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Segmentation and Classification of Dermatoscopic Skin Lesion images using U-Net and MobileNet models

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Abstract

The 17th most prevalent cancer in the world is cutaneous melanoma. Early detection and adequate treatment are essential for skin cancer success. It might not be possible to tell benign lesions from malignant tumours just by looking at them. The histopathological study of the skin biopsy is the gold standard procedure. Skin biopsy has some drawbacks, including its invasiveness, the pain it causes, and the requirement for many samples for suspected lesions with multiple presentations. Clinical diagnosis can also be aided by non-invasive tools. Several non-invasive imaging techniques are now available to diagnose melanoma because of numerous scientific and technological developments. The most advanced network for pattern identification in medical image analysis is the convolutional neural network (CNN). Thus, utilizing these advanced techniques a Skin Lesion Classifier can be built, which performs segmentation of the Lesion area in the pre-process step to avoid extracting and remembering other additional features from the background of the dermatoscopic image. For the segmentation task U-Net Architecture is utilized on the PH2 dataset and obtained validation accuracy of 95%. And performs well on the test data. The segmented images are then used to train a lightweight CNN Architecture "MobileNet" using some pretrained weights from imagenet dataset and produced validation accuracy of 84.73% which is pretty good performance.

Keywords: Dermatscopic skin lesion images, segmentation, U-Net, Convolutional Neural Networks, Pretrained weights, MobileNet.

Introduction

Skin cancer is a less prevalent kind of malignancy, although its prevalence has been steadily rising over the past fewdecades. The three most common primary skin malignancies are malignant melanoma, basal cell carcinoma, and squamous cell carcinoma. Non-Melanomatous Skin Cancers refers to BCC and SCC collectively. Although

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there has been a steady rise in skin cancer cases over the past few decades, skin cancers still rank outside of the top 10 most prevalent cancers globally. The skin cancer with the worst prognosis is melanoma. It is successfully treatable by surgery if detected early. Nonetheless, survival rates drastically decline after metastasis occurs. Melanoma diagnosis is based on clinical examination and traditional lesion biopsy results. A handheld device called a dermatoscope is used to perform dermoscopy. The process makes it possible to see subsurface skin features that are normally invisible to the human eye in the epidermis, at the dermoepidermal junction, and in the papillary dermis. Dermoscopic pictures can be captured on film or digitally recorded and stored for future change monitoring. The possible impact of skin lesion segmentation on the performance of CNN-based classifiers has been examined, despite the good classification performance of CNN-based techniques for skin lesion classification without employing any lesion segmentation masks. Only a few research have used lesion segmentation data to enhance the effectiveness of CNN-based classification workflows. In this paper we try to propose the methodology that performs better by including the segmentation in the pre-processing step. And then classifying the images after applying the Ground truth masks to the images. The performance of the CNN model on three datasets, skin lesion images without applying masks, segmented images without any background and segmented images with background around the image are compared over the metrics such as validation accuracy and loss. To perform segmentation in the pre-process, step the U-Net architecture for semantic segmentation is employed on the PH2 dataset. And to perform the classification task pretrained MobileNet architecture is used with some pretrained weights from the imagenet dataset.

Literature Survey

There exist many proposed methodologies for SLC, some of the related work is,

1) DermoEpert [1]: In this paper, the authors propose a dermoscopic SLC framework that is automated called Dermoscopic Expert (Dermo-Expert). A hybrid-CNN classifier, transfer learning, and image pre-processing are some of the steps that make up the proposed DermoExpert. Class rebalancing, Segmentation and augmentation make up the suggested preprocessing. A Hybrid-CNN classifier is trained end-to-end by simultaneously passing the input batch of pictures through three separate Feature Map Generators (FMGs) to produce various feature map presentations. The three well-known datasets ISIC-2016, ISIC-2017, and ISIC-2018, with target classes of 2, 3, and 7, respectively, were used by the authors.

2) Skin lesion segmentation with improved U-Net architecture [2]. This paper emphasizes the segmentation of the dematoscopic skin lesions using the improved UNet architecture. The convolution layer, rather than the pooling layer, and the ResNet architecture are both used in the proposed method's encoding part. To determine

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classification error and conduct weight adjustments, the CrossEntropy criterion was utilized. 89% of the test data were accurately predicted by this model.

3) Skin Lesion Classification using Deep Learning Architectures [3]. In this paper, authors proposed a skin lesion classification model which includes augmenting the labelled images, extracting the features, and predicting the skin lesion is proposed. Three different models, MobileNet model, VGG-16 model, and a custom model is trained and tested on two different datasets. On HAM-10000 dataset achieved the accuracy of 82% using the MobileNet architecture.

The proposed methodologies in above mentioned papers helped us to gain knowledge about the present-day technologies used in Skin LesionClassification techniques. [7-15]

Problem Identification

The most prevalent form of cancer in humans, skin cancer is typically identified visually after a first clinical screening and maybe after dermoscopic analysis, a biopsy, and a histological study [7]. The fine-grained variety in how skin lesions form makes it difficult to automatically classify skin lesions using photographs. The aforementioned articles have suggested various methods for classifying and segmenting skin lesions. Thus, this paper aims to propose a methodology to improve the performance of classification of skin lesion images using the HAM-10000 dataset.

Methodology

In this paper, the proposed methodology for effective skin lesion classification consists of the segmentation, augmentation as the pre-processing steps and the segmented images are given as input to a pretrained model to train and a model is generated which classifies the image into the 7 different classes of lesions.

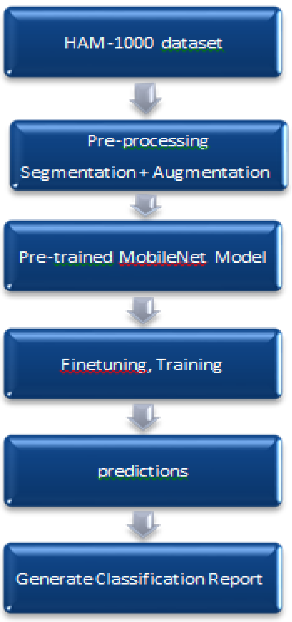

Fig-1: Proposed Methodology.

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To implement the proposed methodology popular deeplearning technique CNN is used. The segmentation task is carried out using the U-Net architecture and pretrained MobileNet architecture is utilized for the classification task.

Implementation

1.Datasets:

- HAM–10000 dataset [4]:

Actinic keratosis, basal cell carcinoma, melanocytic nevus, actinic keratosis, benign keratosis, dermatofibroma, and vascular lesion are among the seven groups of skin diseases represented in the data set, which has 10,015 labelled images of size 450x600 (HAM 10000 dataset). Images.

- PH2 dataset [5]:

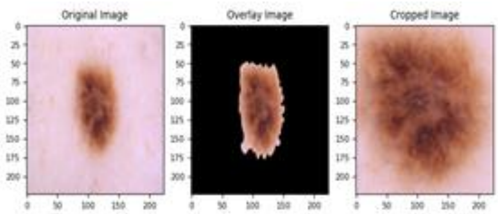
The Tuebinger Mole Analyzer equipment was used to obtain the dermoscopic skin lesion images at the Dermatology Service of Hospital Pedro Hispano in Matosinhos, Portugal, under identical circumstances. A 20x magnification was used. They are 768x560 pixel images in an 8-bit RGB color format.

Classes	Non-Melanoma		Melanoma
	Atypical Nevi	Common Nevi	
Total Images	80	80	40

Table-1: Data distribution in PH2 dataset.

Utilising these datasets three different datasets are created to analyse the effect of the segmentation of Lesion area.

- Dataset1: The original unmasked images of HAM-10000 dataset.
- Dataset2: The original images of HAM-10000 dataset are overlayed with the binary mask from the HAM10000 lesion segmentation dataset and referred as masked image dataset.
- Dataset3: The contour parts of the Binary Masks are extracted using CV2 and the original image is cropped along the contour part. This dataset is referred as Cropped dataset.



Fig–2: Demonstrating three datasets.

2.Pre-processing: Segmentation and augmentation are the pre-processing techniques used in the proposed methodology.

➢ **Segmentation:**

As it collects aspects of the skin lesion and provides significant shape, structure, texture, and colour information, the segmentation process is considered an essential component for diagnosis and a crucial prerequisite for skin lesion diagnosis [4]. The recently published U-Net architecture for semantic segmentation is adopted and used as the ROI extractor. The U-Net model is finetuned and trained on the PH2 dataset and used to extract the lesion segmentation for the testing dataset.

➢ **Augmentation:**

To avoid overfitting, CNNs largely rely on vast volumes of data. Unfortunately, due to the dearth of extensive accurate manual annotations, several application fields, including lesion diagnostics, suffer from tiny database volumes. Data augmentation produces realistic changes of the original photos, which helps to partially alleviate the problems associated with data insufficiency. This increases the dataset's heterogeneity and generalizability and improves training accuracy [4]. The ImageDataGenerator is used for the augmentation of the images with the values corresponding to each attribute, rotation_range is 180, width_shift_range is0.1, height_shift_range is 0.1, zoom_range value is 0.1, horizontal_flip is True, vertical_flip as True, brightness_range of [0.9,1.1], fill_mode value as 'nearest'. By performing this operation, the images of all three datasets are increased.

3.DeepLearning Model:

In this paper the deeplearning architecture utilized is CNN. Among the many pre-trained CNN architectures available in keras.applications. MobileNet architecture is being utilized because it is a lightweight model compared to the other architectures. In the pre-trained models, the output is the number of classes available in imageNet dataset (1000) categories for all the architectures. For the HAM10000 dataset, we classified the input test images into 7 groups by creating a dense layer of 7 neurons [6]. A 224 x 224 x 3 RGB image is the required input image size for the MobileNet architecture. ReLU, softmax are the activation function used and Adam optimizer with starting learning rate of 0.001 is used later finetuned using the call-backs. The categorical cross entropy is utilised as the loss function.

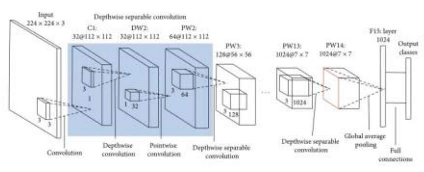


Fig-3: MobileNet Architecture

Results

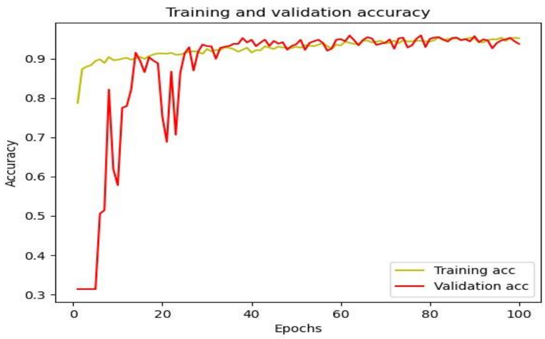
In this paper the proposed system makes use of segmentation in the pre-process step to try to increase the performance of the MobileNet SLC model.

- **Segmentation Results:**

Segmentation of lesions area is performed utilizing the basic U-Net architecture is implemented on the PH2 dataset and achieved pretty good result with an accuracy of 95.69%.

Table-2: Segmenation Results on Test data.

Metrics	**Value %**
IOU	96.06
Dice Coef	91.97
Precision	92.69
Recall	93.84
Accuracy	95.69
Loss	3.94



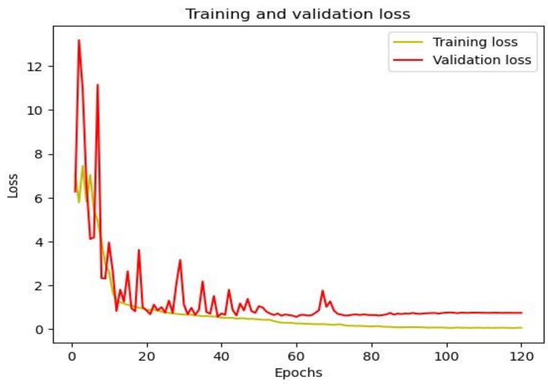


Fig-4: Train, validation Accuracy of U-Net architecture. **Fig-5:** Train, validation Loss of U-Net architecture

- **Classification Results**

The proposed mobileNet architecture is trained with the generated datasets, the cropped dataset performed better among the three datasets. The training, validation accuracy and loss are shown in the below figures.

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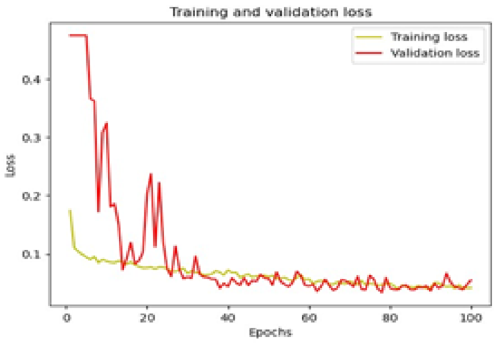

Fig-6: Train, validation Accuracy of cropped images dataset(dataset-3) **Fig-7:** Train, validation Loss of Cropped image dataset (dataset 3)

The classification accuracy of the other three datasets when trained using the same mobilenet model i.e., for unmasked dataset is 82% and overlay images dataset is 79%, and copped images dataset is 84%.

	precision	recall	f1-score	support
akiec	0.67	0.61	0.63	33
bcc	0.83	0.76	0.80	51
bkl	0.65	0.75	0.70	110
df	0.73	0.67	0.70	12
mel	0.63	0.66	0.65	111
nv	0.93	0.91	0.92	671
vasc	0.85	0.79	0.81	14
accuracy			0.84	1002
macro avg	0.76	0.74	0.74	1002
weighted avg	0.85	0.84	0.85	1002

	precision	recall	f1-score	support
akiec	0.60	0.55	0.57	33
bcc	0.69	0.65	0.67	51
bkl	0.63	0.72	0.67	110
df	0.78	0.58	0.67	12
mel	0.61	0.47	0.53	111
nv	0.89	0.92	0.91	671
vasc	1.00	0.86	0.92	14
accuracy			0.82	1002
macro avg	0.74	0.68	0.71	1002
weighted avg	0.81	0.82	0.82	1002

Fig-8: Classification report of cropped image dataset. **Fig-9:** Classification report on unmasked dataset.

	precision	recall	f1-score	support
akiec	0.59	0.52	0.55	33
bcc	0.73	0.65	0.69	51
bkl	0.61	0.64	0.62	110
df	0.78	0.58	0.67	12
mel	0.51	0.41	0.46	111
nv	0.88	0.92	0.90	671
vasc	0.86	0.86	0.86	14
accuracy			0.80	1002
macro avg	0.71	0.65	0.68	1002
weighted avg	0.79	0.80	0.79	1002

Fig-10: Classification report on Masked images dataset.

Conclusion

In this paper, the results produced by the proposed methodology are better when compared to the results produced by other methodologies. The segmentation task using basic U-Net architecture gave test accuracy of 95%. The classification using the MobileNet Architecture model on the cropped dataset is performed well on the test dataset and produced 84% accuracy, with a loss value of 0.74.

Table-3: Comparison of Segmentation results

Architecture	Error rate	Accuracy of test data
U-Net **Modified by ResNet in decoder and convolution layer**	0.26	0.89
Proposed U-Net	0.03	0.95

The classification results are also compared based on the metrics, accuracy and F1-score.

Table-4: Classification Result comparison

Metrics	VGG-16	Proposed method
Test Accuracy	79.71%	84.53%
F1 Score	0.597	0.74

Limitations and Future scope

The test performance of the proposed classification model is degraded when we try to evaluate the images which are segmented by the proposed U-Net segmentation model. One of the reasons maybe because segmentation masks utilized to extract ROI for train images of classification are not generated by the proposed segmentation model instead, they are taken from the HAM-10000 lesion segmentations dataset. Further, in future work we would like to train the classification model with the masks generated by the proposed segmentation model.

References

[1] [1] Md. Kamrul Hasan, Md. Toufick E. Elahi, Md. Ashraful Alam, Md. Tasnim Jawad, Robert Martí, DermoExpert: Skinlesion classification using a hybrid convolutional neural network through segmentation, transfer learning, and augmentation, Informatics in Medicine Unlocked, Volume 28, 2022, 100819, ISSN 2352-9148, https://doi.org/10.1016/j.imu.2021.100819.

Research paper © 2012 IJFANS. All Rights Reserved, UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, Dec 2022

[2] [2] R. Iranpoor, A. S. Mahboob, S. Shahbandegan and N. Baniasadi, "Skin lesion segmentation using convolutional neural networks with improved U-Net architecture," *2020 6th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS)*, Mashhad, Iran, 2020, pp. 1-5, doi: 10.1109/ICSPIS51611.2020.9349577.

[3] [3] A. C. Salian, S. Vaze, P. Singh, G. N. Shaikh, S. Chapaneri and D. Jayaswal, "Skin Lesion Classification using Deep Learning Architectures," *2020 3rd International Conference on Communication System, Computing and IT Applications (CSCITA)*, Mumbai, India, 2020, pp. 168-173, doi: 10.1109/CSCITA47329.2020.9137810.

[4] [4] Tschandl, P., Rosendahl, C. & Kittler, H. The HAM10000 dataset, a large collection of multi-sourcedermatoscopic images of common pigmented skin lesions. *Sci Data* **5**, 180161 (2018). https://doi.org/10.1038/sdata.2018.161

[5] [5] T. Mendonça, P. M. Ferreira, J. S. Marques, A. R. S. Marcal and J. Rozeira, "PH2 - A dermoscopic image database for research and benchmarking," *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Osaka, Japan, 2013, pp. 5437-5440, doi: 10.1109/EMBC.2013.6610779.

[6] [6] AmirrezaMahbod, Philipp Tschandl, Georg Langs, Rupert Ecker, Isabella Ellinger, The effects of skin lesion segmentation on the performance of dermatoscopic image classification, Computer Methods and Programs in Biomedicine, Volume 197, 2020, 105725, ISSN 0169-2607, https://doi.org/10.1016/j.cmpb.2020.105725.

[7] Sri Hari Nallamala, et al., "A Literature Survey on Data Mining Approach to Effectively Handle Cancer Treatment", (IJET) (UAE), ISSN: 2227 – 524X, Vol. 7, No 2.7, SI 7, Page No: 729 – 732, March 2018.

[8] Sri Hari Nallamala, et.al., "An Appraisal on Recurrent Pattern Analysis Algorithm from the Net Monitor Records", (IJET) (UAE), ISSN: 2227 – 524X, Vol. 7, No 2.7, SI 7, Page No: 542 – 545, March 2018.

[9] Sri Hari Nallamala, et.al, "Qualitative Metrics on Breast Cancer Diagnosis with Neuro Fuzzy Inference Systems", International Journal of Advanced Trends in Computer Science and Engineering, (IJATCSE), ISSN (ONLINE): 2278 – 3091, Vol. 8 No. 2, Page No: 259 – 264, March / April 2019.

[10] Sri Hari Nallamala, et.al, "Breast Cancer Detection using Machine Learning Way", International Journal of Recent Technology and Engineering (IJRTE), ISSN: 2277-3878, Volume-8, Issue-2S3, Page No: 1402 – 1405, July 2019.

[11] Sri Hari Nallamala, et.al, "Pedagogy and Reduction of K-nn Algorithm for Filtering Samples in the Breast Cancer Treatment", International Journal of Scientific and Technology Research, (IJSTR), ISSN: 2277-8616, Vol. 8, Issue 11, Page No: 2168 – 2173, November 2019.

ISSN PRINT 2319 1775 Online 2320 7876
Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, Dec 2022

[12] Kolla Bhanu Prakash, Sri Hari Nallamala, et al., "Accurate Hand Gesture Recognition using CNN and RNN Approaches" International Journal of Advanced Trends in Computer Science and Engineering, 9(3), May – June 2020, 3216 – 3222.

[13] Sri Hari Nallamala, et al., "A Review on 'Applications, Early Successes & Challenges of Big Data in Modern Healthcare Management'", Vol.83, May - June 2020 ISSN: 0193-4120 Page No. 11117 – 11121.

[14] Nallamala, S.H., et al., "A Brief Analysis of Collaborative and Content Based Filtering Algorithms used in Recommender Systems", IOP Conference Series: Materials Science and Engineering, 2020, 981(2), 022008.

[15] Nallamala, S.H., Mishra, P., Koneru, S.V., "Breast cancer detection using machine learning approaches", International Journal of Recent Technology and Engineering, 2019, 7(5), pp. 478–481.