Diagnosis of Skin Cancer using Deep Learning

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Skin diseases consists a wide range of ailments that affect the skin, including microbial infections, viral, fungal, allergies, epidermis malignancies, and parasitic diseases. In South-Asian countries like India people don't care much about the skin conditions. In our country, people prefer home remedies to cure skin conditions instead of visiting a dermatologist which can lead to serious skin conditions. Early diagnosis of skin disease is very important as it can reduce the severity of the condition. Melanoma is the deadliest type of skin cancer, and it is the most prominent form of cancer. Melanoma could be diagnosed early, which would reduce overall illness and death. The odds of dying from the ailment is proportional to the extent of the malignancy, which is proportional to the length of time it has been growing. The keys to early detection are patient self-examination of the skin, full-body skin screenings by a dermatologist, and patient engagement. This work aims to categorize skin cancer into two types: malignant and benign. Two different approaches were used. Starting with a simple Convolutional Neural Network and then moving on to transfer learning. In our experiment, we were able to attain a classification accuracy of 82 percent.

Keywords: Dermatitis, Melanoma, Deep Neural Network, Convolution Neural Network, Transfer Learning.

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1 Introduction

Dermatitis is a disease or abnormal condition of the skin. The term is often used to refer to diseases that do not feature inflammation, because inflammation of the skin is referred to as dermatitis. The Skin diseases encompass a wide range of ailments that affect the skin, including microbial infections, viral, fungal, allergies, epidermis malignancies, and parasitic diseases. In South-Asian countries like India people don't care much about the skin conditions. Instead of visiting a dermatologist people prefers home remedies to cure skin conditions which can lead to serious skin ailments. Early diagnosis of skin disease is very important as it can reduce the severity of the condition. Melanoma is the deadliest type of skin cancer, and it is the most prominent form of cancer. Melanoma develops in the cells (melanocytes) that produce melanin, the pigment that gives human skin its tone. Melanoma can also develop in the eyes and, in exceptional situations, inside the body, such as the nose or throat. Although the specific causes of all melanomas are unknown, ultraviolet (UV) radiation from the sun, tanning rays, and sunbeds enhances the likelihood of developing melanoma. Melanoma risk can be minimized by limiting the exposure to UV light. Melanoma risk rises steeply in people under the age of 40, particularly in women.Knowing the signs and symptoms of skin cancer may probably ensure that malignant changes have been discovered and treated before the disease spreads. Melanoma can be successfully treated if diagnosed early. Melanoma diagnosis at a later stage is linked to a substantial increase in melanoma mortality over 5 years of diagnosis. Melanoma could be diagnosed early, which would reduce overall illness and death. The odds of dying from the ailment is proportional to the extent of the malignancy, which is proportional to the length of time it has been growing. The keys to early detection are patient self-examination of the skin, full-body skin screenings by a dermatologist, and patient engagement. Self-examiners are more likely to have lighter malignant tumors than quasi (0.77 mm versus 0.95 mm). are very promising and show that the proposed algorithm is a competitive algorithm in the field of swarm intelligence-based algorithms.

2 Related Work

The field of image analysis-based melanoma diagnosis has evolved immensely over the years. A variety of strategies have been explored. By organizing a challenging event, the 2018 International Skin Imaging Collaboration (ISIC) program has become an unofficial norm in melanoma diagnosis. A mobile app could also be used to diagnose skin cancer, as per reports. Scholars have applied categorization approaches and procedures to try to improve the diagnosis accuracy in all these endeavours. When Fukushima (1988) and later LeCun(1989) proposed the convolutional neural network (CNN) structure, image categorization hit a record high (1990). CNN's are the ideal state-of-the-art techniques for image categorization as they effectively emulate the human vision cognitive mechanism. We confine the analysis of relevant literature to deep learning approaches for melanoma data, despite the fact that there is a substantial literature on image categorization. Esteva et al. achieved the first success in melanoma categorization that used a pre-trained Google Net Inception V3 CNN model. They evaluated 129,450 clinical radio-graphs of melanoma, comprising 3,374 dermatoscopic images. The reported categorization accuracy is 72.1± 0.9. On the ISBI (International Symposium on Bio-Medical Imaging) 2016 challenge dataset, Yu et al. constructed a CNN including almost 50 layers for the categorization of melanoma malignancy in 2016. In this assignment, the best categorization accuracy was 85.5 percentage. Haenssel et al. used a deep CNN to categorize a binary diagnosis section of dermatoscopy melanoma images, exhibiting 86.6 percent accuracy and precision. Dorj et al. designed a classification task combining (Error-correcting output coding) SVM and deep learning CNN. The method was to categorize multi-class data combining ECOC-SVM and pre-trained Alex-Net Deep Learning CNN. According to the study, the average accuracy is 95.1 percent. Han et al. used a deep convolutional neural network to classify medical images of 12 atopic dermatitis patients. The best categorized performance incident recorded ranged from 96±1 percent. Ali et al. introduced a cloud-based prototype paradigm that incorporates deep learning algorithms in its primary implementations to develop models that support the accurate prediction of melanoma. The work has demonstrated how and where to create the models and why they are needed to categorize dermal cell images. On publicly available data-sets, various deep learning models proposed here have been tested, as well as a quantitative trend-line of 99.77 percentage was achieved.

3 Our Work

We propose a method for detecting the condition early enough in order to prevent the disease from progressing to the next stage. Early detection would allow the skin problem to remain in the benign stage rather than progressing to the malignant stage. We provide a way to find out whether a condition is in the benign or malignant stage rather than consulting any experts nearby.In Asian countries such as India, where people seldom visit a dermatologist. The solution will be cost-effective, so it will not have a major impact on a person's wallet. We are implementing a Deep Learning approach to categorize the images in this work. Skin cancer detection heavily relies on deep neural networks. They are comprised of multiple interconnected nodes. In terms of synaptic connections, their structure is very similar to that of the cerebral cortex. To solve specific issues, its nodes collaborate. Neural networks are intended to perform specialized operations, and then they function as specialists in the disciplines in which they have been programmed. A deep neural network is trained to categorize images and address a variety of melanomas in our experiments. For the diagnosis of skin cancer, we utilize binary classification. We'll take two different approaches. We'll begin with a simple Convolutional Neural Network and then move on to transfer learning. This is primarily to compare the performance of the two models and evaluate how transfer learning can enhance precision while we lack sufficient data. We proposed categorizing the images into 2 categories: benign and malignant. The dataset we used in this research comprised of training dataset of 2637 images separated into two classes: malignant and benign, with a malignant portion of 45 percent and a benign portion of 55 percent, and testing dataset of 660 images separated into two classes: malignant and benign, with a malignant portion of 46 percent and a benign portion of 54 percent.

3.1. Data Preparation

Data preparation was one of the critical steps of our method. Without accurate data, learning is not possible. For data gathering, we have collected data from various sources and kept it in a folder. This folder contains two subfolders with skin disease data of malign and benign cancer. The images of malign and benign cancer have been collected under supervision with a skin doctor and were publicly available. Now that we have data collected into folders, we have to applylearning algorithms to this data. After this step, we can assume that we have completed data libeling. We are aware that deep learning add neural network frameworks have a fixed input size. So we have to write an algorithm that can convert each image to a fixed number of 2-dimensional pixels. While converting into a set number of pixels, it should be kept that the quality of the image should not be compromised; otherwise, learning will be compromised. We have written an algorithm written in Python to resize the images using OpenCV package functions. After we resize all pictures, we have to exclude those images which have lost their quality. After performing all the above steps, our data is prepared for further learning.Figure 1 Shows approach of our method.

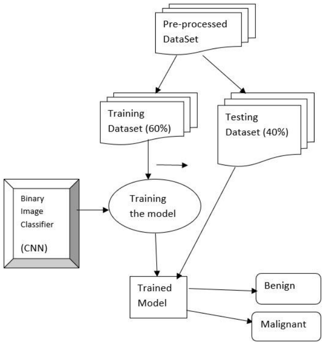

Fig. 1. Data Preparation

3.2. Learning from Data

We have proposed learning to form the skin data that we have collected and cleaned as discussed in Figure 1. To learn from the skin cancer dataset, which is pictorial in nature, we propose a Convolutional neural network (CNN) for learning patterns hidden in the data. We suggest the following steps data set is divided into training and testing data set and validation data set. Different percentage combinations are used in our experiment. Due to our data's quantity and availability, we have taken a 60-40 ratio for training and testing data sets. This ratio is decided after trying various ratios. The experiment is set up on the Kaggle server. We have used different epoch and got different results. The learning model is taken from home by the combination of the varying epoch that gives good results on validation data set as well as unknown data sets. The architecture of the method is discussed in Figure 2.In this architecture of our approach, we have taken pre-processed data set 10 divided it into training and testing data set. This data set has been fed into a binary image classifier which is based on a Convolutional neural network. It generates a trained model which can classify between Malign and benign skin disease cancer conditions. After testing, it is proven that this method works for unknown images and classifiers correctly on more than 80% of unrelated images. However, efficiency increases if the quality of images matches with pictures in the collected data set.

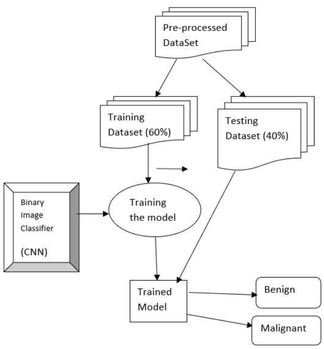

Fig. 2. Architecture Proposed Solution

4 Results

The images from the dataset were categorized into the Training and Testing dataset. 60 percent of the images were used as the training dataset and remaining 40 percent images were used as the trainingdataset.The Binary Image Classifier of CNN(Convolutional Neural Network) has been used and after the training and testing of the model the images are classified into two categories:benign and malignant. The number of Epochs, Training loss, Training accuracy, Validity loss, Validity accuracy and Learning rate of the dataset based on our algorithm is shown in the table. Starting with a simple Convolutional Neural Network and then Moving to Transfer Learning,We were able to attain a classification accuracy of 82 percent.

Table 1. Table of Results

Epochs	Training Loss	Training Accuracy	Validity Loss	Validity Accuracy	Learning Rate
13	.3719	.8194	.4194	.8045	.001
15	.3628	.8230	.3815	.8091	.002
20	.3668	.8223	.3815	.8136	.003
23	.3583	.8343	.3899	.8227	.003
23	.3770	.8325	.3472	.8409	.004
25	.3557	.8391	.4469	.8061	.003
25	.3724	.8192	.3707	.8303	.004
30	.3324	.8447	.4021	.8015	.003
35	.3348	.8492	.4208	.8197	.003
40	.3338	.8462	.3584	.8288	.002
45	.3395	.8429	1.02	.6591	.001

5 Conclusion

Our method detects the intensity of cancer and helps patients save their lives and medical expenses. Our approach is scalable and reaches places where the doctor is not available. Since we will be implementing the cloud-based approach, it will Reach everywhere, and continuous Improvement is possible as we collect more and more data sets. As more users will be added to the system, More and more data will be collected, and Improvement in the system is guaranteed. Our work opens the scope of future work for upcoming researchers to improve their performance—using the mix of object detection algorithms from image processing and deep learning methodology was suggested by us in the paper.

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