Analysis of Algorithms for Effective Skin Cancer Detection Model

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Abstract-
Melanoma is the deadliest of all skin cancers, yet early detection can increase your chances of survival. Due to the lack of knowled ge of general practitioners, early diagnosis is one of the most d ifficult challenges. A clinical decision support system for general practitioners is described in this study, with the goal of saving time and money throughout the diagnosis process. The key steps in our approach are segmentation, pattern recognition, and change detection. The performance of Artificial Neural Network (ANN) learning algorithms for skin cancer diagnosis is also investigated in this paper. The capabilities of three learning algorithms, namely Levenberg-Marquardt (LM), Resilient Back propagation (RP), and Scaled Conjugate Gradient (SCG), in discriminating melanoma and benign lesions are investigated and compared. The results suggest that the Levenberg-Marquardt algorithm was quick and efficient in determining benign lesions, with specificity 95.1 percent, while the SCG algorithm produced superior results in diagnosing melanoma with sensitivity 92.6 percent at the cost of a larger number of epochs.

Keywords – Artificial Neural Network, Levenberg-Marquardt, Resilient Back Propagation, Scaled Conjugate Gradient.

I. Introduction

In Europe, North America, and Australia, malignant melanoma is on the rise. In the United States, an estimated 76,250 new cases of invasive melanoma were detected in 2012, with an estimated 9,180 deaths. Each year, about 1,890 Australians succumb to skin cancer. The cost of skin cancer therapy is high. Non-melanoma skin cancer therapy cost $264 million in 2001, whereas melanoma treatment cost $30 million. However, early detection can help, as melanoma has a near-95 percent cure rate when detected and treated early. According to dermatologists' data, visual diagnostic accuracy is low even in specialist institutions, and they are also overburdened by GP referrals.

The coverage of the training and test datasets is another issue in deploying deep learning algorithms in a real clinical practice. [1] Deep learning algorithms can only offer reliable findings for pre-selected ailments; for untrained situations, an algorithm may show epistemic uncertainty. In actual life, clinical concerns frequently include an infinite number of diagnoses. If an issue involves a wide range of classifications or if training data does not cover appropriate conditions, an algorithm's accuracy may be jeopardized.

Computerized diagnostic tools must be employed as stand-alone warning tools to assist GPs in early diagnosis and to offer quantitative information about the lesion for - professionals to consider during biopsy decision-making. Image processing, segmentation, feature extraction, and classification techniques are all required in diagnostic tools. As previously indicated, thorough study is required to make the optimal decision and establish standards for the creation and validation of diagnostic systems. Our goal is to find the optimal mix of algorithms that can serve as the foundation for a generalized and accurate skin cancer diagnosis system.

The goal of this research is to show that our algorithm's performance in identifying malignancy in most forms of skin neoplasms is generalizable, as well as to investigate the differences in sensitivity and specificity between the experimental and real-world settings.

Finally, for the classification of malignant and non-cancerous skin lesions, an artificial neural network is used. The performance of three common ANN learning algorithms, Levenberg-Marquardt (LM), Resilient Back Propagation (RP), and Scaled Conjugate Gradient (SCG), was investigated in this work (SCG). The generalization and prediction performances of these algorithms are compared during training and testing, respectively.

II. Related Study

There have been various classification methods established, each of which used a distinct algorithm for classification, as well as the accuracy and load of those current methods varying. The suggested analysis focuses on the performance of such algorithms. Multipliers can be very confusing.

II. Methodology

A. *Feature Extraction*

Because of the wide range of features, it's difficult to create a general mathematical model for varied textures while analyzing skin lesions. Despite the fact that texture is important in image analysis and pattern recognition, only a few architectures include textural feature extraction on board. We used both histogram-based and texture-based features in this research, which are then used for classification. Mean, Variance, Standard deviation, Skewness, Energy, and Entropy are all histogram-based properties.

One of the most prominent statistical approaches for analyzing grey tones in a picture is the LCM (Grey Level Co-occurrence Matrix). The GLCM functions characterize image texture by calculating how many pairs of pixels with given values and in a specified spatial relationship appear in an image, constructing a GLCM, and extracting statistical measures from this matrix.

Autocorrelation, Contrast, Correlation, Cluster Prominence, Cluster shade, Dissimilarity, Energy, Entropy, Homogeneity, Maximum probability, Difference variance, Difference entropy, Inverse difference normalized, Inverse difference moment normalized, Information measure of correlation, and Information measure of correlation are among the GLCM features that we have chosen for the classification stage.

B. *Histogram Equalization*

Because local melanoma details are more important than global details in skin cancer detection systems, the Histogram Equalization (HE), Adaptive Histogram Equalization (AHE), and Unsharp Masking as three well-known local enhancement methods are more relevant in such diagnostics. Although the HE, like other contrast enhancement techniques, can brighten the image, it also lowers the surrounding detail. As shown in Fig. 1, the outcomes of the histogram equalisation technique on skin cancer photos are as follows.

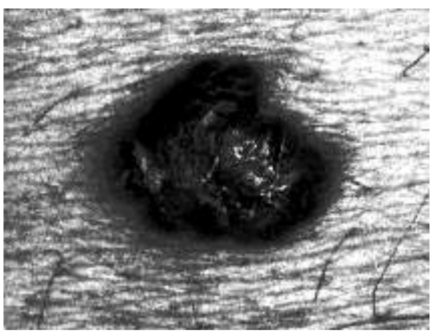

Figure 1: Image after performing Histogram Equalization

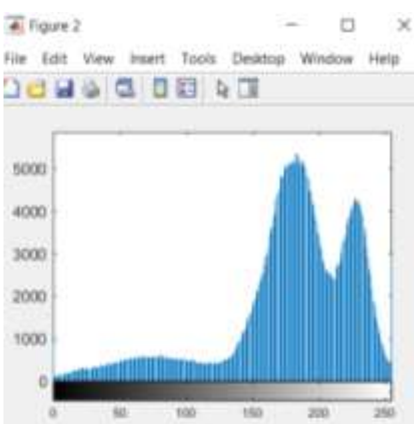

Figure 2: Histogram plotted in form of Graph

C. *Segmentation*

One of the most critical processes in this technique is segmentation. Traditional Otsu Segmentation Algorithm is one of many segmentation algorithms now in use. The main flaw in this technique is that in the presence of fluctuating illumination, the segmentation is incorrect. Fig. 3 shows the resultant image after implementation of Otsu thresholding.

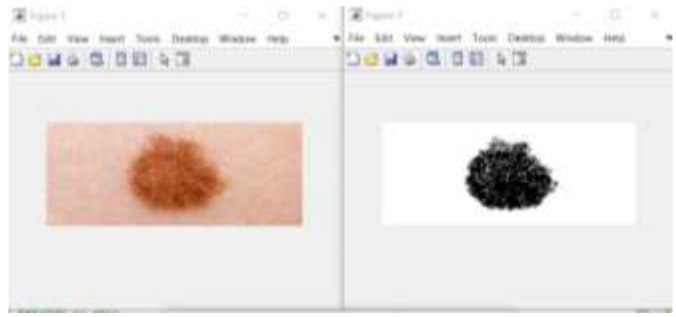

Figure 3: Segmented Skin cancer images using Otsu thresholding

D. *Classification*

There are many distinct types of skin lesions, each with its own set of characteristics that can indicate malignancy. Developing statistical techniques for diagnosis is difficult. In a survey of existing automated skin lesion diagnostic systems, it was discovered that neural networks (NN) are capable of performing well in diagnostic systems. Because neural networks are better at handling complex interactions between variables and establishing classifications based on learning from training data, they are more effective. Better diagnosis can be achieved with proper NN training and validation.

A set of three n vectors was used to investigate the aspects of pixel colour (R, G, and B band) for the image. [2]
The rectified linear unit (ReLU) is CNN's only transmission function, and the performance of the proposed approach was tested using simulation on the Dermquest dataset. The suggested CNN was trained and verified on the dataset, with 80% of the dataset being utilized for training and 20% for testing, with the best CNN training used 10000 images. In order to undertake independent analysis, this work repeats the training steps 45 times. The outcomes, on the other hand, were taken into account, depending on the average value of the results.

Figure 4: Validation Accuracy for 3 Convolutional Layers

III. EFFECTIVE FACTORS IN TRAINING NEURAL NETWORKS

The number of neurons in the input and output layers is generally decided by the problem when employing ANN in various applications. The model size grows as the number of neurons in the input and output layers grows, which may be detrimental to learning quality and time. However, in applications like skin cancer diagnosis, where numerous factors play a role in diagnosis, restricting the neural network's inputs and ignoring the impact of some factors for improved network learning is usually problematic. However, learning quality can be improved by limiting the number of input variables, which necessitates the selection of a small number of significant input features.

There are no strict guidelines for determining the number of hidden layers and neurons in the hidden layers. It is well known that a network with fewer hidden neurons generalises better than one with more. In addition, trial and error is used to pick the best network from among a number of individually trained networks.

A. *Algorithm of training artificial neural network*

The backpropagation method is the learning algorithm for multilayer Perceptron networks. This was refined over time, and different forms of backpropagation algorithms for training the network were demonstrated. [6] The optimal learning algorithm for artificial neural networks is usually decided through internal mental medicines and trial and error. The following are the learning methods for perceptron neural networks that were chosen for this study:

B. *LM (Levenberg–Marquardt) algorithm*

The LM (Levenberg–Marquardt) algorithm finds a minimum of a function that is defined as the sum of squares of linear functions as an approximation to Newton's approach. In contrast to the former category, which uses a first order expression, the Newton technique uses a second order expression to estimate the network error. The LM approach, which is a very simple but robust method for estimating a function, is prominent in the ANN area.

C. *SCG (scaled-conjugate gradient) algorithm*

To circumvent the time-consuming line search, the scaled conjugate gradient algorithm was created. Combining the model-trust region technique (used in the LM algorithm) with the conjugate gradient approach is the main notion. SCG is not like other conjugates. This reduces the number of computations in a single epoch.

C. *Resilient Back Propagation (RP)*

Because sigmoid functions are ‘‘squashing" functions, when they are utilised as the functions for every activity on a set of hidden layer neurons, big numbers have problems at the network entrance. Only the sign of the derivation is used to determine the direction of the weight update in the robust back propagation algorithm;

This study focuses on evaluating the performance of these learning algorithms in the context of pattern recognition for skin cancer diagnosis.

IV. PERFORMANCE ANALYSIS

Several neural networks with variable numbers of neurons in the hidden layer, as well as different learning methods, were created for experimental investigation. To produce a decent performance index of these networks, measurements of the performance index (Mean Square Error), classification accuracy, and the number of epochs (number of training examples iteration) are gathered. It provides comparative results for different training algorithms in the network training process, with respect to modifying the number of neurons.

According to the data, the LM and SCG algorithms performed similarly to the BP algorithms in terms of performance index (MSE) and performance accuracy, and they had higher predictive accuracy. SCG outperformed LM in terms of accuracy, but at the cost of a higher number of epochs. However, the vast number of epochs required to get a good performance index makes this algorithm's training application difficult.

LM beat the other two algorithms based on this concept, which is consistent with its success in other classification applications.

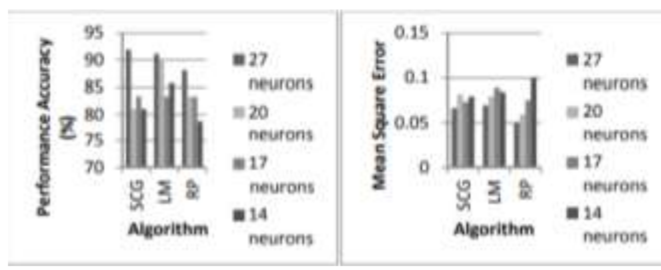

Figure 5: In the ANN training process, a diagram showing accuracy and the respective performance index (MSE)

Figure 6 illustrates the confusion matrix for each training algorithm's best diagnosis performance. It can be shown that SCG provided the best overall classification (91.9%), with a sensitivity of 92.6 percent and a specificity of 91.4 percent. Although LM performed similarly to SCG in terms of overall performance, it can be noted that while it was more accurate in recognising benign lesions (95.1%), it had a lower classification efficiency for melanoma (sensitivity 85.2 percent). While the Resilience BP algorithm achieved accuracy of 88.1 percent, specificity of 95.1%, and sensitivity of 77.8%

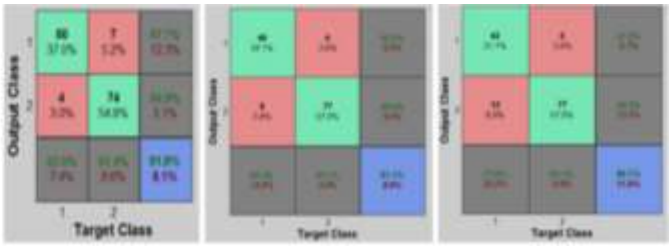

Figure 6: Confusion Matrix for SCG , LM, RP algorithm (arranged left to right)

integrating multiple neural networks and other classification methods such as SVM and extreme learning machine for this goal.

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Table 1: Research works carried out in recent years (2017-21)			
Authors/years	**Methodology**	**Domain**	**Article Type**
Adekanmi Adegun · Serestina Viriri (2020)	Deep neural networks, Convolutional Neural Network	Machine learning	Development
Ni Zhang, Yi-Xin Cai, Yong-Yong Wang, Yi-Tao Tian, Xiao-Li Wang, Benjamin Badami(2019)	Convolutional Neural Network	Deep learning, whale optimization algorithm	Analytical J
A. Murugan & S.Anu H. Nair & K. P. Sanal Kumar (2019)	ABCD rule	KNN classifier	Experimental
Enakshi Jana, Dr.Ravi Subban , S. Saraswathi (2017)	Artificial Neural Network (ANN), Image Segmentation	Neural Networks	Development
N.DurgaRao , Dr. G.Sudhavani (2017)	Artificial Neural Network , ABCD rule	Image Processing	development
Long Zhang, Hong Jie Gao, Jianhua Zhang, Benjamin Badami(2019)	Convolutional neural networks, Image segmentation	Image Processing	Analytical
M.Julie Therese , Christo Ananth (2020)	Computerized diagnosis	Image Processing	Descriptive
B. Sreedhar, M. Sunil Kumar, Manjunath Swamy B.E(2019)	ABCD rule	Image Processing	Descriptive
Tanvi Goswami, Vipul K. Dabhi, Harshadkumar B. Prajapati(2020)	Deep learning, CNN, SVM	Medical Image Processing	Experimental
Rabia Javed, Mohd Shafry Mohd Rahim, Tanzila Saba, Amjad Rehman(2020)	Artificial intelligence	ABCD rule, Image Processing	Experimental
Jwan Najeeb Saeed, Subhi R. M. Zeebaree(2021)	Convolutional neural networks, Deep Learning.	Image Processing	Descriptive

CONCLUSION AND FUTURE WORK

A methodical approach to classification of skin lesion photos is described in this work. The performance of the most popular learning algorithms for skin cancer diagnosis is analyzed, taking into account the capabilities of ANN in categorization of difficult data. Despite the excellent accuracy that computer-aided diagnostic systems that use statistics derived from low-level features like the one shown here may accomplish, at least two difficulties must be solved before these systems can receive widespread clinical acceptability.

The advancements in image collecting and processing technology in recent years have made it possible to develop image analysis systems. We plan to conduct experiments

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

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