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An Enhanced Optimization Based Deep Learning Framework for Skin Cancer Detection

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ABSTRACT

Skin cancer is one of the cancers that spreads the fastest amid the many others that affect people. Particularly melanoma skin cancer is currently an important public health concern. In practise, many skin cancers are curable when they are found in their earliest stages. An automated computerised technique is needed to detect skin cancer in its early stages due to the skin cancer epidemic's rapid increase. The visual aspects of numerous skin cancer images are identical. Identifying the characteristics in skin cancer photos is a crucial and difficult endeavour. Automated computerised diagnostics mechanisms aid in more precise evaluation of skin conditions, allowing dermatologists to diagnose patients more quickly and provide better care. Hence, in this paper using the Fire-Fly Optimized Convolutional Neural Network (FFO-CNN) based classifier to predict the skin cancer accurately. The median filter is used to pre-process the input image for the purpose noise reduction. For segmentation stage, in this research utilizes the OTSU method to segment the pre-processed image. The optimal features from segmented image extracted by application of Gray Level Co-occurrence Matrix (GLCM). Finally, the obtained results show that the proposed system achieves the better results when compared other existing methods.

Keywords: FFO-CNN, OTSU, GLCM, Median filter

1. INTRODUCTION

Complicated instability in genes and the formation of many molecular alterations are the main causes of human cancer. The clinical variability of tumours is not fully reflected by present diagnostic and prognostic categories, which further renders it difficult to anticipate effective treatment and patient outcomes [1, 2]. The majority of anti-cancer medications used today are unable to differentiate among malignant and normal cells very well. Additionally, cancer is frequently discovered and treated after it has spread to other organs of the human body and metastasized. Many patients with breast, prostate, colon, lung and ovarian cancer possess undetected and over metastatic colonies at the moment of clinical diagnosis. The efficacy of therapeutic techniques is currently constrained. Because of these issues, cancer now ranks higher than heart disease as the most common cause of mortality worldwide for people of all ages [3-6].

The most prevalent type of cancer in humans, between a lots of others is skin cancer. The fair-skinned majority in Europe Australia and North America, suffers severely from it. Malignant melanoma and non-melanoma (basal cell, squamous cell, and markel cell carcinomas, etc.) are the two main subtypes of skin cancer [7]. If untreated, melanoma becomes more severe and can be lethal. Melanoma is largely treatable if discovered in its early stages, but advanced melanoma is fatal.

It is widely accepted that timely identification and treatment of skin cancer can lower death rates and illness. One of the most efficient and least expensive ways to detect and categorise skin cancer is commonly regarded as digital dermoscopic [8, 9]. The following phases are often included in a computerised dermoscopic image evaluation system: (1) Optimal Segmentation, (2) Feature Extraction and Selection, and (3) Efficient Classification. The accuracy of the remaining phases depends on correct segmentation, which is the most crucial step. By adjusting its parameters for a variety of lesion forms, sizes, and colours as well as various skin types and textures, supervised segmentation is comparatively simple to apply [10-13]. But because of the aforementioned characteristics, unsupervised segmentation is a challenging task.

Although much research has been put into creating computerised methods that accurately segment dermoscopic images, every attempt yet has some serious shortcomings. Additionally, the computerised segmentation of dermoscopic images was the subject of very few investigations. Digital photographs of melanoma skin lesions have been studied in an effort to find a reliable approach to detect skin cancer at its earliest stages without undergoing any unneeded skin biopsies [14, 15]. Feature extraction is regarded as a crucial tool for using an image effectively in order to accomplish this purpose. This study used segmentation method to assess various digital photos. The segmented images are then subjected to feature extraction techniques. Following this, a thorough analysis of the findings has been conducted.

This paper emphasis on the detection of skin cancer in earlier stage with the adaption of FFO-CNN classifier. The median filter is employed to remove the noises from raw input image. OTSU method segments the pre-processed image for further applications. High ranked features are extracted using GLCM technique. At last, the optimized CNN efficiently classify the skin cancer.

2. PROPOSED SYSTEM

Figure 1 represents the block diagram for skin cancer prediction using FFO-CNN classifier. This layout model consists of median filter, OTSU, GLCM and FFO-CNN.

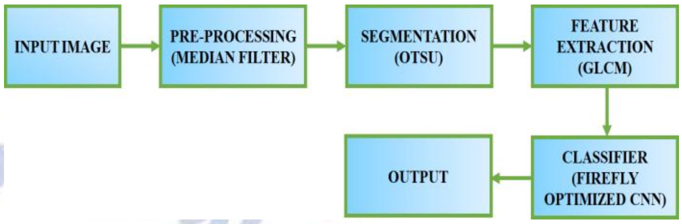

Figure 1 Proposed System

To reduce noise from the input image throughout pre-processing, a median filter is employed. The image is fed into a segmentation block after pre-processing, where the noise has been removed, and the image is subsequently split into several segments for further processing. The OTSU approach is used in this system for edge detection. The segmented pictures have been handled using the approach known as feature extraction to extract several features and select the necessary traits, simplifying categorisation. The GLCM strategy is used in the present study to extract features and select features. Lastly, the selected traits are given into the FFO- CNN classifier with the goal to successfully classify the image. The categorised image is statistically more accurate.

A) MEDIAN FILTER

Every pixel in the picture is subjected to the median filter, and every pixel's immediate neighbours are analysed to determine the extent to which it is typical of its surrounds. In most cases, the median filter substitutes a pixel value with the median of nearby pixel values rather than the mean of the individual values. In other words, the actual value of the pixel in concern is substituted with the middle (median) pixel value after the values from the immediate vicinity have been organised into the correct numerical sequence. The symbol on the window is the name of the neighbourhood. The desired pixel can be the middle of a variety of window designs. A common shape for windows designed for 2D images is square.

Interactive Experimentation

By selecting here, this is dynamically test out this operator.

Example

1. Employing the image

1. Examine whether median filtering affects various neighbourhood sizes.
2. Utilising the same-sized neighbourhood and picture, examine the corresponding processing times of the mean and median filters. So can each function based on the size of the image and neighbourhood.

1. The median filter is non-linear, in contrast to the mean filter. As a result, for the two photos $A(x)$ and $B(x)$,

$$median\ [\mathbf{A}(\mathbf{x}) + \mathbf{B}(\mathbf{x})] \neq \text{median}\ [\mathbf{A}(\mathbf{x})] + \text{median}\ [\mathbf{B}(\mathbf{x})] \quad (1)$$

B) SEGMENTED BY OTSU METHOD

The division of an image into a collection of items is known as segmentation. Numerous colour spaces have been employed, including LAB, HSI, and RGB. Since it immediately works with the green, red and blue image that is extremely similar to the eyes of humans, the RGB system is the easiest to comprehend. The use of a colour circle can best convey design, hue, and saturation. A colour's hue is defined as the spectrum wavelength it closest resembles. The originality of the colour is represented by the saturation, which is the distance of the point from the colour circle's centre. It is simple to convert between the RGB and HSI formats. By combining the RGB elements together, a colour image can be turned into a picture that is monochrome while omitting all chrominance data. The segmentation phase of the suggested approach is carried out utilising distinct methods, the Otsu threshold.

The image initially undergoes conversion to HSI format, after which the S element is extracted for further processing. Nearly identical pixel values and shapes to the original blasts can be provided by the S component. The cells are then divided using the Otsu threshold. With the goal to determine the number of the cells, the image's artefacts required to be improved. Small-pixel objects have been eliminated using morphological aperture (a disc structure feature). Features are retrieved to identify both individual and clustered cells (leukocytes). Since the form of the nucleus is crucial for identifying blasts, four characteristics of the cell's structure are taken into consideration. These characteristics are area, solidity, perimeter, and thinness ratio. The adaption of OTSU method effectively segments the image of skin cancer.

C) GLCM TECHNIQUE

The GLCM is employed for texture evaluation. The simply take consideration of two pixels at a time: the reference and neighbour pixels. The reference and nearby pixels must have a certain spatial link in order to calculate the GLCM. If a pixel is 1 pixels to the right of the current pixel, 3 pixels above it, or 2 pixels diagonally (towards one of NW, NE, SE, or SW) from the reference, it is said to be the neighbour. After a spatial relationship is established, we construct a GLCM of size (Range of Intensities x Range of Intensities) with all of its initial values set to zero. A single channel image with 8 bits, for instance, will have a GLCM.

The matrix need to be changed symmetrically so that each cell indicates the probability of a particular pair of intensities occurring in the image by adding it to its inversion and normalising it. Use the texture properties of the matrix to represent the textures in the image after computing the GLCM.

GLCM ALGORITHM

Input: *Image*
Output: *Vector of textual features*
Begin
Step 1: *Call the Algorithm of computing GLCM matrix in four direction with distance* $d = 1$
Step 2: *Call the Algorithm of normalizing each GLCM matrix.*
Step 3: *For each GLCM matrix in certain angle*
Step 4: *Calculate textural features according to their equations.*
Step 5: *store computed features in a vector.*
End

D) FIREFLY OPTIMIZED CNN

CNN

Figure 2 illustrates the architecture of CNN and that is contains 3 major layers including convolutional layer, max-polling and fully connected layer.

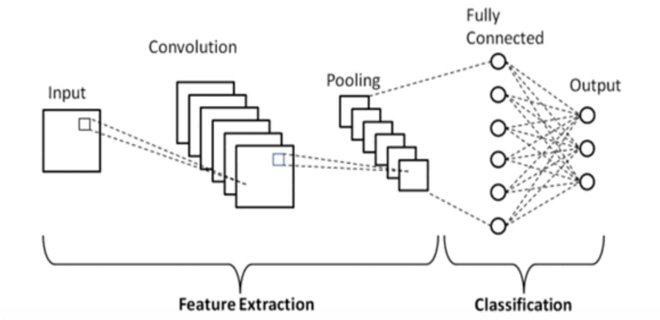

Figure 2 CNN structure

Each of the characteristics from the input images are primarily extracted by this layer. Convolution is a computational process that isobtainable by the input image and a filter with MxM dimensions at this layer. The dot product comparing the filter's specific elements with those in the input image is determined by takingfilter across the raw image (MxM). Implementing the convolution process on the input, CNN's convolution layer sends the output to the following layer. Since they declare the preservation of the spatial connection among the pixels, convolutional layers in CNN are extremely useful.

A pooling level is usuallydeployed after a convolutional layer. This level'skeyobjective is to balance the complicated feature map with the goal to decrease expense on computation. This is done by changing every map of features and utilising lesser linkages among the layers. A number of several pooling processes, which differ based on the approach employed. Basically, it is a list of the characteristics that a convolution layer generated. The Pooling Layer often serves as a connection between the fully connected and convolutional Layer. The CNN approach permits the systems to identify the features on their own by expanding the features that are acquired by the convolution layer. This makes a network's computations more energy-efficient.

The Fully Connected (FC) layer, that links the neurons across layers, contains biases and weights. The last couple of layers of the CNN design are commonly located preceding the output layer. This provides the FC layer with a compressed version of the raw image from the levels below. The flattening path is then exposed to the standard procedures on functions of mathematics after flowing via some added FC levels. The identification technique starts to take place at this point. Since two fully connected layers operate better than one connected layer, two layers are connected. These CNN levels decrease the need for human control.

FFO

Winged beetles termed fireflies discharge light and flashthrough the night. Bioluminescence is the label for a naturally occurring light that derives from the lesser abdomen and has neither an infrared nor an ultraviolet frequency. Predators specifically employ the flash light to draw in potential mates or prey. The flashing light is also employed as a warning system to notify the firefly of potential predators. The bioluminescent phenomenon of communication and flashing behaviour of fireflies served as the inspiration for the metaheuristic method known as the "firefly algorithm.”. The brightness of the fireflies should be related to the problem's relevant goal function. They can split themselves into small groups owing to their attraction, and each subgroup assembles around the local model. The objective function $f(x)$ of FFO is

$$f\ (x\ *) = \min_{x \in S} f(x) \qquad (1)$$

The algorithm of FFO is presented below.

Algorithm 1: FFO Algorithm
Objective function $f(x), x = (x_i, \dots, x_d)^T$
Generate initial population of fireflies $x_i\ (i = 1,2, \dots, n)$
Light intensity I, *at* x_i *is determined by* $f(x_i)$
Define light absorption coefficient γ
while$(t < MaximumGeneration)$
for $i = 1 : n$ *all n fireflies*
for $j = 1 : i$ *all n fireflies*
if$(I_i > I_j)$, *Move fire fly i towards j in* $d_{dimension}$;
end if
Attractiveness varies with the distance r via $\exp[-\gamma r]$
Evaluate new solutions and update light intensity
end for j
end for i
Rank the fireflies and find the current best
end while

Moreover, for the purposes of fine tune the parameter of CNN classier is achieved by using FFO algorithm.

3. RESULTS AND DISCUSSION

The proposed FFO-CNN classifier model is trained using MATLAB Simulink platform. The attained results are presented below. The input image of skin cancer is represented in Figure 3 and similarly, the pre-processing method is used to convert the colour raw image is into grayscale image for further processing indicated in Figure 4. With the support of median filter, the noises are removed from the pre-processed image that is denoted in Figure 5.

Figure 3 Input Image

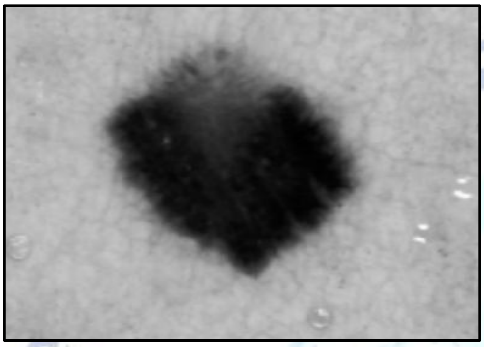

Figure 4 Gray scale Image

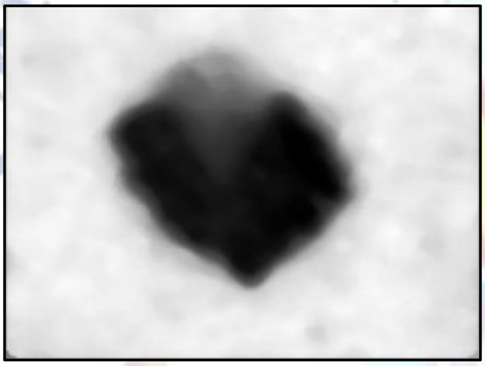

Figure 5 Gray scale Image

Figure 6 Segmented image

Figure 6 shows that segmented image using OTSU method and accuracy and model loss of optimized CNN classifier is denoted in Figure 7.

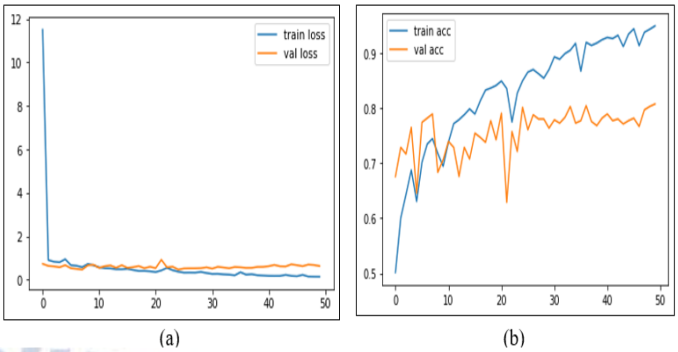

Figure 7 Trained CNN model of (a) Loss and (b) Accuracy

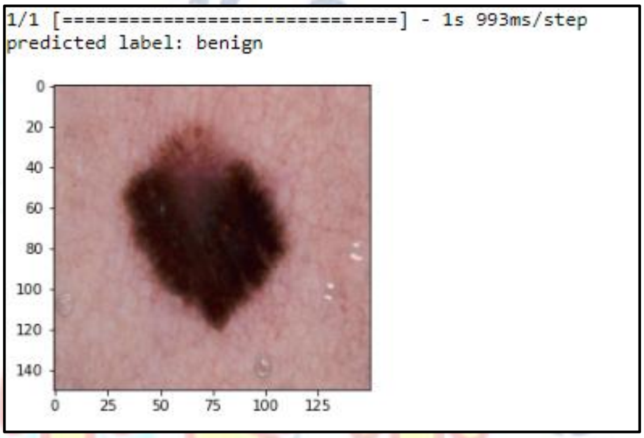

Figure 8 Predicted output

From the above outcomes is it clear that, the proposed FFO-CNN attains high accuracy value of 96.8% with reduced loss compared to other conventional approaches.

4. CONCLUSION

Among the many malignancies that harm people, skin cancer represents one of the ones that rises most rapidly. Skin cancer is an important issue for society right now. When skin malignancies are discovered in the beginning stages, they are frequently treatable. In order to precisely identify skin cancer, this research uses a FFO-CNN based classifier. The input image is first pre-processed with the median filter in order to reduce noise. The pre-processed image is segmented in this research's segmentation stage using the OTSU approach. The best features from a segmented image that GLCM implementation. Furthermore, the findings gathered demonstrate that, in comparison to other systems currently in use, the proposed system yields superior outcomes.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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