A Method of Skin Disease Detection using Machine Learning

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***Abstract* - Skin diseases may be caused by fungal infection, bacteria, allergy, or viruses, etc. The advancement of lasers and Photonics based medical technology has made it possible todiagnose the skin diseases much more quickly and accurately, but the cost of such diagnosis is limited while it costs high. This can be solved with the application of automated methods that will help in early diagnosis especially with the set of images with variety of diagnosis.**

This work contributes in the research skin disease detection with the objective to Identify unique skin problems using image input with high accuracy, which will be useful for places with less clinical expertise. Our proposed approach is simple and fast. Our model presents a completely automated system of dermatological disease recognition through lesion images. The approach works on the resize of the image to extract features using pretrained model (VGG 16). The VGG16 model was tested on the dataset to classify 6 types of skin cancer such as akiec, vasc, df, mel, bkl, bcc, nv. The pre-trained model of VGG16 has given a novel result of 94% accuracy compared to the other CNN or DNN models used in the different researches which provides the accuracy of 75 to 90%

Using VGG16 which is unique property of having a smaller number of hyper-parameters, which focus on having convolution layers of 3 x 3 filter with a stride 1 and always uses the maxpool layer of 2 x 2 filter of stride 2 that helps the model to be more compact.

I. INTRODUCTION

Skin disease contribute 1.79% trusted source of the global burden of disease worldwide. The American Academy of Dermatology Association reports that 1 in4 people have a skin disease. [1]

Skin cancers including melanoma, basal cell carcinoma and squamous cell carcinoma often start as changes to your skin. They can be new growths or precancerous lesions changes that are not cancer but could become cancer over time. An estimated 40% to 50% of fair-skinned people who live to be 65 will develop at least one skin cancer. Skincancer can be cured if it's found and treated early.

While learning to tell one condition from another can help a person provide home care,it can be crucial to receive a diagnosis and treatment from a health care professional, such as a dermatologist. [2]

The approach here is with VGG16, Softmax and ReLU and NADAM.

ReLU has constant derivative. That make is very good for deep neural network which suffers from vanishing and explosion gradient when the gradient of the activation function is not constant because the gradient of a layer gets multiplied by the gradient of the next layer when you back-propagate it so that make it gets larger exponentially thus we call it exploding gradient if the gradient is bigger than one (thus not constant) or it will gets smaller exponentially thus we call it vanishing when the gradient is less than one. It is not differentiable on zero which makes not the very good choice when you want to output a continuous function. But it is much more powerful when you what just to extract features of pattern recognition.

NADAM have faster computation time, and require fewer parameters for tuning.

II. RELATED WORK

Several researchers have proposed image processing-based techniques to detect the typeof skin diseases. Here we briefly review some of the techniques as reported in the literature.

In [3], a system is proposed for the dissection of skin diseases using colour images without the need for doctor intervention.

The system consists of two stages, the first the detection of the infected skin by uses colour image processing techniques, k-means clustering and colour gradient techniques to identify the diseased skin and the second the classification of the disease type using artificial neural networks. The system was tested on six types of skin diseases with average accuracy of first stage 95.99% and the second stage 94.016%.

In the method of [4], extraction of image features is the first step in detection of skin diseases. In this method, the greater number of features extracted from the image, betterthe accuracy of system. The author of [4] applied the method to nine types of skin diseases with accuracy up to 90%.

In [5], a new approach is proposed to detect skin diseases, which combines computer vision with machine learning. The role of computer vision is to extract the features fromthe image while the machine learning is used to detect skin diseases. The system was tested on six types of skin diseases with accurately 95%.

III. HUMAN IMPACT

Generally, doctors diagnose skin problems by looking at the current conditions of the skin. For other problems, they will use tests like biopsy. Biopsy for the skin cancer includes examination skin, including scalp, ears, palms, feet, between the toes, around the genitals. If a skin lesion is suspicious, a biopsy may be performed. In a biopsy, a sample of tissue is removed and sent to a laboratory to be examined under a microscope by a pathologist. The dermatologist will tell if the skin lesion is skin cancer, what type of cancer one has and discuss treatment options which may take a longer time than expected.[6]

This may take few hours or days as even the simplest test like patch test/lesion test takesnearly 48 hours with chemical patch left on the skin. Various chemicals may react with some types of skin that may lead to few side effects like itchiness redness in skin, etc which may further cause severity in the disease.

To avoid these side effects and produce speedy results with high accuracy, the belowmentioned model is designed. The model takes the image of the patch as input and recognizes the skin disease within minutes.

IV. DESCRIPTION OF THE DATA SET

The HAM10000 training set includes pigmented lesions from different populations. Theimage set consists of lesions of patients who has early detection of melanoma in high- risk groups. This group of patients often have a high number of nevi and a personal or family history of melanoma. It also includes lesions from patients of a primary care facility in a high skin cancer incidence area. Chronic sun damaged skin is characterized by multiple solar lentigines and ectatic vessels, which are often present in the periphery of the target lesion. Very rarely also small angiomas and seborrheic keratoses may collide with the target lesion. We did not remove this "noise" and we also did not remove terminal hairs because it reflects the situation in clinical practice.

In most cases, albeit not always, the target lesion is in the center of the image. Dermatoscopic images of both study sites were taken by different devices using polarized and non-polarized dermatoscopy. The set includes representative examples of pigmented skin lesions that are practically relevant. More than 95% of all lesion encountered during clinical practice will fall into one of the seven diagnostic categories.In practice, the task of the clinician is to differentiate between malignant and benign lesions, but also to make specific diagnoses because different malignant lesions, for example melanoma and basal cell carcinoma, may be treated in a different ways and time frame. With the exception of vascular lesions, which are pigmented by hemoglobinand not by melanin, all lesions have variants that are completely devoid of pigment (for example amelanotic melanoma). Non-pigmented lesions, which are more diverse and have a larger number of possible differential diagnoses, are not part of this set.

V. DESCRIPTION OF CLASSES:

akiec: Actinic Keratoses (Solar Keratoses) and Intraepithelial Carcinoma (Bowen’s disease) are common non-invasive, variants of squamous cell carcinoma that can be treated locally without surgery. Some medical books referred them as precursors of squamous cell carcinomas and not as actual carcinomas. There is, however, agreement that these lesions may progress to invasive squamous cell carcinoma – which is usuallynot pigmented.

Bcc: Basal cell carcinoma is a common variant of epithelial skin cancer that rarely metastasizes but grows destructively if untreated. It appears in different morphologic variants (flat, nodular, pigmented, cystic), which are described in more detail by Lallas et al.

Bkl: "Benign keratosis" is a generic class that includes seborrheic keratoses ("senile wart"), solar lentigo - which can be regarded a flat variant of seborrheic keratosis - and lichen-planus like keratoses (LPLK), which corresponds to a seborrheic keratosis or a solar lentigo with inflammation and regression. The three subgroups may look differentdermatoscopically, but we grouped them together because they are similar biologically and often reported under the same generic term histopathologically. From a dermatological view, lichen planus-like keratoses are especially challenging because they can show morphological features mimicking melanoma and are often biopsied or excised for diagnostic reasons.

Df: Dermato fibroma is a benign skin lesion regarded as either a benign proliferation or an inflammatory reaction to minimal trauma. The most common dermatoscopic presentation is reticular lines at the periphery with a central white patch denoting fibrosis28.

Nv: Melanocytic nevi are benign neoplasms of melanocytes and appear in a myriad of variants, which all are included in our series. The variants may differ significantly from a dermatoscopic point of view. In contrast to melanoma, they are usually symmetric with regard to the distribution of color and structure.

Mel: Melanoma is a malignant neoplasm derived from melanocytes that may appear in different variants. If excised in an early stage it can be cured by simple surgical excision.Melanomas can be invasive or non-invasive (in situ). We included all variants of melanoma including melanoma in situ, but did exclude non-pigmented, subungual, ocular or mucosal melanoma.

Melanomas are usually, albeit not always, chaotic, and some melanoma specific criteria depend on anatomic site.

Vasc: Vascular skin lesions in the data set range from cherry angiomas to angiokeratomas and pyogenic granulomas. Hemorrhage is also included in this category.

Angiomas are dermatoscopically characterized by red or purple color and solid, well circumscribed structures known as red clods or lacunes.

The number of images in the data sets does not correspond to the number of unique lesions, because we also provide images of the same lesion taken at different magnifications or angles.[4]

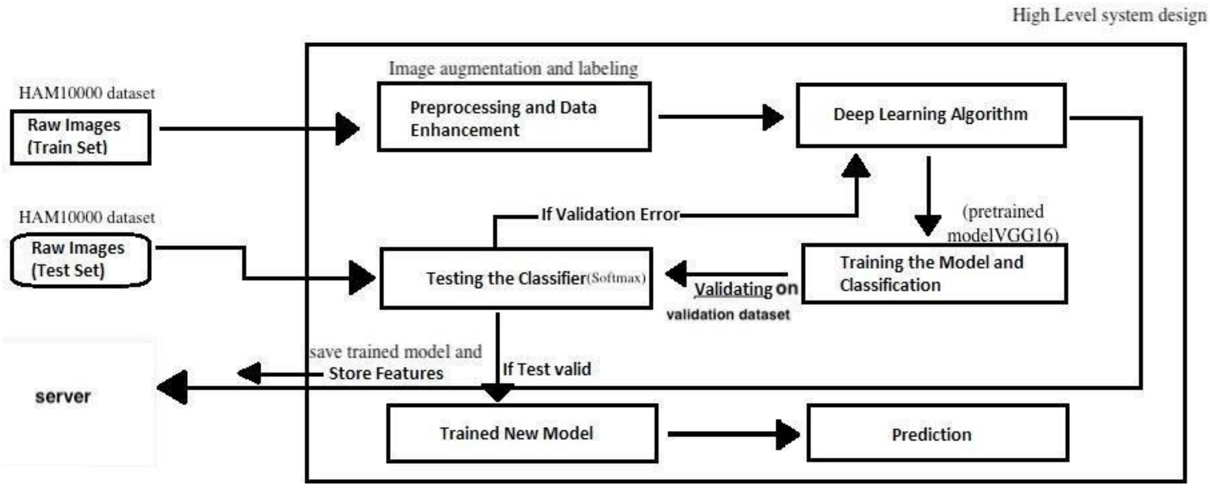

Figure 1a: The proposed system block diagram

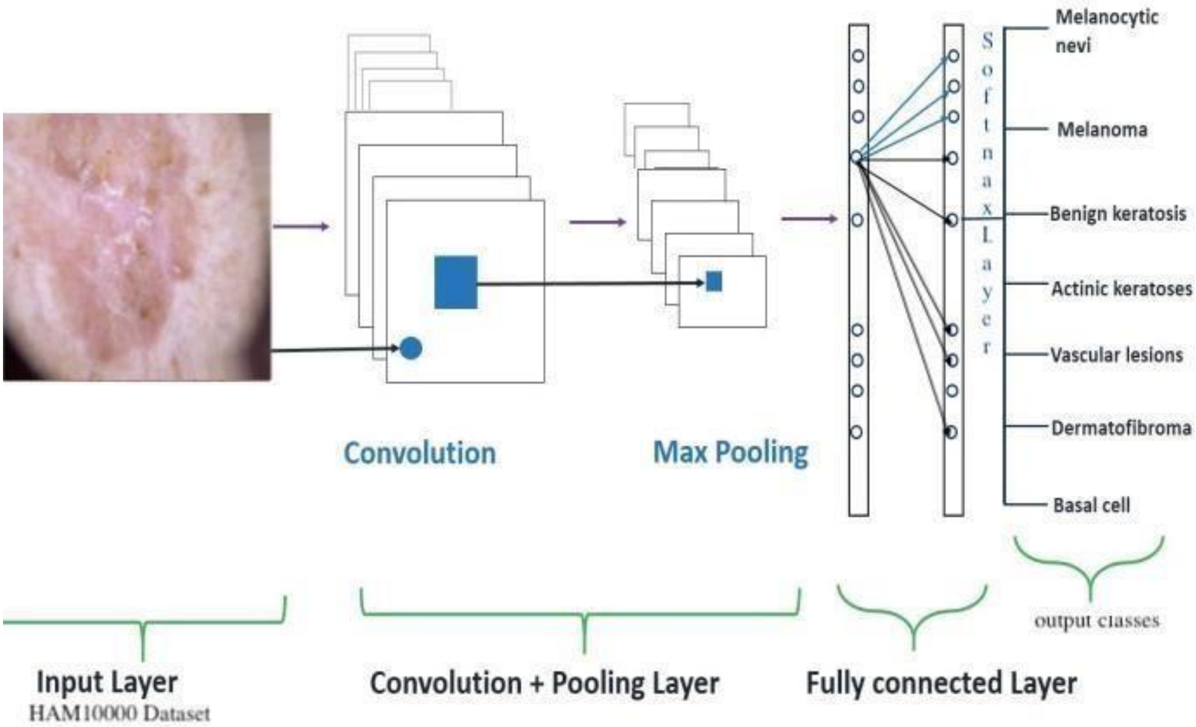

Figure 1b: Components of VGG16

VI. PRE-PROCESSING AND DATA PREPARATION

There were originally *10012* data present in the data set HAM10000 which was biasedtowards akiec class. Data augmentation techniques may be a good tool against challenges which artificial intelligence world faces.

S.no	Class	Data Count
1.	nv	6705
2.	mel	1113
3.	df	115
4.	bkl	1099
5.	vasc	142
6.	akiec	327
7.	bcc	514

Table 1: Data count of classes before augmentation

Data augmentation is useful to improve performance and outcomes of machine learning models by forming new and different examples to train datasets. If dataset in a machine learning model is rich and sufficient, the model performs better and more accurate.

For machine learning models, collecting and labeling of data can be exhausting and costly processes. Transformations in datasets by using data augmentation techniquesallow companies to reduce these operational costs.

VII. DATA AUGMENTATION

One of the steps into a data model is cleaning data which is necessary for high accuracy models. However, if cleaning reduces the representability of data, then the model cannot provide good predictions for real world inputs. Data augmentation techniques enable machine learning models to be more robust by creating variations that the model may see in the real world.[6]

So, the data was augmented using r*otation*, *flip and shifts* so as to increase the size of thedata set to *42650 images* and the image was *resized to 64px X 64px from 600px X 450px.*

Given below is the table that gives the number of data present in each class after augmentation:

S.no	Class	Train Data	Test Data
1.	nv	5364	1341
2.	mel	5208	1302
3.	df	5025	1256
4.	bkl	5012	1253
5.	vasc	4903	1226
6.	akiec	4485	1121
7.	bcc	4125	1031

Table 2: Data count of classes after augmentation

The data is labelled using the metadata file and the meta data file is updated with the name of augmented data also. The data was split into training, validation and test sets.

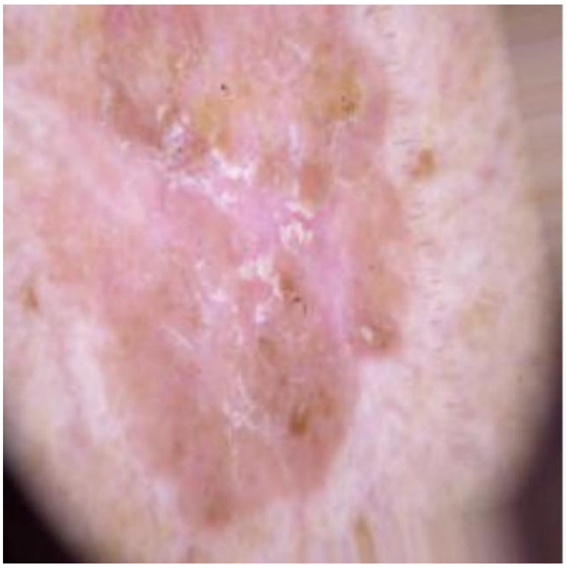

Figure 2: Example of original image of Ham10000 database

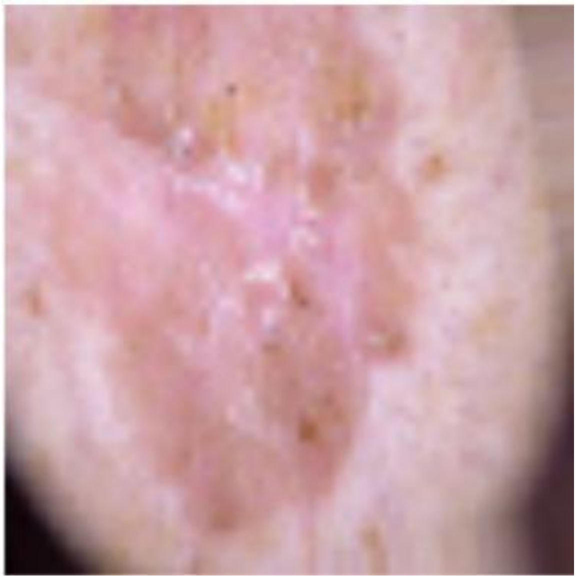

Figure 3: Example of resized image of Ham10000 database

VIII. METHODOLOGY

- Feature Extraction

At the beginning, Convolutional Neural Network (CNN) is a set of stacked layers involving both nonlinear and linear processes. These layers are learned in a joint manner. The main building blocks of any CNN model are: convolutional layer, pooling layer, nonlinear Rectified Linear Units (ReLU) layer connected to a regular multilayer neural network called fully connected layer, and a loss layer at the backend. CNN is known for its significant performance in applications as the visual tasks and natural language processing.[7]

- About the model

VGG16 is a convolutional neural network model proposed by K. Simonyan and A. Zisserman. It consists of *16 convolutional layers* and is very appealing because of it's very uniform Architecture. it has only 3x3 convolutions, but a lot of filters. It can betrained on 4 GPUs for 2–3 weeks. It is currently the most preferred choice in the community for extracting features from images. The weight configuration of the ImageNet is publicly available and has been used in many other applications and challenges as a baseline feature extractor.

VGG can be achieved through transfer Learning. In which the model is pretrained on adata set and the parameters like *epoch (3), optimizer (NADAM), loss function (categorical crossentropy)* are updated for better accuracy and you can use the parameters values. The performance metrics considered was *accuracy* and the other performance metrics like *confusion matrix, Precision-recall and F1 score* were given.

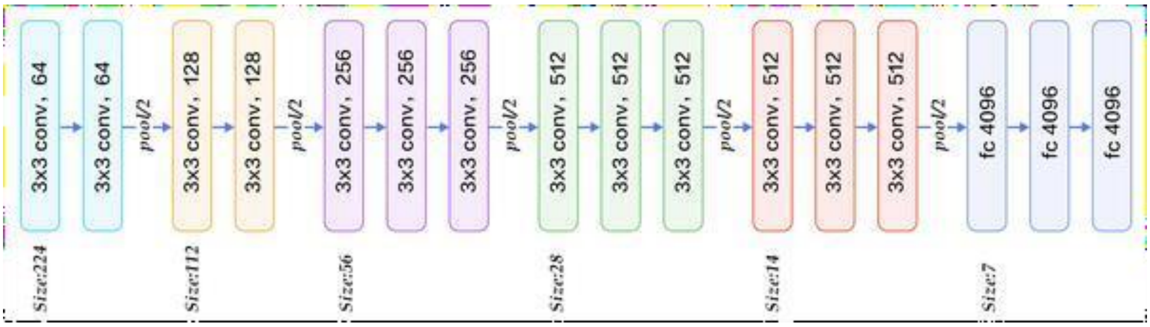

Figure 4: VGG16 Layers [8]

Additionally, *4 dense layers of 512,256,64 and 7 neurons* each are used with *ReLU and Softmax activation functions along with 2 dropout layers and lr=.0001. One hot encoder*is used for conversion of image into arrays.

- **End to End Model Description**

Figure 5: End-to-end Flowchart of the model

IX. RESULT

The model was tried with ADAM and RMSPROP optimizer but NADAM could achieve the accuracy of 94.14% during training, 92.05% during validation and 92.64% during testing. When comparing to models done using MobileNet V2 and LSTM which has the accuracy of nearly 85.34% and the precision which was below 80%.

	precision	recall	f1-score	support
0	0.97	0.95	0.96	1073
1	0.95	0.94	0.94	987
2	0.85	0.90	0.87	1205
3	0.98	0.98	0.98	1198
4	0.97	0.84	0.90	1248
5	0.83	0.90	0.86	1341
6	0.98	0.98	0.98	1169
accuracy			0.93	8221
macro avg	0.93	0.93	0.93	8221
weighted avg	0.93	0.93	0.93	8221

Figure 6: Result: Confusion matrix, Precision - Recall and F1 score

REFERENCES

[1] Melanoma Skin cancer detection using Image Processing and Machine Learning, Vijayalakshmi M M, *International Journal of Trend in Scientific Research and Development*, Volume:3, Issue:4 May-Jun 2019

[2] www.cancercenter.com/cancer-types/skin-cancer/diagnosis-and-detection

[3] 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.*

[4] Yasir, R., Rahman, A., & Ahmed, N. (2014) “Dermatological Disease Detectionusing Image Processing and Artificial Neural Network. “Dhaka*: International Conference on Electrical and Computer Engineering.*

[5] Kumar, V., Kumar, S., & Saboo, V. (2016) “Dermatological Disease DetectionUsing Image Processing and Machine Learning.” IEEE.

[6] https://my.clevelandclinic.org/health/diseases/15818-skin-cancer

[7] Krizhevsky, A., ILYA, S., & Geoffrey, E. (2012) “ImageNet Classification with Deep Convolutional Neural Networks.” Advances in Neural Information ProcessingSystems.

[8] https://www.nature.com/articles/sdata2018161