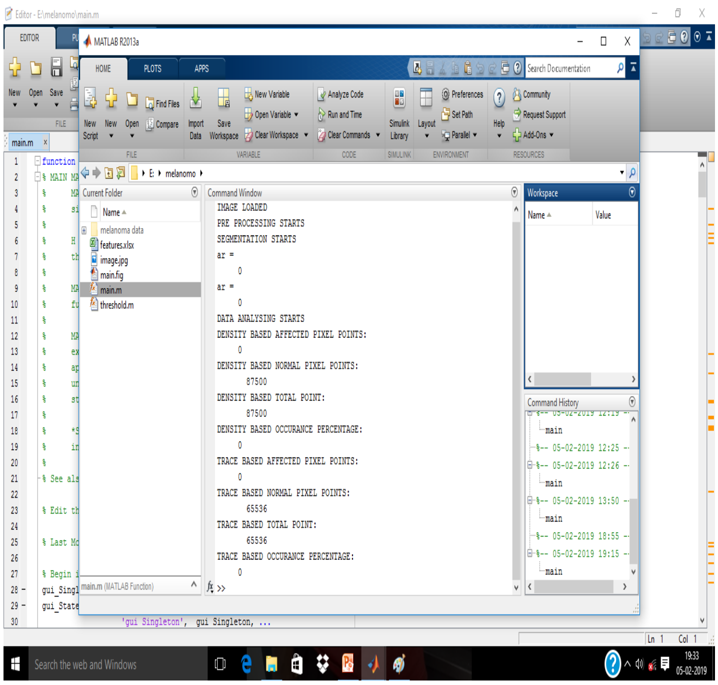

Fig-5 Command Window for Affected image

GRAPH

In this graph it shows the stage of the disease. This graph represents the non-affected image performance fig-6.

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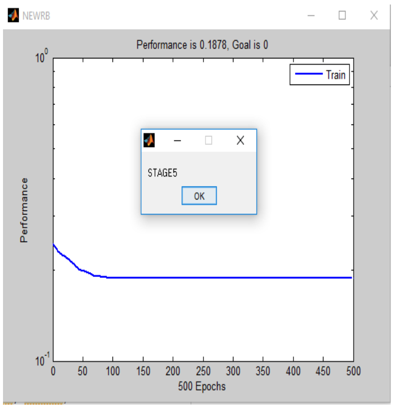

Fig-6 Affected image graph

IV. CONCLUSION

The incidence of skin cancers has reached a large number of individuals within a given population, especially among whites, and the trend is still rising. Early detection is important, especially concerning melanoma, because surgical excision currently is the only life-saving method for skin cancer. This paper presented the components of a system to aid in the malignant melanoma prevention and early detection. Pre-processing is done using median filter. Feature extraction is done using RBFN Algorithm. Future work could allow further improvement, primarily in the art-fact removal steps and in structures detections.

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