# CNN BASED SKIN CANCER CELL DETECTION SYSTEM FROM DERMOSCOPIC IMAGES

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**Abstract: In these days, the use of machine learning and internet has occupied a large space in the field of Bio medical Technology. The machine learning is capable of make decisions based on the past data and it will used for many disease identification and treatment. It has changed our way of health monitoring, diagnosis the disease and its level. In this proposal we use the Machine learning to acquire data from dermoscopy image and from that we diagnosis the impact of disease and monitor it on realtime process. Deep learning methods such as deep convolutional neural networks (CNNs) have established an overwhelming presence in image recognition tasks in the past few years. The main advantage of CNN is that it is endowed with an impressive visual representation capability for the recognition or detection task depending on the given training dataset. We present our proposed framework in details. Here the deep residual neural network is applied in our method, followed by the extraction of local dense activations as deep convolutional features in our framework. Then, FV (fisher vector) encoding strategy is utilized to aggregate these deep features for more discriminative and robust representations. Finally, the classification method of the FV representations is present. Then the result is updated to a webserver by using IOT. Based on the data received from the MATLAB we will indicate the types of disease.**

**Key terms: MATLAB, Convolutional Neural Network, IOT**

## I. INTRODUCTION:

Malignant melanoma is nowadays one of the leading cancer have been increased in the last decades in Australia, America and Europe. Fortunately, if the skin cancer is detected early, the curability is very high and over 92%. In many cases, dermatologists must perform a biopsy (a laboratory medical procedure) to determine whether a tumor is malignant or benign. Since this procedure involves some expense and morbidity, automatic early detection techniques are being as rapid and convenient skin cancer screening. Dermatology imaging researchers believe that diagnosis of skin melanoma can be automated based on certain physical features and color information that are characteristic of the different categories of skin cancer. It has been revealed that the major diagnostic and prognostic parameters of

melanoma are the vertical thickness, three-dimensional (3D) size and shape, and color of the lesion. The other characteristic features of early melanoma include irregularities in the boundary of the lesion, and the appearance of non-uniform pigmentation with a variety of color Dermoscopy, also calls Dermatoscopy or Epiluminescence light microscopy (ELM). It was first announced on 1987, it is a kind of imaging technique uses to exanimate lesions with a dermatoscope. ELM has evolution and digitalize that can be used to classification with computer. It given several advantages in diagnosing like considering small suspicious lesion and objective evaluation of parameters: geometry, color and texture; and storage of image and comparable for future development

## II. LITERATURE SURVEY:

### Reda Kasmi; Karim Mokrani:

The ABCD (asymmetry, border irregularity, colour and dermoscopic structure) rule of dermoscopy is a scoring method used by dermatologists to quantify dermoscopy findings and effectively separate melanoma from benign lesions. Automatic detection of the ABCD features and separation of benign lesions from melanoma could enable earlier detection of melanoma. In this study, automatic ABCD scoring of dermoscopy lesions is implemented. Pre-processing enables automatic detection of hair using Gabor filters and lesion boundaries using geodesic active contours. Algorithms are implemented to extract the characteristics of ABCD attributes. Methods used here combine existing methods with novel methods to detect colour asymmetry and dermoscopic structures. To classify lesions as melanoma or benign nevus, the total dermoscopy score is calculated. The experimental results, using 200 dermoscopic images, where 80 are malignant melanomas and 120 benign lesions, show that the algorithm achieves 91.25% sensitivity of 91.25 and 95.83% specificity. This is comparable to the 92.8% sensitivity and 90.3% specificity reported for human implementation of the ABCD rule. The experimental results show that the extracted features can be used to build a promising classifier for melanoma detection.

### Omid Sarrafzade; Mohammad Hossein Miran; Pejhman Ghassemi:

Dermoscopy is one of the major imaging modalities used in the diagnosis of skin lesions such as melanoma and other pigmented lesions. Due to the difficulty and subjectivity of human interpretation, computerized analysis of dermoscopy images has become an important research area. One of the most important steps in dermoscopy image analysis is the automated detection of lesion borders. In this paper we propose a novel approach for border detection of lesions in dermoscopy images. First, the color input image is converted into a gray-level image. Then, the wavelet coefficients of gray-level image are calculated. The wavelet coefficients are modified using gradient of each wavelet band and a nonlinear function. The enhanced image is obtained from the inverse wavelet transform of modified coefficients. Morphology operators are used to segment the image, and finally the lesion is detected by an automated algorithm. The results show that the proposed method has a low percentage border error in a vast majority of skin lesions compared recent methods.

## III.    EXISTING SYSTEM:

The existing system is human based system to be controlled and monitored by the human. This causes a drawback in the system it requires time for result of data analysed from the sample. Skin diseases are one of the most rapidly increasing and deadliest cancers in the world, which accounts for 75% of skin cancer deaths. Early diagnosis is of great importance for treating this disease as it can be cured easily at early stages. To improve the diagnosis of

this disease, dermoscopy has been introduced to assist dermatologists in clinical examination since it is a non-invasive skin imaging technique that provides clinicians. The realtime monitoring of the disease is not done using this system. It only helps to diagnosis the disease at some predicted time by Medical advisories

## IV. PROPOSED SYSTEM:

The disadvantages of the existing system are overcome by this system. This system enables the use of Machine learning for real time monitoring and data history of patients have maintained. Deep learning methods such as deep convolutional neural networks (CNNs) have established an overwhelming presence in image recognition tasks in the past few years. The main advantage of CNN is that it is endowed with an impressive visual representation capability for the recognition or detection task depending on the given training dataset. We present our proposed framework in details. We first introduce the deep residual neural network applied in our method, followed by the extraction of local dense activations as deep convolutional features in our framework. Then we elaborate how FV (fisher vector) encoding strategy is utilized to aggregate these deep features for more discriminative and robust representations. Finally, the classification method of the FV representations is present

## V. DESCRIPTION:

### Convolutional Neural Network:

In machine learning, a convolutional neural network (CNN, or ConvNet) is a class of deep, feed-forward artificial neural networks that has successfully been applied to analyzing visual imagery.

CNNs use a variation of multilayer perceptrons designed to require minimal preprocessing. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on their shared-weights architecture and translation in variance characteristics.

Convolutional networks were inspired by biological processes in that the connectivity pattern between neurons resembles the organization of the animal visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field. The receptive fields of different neurons partially overlap such that they cover the entire visual field.

CNNs use relatively little pre-processing compared to other image classification algorithms. This means that the network learns the filters that in traditional algorithms were hand-engineered. This independence from prior knowledge and human effort in feature design is a major advantage.

A CNN consists of an input and an output layer, as well as multiple hidden layers. The hidden layers of a CNN typically consist of convolutional layers, pooling layers, fully connected layers and normalization layers

Description of the process as a convolution in neural networks is by convention. Mathematically it is a cross-correlation rather than a convolution. This only has significance for the indices in the matrix, and thus which weights are placed at which index.

### FEATURES:

- Convolutional
- Pooling
- Fully connected
- Weights

**APPLICATIONS:**

- Image Recognition
- Video analysis
- Natural language processing
- Drug discovery

**Image Processing with MATLAB:**

The purpose of this tutorial is to gain familiarity with MATLAB's Image Processing Toolbox. This tutorial does not contain all of the functions available in MATLAB. It is very useful to go to Help\MATLAB Help in the MATLAB window if you have any questions not answered by this tutorial. Many of the examples in this tutorial are modified versions of MATLAB's help examples. The help tool is especially useful in image processing applications, since there are numerous filter examples.

The Command Window is the window on the right hand side of the screen. This window is used to both enter commands for MATLAB to execute, and to view the results of these commands. The Command History window, in the lower left side of the screen, displays the commands that have been recently entered into the Command Window. In the upper left hand side of the screen there is a window that can contain three different windows with tabs to select between them. The first window is the Current Directory, which tells the user which M-files are currently in use. The second window is the Workspace window, which displays which variables are currently being used and how big they are. The third window is the Launch Pad window, which is especially important since it contains easy access to the available toolboxes, of which, Image Processing is one. If these three windows do not all appear as tabs below the window space, simply go to View and select the ones you want to appear. In order to gain some familiarity with the Command Window, try Example 2.1, below. You must type code after the >> prompt and press return to receive a new prompt. If you write code that you do not want to reappear in the MATLAB Command Window, you must place a semi colon after the line of code. If there is no semi colon, then the code will print in the command window just under where you typed it.
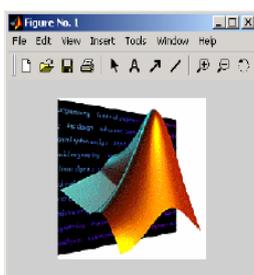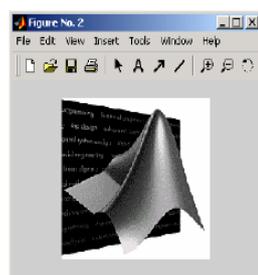
Figure 4.2: Bitmap Image

Figure 4.3: Grayscale Image

**Fig 1.** IMAGE PROCESSING

**Image Properties:**

Histogram – A histogram is bar graph that shows a distribution of data. In image processing histograms are used to show how many of each pixel value are present in an image. Histograms can be very useful in determining which pixel values are important in an image. From this data you can manipulate an image to meet your specifications. Data from a histogram can aid you in contrast enhancement and thresholding. In order to create a histogram from an image, use the imhist function. Contrast enhancement can be performed

by the histeq function, while thresholding can be performed by using the graythresh function and the im2bw functionVII.

## VI. METHODOLOGY:

The dermoscopic image provided by the dermatologist is give as the input in the MATLAB. The images are first pre processed. Then the images are under gone in the convolutional process and we obtain the spatial feature map. Then it is compared to the stored images .After the testing the are classified to which disease it is and the result is obtained. The result is also uploaded in the website using IOT.
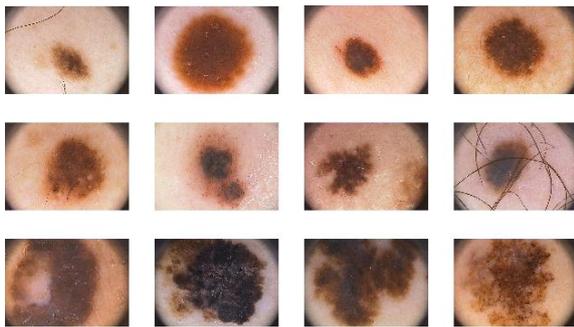


**Fig 2: Dermoscopic Images**
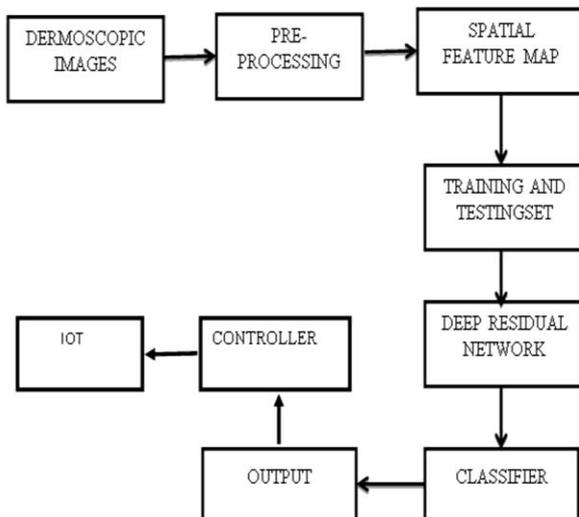


**Fig 3: Block diagram of the proposed system.**

## VII. EXPERIMENTAL RESULT:

The result is uploaded in the website through IOT which can be seen using mobile. This helps the doctor to see the result from home and send the report to the patient .All the results are stored in IOT.

These are the software output of the program when it is complied. There are three different output for three different cases.

### Ringworm:

Ringworm is spread by skin-to-skin contact or by touching an infected animal or object. Ringworm is typically scaly and may be red and itchy. Ringworm of the scalp is common in children, where it may cause bald patches. The treatment for ringworm is antifungal medication
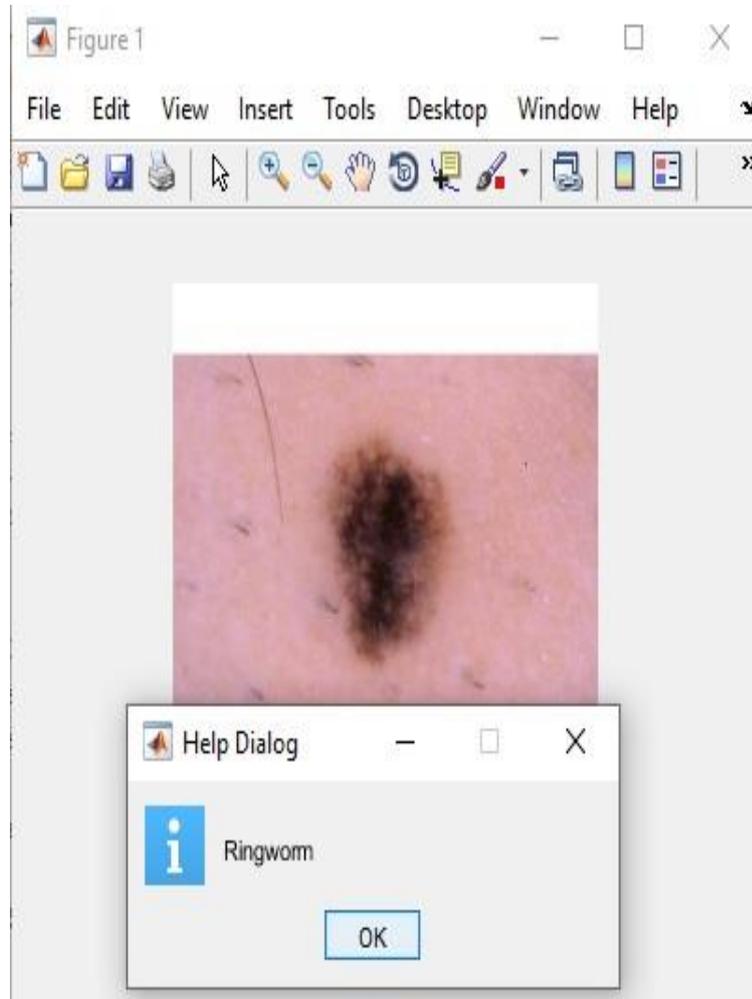


**Fig 4 : RINGWORM OUTPUT**

### IMPETIGO:

Impetigo (im-puh-TIE-go) is a common and highly contagious skin infection that mainly affects infants and children. Impetigo usually appears as red sores on the face, especially around a child's nose and mouth, and on hands and feet. The sores burst and develop honey-colored crusts. Impetigo occurs when the skin becomes infected with bacteria, usually either Staphylococcus aureus or Streptococcus pyogenes. The bacteria can infect the skin in two main ways: through a break in otherwise healthy skin – such as a cut, insect bite or other injury this is known as primary impetigo.
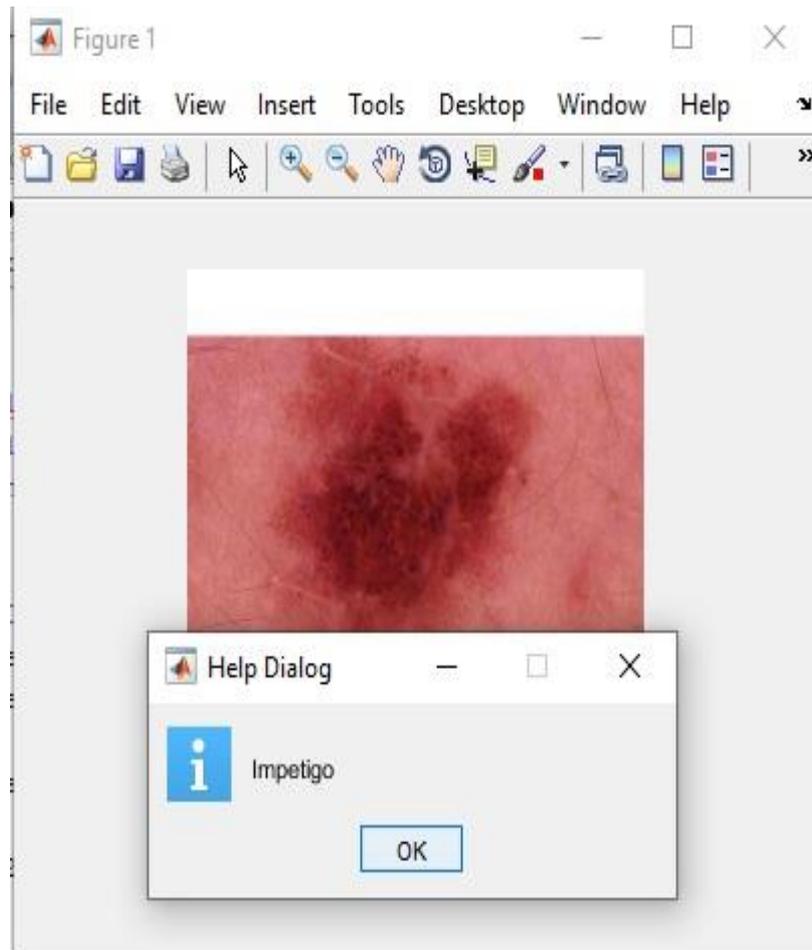
**Fig 5:** Impetigo Output

## X. CONCLUSION:

This system provides a real time analysis of cancer cell based on Convolutional Neural Networks which helps in diagnosing the impact of disease and monitor it on realtime process. In this paper we simulate the result based on the data received from the MATLAB and found the types of disease. This system not only stimulates the sample but it sends the results to the Iota to store the result. In future this system can be enhanced by using a camera to capture the real time image and identifying the type of cancer cell image.

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