Dermatologist Assistant Research Paper

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Abstract

Several researchers have developed methods to differentiate between melanoma and nevus, both categorized as melanoma skin lesion. However, most of these studies did not focus on non-melanoma skin lesion such as basal cell carcinoma (BCC) the most common skin cancer despite its high incidence rates. It is preferable to deal with both melanoma and non-melanoma skin lesions especially for the potential users who are not enough capable of diagnosing pigmented skin lesions on their own such as dermatologists in training and physicians with different expertise and patients themselves. Current machine learning analyses of BCC dermoscopy images have failed to create a model viable for use in clinical systems. In this paper, we demonstrate an approach that could make neural networks a trusted tool. The objective is to build a computer-aided diagnosis (CAD) tool that can speed up the detection of lesion areas in skin. Since there is little prior knowledge about the appearance of lesion cell morphology in this type of imagery, deep learning techniques are applied. Using convolutional neural networks (CNN), we train a feature extractor to find representative characteristics for FFOCT data and a classifier that learns a generalized distribution of the data. The original image is preprocessed and fed into the segmentation model, A black and white lesion map is produced to extract the minimum area of the image, we segment vascular structures of the lesion by first decomposing the image using independent component analysis into melanin and hemoglobin components. The classification model is introduced for classifying whether an input image is melanoma, nevus or BBC, the hemoglobin component is then clustered into normal, pigmented and erythema regions.

1 Introduction

Skin diseases impact people of all ages, races, ethnicities, and sexes, it does not always affect them equally. Differences in genetics, hormones, environmental exposures, and other factors can lead to differences in risk among different groups of people. Skin Diseases shared a 1.79% of the global burden of disease measured in disability-adjusted life years (DALYs), skin and subcutaneous diseases were the 18th cause of the global DALYs in 2013. Excluding mortality, skin diseases were the 4th leading cause of disability worldwide. Even tho skin diseases are visible to the naked eyes, early-stage of it can be difficult to distinguish because of the similarity of appearances. This has led to many missed diagnoses and wrong treatment. The main goal of this project is to reduce skin diseases-related deaths by developing a mobile application that can be used by any user and everywhere for early detection of these skin diseases, this application will reduce the cost of diagnosing and treatment for patient. To this end we are developing the proposed dermatologist assistant application and creating a public archive of clinical and dermoscopic treatment for some of the skin diseases. The presence of vascular structures in lesions, their morphology and architectural arrangement are specific signs for malignancies and certain skin abnormal conditions. Moreover, formation of new vessels could be an indicator of tumor development. Detection and quantification of cutaneous blood vessels provide critical information for diagnosis and assessment of skin conditions. Also the presence of telangiectasia has been considered as a diagnostic indicator of Basal Cell Carcinoma (the most common type of skin cancer). The clinical appearance and visual properties of blood vessels in skin lesions can provide important clues for diagnosis. The presence of vascular structures in skin lesions, their morphology and architectural arrangement could serve as a biomarker for specific conditions, especially in malignant tumors. Blood vessels are considered a dominant diagnostic feature in several nonmelanocytic cancerous and benign skin lesions. Many non-cancer skin disorders are comprised of and related to vascular disorders and vasculature malformations. Vascular formation and angiogenesis could be an indicator of tumor development and growth. Therefore, detection, recognition and quantification of cutaneous blood vessels provide critical information during the evaluation of skin lesions. The technique of Mohs Surgery, which is gold standard procedure for treating non-melanoma skin cancer in high risk areas, involves the consecutive removal of thin layers of skin, followed by histological preparation and microscopical examination for tumor clearance. Histology slides are 3m thick, performed at any desired depth in the resection, and observed with high resolution microscopes. So only thin optical slicing systems which en-sure cellular-level resolution and enough penetration depth can compete with this standard.

Detection of skin lesions is difficult due to the confusing appearance of wide variety of skin lesions. Biopsy provides a definitive diagnosis, however it can cause metastasis and therefore is only allowed based on the premise of following surgical operation within a month. In addition, these are invasive operations and make unpleasant experiences to the patient. To avoid unnecessary biopsy, several researchers investigated non-invasive computer-aided methods to distinguish melanomas from nevi using dermoscopy images. Visual inspection, as the only current technique for assessing vasculature, suffers from subjectivity and lack of precision. Moreover, these features are small and normally occluded by other structures which make the detection a challenging task even

by experts. There are very few studies on the automated analysis of cutaneous vasculature. Most of these studies focus on detecting erythema by color processing. Dermoscopy was primarily used to study pigmented skin lesions and there is very few studies on skin vasculature in dermoscopy.The presence of skin pigmentation and hair occludes vessel visibility and adds to the problem challenges. In order to get a clear image of a lesion, dermatologists use dermoscopy imaging. Dermoscopy has improved the diagnostic accuracy of melanoma by 10-27% over naked eye examinations. Nevertheless, the accuracy of analyzing dermoscopy images still depends on the experience of a physician. A dermatologist not trained in reading dermoscopy images can be less accurate than naked eye analysis. Once the time required to obtain dermoscopy images is considered, it is clear that automated recognition systems are more efficient. There are major differences between the vessel segmentation problem in dermoscopic and retinal images. Retinal vessels are usually larger and hence more detectable than cutaneous vessels. Moreover, in retinal vessel analysis, the anatomy of the retina could be used as a priori information towards the segmentation problem, whereas in skin, the shape of the lesion varies from image to image. The gold standard procedure for treating non-melanoma skin cancer in high risk areas is Mohs Surgery. This Surgery can take up to an hour and guides further tissue extraction. Nowadays, They investigate the feasibility of using a non-invasive optical slicing modality, together with an automated diagnosis of the cancerous areas, which would lead to speeding up the procedure, consequently, improving patient comfort and physician throughput. This motivated us to sign up in the ISIC Challenge of 2019, ISIC is the organization that we are using its dataset. This challenge is broken into three separate tasks:

1. Lesion Segmentation
2. Lesion Attribute Detection
3. Disease Classification

Each competitor may participate in any or all of these tasks. Cash prizes of $2500 USD will be awarded to winners of each of the tasks. The monetary prizes for the winners of the challenge will be awarded at the time of the MICCAI Workshop. The prizes are being provided by Canfield Scientific, Inc., a US company, and are subject to any restrictions incumbent on the sponsor. Winners will be asked to identify a recipient individual or entity who will be required to provide tax documentation (U.S. citizens- IRS form W-9, non-U.S. citizens Form W-8 BEN).

Simple neural networks that achieve a modest level of accuracy are not difficult to create; however, a system that can achieve an accuracy viable for clinical use is quite challenging and depends on several features such as: variations between size and shape, contrast between where the lesions begin and end, and artifacts such as hair color and veins. Also vascular structures are small, complex and normally occluded by other cutaneous structures such as skin pigmentation, which makes their detection even more challenging. There are major differences between the vessel segmentation problem in dermoscopic and retinal images. Retinal vessels are usually larger and hence more detectable than cutaneous vessels. Moreover, in retinal vessel analysis, the anatomy of the retina and distribution of the vessels over the image could be used as a priori information towards the segmentation problem, whereas in skin, the appearance, shape and distribution of both the lesion and blood vessels vary from image to image. The presence of skin pigmentation occludes the vessel visibility and further adds to the problem challenges. Therefore, specific algorithms for automatic skin vasculature analysis are still needed by addressing these problem-specific challenges. The above previous conventional studies have several problems:

1. Only limited types of skin lesions are acceptable for classification.
2. The systems do not explain the reasons for the classification results.
3. The systems were developed and evaluated with only ideal condition images and did not consider the condition of test images.

We develop system that works on several skin lesions types, witha general border detection algorithm for MSLs and NoMSLs, as it's a challenging task because they often have unclear borders. Also output an analysis report for the calssification results.

2 Related Work

1. **Automatic detection of basal cell carcinoma using vascular-extracted features from dermoscopy**

   Visual inspection, as the only current technique for assessing vasculature, suffers from subjectivity and lack of precision. Moreover, these features are small and normally occluded by other structures which make the detection a challenging task. Also retinal vessels are usually larger and hence more detectable than cutaneous vessels. Moreover, in retinal vessel analysis, the anatomy of the retina could be used as a priori information towards the segmentation problem, whereas in skin, the shape of the lesion varies from image to image. They present an effective method to extract vascular information towards lesion diagnosis. Given a dermoscopy image, they first segment vascular structures of the lesion by decomposing the image using independent component analysis into melanin and hemoglobin components and further applying shape filters at different scales. A vessel mask is generated as a result of global thresholding. A set of vascular features are then extracted from the final vessel image of the lesion and fed into a Random Forest classifier. A major challenge in skin vessel segmentation is that skin pigmentation occludes the visibility of vessels. As a solution, they propose an approach based on skin decomposition. Three different sources of data were used in this paper from Atlas of dermoscopy by Argenziano, University of Missouri and Vancouver Skin Care Centre. The proposed method was implemented on a dataset of 659 images among which 299 were BCCs and 360 were non-BCC. The method demonstrates performance of 90.3% in terms of AUC in differentiating BCC from benign lesions.

2. **Four-Class Classification of Skin Lesions with Task Decomposition Strategy**

Most of the conventional works handled only melanocytic skin lesions (MSLs) such as melanomas and nevi which originate from melanocytes, whereas nonmelanocytic skin lesions, (NoMSLs) indicating all the other pigmented skin lesions except MSLs such as basal cell carcinomas (BCCs) and seborrheic keratoses (SKs) have been relatively neglected. This is because melanoma is the most fatal skin cancer and especially difficult to differentiate from nevus even by expert dermatologists. However, BCC is also harmful and accounts for 80% of the skin cancer incidences. SKs are observed in most Caucasian people above the age of 50 and are sometimes confused with melanomas. Although classification of NoMSLs is considered to be easier than that of MSLs for expert dermatologists, it is not always easy for inexperienced dermatologists or physicians with different expertise. Therefore, if they open the system also for those potential users, as was the case with the abov ementioned internet-based system, it is necessary to handle both MSLs and NoMSLs. Their framework consisted of the three basics known methods. These methods usually consist of three steps:

(a) Border detection of skin tumor
(b) Feature extraction
(c) Classification

The border detection process finds the border of the tumor in the dermoscopy image, which is essential for accurate skin lesion classification. Several methods have been proposed such as dermatologist-like method, SRM, hybrid thresholding, threshold fusion, and so on. The feature extraction process obtains discriminating image features that facilitate classification such as general color statistics, contour shape, and texture information. Wavelet coefficients that capture color and shape information have also been investigated. The classification process determines the type of skin lesions from the extracted image features. General pattern classifiers such as linear discriminant classifier, k-NN, artificial neural networks, and SVMs are often used. Based on the aforementioned three steps, researchers have improved the automated classification methods. Although there are several limitations, these studies reported superior classification performance compared to experts.They developed an internet-based melanoma screening system (current URL is https://dermoscopy.k.hosei.ac.jp) which they continually update to improve accuracy and reliability. The above mentioned conventional studies have several problems:

(a) Only limited types of skin lesions are acceptable for classification
(b) The systems do not explain the reasons for the classification results
(c) The systems were developed and evaluated with only ideal condition images and did not consider the condition of test images

They developed a general border detection algorithm for MSLs and NoMSLs. Finding the border of NoMSLs was a challenging task because they often have unclear borders. With this sophisticated algorithm, they found that a linear classifier with only two image features ('skewness of bright region on the major axis' and 'difference in blue intensity between the peripheral and the normal skin') discriminated MSLs from NoMSLs with performance of 98.0% SE and 86.6% SP. They further developed a system to detect melanomas from other MSLs (nevi) and NoMSLs. Using 548 MSL and 110 NoMSL images, the system achieved 97.6% SE and 87.7% SP (89.5% SP for nevi and 79.1% SP for NoMSLs). However, this study focused only on discriminating melanomas from all other lesions, thus clumping BCCs with benign skin tumors. In this paper, they propose a method to distinguish among four types of skin lesions: melanoma, nevus, BCC, and SK, using a significantly larger dataset.

Finding the border of NoMSLs was a challenging task because they often have unclear borders. With this sophisticated algorithm, they found that a linear classifier with only two image features ('skewness of bright region on the major axis' and 'difference in blue intensity between the peripheral and the normal skin') discriminated MSLs from NoMSLs with performance of 98.0% SE and 86.6% SP. They resized the images such that the major axis of the whole tumor was 512 pixels in length due to the disparate image resolutions and to reduce computation time. For the flat model I, it is necessary to take all four classifiers into consideration when selecting a feature to add or remove in the stepwise method. This issue was addressed in which examined multiclass classification. It suggests two methods: either to optimize 'average' or 'maximum' of the four error reduction amounts associated with the four outputs. They chose the 'average' method because it showed better performance in our preliminary experiments. They Used dataset consists of:

(a) Melanoma: 105 images (30 from Keio University Hos-pital and 75 from University of Naples and Graz), a malignant melanocytic tumor (MSL) the most fatal skin cancer.

(b) Nevus: 692 images (448 from Keio University Hospital and 244 from University of Naples and Graz), a benign melanocytic tumor (MSL), often difficult to differentiate from melanomas.

(c) Basal cell carcinoma (BCC): 69 images (20 from Keio University Hospital and 49 from Tokyo Women's Med-ical University), a malignant nonmelanocytic tumor (NoMSL), the most common skin cancer.

(d) Seborrheic keratosis (SK): 98 images (42 from Keio University Hospital and 56 from Tokyo Women's Medical University), a benign non-melanocytic tumor (NoMSL), which commonly occurs in the elderly and is sometimes confused with melanomas.

The layered model with 25 features achieved a detection rate of 90% for melanomas and over 80% for each of the three other types of skin lesions. The result of this study shows promise for broadening the range of users for classification and enhancing the capability of computer-aided skin lesion classification. The melanoma (VII) was misclassified as nevus due to the lack of certain characteristics of melanoma, e.g. the difference in color between the anglewise subregions. Nevertheless, the presence of the irregular dark globules might be seen as a sign of melanoma. Dealing with such detailed patterns will be the goal of future work. In this study, they dealt with four types of skin lesions, while they did not include squamous cell carcinoma (SCC) the second most common skin cancer due to unavailability of datasets. they are planning to deal with those skin lesions in near future.

3. **Deep Residual Neural Networks for Automated Basal Cell Carcinoma Detection**

There is little research on BCC and neural networks, and the works provided have been insufficient thus far. To their knowledge, there is no previous work done on residual neural networks being trained on a dataset of BCC images. In this paper, they present, the first attempt to solve this problem. By using a fully convolutional residual neural network (FCRN) for segmentation and a deep residual neural network (NN) for classification, we seek to automatically diagnose a malignant lesion, providing a starting mode that can one day be used on images taken with an optical camera. Their inspiration is drawn from Lequan, et al., paper on Automated Melanoma Recognition in Dermoscopy Images via Very Deep Residual Network. They base their work on improving upon the techniques they used. They built their model into two stages:

(a) Segmentation

(b) Classification

Their segmentation model uses an FCRN capable of identifying a lesion in an image and eliminating extraneous information. Their classification model then takes this segment and analyzes it using a deep residual network 152 layers deep. This model works seamlessly from a single input image to a final output without any requirement of manual work. Those familiar with dermoscopy may make the argument that an additional preprocessing step is required due to the surrounding structures such as hair, moles, or droplets of water created when preparing the dermoscopy images. Similar images in their dataset also suffered no loss in accuracy with occlusion, as they believe that their NN model is capable of interpreting extraneous information as non-pertinent to the lesion at hand. Simple neural networks that achieve a modest level of accuracy are not difficult to create; however, a system that can achieve an accuracy viable for clinical use is quite challenging and depends on several features such as: vari-ations between size and shape, contrast between where the lesions begin and end, and artifacts such as hair color and veins. In many deep CNNs the gradient tends to be unstable and is a fundamental issue in gradient based learning. To avoid these issues, their model draws upon the work done by He, et al., on Residual Neural Networks (Resnets). Due to the nature of their dataset being a combination of two different databases, their first step was to normalize our inputs by resizing our dermoscopy images down to 480x480. This has the added benefit of allowing them to decrease training times by increasing their batch size, due to the increased free memory space. Due to their utilization of Keras and Theano instead of Caffe, there were several steps which had to be performed before their model could be utilized. The main focus was recognizing how Caffe and Keras differ in terms of model network setup. The most pertinent difference was that many parameters do not translate directly over from Caffe to Keras. For this they used either defaults or their best intuition for rebuilding the model e.g. using a Glorot Uniform Initializer (a.k.a Xavier uniform initializer) for their deconvolution layers. Acquiring access to a high quality dataset for BCC dermoscopy images, and dermoscopy images in general. Compared to models like Imagenet, which have millions of training images, they struggled to find several thousand images. This problem is not unique, and numerous other manuscripts, models based on medical imaging almost always suffer from either a lack of images or a low quality dataset. Due to the restrictions of their environment, re-sizing their images to 480x480 allowed them to train their models within a reasonable amount of time, and within memory limits of their GPU. However, down-sampling their image resulted in a loss of quality and features that their NN is no longer able to pick up. The last limitation of their model is their restricted un-derstanding of the clinical accuracy vs. quantitative dataset accuracy. The most common reason that research, just like the one presented in this paper, is not used in a clinical setting is because the metrics used to analyze a model do not fully encompass what we define as clinical accuracy. Model optimization such as using non-fully connected layers in the beginning of their etwork or reducing the dimensionality of their etwork would allow them to keep the images at a higher resolution and train in a reasonable time frame. Their research shows an accuracy of 93%. Their best model was at a depth of 152, in which our overall weighted sensitivity and specificity for detecting BCC from non-BCC was 97% and 96%, respectively.

4. **Automated Detection and Segmentation of Vascular Structures of Skin Lesions Seen in Dermoscopy, with an application to Basal Cell Carcinoma Classification**

So far, a number of observations on the clinical and frequency of appearance of a variety of cutaneous vascular types have been reported. Although these studies all confirm the importance and significant diagnostic value of cutaneous vasculature, there have been very

few studies on quantitative and systematic analysis of skin vascular structures in dermoscopic images. There is no objective way to quantify and assess the vasculature in skin lesions. Visual inspection, as the only current technique in clinic, suffers from subjectivity and lack of precision. Moreover, vascular structures are small, complex and normally occluded by other cutaneous structures such as skin pigmentation, which makes their detection even more challenging. There are very few studies related to the automated analysis of cutaneous vasculature. Majority of the previous studies focus on detecting erythema rather than detecting vasculature. To our knowledge, there is a great need for a framework dedicated to automatic segmentation and quantification of blood vessels in both pigmented and non-pigmented skin lesions. The main aim of their current investigation is to fill this gap. The dataset used in this paper consists of 759 images obtained from three different sources:

(a) Atlas of dermoscopy by Argenziano [22] comprised of images of 768 by 512 pixels by the so-called 'wet' dermoscopy approach.

(b) The University of Missouri comprised of images of 1024 x 768 pixels using 'wet' dermoscopy.

(c) Vancouver Skin Care Centre comprised of images of 1930 x 1779 pixels by Dermlite smartphone dermoscope with polarized light, i.e. 'dry' dermoscopy.

The diagnosis (BCC and non-BCC) of these lesions were given along with the images. A novel framework is presented to address the detection and segmentation of cutaneous vascular structures in dermoscopy images. To the best of our knowledge, the presented method is the first attempt to develop an automatic skin vessel segmentation framework. The proposed method incorporates skin color decomposition along with shape filtering and thus accounts for both underlying color components of the skin and the vascular shape. This eliminates the problem of vessel occlusion and further expands the applicability of the method from erythema detection to vessel segmentation. Furthermore, more accurate segmentation allows us to extract more accurate and meaningful vascular features improving the classification accuracy in differentiating BCC from non-BCC lesions. No preprocessing was performed on the lesions in their study. pigmentation occludes the visibility of blood vessels, interferes with vascular structures and is sometimes mistakenly classified as vasculature. This causes the sensitivity and specificity of segmentation methods to fail in such cases. As a solution, we propose an approach based on skin decomposition. ICA has an ambiguity on permutation. In other words, it does not automatically determine which of the two components corresponds to each chromophore. Therefore, after decomposing the skin and extracting the two component densities, it requires the expert user to determine which component represents which chromophore. As an empirical solution, considering that hemoglobin deals with the erythema and redness of the skin, the hemoglobin channel should have a correlation with redness. Knowing that a* channel in the L*a*b* color space could show the redness of an image (larger a*, more redness), the hemoglobin component is the component with higher correlation with a* channel. Detecting redness is an essential step towards cutaneous vessel segmentation. However there are multiple sources such as inflammation, pressure (due to contact dermoscopy imaging) and temperature that may affect skin redness and interfere with vessels.Therefore they proposed to take shape information into account along with color. It is worth mentioning that although BCC is classified as a non-melanocytic skin cancer, epidermis is a pigmented layer of skin with normal amount of melanin which might interfere with vessel visibility. In addition, there are certain types of BCC that are pigmented. Hence, as an application of our vascular segmentation framework, they performed a computer-assisted disease classification to differentiate skin cancer (BCC) from benign lesions. For this purpose, using the vessel mask resulted from the segmentation step, a set of 12 vascular features were defined and extracted from each lesion among a dataset of BCC and non-BCC lesions. Though there have been a few related studies in the literature, vascular segmentation problem has not been addressed explicitly and hence they can't compare their segmentation results directly with other methods. Therefore, to compare with different methods indirectly, they investigate the vessel detection and BCC classification application using different methods and different features. Since the proposed method is based on the assumption that variations of skin color are mainly due to melanin and hemoglobin, the presence of artifacts that interfere with the visibility of true colors of the skin can affect the accuracy of the method. Furthermore, in this study they only consider three clusters whereas in general up to six colors may be present in skin lesions. Although the proposed method has demonstrated superior performance compared to previous techniques, considering more color clusters may improve the clustering accuracy. Segmentation performance was tested on the test set of 500000 manually outlined pixels where a sensitivity and specificity of 90% and 86% were achieved respectively. The decomposition framework and including shape filters by their proposed method demonstrates an improved detection performance. The overall accuracy in term of AUC was 96.5%. As for the computational cost, the segmentation, feature extraction and classification were performed in less than 10 seconds, using a regular PC.

5. **SKin Melanoma Segmentation Using Recurrent and CNN** [1]

In this paper, threy proposed a deep neural network for lesion segmentation using convolutional and recurrent neural networks. They tested our network on images from publicly accessible dermatology image analysis benchmark challenge. The challenge name is "Skin lesion analysis toward melanoma detection: A challenge". It was subdivided into three tasks: lesion segmenta-

tion, dermoscopic feature detection, and disease classification. The Ground truth for images was prepared by a group of expert dermatologists. In the segmentation task of this challenge, 24 participants submitted the results of their algorithms. The first place winner was "ExB" team. They compared their results to the first place winner and other implementations. Fully convolutional neural networks with auto encoderdecoder architectures were used in semantic segmentation such as FCN [2] and SegNet [3]. However, output of these networks were coarse segmentation masks. To overcome this problem, a recurrent neural network (RNN)is trained to model contextual relationships between pixels. RNN are used to preserve local and global contextual dependencies even over large proximal distances. Long Short Term Memory (LSTM) is introduced to learn these spatial dependencies between neighboring pixels. LSTM has four different schemes to scan images in all direction (up to down, down to up, left to right and right to left). Each two coupled directions exhibit parallelization capabilities since they are working independently. In the presented work, The convolutional neural network layers are used to extract deep encoded feature maps. while, recurrent neural networks are used to model spatial dependencies between these deep encoded feature maps. Then, the deep encoded features maps are used to reconstruct segmentation mask at the same resolution of the input. Fractionally strided convolutions were used in reconstruction of final output. In strided convolutions, predictions are calculated by inner product between the flattened input and a sparse matrix, whose non-zero elements are elements of the convolutional kernel. This method is computationally and memory efficient method to support joint training of convolutional and recurrent neural networks [4].The proposed network was trained using 900 lesion images provided along with ground truth. These images were provided for the first task of ISBI 2016 challenge "Skin Lesion Analysis Toward Melanoma Detection" [5]. Also, proposed network was evaluated using 375 test images with the ground truth, as designated in the same challenge. The performance of the proposed method is compared to other methods using same metrics on the pixel-level, as defined in the challenge: Jaccard index, accuracy, sensitivity, specificity and dice coefficient [5]. The proposed architecture achieved accuracy of 0.98 in comparison to 0.95 for ExB. Also, Jaccard index for proposed method was 0.93, compared to 0.86 for SegNet. The proposed method provided highest accuracy with robust performance.

6. **Semi-Automatic Skin Lesion Segmentation via Fully Convolutional Networks** [6]

Motivated by the work proposed by Xu et al [7], They propose a new skin lesion segmentation method using semiautomated FCNs and multi-scale integration. their semiautomated method takes advantage of using a priori knowledge to solve the segmentation problems for challenging and rare skin lesions. In addition, the proposed multi-scale integration is capable of providing precise boundaries of skin lesions of various sizes and contrasts. The novelty of their algorithm when compared to previous studies is as follows:

(a) They leverage FCNs to extract highlevel semantic features to accurately segment the skin lesions with high efficiency;

(b) The proposed method is able to segment challenging and rare skin lesions with minimum amount of user interactions (single click)

The FCN architecture has downsampling and upsampling parts [8]. The downsampling part has convolutional and max-pooling layers, which were widely used in convolutional neural networks (CNN) for image classification task [9]. The upsampling part has convolutional and deconvolutional layers, which upsample the feature maps and output the score masks. By combining the downsampling and upsampling parts, the FCN architecture was able to extract the high-level semantic information while predicting the pixel-wise score mask. Different to the existing FCN based methods, they create two extra channels that encode the probability of the foreground (skin lesion) and the background calculated from the user interactions. Basically, the two channels indicate the probability of a pixel belonging to the fore- and background. The calculation of these two channels was achieved by applying Euclidean distance transform to measure the shortest distance from a pixel to the user clicked points. For each training image, we randomly sampled a couple of foreground and background clicks from the ground truth. There were 9 combinations of fore- and background clicks, which consist of 1, 2, 3 foreground and 0, 1, 2, 3 background clicks. We also determined that the number of background clicks should be always less/equal than the number of foreground clicks because foreground clicks are more useful for detecting challenging and rare skin lesions. In general, the semi-automated FCN outputs are feasible. However, FCN was designed for object detection on general images that cannot provide accurate boundary definitions of skin lesions of various sizes and contrast. Therefore, we used a multi-scale strategy with flip on each scale to segment the skin lesions. For each input skin lesion image, we downsized for 7 different scales and we averaged the segmentation results to produce the final probability map. Downsizing instead of upsizing was used mainly due to the fact that FCN usually produce oversegmented results with many isolated regions for upsized skin lesion images. The final probabilistic map was converted into a binary segmentation result via thresholding (50% of the maximum). For segmentation refinement, they followed previous work of Glaister et al [10] and used a morphological dilation process to smooth the boundary, fill small holes and use connected thresholding to remove small isolated single pixels. Their proposed method had a DSC of 80.21% with a single foreground click and a DSC of 92.19% with an additional background click.

7. **Improving skin lesion segmentation in dermoscopic images by thin artefacts removal methods** [11]

   Accurate image segmentation plays a very important role, since all the subsequent steps in melanoma recognition are directly influenced by it. Before starting to segment an examined image, we first need to pre-process it to a suitable form. The preprocessing step usually involves the thin artefacts removal step, which is the main focus of this paper. The lesion segmentation method is based on Chan-Vese segmentation, they used the implementation introduced by Danek et al.[12] in 2012. In this version, the image domain is divided into two disjoint and disconnected regions. This segmentation algorithm is implicitly robust to hair occlusion of lesions. They used the same parameter settings, which was optimized for this dataset to maximize the segmentation accuracy. They applied all three artefacts removal methods:

   (a) Finding artefact pixels is the kernelbased edge detection. [13] [14]

   (b) Finding artefact pixels is based on the second order derivatives of Gaussian. [15]

   (c) Finding artefact pixels is based on the mathematical morphology. [16]

   as a preprocessing step to the previously described skin lesion segmentation approaches. The Chan-Vese segmentation via graph cuts exhibits only slight improvement over the evaluation without artefacts removal, which they ascribe to its uniformity settings. Despite the fact that this method is implicitly robust to hair occlusion of skin lesions, small improvements are still achieved with the artefacts removal step applied prior to the segmentation. The Chan-Vese segmentation via graph cuts is also a more consistent method with the lowest standard deviation in all the tested scenarios. They decided to produce a union of all pixels found by all the previously discussed methods. This united set of potential artefact pixels is subsequently improved with the coverage segmentation of thin structures introduced in 2013 by Lidayova et al. [17]. The coverage segmentation was originally proposed for retinal vessels segmentation. However, the method can be straightforwardly applied to localization of any long and thin structures.

8. **Combining Deep Learning and Hand-Crafted Features for Skin Lesion Classification** [18]

   In this paper, They propose a combination of both types of features to be used for the skin lesion classification problem. They directly compare their results with the results from the recent melanoma classification challenge, which was hosted by the International Skin Imaging Collaboration (ISIC) and organized to support research and development of algorithms for automated diagnosis of melanoma [19]. The dataset used for this competition contains hundreds of images from different sources and competition problem. Their proposed method combines two different SVM classifiers. The first one is based on RSurf features and LBP. These image descriptors expect greyscale image as the input. Therefore, They first converted the original RGB image to greyscale by considering only the channel with the highest entropy E. This approach was used in [20], [21] and they chose it because the resulting greyscale image better captures the varying spatial distribution of the intensity values than traditional conversion from RGB to greyscale. Since the dataset images were from different sources and therefore had different resolutions, they also downsampled each of them to speed-up the feature extraction process, thus the resolution in the longest axis does not exceed 800 pixels. The first method they used for image description was introduced in 2014 and is called RSurf features [22]. Despite the fact that it was designed for images from a different domain, the high potential of RSurf features for melanoma recognition was also demonstrated [23]. The idea behind this feature set is based on dividing the image into parallel sequences of intensity values from the upper-left corner to the bottom-right corner. In these intensity sequences, all the local intensity maxima and minima are localized. Therefore, intensity values between two extreme points form either non-increasing or non-decreasing intensity sequences. they refer to them as to slopes in further text. In general, one can sequentially scan the image and extract slopes in any direction. It was already recommended in 22 to scan the image in various directions in order to increase the robustness to rotational differences. The Second method is Local Binary Patterns (LBP), it were first introduced in 1994 by Ojala et al. 24. The idea behind this descriptor is based on the model of texture units, where an input image is described through its texture spectrum. Ojala et al. extended this model and proposed its two-level version, which is now the core of the original LBP. The computation of the original LBP consists of several steps. First, each pixel of the image is compared with its 8 immediate neighbours. If the intensity value of the neighbouring pixel is greater than or equal to the value of the examined pixel's intensity, write 1 in the neighbouring pixel. Otherwise, write 0. The described process gives us an eight-digit binary number for each pixel in the image. For convenience, we convert this number to decimal by taking the neighbours in clockwise order from the top-left corner. These decimal numbers are used to form a histogram and in the end, a concatenation of the normalized histogram values gives us the feature vector. The First Class is based on SVM classifier with Gaussian kernel and standardized predictors. It combines RSurf features and LBPR=1,3,5 to estimate the class for a given input image. The input feature vector consists of 2768 components. Each image class label is predicted with a certain score representing the posterior probability that an observation belongs in a particular class, given the data 20. It can be interpreted as the strength of classification decision and they use it later in they final solution. The second SVM classifier with Gaussian kernel and standardized predictors uses features derived from CNN. Specifically, they used

the AlexNet 25 proposed by Krizhevsky et al. in 2012. Authors employed the CNN for the first time for image classification and won the ImageNet Large Scale Visual Recognition Challenge 2012 with significant lead over the other participants. Despite the fact that AlexNet was created for real world images, it was also applied in combination with SVM for melanoma recognition 26, 27. Both of the tested SVM classifiers provide also scores defined as the mean accuracy of the given test data and labels. They use these values to determine, which classifier is more confident about the assigned label. For each tested image, they choose the label with the highest absolute score value. The final classifier is therefore a combination of both principles, the handcrafted features and the features derived from the deep learning mechanism. Their final classifier has the average precision of 0.473, which is only slight improvement over the previously mentioned results but the classification accuracy is 0.826 with the sensitivity of 0.533 and specificity of 0.898. This performance is among the top state-of-the-art classifiers, which summarises the results of the melanoma classification challenge.

9. **Automated Melanoma Recognition in Dermoscopy Images via Very Deep Residual Networks** [28]

The main contributions of their work can be summarized as follows:

(a) They propose a novel and comprehensive two-stage approach based on very deep CNNs with a set of effectivetraining schemes to ensure the performance gains of increasing network depth with limited training data for automated melanoma recognition. They are not aware of any previous work that employs such substantially deeper networks (more than 50 layers) in medical image analysis field. Experiments demonstrate that, compared with much shallower counterparts, the very deep CNNs are capable of acquiring richer and more discriminative features and achieving better performance.

(b) They propose a very deep fully convolutional residual network (FCRN) for accurate skin lesion segmentation, and further enhance its capability by incorporating a multi-scale contextual information integration scheme. The network is general enough and can be easily extended to solve other medical image segmentation tasks with targeting objects having large variations.

(c) They compare the performance of networks with different depths and corroborate that very deep CNNs with effective training mechanisms can be employed to solve complicated medical image analysis tasks, even with limited training data. This may inspire more studies to tap the potentials of network depth of CNNs to solve challenging medical image analysis problems.

The networks proposed in [29] are designed for classification. In order to achieve accurate and efficient skin lesion segmentation, they construct a fully convolutional residual network (FCRN) based on residual blocks, which can take an arbitrarysized image as input and output an equal-sized prediction score mask. After successive down-sampling operations in the original residual network, the dimensions of feature maps are gradually reduced and become much smaller than that of the original input image. To bridge the resolution gap so that both the learning and inference procedures can be performed in an efficient end-to-end way, they exploit deconvolutional layers as the up-sampling operation to connect coarse predict maps and dense pixels predictions [30] [31]. Specifically, they use deconvolutional layers to upsample small prediction maps and get the equal-sized prediction maps with input images. Note that the weights within the deconvolutional layers are also trainable during the learning process. . The proposed FCRN contains 16 residual blocks in down-sampling path. Each residual block consists of two 11 convolutional layers, one 33 convolutional layer, three batch normalization layers and three ReLU layers. Besides these residual blocks, it also contains one 77 convolutional layer and one 33 max pooling layer (both with stride 2) as prelayers.To train the FCRN, they first crop an sub-image from every original dermoscopy image with ground truth by automatically figuring out the smallest rectangle containing the lesion region and enlarging its length and width by 1.1 1.3 times in order to include more neighboring pixels for training. Then they randomly crop another sub-image with the same length and width on the dermoscopy image to increase the negative training samples. Note that as the objective of the FCRN is for segmentation, every pixel can considered as a training sample. They take all the pixels on these cropped sub-images as training samples to train the FCRN. In the testing phase, they do not perform the subimage cropping procedure or other detection-like processes. they directly segment the whole dermoscopy images and the prediction masks of the whole image were produced with an overlap-tile strategy.

They construct a very deep residual network to classify skin lesions based on the segmentation results. The architecture of the network is almost the same with that of the down-sampling path of the proposed FCRN for segmentation. The difference is that they add a 77 average pooling layer followed by the 16th residual blocks to extract the global deep residual features. Some researchers found a small but consistent advantage of replacing the Softmax layer with a linear support vector machine layer when training CNNs [32]. Inspired by these findings, we exploit two classifiers, Softmax classifier and support vector machine (SVM) classifier, to obtain two predictions and then average them to get the final results. Note that the Softmax classifier and the SVM classifier are trained independently in an end-to-end way with the proposed residual networks.

10. **A General Algorithm for Automatic Lesion Segmentation in Dermoscopy Images** [33]

Their goal in this article is to introduce a general method for lesion segmentation in dermoscopic images. There is several drawbacks in designing such a general algorithm. These problems originated from the fact that most of the dermoscopic images are defected with noise, hairs, dark corners, color charts, uneven illumination, marker ink, etc. So far, the other researchers in the literature tested their algorithms on limited datasets, in which all the images have similar specifications. In real terms, dermoscopy image datasets are more complicated. They may have different properties for each image and all kind of disturbance may exist, like the dataset we working on. A general framework for segmentation should be capable of overcoming these difficulties. Preprocessing is a way to handle most of these deficiencies. The preprocessing procedure has several tasks or steps. Each of which has been designed to eliminate the effect of particular deficiency in the image. Since further operations are based on a single-channel gray-level image, the first step in the preprocessing must be the color to gray-level image conversion. This task could be simply done by selecting Blue channel of RGB color space or can be done using more sophisticated approaches to selected/construct the optimal color channel. According to the available dataset, we select or design the most appropriate algorithms for different task as follow:

(a) Hairs and ruler marks inpainting: They use the well-known DullRazor filter 34 to remove the hairs from the image.

(b) Dark corner detection: To obtain the initial corner mask, They used a constant threshold for Y channel of CMYK color system, because this channel represents the Black color in the image and has a good discriminant between the dark corner and other parts of the image.

(c) Illumination Correction: They use homomorphic filtering [35] for this part of preprocessing, it simultaneously normalizes the brightness across an image and increases the contrast. The homomorphic filter is an old but yet efficient and stand-alone technique to correct for non-uniform illumination.

In this article, They use deformable models for melanoma segmentation. They use level sets to represent the contour. This type of contour representation has been taken into consideration in many medical image applications. We use the level set approach introduced by Malladi et al. [36] in a novel framework to propagate an initial contour toward the lesion boundary. In addition to image gradient information, here they use image color information to form the speed function. So, their approach would benefit from both gradient and region information. This property makes the algorithm robust against weak edges and faded color regions. To be able to capture the correct color information of the desired region to form the speed function and also initializing the model contour, they need a primary mask of the lesion in the image. This binary mask is obtained using Otsu's thresholding technique [37]. This binary mask is processed and its contour extracted to be used in further operations. A very challenging issue in designing of an automatic lesion segmentation algorithm, which could be generalized to a variety of lesions, is handling the images with weak gradient magnitude i.e. images with weak edges and strokes. Unfortunately, most of the model-based segmentation algorithms employ edge information and are not appropriate for this situation. They propose to somehow engage the color information as well to handle this kind of problem. For this end, They need to model the color information of some lesion's pixels and then use this model to classify all the pixels in the image. In this way, They can obtain a probability map of each pixel contribution to the lesion. The dataset that they used in this research consists of 900 dermoscopy images. These images have been selected from the International Skin Imaging Collaboration (ISIC) archive to be used as a training set in the challenge of "Skin Lesion Analysis toward Melanoma Detection" at the International Symposium on Biomedical Imaging (ISBI) 2016. [38] The evaluation experiments of the proposed method result in Dice and Jaccard coefficient values of 0.89 and 0.79, respectively.

11. **A Novel Multi-task Deep Learning Model for Skin Lesion Segmentation and Classification** [39]

In this article, a novel multi-task DCNN model will be used for the analysis of the skin lesion. Different from conventional DCNN, in the multi-task learning architecture, the input dermoscopic image can be associated with multiple labels that describe different characteristics of the lesion. This multi-task technique can then be used in the segmentation of lesion and classifications of lesion categories at the same time with improved learning efficiency and prediction accuracy. This equips the dermatologist with a robust tool for analyzing dermoscopic dataset. The DCNN is a set of neural networks with many different convolutional layers that can be trained to extract features from images. During the training phase, the DCNN will minimize the difference between its current model and thelabelled components. In the process, features of different scales are also extracted at the different convolutional layers. This will allow for robust detection and categorization of structural components in the evaluation of a new input image. The DCNN technique can therefore be used in the categorization of skin lesion in a dermoscopic dataset. The multi-task DCNN technique allows different components to share the detected features among different attribute categories. These components will generate feature representations specific to the attribute categories, and a multi-task training on the features can be used to infer the attributes. This will allow robust detection of the skin lesion from a dermoscopic dataset. The segmentation of the lesion from dermoscopic im-

ages is an important aspect of melanoma detection, as some of the features which are used by clinicians in dermoscopy algorithms are based on the shape of the skin lesion. The segmentation of the lesion is therefore incorporated in the multi-task network model for skin lesion analysis. The detected features learned by the DCNN can be used by the different components in the multi-task inference, i.e., thesegmentation of the lesion and the detection of melanoma in the skin dataset. The output of the multi-task network includes (a) the binary mask of the skin lesion, (b) theprobability of detected skin lesion belonging to melanoma, and (c) the probability of detected skin lesion belonging to seborrheic keratosis.

12. **Machine Classification of Melanoma and Nevi from Skin Lesions**
Their motivation was to help people to determine the diseases they have on their Their problem they are trying to solve to classify the different between the melomna and nevi by each one feature because they looks similar the steps they made was First was segmentation they used color based segmentation that there are three color primaries existing in the image. The blue area represents nuclei while the light staining areas represent tissue retraction or cytoplasm. Darkly staining red areas represent extra cellular structure or red blood cells that are not of interest in their analysis, since important differential diagnosis criteria for distinguishing melanoma from nevi are associated with nuclei and cytoplasm, it is essential to identify nuclei and cytoplasm from other tissues such as connective tissue they also hue to remove irrelevant areas Two criteria are used to indicate a melanoma case. First, the size of a nucleus becomes larger within melanocytes as the chromosomes develop aberrations and become both progressively more polyploid and mitotically active. their first two features pick up on these elements. Second, the shape of nucleus of a melanocyte tends to become more asymmetric which is the focus of the 3rd and 4th features. Which are The ratio of the perimeter of a nucleus to its area and The ratio of the major axis length of a nucleus to its minor axis length THEN FOR TRAIN PERDICTION they used svc which is a type of svm to compare between feature the accomplish was to classify the between the melanoma and nevi but they used the Digital Clinical Imaging Despite their success they do not expect their SVM to perform as well as more developed clinical skin imaging systems and they are not yet confident that their tool is ready for use in the laboratory. However the addition of machine analysis to the histology realm allows a digital diagnosis to be made from distinct sets of images. Combining clinical and histological images could reduce the number of false negatives which are the most serious diagnosis error since they leave a potentially malignant melanoma skin cancer undiagnosed and untreated. they view our approach as complementary to digital clinical imaging of suspicious moles rather than competitive, their future work where The most obvious source of future improvement would be the addition of new features for our SVM, particularly those features not based on irregularities in the nucleus. they are considering asymmetry of the lesion and the presence of melanocytes in the upper layers of the dermis as two strong candidates. Another major improvement would be a proper segmentation of melanocytes. Currently their approach (which is most effective at high power) relies on melanocytes making up the majority of the image. This is generally true for our data set, but it means that we also examine keratinocytes, leucocytes and other cells for irregular nuclei. This lowers accuracy

13. **Pattern Classification of Nevus with Texture Analysis**
That incidence of a melanoma of most malignant skin tumor is increasing in recent years. When man does not perform suitable medical treatment, it might occur that cancer may metastasize to other parts of body, it is necessary to perform discovery and medical treatment before metastasis. Since an early melanoma and a benign nevus have a close resemblance each other, if an experienced dermatologist did not diagnose the lesion, a discovery of an early melanoma is difficult. The purpose of this research is to classify the pattern on the surface of the nevus. The digital image that contains one nevus is classified into three kinds of patterns of homogeneous pattern, globular pattern, and reticular pattern by the texture analysis. The tumor part in the image is specified first, and the specified tumor part is divided into some sub-images. Afterwards, the amount of the texture features of each sub-image was calculated. The pattern was classified by the discriminant analysis based on the amount of the texture feature This research requires images of homogeneous pattern, globular pattern and reticular pattern among pigmented nevus such as blue nevus, Clark nevus and dermal nevus. they convert each image into the image of the same magnification. Consequent magnification of images is 30 pixel/mm (=0.033mm/pixel). Next, they convert color images into grayscale images with 256 brightness levels Since healthy skin is also taken photograph into the images, man requires specification of tumor region within the images before texture analysis Then hreshold is obtained using Laplacian histogram method and discriminant analysis. The results of Laplacian histogram method and discriminant analysis have noise 1 such as ones described below. (1) Pixel noise in background (2) Hole within tumor region Since noise of relative large region exists in many images, we apply a labeling method to the elimination of pixel noise from images. Next, for the hole within tumor, man performs hole shrinking using the similar method to that of pixel noise. After noise reduction, they obtain a contour of tumor in the image from bi-level images Then feature extraction they use intensity histogram, differential statistical feature, Fourier power spectrum, run-length matrix and co-occurrence matrix for texture analysis. There are well known 7 features for intensity histogram, 7 features for differential statistical feature, 14 features for Fourier power spectrum, 5 features for run-length matrix and 13 features for co-occurrence matrix in our method.

When man uses these 46 texture features, man can show the difference between homogeneous pattern and globular pattern, or the difference homogeneous pattern and reticular pattern. However these features cannot show the difference between globular pattern and reticular pattern. they require the method that classifies globular pattern and reticular pattern From investigation of the texture analysis, they obtain 110 features for classification of homogeneous pattern, globular pattern and reticular pattern. In this paper we use the four methods for statistical analysis. (1) F-test F-test is the test whether each pattern has the same variance for 110 features or not. By the result of F-test man must use the different t-test method. (2) t-test T-test is the test whether each pattern has the difference of feature value for 110 features or not. When there is not enough the difference between the features each other, man removes the feature from the computational method. (3) Stepwise method We search the minimal number of features by stepwise method. (4) Discriminant method Finally man performs pattern classification by discriminant metho5 The purpose of this research is to classify the pattern of the tumor automatically with a computer as a stage before distinguishing a benign tumor and a malignant tumor. The texture analysis that is the technique of the image processing is used for pattern analysis. Before texture analysis, the tumor part was extracted by binalization and divided into some subimages. After that, the texture features of each subimage were calculated. Discriminant analysis classified the patterns based on the texture features selected by the stepwise method. They think that they did not get high accuracy in the classfiction of 46 features and they think that Leave-oneout cross validation method has the similar ratio 2 that man uses in the actual clinical scene. The ratio of this method reached 89.0 percent they think that this ratio is good in the first step of this research. 3

14. **Artifacts Removal in Nevi Medical Images Based on Moving Frame Domain Texture Analysis**

procedure for user-assisted artifact removal from medical images, namely photographic images of nevi and melanomas and to find in the components around the selected area. These values correspond to neighbors to the artifact pixels and not to artifact pixels themselves. Still, being calculated on the base of the estimated gradie .Medical images represent a challenge in image processing since they vary in nature, acquisition techniques, diagnostic information content. As for nevi images, the diagnostic information on the nature of the skin lesion is strictlyrelated on the structured nature of nevi, while pathological textures are recognized by the lack of structures. This phenomenon led to skin lesion detection by image segmentation, as in [6] where the authors exploit the joint statistical texture distinctiveness for texture classification purpose .First they recall the basics of the moving frame domain representation then they used it in the artifact removal algorithm The first stage encompasses the calculation of the transformed component. Then they extract the structure by threshold then they apply interpolation on the pixels that have been classified as artifacts. Then comparing purpose they compare the results obtained by interpolating the image using thresholding for classification and then reconstructing the image from these interpolated components; since the distortion is low contrast, they highlight here the detail of the reconstructed images. they recognize that this approach is affected by a survival artifact component. The artifact is not visible when the interpolationis realized in the original image domain,they tackled the problem of user-assisted artifacts removal on medical nevi images. Specifically, they proposed a procedure based on nevi representation in the moving frame domain, and show that in this domain artifacts and information content are well distinguished. Based on this observation, they adopt the moving frame domain for detecting artifact pixels and they apply interpolation to substitute the artifacts pixels with estimates based on the neighboring pixels. The technique proved to be effective, and the moving frame domain proves promising for nevi images preprocessing and restoration.

15. **Study of Melanocytic Nevi using Image Processing**

Misclassifion of Clark Nevi based on the dermoscopic criteria. Their goal is to assess the significance of features that aid in differentiating benign and malignant lesions. The main contributions are as follows. x Pathological significance of dermoscopic features is provided x The article presents key ideas that will help researchers judge the importance of the features that aid in diagnosing malignant and benign lesions x This kind of study combining domain and technical aspects is scarcely been performed in literature The term “nevi” refers to a mole. The origin and natural history of melanocytic nevi is an ongoing matter of debate. Two theories were set forth in this regard, the “Abtropfung” theory and the “Hochsteigerung” theory. Both these theories are contradictory to each other. The “Abtropfung” theory states that melanocytic nevi originate from the epidermis and drop of to the dermis The Hochsteigerung theory states that melanocytes that originate at the neural crests start at the dermis and migrate up to the epidermis Basically, a melanocytic nevi is divided into two categories the Congenital Melanocytic Nevi (CMN) and the Acquired Melanocytic Nevi (AMN). Maintaining the Integrity of the Specification During infancy the size of the CMN increases. In a study conducted in [7] 41 congenital nevi were observed to measure the relative and absolute area of expansion with respect to the anatomic region expansion. It was observed that most of CMN showed a proportionate area of expansion, however 9 CMN represented a variable growth rate during the first six months of life. It was inferred that velocity of growth of congenital nevi is proportional to the growth rate of human body, it is very large during the initial 6 months of life. Mitotic activity of the cells increases with stretching and genetic factor Acquired nevi can be divided as Reed and Spitz nevi in one cate-

gory and Clark nevi (dysplastic nevi) as the other category. The number and size depends on the genetic factors including the environmental factors and the skin type. After the Clark nevi has reached a certain size the growth stops. In some individuals, even after the age of 30 years there exists a higher growth rate, however epidemiological studies have not been conducted to show that this is an indication of melanoma. Pigment networks are honey comb like structures with hypopigmented holes and pigmented lines. The network corresponds to the ridge kind of epidermis pattern. The histopathological co-relation is the presence of melanin in the keratinocytes and melanocytes in the dermal and epidermal junction. The Blue whitish veil is a distinct and irregular structure with blue colored pigmentation surrounded by a white hazy glass like structure. Histopathologically this corresponds to melanocytes in the dermis in conjunction with orthokeratosis Dots are circular, miniscule dermoscopic structures that less than 0.1mm in diameter. The color of the dots is based melanin localization. The black dots indicate the presence of melanin the epidermis, the brown dots indicate the melanin presence in the dermis-epidermis junction and the blue-grey dots indicate the melanin presence in the dermis. Globules are oval well demarcated structures having diameter greater than 0.1mm. Histopathologically the presence of globules indicate the melanin nests in all the three skin layers

The STATE OF ART DIAGNOSIS TECHNIQUE they used pattern anayalisis and abcd rule and . 7 point Checklist and Menzies Rule Argenziano and colleagues analysed 342 lesions and formulated the 7 point checklist [26]. The features are divided as minor and major criteria. The major criteria includes blue whitish veil, vascular pattern and pigment network. The presence of irregular streaks, pigmentation and dots/globules correspond to minor criteria. Diagnosis of nevi and The study implies that for building up a reliable computer aided diagnostic tool the dermoscopic structures such as blue-white veil and pigmented network need to be incorporated along with the shape, texture and color of the pigmented skin lesion.

16. **Classification of melanoma and clark nevus skin lesions based on Medical Image Processing Techniques**

Melanoma is outwardly troublesome for clinicians to separate from Clark nevus injuries which are generous. The use of picture handling procedures to these injuries might be helpful as an instructive device for instructing doctors to separate sores, and also to contribute data about the basic optical qualities for distinguishing This exploration attempted locate the best highlights to separate from melanoma, melanoma in situ and Clark nevus sores, and to locate the best example characterization criteria and calculations for separating those sores. The shading contrasts between pictures that happen as a result of contrasts in encompassing lighting amid the photographic procedure were limited by the utilization of dermoscopic pictures. Contrasts in skin shading between patients was limited by utilizing normalizing them by methods for changing over them to relativecolor pictures, and contrasts in surrounding lighting amid photography, and the photographic and digitization forms, unique shading pictures were standardized by changing over them into relative-shading pictures. Tumors in the relativeshading pictures were then divided out and morphologically separated. Their Picture 3Database: A database of 60 shading dermascopic sore pictures was utilized. The database was subdivided into three classifications comprising of 20 pictures every: melanoma, melanoma in situ and Clark nevus. Every one of the pictures were 768 x512 pixels and putten in a row, packed configuration, to reduce border image artifacts. 1 Programming Library: CVIPtools was utilized to perform the vast majority of the picture preparing and computer vision tasks. Border pictures (BIs) are binary images having a dark foundation and a white object of interest . They are produced by utilizing a mouse to physically draw a border around a interest of intrigue (tumor) in the first shading picture. The border images were used to mask tumors out of the first shading pictures to recover "only skin " pictures. A logical NOT of the BIs was utilized to mask tolerant skin out of the first shading pictures to create "tumor only" pictures. They made algorithm for generating relative-color images, extracting tumor features and classifying them. And but in their mind the light difference and the skin color difference Their have made 7 step for feature extraction and pattern classification

(a) Preprocess the originalimage: In order to minimize artifacts dermoscopic-gel bubbles and camera flash were removed from dermoscopic images using a second-order, Contra-Harmonic Filter (CHF)

(b) . Generate border images. (See the Materials section.) and Generate relative-color images: For one original-color

(c) Lessen the quantity of articles in the sores utilizing division and morphological sifting. segmentation: CVIPtools' Principal-Color-Components Transform algorithm was utilized to segment the relative-shading image into four, vital, homogeneous region of color. Morphological filtering : with a specific end goal to smooth the states of image , their projections were pared and holes were filled,using a 9-pixeldiameter circle as a structuring element

(d) Extract features from the lesion's objects: A variety of feature vectors were generated using various combinations of the following features: area (ar), thinness (th), perimeter (per) and histogram features, including the mean (m), standard deviation (sd), energy (en), and entropy (ent). The texture features that were extracted included inertia (tx-inr) and entropy (tx-ent). In some experiments, the above features were extracted from the two, largest objects in the lesion; in other experiments, features were extracted from the whole lesion which was treated as one object.

(e) . Choose a metric to be used in the pattern-

classification algorithm: Three different distance metrics were used to compare the training-set feature vectors to those in the test sets, including the city-block, Euclidean-distance and maximum-value (max-value) metrics"

(f) . Develop a pattern-classification algorithm: The database of 60 lesion images was divided into sets of 30 images each. One 30-image set was divided into training and test sets of 15 images each. After training and testing, if the classification results were consistent, the algorithm that was developed was executed on the other set of 30 images. If the consistency prevailed on that set of 30, the algorithm was then executed on a set of 50 images

In separating melanoma from Clark nevus sores, gathering melanoma and melanoma in situ together, got the best outcomes on the grounds that those two arrange2 ments of tumors (melanoma and in situ) have features and features values that are sufficiently comparable to be viewed as one class of tumor that altogether varies from Clark nevus. Thus, gathering them together expands the characterization rate. They did not approach a high accuracy in differentiation between the 2 diseases and Misclassification of melanoma and melanoma in situ for an expanded training set, suggests that there is a considerable overlap between the two categories of melanoma. This indicates that some additional features are required to automatically differentiate those classes

17. **Melanoma Detection by Analysis of Clinical Images Using Convolutional Neural Network[39]**
In this paper, The aim was to develop tools for mobile aided diagnosis of the most common skin cancer. Also to take advantage of deep learning methods to form an automatic diagnosis system for melanoma detection.This can be applicable in web based and mobile application as a telemedicine tool and as a supporting system that assists physicians.In this paper an implementation of a deep learning system on a computer server, equipped with graphic processing unit (GPU), is proposed for detection of melanoma lesions. Clinical (non-dermoscopic) images are used in the proposed system, which could assist a dermatologist in early diagnosis of this type of skin cancer.Melanoma, also referred to as malignant melanoma, is a type of skin cancer caused by abnormal multiplication of pigment producing cells that give color to the skin . Despite significant death rate, early stage detected melanoma is curable in most cases [11]. Meanwhile differentiation between melanoma and other benign moles in their initial growth phases is a challenging task even for experienced dermatologists [40]. Computerized algorithms are being developed for this purpose. Some low complexity methods are designed, which are intended for running on tablets and smart phones, and can help non-specialists. But professional decision making, in this regard, requires sophisticated algorithms and equipment. There are various methods in dermatology such as ABCD (asymmetry, border irregularity, color patterns, and diameter) rule [41] and the seven-point checklist [42] that guide physicians in this task. Firstly part is preprocessing; to take Images of skin surface, even those taken by professional digital cameras, usually contain illumination and noise effects that should be eliminated. These effects are the result of nonuniform lighting, and reflections of incident light from skin surface. To reduce effects of these misleading factors on CNN's training and classification, firstly an illumination correction step is performed on input images. This step is similar to the algorithm of [43], where the illumination effects are detected as sharp changes in the saturation and value channels of the HSV color space. Thus, the illumination effects are discarded by excluding a specific range of gradients. This is done without destroying the real edges of the original image.Another factor that should be considered is that an input image contains both healthy (normal skin) and lesion parts. This can mislead the training of CNN. Texture of the healthy areas is an irrelevant criterion for melanoma detection. Meanwhile, cropping healthy areas could cause loss of information, such as color difference between lesion and patient's normal skin. Such information could be a discriminative clue. For this purpose, a segmentation mask is produced by applying a k-means classifier (K = 2) on the preprocessed image. This mask is further enhanced by some morphological operations. The attained mask extracts the lesion's region. For reducing the effects of the normal skin's texture on the classification process, we use the segmentation mask for smoothing the area outside of the lesion. For this aim, a Gaussian filter (with alpha = 2) is applied on the normal parts of the skin based on the information of the segmentation mask. In this paper CNN, as a deep learning framework, is used for automatic detection of melanoma. CNNs take advantage of a set of powerful convolve-filters. They can examine various structures in input images. Hence, in utilization of CNN, the input is the image itself and the network automatically extracts appropriate aspects of the image. The training set of CNNs must be sufficient enough. This dataset of 170 images is increased to 6120 original and synthesized images. To perform training and testing the dataset is split into two randomly selected groups. A 80% - 20% ratio is used where 80%of the dataset images are randomly selected for training and the rest is used for test while there is no overlap between the test and train samples. The training data is fed to a network with a batch size of 64. The overall accuracy of CNN with the Deep learning approaches was 92.5%.

18. **Automated Skin Lesion Analysis Based on Color and Shape Geometry Feature Set for Melanoma Early Detection and Prevention [44]**
Skin cancer has been increasingly identified as the major cause of deaths. Skin cancer can be classified into 3 types: melanoma, basal cell carcinoma (BCC), and squamous cell carcinomas (SCC). Melanoma is most dangerous originates from melanocytes and tops the threat scale since it grows quickly and metastasizes rapidly.The problem they are trying to solve Early Detection and Prevention of malignant melanoma in

the early stage to increase the chance of cure significantly.Doukas et al.[45] developed a system consisting of a mobile application that could obtain and recognize moles in skin images and categorize them according to their brutality into melanoma, nevus and benign lesions. As indicated by the conducted test, Support Vector Machine (SVM) resulted in only 77.06% classification accuracy.The outcome of this system is intended to help users to prevent developing skin cancer by triggering a real-time alert that informs the users to avoid exposure to harmful UV radiation. The system will also allow users to capture images of skin lesions and analyze it at real-time. Users will be able to have an early detection of malignant melanoma which increases the chances of successful treatment. Essential step before starting with the features extraction in order to classify the 3 different types of lesion (i.e. normal, atypical and melanoma).The segmentation steps follow: First, we read the RGB (i.e. color image) dermoscopy image (step 1) and convert to gray scale image. We convert RGB values to gray scale values by forming a weighted sum of the R, G, and B components. then apply two dimensional filter of the Gaussian filter type (Step 2).After the Gaussian filter is applied, we compute a global threshold that can be used to convert an intensity image to a binary image.The next step is to convert the gray scale image to a binary image using the calculated threshold (step 3).The next step is to remove the white corners in the dermoscopy image(step 4).After applying the threshold, the edges of the output image become irregular. To smooth the edges, they first create a disk-shaped structure element(step 5).Next, we applied the morphological open operation on the binary image(step 6). In the next step, we used an algorithm based on morphological reconstruction in order to fill the holes in the binary image(step 7).The output image is a binary image where the foreground is white (logical true) and the background is black (logical false) (step8).The next step is to remove the small objects. To do that, they determined the connected components. Second, we computed the area of each component. Third, we removed all small objects that have fewer than 50 pixels(step 9). Finally we used the disk structure element that we created in the previous steps to perform a morphological close and open operation. After that, we mask the resuling image with mask2 to preserve the corners (step 10). We compared two types of classifiers: One level classifier and Two-level classifier. In the one level classifier, only one classifier is used to classify the ROI into three categories, normal, atypical or melanoma. However, in the two-level classifier we use two classifiers, classifier I and classifier II. Classifier I classifies the image into normal or abnormal, and classifier II classifies the abnormal ROIs into atypical or melanoma. We found that the two-level classifier approach gives better results, as explained in the result section.In particular, the framework compared the performances of two classifier techniques, one level classier and two-level classifier. We concluded that the two-level classifier outperforms the one level classifier. Future work will focus on defining and extracting novel features, for example pigment network, to improve the accuracy of classification.They used 2-D Fast Fourier transform (FFT) feature set [46] computes the Discrete Fourier transform (DFT) and its inverse. A 2-D Discrete Cosine Transform (DCT) [47] expresses a finite sequence of data points in terms of a sum of cosine functions oscillating at different frequencies. As a result, 2-D FFT and 2-D DCT are widely used for many applications. Therefore, we used such features to classify the malignant melanoma cases. However,The proposed framework compared two types of classifiers. Consequently, the two-level classifier outperforms the one level classifier. In the one level classifier, we were able to classify the normal, atypical and melanoma images with accuracy of 90.3%, 92.1% and 90.6% respectively. On the other hand, the two-level classifier was able to classify the dermoscopy images with accuracy of 90.6%, 91.3% and 97.7% respectively.

19. **Malignant Melanoma Detection by Bag-of-Features Classification[48]**
There are important features for early melanoma detection. Many criteria like the ABCD rule, 7-point checklist, and Menzies' method used by dermatologists are based on the presence of certain texture patterns. And studies also focus on detecting a specific texture pattern, such as a dark area by Pellacania , asymmetric blotches by Stoecker , and irregular streaks and atypical pigmented network by Betta .Their motivation in this paper, they attempt to build classifiers for melanoma detection based on the distribution of local patterns.Local patterns are important features for early melanoma detection. Many criteria like the ABCD rule, 7-point checklist, and Menzies' method used by dermatologists are based on the presence of certain texture patterns. Most existing studies focus on detecting a specific texture pattern, such as a dark area by Pellacania et al. [49], asymmetric blotches by Stoecker et al. [50], and irregular streaks and atypical pigmented network by Betta et al. [51]. In this paper, we attempt to build classifiers for melanoma detection based on the distribution of local patterns. Bag-of-Features based image classification is widely used in computer vision [52],[53]. They applied their algorithm to discover the shared clusters among skin lesion images. As before, the histogram of the "topics" can also be the "signature" of a skin lesion. Controlling the sensitivity and specificity of the classifier is crucial. The "2CSVM" algorithm [54] is applied to generate a classifier by placing different weights on positive and negative samples.

    (a) Bag-of-Features
    Each skin lesion is represented by a Bag-of-Features defined on several patches sampled on the image. To describe each patch, we used wavelets and "Gabor-like" [55] filters in our experiment, but several other texture features can also be used. A 3-level wavelet decomposition is applied to 1616 image patches and the energies of the 10 subbands are used as patch descriptors. The advantage of the "Gabor-like" [7] filters developed by Schmid is that they are invariant to rotation.

(b) Classifiers
Two types of classifiers are employed in this study: Naive Bayes classifier and Support Vector Machines (SVM). In order to control the sensitivity and specificity of SVM, the so-called "2C" formulation of SVM described below is used in our experiment to generate ROC curves and control false negative error rate.

(c) Code book and Shared Cluster
Wavelet and "Gabor-like" filters are applied to each 1616 image patch. A set of 10 features are obtained from the wavelet filter and 13 more are obtained from the "Gaborlike" filter. A widely used method for quantization is k means clustering. A universal way to determine the codebook size has not been developed yet. It is observed that larger codebook sizes can lead to obtain higher accuracy [52], [53].

The "signature" of a skin lesion is obtained by building a codebook with texture features and k-means quantization. A method to discover shared clusters among lesions by the Dirichlet process has also been tested .Overall the best classifier was obtained with an AUC of 82.21% from wavelet features and a codebook size of 512. Neyman-Pearson score is used to choose a single classifier and to control the false negative rate.

20. **Determination of Border Irregularity in Dermoscopic Color Images of Pigmented Skin Lesions[56]**
Malignant melanoma is predicted to become one of the most common malignant tumors in the future, with even a ten times higher incidence rate. One of the major contributors to the development of melanoma is ultraviolet radiation (long-term sun exposure and sunburn) that causes damage to the cell DNA. One of the main tasks of modern dermatology is the detection of melanoma in its early stage of development, because the survival rate after identification of less than 0.75 mm thick melanomas is near 100 % [6, 57, 58]. In the light of the above data, prevention and early diagnosis of melanoma become an extremely important issues. The dermoscopic diagnosis of pigmented skin lesion is based on the assessment of the presence or absence of different global and local features. Various analytic methods and algorithms have been set forth in the last 25 years. The most important and widely used are: Pattern analysis, ABCD rule of dermoscopy, 7-point checklist and Menzies method [6, 59].For calculating the ABCD rule of dermoscopy score need the 'asymmetry, border irregularity, color, and differential structure' criteria have to be assessed semiquantitatively. The most important warning sign for melanoma is a change in size and shape of a mole or other skin growth. One of the main warnings is border irregularity. Border irregularity is a ragged, notched, or blurred edge at the periphery of the skin lesion For semiquantitative evaluation, the lesion is divided into eight similar parts and a sharp, abrupt cut-off in each part has a score of 1. So, if the whole border is irregular the maximum border score is 8. If the mole is round with no ragged borders the score is 0. As a rule the border score in nevi is very low and in melanomas is between 4 and 8 [6].The most successful detection and classification method is presented in [60]. Different parameters are being estimated including: compactness index [57], solidity [61], fractal dimensions [62] and indentation irregularity index [63]. Many papers analyze the radial distance between the center of the mass and the border.

(a) Preprocessing
The preprocessing stage consists of three parts: black frame removal, smoothing and black hair in painting. The black frame is introduced during the digitization process. In order to determine the darkness of a pixel with (R;G;B) coordinates, the lightness component of the HSL color space are calculated [64, 65]. The smoothing filter (Gaussian filter) helps to reduce the influence of skin lines, air bubbles and light, thin hairs. The last stage is the black hair detection and in painting. For removing black and thick hairs we chose the white top-hat transform. Hair line pixels are replaced with values calculated on the basis of the neighborhood pixels.

(b) Segmentation
The last step before border irregularity detection is the segmentation process. The aim of the image segmentation stage is to extract the lesion area from the healthy skin. In our case the most important information will be the border line. The applied segmentation algorithm for the skin lesion extraction is based on seeded region-growing algorithm.

(c) Border irregularity detection
It divided into 4 steps; Firstly, we compute a bounding box of the segmented skin lesion. Secondly, we find the boundary pixels lying on the lines connecting the center of the mass with the vertices, In the next step we calculate the distance between the border and the image edge,After the smoothing filter should calculate the derivative to find local maximum points of the function. The local maximum is detected when the function crosses the zero point and the slope changes form + to -. Finally; presents the detected border irregularities with red arrows then the detected border irregularities are marked with red crosses on the skin border line.

(d) Border irregularity classification
After the border irregularity detection the border score has to be obtained. The maximum border score is 8, and the minimum score is 0. The final score is one of four parameters in the diagnostic algorithm ABCD rule of dermoscopy.

Overall, they achieved accuracy of 91%. The final medical score for border irregularity is based only on correct identification of only one cut-off in every region.

3 Project Description

3.1 Overview

To address the previous mentioned challenges, in this paper we present a novel segmentation technique for accurate feature extraction of dermoscopy images for skin lesions classification. Our approach has the basic methods that usually consist of three steps:

1. Border detection of skin tumor
2. Feature extraction
3. Classification

The border detection process finds the border of the tumor in the dermoscopy image, which is essential for accurate skin lesion classification. The feature extraction process obtains discriminating image features that facilitate classification such as general color statistics, contour shape, and texture information. The classification process determines the type of skin lesions from the extracted image features. Based on the previous mentioned three steps, we build our system to a new approach that aim to achieve high accuracy and fast performance not just on the server but also on a mobile phone so that users be able to use it everywhere. In this paper, our main challange is the limitation of applicable skin lesion types. Most of the conventional works handled only melanocytic skin lesions (MSLs) such as melanomas and nevi which originate from melanocytes, whereas nonmelanocytic skin lesions, (NoMSLs) indicating all the other pigmented skin lesions except MSLs such as basal cell carcinomas (BCCs) has been relatively neglected. Although classification of NoMSLs is considered to be easier than that of MSLs for expert dermatologists, it is not always easy for inexperienced dermatologists or physicians with different expertise. Therefore, it is necessary to handle both MSLs and NoMSLs. There is a growing tendency for medical diagnosis applications to rely on deep learning, especially convolutional neural networks (CNN) which are most suitable for image inputs. Their efficiency is proven by the fact that CNN architectures are winning the grand challenges in the domain: TUPAC16 (MICCAI), CAMELYON16-17 (ISBI). Recently, neural networks conquered the field of dermatology, with, which classifies cancerous lesions from macro images of the skin surface. Although dermoscopy was primarily used to study the pigmentation pattern within skin lesions, in the last decade it has been increasingly used to assess the vascular components as well. Although there is studies that confirm the importance and significant diagnostic value of cutaneous vasculature, there have been very few studies on quantitative and systematic analysis of skin vascular structures in dermoscopic images. There is no objective way to quantify and assess the vasculature in skin lesions. Visual inspection, as the only current technique in clinic, suffers from subjectivity and lack of precision. In this paper, we propose a system that deals with dermatology issues, therefor, our users are specific. Expert Dermatologist will be the first to use our system so they can approve it's accuracy and performance, then we will open the system for the public usage. Once the public usage is opened we will be exposed to two more different types of users which are:

1. Dermatologist Trainees who will have this system as a tool to sharp their skill and improve their diagnosing.
2. Patients, as we aim to share with the proposed system to help them with having a self diagnosing tool so they can be self treated without the need of going to an expert doctor and spending time and money on it.

3.2 Scope

We develop a general border detection algorithm for MSLs and NoMSLs. Within our search Throught the exsited algorithm, we found that a linear classifier with only two image features ('skewness of bright region on the major axis' and 'difference in blue intensity between the peripheral and the normal skin') discriminated MSLs from NoMSLs with performance of 98.0% SE and 86.6% SP. A framework is presented to address the detection and segmentation of cutaneous vascular structures in dermoscopy images. The proposed method incorporates skin color decomposition along with shape filtering and thus accounts for both underlying color components of the skin and the vascular shape. This eliminates the problem of vessel occlusion and further expands the applicability of the method from erythema detection to vessel segmentation. More accurate segmentation allows us to extract more accurate and meaningful vascular features improving the classification accuracy in differentiating MSLs from NoMSLs. There is a great need for a framework dedicated to automatic segmentation and quantification of blood vessels in both pigmented and non-pigmented skin lesions. The aim of our system is to fill this gap.

4 Method

4.1 Dataset

We chose ISIC Archive as our source for the dataset because The International Skin Imaging Collaboration Project is an academiac and industry partnership designed to facilitate the application of digital skin imaging to help reduce skin lesions rates. The Site may be accessed and used without creation of an account with MSKCC.

We have selected the 3 top skin diseases that occurs the most:

1. **Melanoma:** Typically occur in the skin, but may rarely occur in the mouth, intestines, or eye. In women, they most commonly occur on the legs, it appears to be increasing for people over the age of 40 years, especially women. While in men they are most common on the back. Sometimes there are changes such as an increase in size, irregular edges, and change in color, itchiness, or skin breakdown. The primary cause of melanoma is ultraviolet light (UV) exposure in those with low levels of skin pigment. It has different colors shades of brown or black, or sometimes with patches of pink, red, white, or blue.
2. **Nevus:** It has many shapes not a one shape and there are a lot of type of it that w gone discuss the harmful

one only which they are atypical mole which are common small brown spots or growths on the skin that appear in the first few decades of life in almost everyone. They can be either flat or elevated and are generally round and regularly shaped. Many are caused by sun exposure.

3. **Basal Cell Carcinoma:** It is a non-melanoma skin cancer, and is the most common type, 80% of all skin cancer. BCC are sometimes referred to as 'rodent ulcers'. BCC arises from basal cells (ie, small, round cells found in the lower layer of the epidermis). The prognosis for patients with BCC is excellent, but if the disease is allowed to progress, it can cause significant morbidity. This the most common type of skin cancer. About 8 out of 10 skin cancers are basal cell carcinomas (also called basal cell cancers). When seen under a microscope, the cells in these cancers look like cells in the lowest layer of the epidermis, called the basal cell layer.

Disease	**Epidemiology**	**Location**	**Size**	**Color**	**Morphology**
Melanoma	It appears to be increasing for people over the age of 40 years, especially women	Anywhere, the mouth, intestines, eye or leg. but most common on the the back	larger than 6 millimeters across (about inch – the size of a pencil eraser)	Shades of brown or black, or sometimes with patches of pink, red, white, or blue.	Round, oval, asymmetrical
Nevus	After 6 months, usually by 20 years of age	Anywher, but most common on the trunk, especially the back	Usually 6mm although they may be larger	variegated with more than 2 shades of color, most commonly brown or tan, but possibly including pink or black	Round, oval, asymmetrical with pebbled surface and irregular or poorly demarcated borders

Disease	**Epidemiology**	**Location**	**Size**	**Color**	**Morphology**

BBC	It is most often found in light-skinned individuals (type 1 or type 2 skin). Also, historically, men are affected twice as often as women. Data indicate that BCC incidence is far higher (more than 100-fold) in persons aged 55-70 years than in those aged 20 years and younger.	Tumors are most often discovered on hair-bearing areas. It occurs mostly on the face, head (scalp included), neck, and hands. It rarely develops on the palms and soles.	• Stage 0: Cancer involves only the epidermis and has not spread to the dermis • Stage I: Cancer is not large (ie, 2 cm) and has not spread to the lymph nodes or other organs • Stage II: Cancer is large (ie, 2 cm) but has not spread to lymph nodes or other organs •Stage III: Cancer has spread to tissues beneath the skin (eg, muscle, bone, cartilage), and/or to regional lymph nodes but not to other organs. • Stage IV: Cancer can be any size and has spread to other organs	pink or red. An ulcerative area in the center that often is pigmented, and black-blue or brown areas	Appears as a flat, firm, pale area that is small, raised, translucent, shiny, and waxy, and the area may bleed following minor injury. BCCs may have one or more visible and irregular blood vessels, . Large BCCs may have oozing or crusted areas. The lesion grows slowly, is not painful, and does not itch.

4.2 Input

Our input for the system will be through a friendly interface on the mobile using our application and the mobile camera. The user will be asked to determine which part of the body he suspect of it having a skin infection, then will be asked to take a capture of this area using his mobile cam with a certain distance between the camera and the area and in a proper light. The input lesion's original image will be preprocessed and fed into the segmentation model.

4.3 Pre-processing

Our first step was to normalize our inputs by re-sizing our dermoscopy images down to 480x480. This has the added benefit of allowing them to decrease training times by increasing their batch size, due to the increased free memory space. Our next step was data augmentation. Data augmentation allows them to create new dataset samples from existing ones while still maintaining labels for training. During training, we augmented the dataset by random rotations (maximal range of 270), and random flipping (vertical). This allowed them to increase their dataset from 1,520 images to 12,160 images. In dermoscopy images, if hair exists on the skin, it will appear clearly in the dermoscopy images, so infection can be partially covered by body hair. To detect and exclude the hair from the lesion, the hair is segmented form the lesion then the image is reconstructed to fill the hair gap with actual pixels.

4.4 Processing

4.4.1 Segmentation

Boundary detection is a critical problem in dermatoscopic images because the transition between the lesion and the surrounding skin is smooth and hard to detect accurately, even for a trained dermatologist. From each skin lesion image, we extracted the border between the tumor and the surrounding normal skin area. Accurate border detection usually results in better classification performance. The core of our algorithm is color thresholding, removal of artifacts such as microscope border, and inclusion of bright area seen specifically in NoMSLs. From each skin lesion image, we extracted the border between the tumor and the surrounding normal skin area. Ac-curate border detection usually results in better classification performance. We developed a general bor-

der detection algorithm for both MSLs and NoMSLs. The core of the algorithm is color thresholding, removal of artifacts such as microscope border, and inclusion of bright area seen specifically in NoMSLs. The to ensure the segmentation process we preformed a blood vessel segmentation. A major challenge in skin vessel segmentation is that skin pigmentation occludes the visibility of vessels. As a solution, we propose an approach based on skin decomposition. Human skin has a layered structure, with different pigments being responsible for different color components. Among all skin pigments, melanin and hemoglobin are the most dominant with the latter being responsible for blood color. We used Independent Component Analysis (ICA) to decompose the skin color image into melanin and hemoglobin channels. To learn reference color values for normal skin, pigmented skin and vessels, reference regions of the three clusters were outlined by an expert among 100 selected images and over 500000 pixels. For each cluster, mean and standard deviation of R, G and B channels of hemoglobin component were derived as the reference color vector. Using the reference values, a clustering framework is designed using the Mahalanobis distance on the hemoglobin component. Going through every pixel, the Mahalanobis distance from the reference color values of the three clusters (normal skin, pigmented skin and blood vessels) in hemoglobin component is calculated and the pixel is classified into the group with the closest distance. The Frangi filter is applied to the extracted red areas resulting from the previous step. Otsu's global thresholding is finally applied to segment the vascular structures and produce a binary vessel mask. After our segmentation algorithm processes an input image, the output is a set of matrix values between 0 and 1 that are converted to a single channel PNG and scaled between 0 to 255, with a value of 0 corresponding to a high probability of extraneous information and 255 indicating a high probability of lesion. wE use this PNG to crop an overlay of the original lesion using a simple algorithm written in Python that draws a bounding box around the original lesion. Aside from the decrease in memory cost when loading a smaller image into the NN, there are added benefits, for example avoiding features that are not important to the lesion such as moles or hairs adjacent to the lesion, preventing accidental data leakage.

4.4.2 Feature Extraction

After determining the border of the tumor, we segmented the skin lesion image into four regions as illustrated in above figure: normal skin, peripheral, central tumor, and whole tumor.

1. The whole tumor consists of all pixels within the extracted border.
2. The normal skin is all pixels on the outside of the border.
3. The peripheral is the first 30% of the whole tumor area, obtained by going inward from the border as in our previous studies
4. The central tumor is obtained by removing the peripheral from the whole tumor.

We calculated 828 candidate image features which are mostly variants of the 428 image features from our previous studies. The reason for introducing new features is that the previous 428 features were designed purely for detecting melanomas while in this study we distinguish among four types of skin lesions. The 828 features are grouped into the three categories:

1. Color (300)
2. Subregion (144)
3. Texture (384)

The numbers in the parentheses denote those of the features in the corresponding categories.

1. **Color Related Features**

   The Above Figure demonstrates the dermoscopy images of a number of skin lesions, including a variety of different vascular patterns and erythema with or without the presence of lesion pigmentation. As seen in the above figure, pigmentation occludes the visibility of blood vessels, interferes with vascular structures and is sometimes mistakenly classified as vasculature. This causes the sensitivity and specificity of segmentation methods to fail in such cases. As a solution, we propose an approach based on skin decomposition. Why using skin color information? Human skin is a multi-layered structure with various components contributing to its color. Among those, melanin and hemoglobin are the most dominantly present in the epidermal and dermal layer, respectively. Melanin, produced by melanocytes, is responsible for the characteristic brown color of human skin and hemoglobin gives blood its color and its circulation within vessels results in the red and purplish color of the skin. Both these components absorb light in the visible spectrum and this triggers the motivation to use skin color information towards understanding the underlying structures. Also, the quantities of melanin and hemoglobin in human skin are mutually independent from each other. These two valid assumptions make the basis for our analytical framework as an extension to, where ICA was first proposed for facial color image analysis. Following the previous assumptions, They decompose the skin image into melanin and hemoglobin channels, automatically detect the hemoglobin channel and further analyze it to cluster erythematous areas and segment the vasculature using shape information. Independent Component Analysis (ICA) is a computational technique to separate a multivariate signal from its constructing components and was first proposed in the skin analysis field by Tsumura. ICA could be applied to skin images in order to extract each of the components. Since hemoglobin is the component responsible for blood color and in order to solve the problem of skin pigmentation occluding the appearance of blood vessels, their approach is based on the extraction of melanin and hemoglobin component of skin and further analyzing the hemoglobin channel to segment the cutaneous vasculature. Using a vessel mask , a set of 12 vascular features were defined and extracted from each lesion among the dataset. These features include: maximum vessel length, average vessel length, standard

deviation of length, maximum vessel area, average vessel area, standard deviation of vessel area, ratio of vessel area to lesion area, maximum vessel width, average vessel width, standard deviation of vessel width, number of vessel branches and ratio of branches to lesion area.

We calculated 10 statistics (min, max, standard deviation, skewness, entropy

(a) 5%-tile
(b) 25%-tile
(c) 50%-tile
(d) 75%-tile
(e) 95%-tile

of the intensity of 6 color channels

(a) R: red
(b) G: green
(c) B: blue
(d) H: hue
(e) S: saturation
(f) V: luminance

for each of the 3 tumor regions peripheral, central tumor and the whole tumor. This yielded 180 parameters (10 statistics x 6 channels x 3 regions). we also calculated the difference in the same 10 statistics on the 6 color channels between central tumor and peripheral and those between peripheral and normal skin area, which yielded 120 parameters (10 statistics x 6 channels x 2 pairs-of-regions). We expect these difference-oriented features to be robust over variations of dermoscopy images caused by different photographic conditions. In total, there are 300 color related features (180+120). The reason for using %-tile is that they are expected to be robust over artifacts such as black hairs and shiny bubbles compared to min, mean, or max.

2. **Sub-region Related Features**

Subregion related features describe geometrical distribution of the color. First, we divided the central tumor and the peripheral into smaller even subregions as illustrated in below figure.

We used 2 types of subdivisions, angle-wise and distance-wise.

(a) The angle-wise is based on the angle from the center of gravity of the central tumor to the edge of the region.
(b) The distance-wise is based on the Euclidean distance from the outer border.

We then used 3 numbers of subregions: 4, 8, and 16 for the angle-wise manner and 2, 4, and 8 for the distance-wise manner. For each subregion, we calculated 3 statistics (mean, standard deviation, and skewness) on 4 color channels (R, G, B, and S). We left out H and V because these two channels did not contribute to classification performance in their reliminary experiments. We calculated the standard deviation of these statistics within all subregions. This yielded 144 subregion features (2 target regions x 2 types of subdivisions x 3 numbers of subregions x 4 color channels x 3 statistics for each subregion).

3. **Texture Related Features**

As for texture related features, we adopted the gray level co-occurrence matrix (GLCM). We obtained the GLCMs with the following settings:

(a) 2 target regions (central tumor and whole tumor)
(b) 3 quantization levels (N = 16, 32, and 64)
(c) 4 distances (δ = 1, 2, 4, and 8 pixels)
(d) 4 directions (θ = 0, 45, 90, and 135 from the major axis)

From each GLCM, we extracted 4 GLCM-statistics: energy, correlation, entropy, homogeneity. To make the directional settings (θ) more meaningful, we extracted min, mean, max, and difference (i.e. maxmin) of the abovementioned GLCM-statistics in 4 main directions (θ) as was also recommended in the original literature of the GLCM. In total, there are 384 texture features (2 regions x 3 quantization levels x 4 distances x 4 directions (e.g. max) x 4 GLCM-statistics).

4.4.3 postprocessing

For postprocessing, we normalized all of the 828 features so that we have mean of 0 and variance of 1 over all images in the datasets.Note that only a small number of features were selected from the 828 for the classifier development as will be described later.

4.4.4 Classification

The endpoint of the analysis is automated disease classification to differentiate skin lesions. For this purpose, we used the feature extracted as described in the previous section and employed a deep residual network as our classification model, with an input from our integration state.

4.4.5 Output

The Result Screen: Shows the disease name. The hospital screen which will show the hospitals that deal with this kind of disease and this screen will only shows when the classified disease can't be self treated, and the treatment screen which will shows the treatments suitable to the classified disease.

5 Conclusion

Developing computer-aided diagnosis tools could ease the integration of this optical biopsy technology in the clinical environment by assisting pathologists in their familiarization with the new modality and, ultimately, it could reduce the costs and duration of certain medical procedures, like Mohs surgery. In this paper we proposed an approach for analyzing dermoscopy images. The approach could be used in practice as a screening tool. we built our model into four stages: preprocessing, segmentation, features extraction and classification. This model works seamlessly from a single input image to a final output without any requirement of manual work. We trained a convolutional neural network in the purpose of discriminating lesions skin from normal skin. We aslo combined analyzing FFOCT images with the deep learning methods. To improve upon this model in the future, we can retrain the model on optical images, and possibly employ the use of transfer learning, drawing upon models pre-trained on different textures. For future work we also intend to adopt a multi-scale approach, inspired by MIMO-Net, for capturing a larger context and extracting specific information at different levels of zooming. Also in order to accurately assess the efficiency of such a model, we need to understand the reasoning learned by the machine. Therefore, we are aiming towards demystifying artificial neural networks.

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