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A Comparative Study on the Diagnosis of Skin Cancer using different Models in Deep Learning

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Abstract: ***Skin cancer is a common form of cancer, and early detection increases survival rates. This paper presents a comparison of the different types of deep learning models used to detect skin cancer. Based on Convolutional Neural Networks (CNN), the skin cancer detection is done. The different networks in CNN are used, namely ResNet18, AlexNet and ResNet50. Transfer learning is a neural network model, which is also used in skin cancer diagnosis. HAM10000 is the skin cancer dataset used and the accuracy obtained in using different models is then compared.***

Keywords: Deep Learning models, CNN, ResNet18, AlexNet, ResNet50, Transfer Learning

1. Introduction

The annual number of people with skin cancer has gradually increased over the past decade, resulting in increased UV risk [1]. Diagnosis of skin cancer is very important because even death can occur in severe cases. Several methods have been developed to detect skin cancer and much research is being done to achieve high accuracy with less damage.

It has been found that [2] a skilled specialist usually follows a series of steps beginning after the naked eye observation of suspicious lesions, then dermoscopy microscopically extending the lesions and then biopsy. This can be time-consuming and the patient may progress to later stages. Accurate diagnosis is also possible based on the ability of physicians. It has been found that the best dermatologists have less than 80% accuracy in correctly diagnosing skin cancer.

Extensive research solutions have been developed to detect skin cancer at an early stage and to address some of the above problems which is developing computer image analysis algorithms [3]. Most of these algorithmic solutions had parametric meanings that were essential data normally distributed. Since the nature of the data is uncontrollable, these methods would be insufficient to detect the disease. However non-parametric solutions do not rely on the constraint that the data are in a normal distribution.

Skin cancer is a frightening problem and should be recognized early [4]. Diagnosis is a time-consuming and expensive procedure. However modern world science has improved the use of intensive education and it can be useful in many ways. Therefore deep learning makes it easy to detect cancer cells. This is why deep learning of a proven neural network is used to quickly and effectively detect cancer cells.

This paper discusses skin cancer detection using intensive learning models. The convoluted neural network is optional because it automatically detects important features without being hired by anyone. The Ham 10000 dataset is used to detect skin cancer. Resnet 50, AlexNet and Resnet 18 are used in skin cancer diagnosis for Transfer Learning. The obtained accuracy is then compared.

2. Related Work

Skin cancer research supporting image analysis has improved significantly over the years. Many different strategies are attempted [5]. The 2018 International Skin Imaging Collaboration (ISIC) program has become a special benchmark for the detection of carcinoma by hosting a challenging competition. It has also been reported that the mobile app is accustomed to detect carcinoma. During these efforts, researchers have tried to boost the accuracy of diagnostics by using different techniques when the Neural Network (CNN) structure introduced Fukushima (1988) and later Le-Qin (1990) on new dimensions. Image segmentation began. They used CNN for image classification. CNN basically mimics the human sensory system and is believed to be the best medium in the state. Although an abundance of books are available within the categories of images, we limit our review of the literature on in-depth study of carcinoma images.

The first introduction to carcinoma classification is the primary Google Net Incept V3 CNN model from Esteva et al. [5]. He has used 129,450 carcinoma images, including 3, 374 dermatoscopic images. The reported accuracy ofclassification is 90%. In 2016, Yu et al. [4] developed a CNN with 50 horizontal data on the ISBI 2014 challenge for the classification of melanomas. The best accuracy for this challenge was 85.5%. In 2018, Hensel et al. [Deep] dermatoscopy used a deep sensory neural network to separate the binary diagnostic range of melanocytic images, and, reported high sensitivity and specificity.

The classification using the multiscale ECOC SVM and Deep Learning CNN was developed by Dorj et al. In ref. [8]. This approach would be to use ECOC SVM with AlexNet Deep Learning CNN and to separate multi-level data. An accuracy of 95.1% has been reported for this task. In ref. [4] Han et al. They used a deep neural network to classify clinical images of 12 skin diseases. Model specifying the best accuracy 96.0%. Varies between 1%. This page is not an in-depth review by sophistication readers; However, a scientific review of deep learning is found in [1].

Similar applications are made within the diagnosis of plant diseases [10]. This work investigates possible solutions to this problem using fragmented image data to educate complex neural network (CNN) models. The SCNN model provides higher accuracy than the FCNN model.

Another work [11] presented an in-depth review of intensive learning strategies used in sentiment experiments. Conceptual analysis is one in each of the leading areas in language processing. Language processing has a wide range of applications such as voice recognition, linguistics, product reviews, product analysis, sentiment analysis and text segmentation such as email segmentation and spam filtering. Common methods used in cognitive analysis are lexicon-based analysis. However, with the progress in the field of applied intelligence, machine learning algorithms have started to play a major role in standard analytical applications. Currently deep learning is the process that the most recent invention predicts accustomed emotions. Many research projects in language processing (NLP) using deep learning methods are carried out.

Some work has also been done to identify food categories. This study [12] proposed a method to detect different food varieties and ingredients in each food item. Conversational neural networks (CNN) are accustomed to perform these functions. Mobile nets are used to classify ships and thus you only see once (YOLO) networks that operate as a compilation and integration group. Later image processing and network segmentation are transferred to the Raspberry Pi platform.

Several other experiments were performed that used hyper spectral images to induce high accuracy [13]. The purpose of this study is to measure and evaluate HSI methods including in-depth studies on embedded platforms and limited resources. Vector machine (SVM), multi-layer perceptron (MLP) and convergent neural network (CNN) classification methods were used during this study. These algorithms are performed on a desktop PC with two embedded platforms: ODROID-C2 and Raspberry Pi 3B. Accuracy, runtime, and memory benches determine the appropriate model for each platform. Supported the results collected during this study, the CNN classification is sometimes recommended for desktop PCs due to its high 97% accuracy.

Other research activities were also carried out to improve neural architecture. [13] To reach maximum effectiveness, researchers must prepare neural structures and carefully select training strategies. The book's trial and error process consumes too much energy to find the best neural configuration. The purpose of neural architecture discovery (NAS) is to reduce this problem by automating neural networks. Recently, the rapid development of NAS has shown great success. Novel neural network structures that work best in virtual world networks are found in image segmentation benches.

3. Background Study

1) Deep Learning

Deep learning, a computing work that mimics the processing data of the human brain and creates patterns utilized in higher cognitive processing. Deep learning computing (AI) is a subset of machine learning that consists of networks which will read unattended data from informal or uneducated data. It's also called Deep Neural Network. Deep Neural Network (DNN) could be a synthetic neural network (ANN) with multiple layers between input and output layers. DNN finds the proper mathematical idea to indicate on input, be it linear equations or nonlinear relationships. The network goes through a calculation to calculate the probability of an output

2) Convolutional Neural Network (CNN)

CNN with selected structures are shown to be very powerful in areas like image recognition and segmentation. CNN has been shown to specialize in faces, objects, and road signs over humans and might therefore be found in robots and self-driving cars. CNN could be a supervised learning method and is therefore trained using label data with appropriate classrooms. In fact, CNN studies the link between content and class labels and combines two things: hidden layers within which clues are extracted and, on top of alignment, fully interconnected layers used for the classification function is finished. Unlike normal neural networks, the hidden layers of CNNs have a particular structure. In normal neural networks, each layer is created from a gaggle of neurons and one layer neuron is connected to every neuron of the preceding layer. The structure of hidden layers on CNN is also slightly different. The neurons within the layer aren't connected to all or any or any of the neurons within the previous layer, but rather, they're connected to only a tiny low number of neurons. This restriction on spatial valency and extra swimming layers also summarize the results of neuron occlusion on a sway on gain effects on translational-invasive features. This ends up in a neater and more complex training process for the lower model.

3) Supervised Learning

The most common kind of machine learning, deep or not, is machine learning. Imagine that we wish to form a program during which pictures is classified, like a house, car, person, or animal. First start by collecting an oversized data set of images of homes, cars, people and pets, each listed in its own category. During training, the machine is shown a diagram and produces an end within the shape of a vector of scores, one for every category. The specified class may own the simplest number of classes, but this can be likely to happen before training. We include a scoring function that measures the error (or distance) between the output score and therefore the included pattern of digits. The machine then adjusts its internal flexibility parameters to fulfill this error. These variable parameters, often invoked as metals, are real values that is identified as 'knots' that underlie the input function of a machine. In a very highly specialized deep learning program, there'll be many fluctuating loads, and there'll be many sufficient examples with machine manuals.

4) Transfer Learning

Transfer learning refers to a process where a model trained for one problem is utilized in a technique or another in a very related problem. Take a trained model on the oversized dataset and transfer its information to smaller datasets. Train the essential network within the essential dataset and performance first, then return the learned objects, or transfer them to a different target network for training within the target data and performance. This process will occur when the features are general, which is suitable for both foundation and work purposes, instead of specifying basic tasks.

5) ResNet 18

Residual neural network (ResNet) is a kind of artificial neural network (ANN) that builds on known constructs from pyramidal cells in the cerebral cortex. Residual neural networks do this by using skip connections, or shortcuts to jump to certain layers. Typical ResNet models are implemented with double- or triple-layer skips, with nonlinearities (ReLU) and batch normalization in between. An additional weight matrix can be used to learn skip weight; these models are known as HiveNets. Many parallel skid models are known as densenets. In the context of residual neural networks, a non-residual network can be described as a plain network. ResNet-18 is a sensory neural network that is 18 layers deep. We can load a pretrain version of a network trained on more than one million images from the Image Net database. The pretense network can classify images into 1000 object categories

6) AlexNet

AlexNet is a convolutional neural network (CNN). AlexNet consisted of eight layers; the first five were Convolutional layers, some of them followed the Max-pooling layers, and the last three were fully connected layers. .AlexNet, proposed by Alex Krizhevsky, uses ReLu (rectified linear unit) for the non-linear part, rather than a tan or sigmoid function that was previously the standard for traditional neural networks. ReLu is given by

$$f(x) = \text{maximum}(0, x)$$

ReLU has an advantage in training time; CNN using ReLU was able to reach a 25% error on the CIFAR-10 dataset six times faster than other functions.

Multiple GPUs: Back in the day, GPUs were still roaming with 3 gigabytes of memory (now-a-days those types of memory would be paused numbers). This was particularly bad because the training set contained 1.2 million images. AlexNet allows multi-GPU training by placing half of a model's neurons on one GPU and half on another GPU. Not only does this mean that a larger model can be trained, but it also cuts training time.

Overlapping pooling: CNN traditionally has no overlap with outputs from neighboring groups of "pooled" neurons. However, when the authors introduced overlap, they observed a decrease of about 0.5% and found that models with overlapping pooling are generally harder to overfit.

7) ResNet 50

ResNet-50 is a strongly neural network with a depth of 50 layers. You can load a pretrain version of a network trained on more than one million images from the Image Net database. The pretended network can classify images into 1000 object categories. The ResNet-50 model consists of 5 stages with a convolution and identity block. Each convolution block has 3 convection layers and each detection block also has 3 convolution layers.

4. Proposed System

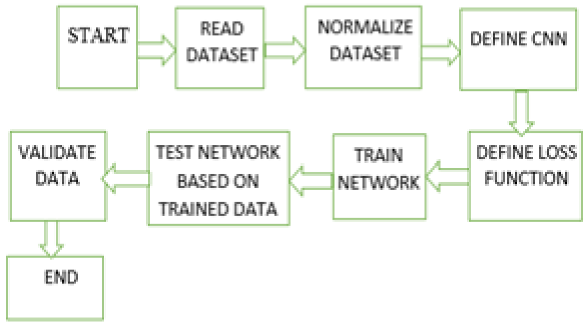

Figure 1: Work flow of Skin cancer detection using CNN

The work flow of Skin Cancer detection using CNN is shown in figure1.Initially load the dataset and normalize the dataset. The data normalization can be done using image augmentation and the need to define the model used and also the network. The Convolutional Neural Network (CNN) is used and the network used includes ResNet 18, AlexNet and ResNet 50. Now define the loss function of the dataset, then train the network. Here supervised learning is used to train the network. Then split the data into test and train data, followed by testing and training. Now validate the data and finally accuracy and loss is obtained.

1) Skin Cancer detection using ResNet18 & AlexNet

To obtain the accuracy, skin cancer detection was performed using deep learning models. The HAM10000 dataset was taken and skin cancer detection was performed by looking at images from the dataset. Skin cancer is divided into 7 categories: Bowen's disease (akiec), Basal cell carcinoma (bcc), Benign keralosis-like lesions (bkl), Dermato fibroma (df), Melanoma (mel) Melanocytic nevi (nv), Vascular lesions (vasc).The code is executed in google colaboratory using python. The deep learning model used is Convolutional Neural Network (CNN).The work is done with both ResNet18 and AlexNet, which are pretrained CNN networks. First the data is downloaded in colab environment. After downloading extract the dataset.Then any one content from the dataset can be displayed. This is done to check whether the dataset has been loaded properly. Next the dataset is divided into different classes, say seven classes which has been described. Then the dataset is converted to pytorch data structure. In order to balance the dataset proceed with partial image augmentation. For image augmentation, use keras image generator APIs. All images are augmented and inserted them into a metaframe. Now input the image in a transformed format (Tensor).Split the data into train and test set .Therandom split () inside torch.utlis.data is used to split dataset into 80% training and 20% validation.The pre-trained ResNet 18 model and then Alexnet isutilized and tune it with final output layers matching the requirements. Next the iteration is done, in 32

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layers for 7 classes. The test and validation accuracy and loss is tested. Finally the skin cancer detection is done and identified different classes of skin cancer.

2) Skin Cancer detection using Transfer Learning

Transfer learning is the process by which a model trained for one task is intended for a second related task. The procedure is just similar to that done using ResNet18 and AlexNet. In this work we first trained the histopathological cancer diagnostic dataset (Identify metastatic tumors in histopathology sections of lymph node sections).Using this dataset training and test validation is done to obtain the accuracy. After this the HAM10000 skin cancer dataset is loaded and the information obtained from training the histopathological dataset is transferred into this. Then upgraded the data section, performed the training and the validation of the test, and then gained accuracy. Modeling was done on CNN using Resnet50.

5. Result and Observation

Table1: Accuracy obtained using different models

MODEL	CNN (ResNet18)	AlexNet	Transfer Learning
Test Accuracy	76.3	78.4	88.9
Test Loss	64.3	60.02	7.1
Validation Accuracy	77.3	84.7	91.3
Validation Loss	63.6	56.8	12.1
Total Accuracy	78.03	98.32	96.129

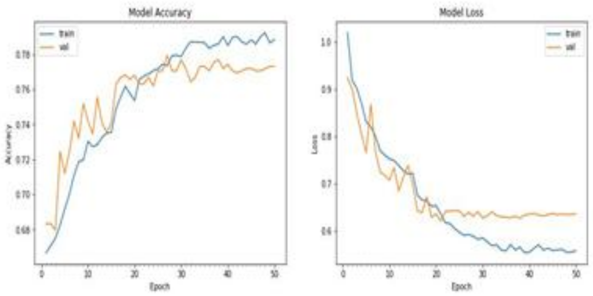

Figure 2: Accuracy and Loss curve of skin cancer detection using ResNet18

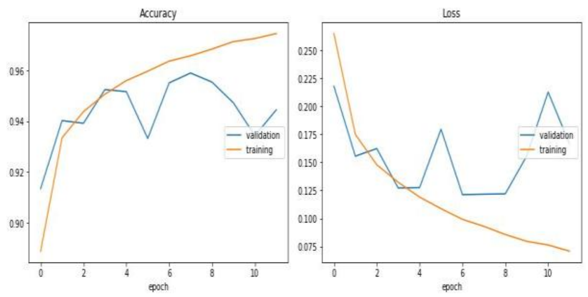

Figure 3: Accuracy and loss curve of skin cancer detection using transfer learning

6. Conclusion

Skin cancer detection can be done using various deep learning models with improved accuracy. This is a comprehensive paper on the diagnosis of skin cancer using Convolutional Neural Networks (CNN) .Another important benefit of CNN is that it detects important features without being monitored by anyone. And different layers on CNN, give more selective results.. Here ResNet18, AlexNet and transfer learning in CNN using ResNet50 was used for skin cancer detection and different accuracies were obtained. The accuracy obtained using ResNet18 was 78.03%, using AlexNet was 98.32% and using transfer learning with ResNet50 was 96.129%.

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