SKIN CANCER PREDICTION USING DEEP LEARNING

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ABSTRACT

Skin cancer is becoming increasingly common. Fortunately, early discovery can greatly improve the odds of a patient being healed. Many Artificial Intelligence based approaches to classify skin lesions have recently been proposed. but these approaches suffer from limited classification accuracy. Deep convolutional neural networks show potential for better classification of cancer lesions. This paper presents a fine-tuning on Xception pretrained model for classification of skin lesions by adding a group of layers after the basic ones of the Xception model and all model weights are set to be trained. The model is fine-tuned over HAM10,000 dataset seven classes by augmentation approach to mitigate the data imbalance effect and conducted a comparative study with the most up to date approaches. In comparison to prior models, the results indicate that the proposed model is both efficient and reliable

KEYWORDS: Skin cancer. Deep learning, CNNs, Transfer learning, Xception

1. INTRODUCTION

Skin cancer is the growth of abnormal cells in the outermost layer of the skin epidermis, due to DNA damage that causes mutations. Which cause tumour formation due to skin cells grow rapidly as shown in figure 1. These tumours may be malignant or benign. Skin cancer can be treated more easily if detected in its early stage especially before it develops into a full-blown skin cancer or reaches the inner layers of the skin [1]. Artificial intelligence (AI) and deep learning (DL) algorithms have lately been demonstrated to outperform humans in visual tasks, thanks to enhanced processing capabilities and extremely huge datasets automated classification can help in the early detection of skin cancer which may not be detected with the traditional diagnosis techniques. Transfer learning is a common technique for deep learning that uses pre-trained models as MobileNet [2], DenseNet [3], Inception [4] and Xception [5] as a starting point to speed up training and to enhance the deep learning model's performance in general, the lower layers of the deep learning model provide general features, while the higher layers provide specific features.

Figure 1. Sample of skin cancer images.

The pre-trained model task is related to the learned features. Therefore, the new task of the transfer learning can be affected by two main factors 1) Dataset size and 2) The pretrained model and new model domain functionality similarity. These factors result four different cases, as shown in figure 2. • Case 1 Small dataset and same domain functionality; The only modification is done on the top layer classifier which can be trained. While the whole pre-trained model behaves as a feature extractor. • Case 2 Small dataset and different domain functionality; This model can be considered as a feature extractor that must be retrained for each layer. The pre-trained model's low-level layers are held frozen. • Case 3 Large dataset and same domain functionality; The pre-trained weights must be fine-tuned in the model's lower layers. • Case 4 Large dataset and different domain functionality; The overall base model is required to be fine-tuned by retraining with the large dataset [6].

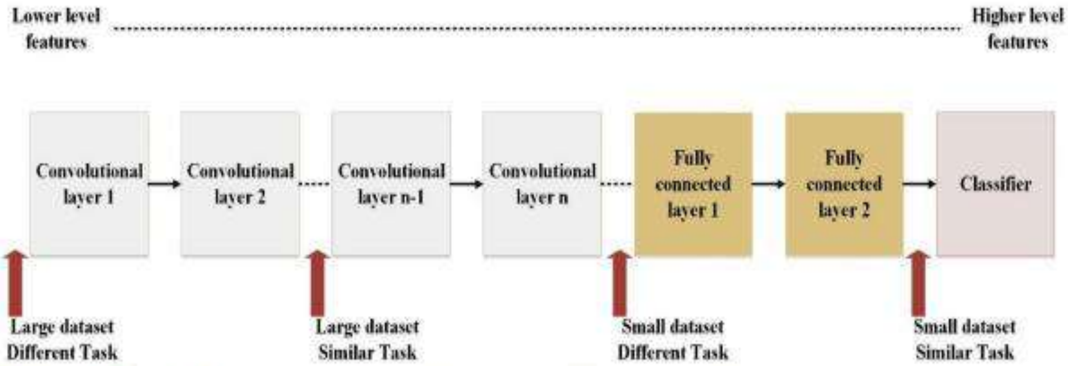


Figure 2. Different cases of transfer learning based on dataset size and similarity between pre trained model and new model domain functionality.

The following is an overview of the paper's structure. In Section 2, the related work is provided. The methodologies employed in this research are described in Section 3, which includes the basic Xception model and the fine-tuned Xception model. The description and pre-processing of the dataset are introduced in Section 4. Section 5 reports the results and discussion. Finally, in Section 6, the conclusion is stated.

PREVIOUS WORK

Throughout recent years, researchers have put in significant effort to develop intelligent systems for healthcare applications. Deep CNNs have proven their efficiency in both detection and classification tasks for image processing applications in the medical field. Several research employing deep learning approaches to classify skin cancer have been mentioned in the literature. Saket S. Chaturvedi et al. [7] used the HAM10,000 dataset, which contains 10,015 images divided into a training and validation sets each has 8,912 and 1,103 images respectively. To fine tune the Xception model, a dense layer with 'Relu' activation function is added with a seven-class output softmax layer. For faster model optimization, (Adam) optimizer is used with an 0.001 learning rate. The accuracy was reported to be 91.47 %. Aldwgeri A. and , Abubacker N.F. [8] Investigated several cases. First CNN model trained from scratch, this model is experimented for both balanced and unbalanced HAM 10,000 dataset. The results were 64%, 57% accuracy for balance and unbalanced dataset respectively. Then they modified (VGG19, ResNet50, InceptionV3, DenseNet121, Xception and VGG16) models to classify skin lesions. A softmax layer and a global average pooling layer were added, followed by a 0.5 dropout. The input images are resized to 299 x 299 pixels. The used loss function is categorical cross entropy, while the optimizer is Adam. The batch size and number of epochs were selected to be 32 and 60 and learning rate of 0.0001. each model resulted accuracy of 79%, 74%, 76%, 76%, 76%, and 77%. Then they ensembled the models together an accuracy of 80% was reported. Filali et al. [9] Developed a model to detect melanoma skin cancer. They used a combination of pre-trained and trained from scratch Convolutional Neural Network models. Then, irrelevant features are removed via feature engineering. To eliminate the artefacts, decompose the image using the Aujol model to recognise the object's contour. Then, to process the input image to CNN, the new object is segmented using the otsu algorithm. Using PH2 dataset, the authors reported 87.8% accuracy. Sara Hosseinzadeh Kassani et al. [10] Investigated the detection of melanoma using different deep learning architectures using augmented HAM 10,000 dataset the least achieved accuracy was 84% by AlexNet model then accuracies 89% and 90% for VGGNet 19 and VGGNet 16 respectively. The highest reported accuracy in this study was 92% for ResNet50 while Xception achieved 90%. Hossin et al. [11] For malignant melanoma classification, a CNN-based technique with an improved regularizer was proposed. The authors built a multilayered CNN architecture from scratch, using dropout and BatchNormalization as regularization techniques. The suggested method detected malignant melanoma with 93.5% accuracy using a dataset of 3,297 dermoscopic images, according to performance results. Ly et al. [12] Introduced a CNN model consists of five sets of Conv2D, BatchNorm, and MaxPooling2D CNN model. This model was trained from scratch with balanced dataset to classify benign and malignant skin cancer with 86% accuracy. They utilized a composite dataset called “PHDB” which consists of different datasets, ISIC Archive, Dermnet NZ, and PH2.They stated that by the aid of HAM 10,000 dataset which was not available at that time the model is expected to perform better and the curves of training and validation will be smooth for both cases accuracy and loss. E. Nasr-Esfahani et al. [13] A model with two convolving layers and a 5x5 kernel was proposed. Feature maps for the first and second convolution layers are 20 and 50 respectively. Each convolution layer is followed by a pooling layer. The final classification decisions are taken using a linear transfer function. This model results an accuracy of 81%. Andre Esteva et al. [14] Fine-tuned all the layers InceptionV3 network and learning rate of 0.001as well as for every 30 epochs, decay factor of 16 is applied. This model was trained on 129,450 skin lesions collected from different available datasets as Dermofit, Dermoscopic Archive and data from the Stanford Hospital.comprising 2,032 different diseases. they reported 72.1% accuracy.

EXISTING SYSTEM

The machine learning methods such as Artificial Neural Networks (ANNs), decision trees, KNN that are used for skin cancer prediction where features observed might not give accurate results in terms of accuracy and efficiency as compared to Convolutional Neural Network(CNN).

Disadvantages:

1. Poor Performance

2. Accuracy is less

PROPOSED SYSTEM

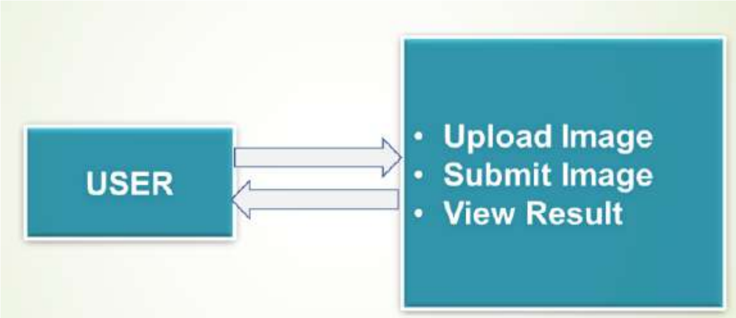
Proposed system works based on the Dermographic image for classification and prediction of the type of Skin Cancer and extracts CNN features from multiple convolutional layers. These features are aggregated and then given to the classifier for classification purpose using EfficientNet models to achieve both higher accuracy and better efficiency over existing CNN architecture models.

Advantages:

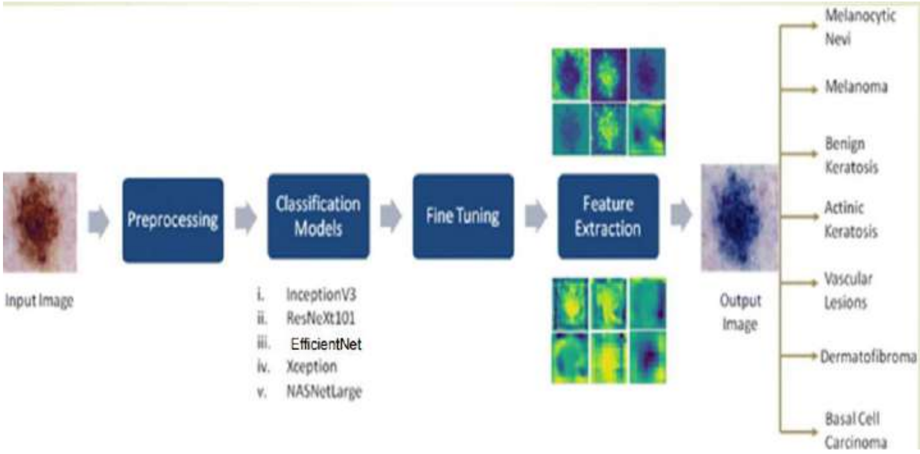
• Accuracy is high

• High Performance

ARCHITECTURE



SYSTEM ARCHITECTURE



CONCLUSION

The proposed deep CNN model could classify the melanoma types into benign class or malignant class. In this work, a less complicated model is used and the accuracy obtained was around 70%. The future extension to this work includes improving the prediction accuracy by parameter tuning, remodeling the network to multiclass case, which could detect different categories of skin lesions. The system which is put forward is to a great extent an effective tool that helps in the timely as well as lively evaluation of the disease. The system further has an integrated user-friendly and user accountable form of GUI.

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