Skin Lesion Analyser: An Efficient Seven-Way Multi-Class Skin Cancer Classification Using MobileNet

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Abstract. Skin cancer, a major form of cancer, is a critical public health problem with 123,000 newly diagnosed melanoma cases and between 2 and 3 million non-melanoma cases worldwide each year. The leading cause of skin cancer is high exposure of skin cells to UV radiation, which can damage the DNA inside skin cells leading to uncontrolled growth of skin cells. Skin cancer is primarily diagnosed visually employing clinical screening, a biopsy, dermoscopic analysis, and histopathological examination. It has been demonstrated that the dermoscopic analysis in the hands of inexperienced dermatologists may cause a reduction in diagnostic accuracy. Early detection and screening of skin cancer have the potential to reduce mortality and morbidity. Previous studies have shown Deep Learning’s ability to perform better than human experts in several visual recognition tasks. In this paper, we propose an efficient seven-way automated multi-class skin cancer classification system having performance comparable with expert dermatologists. We used a pretrained MobileNet model to train over HAM10000 dataset using transfer learning. The model classifies skin lesion image with a categorical accuracy of 83.1 percent, top2 accuracy of 91.36 percent and top3 accuracy of 95.34 percent. The weighted average of precision, recall, and f1-score were found to be 0.89, 0.83, and 0.83 respectively. The model has been deployed as a web application for public use at (https://saketchaturvedi.github.io). This fast, expandable method holds the potential for substantial clinical impact, including broadening the scope of primary care practice and augmenting clinical decision-making for dermatology specialists.

Keywords: Skin Cancer, Dermoscopy, Image Classification, Convolutional Neural Network.

1 Introduction

Skin cancer is the vital form of cancer contributing to 123,000 newly diagnosed melanoma cases and around 3 million non-melanoma cases worldwide each year [1]-[5]. Melanoma, Basal cell carcinoma, and Squamous cell carcinoma are the prime skin cancer malignancy. About 90 percent of non-melanoma and 86 percent of melanomas skin cancers are caused by exposure to ultraviolet (UV) radiation [6], [7]. The UV radiation
can detriment the DNA present at the inner layers of skin leading to uncontrolled growth of skin cells emerging in skin cancer [8]. Skin cancers incidence has been increasing over the past decades. As ozone levels are evacuated, the atmosphere loses more and more of its protective filter function, and more solar UV radiation reaches the Earth's surface. It has been evaluated that a further 10 percent decline in ozone levels will result in an additional 300,000 non-melanoma and 4,500 melanoma skin cancer cases [5].

Early detection and screening of skin cancer have the potential to reduce mortality rate of skin cancer. The five-year survival rate for melanoma patients when detected and treated before it unfurl to the lymph nodes is 99 percent [9], [10]. Basal cell and squamous cell carcinomas, the two most mundane forms of skin cancer, are highly curable if detected early and treated adequately [9], [11]. Skin cancer is primarily diagnosed by a dermatologist using visual inspection. Dermoscopy is a non-invasive diagnostic technique for evaluation of pigmented and non-pigmented lesions on the skin which are not discernible by examination with the naked eye. Reports on diagnostic accuracy of clinical dermatologist have claimed 80 percent diagnostic accuracy for a dermatologist with experience greater than ten years, whereas the dermatologists with experience of 3-5 years were able to achieve diagnostic accuracy of only 62 percent, the accuracy further dropped for less experienced dermatologists [12]. It has also been revealed that the dermoscopy in the hands of inexperienced dermatologists may cause a reduction in diagnostic accuracy [13]–[16]. This implies a need to develop more reliable and robust system for the diagnosis of skin cancer.

Deep learning algorithms have shown great performance in visual tasks and even outperformed humans in gaming, e.g., Go [17], Atari [18] and object recognition [19], which has lead to conduct the research on automated screening of skin cancers [9]. Several studies have been done to compare the dermatologist-level, and Deep Learning based automated classification of skin cancer [20], [21]. Esteva et al. reported a benchmark study comparing the performance of dermatologists and a CNN model over 129,450 clinical images; showing the CNN model perform at par or better than dermatologists [21]. In recent years, the trend has shifted to Deep Neural Networks (DNNs) [22] which were proposed to improve accuracies over previous models [9], [23]–[30]. DNNs has an appealing impact on image classification, but their use for medical images is challenging since they require large training data [30]. The current literature mostly employs transfer learning to solve large dataset problem, a technique where a model trained for a given source task is recycled for a new targeted task. The works employing DNNs for melanoma screening have trained a network from scratch [26], [31] or transfer knowledge [24], [25], [27], [28] from ImageNet. The main difference between them is the choice of DNN architecture, and implementation framework — Caffe [24], [27] is the most common framework, and ResNet [28], AlexNet [25], VGG-16 [29] are most common architectures.

Previous work in dermoscopic computer-aided classification has lacked in generality capability [30], [32], [33] and have not achieved pleasing results for multi-class skin cancer classification [21], [34]–[38]. In this paper, we propose an efficient seven-way automated multi-class skin cancer classification of dermoscopy skin lesion images. We utilized a MobileNet convolutional neural network [39] pretrained on approximately
1.28 million images from the 2014 ImageNet Large Scale Visual Recognition Challenge [31] and train it on HAM10000 dataset [40] which contain 10015 dermoscopy images using transfer learning [41]. The MobileNet model classified skin lesion image with performance better or comparable to expert dermatologists among seven classes: Actinic Keratosis, Basal cell carcinoma, Benign keratosis, Dermatofibroma, Melanocytic nevi, Melanoma, Vascular lesions. We also conducted data-analysis on the dermoscopy images of skin cancer from HAM10000 dataset to uncover relation of skin cancer with several parameters to strengthen the understanding of skin cancer.

2 METHOD

2.1 Dataset

HAM10000 Dataset [40]: A Large Collection of Multi-Source Dermoscopy images of Common Pigmented Skin Lesions was used for training and validation of the model. HAM10000 dataset is a benchmark dataset with over 50% of lesions confirmed by pathology, while the rest of the cases was either follow-up, expert consensus, or confirmation by in-vivo confocal microscopy.

Fig. 1. Sample images from HAM10000 dataset for cancer types (a) Actinic keratosis (b) Basal cell carcinoma (c) Benign keratosis-like lesions (d) dermatofibroma (e) Melanocytic nevi (f) Melanoma (g) Vascular lesions
The dataset consists a total of 10015 dermoscopy images which includes 6705 Melanocytic nevi images, 1113 Melanoma images, 1099 Benign keratoses images, 514 Basal cell carcinoma images, 327 Actinic keratoses images, 142 Vascular images and 115 Dermatofibroma images with 600X450 pixels resolution. Sample images of skin cancer types from HAM10000 are represented in Figure 1.

2.2 Data pre-processing

The pre-processing of skin lesion images was done by using Keras ImageDataGenerator [42]. The 57 null Age entries in the dataset were filled using the mean filling method [43]. The Dermoscopy images in the dataset were downscaled to 224X224 pixel resolution from 600X450 pixel resolution to make images compatible with MobileNet model [39]. The 10015 images in the dataset were split into the training set (9077 images) and validation set (938 images). The dataset images with no duplication in training data were selected for the validation set so that the authenticity in the validation process can be maintained.

2.3 Data augmentation

HAM10000 dataset has an unbalance distribution of images among the seven classes. Data Augmentation [44] brings an opportunity to rebalance the classes in the dataset, alleviating other minority classes. Data Augmentation is an effective means to expand the size of training data by randomly modifying several parameters of training data images like rotation_range, zoom_range, horizontal_flip, vertical_flip, fill_mode, etc [44]. We conducted data augmentation of minority classes: Melanoma, Benign Keratosis, Basal Cell Carcinoma, Actinic Keratosis, vascular lesion, and dermatofibroma to generate approximately 6000 images in each class giving a total of 38,569 images in the training set. The parameters used for data augmentation of the images are as follows: ‘rotation_range’ = 180, ‘width_shift_range’ = 0.1, ‘height_shift_range’ = 0.1, ‘zoom_range’ = 0.1, ‘horizontal_flip’ = True, ‘vertical_flip’ = True, ‘fill_mode’ = nearest.

2.4 Training algorithm

MobileNet’s are ideal for mobile and embedded vision applications as they have lightweight DNN architecture [39]. We used MobileNet convolutional neural network [39] pretrained on 1.28 million images containing 1,000 object categories from the 2014 ImageNet Challenge [31]. The 25 layered MobileNet architecture was constructed for the current study which employs four Conv2D layers, seven BatchNormalization layers, seven ReLU layers, three ZeroPadding2D layers, and single DepthwiseConv2D, GlobalAveragePooling, Dropout, and Dense layers as shown in Figure 2. The training of model was done on a training set of 38,569 images using Transfer Learning [41] with batch size and epochs as 10 and 50 respectively. The Categorical Crossentropy loss function, Adam optimizer, and metric function Accuracy, Top2 accuracy, and Top3 accuracy were used to evaluate MobileNet model performance.
2.5 Evaluation metrics

The overall performance of the model was measured in terms of the Accuracy, Micro Average of Precision (MAP), Micro Average of Recall (MAR), and Micro Average of F1-score (MAF). The weighted average for Recall, Precision and F1-score were also evaluated.

\[
\text{Accuracy} = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (1)
\]

\[
\text{Precision} = \frac{TP}{(TP+FP)} \quad (2)
\]

\[
\text{Recall} = \frac{TP}{(TP+FN)} \quad (3)
\]

\[
F1 - score = 2 \frac{Precision \times Recall}{Precision + Recall} \quad (4)
\]

3 RESULTS

The calculations were performed on Kaggle kernel having 4 CPU cores with 17 GB RAM and 2 CPU cores with 14GB RAM [45]. Model Evaluation was performed by calculating categorical accuracy, top2 accuracy, top3 accuracy, classification report, and confusion matrix. Further, the loss and accuracy curves were plotted to validate the model’s performance for optimization and prediction phase.
3.1 Data-set analysis

The important observations recorded during the data analysis of HAM10000 dataset are shown in Figure 3 (i) Actinic Keratosis, Basal cell carcinoma, Dermatofibroma, and Melanocytic nevi are not much prevalent below the age of 20 years. Whereas, Melanoma and Vascular lesions can occur at any stage of life. (ii) The peak age for skin cancer is found at 45 years, while they are more common between the age of 30 to 70. (iii) Back, Lower Extremity, Trunk, Upper Extremity and Abdomen are heavily compromised regions of skin cancer.

Fig. 3. Exploratory Data Analysis performed on HAM10000 dataset (a) Comparative study of Skin cancer type on the y-axis with respect to age on the x-axis: Actinic Keratosis, Basal cell carcinoma, Benign keratosis, Dermatofibroma, Melanoma, Melanocytic nevi, and Vascular lesions are labeled as 0,1,2,3,4,5 and 6 respectively on the y-axis. (b) Comparison of a number of cases of skin cancer on the y-axis with respect to age on the x-axis. (c) The number of skin cancer cases on y-axis with respect to the location of skin cancer on human body on the x-axis.

3.2 Model Validation

The validation of the model was conducted on 938 unknown sample images from the validation set. We evaluated micro and weighted average for precision, recall and f1-score to understand generalized performance of the model. The weighted average and the micro average for precision, recall, and f1-score were evaluated for seven classes.
The Weighted Average of 0.89, 0.83, 0.83 and Micro Average of 0.83, 0.83, 0.83 were recorded for Precision, Recall, and F1-score. Our model shows best precision, recall, and f1-score value for Melanocytic Nevi. The Multi-Class Classification Report showing Micro Average and Weighted Average for Precision, Recall, and F1-Score are represented in Table 1.

| Classes            | Precision | Recall | F1-Score |
|--------------------|-----------|--------|----------|
| Actinic Keratosis  | 0.36      | 0.38   | 0.37     |
| Basal Cell Carcinoma | 0.55      | 0.87   | 0.68     |
| Benign Keratosis   | 1.00      | 0.13   | 0.24     |
| Dermatofibroma     | 0.21      | 0.50   | 0.30     |
| Melanoma           | 0.28      | 0.69   | 0.40     |
| Melanocytic Nevi   | 0.95      | 0.93   | 0.94     |
| Vascular Lesions   | 0.73      | 0.73   | 0.73     |
| **Micro Average**  | **0.83**  | **0.83** | **0.83** |
| **Weighted Average** | **0.89**  | **0.83** | **0.83** |

Table 1. Multi-Class Classification Report showing Micro Average and Weighted Average for Precision, Recall and F1-Score

The comparison of the current study with other related previous work is represented in Table 2. The majority of previous work is done on two or three classes and their accuracies and recall varies between approximately 66 percent to 81 percent and 60 percent to 76 percent, respectively. In the study [21], they reported 48.9 percent and 55.4 percent classification accuracy evaluated for nine classes using CNN models. In the Study [38], classification accuracy for ten classes using Multi-tract CNN was reported to be 75.1 percent. Also, in study [40] they reported recall as 64.3 percent and 65.8 percent for seven classes using DenseNet models. Our seven-way skin cancer classification method has performed better than previously proposed computer-aided diagnosis systems in terms of both accuracy and recall even though we have done analysis for seven classes of skin cancer. We achieved categorical accuracy of 83.15 percent, top2 accuracy of 91.36 percent, top3 accuracy of 95.3 percent, and recall of 83 percent using MobileNet. Additionally, our method is more efficient considering the faster processing capability and lightweight architecture of MobileNet model.

### 3.3 Confusion Matrix

Confusion matrix for our model was evaluated for seven classes and is shown in Table 3. Each element of confusion matrix shows the comparison between the True label and Predicted label for each image in the validation set. Our model showed the best result for Melanocytic nevi by making a correct prediction for 696 images out of 751. Basal cell carcinoma and Melanoma were correctly determined for 26 images out of 30 and for 27 images out of 39 respectively. The diagnosis of Benign keratosis was most challenging due to their similar appearance with Melanoma and Melanocytic nevi. Only ten correct predictions were recorded for Benign keratosis.
Table 2. Comparison results of Current Study with previous related work. * we have converted the recall and accuracy in percentage to compare them with the current study

| Source | Year | Classifier | No. of Classes | Accuracy % | Recall % |
|--------|------|------------|----------------|------------|----------|
| [34]   | 2011 | KNN        | Two            | 66.7       | 60.7     |
| [35]   | 2011 | KNN        | Two            | 73.47      | 76.4     |
|        |      | Bayesian   |                | 80.6       | 76.4     |
|        |      | Multilayered Perceptron |          | 86.73 | 78.4   |
| [36]   | 2016 | VGGNet     | Three          | *79.3      | *79.9    |
|        |      | GoogleNet & VGGNet |        | *81.2      | *80.7    |
| [37]   | 2016 | Multi-tract CNN | Ten     | *75.1      |
| [21]   | 2017 | CNN        | Three          | 69.4       | 72.1     |
|        |      | CNN-PA     |                |            |          |
|        |      | CNN        | Nine           | 48.9       | 55.4     |
|        |      | CNN-PA     |                |            |          |
| 2019   |      | Current Study | Seven | 83.15 (cat) | 91.36 (top2) | 95.84 (top3) | 83.0 |

Table 3. Confusion Matrix: Each element of confusion matrix shows the comparison between the True label and Predicted label for each image in the validation set. Actinic Keratosis, Basal cell carcinoma, Benign keratosis, Dermatofibroma, Melanoma, Melanocytic nevi, and Vascular lesions are labeled as akiec, bcc, bkl, df, mel, nev, and vasc respectively.

| True label / Predicted label | akiec | bcc | bkl | df | mel | nev | vasc |
|-----------------------------|-------|-----|-----|----|-----|-----|------|
| akiec                       | 10    | 2   | 0   | 2  | 9   | 3   | 0    |
| bcc                         | 2     | 26  | 0   | 0  | 1   | 1   | 0    |
| bkl                         | 10    | 9   | 10  | 0  | 27  | 19  | 0    |
| df                          | 0     | 0   | 0   | 3  | 0   | 3   | 0    |
| mel                         | 4     | 1   | 0   | 0  | 27  | 7   | 0    |
| nev                         | 2     | 9   | 0   | 9  | 32  | 696 | 3    |
| vasc                        | 0     | 0   | 0   | 0  | 0   | 3   | 8    |

3.4 Loss and accuracy curves

In order to examine learning, generalizing and performance of the model, we computed training-validation loss curve (Figure 4(a) and training-validation accuracy curves for categorical (Figure 4(b)), top2 (Figure 4(c)) and top3 (Figure 4(d)) accuracies. The model shows a good learning rate as the training accuracy increase with the number of iterations along with symmetric downward sloping of training loss curve. The small
gap between training and validation curves represents a good-fit, showing model can generalize well on unknown images.

Table 4. Figure 4. Skin cancer classification performance curves of MobileNet model (a) Training and Validation loss (b) Training and Validation categorical accuracy (c) Training and validation top2 accuracy (d) Training and Validation top3 accuracy

We have developed a web application to provide an effective automated online tool for the multi-class classification of dermoscopy skin lesion image. This web application is available for public use at https://saketchaturvedi.github.io

4 CONCLUSION

The incidences of skin cancer are increasing over the past decades; the need of an hour is to move towards an efficient and robust automated skin cancer classification system, which can provide highly accurate and speedy predictions. The diagnosis of skin cancer is challenging for expert dermatologists considering minute variability in the appearance of skin lesions. In recent years, Deep Learning has made remarkable progress in visual recognition tasks including gaming, object recognition, and medical diagnosis. Here we demonstrate the effectiveness of deep learning in dermoscopic multi-class skin cancer classification. Using MobileNet convolutional neural network trained on a total of 38,569 dermoscopy images from HAM10000 dataset, we match the performance of expert dermatologists across seven diagnostic tasks: Actinic Keratosis, Basal cell carcinoma, Benign keratosis, Dermatofibroma, Melanoma, Melanocytic nevi, and Vascular lesions. The model shows a categorical accuracy of 83.15 percent, top2 accuracy of
91.36 percent and top3 accuracy of 95.34 percent. The weighted average of precision, recall, and f1-score were found to be 0.89, 0.83, and 0.83 respectively. The MobileNet model can be used to develop efficient real-time computer-aided systems for automated medical diagnosis systems. As compared to previously proposed models the MobileNet model has shown accurate and robust performance in addition to its faster, and light-weight architecture. We had deployed our model as a web application for public use at (https://saketchaturvedi.github.io). Although additional research is necessary to account for different lesion types encountered in the course of regular practice, current study holds the potential to augment clinical decision-making for dermatologists.

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