

Detection of Skin Cancer Using Convolution Neural Network Models

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Abstract

In recent days, skin cancer is seen as one of the most Hazardous forms of the Cancers found in Humans. Skin cancer is found in various types such as Melanoma, Basal and Squamous cell Carcinoma among which Melanoma is the most unpredictable. Early detection of Melanoma can potentially improve survival rate. In this project, we will study the performance of various Convolution Neural Network models for diagnosing melanoma, the deadliest form of skin cancer. Which is helpful for identification of melanoma disease at an early stage.

Keywords: Melanoma, Basal and Squamous cell Carcinoma, Convolution Neural Network.

Introduction

Skin cancer is one of the top three perilous types of cancer caused by damaged DNA that can cause death. This damaged DNA begins cells to grow uncontrollably and nowadays it is getting increased speedily. There exists some research for the computerized analysis of malignancy in skin lesion images As a result, the early detection of skin cancer may lead to diagnosis and treatment with increasing the chances of lives. Over the last decades, there are different types of computeraided diagnosis (CAD) systems that are proposed to identify skin cancer. Traditional computer vision algorithms are mainly used as a classifier to extract a large number of features like shape, size, color, and texture in order to detect cancer. Nowadays, artificial intelligence (AI) has become an aptitude to face these problems. The most authorized deep-learning architectures such as deep neural networks (DNN), convolutional neural networks (CNN), recurrent neural networks (RNN) are used in the medical field to detect cancer cells. These models are also successfully performed in classifying skin cancer. Moreover, CNN is a DNN in particular and has already achieved remarkable results in this field. CNN is the most popular model which is the collection of machine learning algorithms used for feature learning and object classification. In addition, transfer learning is being used in these fields in large data sets to improve the results accurately.

In this Project we classify the skin cancer images of forms Nevus,Seborrheic-keratosis, and Melanoma by using the transfer learning models of CNN. They are Xception, Inception V3, Resnet50, InceptionResent V2, and EfficientNetB0.

Literature Survey

Several attempts to diagnose skin cancer cases using deep learning techniques, such as CNN. Esfahani et al. proposed CNN architecture for diagnosing melanoma lesions, clinical images were preprocessed in order to reduce image illumination, then images fed to convolutional neural network models. The CNN model was successful in distinguishing between malignant and benign images. Experimental results show that the proposed method was capable of diagnosing melanoma lesions cases. Mahbod et al. showed that convolutional neural networks are superior over traditional methods. They proposed a hybrid fully automatic computerized method for skin lesion classification; they used three pre-trained deep models (AlexNet, VGG16, ResNet-18) to extract features. The extracted features then are used to train SVM (support vector machine) classifiers and evaluated on the 150 validation images from the ISIC 2017 dataset, Jaisakthi, Chandrabose, and Mirunalini proposed a method for skin lesion segmentation in images and to classify skin cancer types from images. The method consists of preprocessing and segmentation using a semi-supervised learning algorithm. The purpose of the first phase is noise removal using filtering technique, the second phase skin lesions are segmented based on clustering technique. The training images were downloaded from the ISIC 2017 challenge website, the experimental results shown low accuracy but will draw a map for future improvement.

Proposed System:

In this project we classify the skin cancer of types Melanoma, Nevus and Seborrheic Keratosis. We collected the dataset from the Kaggle website. After that we need to pre-process the data for further operations. After pre-processing of the data we need to convert the image data into numerical data to feed into the CNN model. The dataset is divided into training data for building the model and testing data for prediction. We used transfer learning models of CNN like Xception, Resnet50 to extract the features from the image dataset. After building the model on the training data we need to predict the model on the testing data.

First of all we collect the dataset from the available sources and then we need to preprocess the data for further computation by using some techniques and then convert the image data into numerical data. The next step is to build the classification model by adding various convolutional layers into the model. After that we need to train the model by feeding the preprocessed data known as training data which is 80% part of the total data. After training the model the next step is to test the accuracy of the model by making predictions of the testing data.

Requirements And Technical Description

Python is a high-level, general-purpose and a very popular programming language. Python programming language (latest Python 3) is being used in web development used in this research

Colab is used extensively in the machine learning community with applications including:

Getting started with TensorFlow, Developing and training neural networks , Experimenting with TPUs , Disseminating AI research, Creating tutorials.

Keras:

Keras is a deep learning framework. Keras is a central part of the tightly-connected TensorFlow 2.0 ecosystem, covering every step of the machine learning workflow, from data management to hyper parameter training to deployment solutions. Keras is a high-level library intended to stream-line the process of building deep learning networks.

Scikit-Learn:

It is a Python library associated with NumPy and SciPy. It is considered as one of the best libraries for working with complex data. There are a lot of changes being made in this library. One modification is the cross validation feature, providing the ability to use more than one metric. Lots of training methods like logistics regression and nearest neighbors' have received some little improvements. It contains a numerous number of algorithms for implementing standard machine learning and data mining tasks like reducing dimensionality, classification, regression, clustering, and model selection.

SciPy:

SciPy is a machine learning library for application developers and engineers. However, you still need to know the difference between SciPy library and SciPy stack. SciPy library contains modules for optimization, linear algebra, integration, and statistics. SciPy is a library that uses NumPy for the purpose of solving mathematical functions. SciPy uses NumPy arrays as the basic data structure, and comes with modules for various commonly used tasks in scientific programming.

Tensor flow:

TensorFlow is a popular framework of machine learning and deep learning. It is a free and opensource library which is released on 9 November 2015 and developed by Google Brain Team. It is entirely based on Python programming language and use for numerical computation and data flow, which makes machine learning faster and easier. TensorFlow can train and run the deep neural networks for image recognition, handwritten digit classification, recurrent neural network, word embedding, natural language processing, video detection, and many more. TensorFlow is run on multiple CPUs or GPUs and also mobile operating systems. The word TensorFlow is made by two words, i.e., Tensor and Flow Tensor is a multidimensional array and Flow is used to define the flow of data in operation.

cv2:

OpenCV

It is a cross-platform library using which we can develop real-time computer vision applications. It mainly focuses on image processing, video capture and analysis including features like face detection and object detection.

Methodology

Image Acquisition:

Image acquisition is the creation of a digitally encoded representation of the visual characteristics of an object, such as a physical scene or the interior structure of an object. The general aim of Image Acquisition is to transform an optical image (Real World Data) into an array of numerical data which could be later manipulated on a computer. Images used for facial expression recognition are static images or image sequences

Reading Image:

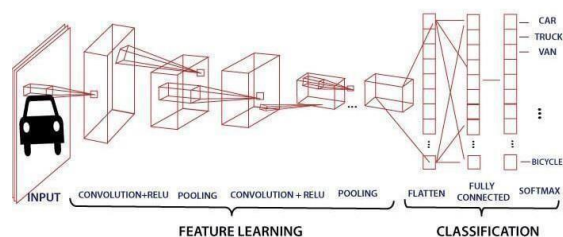
In this step, we simply store the path to our image dataset into a variable and then we create a function to load folders containing images into arrays so that computers can deal with it.

Data Augmentation:

Data augmentation is a way of creating new 'data' with different orientations. The benefits of this are two-fold, the first being the ability to generate 'more data' from limited data and secondly, it prevents overfitting.

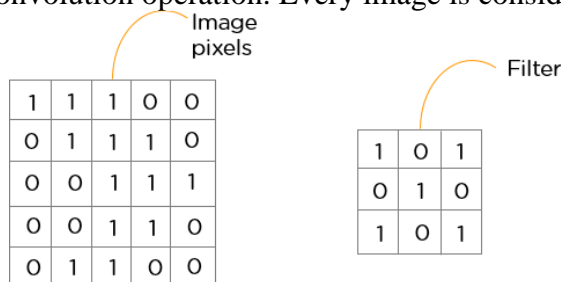
Convolution Neural Network

It is one of the main categories to do image classification and image recognition in neural networks. Scene labelling, objects detections, and face recognition. are some of the areas where convolutional neural networks are widely used.



CONVOLUTION LAYER

This is the first step in the process of extracting valuable features from an image. A convolution layer has several filters that perform the convolution operation. Every image is considered as a matrix of pixel values.



Pooling

It progressively reduces the size of the input representation. It makes it possible to detect objects in an image no matter where they're located. Pooling helps to reduce the number of required parameters and the amount of computation required. It also helps control overfitting. If pooling is not done periodically then the size of output will be increased exponentially. There are two types of poolings that can be applied in convnets. They are Global Average pooling, Max pooling. In global average pooling, the given matrix will be replaced by its average and in Max pooling It will be replaced by the maximum value.

Fully Connected Layer

A fully connected layer that utilizes the output from the convolution process and predicts the class of the image based on the features extracted in previous stages. The fully connected layer is a layer in which the input from the other layers will be flattened into a vector and sent. It will transform the output into the desired number of classes by the network.

Softmax Layer:

A Softmax function is a type of squashing function. Squashing functions limit the output of the function into the range 0 to 1. This allows the output to be interpreted directly as a probability. Similarly, SoftMax functions are multi-class sigmoid, meaning they are used in determining probability of multiple classes at once. Since the outputs of a SoftMax function can be interpreted as a probability (i.e., They must sum to 1), a SoftMax layer is typically the final layer used in neural network functions.

Flatten:

Flatten is the function that converts the pooled feature map to a single column that is passed to the fully connected layer. Dense adds the fully connected layer to the neural network. Flattening is converting the data into a 1-dimensional array for inputting it to the next layer. We flatten the output of the convolution layers to create a single long feature vector

Datasets

Skin cancer database is a collection of images with diagnostic categories of a range of diseases. Well-annotated (disease-tagged) media content of skin affected images is essential for training, testing, and validation of algorithms for the development of classification systems. Training of

- i) Melanoma
- ii) Nevus
- iii) keratosis

neural networks for automated diagnosis of pigmented skin lesions is hampered by the small size and lack of diversity of available dataset of dermatoscopic images.

Results And Discussions

Transfer Learning is a learning method in which a model trained for a particular task is reiterated as the origin for another model on a similar task. This approach is very mainstream in deep learning due to the vast computation resources and time consumed to train neural network models. In the case of problems in the computer vision domain, low-level features, such as shapes, corners, edges and intensity, can be shared across tasks, and thus enable knowledge transfer.

In this project, the CNN is trained by transfer learning from the pretrained weight of ImageNet classification. ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is the classification challenge involving 14 million training images of approximately 20,000 classes. Fine-tuning from the pretrained weight significantly increases the classifier training speed, overcomes the limit of small number of training data and makes the convergence more realistic to occur. The front layers of the CNN serve to detect the edges, points, corners and simple structures in the image and the pretrained weight enables the trained model has higher adaption speed. The model is trained and tested on the state-of-art CNNs, namely InceptionV3, ResNet50, VGG16, MobileNet and InceptionResnet to perform the seven-class classification of the skin lesion images.

We have taken already existing transfer leaning models of CNN. They are: Xception, InceptionV2, Resnet50, EfficientNetB0, InceptionResnetV2

```

Model: "sequential_1"
-----
Layer (type)                Output Shape                Param #
-----
xception (Functional)       (None, 8, 8, 2048)         20861480
flatten_1 (Flatten)         (None, 131072)              0
Dense_Intermediate (Dense)  (None, 256)                 33554688
Dropout_Regularization (Drop (None, 256)              0
Output (Dense)              (None, 3)                   771
-----
Total params: 54,416,939
Trainable params: 54,362,411
Non-trainable params: 54,528
    
```

Summary of the Xception model

```

Model: "sequential_3"
Layer (type)                Output Shape                Param #
-----
inception_v3 (Functional)   (None, 6, 6, 2048)         21802784
Flatten_3 (Flatten)         (None, 73728)              0
Dense_Intermediate (Dense)  (None, 512)                 37749248
Dropout_Regularization (Drop (None, 512)              0
Output (Dense)              (None, 3)                   1539
-----
Total params: 59,553,571
Trainable params: 59,519,139
Non-trainable params: 34,432

```

Summary for Incept

Conclusion and Future Scope

In this project we have proposed performance of various convolution neural network models for skin cancer identification. Our study gives an important contribution to this research area for several reasons. First, it is a study that combines the research being done related to all the steps needed for developing a classification system for skin cancer detection and classification. Second, it presents knowledge that helps the researchers judge the importance of high level feature extraction and proper feature selection methods which needs more effort for making the correct diagnosis of skin cancer. Third, it proposed a method that highlights the importance of standar for model validation which is generally overlooked in the previously published studies.d approaches

Future Work:

In future this work can be extended by creating own neural network model for detecting skin cancer. By considering the larger datasets we can build the model according to it so that there is a possibility to achieve the maximum accuracy of the prediction. And also by combining the various classification models to predict the classes leads to the maximum prediction accuracy. This work can also be extended to analyze skin cancer in the medical diagnosis..

References

- [1] <https://machinelearningmastery.com/what-is-deep-learning/>
- [2] <https://towardsdatascience.com/wtf-is-image-classification-8e78a8235acb>
- [3] <https://iq.opengenus.org/basics-of-machine-learning-image-classification-techniques/>
- [4] Arifin, S., Kibria, G., Firoze, A., Amini, A., & Yan, H. (2012) "Dermatological Disease Diagnosis Using Color-Skin Images." Xian: International Conference on Machine Learning and Cybernetics.
- [5] Krizhevsky, A., ILYA, S., & Geoffrey, E. (2012) "ImageNet Classification with Deep Convolutional Neural Networks." Advances in Neural Information Processing Systems.
- [6] Al-Masni M.A., Al-Antari M.A., Choi M.-T., Han S.-M., Kim T.-S. Skin lesion segmentation in dermoscopy images via deep full resolution convolutional networks.
- [7] Georey E. Hinton, Alex Krizhevsky, Ilya Sutskever. 2012. ImageNet Classification with Deep Convolutional Neural Networks. Neural Information Processing Systems(2012).
- [8] Swati Srivastava Deepti Sharma. 2016. Automatically Detection of Skin Cancer by Classification of Neural Network. International Journal of Engineering and Technical Research 4, 1 (2016), 15–18.

- [9]Z. Liu and J. Zerubia, “Skin image illumination modeling and chromophore identification for melanoma diagnosis,” *Physics in Medicine & Biology*, vol. 60, pp. 3415– 3431, 2015.
- [10]N. K. Mishra and M. E. Celebi, “An overview of melanoma detection in dermoscopy images using image processing and machine learning,” arXiv preprint arXiv:1601.07843,2016.
- [11]H.-C. Shin, H. R. Roth, M. Gao, L. Lu, Z. Xu, I. Nogues, J. Yao, D. Mollura, and R. M. Summers, “Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning,” *IEEE Transactions on Medical Imaging*.