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SKIN CANCER PREDICTION BY APPLYING DEEP LEARNING

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ABSTRACT

Skin cancer is a common form of cancer, and early detection increases the survival rate. Objective: To build deep learning models to classify dermal cell images and detect skin cancer. Methods: A model-driven architecture in the cloud, that uses deep learning algorithms in its core implementations, is used to construct models that assist in predicting skin cancer with improved accuracy. The study illustrates the method of building models and applying them to classify dermal cell images. Skin cancer (SC), especially melanoma, is a growing public health burden. Experimental studies have indicated a potential diagnostic role for deep learning (DL) algorithms in identifying SC at varying sensitivities. Previously, it was demonstrated that diagnostics by ceroscopy are improved by applying an additional signification layer on DL algorithms. The aim of the study was to determine the impact of image quality on accuracy of diagnosis by signification employing a rudimentary skin magnifier with polarized light (SMP). Skin cancer is one of the dangerous and serious health issue spreading now a days. Early Identification of this tumor is a challenging task. Even though there are several existing methodologies, predicting skin cancer in early stage does not reach the satisfactory levels. The proposed Skin Cancer Prediction method by Applying Deep Learning aims to detect skin cancer and stage prediction using Image Processing and Deep Learning Techniques. Stage is predicted by taking affected image as input and various preprocessing techniques are applied to remove Noisy and get the Eccentricity values. Those values are then fed into the Neural Networks using Back Propagation algorithm in order to predict the Stage and type of the Skin cancer. The proposed method exhibits better prediction rate when compares to traditional methods.

Keywords: Segmentation, skin cancer, convolutional neural networks, lesion classification, deep learning, melanoma classification, carcinoma classification

1. INTRODUCTION

The Malignant melanoma is a very baneful skin cancer it is rapidly increasing in all over the world. In united states, skin cancer is very common cancer by the estimation there 9,500 peoples diagnosed per day. There are various techniques for detecting skin cancer from dermoscopic images. the dermoscopy is major imaging that plays an important role in skin cancer diagnosis. Dermoscopy is one of the tools that use by the dermatologist for examining the skin lesion based on the set of morphological features. For evaluating the dermoscopy, the dermatologist uses the ABCD rule of dermoscopy for classifying melanoma or nonmelanoma. ABCD rule is the best rule of dermoscopy that is Asymmetry, Border irregularity, Colour, Diameter. Every parameter value will be utilized the prediction of skin cancer. Image acquisition, Image Pre-processing, Segmentation, Feature Extraction and Classification these steps utilized the skin lesion is dangerous or generous. A lot of research has been carried out on the parameters for detecting and classifying the melanoma in an

early stage so the patient can be given appropriate treatment.

Skin cancer, the most common human malignancy, is primarily diagnosed visually, beginning with an initial clinical screening and followed potentially by dermoscopic analysis, a biopsy and histopathological examination. Automated classification of skin lesions using images is a challenging task owing to the fine-grained variability in the appearance of skin lesions.

Deep convolutional neural networks (CNNs) show potential for general and highly variable tasks across many fine-grained object categories. Here we demonstrate classification of skin lesions using a single CNN, trained end-to-end from images directly, using only pixels and disease labels as inputs. We train a CNN using a dataset of 129,450 clinical images—two orders of magnitude larger than previous datasets — consisting of 2,032 different diseases. We test its performance against 21 board-certified dermatologists on biopsy-proven clinical images with two critical binary classification use cases: malignant carcinomas versus benign seborrheic keratoses; and malignant melanomas versus benign nevi. The first case represents the identification of the most common cancers, the second represents the identification of the deadliest skin cancer.

The CNN achieves performance on par with all tested experts across both tasks, demonstrating an artificial intelligence capable of classifying skin cancer with a level of competence comparable to dermatologists. Outfitted with deep neural networks, mobile devices can potentially extend the reach of dermatologists outside of the clinic. It is projected that 6.3 billion smartphone subscriptions will exist by the year 2021 and can therefore potentially provide low-cost universal access to vital diagnostic care.

About 1 million non-melanoma skin cancers and 288,000 malignant melanoma (MM) cancers occurred globally in 2018 [1]. Due to an aging population and limited health care resources, accurate diagnosis and feasibility of detection are a requisite for a generalized skin cancer prevention policy. The impact of immunotherapies on survival and cost further strain the already overburden healthcare system and raise the question of financial sustainability [2]. Skin cancer and especially MM early detection is challenging for both dermatologists and general practitioners. Dermoscopy is considered the standard of care [3], but in objective tests dermatologists achieve a limited diagnostic sensitivity of 40% MM detection [4] due to the complexity of visual inputs embedded in a dermoscopy image [5]. General practitioners seem to benefit from use of a dermoscopy course, while a figure of 51% correctly diagnosed lesions calls for further improvements [6]. Likewise, specificity of diagnosis by dermatologists calls for a further improvement, as reflected by a spectrum of 28:1 to 9:1 number of biopsies that need to be excised in order to identify one melanoma and a 3:1 ratio for overall skin cancer [7][8].

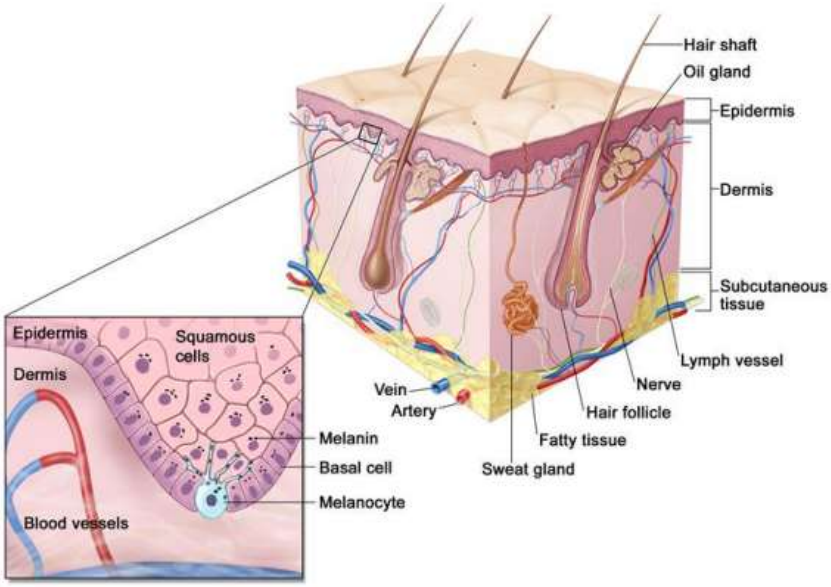


Figure 1: The epidermis and dermis layers in human skin with squamous cells, basal cells and melanocyte.

Deep learning (DL) classifiers are a promising candidate for detection of skin cancer [9][10]. Nonetheless, laboratory studies reported a clinical sensitivity from 29%–87% [11][12], a discrepancy which might be attributed to the quality of the dataset input, therefore rendering technology as experimental. Recently, a first prospective clinical observational study [13] reported on a two step approach, adding a second layer of sonification (visual data turned into sounds) to a DL classifier in order to improve accuracy of detection. This dual DL utilized an advanced dermoscope, a relatively expensive device, and a technique highly dependent on physician experience [14], rendering it less suitable for widespread primary care physicians use.

Consequently, the impact of image quality on accuracy of diagnosis was further examined. It was decided to test a low priced device classified by its manufacturer as a skin magnifier with polarized light (SMP). Images quality acquired by SMP preclude in most cases a precise clinical diagnosis due to haziness and lack of fine high level dermoscopy patterns and diagnostic structures. Images were processed by DL algorithms, sonified and diagnostic metrics were validated versus the histopathology report.

In this section, the individual CNN methods used to classify skin lesions are presented. CNNs can be used to classify skin lesions in two fundamentally different ways. On the one hand, a CNN pretrained on another large dataset, such as ImageNet [18], can be applied as a feature extractor. In this case, classification is performed by another classifier, such as k-nearest neighbors, support vector machines, or artificial neural networks. On the other hand, a CNN can directly learn the relationship between the raw pixel data and the class labels through end-to-end learning. In contrast with the classical workflow typically applied in machine learning, feature extraction becomes an integral part of classification and is no longer considered as a separate, independent processing step. If the CNN is trained by end-to-end learning, the research can be additionally divided into two different approaches: learning the model from scratch or transfer learning.

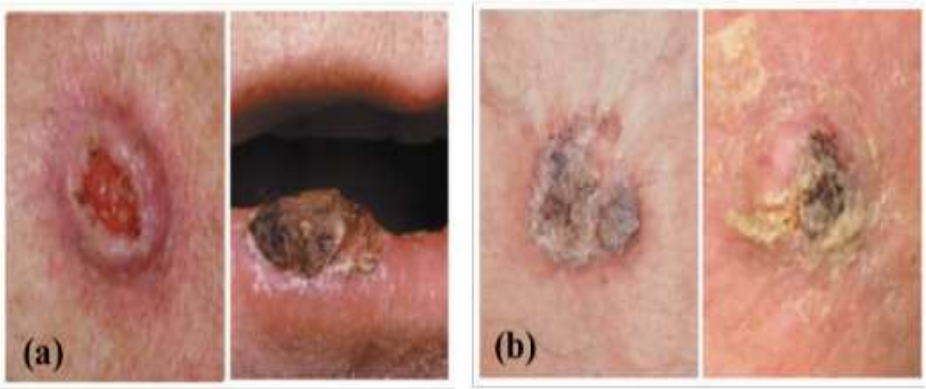


Figure 2: An elevated growth (a) and irregular borders (b) of squamous-cell carcinoma

It is found that a skilled dermatologist usually follows a series of steps, starting with naked eye observation of suspected lesions, then dermoscopy (magnifying lesions microscopically) and followed by biopsy. This would consume time and the patient may advance to later stages. Moreover accurate diagnosis is subjective, depending on the skill of the clinician. It is found that the best dermatologist has an accuracy of less than 80% in correctly diagnosing the skin cancer [6]. Adding to these difficulties, there are not many skilled dermatologists available globally in public healthcare. In order to diagnose skin cancer speedily at the earliest stage and solve some of the aforementioned problems, there has been extensive research solutions by developing computer image analysis algorithms The majority of these algorithmic solutions were parametric, meaning that they required data to be normally distributed. As the na-ture of data cannot be controlled, these methods would be insufficient to accurately diagnose the disease. However, non-parametric solutions do not rely on the constraint that the data is in normal distribution form. In this paper, an augmented assistance to the dermatologist is pro-vided using deep learning. The essence of the approach is that a com-puter is trained to determine the problem by analyzing the skin cancer images. The novelty of the presentation is that the computer model can be developed without having any programming knowledge. The average accuracy of diagnosis using this model is found to be approximately 98.89% and the best is 100%. The machine assisted diagnosis presented here overcomes the problem of delay, accuracy, and scarcity of derma-tologists in public health.

The manual skin lesions detection system is human-labor intensive, which needs magnifying and illuminated skin images to improve the clarity of spots. ABCD-rule (Asymmetry, Border, Irregularity, Color variation, and Diameter), 3-point checklist, 7-point checklist, and Menzies method are several procedural algorithms to boost the dermoscopy and observe the malignant melanoma in the very early stage [11][14] however, and many clinicians steadily rely on their experiences [15]. The manual dermoscopy imaging procedure is more prone to mistake because it needs years of experience over difficult situations, vast amounts of visual exploration, similarities, and dissimilarities between different skin lesions.

In recent times, deep learning (begin with AlexNet [16] in 2012) provides many computerized automated systems to detect, classify, and diagnosis of several diseases through medical image analysis [17]. Last few years, dermoscopy produce a significant amount of well-annotated skin lesions images that help supervised machine learning techniques actively to classify, predict, and detect different skin wound [18][19]. Hence, deep learning-based medical image analysis tools can be useful to assist the dermatologist to emphasis on several areas like skin lesion segmentation, classification, and detection.

Here, we proposed a deep learning method, namely dilated or, atrous convolution, with transfer learning to classify seven different class skin lesions.

Compared to traditional CNN, we used dilated convolution to increasing accuracy with the same computational complexities. We choose four pre-trained deep learning architectures such as VGG16, VGG19, MobileNet, and InceptionV3 and select a different strategy to put different dilation rates in separate layers[20]. To the best of our knowledge, we are the first who proposed the approach to employ different dilation rates in the different layers of InceptionV3 and MobileNet network and achieve better overall performance than the original architectures. Moreover, we utilize a fine-tuning technique to train these proposed architectures. We use the HAM10000 dataset to train, validation, and test, which contains 10015 dermatoscopic images of seven skin lesions like Vascular lesions, Actinic Keratoses, Benign keratosis-like lesions, Dermatofibroma, melanoma, melanocytic nevi, and Basal cell carcinoma [21]. Melanoma is extremely dangerous, Basal cell carcinoma, Actinic keratoses can be cancerous, and the other skin lesions in this dataset are benign.

2. LITERATURE SURVEY

As previously described [22] a convolutional neural network architecture based on the Inception V2 network was utilized. Dermoscopic images validated by biopsy reports were classified into either malignant or benign and a feature representation was obtained. Publicly-available datasets, such as the International Skin Imaging Collaboration (ISIC) 2017 dataset [24] were used for training to a total of 4361 advanced dermoscope images and 800 non-dermoscopic regular photos. Data augmentation, training and fine tuning were performed as mentioned [23] and the weighted activations of all of the 1024 nodes in the penultimate layer of the DL classifier were sonified, i.e. representation of data using non-speech [25] in order to generate sounds. A K-means clustering algorithm [26] was employed to cluster the activations into groups of related observations. The K-means algorithm was initialized by randomly choosing N data points without replacement to constitute the initial cluster centers, where N is the number of clusters. In order to address the sensitivity to initialization, K-means was run 100 times, each with a different random starting point[27]. The clustering solution with the lowest error (i.e. the one that maximizes the likelihood of the data) was chosen as the final model. Cluster centroids represented by individual pitches and malignant “alert” sounds were mapped onto loudness, timbre, and duration of a sonification, thus an audio signal for each of the centroids of data was derived, providing for an audio output that acoustically differentiated the malignant from benign lesions and conferring information about the image[28][29].

Recently several deep learning models have been build for classification, detection, and segmentation. AnveshiniDumala et al. [30] execute deep learning methods to classify histopathologic diagnosis of melanoma, to augment the human evaluation, and contrasted the outcome with skillful histopathologists. Sk.Reshmi Khadherbhi et al. [40] implemented pre-trained inceptionv3 for nine class classification where they used a labeled dataset by dermatologists, which have 3374 dermoscopy images, 129,450 clinical images, and achieve 72.1 ± 0.9% (mean ± s.d.) accuracy. K.Santhi Sri et al. [21] utilize an ensemble DCNN (deep convolutional neural network) method, where they combine the result of four different architectures with improving the accuracy of the ISBI 2017 . dataset. Rather than training CNN (Convolutional Neural Network) from scratch, R S M Lakshmi et al. [23] attempted to employ pre-trained ConvNet as their feature extractor, and they classify ten classes of non-dermoscopic skin images. P.Sandhya Krishna [40] displayed a skin lesion segmentation method where a self-generating CNN merged with a genetic algorithm. Recently, R. S. M. Lakshmi et al. [27] proposed a research work based on a multilevel DensNet network to classify seven different skin lesions of HAM10000. VellalacheruvuPavani et al. [36] published a skin lesion segmentation architecture, namely Independent Histogram Pursuit (IHP), where they tested their method on five different dermatological datasets and obtained 97% precision on segmentation. Anusha Papasani et al. [37] proposed a deep residual model for classification of skin pigmented lesions, which upgraded by class weight update dynamically, Excitation, and Squeeze module in batches. A new fully CNN segmentation method proposed with new pooling layers for skin lesions region in [38]& [39], Mask R-CNN and U-net

utilized for skin lesion segmentation in dermoscopic images, particularly on ISIC 2017 dataset to differentiate melanoma images from non-melanoma, a very deep residual CNN has proposed.

3. PROPOSED METHOD

It is known that to apply deep learning approaches it is necessary a large amount of data. However, collecting medical data, particularly from skin cancer, is a challenging task. Therefore, one of the main concerns of applying deep learning for this task is the lack of training data [20][13]. As stated before, the ISIC archive is very important to tackle this issue. However, the number of samples available is still insufficient and very imbalanced among the classes. In order to deal with these problems, several approaches have been proposed, such as transfer learning, data augmentation, up/down-sampling, and weighted loss [33][34]. Nevertheless, there is still room for improvement and approach. Deep learning models require a decent amount of data to produce good results , so we use different data augmentation processes to train our model. We train our models for 200 iterations and able to create new transformed 1,602,200 (200 × 8011) images for the whole training process. Hence, for each iteration, 8011 newly transformed augmented images have been provided. Additionally, for the validation set, we employ the same strategy and able to produce 1002 new augmented images to validate our training. In our training set, we applied many geometrical transformations for data augmentation.

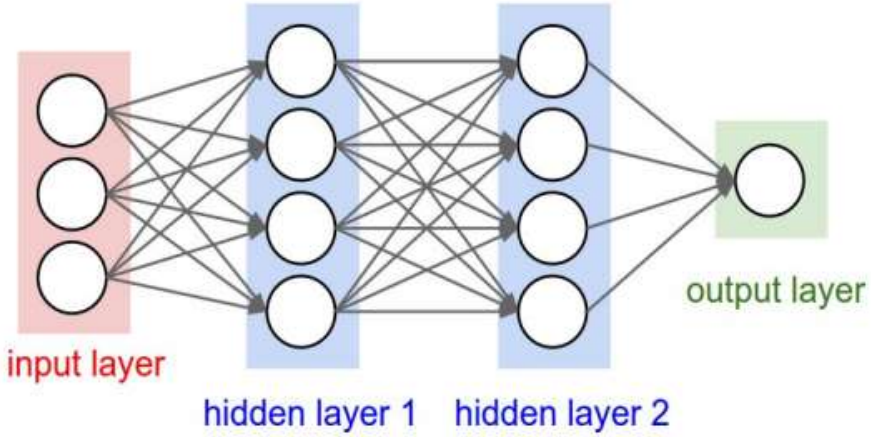


Figure 3: Fully-connected multi-hidden layer NN architecture

Image Acquisition is the first stage in image processing, dermoscopy is a medical imaging technique for observing the pigmented skin lesion based on the biomedical entities in melanoma diagnoses. Identifying malignant melanoma in dermoscopic images exploitation human vision alone inaccurate, subjective [40] [41]. We used dataset released by the 2016 International Symposium on Biomedical Imaging (ISBI 2016). This dataset is a challenging dataset for segmentation in dermoscopic images. Gaussian filter for removing the air bubbles on the skin lesion. Gaussian filter is effectively used in smoothening the dermoscopic images and it is basically used to blur the images with reducing the contrast [42] [43]. The hair existence is a major problem in dermoscopic images, in this, if the skin lesion is covered by hair it will be difficult for segmentation, pattern recognition, and classification task. Morphological filtering is the best technique for removing the hair particle on skin lesion [44] [45]. In figure 3 shows the result of Gaussian filter and DullRazor filtering applied on dermoscopic images for removing the noise and hair on skin lesion respectively

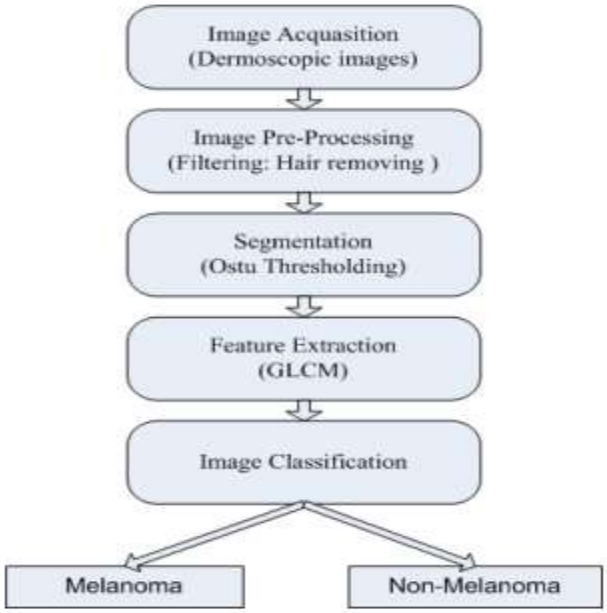


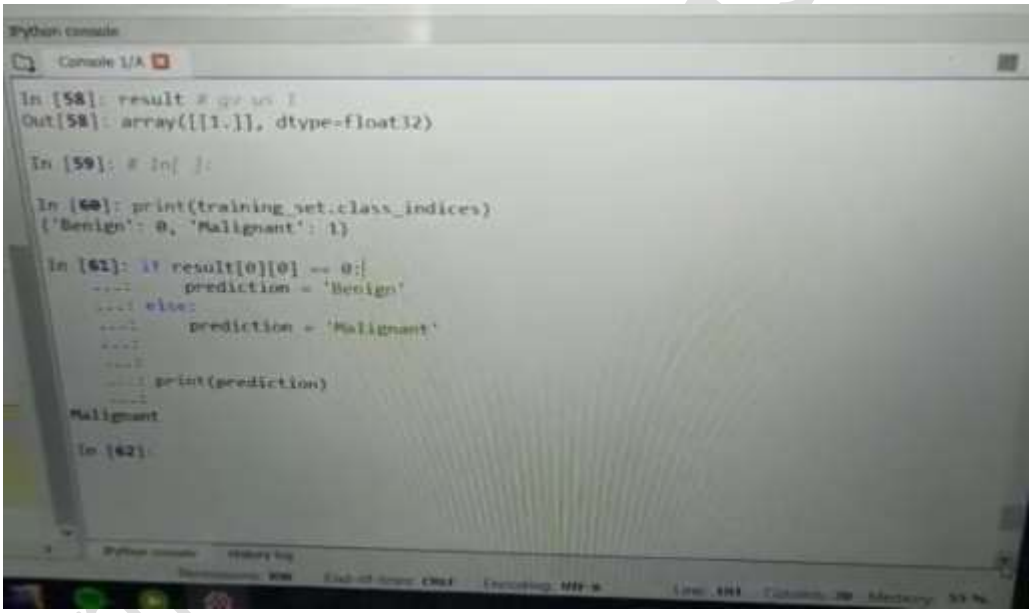
Figure 4 : Proposed system for skin lesion classification

Even though dermoscopy enhances the visual perception of a skin lesion, automatic recognition of melanoma from dermoscopy images is still a difficult task, as it has several challenges. First, the low contrast between skin lesions and normal skin region makes it difficult to segment accurate lesion areas [46] [47]. Second, the melanoma and non-melanoma lesions may have a high degree of visual similarity, resulting in the difficulty of distinguishing melanoma lesion from non-melanoma. Third, the variation of skin conditions, e.g., skin color, natural hairs or veins, among patients produce different appearance of melanoma, in terms of color and texture, etc. The misdiagnosis of a malignant skin lesion as benign (false-negative) is more harmful than misdiagnosing a benign skin lesion as malignant (false-positive) since the former case can become fatal due to under treatment while the later case will just cause over treatment (unnecessarily costly). Early detection is important for increasing the life expectancy up to 98% compared to 17% of diagnosis in later stages [48]. Thus, there is a need for a favorable treatment process that does an early and fast detection of skin cancer that is vital for the patient's life.

4. RESULTS

We used 12,600 benign and 1,084 malignant images on our first experiment (The number of images in the ISIC dataset was around 13,700 at the time). In this case, images were not preprocessed before feeding the algorithm. The purpose was examining the performance of Inception v3 algorithm based on the existence of the noise and other artifacts to see how much it tolerates the noise. Images were randomly split into training and testing subsets. Skin cancer classification performance of the CNN and dermatologists. a, The deep learning CNN out performs the average of the dermatologists at skin cancer classification (keratinocyte carcinomas and melanomas) using photographic and dermoscopic images. For each test, previously unseen, biopsy-proven images of lesions are displayed, and dermatologists are asked if they would: biopsy/treat the lesion or reassure the patient. A dermatologist outputs a single prediction per image and is thus represented by a single red point. The green points are the average of the dermatologists for each task, with error bars denoting one standard deviation (calculated from n = 25, 22 and 21 tested dermatologists for carcinoma, melanoma and melanoma under dermoscopy, respectively).


Console 1/A
In [42]:
In [43]:
In [44]: test_image
Out[44]:
In [45]: # In[ ]:
In [46]: test_image = image.img_to_array(test_image)


Console 1/A
In [58]: result
Out[58]: array([[1.]], dtype=float32)
In [59]: # In[ ]:
In [60]: print(training_set.class_indices)
{'Benign': 0, 'Malignant': 1}
In [61]: if result[0][0] == 0:
...: prediction = 'Benign'
...: else:
...: prediction = 'Malignant'
...:
...: print(prediction)
...:
Malignant
In [62]:

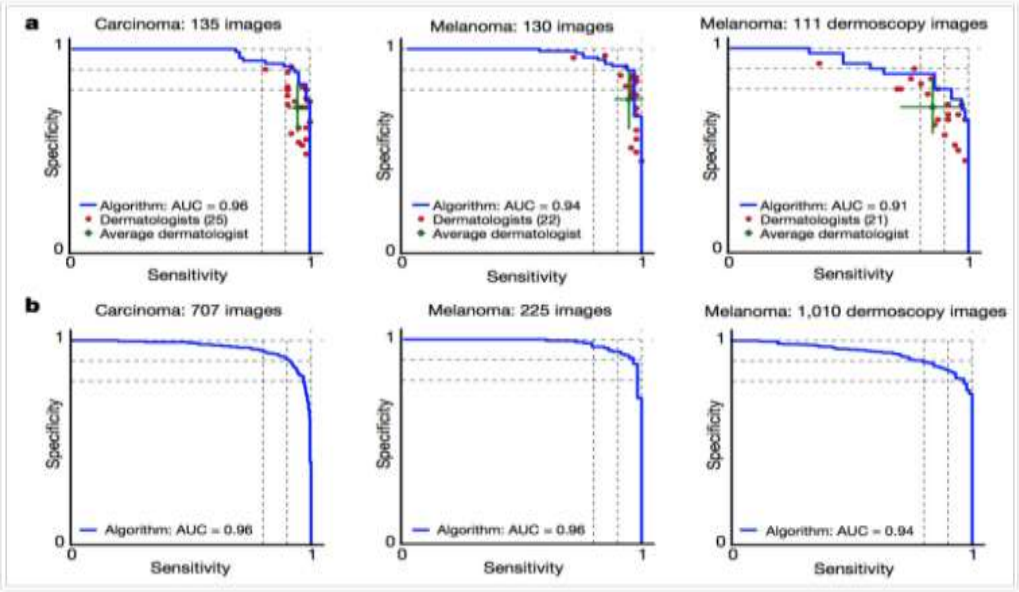


Figure 5: The deep learning CNN out performs the average of the dermatologists at skin cancer classification

5. CONCLUSION

Skin cancer is increasing and affects many people every day. This cancer can be treated successfully if it is detected in early stages. Early diagnosis and treatment will lead to an increased survival chance and reduced mortality rates. However, current clinical techniques used for the diagnosis of malignant melanoma are prone to human error due to the subjectivity and novice physicians. Therefore, there is a need for more reliable and accurate systems that can be beneficial to both expert and novice physicians. This thesis proposed creative and effective methods to eliminate the subjectivity in visual interpretation of dermoscopy images and decrease the number of falsenegative/false-positive diagnoses by introducing a new method for measuring abrupt cutoff and increasing the performance of feature extraction algorithms. There are two main studies done in this thesis: (1) skin lesion abruptness quantification, and (2) skin lesion malignancy classification. Skin cancer is one of the dangerous forms of cancer as the affected cells can spread easily across the body. It can be either Melanoma or Non-Melanoma. There are various solutions such as Dermos- copy and other devices to detect the skin cancer, these devices involve costs as well as requires a doctor to equip them on the patients. Proposed method aims at detecting and prediction of skin cancer using Image Processing Techniques that can be easily used by Doctors for the Patient's skin cancer analysis.The system em- ploys methods such as Preprocessing, Feature Selection, Feature Extraction and Backpropagation Neural Networks. The outcome of the model is determined by the BPN (Backpropagation Net- work) that predicts the type of the cancer.This kind of models help the patients to take care of their skin as well as take precautionary measures if the Skin cancer is encountered. The model was applied on a ISIC (International Skin Imaging Collaboration) dataset and resulted in the classification of the cancer types.

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