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

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Abstract: Malignant melanoma is the most recurrent type of skin cancer but it is remediable, if diagnosed at a premature stage. Dermoscopy is a non-invasive,diagnostic tool having inordinate possibility in the prompt diagnosis of malignant melanoma, but their interpretation is time overwhelming. Numerous algorithms were established for classification and segmentation of Dermoscopic images. This Proposed work proposes the tasks of extracting, classifying and segmenting the Dermoscopic image using a more Efficient supervised learning approaches for more accurate and computationally efficient segmentation. The features are extracted from the Dermoscopic image using matlab program approach and these accurate features are used to train the neural classifier.

***Index Terms* - MatLab, Nuero Solution Software, Microsoft excel, Various Transform Technique**

I. INTRODUCTION

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].

(a) (b)

(c) (d)

Fig. 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. RELATED WORK

Recently, deep learning paradigm has become state-of-the art in image classification since the publication of AlexNet in 2012.For example, U-Net and fully convolutional network (FCN) have produced a promising results in image segmentation. U-Net was successfully rated for wining ISBI cell tracking challenge in 2015 [11]. The fully convolutional network was published in 2012 at Berkeley Vision and Learning Center and has been state-of-the-art in image segmentation using convolutional layers [12]. In addition, a novel proposal for semantic segmentation introduces the idea of using transpose convolutional layers on top of the convolutional layers [13].

In image classification, CNNs became state-of-the-art since the publication of AlexNet in 2012. Since then, CNNs architectures such as VGGNet (2014) [14], GoogleNet (2014) and ResNet (2015) have produced outstanding results and has been used widely in this field.

The ABCDEs are characteristics often used by dermatologists to classify melanomas. These include Asymmetry, irregular Borders, more than one or uneven distribution of Color, or a large (greater than 6mm) Diameter, and finally,the Evolution of the moles (how the first four characteristics change over time) [15]. Other similar rules or guiding principles include the 3-point checklist [16], the 7-point checklist [17] and Color, Architecture, Symmetry and Homogeneity (CASH) [18]. But visual diagnosis can be complicated and can lead to subjective results. Skin lesion analysis involves challenging visual classification and segmentation tasks because of the wide variability in the manifestation of the disease and also because of the wide variation and diversity of patients' skin. Computer vision and machine learning scientists have attempted melanoma classification and general skin disease analysis, and in this section we discuss some of these related past approaches.

Masood and Al-Jumaily [19] summarized the comparative analysis of different algorithms for feature selection and classification of Melanoma. Computer aided systems are built using the data collected from the actual cases, and the model is expressed as set of rules with the help of domain experts. This method was quite expensive as the system demanded very fast image processing and a detailed knowledge to develop the best set of rules. They did not apply deep learning techniques at this time.

Sabbaghi et. al [20] approached the problem of classifying melanomas in dermoscopy images from a different perspective.They applied stacked sparse auto-encoders for discovering the latent information features from input image pixel intensities. The learned high-level features were subsequently fed into a classifier for classifying dermoscopy images. The accomplished this by utilizing a bag-of-features representation for the images, thus improving the overall accuracy of their system. Their method was evaluated on a dataset of dermoscopy images; total image set consisted of 814, of which 640 were benign and 174 malignant. They tested on a total of 244 images. Unlike many other deep learning techniques applied on melanoma detections, this work did not implement convolutional neural networks.

Kawahara et. al [21] present a CNN architecture which they apply on the Dermofit Image Library provided by the American Cancer Society. The dataset was composed of 1300 skin images with corresponding class labels and lesion segmentations with 10 lesion categories, of which melanoma was one. The improved the state-of-the-art resutls on that dataset to 85.8% from the previous results of 75.1%. No lesion segmentations were performed. Similarly, Majtner et. al [22] presented a technique for skin lesion classification, which combined CNN and handcrafted features, specifically RSurf features and local binary patterns (LBP). They also compared the results using their technique with the results from the melanoma classification challenge, hosted by the International Skin Imaging Collaboration (ISIC) - the same dataset we test our approach on. Their reported accuracies were between 79.4 and 80.5% on the ISIC dataset.

Yu et. al [23] placed first-place in the ISIC 2016 challenge, a very similar challenge to that on which we report our test results.The achieved this by using a very deep CNN architecture (having more than 50 layers). They applied residual learning to and then constructed a fully convolutional residual network (FCRN) for lesion segmentation process. They reported accuracies of 85.5% on the 2016 classification challenge, and report up to 85.3% accuracy on the segmentation task.

Other very successful deep learning techniques that have been applied to skin lesion analysis include works by Shimizu et. al [24], Schaefer et. al [25], Barata et. al [26], Abbas et. al [27], Iyatomi et. al [28] and one of the most highly cited dermoscopy image analysis paper by Celebi et. al [29].

To perform a semantic segmentation Noh et. al [30] uses CNN. A multi-layer convolution-deconvolution is learned which is composed of convolution, deconvolution, unpooling and ReLu operations. Segmentation using a CNN is basically a pixel wise classification and the network is based off the VGG16 layer net [31] architecture. They achieved an accuracy of 72.5% on PASCAL VOC dataset using a similar architecture. Also, Ronneberger et. al [32] described a network architecture named U-net which is similar to conv-deconv architecture described above. Additional details on U-net are provided in Section III-D.

An article in the journal Nature presented a CNN trained end-to-end system where the disease labels were estimated from images directly, similar to the techniques described above. The classification task was implemented using a proprietary dermatologist-labeled dataset of 129,450 clinical images, including 3,374 dermoscopy images. They utilized GoogLeNet Inception v3 CNN architecture that was pre-trained on approximately 1.28 million images (1,000 object categories) from the 2014 ImageNet Large Scale Visual Recognition

Challenge. They used this pre-trained network to train their skin lesions image dataset using transfer learning. For one of the partition, CNN achieves the accuracy of around 4036 72.1% as compared to two dermatologists who attain the accuracy of 65.56% and 66% respectively.

To classify melanoma images, used a very simple architecture of convolutional neural network. They classify the lesion images without segmenting or cropping the lesions. Simple pre-processing techniques were applied to the images like resizing the images to 256 x 256 and subtract the mean to center the data. They arranged the labels of the images so that the learning algorithm doesn't get same label images consecutively. The CNN classifier has 17 layers which make total 5 convolutional blocks. The testing error, after the classifier is trained, is 0.189.

A method based on Mahalanobis distance learning and constrained graph regularized nonnegative matrix factorization is proposed by [33]. The approach works by reducing the dimensions of the features. This work is based on the idea that feature vectors with the dimensionality of a few hundreds may not work well with a classifier. If the dimensionality is reduced, the performance of the classifier should be improved. Training data is used to learn Mahalanobis distance which is then later used for local manifold construction.

Codella et. al [34] works with ensemble of classifiers. They use a fully connected CNN, ResNet and Unet to extract features and feed the features to a Support Vector Machines for classification.

III. PROPOSED METHODOLOGY

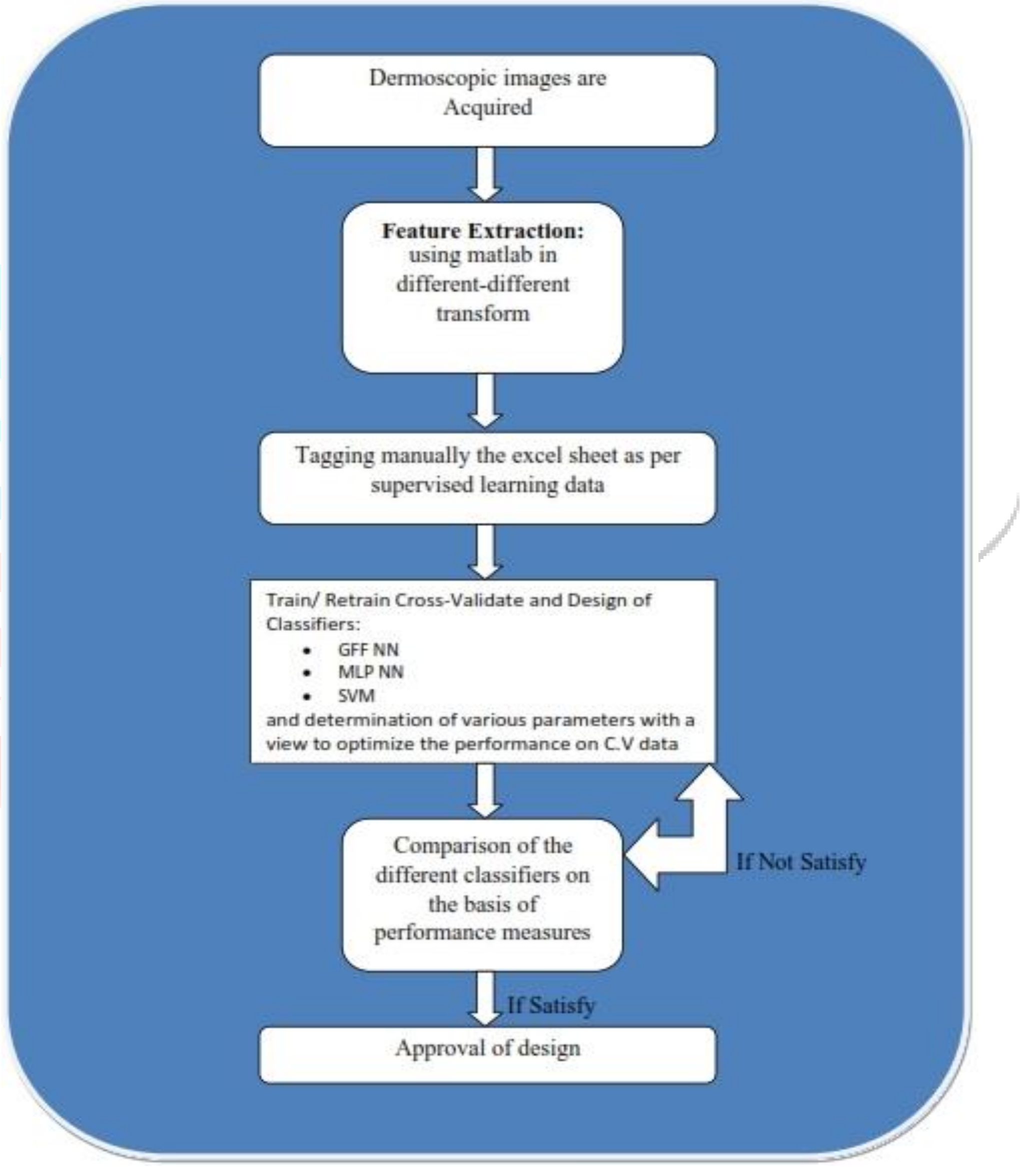

Fig 2:Flow Chart

It is proposed to think about the grouping of three sort of dermoscopic images Using Neural Network Approaches.. Information securing for the proposed classifier intended for the Recognition of three kind dermoscopic images .The most vital un corresponded includes and in addition coefficient from the images will be extricated . In order to extract features, statistical techniques, transformed domain will be used.

Computational Intelligence techniques include the following will established techniques.

i) Statistics
ii) Learning Machines such as neural network .
iii) Transformed domain techniques such as FFT, SVD,WHT, etc.

For choice of suitable classifier following configuration will be investigated.

i) Support Vector Machine.
ii) Multilayer perceptrons (MLPs) Neural network.
iii) Generalized Feed Forward Neural Network

For each of the architecture, following parameters are verified until the best performance is obtained.
i) Train-CV-Test data
ii) Variable split ratios
iii) Retraining at least five times with different random initialization of the connection weights in every training run.
iv) Possibility different learning algorithms Standard Back-Propagation, and learning rules such as Conjugate gradient , Quick propagation, Delta Bar Delta,Momentum
v) Number of hidden layers
vi) Number of processing elements of neurons in each hidden layer.

After regions training & retraining of the classifier, it is cross validated & tested on the basis of the following performance matrix.
i) Mean Square Error
ii) Normalized Mean Square Error
iii) Classification accuracy

In order to carry out the proposed research work, Platforms/Software's such as Matlab, Neuro solutions, Microsoft Excel will be used.

IV. Research objective

i) To maintain the correctness & accuracy in three type of Nevi (mole) Dermoscopic images Classification even though the input images are contaminated by known or unknown noise.
ii) To increase the classification accuracy for the dermoscopic Images of three type of Nevi (mole)

V. Conclusion

This paper demonstrated how to using artificial neural networks(ANN)could be used to build accurate three type of Nevi (mole) Dermoscopic images classifier and i am also try to achieved result more accurate and reliable.

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