Applied Deep learning for categorizing dermoscopic images

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Abstract— **Melanoma is a serious form of skin cancer that begins in cells known as melanocytes. While it is less common than basal cell carcinoma (BCC) and squamous cell carcinoma (SCC), melanoma is more dangerous because of its ability to spread to other organs more rapidly if it is not treated at an early stage. The basic examination for melanoma is dermoscopy, an image modality of the skin part that is affected. In this work, we propose a new deep learning approach, based on convolutional neural networks, to classify dermoscopic images in one out of 32 categories. An existing dataset, containing 2013 images from different categories of melanoma [10] has been used for the training and validation of our approach.**

Keywords—Skin cancer, convolution neural network, dermoscopic images, classification

I. INTRODUCTION

Skin cancer is one of the most common cancers. Melanoma is a form of cancer in the body that develops from melanocytes. It can occur anywhere on the body that contains melanocytes, even in the eyes. It is a dangerous form of cancer if we do not detect it and treat it in early stages.

Diagnosis of melanoma is difficult and many times the dermatologist cannot make the appropriate decision for the patient. Machine learning [44] can assist dermatologists in the early diagnosis of melanoma by applying artificial intelligence algorithms. A unique category of machine learning, Deep learning, is often used to process and evaluate an image [24]. Deep learning uses multiple levels to extract higher-level features from raw input. Deep learning algorithms have greatly improved the evolution image based diagnosis.

Many algorithms and methods have been proposed in the past, using convolutional neural networks for classifying images to detect skin cancers [5-6,10-11,19-20], machine learning algorithms to classify and evaluate [7,9] and creating their own algorithms [4]. In most cases, dermoscopic images were used as input data.

In this paper, a convolutional neural network is used for the classification of melanoma images in different categories.
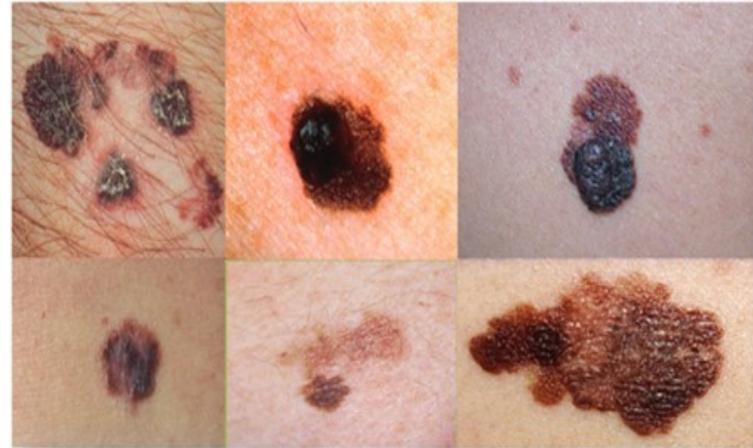

Figure 1 Different Types of Melanoma

II. RELATED WORK

Kawahara et al [6,10] proposed convolutional neural networks for analysing clinical dermoscopic images[6] and for the classification of melanoma images [10] helping in skin cancer diagnosis. The convolutional neural network uses different types of images, for the diagnosis of melanoma.

Yuan et al [5] proposed an automated injury detection system with convolutional neural networks used as methodology for classifying dermoscopic images of injuries.

Guarracino et al [4] proposed his own algorithm for segmentation. His methodology was for classifying images with melanoma and using them in his own algorithm.

Farhan Riaz et.al [7] proposed a new diagnostic system for melanoma detection with dermatological images and a new methodology for the separation and classification of images to detect melanoma.
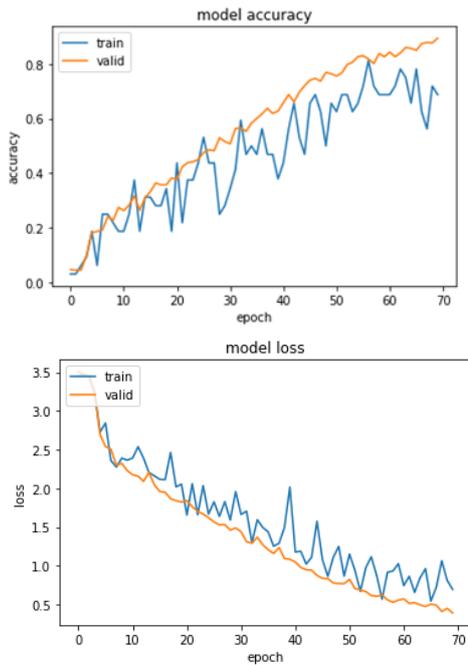
Figure 2 Charts for model accuracy(Up) and for loss(Down)

Mahmouei et al [9] proposed a color-based melanoma detection system (Quad Tree). The methodology was based on the pre-processing of images, separating melanoma and non melanoma images, constructing five coating molecules, palette colors, Quad Tree collection and pallets.

III. METHODOLOGY

A. Dataset

The dataset of our method is from Kawahara et.al [10] that contains 2013 melanoma images divided into 34 categories.

B. Libraries and Applications

For the development of the convolutional neural network, we used python programming language and the following libraries:

- Tensorflow [1,22,33]
- Keras [2,21,34]
- Numpy [18]
- Sklearn [17]
- Matplotbib [39]

Cloud applications, such as google drive, were used in order to apply the convolutional neural networks, where the data were stored, google colab [3] where the convolutional was trained and evaluated.
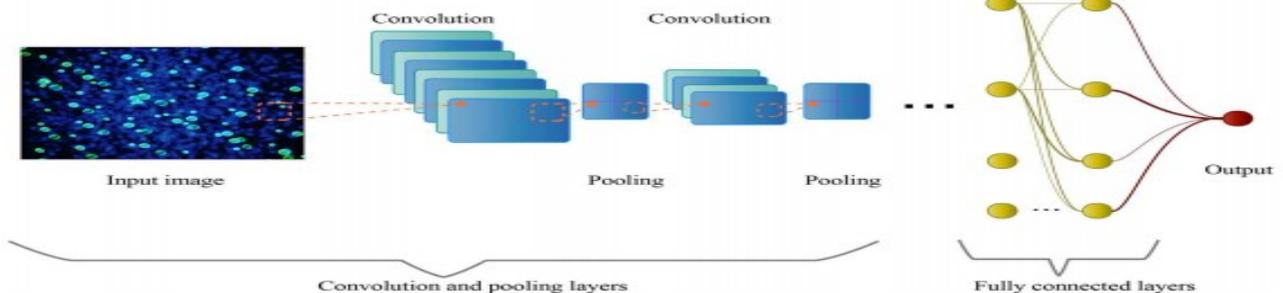
TABLE I COMPARISON OF RESULTS

Author	Algorithm	Dataset	Accuracy	Sensitivity
Guarracino et.al[4]	SDI+	ISCI 2017	88.8%	81.3%
Yuan et.al[5]	CNN	ISBI 2017 (2000)	93.4%	82.5%
Kawahara et.al[6]	CNN	ISIC-ISBI (2000)	98.0%	54.2%
Riaz et.al[7]	SVM & KNN	PH2 (200) ISIC (10000)	82.25% 80.6% (SVM) 74% 79.7% (KNN)	-
Mahmouei et.al[9]	Quad Tree	(825)	-	80.5%
Kawahara et.al[10]	CNN	(1011)	80.8%	64.9%
Li et.al[11]	CNN	ISBI 2016 (1279) ISBI 2017 (1100)	95.9% 93.9%	-
Brinker et al [19]	CNN	(12.378)	-	92.8%
Brinker et al [20]	CNN	(4204)	-	82.3%
This work	CNN	(2013)	90%	87%

C. Convolutional Architecture

For our methodology, we created a simple convolutional neural network Fig.3. Our convolutional network was a 3-level network where each level consists of:

1. The 2d dimension convolutional layer together with the relu activation function [37]
2. The max-pooling layer that is a 2d table
3. The dropout layer to avoid overfitting

In each execution, the convolutional layer must be reduced to half size. The above layers are playing important part in the processing of images but also in the part of the model training.

For the training process, we created the flatten layer to connect the previous layers with the fully connected layer (dense layer) where the training takes place.

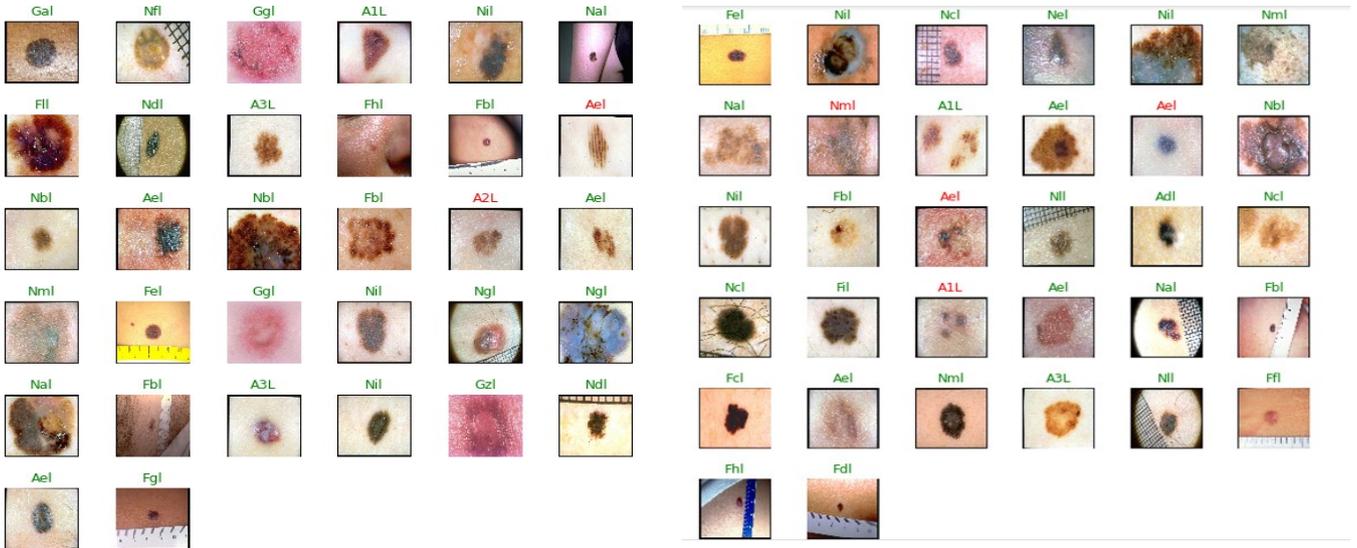Figure 3 Convolutional Neural Network

Figure 4 Samples of Prediction. Images with red name were predicted wrong and with green were predicted correct.

In each layer there is the corresponding dropout layer that increases the training of the model and reduces the execution speed.

D. Training

Our model uses adam [23] as an optimizer and accuracy as metric. In this case, accuracy indicates the effectiveness of the model in training and evaluation and shows how accurate the methodology is.

IV. RESULTS

Training was performed in 70 epochs, each one containing 45 batches of images. Fig.2. shows the effectiveness of the model in the given data. The executions of model training in google colab required 15 minutes reporting a validation accuracy of 88-97%.

For the evaluation we used a part of the dataset, 32 random melanoma images from different categories, as shown in Fig.4.

Based on the predictions of the CNN model and the real annotation, a 32X32 confusion matrix is formulated and the following metrics were extracted:

- Accuracy = (TP+TN)/(TP+TN+FN+FP)   (1)

- Precision(Pre) = TP/(TP+FP)   (2)

- Recall(Rec) or Sensitivity = TP/(TP+FN)   (3)

- F1-score = (2*Pre*Rec)/(Pre*Rec)   (4)

TABLE II EXECUTION SAMPLES

Execution	Accuracy	Precision	Sensitivity	F1-score
1	94%	90%	94%	95%
2	97%	95%	97%	98%
3	88%	90%	88%	87%
4	88%	92%	88%	88%
5	91%	92%	91%	90%
6	91%	97%	91%	92%
7	97%	94%	97%	95%
8	91%	95%	91%	92%
9	94%	94%	94%	93%
10	94%	98%	94%	95%

In our analysis we performed 100 executions. The performance of our model and comparison of results are summarized in Table I. Metrics for some of the steps are shown in Table II.

V. DISCUSSION

The proposed model is reliable in terms of accuracy in the diagnosis of melanoma and provides comparative performance with similar work, as shown in Table I. Future work will focus on the implementation of experiments on better hardware with more powerful GPU in order to decrease the time needed. For better performance a combination of convolutional networks could also be performed and experimentation could be done with more data.

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