MELANOMA SKIN CANCER DETECTION USING CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

Melanoma is the deadliest form of skin cancer. Incidence rates of melanoma have been increasing, especially among non-Hispanic white males and females, but survival rates are high if detected early. Due to the costs for dermatologists to screen every patient, there is a need for an automated system to access a patient's risk of melanoma using images of their skin lesions captured using a standard digital camera. One challenge in implementing such a system is locating the skin lesion in the digital image. A novel texture-based skin lesion segmentation algorithm is proposed. The proposed framework has higher segmentation accuracy compared to all other tested algorithms. Three Classification of skin lesion images are considered in this study such as malignant melanoma, benign melanoma and unknown. Classification of skin lesion images is done through a convolutional neural network(CNN) and shows an accuracy of 98% in the functionality testing and compared with the SVM algorithm.

Keywords: Skin Cancer, Melanoma, Skin lesion, Classification, CNN algorithm.

I.INTRODUCTION

In India, the prevalence of skin cancer is about 10 to 12 per cent of the total population. The skin provides the body with protection and receives sensory stimulus from the outer environmental factors. It consists of seven layers of ectodermic tissue and protects bones, muscles and internal organs, making it the largest organ of the human body[1]. The factors stimulating skin diseases are poor hygiene, increased levels of pollution, global warming and the harmful UV rays. A two to three per cent increase in tumours can be caused due to one per cent of ozone depletion. There are two forms in which a skin cancer may appear: one is benign and the other is malignant. Benign melanoma is a normal appearance of moles while malignant melanoma is the appearance of sores that causes bleeding[3-5]. Malignant melanoma is the deadliest form of skin cancer but can be curable if detected in an early stage[6]. Diagnosis can be through a non-invasive and an invasive method. A non-invasive micromorphological method is through dermoscopy which is an imaging technique that uses dermatoscopy to examine skin lesions but interpretation is time-consuming[7-8]. The other diagnosis is an invasive method called biopsy which involves excision of the skin lesion[2][9]. The development in image processing allows an aid in a non-invasive approach to detection and classification and also impartial interpretation of skin cancer.

Meanwhile, differentiation between melanoma and other benign moles in their initial growth phases is a challenging task even for experienced dermatologists[3]. Computerized algorithms are being developed for this purpose. Some low complexity methods are designed, which are intended for running on tablets and smartphones, and can help non-specialists. But professional decision making, in this regard, requires sophisticated algorithms and equipment. There are various methods in dermatology such as ABCD(asymmetry, border irregularity, colour patterns and diameter) rule[4] and the seven-point checklist[5] that guide physicians in this task.

DISADVANTAGES

- Accuracy is less.
- Supervised technique is applied.
- Precision value is also less.

II.LITERATURE SURVEY

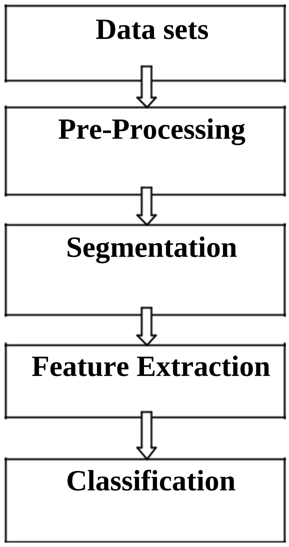
The proposed system consists of Image processing technique [et al.] like adaptive thresholding, edge detection, K-means clustering and morphology-based image segmentation have been used to identify the skin diseases from the given image set. The acquired image is preprocessed and depending on the definite pattern present in the processed image, the disease is detected at the output. [et al.] The classifications of skin lesions are considered and it is done through the K-Nearest neighbours(KNN) algorithm and shows an accuracy of 90% in the functionality testing. The input to the system is the skin lesion image and by applying the novel image processing technique, it analyzes and concludes about the presence of skin cancer. The Lesion Image analysis tools checks for the various Melanoma parameters like Asymmetry, Border, Colour, Diameter(ABCD), etc. with the help of texture, size and shape analysis for image segmentation and feature stages. The extracted feature parameters are used to classify the image as Normal skin or Melanoma cancer lesion. Ada-boost classifier is being used for classification and PCA is used for image segmentation and a rule-based approach is used for classification which gives static range value for different classes. Therefore, different features show different outputs and show different representations during the training phase of classifiers.

III.METHODOLOGY

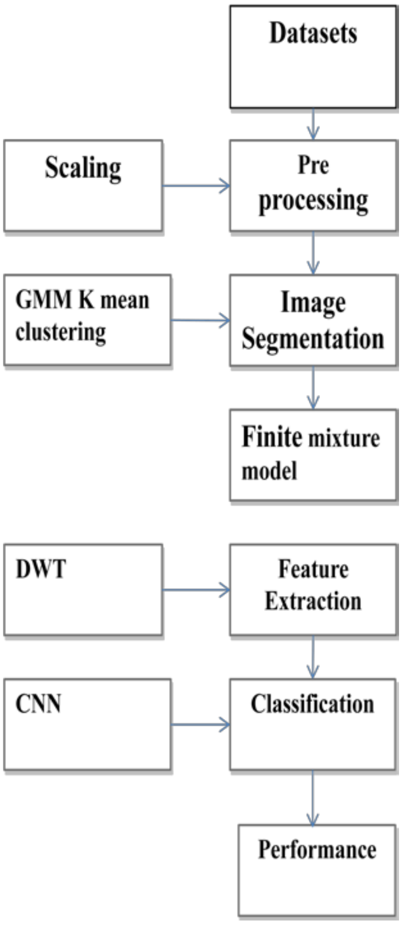
PROPOSED SYSTEM

The disadvantage of the existing system, which is efficiency is overcome in the proposed system. In this paper, we proposed that the mammogram image can be enhanced using the Gaussian filter. Second, the segmentation is done using Fuzzy C-means for partitioning the mammogram image into multiple segments to identify the mass easily and features are extracted using DWT(Discrete Wavelet Transform). Further tumour has been analyzed and classified using CNN classifier. CNN delivers a unique solution since the optimality problem is convex. This is an advantage compared to neural networks, which have multiple solutions associated with local minima and for this reason it may not be robust over different samples.

PROCESS



BLOCK DIAGRAM



PREPROCESSING

The input image given to the system can be obtained in any lighting condition or by using any camera such as a mobile camera. Hence it needs to be pre-processed. Here, the pre-processing includes the image resizing and contrast and brightness adjustment. This has been carried out in order to compensate for the non-uniform illumination in the image. This has been carried by image processing techniques like gamma correction.

CLASSIFICATION

Classification tasks usually involves separating data into training and testing sets. Each instance in the training set contains one target value(i.e. the class labels) and several attributes(i.e. the features).

CNN ALGORITHM

A Convolutional Neural Network (CNN) is a deep learning algorithm that can recognize and classify features in images for computer vision. It is a multi-layer neural network designed to analyze visual inputs and perform tasks such as image classification, segmentation and object detection, which can be useful for autonomous vehicles. CNN's can also be used for deep learning applications in healthcare, such as medical imaging. There are two main parts to a CNN:

A convolution tool that splits the various features of the image for analysis.

A fully connected layer that uses the output of the convolution layer to predict the best description for the image.

The neurons within a CNN are split into a three-dimensional structure, with each set of neurons analyzing a small region or feature of the image. CNN's use the predictions from the layers to produce a final output that presents a vector of probability scores to represent the likelihood that a specific feature belongs to a certain class.

A CNN is composed of several kinds of layers:

Convolutional layer-creates a feature map to predict the class probabilities for each feature by applying a filter that scans the whole image, few pixels at a time.

Pooling layer (downsampling)-scales down the amount of information the convolutional layer generated for each feature and maintains the most essential information.

Fully connected input layer-"flattens" the outputs generated by previous layers to turn them into a single vector that can be used as an input for the next layer.

Fully connected layer-applies weights over te input generated by the feature analysis to predict an accurate label.

Fully connected output layer-generates the final probabilities to determine a class for the image.

The architecture of a CNN is a key factor in determining its performance and efficiency. The way in which the layers are structured, which elements are used in each layer and how they are designed will often affect the speed and accuracy with which it can perform various tasks. The layer's parameters focus around the use of learnable kernels. These Kernels are usually small in spatial dimensionality, but spreads along the entirety of the depth of the input. When the data hits a convolutional layer, the layer convolves each filter across the spatial dimensionality of the input to produce a 2D activation map. These maps can be seen in Fig 1

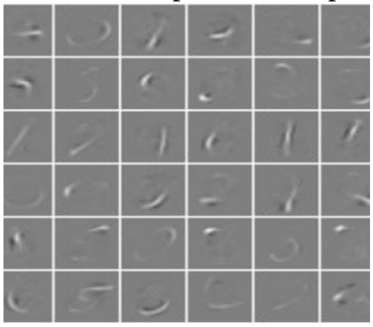


Fig 1. 2D Activation Map

Convolutional layers are also able to significantly reduce the complexity of the model through the optimisation of its output. These are optimised through three hyperparameters, the depth, the stride and setting zero-padding.

The depth of the output volume produced by the convolutional layers can be manually set through the number of neurons within the layer to the same region of the input. This can be seen with other forms of ANNs, where the all of the neurons in the hidden layer are directly connected to every single neuron beforehand. Reducing this hyperparameter can significantly minimise the total number of neurons of the network, but it can also significantly reduce the pattern recognition capabilities of the model. We are also able to define the stride in which we set the depth around the spatial dimensionality of the input in order to place the receptive field. For example if we were to set a stride as 1, then we would have a heavily overlapped receptive field producing extremely large activations. Alternatively, setting the stride to a greater number will reduce the amount of overlapping and produce an output of lower spatial dimensions. Zero-padding is the simple process of padding the border of the input, and is an effective method to give further control as to the dimensionality of the output volumes. It is important to understand that through using these techniques, we will alter the spatial dimensionality of the output of the convolutional layer. To calculate this, you can make use of the following formula:

$(V - R) + 2Z\ S + 1$

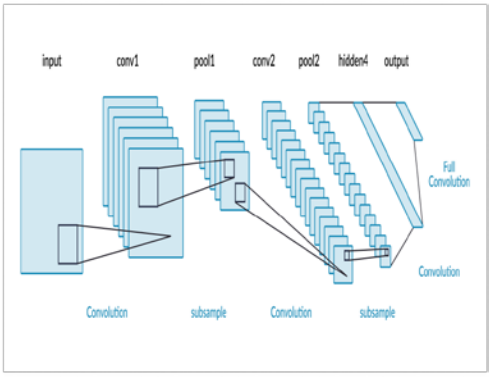
Where V represents the input volume size (height×width×depth), R represents the receptive field size, Z is the amount of zero padding set and S referring to the stride. If the calculated result from this equation is not equal to a whole integer then the stride has been incorrectly set, as the neurons will be unable to fit neatly across the given input.

The ImageNet Challenge

The ImageNet project is a visual database designed for use in the research of visual object recognition software. The ImageNet project has more than 14 million images specifically designed for training CNN in object detection, one million of which also provide bounding boxes for the use of networks such as YOLO.

LeNet-5 (1998)

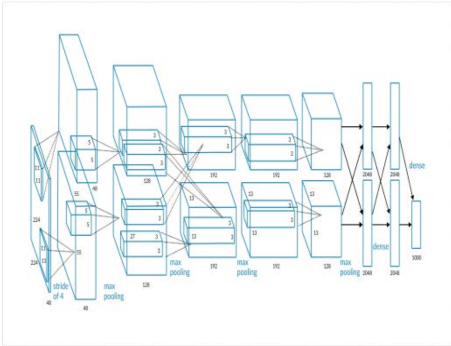
This 7-layer CNN classified digits, digitized 32×32 pixel greyscale input images. it was used by several banks to recognize the hand-written numbers on checks.



AlexNet (2012)

AlexNet is designed by SuperVision group, with a similar architecture to LeNet, but deeper it has more filters per layer as well as stacked convolutional layers. It is composed of five convolutional layers followed by three fully connected layers.

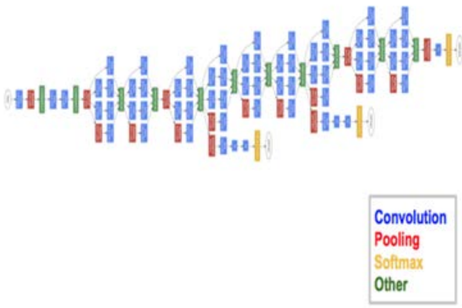
One of the most significant differences between AlexNet and other object detection algorithms is the use of ReLU for the non-linear part instead of Sigmond function or Tanh like traditional neural networks. AlexNet leverages ReLU’s faster training to make their algorithm faster.



GoogleNet (2014)

Built with a CNN inspired by LetNet, the GoogleNet network, which is also named Inception V1, was made by a team at Google. GoogleNet was the winner of ILSVRC 2014 and achieved a top-5 error rate of less than 7%, which is close to the level of human performance.

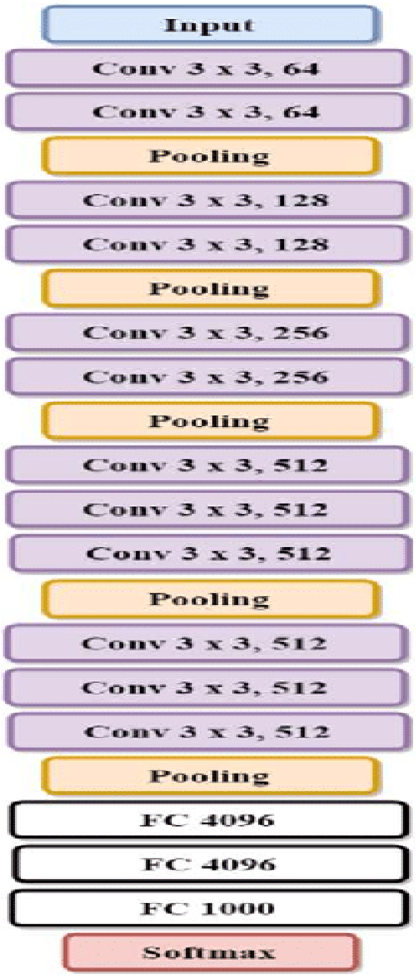
GoogleNet architecture consisted of a 22 layer deep CNN used a module based on small convolutions, called “inception module”, which used batch normalization, RMSprop and image to reduce the number of parameters from 60 million like in AlexNet to only 4 million.

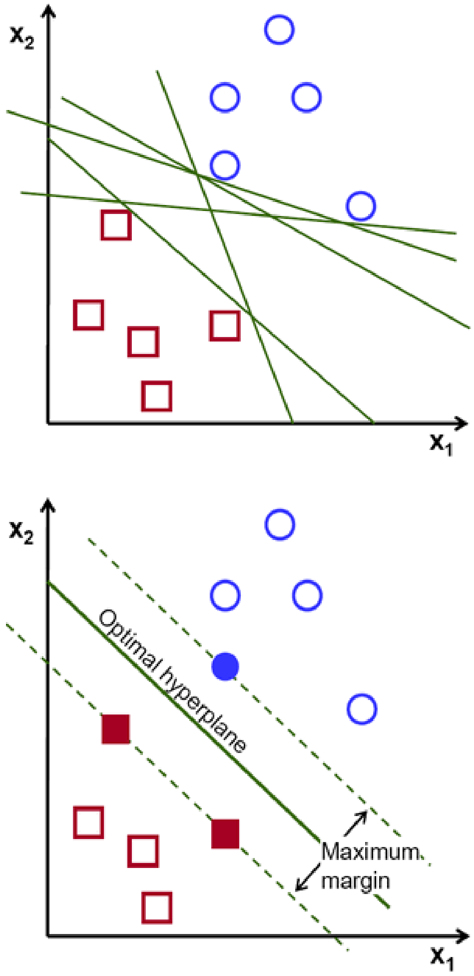


VGGNet (2014)

VGGNet, the runner-up at the ILSVRC 2014, consisted of 16 convolutional layers. Similar to AlexNet, it used only 3×3 convolutions but added more filters. VGGNet trained on 4 GPUs for more than two weeks to achieve its performance.

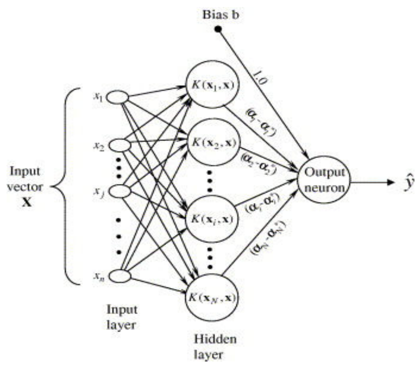
The problem with VGGNet is that it consists of 138 million parameters, 34.5 times more than GoogleNet, which makes it challenging to run.





SVM ALGORITHM

Support Vector Machine (SVM) is a powerful learning method used in binary classification. Its main task is to find the best hyperplane that can separate data perfectly into its two classes. Recently, multiclass classification was achieved by combining multiple binary SVM'S. The objective of the support vector machine algorithm is to find a hyperplane in a N-dimensional space(N-the number of features) that distinctly classifies the data points. To separate the two classes of data points, there are many possible hyperplanes that could be chosen.



Let l be the training instances $\{x_i, y_i\}$,i=1, ..., l each instance consists of an input x_i and a class label $y_i \in \{-1,1\}$. Each hyper plane is parameterized by a weight vector(w) and a bias(b) and can be expressed by the following equation

$$w.x+b=0 \qquad (1)$$

Given the hyper plane the function that classify training and testing data can be expressed as follows

$$f(x)=sign(w.x+b) \qquad (2)$$

If dealing with kernel function, previous function can be expressed as following

$$f(x)=sign(\sum_{i=1}^{N} \alpha_i y_i k(x_i,x)+b) \qquad (3)$$

Where N is the number of training instances, x_i is the input of training instance and y_i is its corresponding class label, b is a bias, and $K(x_i,x)$ is the used kernel function which maps the input vectors into an expanded feature space. The coefficients α_i are obtained subject to two constraints given in (4) and (5):

$$0 \le \alpha_i, i = 1, \ldots, N \qquad (4)$$

$$\sum_{i=1}^{N} \alpha_i y_i = 0 \qquad (5)$$

SVM algorithm (Cortes and Vapnik, 1995) is probably the most widely used kernel learning algorithm. It achieves relatively robust pattern recognition performance using well established concepts in optimization theory. Both dual soft-margin problems are quadratic programming problems. Internally, SVM train has several different algorithms for solving the problems. The default Sequential Minimal Optimization (SMO) algorithm minimizes the onenorm problem. SMO is a relatively fast algorithm. If you have an Optimization Toolbox license, you can choose to use quad prog as the algorithm. Quad prog minimizes the L2-norm problem. Quad prog uses a good deal of memory, but solves quadratic programs to a high degree of precision. The SVM train function uses an optimization method to identify support vectors x_i , weights α_i , and bias b that are used to classify vectors x according to the following equation:

$$c = \sum_{i} \alpha_i K(x_i, x) + b \qquad (6)$$

Linear Kernel

The Linear kernel is the simplest kernel function. It is given by the common dot product $\langle x_a, x_b \rangle$ plus an optional constant c. Kernel algorithms using a linear kernel are often equivalent to their non-kernel counterparts. This kernel is only defined when the data to be analyzed are vectors.

$$K(x_a, x_b)\ x_a^T x_b + c \qquad (7)$$

Where x_a, x_b are any two objects from the dataset and c is an optional constant.

Polynomial Kernel

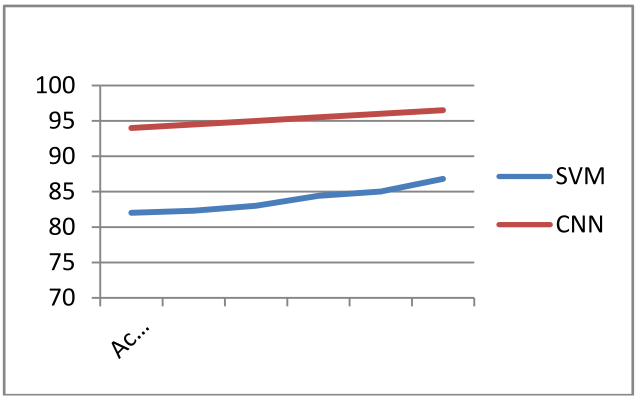
The Polynomial kernel is a non-stationary kernel. It is well suited for problems where all data is normalized.

$$K(x_a, x_b) = (\alpha x_a^T x_b + c)^d \qquad (8)$$

Adjustable parameters are the slope alpha α , the constant term c and the polynomial degree, d.

Radial Basis Kernel

The Radial Basis Kernel function (RBF) is one of the most frequently used kernels in practice. It is a decreasing function of the Euclidean distance between points, and therefore has a relevant interpretation as a measure of similarity: the larger the kernel (x_a, x_b), the closer the points x_a and x_b

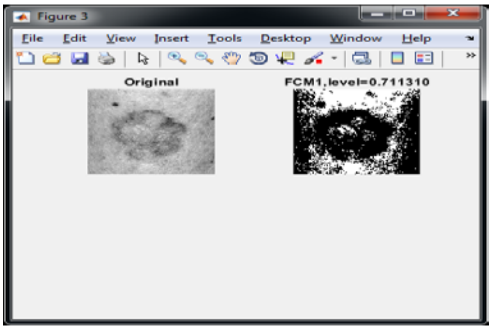


IV.RESULT AND ANALYSIS

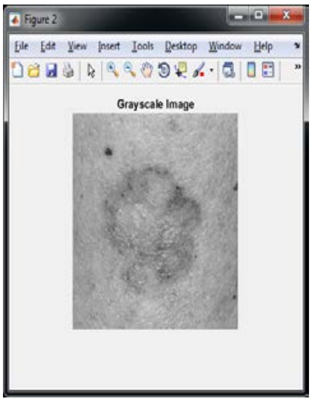
Here we have a case of a skin cancer lesion. The Initial image is the image that is classified with the CNN algorithm and we have the image that is classified with the SVM algorithm followed by the result of the image. Here, both the images classified with CNN and SVM are compared and then the result is displayed.

CNN

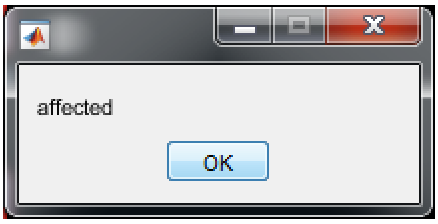
ORIGINAL IMAGE



GRAY IMAGE

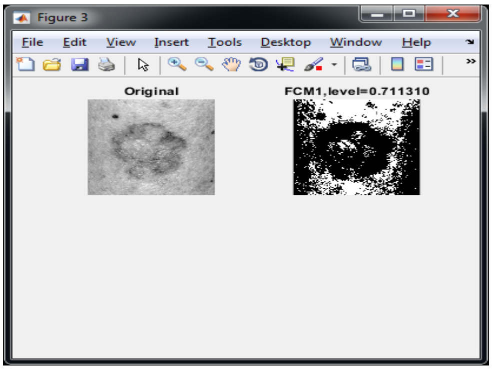


RESULT

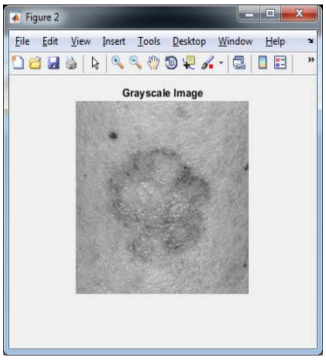


SVM

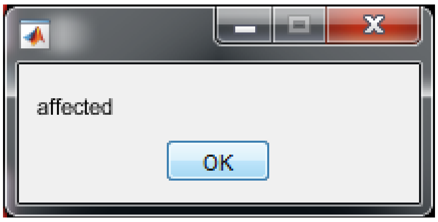
ORIGINAL IMAGE



GRAY IMAGE



RESULT



V.CONCLUSION

Melanoma cancer is the deadliest form of cancer, so detection of the cancer cells in an early stage itself will reduce this rate. The conventional method used is nor arithmetically precise and it is prone to errors. By using the system proposed which uses a deep learning algorithm, which is trained with data sets it is easy to detect the cancer cells with high accuracy and a less time-consuming process. Considering the advantages of the proposed network, it can be implemented to avoid errors that occur in the existing system.

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