

Detection of Skin Cancer using Machine Learning

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Abstract—The paper presents the design and development of concept for detecting the skin cancer using AI & ML approaches. Over the last few years, Deep Learning has been on the spotlight when it comes to solving many complex problems, namely Convolutional Neural Networks (CNN) in the field of image recognition. Since this Neural Networks can sometimes achieve more than 50 layers deep, Transfer Learning (TL) techniques are also getting popular to retrain some of the layers of Neural Networks that learned from a generic dataset, putting it to use in another case. In this work, we attempt using CNNs and TL techniques on pre-trained Neural Networks to distinguish melanoma skin cancer from seborrheic keratosis and nevus benign tumours. The work presented in this paper is the mini-project work of the undergraduate students of the engineering college guided by their supervisors.

Index Terms— Skin, Cancer, Detection, Software, AI, ML, CNN.

I. INTRODUCTION

The human body's first line of defence against outside objects is its skin. It creates the pigment melanin, which protects our bodies from UV light. One of the biomarkers used in the early identification and monitoring of melanoma skin cancer is this pigment as well as the underlying blood vessels. One of the worst forms of skin cancer, melanoma typically develops as a result of excessive exposure to the sun's UV radiation, which damages DNA. [1][2]

The Skin Cancer Foundation estimates that 9,320 persons in the US succumb to melanoma each year, and those 178,560 new instances of the disease were initially anticipated in 2018 alone [1]. Melanoma is treated in its early stages if it is appropriately diagnosed, but if not, it can spread to other parts of the body and be fatal. Since most body marks, such as moles, brown patches, and growths, are typically innocuous and challenging to identify from melanoma, the accuracy of the procedures now utilised by the majority of dermatologists rests in between 75 and 85 percent [2]. The ABCDE indications of melanoma—which stand for Asymmetry, Border irregularity, Color, Diameter, and Evolving—are typically used to distinguish between benign and malignant pigments [3][4]. Although dermatologists have found the ABCDE rule to be quite useful over the years, the detection process often requires a highly experienced practitioner and can take some time. In addition, the rule makes it challenging to distinguish between birthmarks and melanoma moles or even to spot small, early-stage melanoma markings. The initial approach to resolving this issue involved image processing, which involved collecting

statistical features—such as the mean and standard deviation of the pixel density—and feeding those values to widely used shallow neural networks, or SVMs, for classification. However, given the current popularity of Deep Neural Networks (DNN), Convolutional Neural Networks (CNN) may be an excellent alternative because they are able to learn on their own the specifics of typical image processing without the need for feature engineering. Utilizing Transfer Learning (TL), a strategy that entails adjusting the information already stored and used to solve a given situation and using it to solve a related problem, provides an even more complete approximation to address these types of difficulties. As an illustration, suppose the last layers of a DNN are modified and retrained for a new scenario, thereby altering their weights [5][6].

This study focuses on the processing of dermatoscope's pictures utilising DNN architectures like CNN and TL approaches to identify melanoma skin cancer. The International Skin Imaging Collaboration (ISIC) [3] contributed the dataset while running a three-part competition on melanoma identification in 2017. A little over 2,000 photos make up the collection, of which 374 were identified as “melanoma” (a malignant skin tumour generated from melanocytes), 254 as “seborrheic keratosis” (a benign skin tumour derived from melanocytes), and 1372 as “nevus” (benign skin tumour, derived from keratinocytes). In addition to the training dataset, ISIC also offered validation and test datasets, each with 150 and 600 images. The initial challenge was divided into two categories: seborrheic vs. all and melanoma vs. all. However, the detection of the cancerous tumour melanoma will be the sole emphasis of this paper [7][8].

II. REVIEW OF LITERATURE WORKS

Several researchers have used a variety of approaches to work on the diagnosis of skin cancer. Deep Learning has recently shown to be quite successful at classifying and segmenting medical images. There are countless examples, including mass mammogram imaging detection [4] or even Alzheimer's disease diagnosis [5].

Convolutional neural networks, in particular CNNs are a popular subject in the field of medical imaging. They are employed in a number of industries, including dermatology. Nasr-Esfahani *et.al.* obtained encouraging outcomes for melanoma diagnosis utilising data supplied by the Department of Dermatology of the University Medical Centre Groningen (UMCG) [6]. The suggested method began with pre-processing, in which the input images underwent illumination adjustment and were the focus of a Gaussian Filter that was tasked with flattening the area outside the lesion because that information was deemed unnecessary for melanoma diagnosis. Each sample produced 36 additional datasets, which were combined with various cropping processes (different percentages of the image - 5 and 10 percent - and on different sides - top left, top right, etc.) and rotations by 0, 90, 180, and 270 degrees, in order to increase the original dataset. The 188x188 pixel scaled samples from the expanded dataset were then fed into a 7-layer deep CNN. The DNN also included two 5×5 convolutional layers, two max pooling layers, the first with a pool size of 4×4 and the second with a pool size of 6×6 , two fully connected levels, the last of which was the output layer, and two other layers. The model was able to achieve test accuracy, sensitivity, and specificity scores of roughly 80%, which was a relatively good result [9][10].

Aya Abu Ali and Hasan Al-Marzouqi [2] demonstrated that a well-trained model is also capable of delivering extremely accurate predictions of melanoma skin cancer while constructing a relatively simple CNN architecture. Melanoma photos are categorised without the use of lesion segmentation or intricate image pre-processing, as opposed to scaling and mean normalisation. The last block replaced the final two components of the block with a fully connected layer and a SoftMax layer for the final classification. The created model was a 17 layer CNN based on 5 blocks made of convolutional, ReLU activation, pooling, and dropout layers. With a stride value of 2, the first three convolutional layers applied 5×5 filters, the fourth a 4×4 filter, and the final layer a 1×1 filter. The first one worked with 32 kernels (filters), the next three with 64, and the last one with just two. Stride 4 was used to define the pooling layers, whereas 0.1, 0.2, 0.3, and 0.5 were used to configure the dropout layers. Following careful adjustment of the three hyperparameters under consideration—the batch size, or the number of training images in one forward or backward pass, the number of epochs, or the learning rate—the model was able to achieve a testing error of 0.189, along with a sensitivity value of 14.86 percent and a specificity of 98 percent. The authors noted that their model performed very similarly to the competition winner from 2016 in terms of accuracy and that lesion segmentation was likely to boost accuracy and sensitivity. As seen in Fig. 1, one of the architectures employed in the research described in this publication is quite comparable to the one created by Aya Abu Ali and Hasan Al-Marzouqi [11][12].

The 2017 edition's champions took a different route than the majority of the competitors. In order to begin, Kazuhisa Matsunaga et al [7] first created two independent classifiers, melanoma vs. all and seborrheic vs. all, and from there they devised a pretty sophisticated solution. After each sample of the dataset has undergone brightness and colour normalisation, the images are then rotated, translated, scaled, and flipped before being

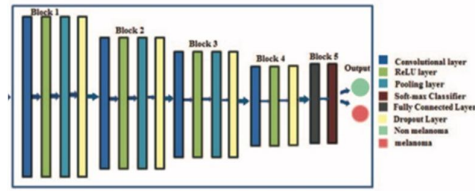


Fig. 1: CNN architecture used by Aya Abu Ali and Hasan Al-Marzouqi [2]

given to a set of CNNs that includes a modified 50-layer ResNet for classification. Age and gender information are verified before producing the final result because seborrheic and melanoma are typically uncommon in young people. This approach was only used on the seborrheic keratosis vs. all classifier because their cross-validation tests revealed no perceptual gain. As a result, if a sample had a very high hypothesis of being a seborrheic keratosis, it is almost guaranteed that it is not a melanoma. They also found that their seborrheic keratosis vs. all classifier was more reliable than the melanoma vs. all classifier. As seen in Fig. 2, this was also considered prior to the final melanoma classifier output [13][14].

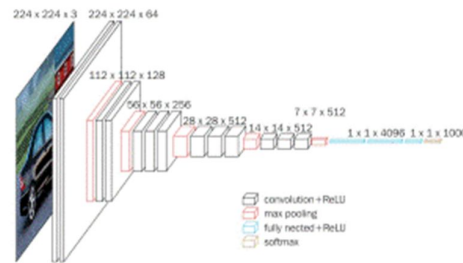


Fig. 3 : VGG16 Architecture

III. BLOCK DIAGRAM

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IV. CONVOLUTION NEURAL NETWORKS

The Residual Neural Network (ResNet) [17], created by Kaiming He *et.al.*, is another example obtained from the ImageNet Project. It introduces a novel design, based on skip connections and intense batch normalisation of data. These skip connections, which are often referred to as gated units or gated recurrent units, are strikingly comparable to recent successful components used in recurrent neural networks (RNN). With less complexity than VGGNet, they were able to train a 152-layer NN using this method. On this dataset, a top-5 error rate of 3.57 percent was attained, outperforming human level performance. By utilising Transfer Learning techniques, these large and intricate Deep Neural Networks may detect melanoma [23][24].

The goal of this research is to present two solutions for the melanoma detection problem on the 2017 ISIC dataset. Both the suggested solutions and the pre-processing operations carried out on the initial data are described in this section. A CNN-based DNN serves as the first solution, while TL approaches are used in the second to apply ResNet and VGG19 pre-trained architectures to the resolution of this particular challenge. The Keras framework was used to build and test both systems. Two strategies were used for each technique in addition to the various techniques. The first concerns a multiclass classifier in which the three classes

(melanoma, seborrheic keratosis, and nevus) were deliberately segregated during the training phase and united into a non-melanoma class when applied to the test set. The second was just a binary classifier, meaning that the dataset had already been divided into the two classes of melanoma and non-melanoma, and the models had only been trained to classify those two [24][25]. Figures 5 & 6 gives the results of simulation.

V. SIMULATION RESULTS

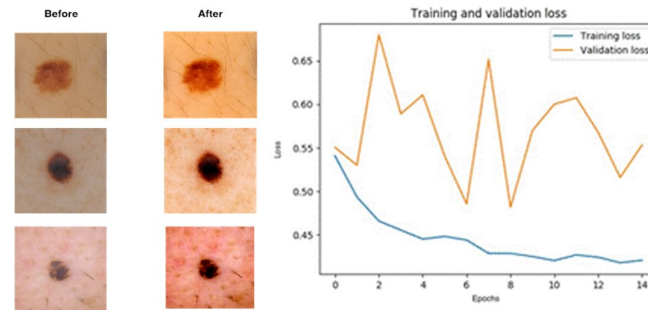


Fig. 4: Application of histogram equalization to the cropped samples & the InceptionV3 loss and accuracy in the train and validation sets (simulation results)

VI. CONCLUSIONS

This paper gave a brief idea of how to detect the skin cancer using AI ML based concepts. Though practically all of the current research on DNN melanoma detection relies on binary solutions, we first chose a different strategy by attempting to categorise all three distinct classes—melanoma, seborrheic keratosis, and nevus. The failure of this effort made it clear that the binary approach should be taken as the next step. Both the pure CNN and the TL solutions performed admirably, but the final one had a slight advantage thanks to its more intricate architecture, which allowed it to achieve a good score on one of the evaluated models.

However, even the best outcomes fall short of the state-of-the-art. One of the reasons could be that we did not spend enough time thoroughly pre-processing the dataset, which was one of the first steps in the ISIC challenge and was entirely justified given that the dataset was made up of a small number of low-quality photographs. Due to time restrictions, it was also not able to fully adjust the hyperparameters of any of these solutions. That is one of the obvious stages to take on a future project. Another option is to train a different classifier using the same ensemble architecture and seborrheic keratosis vs. all categorization.

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