JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

SKIN CANCER DETECTION WITH DEEP LEARNING USING WEB API

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***Abstract* : Skin cancer is a major concern for global health as there is an increase in the number of cases day by day with 123,000 incidences of melanoma and 30,000 cases of non-melanoma cases worldwide per year. High UV radiation exposure has been identified as a major risk factor for skin cancer in recent research. Early detection of skin lesions is the most effective strategy to lower the death rate from skin cancer because melanoma patients have a 99 percent five-year survival probability when discovered and screened at the early stage. The inability of dermatologists to diagnose skin cancer accurately has necessitated the development of an automated, efficient method.**

The purpose of this paper is to offer a means by which anyone can profit by uploading an image of a lesion to our web API to determine whether or not it is a melanoma or a skin cancerous lesion. This work investigates an efficient automated system for classifying skin cancer with better evaluation criteria compared to past studies or skilled physicians. Without computer aid, a qualified dermatologist's physical melanoma detection accuracy ranges from 50-70 %. The ResNext model, which was adjusted on roughly more than 1 million images from the ImageNet Challenge, was utilized. It was transfer-learned using 10015 dermoscopy images from the HAM10000 dataset. For the seven classes in the dataset, the model used in this paper had an accuracy of 89.1 percent. Anyone can obtain a rudimentary diagnosis of their skin lesions and determine whether or not they are among one of the seven classes of skin cancer, using the created web API.

Keywords – **Tensor Flow, HAM10000 Dataset, Melanoma, Skin Cancer, ResNext architecture, Deep Learning, Node.js, Web Development**

I. INTRODUCTION

Given the rising incidence of harmful UV rays in the environment, skin cancer is a growing global health concern. An additional 10% reduction in the ozone layer, according to the study, will make the issue worse**.** With an additional 300,000 non-melanoma cases and 4,500 melanoma cases per year of skin cancer [1]. Currently, 310,000 non-melanoma cases and 123,000 melanomas are reported each year globally**.** According to a recent research on the prevention of skin cancer, excessive UV radiation exposure is to blame for 86 percent of melanoma occurrences and 90% of non-melanoma instances.

The DNA in the inner layers of skin is damaged by UV radiation, which causes unchecked cell development that could eventually lead to skin cancer. The simplest and most successful way to reduce the mortality rate from skin cancer is to promptly diagnose it, as melanoma patients have a 99 percent five-year survival probability when they are identified and tested at an early stage. Furthermore, when detected early and given the appropriate care, the most common skin cancer kinds, BCC and SCC [2] are very curable. Due to the visual similarity of skin malignancies, dermatologists generally use visual inspection to diagnose them, which is a difficult process.

However, due to its capacity to precisely visualise skin lesions[3] that are invisible to the unaided eye, dermoscopy has recently gained popularity for the diagnosis of skin cancer.

Clinical dermatologists' diagnosis accuracy has been reported to be 80 percent for those with more than ten years of expertise, compared to just 62 percent for those with three to five years of experience. The accuracy is further decreased for dermatologists with less experience.

According to studies on dermoscopy, it is imperative to create an automated, reliable, and efficient system for the diagnosis of skin cancer since inexperienced dermatologists run the risk of decreasing the diagnostic adequacy of skin lesions[4]. Deep learning algorithms have demonstrated excellent performance in visual tasks and even surpassed people in video games, such as Go[5], Atari, and object identification, despite the method's complexity. This has inspired research on automated skin cancer detection. The automated classification of skin cancer based on Deep Learning has been compared to dermatologist-level classification in a number of studies. Deep Neural Networks (DNNs), which were designed to address the shortcomings of earlier models, have become more popular in recent years.

DNNs have an appealing effect on medical image classification even if they need a lot of data for training. Transfer learning is frequently used in recent work to address problems involving large datasets. Transfer learning is a technique where a model that has been trained on a task that is similar to the one at hand is adjusted for it. The majority of melanoma screening methods that use DNNs either transfer knowledge from ImageNet or train a network from scratch. The most popular framework is Caffe, while the most popular architectures are ResNet, AlexNet, and VGG-16. The key distinction between them is the DNN architecture and implementation framework[6]. Dermoscopic automatic skin cancer classification hasn't produced particularly satisfying results in the past due to a lack of generality capabilities. Dermoscopy skin lesion image classification using an automated system.

We used a ResNext convolutional neural network that was fine-tuned using the HAM10000 dataset, which contains 10015 dermoscopy images, and pre-trained on roughly 1 million images from the ImageNet Challenge. For seven classes, the ResNEXT model classified skin lesion images with accuracy that was higher than or on par with that of board-certified dermatologists. Additionally, we performed data analysis on dermoscopy images of skin cancer from the HAM10000 dataset to identify the relationship between skin cancer and various parameters and to better understand skin cancer.

II. MOTIVATION

Considering that skin cancer is the most common kind of cancer. Despite being the least common skin cancer, melanoma specifically is to blame for 75% of skin cancer fatalities. Melanoma is a fatal condition, but the majority of cases can be treated with a simple surgery if detected early. Dermatologists will be more accurate at melanoma detection with the aid of image analysis tools. Millions of people can benefit from improved melanoma detection. Designing interventions to promote these behaviours requires taking into account the factors that influence the adoption of preventive behaviours that can lower the risk of skin cancer.

III. MODEL DESIGN

For medical imaging informatics, we have obtained the dataset from a hospital organisation. For the purposes of this study's training and validation, we used the HAM10000 Dataset. Over 50% of lesions in the benchmark dataset HAM10000 had pathological confirmation. The dataset consists of 10015 dermoscopy images in total, including 6705 images of melanocytic nevi, 1113 images of melanoma, 1099 images of benign keratoses, 514 images of basal cell carcinoma, 327 images of actinic keratoses, 142 images of vessels, and 115 images of dermatofibromas with a resolution of 600 x 450 pixels.

Fig 1. Sample images from HAM10000 dataset for cancer types (a) Actinic Keratosis (b) Basal Cell Carcinoma (c) Benign Keratosis (d) Dermatofibroma (e) Melanocytic nevi (f) Melanoma (g) Vascular Lesions

Images of skin lesions were pre-processed using Keras ImageDataGenerator [6]. The mean filling approach [7] was used to fill the 57 null Age entries in the dataset. To make them compatible with the ResNEXT[8] model, the Dermoscopy images in the dataset were downscaled from 600X450 pixels to 224X224 pixels . The dataset's 10015 photos were divided into a training set (9077 images) and a validation set (938 images). In order to ensure the validity of the validation process, the validation set was chosen from the dataset photos that did not duplicate any training data[9][10].

Shuffling the rows and training on only a subset of them during a given iteration, X changes with every iteration, It is actually quite possible that no two iterations over the course of the training epochs and iterations will be carried out on the exact same X. The result is that the solver can quickly "bounce" out of a local minimum; this problem can be resolved by shuffling the dataset[11].

The typical algorithm for stochastic gradient descent, albeit there are various variations of the technique, like Adam, is supplied by the SGD class. Enumerating the DataLoader[12] for the training dataset is a step in the model-training process. A loop is first necessary for the quantity of training epochs. Then an inner loop is required for the mini-batches for stochastic gradient descent.

An early stopping condition was set for the model. The model used ResNext architecture for Deep Neural Network. The early stopping condition made sure that the model doesn't keep running forever and we get the best results out of our model. The early stopping condition was that if in 5 consecutive epochs, there is no improvement in the accuracy then the model is saved with .bin architecture.

We created a web application using Node.js. Then we initialized our application and then loaded the "model.bin" file to the application. Define the app route for the default page of the web-app.after this, redirecting the API to predict the cancerous or not result. You can simply type "localhost:8080″ on your web browser to open your web-application after running node application.

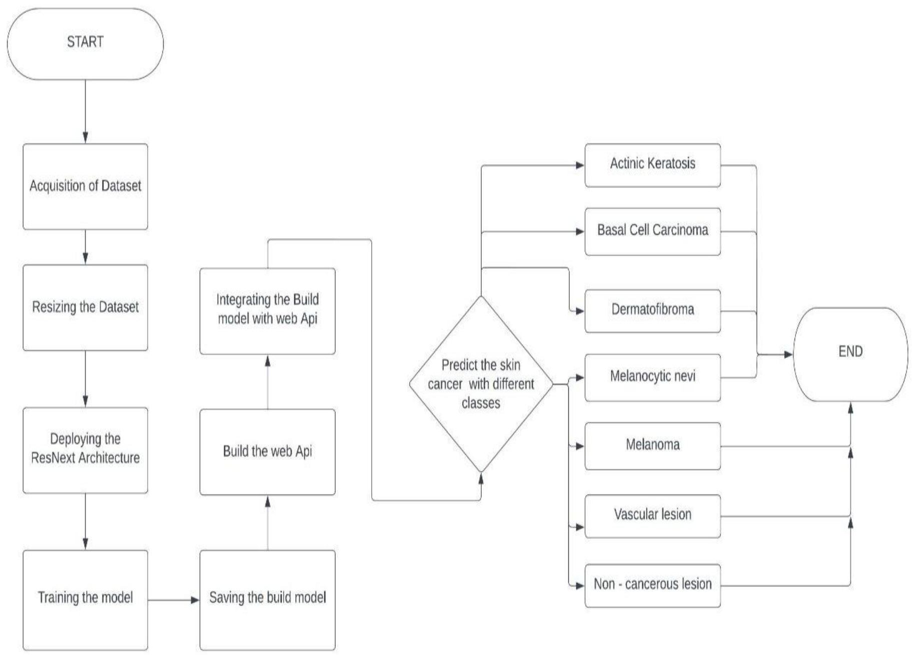


Figure 2: Methodology Flowchart

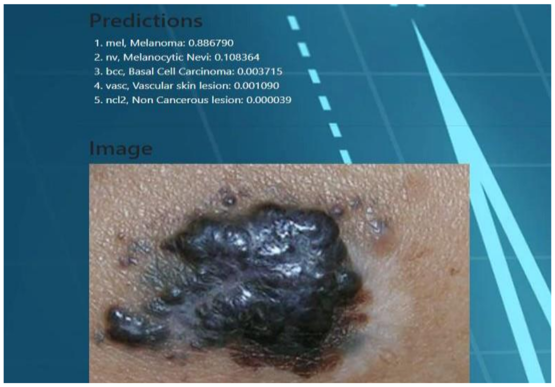
IV.RESULT

An interactive API which uses the machine learning model, takes a photograph of skin lesions as an input from the user and use the above model to predict melanoma. A web application was developed which the makes use of the saved dataset to predict the nature of the skin images with respect to skin cancer. The web application can be used to find out 7 different types of cancers. The name of these cancers is solar keratosis, Basal cell carcinoma, Benign Keratoses, Dermatofibroma, Melanoma, Melanocytic Nevi and Vascular Skin lesion. The web application can be used in 4 easy steps which include Opening the application, selecting the model, uploading the image from the device and then clicking on predict to get the results. The prediction gives the result in a range from 0 to 1, The Prediction value '0' being that the skin image does not correlate with any of the 7 classes of skin cancers and the closer value is to 1 the more likely it is a skin cancer of that type.

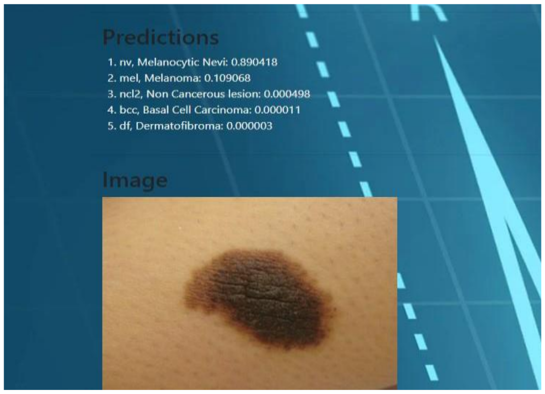
We have taken 7 skin cancer images during the testing. These images have been acquired from multiple trusted sources to cross check the model accuracy. And these sources are:

i. Melanoma- Image source is cancer.org Provide by Dr. Richard P. Usatine
Recognition rate of the web API- 88.6%
ii. Melanocytic Nevi – Image source is dermatologyadvisor.com Provided by Dr. Kara N. Shah
Recognition rate of the web API- 89.06%
iii. Actinic Keratosis- Image source is MSD Manual Professional.com Provided by Dr. P. Marzzi
Recognition rate of the web API- 86.35%
iv. Basal Cell Carcinoma- Image source is cancer.org Provided by Richard P. Usatine
Recognition rate of the web API- 99.99%
v. Dermatofibroma- Image source is medical.net Provided by Dr. Samuel Weinberg, Neil S. Prose
Recognition rate of the web API- 55.54%
vi. Burnt Skin Image – Image source is Google
Recognition rate of the web API- 69.47%

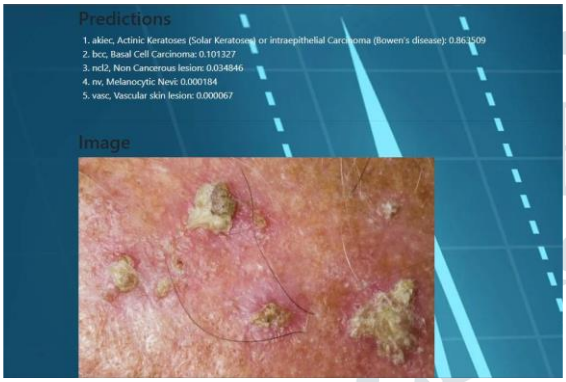
vii. Vascular Skin lesion- Image source is uchicago.edu
Recognition rate of the web API- 55.56%



(a). Melanoma

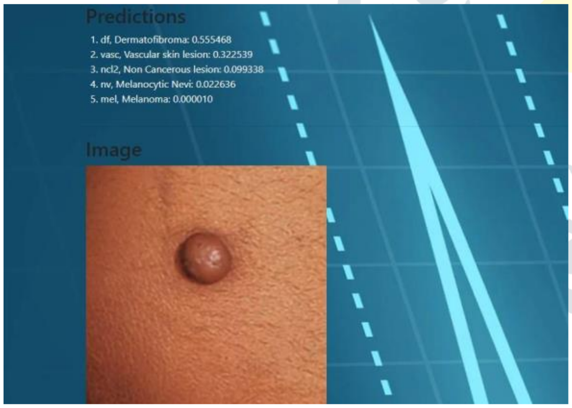


(b). Melanocytic Nevi



(c). Actinic Keratosis

(d). Basal Cell Carcinoma



(e). Dermatofibroma

(f). Burnt Skin

(g). Vascular Skin Lesion

Figure 3: Skin Cancer Images with results from the web API

In the results mentioned in Fig 3 (a). The achieved results coincided with the diagnosis of Dr. Richard P. Usatine i.e. The Web API using the Deep Learning model predicted that the lesion present in the image resembles a Melanoma with 88.6% resemblance. And the second-best result was that the lesion resembles a melanocytic nevi with 10.8%. The other results are non-significant

In the results mentioned in Fig 3 (b). The achieved result coincides with the diagnosis of Dr. Kara N. Shah i.e. The Web API using the Deep Learning model predicted that the lesion present in the image resembles a Melanocytic Nevi with 89.04% resemblance. And the second-best result was that the lesion resembles a melanoma with 10.9%. The other results are non-significant.

In the results mentioned in Fig 3 (c). The achieved result coincides with the diagnosis of Dr. P. Marzzi i.e. The Web API using the Deep Learning model predicted that the lesion present in the image resembles a Actinic Keratosis with 86.35% resemblance. And the second-best result was that the lesion resembles a Basal cell carcinoma with 10.10%. The other results are non-significant.

In the results mentioned in Fig 3 (d). The achieved result coincides with the diagnosis of Dr. Richar P. Usatine i.e. The Web API using the Deep Learning model predicted that the lesion present in the image resembles a Basal Cell Carcinoma with 99.99% resemblance. And the second-best result was that the lesion resembles a Actinic Keratosis with 0.006%. The other results are non-significant.

In the results mentioned in Fig 3 (e). The achieved results are somewhat similar with the diagnosis of Dr. Samuel Weinberg, Neil S. Prose i.e. The Web API using the Deep Learning model predicted that the lesion present in the image resembles a Dermatofibroma with 55.54% resemblance. And the second-best result was that the lesion resembles a Vascular skin lesion with 32.22%. The other results are non-significant.

In the results mentioned in Fig 3 (f). The achieved result coincides with the results provided by google i.e. The Web API using the Deep Learning model predicted that the lesion present in the image resembles a Non-Cancerous Lesion with 69.47% resemblance. And the second-best result was that the lesion resembles Melanocytic Nevi with 11.73%. The other results are non-significant.

In the results mentioned in Fig 3 (g). The achieved results are somewhat similar with the source of the image i.e. The Web API using the Deep Learning model predicted that the lesion present in the image resembles a Vascular Skin Lesion with 55.56% resemblance. And the second-best result was that the lesion resembles a Non-Cancerous Skin lesion with 24.48%. The other results are non-significant.

The web API was able to classify and predict the different types of skin cancers.

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