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Skin Cancer Classification using NasNet

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Abstract

Skin cancer remains one of the major causes of mortality worldwide, with malignant melanoma being the deadliest type due to its high potential for metastasis. Although relatively uncommon, it accounts for nearly 75% of skin cancer-related deaths. Early detection plays a crucial role in improving outcomes, but it is difficult because melanoma often closely resembles benign skin lesions. In this work, we propose an automated system for early melanoma detection using deep transfer learning. Our method leverages a pre-trained NASNet model, from which features are transferred to a new dataset for classification. We adapted the original network by incorporating global average pooling and customized classification layers. The system was trained and evaluated on skin images from the ISIC 2020 dataset.

Keywords: Skin cancer; Deep learning; Melanoma detection; Dermoscopic images; NASNet

1. Introduction

The uncontrollable development of tissues in a specific body area is known as cancer [1]. One of the most quickly spreading diseases in the world looks to be skin cancer. Skin cancer is a disease in which abnormal skin cells develop out of control [2]. In order to determine potential cancer therapies, early detection and accurate diagnosis are essential. Melanoma, the deadliest form of skin cancer, is responsible for most skin cancer-related deaths in developed countries. The major skin cancer types comprise basal cell carcinoma [3], squamous cell carcinoma [4], Merkel cell cancer [5], dermatofibroma [6], vascular lesion [7], and benign keratosis [8].

In order to diagnose abnormalities in various regions of the body, such as skin cancer [9], breast cancer [10], brain tumors [11], lung cancer [12], and stomach cancer [13], diagnostic imaging assessment plays an important part. According to the GLOBOCAN survey, there will be 19.2 million new cancer diagnoses and 9.9 million cancer deaths in 2020. Lung cancer is the leading cause of death (18.2%), followed by colorectal cancer (9.5%), liver cancer (8.4%), stomach cancer (7.8%), breast cancer (6.9%), esophageal cancer (5.5%), and pancreatic cancer (4.7%). The GLOBOCAN survey also points out more than half of cancer deaths occur in Asia, along with about 20% of cancer deaths occurring in Europe.

To ensure better prognosis and death rates, early skin cancer identification is crucial, yet solid tumor detection typically relies mostly on screening mammography with inadequate sensitivity, which is then validated by clinical specimens. Cancer screening and treatment reaction evaluations are usually not appropriate uses for this approach [2,3]. An increasing number of healthcare providers are using artificial intelligence (AI) for medical diagnostics to improve and accelerate the diagnosis decision-making procedure [4].

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Machine learning models can predict diseases that can be detected by a trained physician, which sometimes requires a lot of time, training, and effort, making the whole process costly. AI applications can be trained on data gathered from real-life domains to predict diseases with almost the same accuracy as a trained physician. The training process requires a lot of real data, which must be uploaded to a centralized server to train models. This centralized learning approach sometimes raises serious concerns in terms of data privacy, data ownership, and intellectual property, leading to the inaccessibility of data. The data is usually associated with some hospitals or institutions that are bound not to share private information/ images of a patient. As a result, AI models have a very limited amount of data, which is not big enough to get good training results. Today, AI has evolved a new decentralized approach where models are trained on collaborative devices without needing to access the data. This new form of AI is called federated learning, which is here to unlock private data without transferring it to cloud [5, 6].

However, despite some current evidence of improvement in this domain, the accurate assessment and adequate reporting of predicted flaws have been entirely or partly ignored by currently available AI research for clinical diagnosis.

Computer-aided design (CAD) can quickly, reliably, and consistently diagnose various disorders. CAD also provides the option for advanced tumor disease detection and protection that is both precise and cost-effective. Human organ disorders are typically assessed using a variety of imaging technologies, including magnetic resonance imaging (MRI) [7], positron emission tomography (PET) [8], and X-rays [9]. Computed tomography (CT) [10,11], dermatoscopy image analysis, clinical screening, and other approaches were initially used to visually diagnose skin lesions. Dermatologists with little expertise have shown reduced accuracy in skin lesion diagnostics [12,13,14]. The methods for physicians to evaluate and analyze lesion images are time-consuming, complex, subjective, and error prone. This is mainly because the images of skin lesions are so complicated. Unambiguous identification of lesion pixels is essential to performing image analysis, for evaluation and awareness of skin lesions. Using machine learning approaches in computer vision has led to a significant advance in computer-aided diagnostic and prediction systems for skin cancer detection [15].

2. Related Works

In aspects of extracting features and identifying skin lesions, convolutional neural networks are extremely effective. As a result, most cutting-edge works are built on CNN architectures such as AlexNet [17] VGG-16 [18], GoogleNet [19], ResNet [20], and so on. Even with a limited dataset, transfer learning of these pretrained models can be employed to efficiently classify images. Combining multiple of these CNN networks into an ensemble model outperformed individual models in recent works.

Quang et al. [21] presented deep learning-based approaches for binary classification of skin lesion images. For the segmentation of skin tumor, they used a fully convolutional-deconvolutional architecture, and for classification, they used two approaches. In the first approach, a simple CNN was employed, while in the second approach, a VGG-16 with transfer learning was used. A significant false positive rate was observed due to the unbalanced dataset between the two groups. Because of the transfer learning methodology, which used pre-trained weights, the second way performed the best.

In [22] Harangi aggregated the outputs of various CNN architectures to build an ensemble model of deep neural network. They classified skin lesions into three classes using the weighted ensemble model. They used GoogleNet, AlexNet, ResNet and VGGNet as base models. The ensemble model outperformed individual CNN models in classification accuracy. They used a small dataset with three classes, which is unbalanced, and they did not consider expanding the dataset size by adding more images. They addressed the ensemble model as a way of enhancing the performance of the CNNs while working with a small dataset.

In [23] Murugan et al. proposed a binary classification model in which skin lesion images were segmented using a watershed segmentation technique, and Support Vector Machine (SVM), Random Forest, and k Nearest Neighbour(KNN) classifiers are used for classifying the data. In the preprocessing stage, a median filter is used to eliminate hair and other artefacts from skin lesion images. SVM outperformed other classifiers in the categorization process.

Hosny et al. [24] classified skin lesion photos into seven classes using transfer learning and a pre-trained AlexNet model. They examined the issue of unequal number of images in different classes affecting classification performance. To overcome this, they implemented data augmentation techniques such as rotation and flipping of images.

Chaturvedi et al. [25] did a comparison of five pre-trained CNNs and four ensemble models of them in classifying skin lesion images into seven classes. The base models they used are Xception, InceptionV3, InceptionResNetV2,

NASNetLarge and ResNetXt101. ResNetXt101 performed significantly better in classification than other deep learning models. They led to the realization that training deep learning models with the best hyper-parameter setup outperforms even ensemble models.

In [26] Iqbal et al. presented a stacked CNN model for the classification of seven types of skin lesions along with preprocessing and data augmentation techniques. They examined the results with and without image preprocessing to assess the significance of this step in skin cancer diagnosis.

Rahman et al. proposed a weighted average ensemble model for the classification of seven types of skin lesions [27]. They considered five cutting-edge architectures for the model: ResNet, DenseNet, Xception, ResNeXt, and SeRes-NeXt. The problem of excessive data imbalance was solved by using cost sensitive learning. In terms of performance, DenseNet came out on top, and the weighted average ensemble model outscored the individual models.

3. NasNet

The model has two types of cells, namely: normal cells, and reduction cells. The Normal cells contain convolutional layers and other learnable parameters such as normalization layers. Reduction cells are used to reduce the feature maps' dimensions. A recurrent neural network (RNN) controller was used to search for the structure of normal and reduction cells using reinforcement learning. The NASNet architecture is flexible and scalable in terms of parameters and computational resources. A NASNet model pre-trained on the ImageNet database [29] was used in this study, and the model was fine-tuned on our dataset. The NASNet was chosen as the base model for a few reasons. First, it has fewer parameters as compared to other state-of-the-art models, such as Inception V3 [30] and Xception [31] models. Second, it has a top-1 accuracy of 82.7% on ImageNet while the top-5 accuracy is 96.2%. In the original paper, they introduced a new regularization technique known as ScheduledDropPath, which boosted the generalization of NASNet architectures. With these properties of the NASNet architecture, the final model achieved the state-of-the-art performance but with a small model size and lower computational complexity. Therefore, pre-trained NASNet helps to develop an accurate classification system.

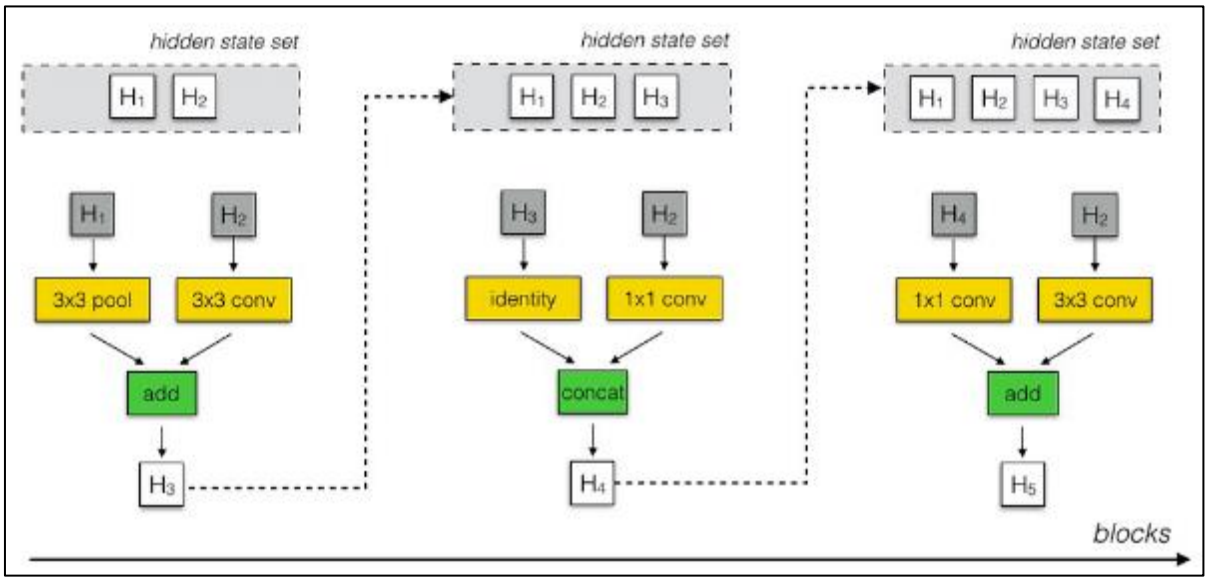

Figure 1 Schematic diagram of the NASNet search space [28]

4. Dataset

We have used the dermoscopic images of skin cancer from a publicly available dataset known as International Skin Imaging Collaboration (ISIC) 2020 [32]. For the development of the automated system, we used the NASNet [28] model for transferring features to the new classifier. In this section, we have provided the details of the dataset and our proposed NASNet-based melanoma classification model. Our dataset comes from the International Skin Imaging Collaboration (ISIC) 2020 competition. The original dataset has more than 30,000 images from 2000 patients. These data were collected by the International Skin Imaging Collaboration (ISIC). There are nine classes in ISIC 2020. The dataset is highly imbalanced; for example, Melanoma has only 584 images, while nevus has more than 5100 images.

Similarly, more than 27,000 images are in unknown classes where no class information is available for these lesions. Developing a classifier using such imbalanced data often results in biased performance for the majority class. Therefore, to overcome this issue, we randomly selected 2000 images from the nevus class and all the images from the melanoma class. Then we performed label and feature-preserving augmentations to increase and balance the dataset for the development of a robust classifier. A total of 4000 images were used in this study for melanoma recognition.

5. Results

The experiments were done using Keras with Tensorflow backend. The Keras package already has a pre-trained NASNet, which was trained on the ImageNet database. The model was trained for 100 epochs, and a batch size of 32 was used during training. We used 75% of the images for training the model, and the rest 25% were used for testing the proposed method. Data augmentations were applied to increase the dataset, and this dataset was used during the training of the algorithm. A dropout value of 0.5 and 0.4 was used after the Global Average Pooling layer and after the final dense layer to help cope with overfitting on the training data. The input to the deep model is RGB images of 224×224×3 size. Non-linear activation function Rectified Linear Unit (ReLU) was used.

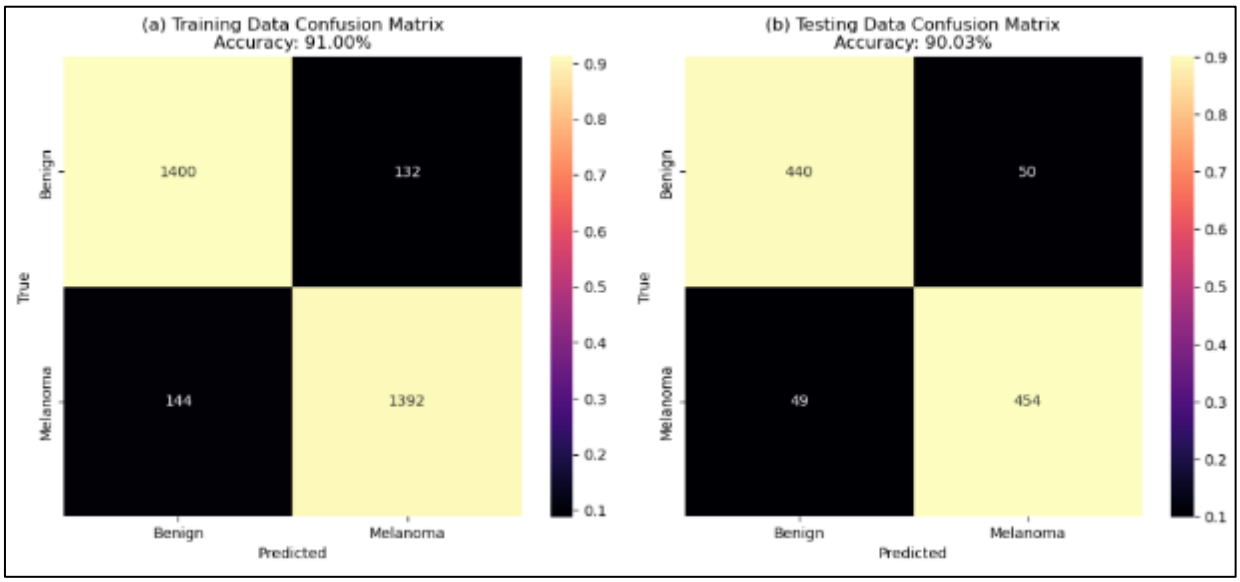

Figure 2 Confusion matrix for melanoma detection

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Classification report for Training Data:

Classification Report
Class       Precision   Recall      F1-score
Benign      0.9067      0.9138      0.9103
Melanoma    0.9134      0.9062      0.9098

Overall Accuracy: 91.0039%

Classification report for Testing Data:

Classification Report
Class       Precision   Recall      F1-score
Benign      0.8998      0.8980      0.8989
Melanoma    0.9008      0.9026      0.9017

Overall Accuracy: 90.0302%
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Figure 3 Classification report for melanoma detection

Table 1 Comparison of our proposed model with non-deep learning methods for melanoma classification

Ref.	Model	Accuracy
[33]	CNN	88.12%
[34]	Inception	88.89%
[35]	Inception ResNet	83.96%
[36]	Alex-Net & Random Forest	82.32%
	DenseNet121 & Random Forest	82.05%
	Alex-Net, VGG16 & densnet121	84.29%
Ours	NasNet	90.03%

6. Conclusion

This study used a NASNet-based deep transfer learning approach for an automated melanoma detection system. By integrating global average pooling and customized classification layers, the model was able to extract and classify dermoscopic image features. Experimental results on the ISIC 2020 dataset demonstrated that NASNet achieved an accuracy of 90.03%, more than several existing CNN-based and ensemble methods.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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