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Article Title: Enhancing Dermatology Diagnosis: Automated Skin Cancer Classification using CNN

Enhancing Dermatology Diagnosis: Automated Skin Cancer Classification using CNN

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ABSTRACT

Cancer incidence is increasing due to rising global temperature, especially skin cancer. Skin cancer is frequently misdiagnosed as moles or other skin tags and is thus identified at a much later stage. As a result, a model that precisely targets the face and identifies benign or malignant tumours in the region is required. This paper proposes skin cancer detection using CNN. Data augmentation is an effective way for increasing the diversity of data points without collecting fresh datasets for CNN training. The input image is preprocessed using an adaptive wiener filter. This preprocessing technique is used to remove noise from images. Fuzzy C means are used to segment the preprocessed image. An effective classifier is used to classify the image after segmentation. CNN is used for classification. Final output will predict by using CNN classifier. This paper is implemented with python software.

Keywords: Skin cancer, Data Augmentation, Adaptive wiener filter, Convolutional neural network (CNN), Fuzzy C means (FCM).

1 Introduction

Skin, the largest organ in the human body, have a variety of disorders. According to one study, there are around 3,000 skin illnesses that might be damaging to this vital organ [1]. Skin cancer is the most frequent type of cancer worldwide, and early and precise detection is important for patient survival. Clinical examination of skin lesions is critical, but it is fraught with difficulties such as extended wait times and subjective interpretations [2]. The difficult task of detecting backdrop and lesion attributes present various obstacles for automatic detection of dermoscopy image lesions. Previous solutions have primarily focused on employing larger and more

International Journal of Advanced Trends in Engineering and Management (IJATEM)
Vol. 2(08), August 2023, pp. 23-33

complicated models to enhance detection accuracy; however, there has been little research on major intraclass differences and inter-class similarities of lesion features [3]. Skin cancer prevalence has progressively increased in recent generation as a result of increased exposure to harsh environmental elements and ageing populations [4]. The goal of the dermoscopy procedure is to enhance the effectiveness of each melanoma patient. Dermoscopy is a noninvasive skin imaging procedure that employs a magnified and lit image of the affected skin area to diagnose skin problems [5]. Malignance is the deadliest and most lethal type of skin cancer among the numerous types. This disease is mostly detected visually through clinical screening and study of dermoscopic, biopsy, and Histopathological pictures [6]. Furthermore, the appropriate diagnosis of a skin lesion depends on an expert's experiences [7]. Image processing and machine learning techniques are commonly used in computer vision-based research in skin cancer detection to increase the accuracy, efficiency, and availability of skin cancer detection and care [8]. However, the complexity of melanoma's form and structure makes it difficult to distinguish handcrafted elements based on the type, colour, texture, and shape of the cancer cells [9]. Convolutional neural networks (CNN) have gained prominence in recent years, and academics have been employing CNN to tackle problems in a variety of disciplines, including diagnostic image classification [10].

An accuracy of the present techniques has to be improved for effective treatments. In this paper, detection of skin cancer is proposed using CNN. The list below demonstrates how the paper is organised: Section II describes the most recent work. Section III defines the proposed work in detail. The outcomes are accessible in Section IV. Section V provides a conclusion.

2 Recent Works

Fulgencio Navarro *et al* (2019) [11] have presented a skin lesion segmentation method based on a novel adaption of super pixel techniques utilised in skin cancer detection. Computer-aided diagnostic (CAD) systems work on individual images of extracting lesion traits to enable doctors classify them further. This technique for lesion segmentation enables for the accurate extraction of features to assess the progression of the lesion. However, the data also indicate that accuracy diminishes as time passes between lesion samples.

Jianpeng Zhang *et al* (2019) [12] have suggested an attention residual learning convolutional neural network (ARL-CNN) model for dermoscopy picture skin lesion classification. Each ARL block improves its discriminative representation ability by combining residual learning and innovative attention learning processes. Instead of employing additional learnable layers, the suggested attention learning process seeks to capitalize on DCNNs' inherent self-attention ability. The ARL-CNN model outperforms the similar ResNet model in classification. But pixel-by-pixel segmentation has little effect on classification.

Peng Tang *et al* (2020) [13] have investigated a GP-CNN model that prioritises fine-grained local information over global context information. A Global Convolutional Neural Network

International Journal of Advanced Trends in Engineering and Management (IJATEM)
Vol. 2(08), August 2023, pp. 23-33

(G-CNN) and a Part Convolutional Neural Network (P-CNN) comprise the Global-Part model. A data-transformed ensemble learning technique can improve the accuracy of classification. Using differing external data, on the other hand, will impact the fairness of algorithm comparison.

Adekanmi A. Adegun *et al* (2020) [14] have developed a new framework for automated detection of skin cancer that does both segmentation and classification of skin lesions. The suggested framework is divided into two stages: the first stage uses an encoder-decoder Fully Convolutional Network (FCN). Another stage provides a new FCN-based DenseNet framework. Techniques for optimizing hyperparameters are used to minimize network complexity and increase computer efficiency. However, these strategies were not tested in real-time clinical settings.

Chen Zhao *et al* (2021) [15] have described the novel skin lesion image classification framework (SLA-StyleGAN), which is based on a Skin cancer enlargement depending on fashion GAN. The suggested framework redesigns the structure of the original generator's style control. A novel function of loss that decreases intraclass samples mobility while boosting interclass sample distance, potentially improving balanced multiclass accuracy (BMA). Skin photos, on the other hand, are required to construct a more thorough dataset. Still significant technological problems in dermoscopy-based skin lesion picture classification.

3 Proposed Work Explanation

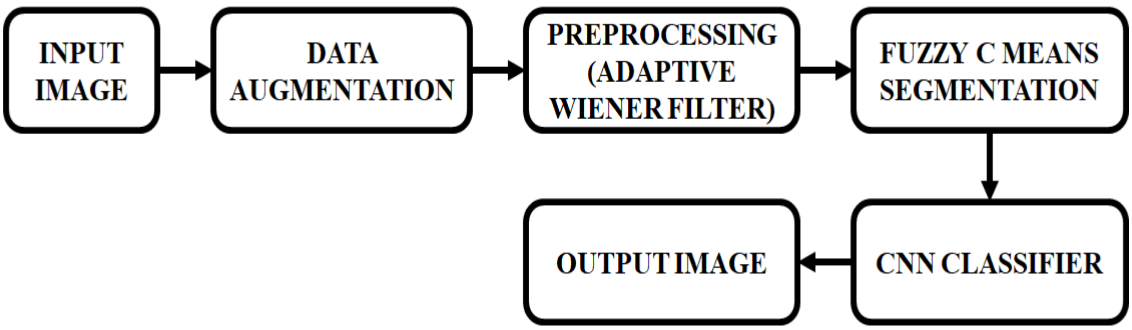


Figure 1: *Block Diagram for Proposed System*

Block diagram of proposed work is shown in figure 1. In this proposed work skin cancer finding using CNN. The input image is taken from the dataset. These images are sent to be augmented with data. Data augmentation is a good way to increase the diversity of information without having to acquire fresh datasets for CNN training. To remove noise, the input image is pre-processed with an Adaptive Wiener filter. Fuzzy C means are used to segment the preprocessed image. An effective classifier is used to classify the image after data pre-processing. CNN is a classification algorithm. The CNN classifier will be used to predict the final output.

International Journal of Advanced Trends in Engineering and Management (IJATEM)
Vol. 2(08), August 2023, pp. 23-33

3.1 Data augmentation

Data augmentation is a strategy for increasing the variety of a dataset by producing new altered replicas of existing occurrences at randomly. It facilitates data cleansing, which is required for high-accuracy models.

3.2 Adaptive Wiener Filter

For preprocessing, an adaptive median filter is used. It modifies the filter's outputs based on the image's regional variance. Its ultimate purpose is to minimize the average square variance between the recovered and original images.

3.3 Fuzzy C means

Segmentation is the process of dividing an image into several subgroups (pixels) known as segmentation. In this system, the Fuzzy-C-Means technique is used for image segmentation, which reduces image complexity.

3.4 Convolutional Neural Networks

This networks is a deep learning approach utilised in a wide range of practical uses. Face recognition, picture categorization, and other computer vision applications are examples of CNN applications. It is similar to a rudimentary neural network. CNN, like neural networks, has characteristics that may be learned, such as weights and biases. CNNs produce detailed findings despite their complexity in terms of resources and expertise.

3.4.1 Classification of CNN

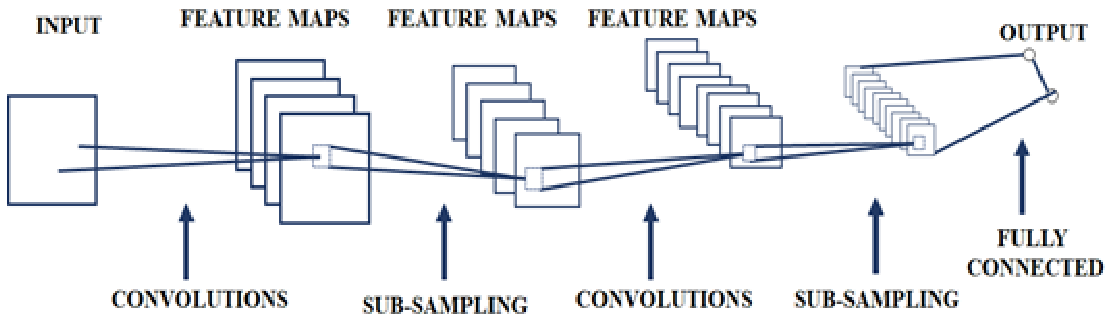


Figure 2: *CNN architecture diagram*

This is an architecture diagram of CNN. In this diagram consist of convolution layers, pooling layers, fully connected layers, sigmoid are illustrated in figure 2.

- The convolution layer is used to extract numerous information from the input images. A calculation is carried out between a source image and MxM filter.

International Journal of Advanced Trends in Engineering and Management (IJATEM)
Vol. 2(08), August 2023, pp. 23-33

- A convolutional layer is normally added after a pooling layer. The primary purpose of this layer is to reduce the overall size of the convoluted feature map in order to reduce the cost of processing.
- The biases and weights are stored in the Fully Connected (FC) layer, which links the neurons between two layers. Typically, the last few layers of a CNN Architecture are positioned prior to the final layer.

4 Results and discussion

4.1 Input image

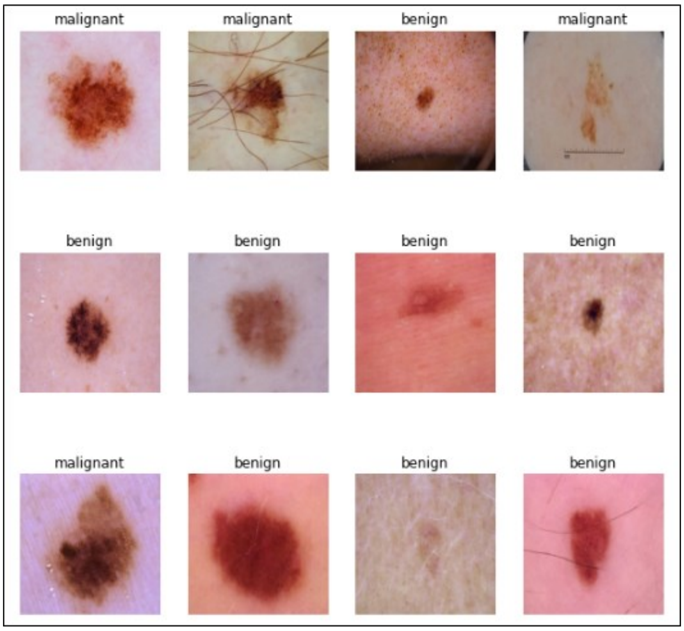


Figure 3: *Input Image*

This figure 3 represents that input image. In this input image shows that benign and malignant types of skin cancer.

International Journal of Advanced Trends in Engineering and Management (IJATEM)
Vol. 2(08), August 2023, pp. 23-33

4.2 Pre-Processing Image

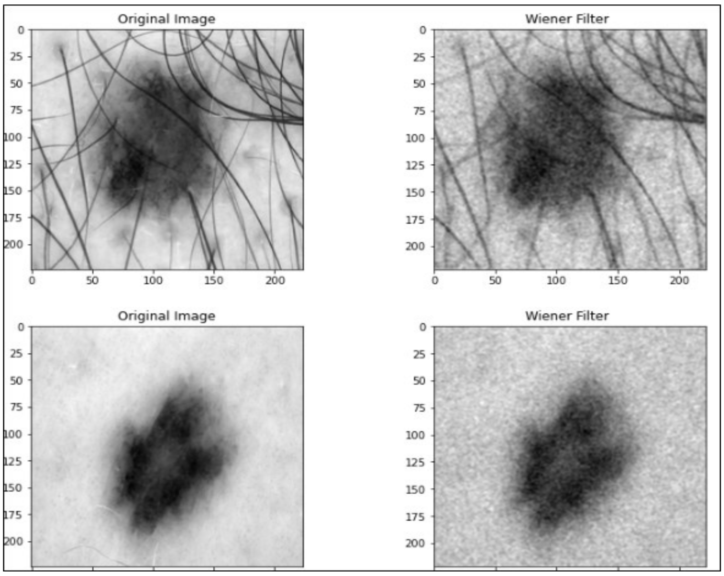
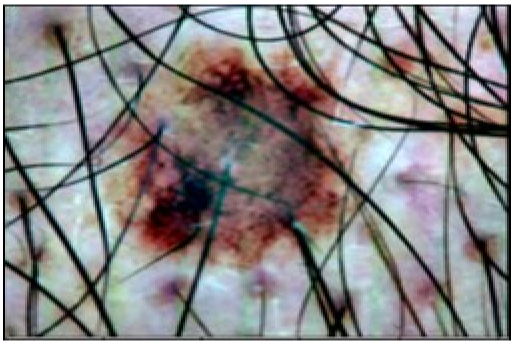


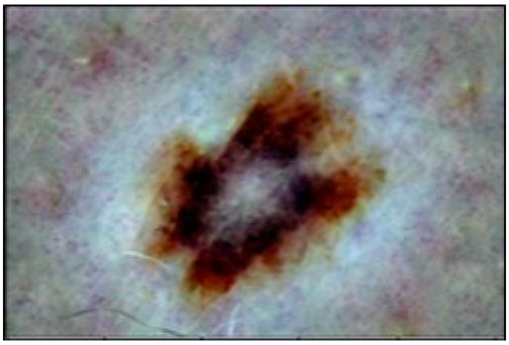
Figure 4: *Preprocessed Image*

The original image, wiener filter image are displayed in figure 3. This original image is not clear so we used wiener filter for removing the noise then the image is clearly obtained.

4.3 Cropped Color Version



(a)



(b)

Figure 5 (a), (b): *Cropped color Version*

Cropped colour version is shown in Figure 5(a), (b), a visual perception quality, is the ability to perceive changes in light frequencies regardless of light intensity.

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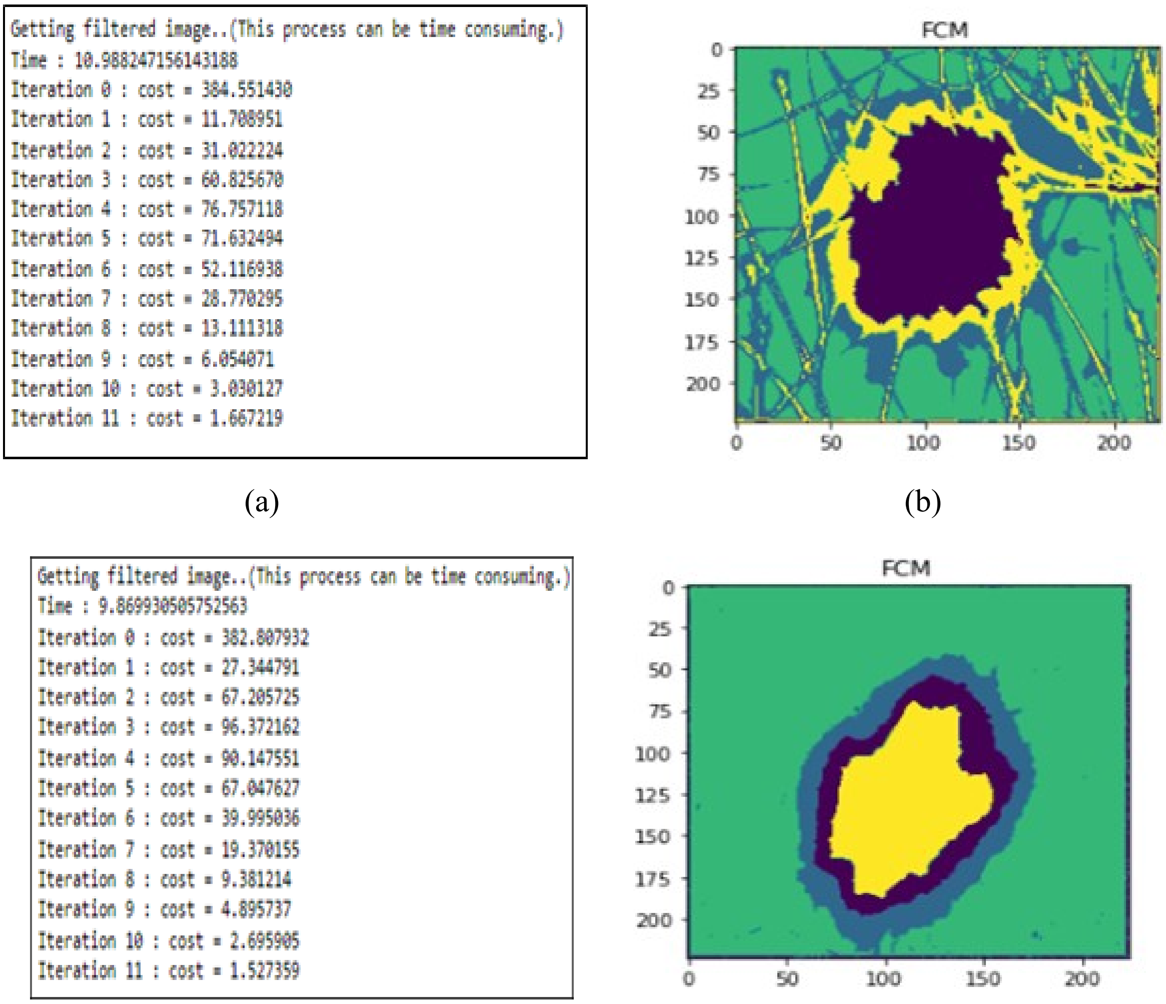
International Journal of Advanced Trends in Engineering and Management (IJATEM)
Vol. 2(08), August 2023, pp. 23-33

4.4 Segmented Image

Figure 6 (a), (b), (c), (d) represent that FCM segmentation. FCM is used to segment these images after they have been preprocessed. In FCM process splitting the image space into different cluster sections with identical image pixel values.



(c) (d)

Figure 6 (a), (b), (c), (d): *FCM Segmentation*

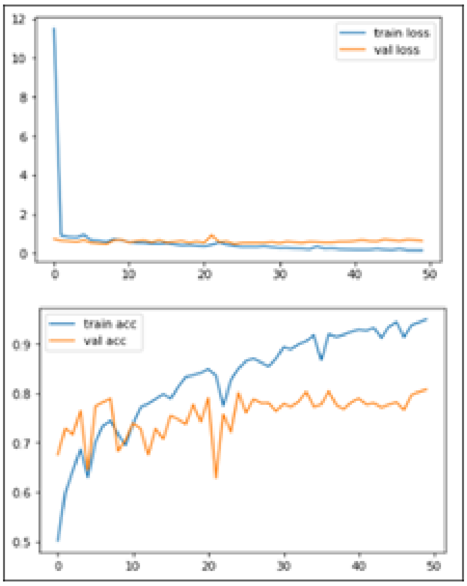
4.5 Classification

The CNN-based categorization training and testing phases are separated. The test image is received by the pre-trained neural network, and after classifying the test image as a reference, CNN classifies the input image. Figure 7(a), (b) shows the accuracy report for the CNN classifier.

International Journal of Advanced Trends in Engineering and Management (IJATEM)
Vol. 2(08), August 2023, pp. 23-33


```
Epoch 45/50
74/74 [==============================] - 54s 735ms/step - loss: 0.1827 - accuracy: 0.9344 - val_loss: 0.7121 - val_accuracy:
0.7773
Epoch 46/50
74/74 [==============================] - 54s 726ms/step - loss: 0.1664 - accuracy: 0.9442 - val_loss: 0.6724 - val_accuracy:
0.7818
Epoch 47/50
74/74 [==============================] - 54s 724ms/step - loss: 0.2290 - accuracy: 0.9136 - val_loss: 0.6265 - val_accuracy:
0.7667
Epoch 48/50
74/74 [==============================] - 54s 733ms/step - loss: 0.1514 - accuracy: 0.9378 - val_loss: 0.6997 - val_accuracy:
0.7970
Epoch 49/50
74/74 [==============================] - 54s 730ms/step - loss: 0.1452 - accuracy: 0.9434 - val_loss: 0.6803 - val_accuracy:
0.8030
Epoch 50/50
74/74 [==============================] - 54s 730ms/step - loss: 0.1433 - accuracy: 0.9493 - val_loss: 0.6337 - val_accuracy:
0.8076
```

(a)



(b)

Figure 7 (a), (b): *Classifier-CNN*

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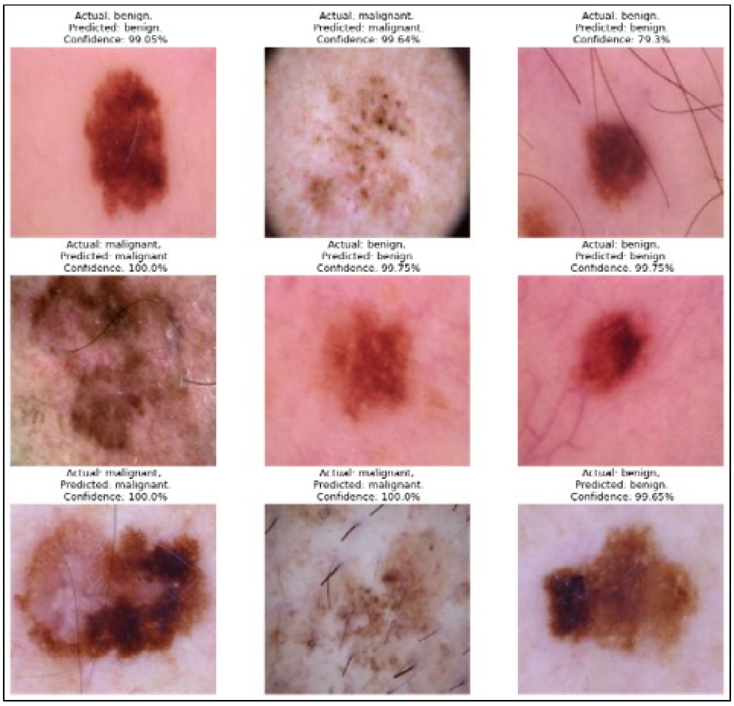
International Journal of Advanced Trends in Engineering and Management (IJATEM)
Vol. 2(08), August 2023, pp. 23-33

4.6 Predicted output



(a)

(b)

```
1/1 [==============================] - 0s 36ms/step
malignant
```

(c)

Figure 7 (a), (b), and (c): *Predicted output*

International Journal of Advanced Trends in Engineering and Management (IJATEM)
Vol. 2(08), August 2023, pp. 23-33

Predicted output is displayed in figure 7(a), (b), (c). This image shows the affected region and represent the types of skin cancer.

5 Conclusion

In this paper identify the skin cancer using CNN was suggested. For this work, for pre-processing and segmentation, the Adaptive Wiener filter and the Fuzzy C Means approach are utilised. CNN (Convolutional Neural Network) is used to extract features, which extracts the most desirable features. The final classification of a skin damage is performed based on the features acquired. In this study, the images are processed by applying a threshold to them, and the lesion area is defined using an edge detector. Furthermore, the results suggest that our proposed methodology outperforms earlier methods.

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Vol. 2(08), August 2023, pp. 23-33

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